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Monetary policy and Bitcoin ☆

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ABSTRACT

I empirically study the impact of monetary policy on Bitcoin, and show that is has evolved over time. First, based on high-frequency data, the paper documents that Bitcoin prices did not immediately respond to US monetary policy announcements in the past; they only started doing so in late 2020, in a manner similar to other risky asset prices. Second, based on a structural VAR analysis I study the impact of monetary policy over longer horizons. I confirm the contractionary impact of a US monetary tightening in the post-2020 time period, but show that, historically, a US tightening used to persistently increase rather than decrease Bitcoin prices. To explain this result, I exploit spreads in Bitcoin valuations across currencies and blockchain data and link increased Bitcoin demand to East Asian economies subject to capital controls, particularly China. I discuss implications for the discussion of where demand for Bitcoin stems from: its recent responses to monetary policy confirm its role as a primarily speculative asset; yet, at least historically Bitcoin seems to have derived part if its value from enabling cross-border value transfers and capital flight.

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

Cryptocurrencies were conceived more than ten years ago when Nakamoto (2008) conceptualized Bitcoin as an electronic form of cash. There are at least two aspects that distinguish Bitcoin from traditional currencies and means of electronically transferring value, both reflected in the quote above. First, its main innovation lies in establishing an essentially borderless peer-to-peer payment system that does not rely on incumbent financial institutions. Second, the rules governing its supply are willfully mechanical, which is sometimes argued to insulate Bitcoin from the supposedly inflationary policies of major

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

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central banks. As a consequence, by some, Bitcoin is seen as an explicit challenge to perceived shortcomings in the existing monetary and financial system.[2] By many others, however, Bitcoin is seen primarily as a speculative asset that holds little to no economic value.

Against the background of this discussion, this paper conducts a structural empirical analysis of the effects of monetary policy on Bitcoin. While there is a growing empirical literature on cryptocurrencies, this literature is mostly concerned with reduced-form analysis and has not studied the role of what Bitcoin was, according to some, designed to challenge, if not replace – the discretionary decisions of monetary policy makers. Not only is such a structural investigation important in light of Bitcoin's supposed role as a hedge against inflation. I argue that it can also provide insights into whether demand for Bitcoin is indeed driven by its ability to facilitate decentralized electronic value transfer – or merely due to speculative motives.

The analysis comprises two parts. First, using high-frequency price data in an event-study format, I document that the price of Bitcoin historically did not respond to monetary policy announcements in a systematic fashion, but has been doing so more recently. I show that realized volatilities of Bitcoin returns in narrow windows around FOMC (Federal Open Market Committee) announcements started to increase some time after the outbreak of the COVID-19 pandemic in late 2020. Since then, Bitcoin valuations respond to monetary news qualitatively similarly to those of other risky assets like stocks, foreign exchange and gold, but quantitatively even more strongly. I then ask whether the increased responsiveness to monetary news can plausibly be attributed to Bitcoin's alleged role as an inflation hedge. Using the event study approach for US CPI releases, I observe a similarly increased sensitivity of Bitcoin valuations to inflation news in the post-2020 high inflation environment. Yet, rather than benefiting from positive inflation surprises, Bitcoin returns again correlate highly with those of other risky assets – consistent with the notion that, also post-2020, Bitcoin is first and foremost perceived as a speculative asset rather than demanded as an inflation hedge.

In the second part of the paper I show that the absence of a systematic immediate response to monetary policy announcements for much of its history does not mean that monetary policy did not play any role for the demand for Bitcoin through other channels. Using daily data from mid-2013 until early 2023, I conduct a structural VAR analysis in order to study the impact of monetary policy shocks on the system more broadly and over longer horizons. To that end I employ external instrument techniques for the precise identification of structural monetary policy shocks. This is essential in order to properly isolate changes in short-term interest rates that are not a response to other shocks but only due to exogenous changes in monetary policy. The analysis reveals a striking pattern: in the post-2020 time sample, Bitcoin prices decline after a US monetary contraction and the effect persists over many months. Yet, prior to 2018 Bitcoin valuations used to persistently increase following a US tightening. Curiously, the picture is different for central bank information shocks – surprise increases in interest rates that are accompanied by rising stock market valuations (Jarocinski and Karadi, 2020): Bitcoin prices used to fall in response to Fed information shocks when stock prices were increasing.

In search for an explanation of these puzzling responses to US monetary policy, I then study its effects on international aspects of the Bitcoin ecosystem. 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 Korean won and, above all, in Chinese yuan increased especially strongly following a contractionary US monetary policy shock. In contrast, this was not the case for the currencies of advanced economies.

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 (Miranda-Agrippino and Rey, 2020; Obstfeld and Zhou, 2022), coupled with Bitcoin's alleged role in facilitating the circumvention of capital controls (Hu et al., 2021; Chen and Sarkar, 2022). The fact that Bitcoin is borderless and technologically largely independent from incumbent financial institutions made it suitable for capital flight when it was largely unregulated. In response to US monetary policy shocks, investors in emerging markets subject to capital controls resorted to Bitcoin due to its technological and institutional characteristics when pressure put on their currencies.

I corroborate this interpretation by exploiting the availability of detailed blockchain transaction data to test if investors indeed used Bitcoin's decentralized borderless payment system to transfer value abroad after a US monetary contraction. By constructing time series of Bitcoin flows and holdings from hundreds of millions of transactions, the analysis reveals that exchanges in China – the long-time dominant market before authorities banned Bitcoin trading in part due to fears of capital flight – experienced net inflows of coins in the aftermath of a US monetary tightening, both in absolute terms and directly from exchanges in advanced economies.

I conclude that these findings provide an indication that in the past there was demand for Bitcoin as an international digital cash, i.e. for its ability to transfer value across borders without relying on regulated financial institutions. In other words, it was the first value proposition of Bitcoin mentioned at the outset – borderless, decentralized value transfer – rather than the second – its mechanical supply scheme meant to work as an inflation hedge – that drove Bitcoin demand in response to US monetary policy shocks. Notwithstanding this international channel historically, more recently it seems to have been relegated to the background: the observation that especially post-2020 Bitcoin prices fall after a US monetary tightening, and do so even more strongly than traditional financial assets, plainly highlights that much of the demand for Bitcoin does stem, after all, from speculative motives. While it is beyond the scope of this paper to establish a causal link, the broadening of the

[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".

investor base after the COVID-19 outbreak (Auer et al., 2022a; Auer et al., 2022b) may well have contributed to the changed nature of this relationship.

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 US monetary policy shocks had qualitatively very different effects on Bitcoin prices than on those of traditional 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 whether demand for it stems from its unique features. Many of these studies are based on reduced-form analysis and find that cryptocurrency valuations have little if any relation to other financial assets (Liu and Tsyvinski, 2020; 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. I argue that this is essential as simply relating Bitcoin returns to changes in interest rates will generally fail to uncover the causal effects of monetary policy (see SECTION 3). Instead, I use macroeconometric techniques to estimate dynamic causal effects of monetary shocks. In terms of content, I draw a connection to one strand of the literature that links Bitcoin demand to the circumvention of capital controls. For instance, using exchange trading data, Chen and Sarkar (2022) show that Bitcoin price premia in China are associated with tighter capital controls.[4] Consistent with this role, I find that Bitcoin prices in Korean won and Chinese yuan appreciate particularly strongly following a US monetary contraction.

By linking Bitcoin demand to contractionary spillover effects of US monetary policy, the paper also relates to 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 general safe haven status of cryptocurrencies (Smales, 2019; Baur and Hoang, 2020), with the notable exception of Asian stock markets (Bouri et al., 2017b).[5]

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; Makarov and Schoar, 2021). In order to make this approach useful for the question at hand, I contribute by adapting this idea to an international context. Specifically, I compute time series estimates of blockchain transfers, identify Bitcoin exchanges and compute time series of Bitcoin flows between them according to which fiat currencies they support. The paper is then the first to use such time series, meant to proxy Bitcoin holdings in different currency areas, in a structural VAR analysis to study how they respond to monetary shocks. While less direct evidence of capital flight, my findings are broadly consistent with those in Hu et al. (2021) who employ blockchain data to identify uneconomical transactions. They estimate that around one quarter of trading volumes on Chinese Bitcoin exchanges prior to 2018 was uneconomical and hence likely linked to the circumvention of capital controls.

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. Jarocinski 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. Miranda-Agrippino and Nenova (2022) show that US monetary policy shocks have quantitatively larger spillover effects globally than those emanating from the euro area. Caporin et al. (2020) present a similar finding regarding the co-movement of global equity prices and credit default swaps. I show that also Bitcoin markets are affected differently by euro area and US monetary policy shocks, and that the latter relationship has evolved over time.

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; Jarocinski and Karadi, 2020). I show that this approach works well in daily (and weekly) instead of longer monthly time samples when using an instrument constructed via sign restrictions.

[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., 2020), 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).

[4] Relatedly, Graf von Luckner et al. (2021) link some of the demand for Bitcoin to its role in facilitating cross-border value transfer by studying off-chain data from an international P2P exchange platform.

[5] The role of Chinese economic conditions for cryptocurrency markets has been emphasized also by Elsayed et al. (2022). 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).

2. FOMC announcements and Bitcoin prices

2.1. Methodology and data

In the first part of the empirical analysis I study how Bitcoin (BTC) valuations respond to monetary announcements using high-frequency price data in an event study approach (see MacKinlay, 1997). Specifically, following the literature on the effects of monetary policy on financial markets (Gürkaynak et al., 2005; Altavilla et al., 2019), I focus on short time windows around policy announcements in which market price movements can plausibly be attributed to the monetary news.

To this end I construct minute-by-minute time series of prices of Bitcoin and other financial assets using data from Bitcoincharts.com and tickstory.com from January 2014 to February 2023.[6] I then compute Bitcoin returns in US dollars (USD) in the FOMC announcement window: the window begins 10 min prior to the press statement; in case there is no subsequent press conference, the window ends 20 min after the press statement, otherwise it ends 60 min after the start of the press conference.[7] Information on how other asset prices change during the window is partly taken from the database in Cieslak and Schrimpf (2019), which I extend manually to cover the period after 2017 using data from Refinitiv and tickstory.com.

I then conduct the analysis in three steps: First, in order to gauge whether monetary policy news are of any relevance for Bitcoin prices at all, I study realized volatilities of Bitcoin returns during the FOMC announcement window. Second, I assess the co-movement of Bitcoin returns with interest rates. Third, I do the same with other risky asset prices that make for an interesting comparison with Bitcoin, including stocks, exchange rates and gold. In all three cases I conduct regression analysis in the spirit of Gürkaynak et al. (2005), with a particular view on the variability of the effects over time.

2.2. The immediate response of Bitcoin prices to monetary policy news

BTC Price Volatility. It is well established that Bitcoin prices feature significantly higher levels of volatility than those of other financial assets (Yermack, 2015). If monetary policy announcements are indeed important for Bitcoin valuations and investors actively monitor policy news, one would expect return volatility to be elevated even more in tight windows around FOMC announcements.

In order to assess whether this is the case, I compute realized volatilities of Bitcoin returns at the minute-by-minute frequency in the FOMC announcement windows.[8] For days without FOMC announcements I compute realized volatilities in comparable time windows of equal length. I then run the following regression:

$$v_t = \beta_0 + \beta_1 \mathbb{I}_t + u_t, \tag{1}$$

in which v_t is the standard deviation of Bitcoin returns (expressed as daily values) and $\mathbb{I}_t$ is a dummy variable indicating an FOMC announcement. Hence, β_0 gives an estimate of the average volatility of Bitcoin returns, and β_1 measures to what extent this volatility differs during the FOMC announcement window.

