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Abstract

Prices for cryptocurrencies have undergone multiple boom-bust cycles, together with ongoing entry by retail investors. To investigate the drivers of crypto adoption, we assemble a novel database (made available with this paper) on retail use of crypto exchange apps at daily frequency for 95 countries over 2015–22. We show that a rising Bitcoin price is followed by the entry of new users. About 40% of these new users are men under 35, commonly identified as the most "risk-seeking" segment of the population. To establish a causal effect of prices on adoption, we exploit two exogenous shocks: the crackdown of Chinese authorities on crypto mining in mid-2021 and the social unrest in Kazakhstan in early 2022. During both episodes price changes have a significant effect on the entry of new users. Results from a PVAR model corroborate these findings. Overall, back of the envelope calculations suggest that around three-quarters of users have lost money on their Bitcoin investments.

JEL Classification: E42, E51, E58, F31, G28, L50, O32

Keywords: Bitcoin

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1. Introduction

Over the past 13 years, cryptocurrencies have evolved from a niche technological proposal for peer-to-peer payments to a financial asset class traded by millions of users around the world. The largest cryptocurrency by market capitalisation remains Bitcoin, introduced in 2009 by an anonymous developer under the pseudonym Satoshi Nakamoto (2008). The price of Bitcoin rose from $1 in February 2011 to a peak of $69,000 in November 2021. Globally, it was estimated that over 220 million people owned a cryptocurrency in June 2021 – up from 5 million in 2016.[2]

To date, the volatile price of cryptocurrencies prevents them from becoming widely used as a means of payment. Nor is crypto used as a unit of account; the same volatility makes it impractical to set a fixed price in a specific cryptocurrency, or to use cryptocurrencies as a yardstick for valuing real economy flows. Moreover, the system is largely self-referential and does not finance real-world investments (Aramonte et al (2022)).

But why do people invest in cryptocurrencies? In advanced economies, there is evidence that distrust of domestic financial institutions or the domestic fiat currency is not a key driver.[3] As they fluctuate widely in value and can sustain only a limited volume of transactions,[4] cryptocurrencies are also not useful to date for payments in real transactions (purchases) or cross-border money transfers. Some users may however see cryptocurrencies as a store of value and safe haven (ie "digital gold") that cannot be appropriated. And certainly, cryptocurrencies could be seen as a speculative investment asset.[5]

In this paper, we shed further light on the role of speculative and safe haven considerations as drivers of cryptocurrency adoption. For this, we investigate the relationship between the use of crypto trading apps, Bitcoin prices and other macroeconomic variables. We assemble a novel cross-country database on retail downloads and use of crypto exchange apps at daily frequency for 95 countries over 2015–22.

Our main findings are as follows.

First, we show that a rise in the price of Bitcoin is associated with a significant increase in new users, ie entry of new investors. This positive correlation remains robust when we control for other potential drivers, such as overall financial market conditions, uncertainty or country characteristics. In particular, the price of Bitcoin remains the most important factor when we control for global uncertainty or volatility, contradicting explanations based on Bitcoin as a safe haven. Likewise, when controlling for variables that proxy institutional quality or trust, as well as the level of economic development, the Bitcoin price still has an economically and statistically significant effect on the number of new users and explains the lion's share of the variation in the entry of new users.

2 See Blandin et al (2021) and de Best (2022). This is a lower-bound estimate of identity-verified users. The estimates are subject to uncertainty given the potential for users to have multiple accounts.

3 See Auer and Tercero-Lucas (2022) and FCA (2021).

4 See Boissay et al (2022).

5 See Foley et al (2019), Hileman (2015), Knittel et al (2019) and Swartz (2020).

Second, analysing the demographic composition of app users we find that 40% of users are men under 35, commonly identified as the most "risk-seeking" segment of the population. These users are more sensitive to changes in the price of Bitcoin than female users and older men. We also find a user sensitivity for Android users, who tend to have lower incomes than iOS users.

Taken together, these patterns are consistent with the speculative motive being caused by feedback trading considerations, ie users being drawn to Bitcoin by rising prices – rather than a dislike for traditional banks, the search for a store of value or distrust in public institutions.

A concern for our estimation strategy is that the entry of new users could also lead to price increases, raising concerns about reverse causality. To address this issue, we perform two complementary analyses. First, we focus on two specific episodes: the crackdown of Chinese authorities on crypto mining activities and the social unrest in Kazakhstan. During both episodes, structural changes affected the global price of Bitcoin, independently of changes in the number of users in other countries. We find that the exogenous change in the Bitcoin price during both episodes had a strong and significant effect on the entry of new users. Second, we estimate a panel vector autoregression (PVAR) model, tackling endogeneity issues by means of a Cholesky decomposition which orders the Bitcoin price last.

Our contribution to the literature is to provide cross-country evidence that retail investors enter the market following Bitcoin price increases. We speak to papers that seek to explain Bitcoin pricing, from a theoretical and empirical perspective (Garratt and Wallace, 2018; Bolt and van Oordt, 2019; Schilling and Uhlig, 2019; Shams, 2020; Liu and Tsyvinski, 2021; Biais et al, 2022). We complement recent evidence on investors' decision to buy cryptocurrencies and stocks, which helps to explain the recent positive correlation in price movements (Somoza and Didisheim, 2022). With our novel new dataset, we are able to assess retail trading adoption at the country level over time, thus better understanding the link between prices and the entry of new retail investors. Moreover, we are able to show how feedback trading, by which past price changes drive buying and selling (Koutmos, 1997; Daníelsson and Love, 2006) is present in crypto markets.

Our findings also have relevance for policy discussions on the regulation of cryptocurrencies for consumer and investor protection and financial stability reasons. Indeed, simple simulations suggest that, at the time of writing, 73-81% of users had likely lost money on their investments in cryptocurrencies. Analysis of blockchain data finds that, as prices were rising and smaller users were buying Bitcoin, the largest holders (the so-called "whales" or "humpbacks") were selling – making a return at the smaller users' expense. Our findings raise concerns that individual decisions are backward-looking and that many retail investors are not fully informed of the risk or volatility of the crypto sector. As recent events have made clear, rising interest rates and other shocks can lead to a persistent fall in prices, as the dynamics that buoyed the market move into reverse.

The paper is organised as follows. Section 2 introduces our dataset and empirical approach. Section 3 presents our key empirical findings on crypto app use and Bitcoin prices. Section 4 presents a number of extensions that further underscore the causal nature of the results. Finally, section 5 concludes.