Table 1 provides results. Focusing for the moment on the first column, results show that – over the entire sample – average Bitcoin returns of around than 3% per day are another 1.5 percentage points larger around US monetary policy announcements. This effect, however, is highly dependent on the time sample. To capture the time-dependency of the effect, I adapt the approach in Ferrari et al. (2021) and conduct rolling regressions, using windows of 1050 days, such that each window includes roughly 25 FOMC announcements. Fig. 1 shows results. Depicted is for each time window the estimated β_1 coefficient and the corresponding confidence bands. The figure indicates that for most of the sample under consideration Bitcoin return volatility was not elevated around monetary policy news, but it has been increasingly so since after the onset of the COVID-19 pandemic.[9] The estimated coefficient becomes statistically significant only in the time window that centers around mid-September 2020. This is roughly in line with the result of a formal statistical test for an unknown break date (see Perron, 2006) that identifies a break in early December 2020.

In accordance with these results, columns two and three in Table 1 estimate the effect when splitting the sample into two parts. Whereas average Bitcoin volatility is roughly comparable on non-FOMC days (as expressed by the estimated β_0 coefficients), the impact of monetary policy announcements (β_1) is almost zero and insignificant in the first part of the sample. In the second part, however, the effect is highly significant and much larger: Bitcoin returns vary almost twice as much during the FOMC window as on afternoons without monetary announcements.

To get a better sense of how the behavior of Bitcoin return volatility differs from that of more traditional risky assets, Fig. 2 compares Bitcoin to stock prices in the form of the S&P 500, the EUR-USD exchange rate and gold. For each asset, the figure reports to what extent realized volatilities of the respective asset's returns are elevated during the FOMC announcement window as a multiple of the average value of an equivalent time window on days without monetary policy announcements. A value of 1 (dashed line) therefore means that no difference is found. The grey bars on the left show values for the period until August 2020, the blue bars on the right for the period afterwards.

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6 Details are provided in APPENDIX A.

7 Ending the window 75 or 90 min, as sometimes also done in the literature, hardly affects results.

8 I remove one outlier on January 28, 2015.

9 To be sure, while the increased responsiveness roughly coincides with the period some time after the COVID-19 outbreak, more research would be needed to establish any direct causal impact of the pandemic itself.

Table 1
Bitcoin return volatility during the FOMC announcement window.

	Full	Before Sep. 2020	Since Sep. 2020
FOMC announcement dummy	0.0152***	0.000238	0.0540***
	(0.002)	(0.932)	(0.000)
Constant	0.0294***	0.0281***	0.0330***
	(0.000)	(0.000)	(0.000)
Observations	3313	2435	878
R^2	0.008	0.000	0.110

Note. Results for the FOMC announcement dummy regression in Eq. (1). Values refer to daily standard deviations based on minute-by-minute data. *, **, *** denotes significance at the 10%, 5%, 1% level, respectively, with *p*-values in parentheses, using robust standard errors.

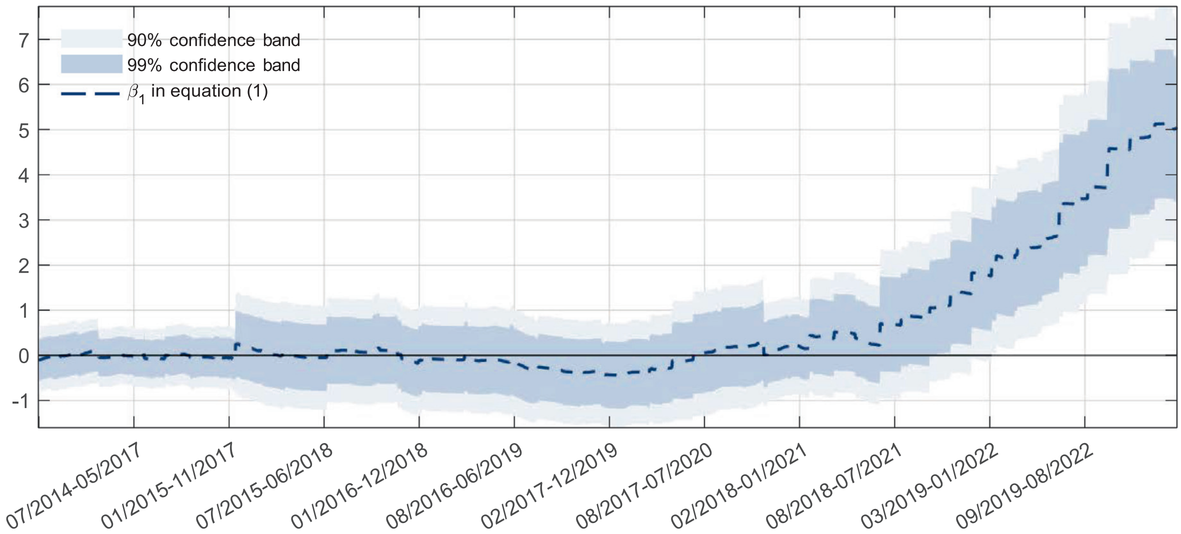

Fig. 1. TIME-VARYING IMPACT OF FOMC ANNOUNCEMENTS ON BTC RETURN VOLATILITY. *Note.* β_1 coefficients in rolling regressions in Eq. (1) for FOMC announcements with a rolling window of 1050 days (25 6-week periods). Values refer to daily standard deviations based on minute-by-minute data. Shaded areas denote 90 and 99% confidence bands.

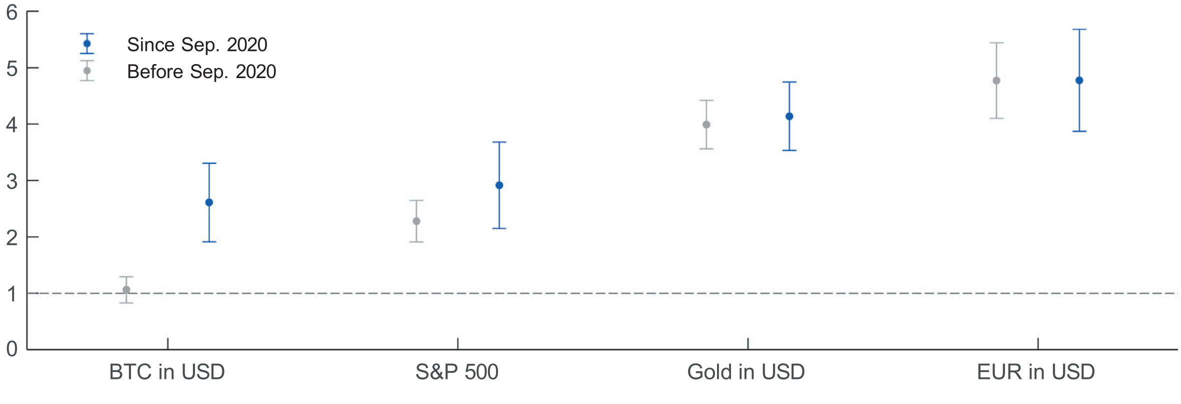

Fig. 2. RELATIVE INCREASE OF RETURN VOLATILITIES AROUND FOMC ANNOUNCEMENTS. *Note.* Mean standard deviation of returns in FOMC window relative to equivalent time window on days without FOMC announcements. For instance, a value of 2 means that Bitcoin returns are twice as volatile around FOMC news as normal. Time sample Jan. 2014 to Aug. 2020 (grey left) and Sep. 2020 to Feb. 2023 (blue right). Bars indicate 95% confidence bands.

Two results stand out: First, the increase in Bitcoin return volatilities around FOMC announcements in the second part of the sample is unusual in that there is no significant difference for the other depicted risky assets. Second, while Bitcoin return volatility is significantly elevated in the second part, the increase is still smaller than that for the traditional risky assets, perhaps with the exception of the S&P 500. To the extent that the increase in volatilities can be thought of as a measure of the importance that market participants attach to US monetary policy, also in the second part of the sample monetary policy news is still somewhat less important for Bitcoin investors than for those of traditional assets.

Co-movement With Interest Rates. The findings so far raise the natural question as to the direction of Bitcoin price responses to monetary news. Standard asset pricing considerations would predict that an increase in interest rates is associated with a decline in the value of non-interest bearing assets such as Bitcoin. To assess whether this is the case, I run the following regression in the style of Gürkaynak et al. (2005):

$$\Delta x_t^{BTC} = \beta_0 + \beta_1 \Delta x_t^i + u_t, \tag{2}$$

in which Δx_t^{BTC} is the percentage change of the price of Bitcoin during the FOMC window and Δx_t^i is the change in two-year US government bond yields in the same window, measured in basis points.[10]

Table 2 reports regression results again for the entire sample and the two sub-samples detected above. In line with the results concerning realized volatilities, the co-movement with interest rates is insignificant in the first part but becomes highly statistically significant in the second subsample: there, an increase in two-year rates by 10 basis points leads to a decline in Bitcoin prices of about 2.4%.

Co-movement With Other Risky Assets. It is well understood that not neessarily the mere direction of interest rate changes determines the response of financial markets to monetary policy news. Instead, central banks regularly also signal their assessment of the state of the economy and can influence market participants' risk perceptions (Cieslak and Schrimpf, 2019; Jarocinski and Karadi, 2020) – something that will be studied in more detail in SECTION 3. It will therefore prove useful to also assess to what extent the response of Bitcoin returns in the monetary policy announcement windows correlates with that of other risky financial assets. This might be especially important shortly after the outbreak of the COVID-19 pandemic when short-term interest rates where quickly reduced to zero but the FOMC's assessment of the macroeconomic outlook continued to impact markets.

I therefore run the regressions in Eq. (2) also with returns of other risky assets as covariates, i.e. with $i \in \{\text{S\&P 500}, \text{EUR in USD}, \text{Gold in USD}\}$, with Δx_t^i measured in percent.[11] Fig. 3 depicts the β_1 coefficients in rolling regressions, again with windows of 25 FOMC announcements. The overall picture is similar to before: the relationship is economically and statistically significant only in the later part of the sample. A small gradual increase is visible even earlier than in Fig. 1 when looking at the EUR-USD exchange rate and the price of gold. Table 3 reports regression results when again splitting the sample into two. The size of the effects in the later part is substantial for stocks and gold (Bitcoin returns respond roughly 1.5 to 2.5 as much) and even larger for the exchange rate (four times as much). When including all three variables in the regression at once (column 8), only the co-movement with stock returns is statistically significant. Also, the R^2 of this regression is only marginally larger than in the regression with only S&P 500 returns (column 5). Both of these findings indicate that, at least when it comes to the response to monetary policy surprises, the behavior of Bitcoin is closer to stocks than it is to gold or a fiat currency.

2.3. Exploring implications – Bitcoin as an inflation hedge?

The results so far show that historically it was not the case that Bitcoin investors responded immediately to US monetary policy news in a systematic fashion. However, this has changed some time after 2020 when Bitcoin returns became increasingly responsive.

One interpretation of the increased sensitivity could have to do with Bitcoin's supposed role as a hedge against inflation.[12] Indeed, the post-2020 environment has featured much higher rates of inflation in the US and globally than were ever present since Bitcoin's inception. To the extent that, say, any surprising monetary tightening by the Fed is expected to be disinflationary, demand for Bitcoin as an inflation hedge would fall alongside that for other risky assets. One would then observe qualitatively similar responses to monetary surprises, but for different reasons.