2. Data description

Our data on adoption of crypto apps come from Sensor Tower, a proprietary app intelligence data provider. Sensor Tower collects data on various app statistics, among which downloads and active use, for apps from the Apple and the Google Play store. These statistics are available for up to 95 countries, where the country refers to the location of the downloading users. The data are at daily frequency. Additionally, we collect information on the operating system of the downloading device – Apple iOS vs Android users, whereby the former is a common proxy for relatively higher-income individuals (see Berg et al (2020)).[6] We also have information on the gender (men vs women) and age group (young vs old) of the user downloading the app. The latter are only available at the app-quarter level. For our empirical analysis, we draw on more than 200 crypto exchange apps at monthly frequency over August 2015 – June 2022. To select the sample of apps, we take the list of crypto exchanges from the CryptoCompare "All Exchanges General Info" application programming interface (API) endpoint. We find a match with the Sensor Tower database for 187 of these exchanges (out of 296). We complement this selection with a list of 26 apps identified as crypto exchange apps by Sensor Tower directly.

Sensor Tower gauges unique downloads per iOS or Google Play account. This methodology avoids double-counting due to re-downloads, ie if a user installs, deletes, then reinstalls the same app on the same device or a new device from the same iOS or Google Play account. Active users are defined as any user that has at least one session on an app over a specific time period (eg day, week or month). If a user has more than one session over the selected time period, they will still only count as one active user for that time period. The active user metric is estimated by Sensor Tower based on a representative sample of users. Bearing this caveat in mind, these data offer the unique possibility of measuring real user-adoption directly rather than through a proxy.

Data on Bitcoin prices are obtained from CryptoCompare, a leading source of data on cryptocurrency prices.[7] In addition to the price and volume data, CryptoCompare, in collaboration with IntoTheBlock, collects statistics on the distribution of Bitcoin holdings at daily frequency. This dataset provides both the number of addresses and the total volume, broken down by various buckets ranging from balances smaller than 0.001 up to more than 100,000 Bitcoin.

We further collect data on stock market prices (MSCI indices), volumes and turnover (Datastream indices), consumer price index (CPI) inflation and foreign exchange (FX) volatility for the country in which the app is downloaded. We also use global gold prices and economic policy uncertainty, as measured by the Global Economic Policy Uncertainty (GEPU) Index of Baker et al (2016). In addition, we collect information on commercial bank branches per 100,000 adults, regulatory quality, total

6 Of course, it is possible that the phone operating system captures other user characteristics – such as a preference for a more competitive ecosystem of app developers relative to Apple's iOS. In the absence of income data, we do not attempt to distinguish between these possible explanations.

7 While Bitcoin and other cryptocurrency markets are in principle borderless, there can be differences in the prices quoted on exchanges in different countries, eg due to regulation. See Auer and Claessens (2018). These price differences are generally small. As such, we use global price indicators.

population, and real GDP at the country-year level.[8] Data on payment app active users and downloads come from Cornelli et al (forthcoming). In this paper the authors collect the top 25 finance apps in each of the countries covered by Sensor Tower and manually tag those apps which are used mainly for payments. For instance, a stock trading app would not be classified as a payment app, while an app like Venmo would be classified as a payment app.

Our final panel includes 95 countries at monthly frequency over the period August 2015 – June 2022. Table 1 provides descriptive statistics for our main variables.

Descriptive statistics

Table 1

	No observations	Mean	Standard deviation	Min	Max
Ln(monthly average daily active users)	6,677	9.01	2.58	–1.13	15.99
Ln(monthly average downloads)	7,170	5.71	2.35	–3.43	12.86
Ln(Bitcoin price)	7,242	8.70	1.60	5.47	11.04
Ln(MSCI equity index price)[1]	5,406	7.38	3.07	–6.21	26.70
Ln(stock market turnover)[2,]	4,775	14.51	3.59	5.34	23.79
Ln(gold price)	7,242	7.29	0.18	6.98	7.60
Ln(global economic policy uncertainty index)	7,147	5.35	0.31	4.62	6.06
FX standard deviation	6,806	1.56	95.19	0	7,852.95
CPI, yoy change	6,996	318	8,076	–100	344,510
Ln(commercial bank branches per 100k adults)	6,903	2.63	0.85	–0.89	4.34
Regulatory quality[3]	7,152	0.50	0.93	–2.36	2.26
Control of corruption[3]	7,152	0.35	1.04	–1.56	2.28
Ln(payment apps active users)	6,954	12.82	2.65	3.00	19.64
Ln(payment apps downloads)	7,240	10.99	2.38	0	17.37
Ln(population)[4]	7,159	16.69	1.67	11.06	21.07
Ln(real GDP)	6,482	26.20	1.58	22.14	30.64

[1] Country-specific MSCI equity index price, in local currency. [2] Based on the country specific Datastream equity index, in local currency. [3] In units of a standard normal distribution. [4] .Data for the most recent period has been estimated with the latest value available.

Sources: Baker et al (2016); CryptoCompare; Datastream; World Bank; Refinitiv Eikon; Sensor Tower; national data; authors' calculations.

Stylised facts

Between August 2015 and its peak in November 2021, the price of Bitcoin rose from $250 to $69,000. Meanwhile, the monthly average number of daily active users (DAUs) has increased from around 119,000 to more than 32.5 million. During the rapid price increases in late 2017 and early 2021, alone, around 105 and 511 million new monthly active app users joined. In mid-2022, there were around 700 million instances of

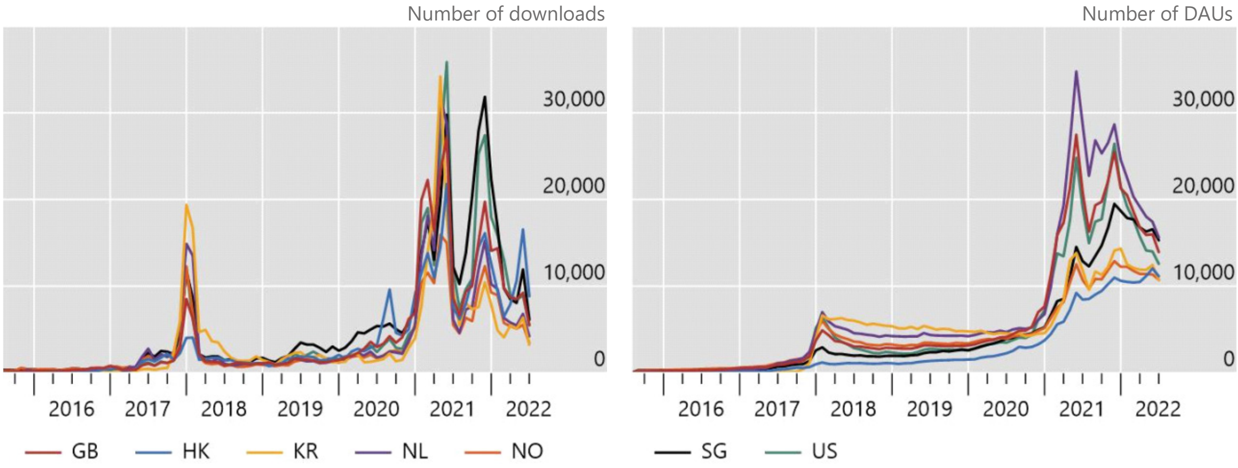
[8] Gold and stock market prices come from Refinitiv Eikon; volumes and turnover come from Datastream; consumer prices indices and FX data come from national sources and Datastream; commercial bank branches per 100,000 adults, regulatory quality, total population, and real GDP come from the World Bank.

monthly active use in our global sample, and a cumulative total of 565 million crypto exchange app downloads over the full sample period.[9]

Some countries registered monthly downloads of crypto exchange apps exceeding 15,000 per 100,000 inhabitants with a peak of more than 35,000 (Graph 1, left-hand panel). Daily active users of these apps exceeded 10,000 per 100,000 inhabitants with a peak of about 35,000 (right-hand panel). The group of top downloading jurisdictions comprised both advanced economies such as the United States, Canada, Australia, the United Kingdom, the Netherlands, Ireland and New Zealand as well as emerging market and developing economies (EMDEs) such as the United Arab Emirates, Hong Kong SAR, Korea, Singapore, El Salvador and Turkey.

The evolution of the adoption of crypto exchange apps | Graph 1

Downloads of crypto exchange apps per 1 million people | DAUs of crypto exchange apps per 1 million people[1]



[1] Monthly average number of daily active users.

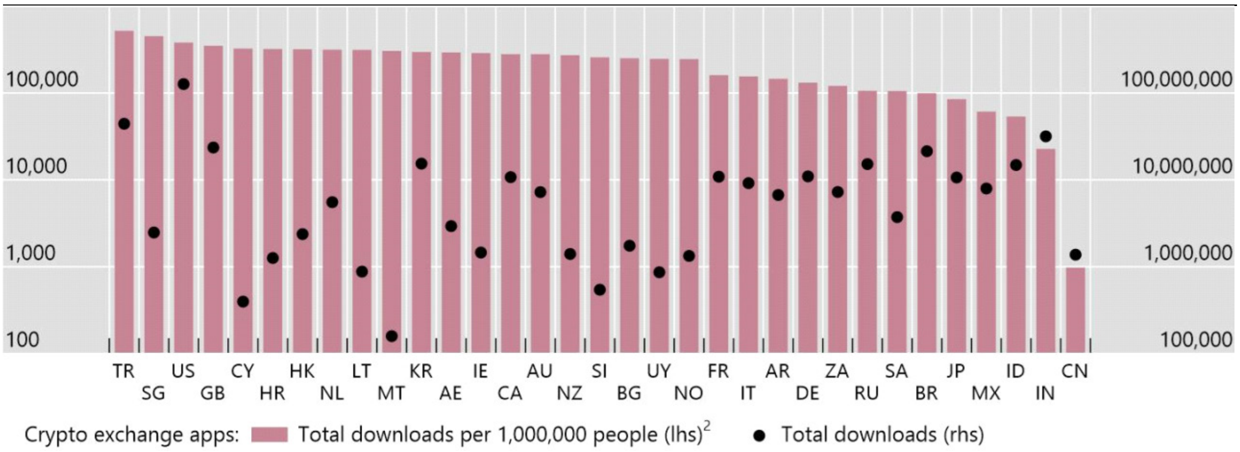
Sources: Sensor Tower; World Bank; authors' calculations.

Over the period of analysis, crypto exchange app adoption, measured with the number of total downloads per 1,000,000 people, is highest in Turkey, Singapore, the United States and the United Kingdom (Graph 2 and 3). It is lowest in China and in India, where legal restrictions likely prevent greater retail adoption.

[9] This number is higher than the global estimates from Blandin et al (2021) and de Best (2022). This likely relates to the same users having multiple crypto exchange apps.

Crypto app adoption is highest in Turkey, Singapore, the US and UK

Number of downloads, logarithmic scale[1] Graph 2



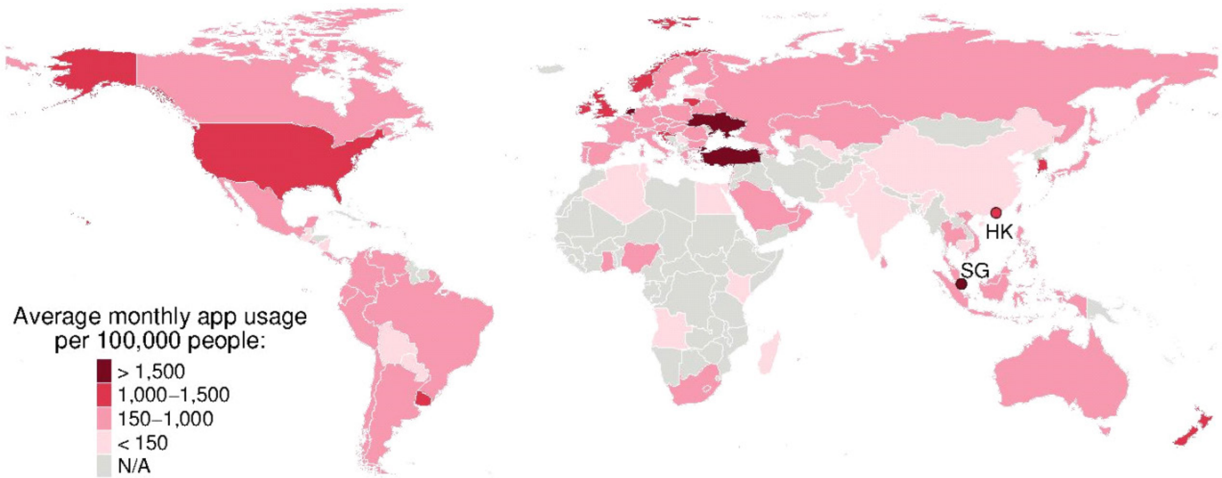
AE = United Arab Emirates, AR = Argentina, AU = Australia, BG = Bulgaria, BR = Brazil, CA = Canada, CN = China, CY = Cyprus, DE = Germany, FR = France, GB = United Kingdom, HK = Hong Kong SAR, HR = Croatia, ID = Indonesia, IE = Ireland, IN = India, IT = Italy, JP = Japan, KR = Korea, LT = Lithuania, MT = Malta, MX = Mexico, NL = Netherlands, NO = Norway, NZ = New Zealand, RU = Russia, SA = Saudi Arabia, SG = Singapore, SI = Slovenia, TR = Turkey, US = United States, UY = Uruguay and ZA = South Africa"

[1] Total downloads are calculated for the period Aug 2015–Jun 2022. [2] Ratio of the total number of downloads to the population for 2020, or latest available.