I test this hypothesis in two ways, mirroring the analysis so far. First, if investors were more attentive to inflation in such a high-inflation environment and only then turn to Bitcoin as an inflation hedge, one would observe an increased responsiveness of Bitcoin returns not only to monetary policy news but also to the publication of inflation data. Fig. 4 repeats the rolling regression analysis of Eq. (1) for inflation releases and shows that this is indeed the case: historically Bitcoin returns were not unusually volatile around the release of inflation figures – 10 min prior to 20 min after the release. In contrast, more recently they are, although the increased responsiveness is visible only somewhat later compared to Fig. 1.

Second, whereas under the inflation hedge hypothesis the co-movement of Bitcoin and other risky assets around monetary policy announcements might be high, one would expect a different response to inflation surprises. For instance, demand for Bitcoin should increase following higher than expected inflation data, whereas e.g. the US dollar should fall in value rel-

[10] I choose two-year rates for reasons of data availability and as these are sufficiently short-term so as to respond to conventional monetary policy but also capture effects of forward guidance, which has increasingly been relied on as a policy tool during the time sample under investigation.

[11] I drop the following two outliers: January 27, 2021 when Bitcoin prices started to substantially rise shortly before the FOMC press statement; December 19, 2018 when Bitcoin fell at the end of the FOMC window but showed no response at the beginning when the S&P 500 fell sharply. What is more, no data is available for the FOMC meeting on March 15, 2020, which fell on a Sunday, and there is a missing value for the S&P 500 on January 29, 2014.

[12] See the quote by Nakamoto at the beginning of the article. In line with this notion, Halaburda et al. (2022, p.53) write that "[e]nthusiastic supporters of cryptocurrencies often argue that Bitcoin will replace gold as the hedge against inflation". Large institutions within the Bitcoin ecosystem often advertise Bitcoin similarly. For instance, Bitstamp, once one of the largest exchanges in the world, twittered in October 2020 that "[a]s central banks continue to print money to keep economies afloat, #Bitcoin remains defiantly set on its pre-programmed course", see https://twitter.com/Bitstamp/status/1313464080926216192.

Table 2
Co-movement of bitcoin returns with interest rate changes during FOMC announcement window.

	Full	Before Sep. 2020	Since Sep. 2020
2-year US gov. bond yield	−0.0981***	−0.00363	−0.243***
	(0.007)	(0.657)	(0.001)
Constant	0.279*	−0.0580	1.232***
	(0.093)	(0.528)	(0.008)
Observations	72	52	20
R^2	0.134	0.001	0.467

Note. Results for the FOMC announcement window regression in Eq. (2). Interest rate changes are measured in basis points. *, **, *** denotes significance at the 10%, 5%, 1% level, respectively, with p-values in parentheses, using robust standard errors.

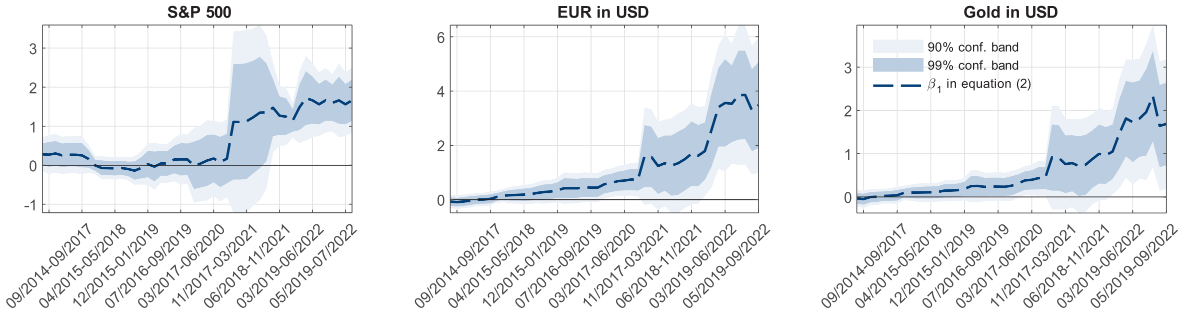

Fig. 3. TIME-VARYING CO-MOVEMENT OF BITCOIN RETURNS DURING FOMC ANNOUNCEMENT WINDOW. *Note.* β_1 coefficients in rolling regressions (Eq. (2)) with a window of 25 FOMC announcements. Shaded areas denote 90 and 99 % confidence bands computed with robust standard errors.

Table 3
Co-movement of bitcoin with other asset returns during FOMC announcement window.

	Before Sep. 2020				Since Sep. 2020			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
S&P 500	0.243*			0.221	1.621***			1.171***
	(0.093)			(0.387)	(0.000)			(0.010)
EUR		0.152		−0.153		4.024***		0.579
		(0.138)		(0.677)		(0.001)		(0.814)
Gold			0.120	0.140			2.575***	0.669
			(0.109)	(0.491)			(0.001)	(0.645)
Constant	−0.0452	−0.00894	−0.0212	−0.0557	0.766**	0.617	0.384	0.598*
	(0.596)	(0.914)	(0.797)	(0.585)	(0.014)	(0.127)	(0.375)	(0.073)
Observations	50	51	51	50	19	19	19	19
R^2	0.039	0.019	0.024	0.045	0.680	0.590	0.540	0.716

Note. The table reports results for the FOMC announcement window regression in Eq. (2) with $i \in \{\text{S\&P 500}, \text{EUR in USD}, \text{Gold in USD}\}$. *, **, *** denotes significance at the 10%, 5%, 1% level, respectively, with p-values in parentheses, using robust standard errors.

ative to the euro. Fig. 5 repeats the analysis in Fig. 3 for inflation releases and shows that this is not the case: In the post-2020 part of the sample, the correlation of Bitcoin returns with that of other assets is essentially identical to that around the monetary policy surprises.

This result suggests that what investors respond to during this period is not primarily surprises in inflation rates themselves. Instead, market participants discern from positive inflation surprises that future rate hikes by the Fed are more likely – that then depress the values of all depicted assets. The fact that an immediate market response to monetary policy-related news is present in the data only in the post-2020 period is then not a consequence of a high inflation regime *per se*,but more likely of the steep global monetary tightening cycle, perhaps coupled with a substantial broadening of the investor base in the post-pandemic era, particularly in the US.[13] It is beyond the scope of this paper to investigate the changed investor composition in any detail. Yet the findings here do speak to – and do not sit well with – the hypothesis that demand for Bitcoin stems from its supposed role as a hedge against inflation in the post-2020 period. They add weight to the notion that, instead, Bitcoin continues to be first and foremost a speculative asset. As it does not bear interest, market participants respond to news of a tighter than expected Fed policy by selling Bitcoin alongside other risky assets.

[13] *Indeed, much has been made about institutional and retail investors entering the market alongside the boom in Bitcoin market valuations in 2021 (Auer et al., 2022a; Auer et al., 2022b). To the extent that this development comes with professional investors more systematically tracking and responding to macroeconomic news, one would expect an increased responsiveness of Bitcoin valuations to monetary policy announcements.*

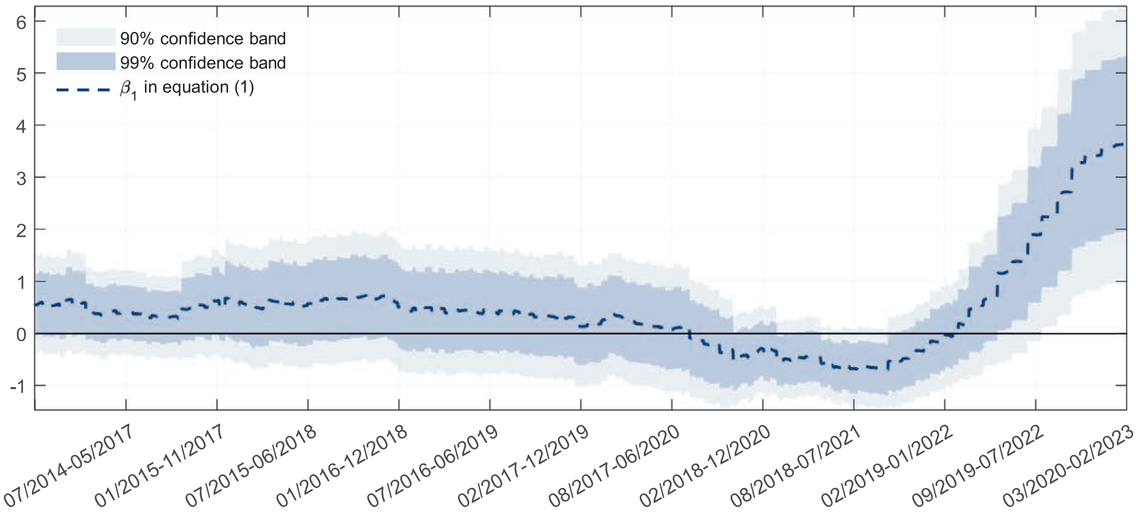

Fig. 4. TIME-VARYING IMPACT OF US CPI RELEASES ON BTC RETURN VOLATILITY. *Note.* The figure depicts the β_1 coefficients in rolling regressions in Eq. (1) for US CPI releases with a rolling window of 1050 days (25 6-week periods). Values refer to daily standard deviations based on minute-by-minute data. Shaded areas denote 90 and 99% confidence bands.

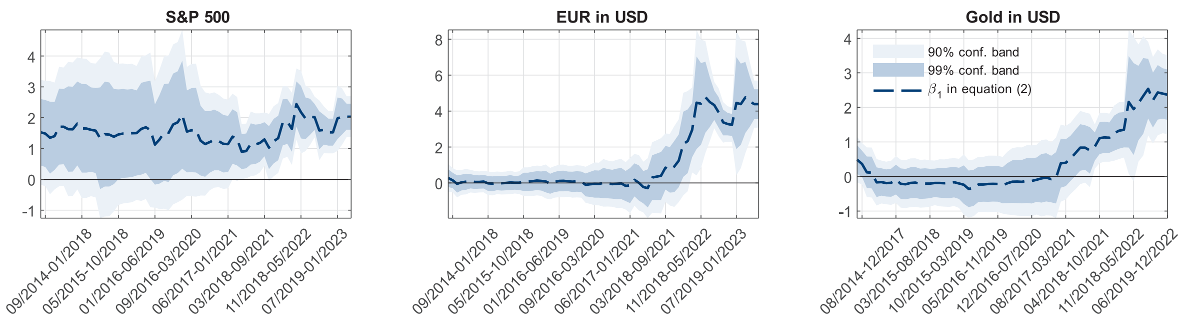

Fig. 5. TIME-VARYING CO-MOVEMENT OF BITCOIN RETURNS AROUND US CPI RELEASES. *Note.* β_1 coefficients in rolling regressions (Eq. (2)) with a window of 40 CPI releases. Shaded areas denote 90 and 99% confidence bands computed with robust standard errors.

Irrespective of the reasons for the increased sensitivity of Bitcoin prices to monetary news: does the absence of a systematic response in the pre-2020 era imply that monetary policy used to have no effect on Bitcoin valuations? This is not necessarily the case: any mechanism through which monetary policy affects the demand for Bitcoin that operates over extended periods of time would not be captured by an event study approach. For this reason, the second part of the empirical analysis features a structural VAR model that identifies the impact of structural monetary policy shocks on Bitcoin over longer horizons.