Sources: World Bank; Sensor Tower; authors' calculations.

World map of crypto trading app adoption

Graph 3



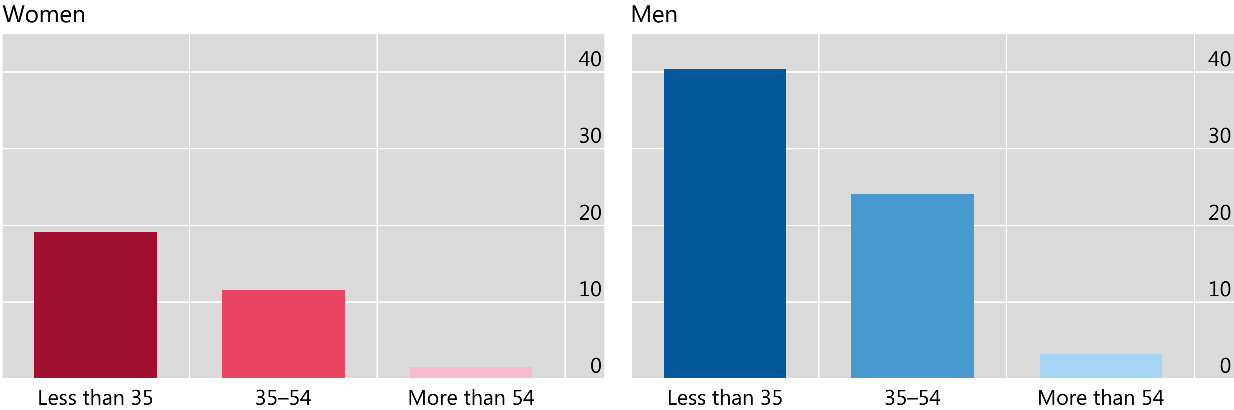
The use of this map does not constitute, and should not be construed as constituting, an expression of a position by the BIS regarding the legal status of, or sovereignty of any territory or its authorities, to the delimitation of international frontiers and boundaries and/or to the name and designation of any territory, city or area. Based on data for June 2022.

Sources: World Bank; Sensor Tower; authors' calculations.

The largest group of users by far – nearly 40% – were men under the age of 35.[10] Men between 35 and 54 made up a further 25% on average. Less than 35% of all users globally are female (Graph 4), and the majority of female crypto app users are under 35. This pattern is consistent with the findings of surveys on cryptocurrency and fintech use; here, too, men are overrepresented (Auer and Tercero-Lucas (2022); Chen et al (2021)).[11]

All the young dudes? More than 40% of crypto app users are young men

In per cent | Graph 4



Based on active users of 45 crypto exchanges android and iOS apps. Simple averages for the period Q1 2020–Q2 2022.

Sources: Sensor Tower; authors' calculations.

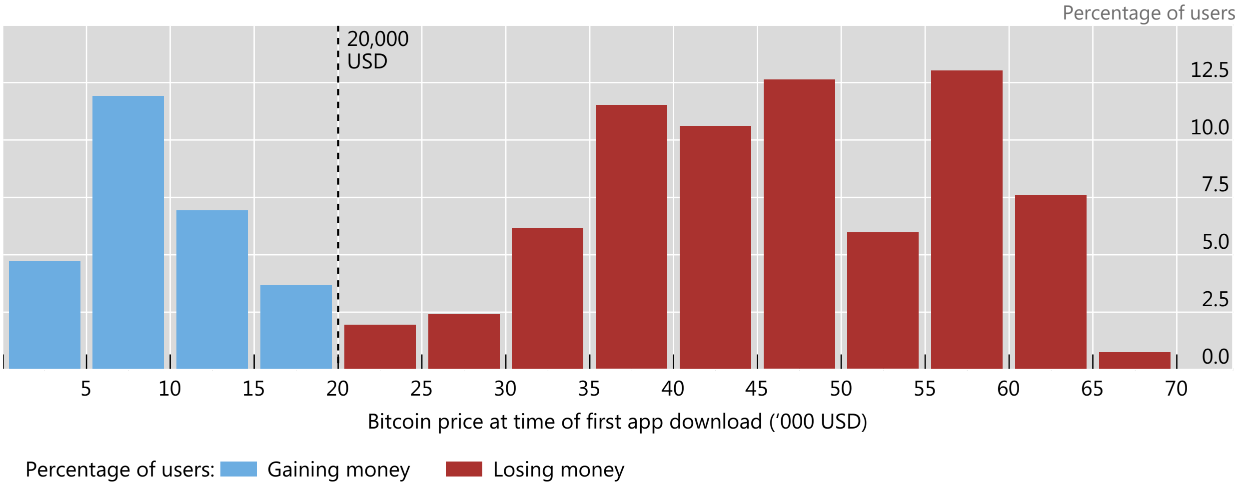
While our database does not contain information on the actual performance of the crypto currency investments of individuals, we can perform simulations to obtain an estimate. First, we estimate the distribution of the number of users downloading the crypto exchange apps for different Bitcoin prices. We find that 73% of the users downloaded their app when the price of Bitcoin was above $20,000 – above the price of Bitcoin in October 2022 (Graph 5). If these users invested in Bitcoin on the same day they downloaded a crypto exchange app, they would have incurred a loss on this initial investment.

10 This compares to 26% of the general population in the countries in our sample – of which 15% are below the age of 19.

11 This finding also mirrors that of Bohr and Bashir (2014), Stix (2019) and Fujiki (2020).

Most retail investors downloaded crypto apps when prices were high

Almost three-quarters of users downloaded the app when Bitcoin was higher than $20,000 — Graph 5



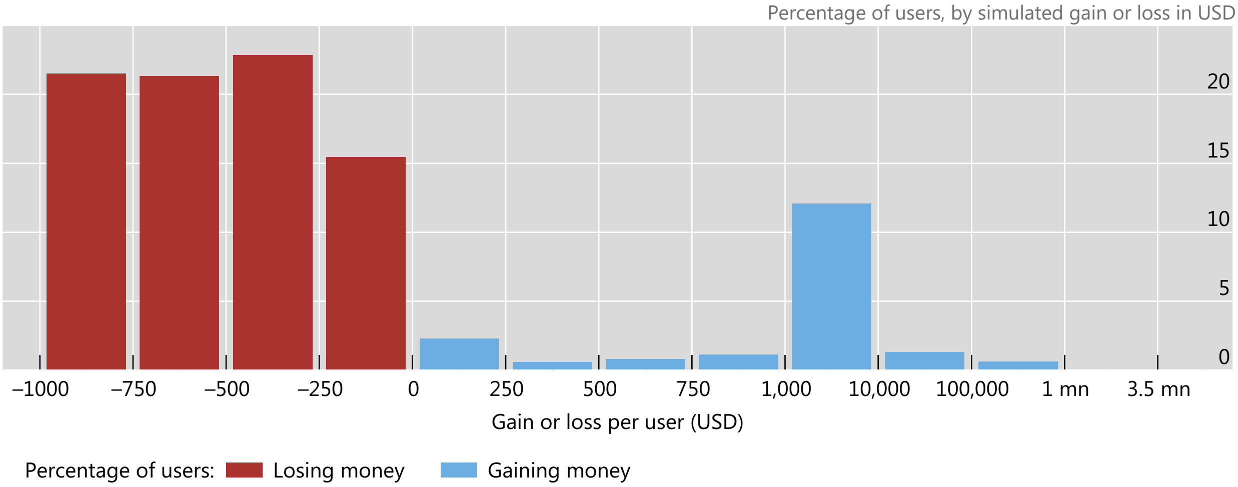
The graph shows a histogram of the share of daily downloads of crypto-exchange apps by Bitcoin price at the time of first download. Estimations of losses or gains assume that the users purchased bitcoin on the same daily they downloaded the crypto-exchange app.

Sources: CryptoCompare; Sensor Tower; authors' calculations.

Second, assuming that each new user bought $100 of Bitcoin in the month of the first app download and in each subsequent month, 81% of users would have lost money (Graph 6). The median investor would have lost $431, corresponding to 48% of their total $900 in funds invested.

Only few investors made large gains, while the majority likely lost money

Assuming an investment of $100 per month, 81% of users have lost money — Graph 6

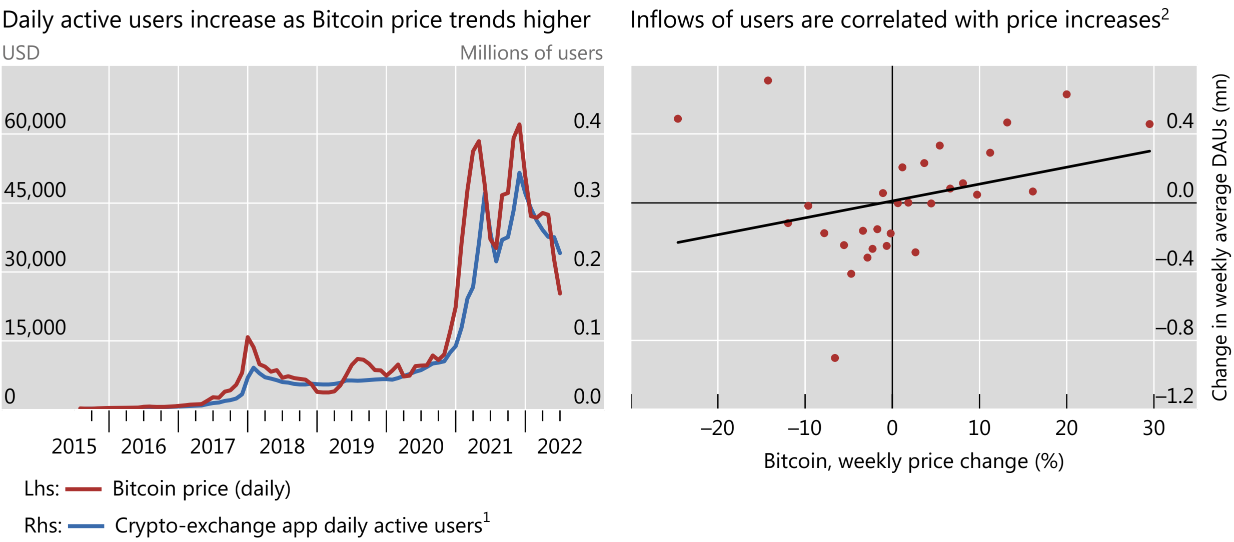


Sources: CryptoCompare; Sensor Tower; authors' calculations.

3. Empirical analysis

Bitcoin prices and user numbers have moved in lockstep, with a correlation coefficient of more than 0.9 (Graph 7, left-hand panel). A scatterplot shows that weekly changes in users are correlated with weekly changes in Bitcoin prices (right-hand panel), but the relationship is not fully contemporaneous. Indeed, rises in user numbers have lagged rises in prices by an average of about two months.[12] This lagged relationship could suggest that users enter the system attracted by high prices and in the expectation that prices continue to rise.

Chained to speculation? New users enter as the Bitcoin price rises — Graph 7



[1] Cross-country monthly average of daily active users. Calculated on a sample of more than 200 crypto-exchange apps over 95 countries. [2] The graph shows a binned scatterplot.

Sources: CryptoCompare; Sensor Tower; authors' calculations.

To investigate the relationship between the Bitcoin price and new users in more detail, we estimate variants of the following regression:

$$DAUs_{i,t} = \beta * BTC_t + \gamma * X_{i,t} + \theta_i + \varepsilon_{i,t}$$

The dependent variable (daily active users or *DAUs*) is obtained summing the daily numbers of daily active users of these apps at the country level and then taking a monthly average. The result is the monthly average number of daily active users in jurisdiction *i* for month *t*. Our main independent variable is the maximum Bitcoin price in month *t*, which likely attracts the greatest attention of the investors. We include a set of macro-economic control variables discussed in more detail below. Further, in each specification we include country fixed effects.

Table 2 shows that an increase in the Bitcoin price is associated with a significant increase in the number of new users. On average, a one-percentage point increase in the Bitcoin price is associated with an increase in the monthly average number of daily active users by 1.1% (column 1), significant at the 99% level. This finding does

[12] Similar price dynamics can be observed for the price of Ether and new users on the Ethereum blockchain (Boissay et al (2022)).

not appear to be driven by other financial market or country-specific conditions, as shown in columns (2)-(5). When controlling for stock market returns (column 2), turnover (column 3), the global gold price (column 4), or economic policy uncertainty, FX volatility and CPI inflation (column 5), the coefficient on the Bitcoin price remains highly significant and large in magnitude. In our most stringent specification in column (5), a one-percentage point increase in the Bitcoin price is associated with an increase in new users by 0.9%. These findings suggest that the relation between the entry of the monthly average number of daily active users and the Bitcoin price is not driven by other observable macro-factors.[13]

Crypto adoption rises following increases in the global Bitcoin price — Table 2

	Dependent variable: ln(monthly average daily active users)				
	(I)	(II)	(III)	(IV)	(V)
Ln(Bitcoin price)	1.109***	1.075***	1.036***	0.946***	0.912***
	(0.008)	(0.008)	(0.009)	(0.013)	(0.012)
Ln(MSCI equity index price)[1]		–0.095***	–0.430***	–0.271***	0.058
		(0.022)	(0.076)	(0.077)	(0.077)
Stock market turnover[2,]			0.304***	0.249***	0.185***
			(0.031)	(0.032)	(0.032)
Gold price				0.967***	0.326***
				(0.085)	(0.092)
Global economic policy uncertainty index[2]					0.556***
					(0.041)
FX standard deviation					–0.041
					(0.028)
CPI, yoy change					0.037***
					(0.003)
Number of observations	6677	5260	4701	4701	4516
R-squared	0.903	0.907	0.902	0.904	0.914

Robust standard errors in brackets; ***/**/* indicates statistical significance at the 1/5/10% level. Regressions include country fixed effects.