3. Monetary policy shocks and Bitcoin

In order to study the impact of monetary policy shocks on Bitcoin over longer horizons, this part of the paper features an empirical analysis based on various versions of a structural VAR model in daily frequency. In the following I first describe the model setup and data, with a focus on shock identification using an instrumental variable approach. I then present the main results as dynamic impulse responses to monetary policy shocks in SECTION 3.2. Finally, SECTION 3.3 explores international aspects and puts the results into context.

3.1. Model and data

Shock Identification. In macroeconomics, VAR models are often employed to account for potential endogeneity stemming from the fact that monetary policy makers will generally respond to what is under study, i.e. macroeconomic or financial market developments. Although this is unlikely in the case of Bitcoin, the identification of structural monetary policy shocks is still essential for the question at hand. For instance, an increase in interest rates might primarily be the result of stronger economic activity or a decrease in investor risk perceptions. Simply relating changes in interest rates to Bitcoin valuations will then not be informative of the effects of monetary policy. In order to instead identify the actual causal effects of monetary policy, the recent macroeconometric literature increasingly relies on instrumental variable techniques that isolate exogenous changes in policy. Here, I adapt this approach to a financial market model in daily frequency as follows (see APPENDIX B for further details).

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 such an instrument Z_t to be valid, it needs to be *relevant* and *exogenous* as follows:

$$\mathbb{E}\left[Z_t \epsilon_t^{p\prime}\right] = \phi \neq 0, \tag{3}$$

$$\mathbb{E}\left[Z_t \epsilon_t^{q\prime}\right] = \mathbf{0}, \tag{4}$$

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

Most 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). As argued in SECTION 2, 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 (3). 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; Jarocinski and Karadi, 2020; Kerssenfischer, 2022; 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 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 (4) is likely to be violated. Against this background, I do not simply use high-frequency responses of interest rates as instruments Z_t, but adopt the following strategy, reminiscent of the one used in Jarocinski and Karadi (2020) and Kerssenfischer (2022). 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 Z_t. As laid out in Table 4, 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.

Data. To compute the instrument series Z_t I rely on the same databases as in SECTION 2, i.e. Cieslak and Schrimpf (2019) extended with high-frequency data from tickstory.com and Refinitiv.[14] 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 again consider responses in time windows that include central bank press conferences.

As endogenous model variables I consider a multitude of time series. Table 5 provides an overview of the model variants. The main time series of interest is the price of Bitcoin in USD, which is obtained in daily frequency from coinmetrics.io.[15] As interest rates I use 2-year government bond yields. As in SECTION 2 this choice reflects that 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. I include stock market indices as well as the EUR-USD exchange rate and the price of gold in US dollars. Further, all VAR model variants contain as a measure of implied stock market volatility the VIX index that is frequently used to capture global uncertainty and investor risk appetite.

In model (2), I include 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 $(P^{i/\text{₿}}/P^{i/\$})/P^{\$/\text{₿}}$, where $P^{j/i}$ is the price of currency i expressed in currency j. Finally, model (3) contains measures of international Bitcoin flows and holdings that will be outlined in SECTION 3.3 below. Further details on the data are provided in APPENDIX A.

3.2. The dynamic response of Bitcoin prices to monetary policy shocks

I report results 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 daily frequency with 20 lags, corresponding to roughly one month (taking into account weekends).[16]

[14] For ECB announcements, I rely on the monetary event study database by Altavilla et al. (2019), available at https://www.ecb.europa.eu/pub/pdf/annex/Dataset_EA-MPD.xlsx.

[15] I verify that results are robust to using data from coinmarketcap.com, bitcoinity.org and computing daily Bitcoin prices from scratch using the high-frequency data employed in SECTION 2.

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

Table 4
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.

Table 5
VAR model specifications.

Variable	Source	(1)	(2)	(3)
2-year interest rates	Bloomberg	•	•	•
VIX	Bloomberg	•	•	•
S&P 500	Bloomberg	•	•	•
Euro-US-dollar exchange rate	Refinitiv	•	•	•
BTC in USD	coinmetrics.io	•	•	•
Gold in USD	Bloomberg	•		
BTC-fiat spreads w.r.t. USD	bitcoinity.org, Refinitiv, AC		•	
BTC holdings at CNY/KRW exchanges	Bitcoin blockchain, AC			•
BTC holdings at AE exchanges	Bitcoin blockchain, AC			•
Inter-exchange flows	Bitcoin blockchain, AC			•
Figures		6, 7	8	11

Note. The table lists the variables included in each proxy VAR model, alongside their sources. *AC* denotes author's calculations, *CNY* stands Chinese yuan, *KRW* for Korean won, *AE* for advanced economies.

I begin the time sample in June 2013 for reasons of data availability and aspects related to the maturity of the ecosystem,[17] and most data is available until February 2023.

Wary of the potential time-varying relationship of monetary policy of Bitcoin given the results in SECTION 2, I split the time sample into three sub-samples based on the following considerations. First, the high-frequency analysis suggests a structural break in the fall of 2020, which therefore constitutes the start of the last time sample. Second, Bitcoin experienced a massive increase in both market valuations and public interest in the winter of 2017/18.[18] It has been suggested that this boom period marks an earlier structural break in Bitcoin's history, also due to the fact that futures trading of Bitcoin became available for the first time (Hale et al., 2018). As will become apparent below, ending the first time sample in late 2017 has the added advantage that it aligns with the end of Chinese dominance in Bitcoin trading that will be relevant below.

Model (1): Monetary Policy Shocks and Bitcoin Prices. Fig. 6 shows responses to a contractionary US monetary policy shock in the baseline model. Each row depicts results for the three time samples. As the figure makes clear, shock identification in the daily setting works well in that it delivers plausible impulse responses that are in line with both standard theory and findings in the literature.[19] In all time samples, the responses of traditional financial market variables are qualitatively essentially identical: following the monetary shock, implied stock market volatility rises whereas risky asset prices in the form of the S&P 500 fall, as does the price of foreign currency (here the euro) and gold.

In striking contrast, however, the response of Bitcoin prices differs significantly over time. As expected from the analysis in SECTION 2, in the post-2020 sample (bottom row) Bitcoin valuations persistently fall, in line with other asset prices, with an on-impact decline of 3%. In the pre-2018 time sample (top row), however, Bitcoin prices persistently *increase* by 5% following the contractionary monetary policy shock. In line with the interpretation that the relationship of Bitcoin to monetary policy shocks has evolved over time, the intermediate time period (middle row) does not feature a clear-cut response with valuations first moderately increasing and then falling.[20]

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 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 surprising results found for monetary policy shocks in the pre-2018 time sample.[21] Fig. 7 shows impulse

[17] 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. Also, Urquhart (2016) finds that Bitcoin prices fail tests of market efficiency before mid-2013 but not afterwards.
[18] For instance, Google search volumes for the term "Bitcoin" reached an all-time high in the winter of 2017/18.
[19] F statistics of instrument relevance for the monetary policy shocks lie between 24 and 75 depending on the time sample, indicating sufficient instrument strength (> 10).
[20] For the sake of completeness, Fig. C.4 shows responses when estimating model (1) over the entire available data sample (June 2013 to February 2023). Bitcoin prices tend to decline gradually after the US monetary policy shock, but not statistically significantly so.

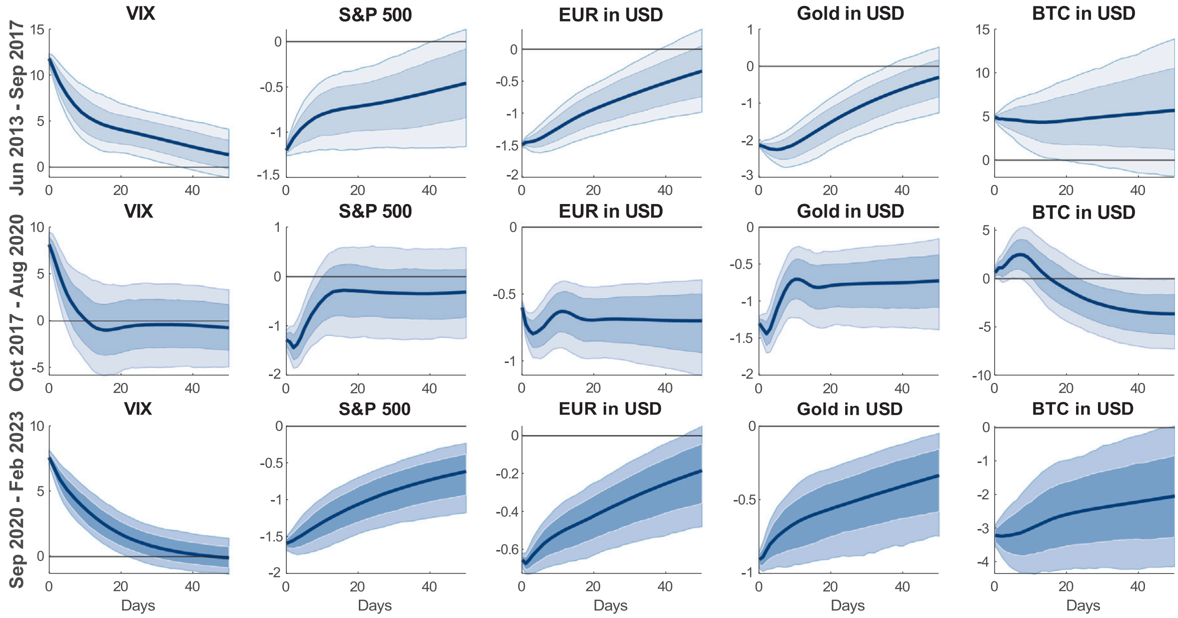

Fig. 6. IMPULSE RESPONSES TO CONTRACTIONARY US MONETARY POLICY SHOCK OVER TIME.*Note.* Impulse responses to a contractionary and US monetary policy shock that increases interest rates by 10 basis points (model (1) in Table 5), identified as explained in Section 3.1. Values in percent. Shaded areas denote 68% and 90% confidence bands.

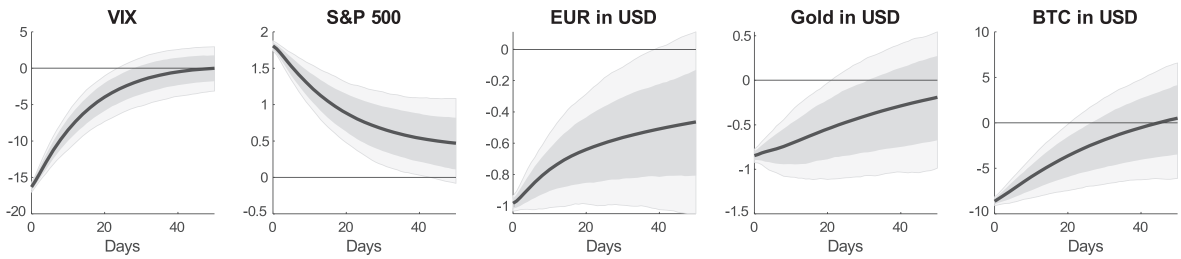

Fig. 7. IRFS TO US CENTRAL BANK INFORMATION SHOCK (PRE-2018). *Note.* Impulse responses to an expansionary US central bank information shock that increases interest rates by 10 basis points (model (1) in Table 5), identified as explained in Section 3.1. Values in percent. Time sample: June 2013 to September 2017. Shaded areas denote 68% and 90% confidence bands.

responses to a central bank information shock, identified as explained in Table 4, in the pre-2018 time sample.[22] Just as the monetary policy shock, the information shock increases interest rates by 10 basis points, but this increase is associated with an expansionary impact: stock market volatility falls, whereas stock prices increase following the rate hike. The price of foreign currency falls and the response of the euro-US-dollar exchange rate seems almost entirely driven by the mechanical increase in the interest differential rather than the economic forces of the underlying shock.[23] The price of gold falls moderately as well, as the rate hike increases opportunity costs of holding the non-interest bearing asset.