[1] Country specific MSCI equity index price, in local currency. [2] Based on the country specific Datastream equity index, in local currency.

Sources: Baker et al (2016); World Bank; CryptoCompare; Datastream; Refinitiv Eikon; Sensor Tower; national data; authors' calculations.

Differences by user and country characteristics

Previous literature has established differences in risk tolerance across groups. For example, data from the Survey of Consumer Expectations (SCE) for the United States shows that younger men are more willing to take financial risks than both women

[13] We additionally control for the *network factors* identified in Y Liu and A Tsyvinski (2021), namely number of wallets, number of active addresses, number of transactions, number of payments, and the first principal component of these four measures. Overall, our results are robust after controlling for these network factors. We do not report this evidence for conciseness.

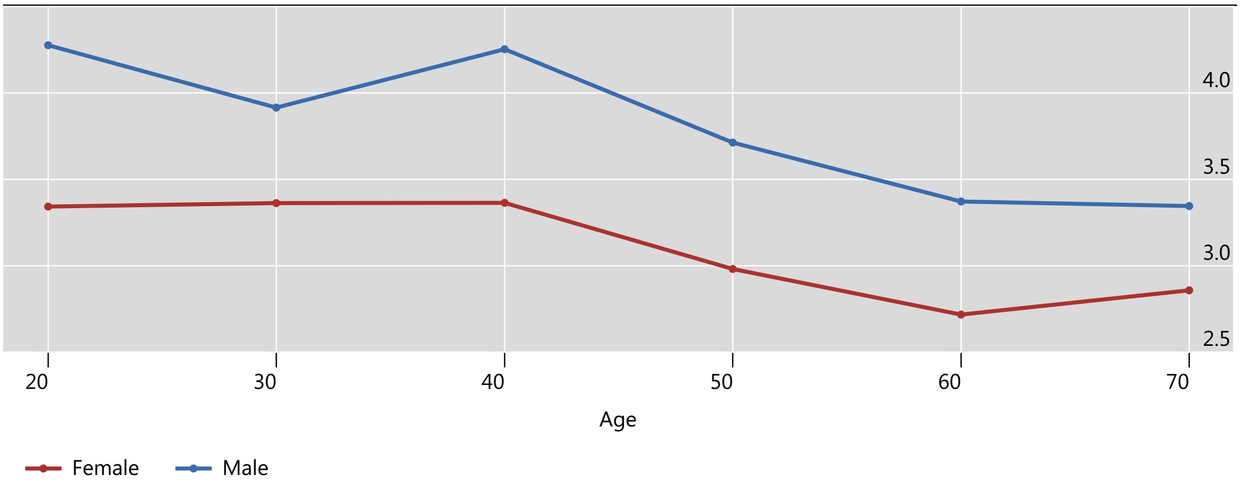
and older male respondents (Graph 8). Similar findings have been reported in other contexts (see, for example, Borghans et al, 2009; Arano et al, 2010).[14]

Investigating to what extent the relationship between price development and new users differs across demographic groups could hence offer additional insights. If, for example, risk-seeking segments of the population (ie young men) respond the most to a rising Bitcoin price, this would be consistent with a speculative motive, rather than the search for a safe asset.

Willingness to take financial risks for US consumers of age 20–79

Index, 1 (lowest willingness)–7 (highest willingness)

Graph 8



Willingness to take financial risks for US consumers of age 20–79. Weighted average (by survey weights) across respondents. The sample covers the period January 2020–July 2021.

Sources: Federal Reserve Bank of New York, *Survey of consumer expectations*; authors' calculations.

To test these arguments, we estimate regressions similar to regression (1), but using the number of new users among different population subgroups as dependent variable.

Table 3 shows that young men have a much higher sensitivity to Bitcoin prices than older men or women of any age. The coefficient on the Bitcoin price is twice as large for young men (column 1) compared to older men (column 2), and more than four times as large relative to women of age 35 and above, which are the least-responsive group. The relationship remains significant at the 99% level for all population groups. These findings suggest that rising prices attract speculative users with a high tolerance for risk. Consistent with this interpretation, recent survey evidence from the UK finds that one of the main reasons for buying cryptocurrencies is "as a gamble that could make or lose money" (FCA (2021)). Further analysis (see Graph A1 in the appendix) confirms that the stronger reaction of young male users occurs mostly during periods of pronounced price swings.

14 A substantial body of work argues that women tend to be more risk-averse than men (Jianakoplos and Bernasek, 1998). Also on the technology side, there are also significant differences in the use of fintech by gender (Chen et al, 2021).

Risk aversion: young vs old, male vs female, iOS vs Android users Table 3

	Monthly average number of users[1]					
	Male below 35	Male above 35	Female below 35	Female above 35	iOS	Android
	(I)	(II)	(III)	(IV)	(V)	(VI)
Bitcoin price	2.142***	1.436***	1.004***	0.683***	1.789***	3.475***
	(0.137)	(0.091)	(0.062)	(0.042)	(0.109)	(0.223)
Number of observations	83	83	83	83	83	83
R-squared	0.903	0.906	0.905	0.906	0.912	0.896

Robust standard errors in brackets; ***/**/* indicates statistical significance at the 1/5/10% level.

[1] Simple average of the country-level monthly average of DAUs by age and gender. Based on active users of 45 crypto exchanges android and iOS apps.

Sources: CryptoCompare; Sensor Tower; authors' calculations.

While we cannot observe user income directly, we can exploit information on the operating system, as Android users on average tend to be of lower income than Apple iOS users (Berg et al (2020)). Columns 5 and 6 in Table 3 show that sensitivity among users with an Android device is about twice as high as for users with an iOS device, suggesting that lower-income investors are more likely to start using crypto exchange apps after prices have risen.[15]

Beyond user characteristics, different arguments have been put forth for why people might want to hold Bitcoin. For example, they may do so because of distrust of domestic institutions or the domestic fiat currency. In light of weak property rights, others may also see cryptocurrencies as a store of value and safe haven (ie "digital gold") that cannot be appropriated by public authorities. Alternatively, they may want to use cryptocurrencies for real transactions (purchases) or cross-border money transfers instead of transfers in fiat currency, particularly in countries with under-developed financial systems.