Most importantly, the response of Bitcoin prices differs from that to a monetary policy shock: the expansionary rate hike leads to a persistent fall in Bitcoin valuations of around 8% on impact. Therefore, it does not seem to be the case that Bitcoin prices are merely driven by changes in interest rates. Instead, the analysis points to a different pattern: in its early history, Bitcoin valuations benefited from conditions that lower risky asset prices, irrespectively if these are caused by rising interest rates (following a monetary policy shock) or associated with falling rates (following a central bank information shock). This finding again underscores the importance of properly identifying exogenous structural shocks and not merely relating changes in short-term interest rates to the variables under study.

[22] F statistics are lower compared to the monetary policy shock but remain around 30 in the pre-2018 sample. In the other two samples, however, they drop substantially below 10, invalidating inference.

[23] See Franz (2020) and Gürkaynak et al. (2021) for an in-depth analysis of central bank information shocks on exchange rates.

What might explain these results? While it can by no means be excluded that a standard asset pricing mechanism – a non-interest bearing asset falling in value when interest rates rise – also plays a role in the early sample, at the very least there needs to be an additional channel at work that dominates the former and predicts an opposite effect. In the following I analyze the response of international aspects of the Bitcoin ecosystem in order to explore potential explanations for the peculiar result. Before doing so, however, I briefly outline some robustness checks for, and extensions of, the main results.

Robustness and Extensions. I make sure that the main results in the VAR analysis are robust along a number of dimensions. In particular, they hold when varying the time sample to exclude certain Bitcoin-specific periods that are otherwise difficult to control for. For instance, results for the first time sample look similar when starting the time series in March 2014 such that the February collapse of Mt.Gox, the largest and most important exchange in Bitcoin's early history, is not part of the sample. The same is true when ending the sample already before the Bitcoin gold hard fork in August 2017. Price responses remain significantly positive when extending the first sample to shortly before the outbreak of COVID-19 or to the fall of 2020, the breakpoint suggested by the high-frequency analysis in SECTION 2.

Results also hold when changing the number of lags in the VAR, when the logged price of Bitcoin enters in first differences, or when using 1- instead of 2-year interest rates. In addition, an earlier version of the paper featured the VAR model in weekly frequency with very similar results. Notably, it also included responses of aggregate blockchain activity to US shocks, which offers another way to capture Bitcoin-specific developments (but did not offer a compelling explanation for the price responses).

In addition to robustness considerations, APPENDIX C.2 provides some further interesting results. First, based on local projections I show that the effects of a tightening of US monetary policy has stronger effects on Bitcoin valuations in the pre-2018 time sample than an equivalent easing of monetary policy (Fig. C.5). Second, I repeat the VAR analysis for euro area monetary policy shocks. In contrast to their US counterparts, there is no qualitative difference in the response of Bitcoin prices over time (Fig. C.3): no matter the time sample under considerations, Bitcoin prices fall after the contractionary shock. Results for euro area therefore are more in line with expectations, adding to the need for an explanation for the US results in the earlier time periods.

3.3. Exploring implications – Bitcoin as international digital cash?

To recap, the analysis in SECTION 3.2 showed that Bitcoin prices fall after a monetary contraction in the more recent time period. Historically, however, they used to increase. What is more, Bitcoin valuations did not simply react to exogenous changes in interest rates *per se*: they responded very differently to monetary policy shocks on the one hand and central bank information shocks on the other. 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. In the following, I study international aspects that might help make sense of the peculiar results.

Model (2): 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, cryptocurrencies 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) point to transaction costs and price risk.[24] 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 increase in the price of Bitcoin following the shock is uniform across currency areas.

Fig. 8 reports impulse responses to the spreads computed for four different fiat currencies. The first two panels show that spreads with respect to advanced economy fiat currencies – here the euro (EUR) and the British pound (GBP) – fall in response to the shock but only briefly. Contrast that with the other two panels which consider fiat currencies of two Asian economies in which Bitcoin had many early adopters: the Korean won (KRW) and the Chinese yuan (CNY). The KRW spread increases after a few days and stays persistently elevated and the CNY spread rises on impact and remains high for many weeks.

In other words, while historically Bitcoin prices in USD used to increase following a US monetary tightening, they increased especially strongly in South Korea and China. In contrast, the rise in value is equally pronounced (and for a short time period even weaker) when measured in euro and pound sterling. Importantly, the increase in spreads in the East Asian 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 tended to be more expensive in KRW and CNY than in USD, and significant deviations from unity are almost exclusively positive.[25] Accordingly, if arbitrage forces indeed were to become weaker after a US monetary tightening – and increased demand for Bitcoin primarily stemmed from advanced economies instead of from Korea and China –, one would expect the spreads to mechan-

[24] Chen et al. (2022) link the spreads to uncertainty during the COVID-19 lockdown period.

[25] See Makarov and Schoar (2020). One exception is a brief period for the CNY spread during which it dropped below unity in mid-2017. However, the result of an increase in the CNY spread after the US shock continues to hold when excluding this episode.

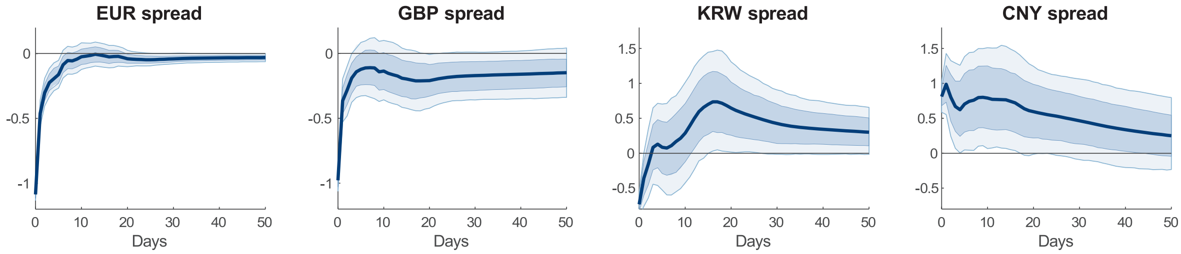

Fig. 8. IRFS TO CONTRACTIONARY US MONETARY POLICY SHOCK: 'ARBITRAGE SPREADS' ACROSS FIAT CURRENCIES. *Note.* Impulse responses to a contractionary US monetary policy shock that increases interest rates by 10 basis points (model (2) in Table 5), identified as explained in SECTION 3.1. Values in percentage points. Time sample: June 2013 to August 2020 (September 2017 for CNY). Shaded areas denote 68% and 90% confidence bands.

ically 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 the two East Asian economies than in the US or Europe.

Conceptualizing an International Channel. Why would Bitcoin experience increased demand in East Asia following a US monetary contraction? A growing literature finds that US monetary policy drives a large part of global capital flows and asset prices (Rey (2015): Miranda-Agrippino and Rey, 2020; Obstfeld and Zhou, 2022). Hofmann and Park (2020) show that a USD appreciation is associated with lower growth prospects in emerging markets. Degasperi et al. (2020) find that detrimental effects of a US monetary contraction are roughly twice as large for the median emerging market economy compared to advanced economies. Relatedly, Kalemli-Özcan (2019) argues that emerging markets are most vulnerable to changes in global investors' risk perceptions that are driven by US monetary policy. Often-cited reasons for large international ramifications of US policy lie in the role of the US dollar in cross-border trade and finance, particularly in Latin America and East Asia (Iancu et al., 2020).

At the same time, both South Korea and China during the time sample under study featured various forms of restrictive capital controls.[26] Yet, as outlined, one defining feature of Bitcoin is that it is inherently borderless due to its institutional and technological particularities. Payments can be made globally with the help of just an internet connection and users are pseudonymous and not easily differentiated according to geographic location. Further, when cryptocurrency markets were largely unregulated, their legal status was ambiguous and hence they were not covered by laws and regulations intended to control the flow of capital (He et al., 2022). These features may have helped users avoid the vetting of transactions by authorities or circumvent limits to cross-border value transfers altogether (Lee and Low, 2018). Indeed, there is anecdotal evidence of Chinese savers using Bitcoin to transfer wealth overseas (Cointelegraph, 2016) and 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 September 2017 (New York Times, 2017). Estimates in Hu et al. (2021) provide an indication of the scale of the phenomenon: they find that a quarter of all Bitcoin trading in China prior to 2018 was associated with Chinese capital flight of approximately $4.6 billion in total.

In other words, particularly when their economies are hit by a US monetary contraction and their own currencies depreciate against the USD, for market participants subject to capital controls Bitcoin may well have been one of the few assets a flight into was possible at all. For them, Bitcoin's value proposition would then not lie in the feature often stressed when it comes to its value, namely its scarcity due to its mechanically increasing finite supply. Instead, it lies 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. Notably, such a mechanism does not only make sense of the peculiar effects of US monetary policy on Bitcoin prices but also of the very different impact of expansionary Fed information shocks,[27] and ECB monetary policy shocks.[28]

Model (3): Testing the International Channel – Bitcoin Flows into China. If Bitcoin indeed used to gain in value after a US monetary policy tightening via the outlined international channel, one would expect coins to systematically flow towards emerging markets in the aftermath of a contractionary shock. In this section I test this prediction more directly by exploiting the availability of blockchain data that I use to estimate cross-border capital flows in Bitcoin.

[26] Korea tightened capital controls in 2010 and limits the amount of money send abroad to $3,000 per transaction and $50,000 per year per person, which is often argued to contribute to the large deviations of Bitcoin prices in KRW, infamously known as the *Kimchi premium* (Choi et al., 2020). Similarly, China tightened controls, allowing Chinese residents to exchange not more than $100,000 per year into foreign currency before 2017, which was then reduced to $50,000. Further, Chinese banks have to report sizable transactions to authorities and scrutiny is reported to have increased during the time sample under consideration. See Appendix A in Chen and Sarkar (2022) for further details.

[27] Ahmed et al. (2021) show theoretically that increases in US interest rates are not necessarilycontractionary and indeed can even have a stimulative effect on emerging markets, reiterating the empirical analysis in Hoek et al. (2020). Camara (2021) shows that Fed information shocks that increase US interest rates can strengthen rather than weaken emerging market currencies. Indeed, Pinchetti and Szczepaniak (2021) show that Fed information shocks trigger changes in global risk appetite. After a surprise rate cut by the Fed that is signaling an unexpectedly negative growth outlook, emerging markets experience capital outflows and their currencies depreciate.

[28] Euro area monetary policy is generally not found to have as pronounced international ramifications as US policy (Caporin et al., 2020; Miranda-Agrippino and Nenova, 2022), in particular in East Asia where the euro is hardly used for trade invoicing or debt markets.

Based on the results in Fig. 8, I focus on South Korea and China where one would expect the mechanism to show up most clearly.[29] What is more, especially the Chinese market used to be of great importance for Bitcoin for quite some time. Fig. 9 depicts the shares of Bitcoin trading volume by fiat currency that Bitcoin is exchanged against, with one clear finding emerging that CNY was by far the most dominant currency from 2014–17.[30] Afterwards, Bitcoin trading in China was first hampered by regulatory means and then essentially banned in September 2017 (Kaiser et al., 2018). Third, limiting attention to the period until late 2017 has advantages when computing measures of cross-border Bitcoin flows from blockchain data, as described below.

Time series of Bitcoin flows between, and Bitcoin holdings in, different geographical regions are not readily available such that I compute estimates from scratch using blockchain data containing hundreds of millions of transactions. In order to make this data useful for the analysis, there 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. 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.

As it is generally difficult to precisely assign addresses to users in certain geographical locations with accuracy, I focus on the largest and most important entities in the ecosystem: the exchanges. This is useful for several reasons. First, exchanges are not mere trading platforms but store large amounts of customer funds (Makarov and Schoar, 2021). Tracking the holdings of large exchanges then allows to assign large amounts of coins to particular fiat currencies that the coins can be exchanged into. Second, and relatedly, a substantial share of transaction activity within the blockchain involves exchanges. To see that, consider Fig. 10, which depicts aggregated blockchain trading relations among the most active entities in the Bitcoin ecosystem. All edges in blue denote transactions where one party is 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 transfers among exchanges are commonplace. Third, whereas many exchanges today often offer trading against dozens of fiat (and other crypto-) currencies, in the earlier years of the ecosystem exchanges could generally be classified according to which geographical market they served by the few fiat currencies – often only one – they offered. Differences in Bitcoin valuations across fiat currencies could then directly be attributed to supply and demand conditions at identifiable large exchanges. This is the case particularly for Chinese exchanges that are the focus of the analysis, in that their trading of Bitcoin was mostly limited to CNY.[31]

I therefore categorize dozens of identified exchanges in two sets of groups. Namely, I classify them according to whether they either allow trading of Bitcoin against CNY and/or KRW, or only against currencies of advanced economies. Table A.1 in Appendix A gives details on which (fiat) currencies could be traded at the exchanges covered. I then compute two sets of time series. First, *inter-exchange flows* (corresponding to the red edges in Fig. 10), 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 that the value transferred across borders, as measured in US dollar terms, was fairly small in the period under study.[32] 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.

In the final empirical specification, I include the estimated Bitcoin flows and holdings into the VAR estimated until the Chinese regulatory crackdown in September 2017.[33] Fig. 11 reports impulse responses. The first panel shows that holdings of coins at Chinese and Korean exchanges tend to increase following the US monetary shock. In contrast, there is a fall in Bitcoin holdings at exchanges that exclusively allow trading against fiat currencies of highly-developed countries (second panel). These findings imply a redistribution of Bitcoin holdings across currency areas after the US monetary tightening. Finally, the third

[29] Results, however, are very similar when instead conducting the analysis instead for emerging market exchanges generally, as in an earlier version of the paper.

[30] A similarfigure appears in Auer et al. (2022b, p.13), that covers a few more fiat currencies but essentially the same pattern emerges with respect to early CNY dominance.

[31] According to data from bitcoinity.org, the important exchange OKCoin also used to offer USD trading, but trading volumes were insignificant relative to CNY.

[32] 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 transactions that actually occur between different geographical locations.

[33] Results are robust to ending the sample already before earlier regulatory measures in February 2017.

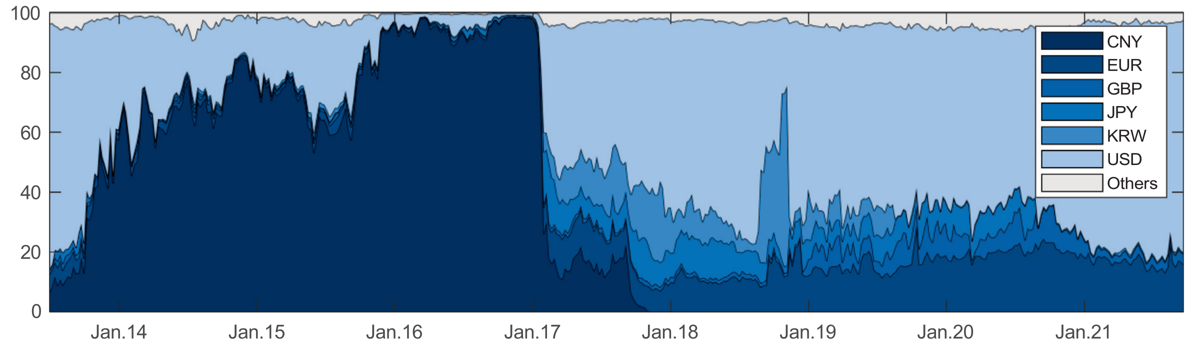

Fig. 9. CURRENCY SHARES OF BITCOIN TRADING VOLUMES. *Note.* Percentage shares of Bitcoin trading volume against different fiat currencies over time. Based on weekly data. *CNY* refers to Chinese yuan, *EUR* to euro, *GBP* to British pound, *JPY* to Japanese yen, *KRW* to Korean won. Source: author's calculations based on data from bitcoinity.org.

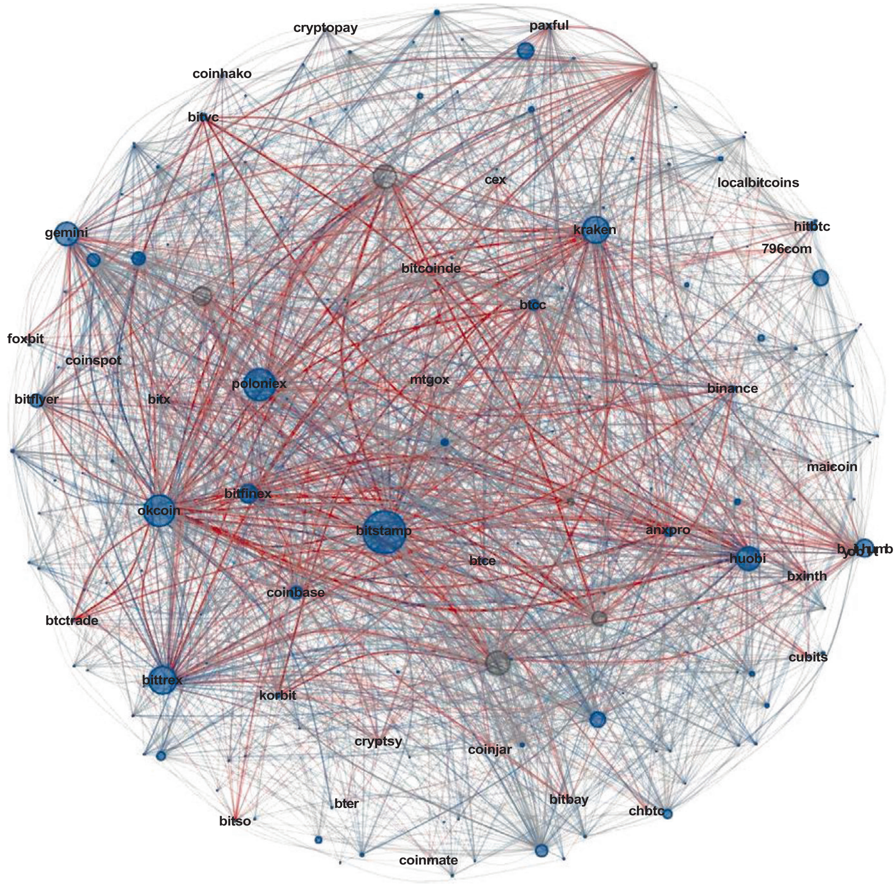

Fig. 10. BLOCKCHAIN TRADE LINKAGES OF HIGHLY ACTIVE ENTITIES. *Note.* Aggregated transaction relations of significant entities in the Bitcoin ecosystem between 2009:01 and 2017:12. Thickness of edges denotes size of trading relation in USD, size of nodes denotes *strength* of entity (number of relations 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.

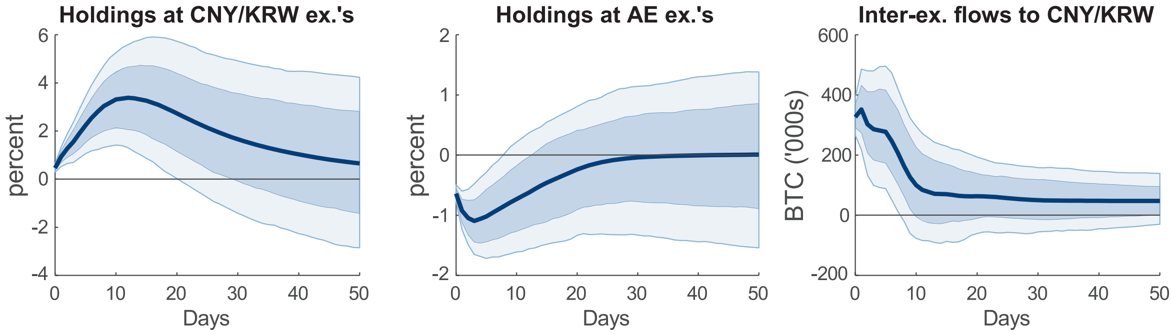

Fig. 11. IRFS TO CONTRACTIONARY US MONETARY POLICY SHOCK: INTERNATIONAL BTC FLOWS AND HOLDINGS AT CNY EXCHANGES. *Note.* Impulse responses to a contractionary US monetary policy shock that increases interest rates by 10 points (model (3) in Table 5), identified as explained in SECTION 3.1. *AE* refers to advanced economies, *CNY* to Chinese yuan, *KRW* to Korean won. Shaded areas denote 68% and 90% confidence bands. Time sample: June 2013 to September 2017, before Bitcoin trading ban in China.

panel shows that there is an immediate increase in the direct net flows of coins from advanced to CNY/KRW exchanges after the shock.[34] Taken together, these findings provide additional evidence that the increased demand for Bitcoin following the US monetary shock used to be particularly large in China and Korea, in line with the international cash channel outlined above.

4. Conclusion

Does demand for Bitcoin result merely from speculative motives or is due to its design features – sometimes seen as an explicit challenge to perceived shortcomings in the existing monetary and financial system? This paper empirically studies the impact of discretionary monetary policy on Bitcoin valuations and its broader ecosystem. The first part of the paper uses high-frequency data and focuses on short time windows around FOMC announcements for identification. Bitcoin prices did not systematically respond to monetary policy news for many years, but have been doing so after 2020 in an environment of increasingly high inflation rates. Bitcoin valuations respond qualitatively similarly to monetary policy announcements as the prices of other risky assets, particularly stocks. However, the same is true in response to inflation surprises, challenging the narrative of Bitcoin as an inflation hedge and confirming its role as primarily a speculative investment.

In the second part of the paper, however, I show that Bitcoin's design as a decentralized, borderless means of payment likely did meaningfully contribute to its demand in the past. I identify monetary policy shocks in a daily proxy VAR and trace out their dynamic effects on Bitcoin over longer horizons. The analysis confirms the contractionary impact of a US monetary tightening on Bitcoin prices in the post-2020 time period. In contrast however, a US monetary contraction used to cause an increase rather than a fall in Bitcoin valuations prior to 2018. I find evidence that links this effect to Bitcoin's role as a means of enabling cross-border transactions without the involvement of regulated financial institutions: a US monetary contraction caused an increase in Bitcoin demand in East Asian economies subject to capital controls – particularly in China, before Bitcoin trading was banned in late 2017.

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, and demand for, Bitcoin. The analysis reveals that while Bitcoin primarily remains a speculative asset, at least in the past it 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. 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.