Table 4 investigates to what extent such country characteristics matter in amplifying or mitigating the relationship between the Bitcoin price and user entry. Column (1) shows that the relationship is stronger in countries with more bank branches, ie in countries with a better-developed traditional financial system. This could reflect the fact that investors need a bank account to transfer fiat money into a crypto exchange. Columns (2) and (3) show that in countries where more users use non-crypto digital payments apps, the relationship between the Bitcoin price and new users is more pronounced. The latter result stands at odds with interpretations based on cryptocurrency as a substitute for transactions and payments in fiat currency. Columns (4) and (5) show that higher regulatory quality and control of corruption mitigate the positive effect of the price on users – consistent with incentives to adopt Bitcoin in countries with weaker public institutions.

[15] The results by gender, age and operating system remain near-identical when we use app-level data and we control for unobservable variation across countries with or without app fixed effects (see Table A1 in the appendix).

Crypto adoption and institutional characteristics Table 4

	Dependent variable: ln(monthly average daily active users)				
	(I)	(II)	(III)	(IV)	(V)
Ln(bitcoin price)	0.854***	0.168***	0.392***	1.046***	1.002***
	(0.028)	(0.042)	(0.034)	(0.015)	(0.014)
Ln(No commercial bank branches per 100k adults)*ln(bitcoin price)	0.037***				
	(0.009)				
Ln(payment apps active users) *ln(bitcoin price)		0.046***			
		(0.002)			
Ln(payment apps downloads) *ln(bitcoin price)			0.038***		
			(0.002)		
Regulatory quality*ln(bitcoin price)				–0.137***	
				(0.009)	
Control of corruption* ln(bitcoin price)					–0.107***
					(0.007)
Number of observations	4481	4645	4645	4645	4645
R-squared	0.905	0.918	0.916	0.914	0.914

Robust standard errors in brackets; ***/**/* indicates statistical significance at the 1/5/10% level. Regressions include country fixed effects. Other controls include the natural logarithm of the MSCI equity index price, the stock market turnover, the gold price and the global economic policy uncertainty index.

Sources: Baker et al (2016); CryptoCompare; World Bank; Datastream; Refinitiv Eikon; Sensor Tower; national data; authors' calculations.

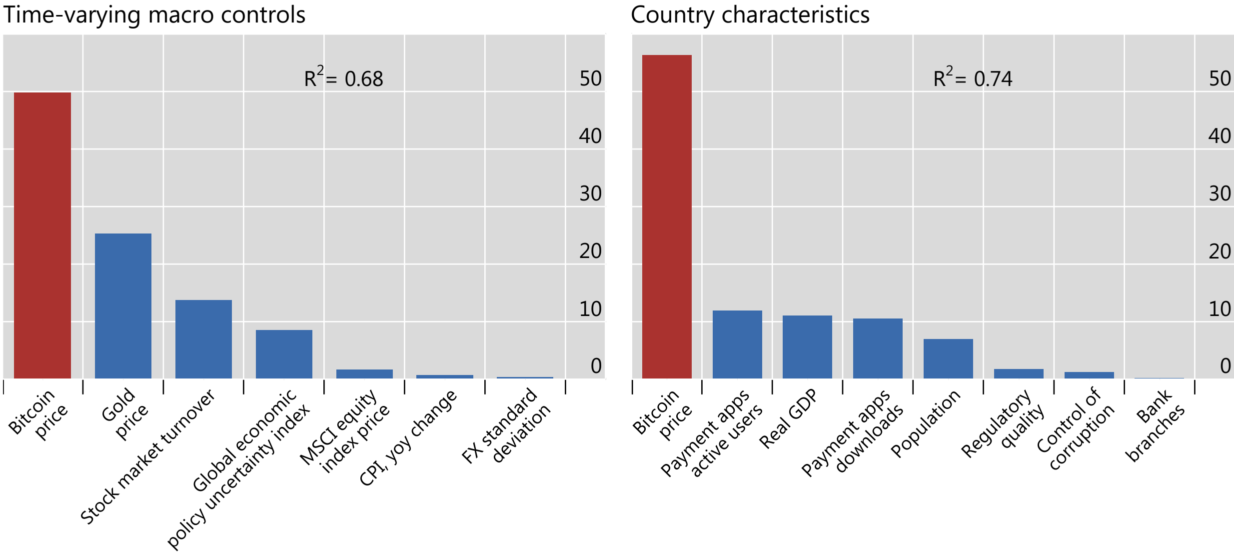
Taken together, results in Tables 2 and 4 suggest that the Bitcoin price has a positive and highly significant association with the entry of new users, even when controlling for other time-varying macro-economic factors or country characteristics. Another way to contrast the relative importance of these different factors is to show how much of the variation in the entry of new users (measured with the R-squared) they can explain.

To this end, Graph 9 plots the results from a Shapley decomposition of the R-squared when we regress the number of new users on the Bitcoin price and time-varying macro controls (panel a) or country characteristics (panel b). As shown in panel (a), the Bitcoin price explains almost 50% of the overall variation in entry of new users, followed by the price of gold with 25%. All other time-varying factors explain less than 15%. Panel (b) shows that these patterns are even more pronounced among country controls. While the price of Bitcoin explains over 55% of the total variation, country characteristics (eg total population, real GDP, the use of payments apps, or institutional quality) explain less than 15% each. These findings suggest that the association between the price of Bitcoin and new users is not only highly significant, but that the price also explains the lion's share of the overall variation in entry of new users across countries and time.

Shapley decompositions

In per cent

Graph 9



The graph shows the shapley decomposition of the R^2 resulting from a regression of the natural logarithm of the monthly average number of daily active users of the crypto apps on the variables indicated on the x-axis of the panels. To all the variables, with the exception of the FX standard deviation and the CPI, is applied the natural logarithm.

Sources: Baker et al (2016); World Bank; CryptoCompare; Datastream; Refinitiv Eikon; Sensor Tower; national data; authors' calculations.

4. Exploiting exogenous variation in the price of Bitcoin

While our analysis so far suggests that new users are attracted by rising prices, the relationship between Bitcoin prices and the influx of new users could also operate in the other direction. As new users download apps and use their fiat money to buy Bitcoin, they drive up the price of Bitcoin. While the patterns in Graph 1 suggest that user inflows tend to follow price increases with a lag of around two periods, in what follows, we perform two complementary analyses to address the issue of reverse causality. First, we focus on episodes of arguably exogenous changes to the price of Bitcoin. And second, we estimate a panel vector autoregression (PVAR) model.