Overall, the changed nature in the relationship of monetary policy and Bitcoin reflects the evolving role of Bitcoin in the financial system generally, and it remains to be seen how this role will evolve in the future. If Bitcoin were to continue to establish itself as an asset in the portfolios of retail and institutional investors, the impact of monetary policy on its price is likely to remain large. By the same token, monetary conditions going forward could themselves shape Bitcoin's role: easy monetary policy could itself be a driver of Bitcoin adoption whereas higher interest rates from tight monetary policy could constitute an impediment. Still, in the longer run, other structural factors are likely to remain more important. These include regulatory policies as well as population aging and environmental concerns due to Bitcoin's energy-intensive consensus mechanism.

[34] Notably, this is the opposite of what would be expected if flows primarily reflected arbitrage: if arbitrageurs were trying to profit from the large CNY/KRW spreads, they would systematically move coins from CNY/KRW exchanges toward those that allow trading in advanced economy currencies in order to trade them for, say USD. The finding of net inflows of coins into CNY/KRW exchanges then adds weight to the notion that there is an increased demand for Bitcoin by users in East Asia.

Data availability

Data will be made available on request.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Data Appendix

High-Frequency Bitcoin Price Data. The high-frequency price data featured in SECTION 2 is gathered from two sources. For later parts of the sample (beginning in September 2017), I rely on pre-processed high-frequency data from tickstory.com. As this data is not available in earlier parts of the sample, I construct a time series from scratch using the website bitcoincharts.com/charts that contains tick data for dozens of Bitcoin exchanges. I download price and volume data in USD for various exchanges with large trading volumes and many observations over as long time periods as possible.[35] 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-min 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. Together with the tickstory data this process results in high-frequency time series of USD Bitcoin prices spanning the period from January 2014 to early February 2023.

Arbitrage Spreads As described in SECTION 3.1, 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. To that end, I use volume-weighted daily Bitcoin price data stemming from bitcoinity.org, in combination with daily exchange rate data from Refinitiv. Reassuringly, Fig. A.1 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. This is also confirmed when I employ high-frequency Bitcoin price data in euro, in addition to minute-by-minute data for the EUR-USD exchange rate from tickstory.com, to construct the spread with respect to the euro.

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.[36]

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*.[37] 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.[38] 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.[39] Following the clustering procedure, the dataset contains a bit more than 655 million transactions

[35] Bitfinex, Bitstamp, BTC-e, Coinbase, Kraken and Mt.Gox

[36] 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.

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

[38] 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.

[39] 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.

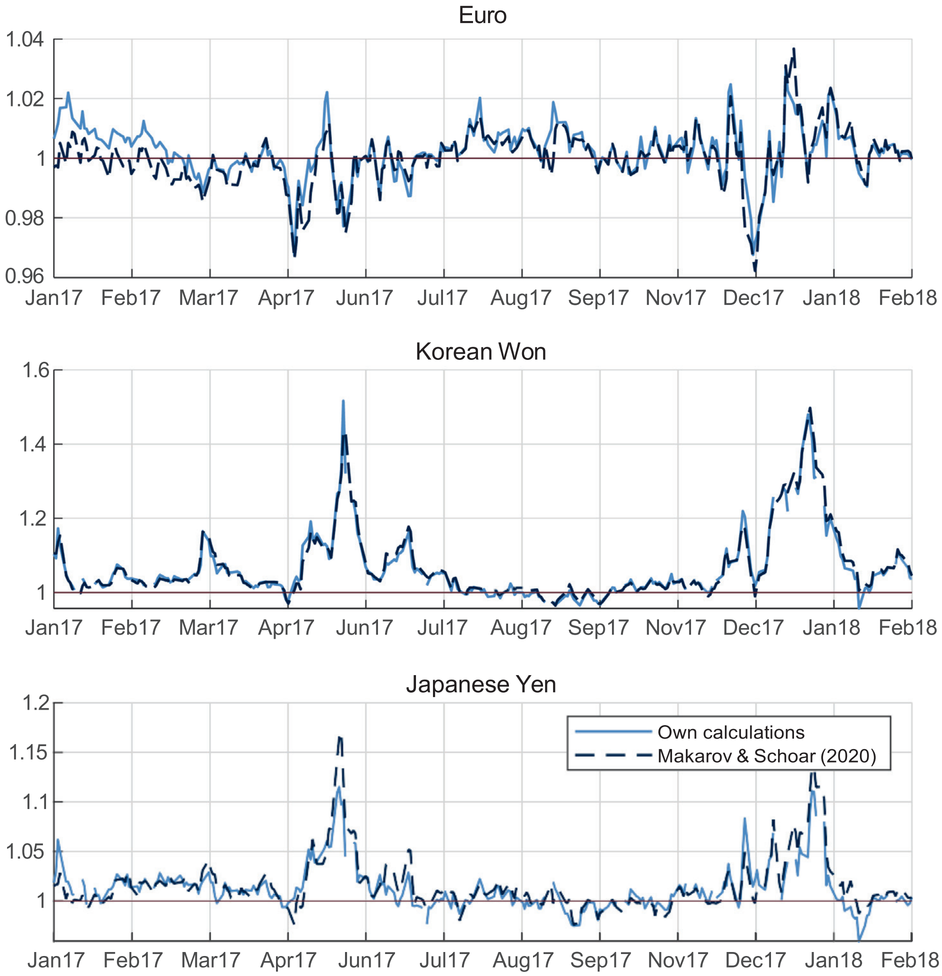

Fig. A.1. BTC ARBITRAGE SPREADS, OWN CALCULATIONS IN COMPARISON TO Makarov and Schoar (2020). *Note.* Bitcoin spreads for three fiat currencies relative to the price in US dollars, plotted as daily averages. In the absence of sizable frictions to arbitrage, the computed series would be close to unity 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.

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 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.[40] 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 web-

[40] 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.

sites 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.

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 Fig. A.2 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

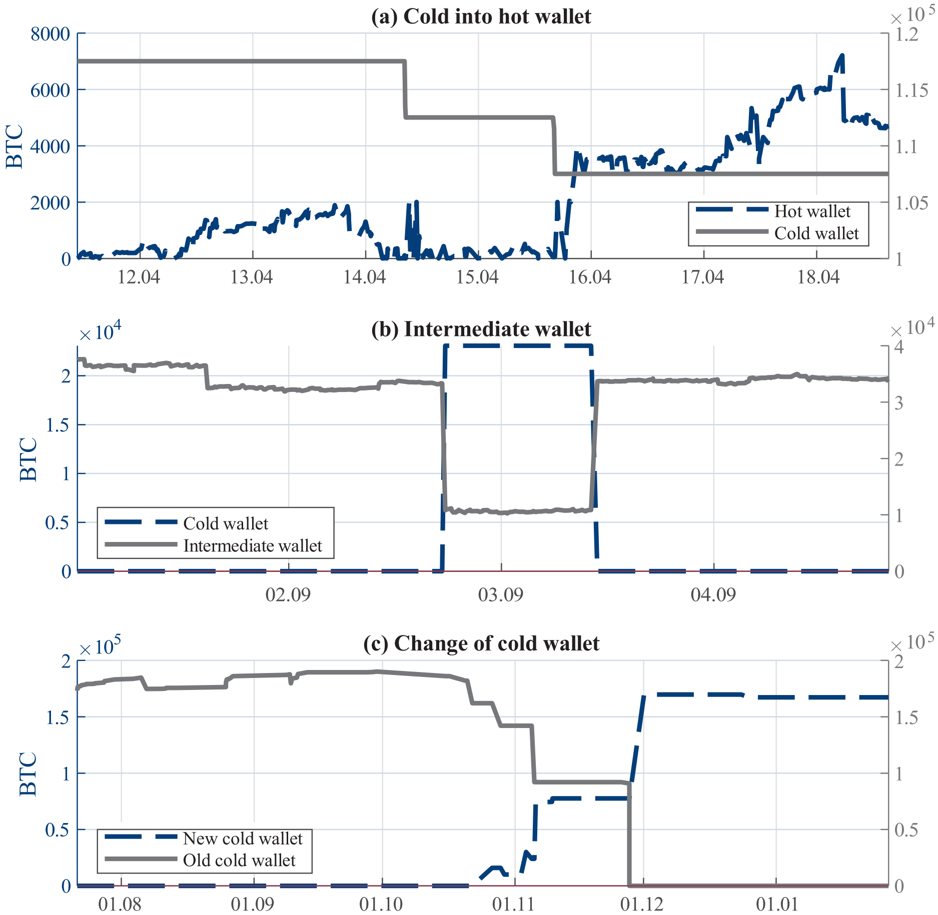

Fig. A.2. EXAMPLES OF HOT AND COLD WALLET INTERACTIONS. *Note.* Examples of Bitcoin flows between hot and cold storage meant to illustrate patterns that guide the manual tracking of exchange wallets. Source: author's calculations based on blockchain data.

Table A.1
Exchanges tracked in blockchain dataset.

Exchange	Supported currencies	CNY/KRW	AE	Residence (if known)
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
Bitfinex	USD		•	
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 3.3. Exchanges classified according to whether they allow trading against CNY/KRW or advanced economy (AE) fiat currencies. Source: Bitfury (2019), Makarov and Schoar (2020), bitcoinity.org and various other websites and online fora.

wallet. An example of this is shown in panel (b) in Fig. A.2 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 Fig. A.2 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`.[41]

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

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

a 3-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.

Appendix B. VAR estimation

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

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

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

$$\mathbf{y}_t = \mathbf{c} + \mathbf{B}_1\mathbf{y}_{t-1} + \ldots + \mathbf{B}_p\mathbf{y}_{t-p} + \mathbf{u}_t, \quad \mathbf{u}_t \sim \mathcal{N}(\mathbf{0}, \Sigma), \tag{A.2}$$

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 $\mathbf{u}_t = \left[u_t^p, \mathbf{u}_t^{q\prime}\right]^\prime$. 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:

$$\mathbb{E}\left[Z_t\epsilon_t^{p\prime}\right] = \phi \neq 0, \tag{A.3}$$

$$\mathbb{E}\left[Z_t\epsilon_t^{q\prime}\right] = \mathbf{0}. \tag{A.4}$$

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 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:

$$\mathbf{u}_t^q = \frac{\mathbf{s}^q}{s^p}\hat{u}_t^p + \xi_t. \tag{A.5}$$

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). 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:

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

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

$\beta = vec([\mathbf{c}, \mathbf{B}_1, \ldots, \mathbf{B}_p]\prime)$ are the stacked coefficient matrices and $\underline{\mathbf{S}}, \underline{\nu}, \underline{\beta}$ and $\underline{\Omega}$ 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 $\mathbb{V}ar(\beta) = \underline{\mathbf{S}} \otimes \underline{\Omega}$.

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:

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

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

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.[42] 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, Eq. (A.9) ensures a decaying variance of parameters for more distant lags and is, together with the assumptions above, achieved by specifying

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

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):

$$\Sigma|\mathbf{y} \sim \mathscr{IW}\left(\bar{\mathbf{S}}, \bar{v}\right) \tag{A.11}$$

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

with

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

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

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

where $\mathbf{x}_t = [\mathbf{1}, \mathbf{y}_{t-1}, \ldots, \mathbf{y}_{t-p}]$ 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.

Appendix C. Additional results

C.1. High-frequency analysis

Fig. C.1 repeats the exercise of Fig. 1 for ECB Governing Council announcements. In contrast to the results for FOMC announcements, confidence bands are wider and no highly significant impact on Bitcoin return volatilities is found, also in the post-2020 period. Announcements by the ECB therefore seem to play a less important role for Bitcoin's market valuations compared to the Fed's. This is also visible in Fig. C.2, which mirrors the analysis in Fig. 3. Only the co-movement of Bitcoin returns with those of the Eurostoxx 50 become statistically highly significant in the later part of the sample, but the effect is smaller than for the S&P 500 and FOMC announcements. Co-movements with exchange rates and gold do not show an upward trend. Instead, the co-movement is higher in the middle of the sample, yet not statistically significantly so.

C.2. Structural VAR analysis

Additional VAR Results. I repeat the main VAR analysis for euro area monetary policy shocks. To construct the euro area instrument I rely on the monetary event study database by Altavilla et al. (2019),[43] which I again extend manually using data from Refinitiv and tickstory.com. Fig. C.3 shows responses of Bitcoin prices in USD to a contractionary monetary policy shock. In contrast to the US results, euro area monetary policy shocks lead to a fall in Bitcoin valuations no matter the time period under consideration. An earlier version of the paper also featured additional euro area results in weekly frequency, inter alia on central bank information shocks, which also contrasted with the US results.

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

[42] As some of the variables could be considered to be a priori stationary – e.g. some of the arbitrage spreads –, I experiment with setting $\delta_i = 0$, as in Banbura et al. (2010), but generally find my results to be hardly affected.

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

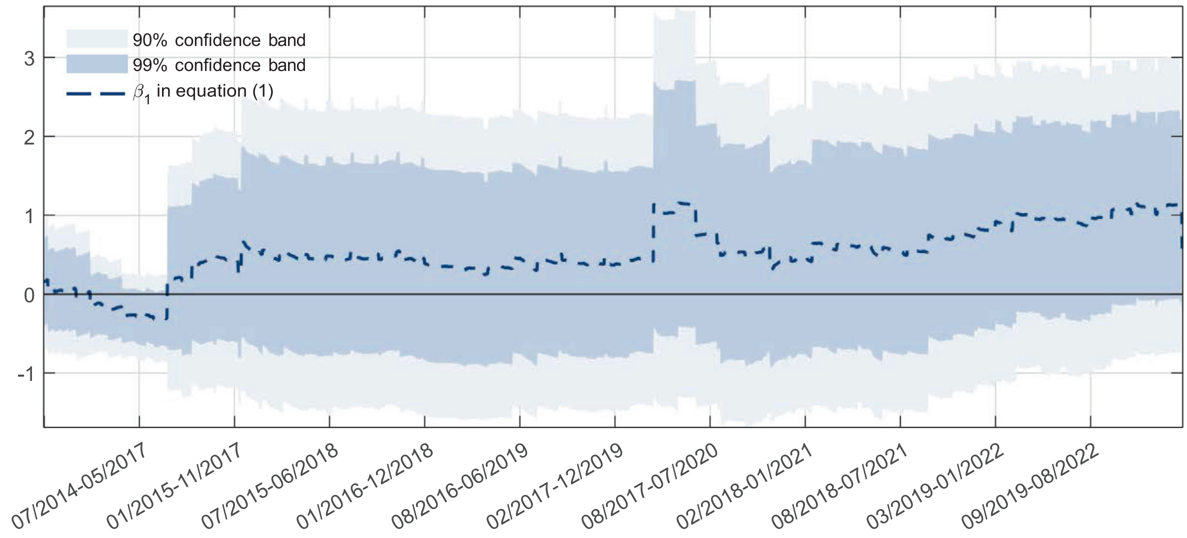

Fig. C.1. TIME-VARYING IMPACT OF ECB GOV. COUNCIL ANNOUNCEMENTS ON BTC RETURN VOLATILITY. *Note.* β_1 coefficients in rolling regressions in Eq. (1) for ECB Gov. Council announcements with a rolling window of 1050 days (25 6-week periods). Values refer to daily standard deviations based on minute-by-minute data. Shaded areas denote 90 and 99% confidence bands.

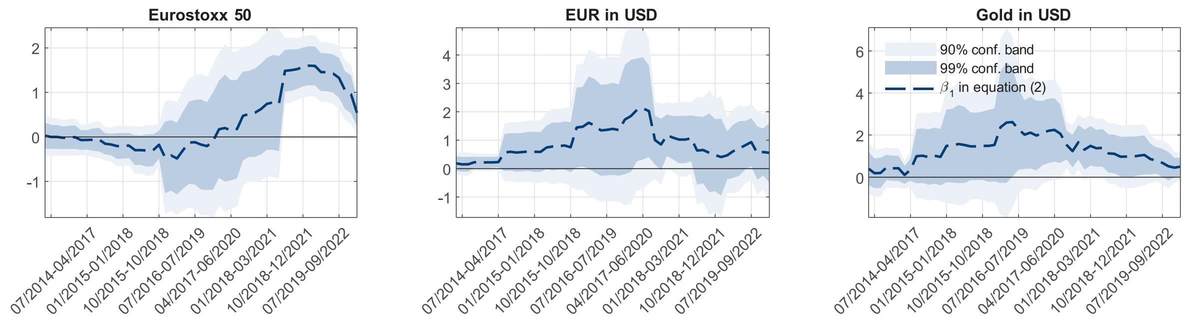

Fig. C.2. TIME-VARYING CO-MOVEMENT OF BITCOIN RETURNS DURING ECB GOV. COUNCIL ANNOUNCEMENTS WINDOW. *Note.* β_1 coefficients in rolling regressions (Eq. (2)) with a window of 25 ECB Governing Council announcements. Shaded areas denote 90 and 99% confidence bands computed with robust standard errors.

estimate the same impulse responses in population, in finite samples the estimates might differ (Plagborg-Møller and Wolf, 2021). It will hence be 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

$$y_{t+h} = \alpha_h + \beta_h \epsilon_{s,t} + \sum_{j=1}^{20} \left(\gamma_h^y y_{t-j} + \gamma_h^\epsilon \epsilon_{s,t-j} + \mathbf{X}_{t-j} \Gamma_h^X \right) + e_t, \quad h = 0, 1, \ldots H \tag{C.1}$$

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,[44] y_t indicates the logged price of Bitcoin in USD, $\mathbf{X}_t$ is a set of controls, mirroring those in the VAR model. The coefficients β_h will then measure the impulse response that are hence constructed without imposing a recursive VAR model structure.

Fig. C.5 depicts results, focusing on the time period until late 2017. Panels one and two use the structural shocks extracted from the VAR as ϵ_t in Eq. (C.1), whereas panels three and four use the instrument Z_t.[45] As in the VAR model, an exogenous monetary contraction leads to an increase in the price of Bitcoin.

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. Panels two and four

[44] Piffer (2016) provides a guide on how to extract the shocks in a proxy VAR setting.
[45] The resulting impulse responses are in population equivalent to those constructed from a recursively identified VAR in which the instrument is ordered first, see Plagborg-Møller and Wolf (2021).

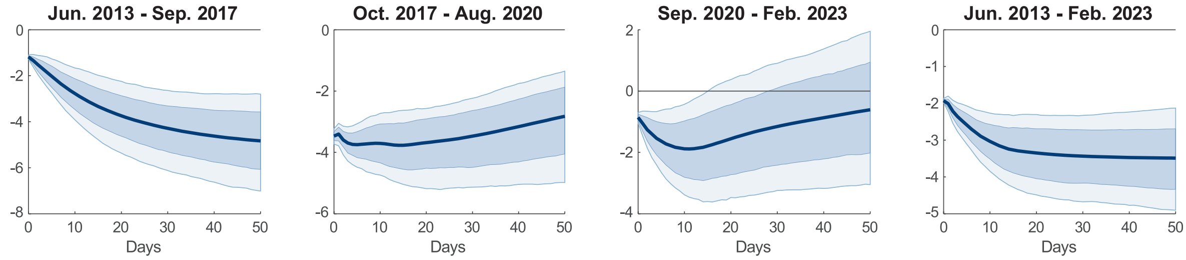

Fig. C.3. IRFS OF BITCOIN PRICE TO EURO AREA MONETARY POLICY SHOCK. *Note.* Impulse responses (in percent) of the USD price of Bitcoin to a contractionary euro area monetary policy shock normalized to lower the Eurostoxx 50 by 1 percent, in different time samples. Remaining details as in Fig. 6.

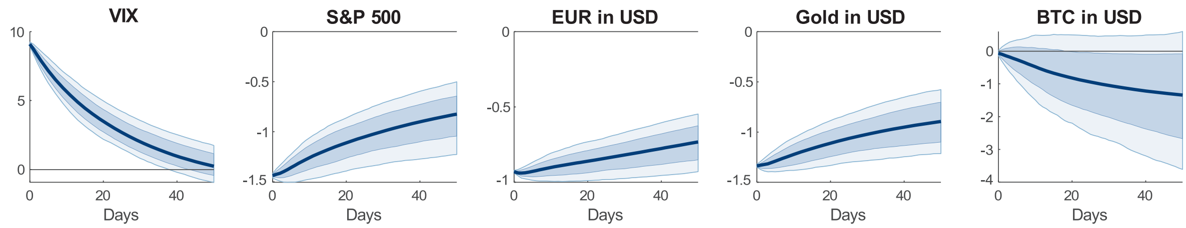

Fig. C.4. IMPULSE RESPONSES TO CONTRACTIONARY US MONETARY POLICY SHOCK (FULL TIME SAMPLE). *Note.* Impulse responses to a contractionary US monetary policy shock in the full time sample (June 2013 to February 2023). Remaining details as in Fig. 6.

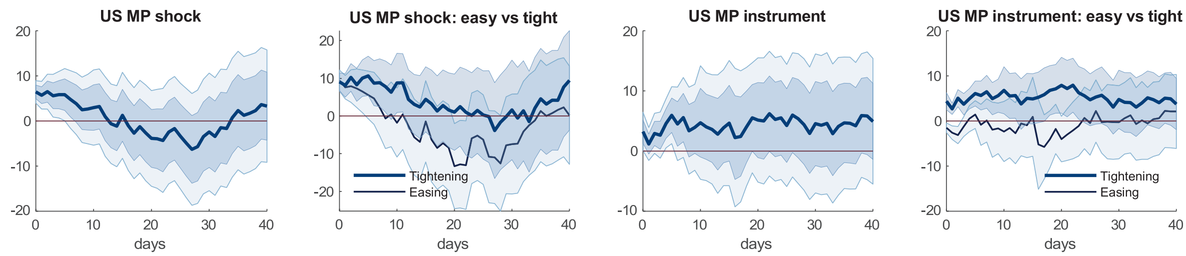

Fig. C.5. IRFS OF BTC PRICE TO US MONETARY POLICY SHOCK: LOCAL PROJECTIONS. *Note.* Impulse responses of Bitcoin prices in USD to US monetary policy shock in local projection analysis in Eq. (C.1). First and second panels use the structural shocks extracted from the proxy VAR as ϵ_t, third and fourth panel use the instrument. The second and fourth panel compares the effects of an easing and a tightening. Shaded areas denote 68% and 90% confidence bands in panels one and three and 90% bands in panels two and four. Time sample: June 2013 - September 2017.

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 it is primarily the tightening shocks (thick lines, dark bands) that affect Bitcoin prices rather than the easing shocks (thin lines, light bands). Notably, this finding further supports the view developed in the main text: it is primarily the negative impact of the tightening that makes Bitcoin attractive, and an easing of monetary conditions arguably would not have same quantitative impact in reverse.

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