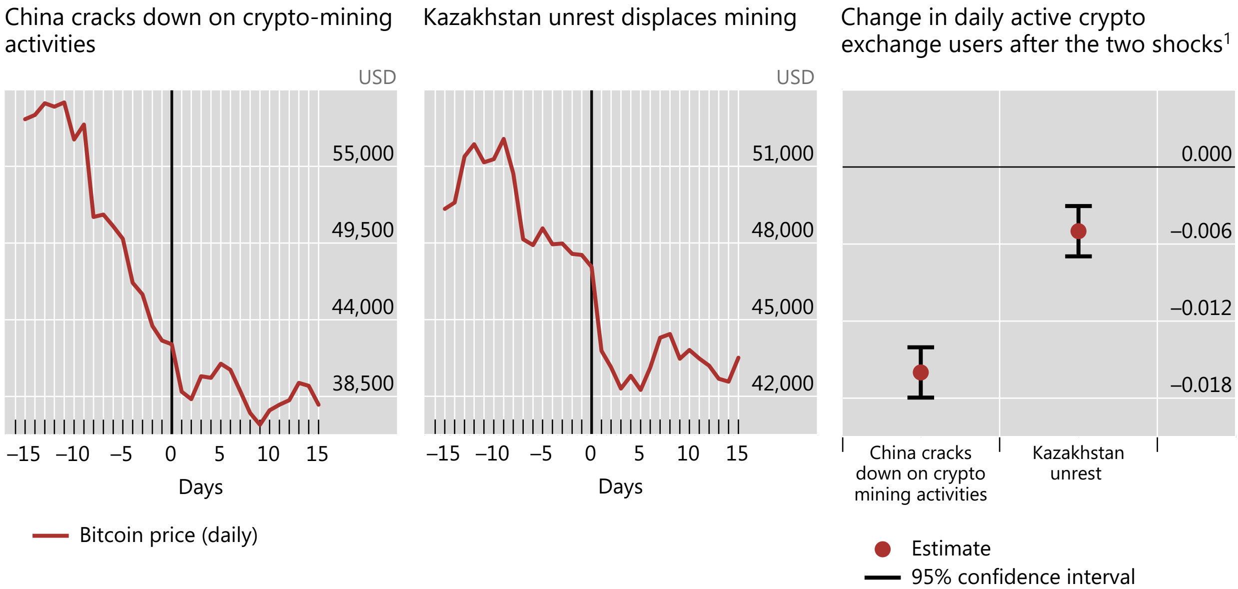
Natural experiments

In what follows we exploit two episodes that led to changes in the price of Bitcoin that were not driven by user adoption: the crackdown of Chinese authorities on crypto-mining activities and the social unrest in Kazakhstan.

In May 2021, the Chinese government announced that it was vowing to crack down on Bitcoin mining and trading in China. Since Chinese miners had been responsible for up to three-quarters of all mining at their peak in September 2019, this policy move had a large and swift effect on Bitcoin mining capacity. As lower mining capacity implies higher transaction costs due to higher fees, the crackdown had a strong effect on the price of Bitcoin – which fell by 39% between eleven days before and nine days after the announcement.[16]

Bitcoin mining equipment was subsequently exported from China and miners eventually set up shop in other countries with cheap and abundant energy supplies, driving a price recovery. One such location was neighbouring Kazakhstan, which had large, vacant warehouses and factories well-suited to house mining operations, and cheap energy from coal (70% of electricity production) and natural gas. This leads to our second event window, when in January 2022 rising fuel prices and deadly riots led to an abrupt reduction in Bitcoin mining in Kazakhstan, once again pushing the Bitcoin price lower – this time by almost 20% between late December and early January.

Case study: impact of exogenous shocks to Bitcoin prices on user numbers — Graph 10



[1] Results from a univariate regression of the daily changes in the natural logarithm of the number of daily active users on a dummy that takes a value of 1 from the day after the event onwards and 0 elsewhere. Regressions include country fixed effects and standard errors clustered at country level.

Sources: CryptoCompare; Sensor Tower; authors' calculations.

Graph 10 (left and centre panels) illustrates these price movements. During both episodes, structural changes arguably affected the global price of Bitcoin, independently of the entry of new users in *other* countries. To strengthen identification, we focus on the adoption of Bitcoin by users outside of China and Kazakhstan in each respective episode. Additionally, one could reasonably think that a drop in mining capacity as large as the ones that happened in the two episodes under analysis could have repercussions on users based outside of China and Kazakhstan too – eg in the form of longer transaction processing times. However, this would affect predominantly on-chain transactions. Instead, our measure of adoption is based on monthly active usage of crypto-exchange apps, and hence captures off-chain adoption. Most of the volume on crypto-exchanges is accounted for by off-

[16] See CNBC: Bitcoin (BTC) price drops on China crypto mining crackdown.

chain transactions which, in turn, would not be affected by such a structural change in a third country.

In Graph 10, right-hand panel we investigate how the change in the Bitcoin price around the two event windows – in June 2021 and in January 2022 – affected the entry of new users. To this end, we estimate variants of regression equation (1) at daily frequency, but limit the sample period to the 15 days around the event window (6 May 2021 for China, 5 January 2022 for Kazakhstan). Importantly, we exclude the country that is responsible for the shock (ie China and Kazakhstan) in each respective exercise from the sample.

Results show that the inflow of new users slows markedly following both events. In June 2021, a 39% drop in the Bitcoin price reduced the inflow of new users by 30%. In January 2022, a price drop of 19% slowed the inflow of new users by 15%. Estimated coefficients are significant at the 1% level. These patterns suggest that the positive relationship between prices and users allows for a causal interpretation.

Panel vector autoregression analysis

To provide additional evidence on the link between crypto trading and bitcoin prices, we develop a simple panel vector autoregression (PVAR) analysis on monthly data for 57 countries over the period October 2015 – April 2022. The interaction between Bitcoin prices, financial markets and crypto exchange users is analysed by means of the following variables: (i) Bitcoin price (bitcoin); (ii) monthly average of crypto exchange app DAUs (users); (iii) country-level equity market price (pk), (iv) equity market turnover (turnover) and (v) the global policy uncertainty index (uncertainty).

To overcome spurious correlation, we express all variables in first differences of logs. We model a five-variable vector autoregression (VAR) system; all the variables that are found to be I(0), are treated as endogenous.[17] Therefore the starting point of the multivariate analysis is:

$$z_t = \mu + \sum_{k=1}^{p} \Phi_k \, z_{t-k} + \varepsilon_t \qquad t = 1, \dots, T$$
$$\varepsilon_t \sim \mathrm{VWN}(0, \Sigma)$$

where $z_t = [uncertainty, turnover, pk, users, bitcoin]$ and ε_t is a vector of residuals, for i = 1, ..., N, where N is the number of countries and time is denoted by t. The deterministic part of the model includes a constant, while the number of lags (p) has been set equal to 1 according to the Andrews and Lu (2001) criteria.[18]

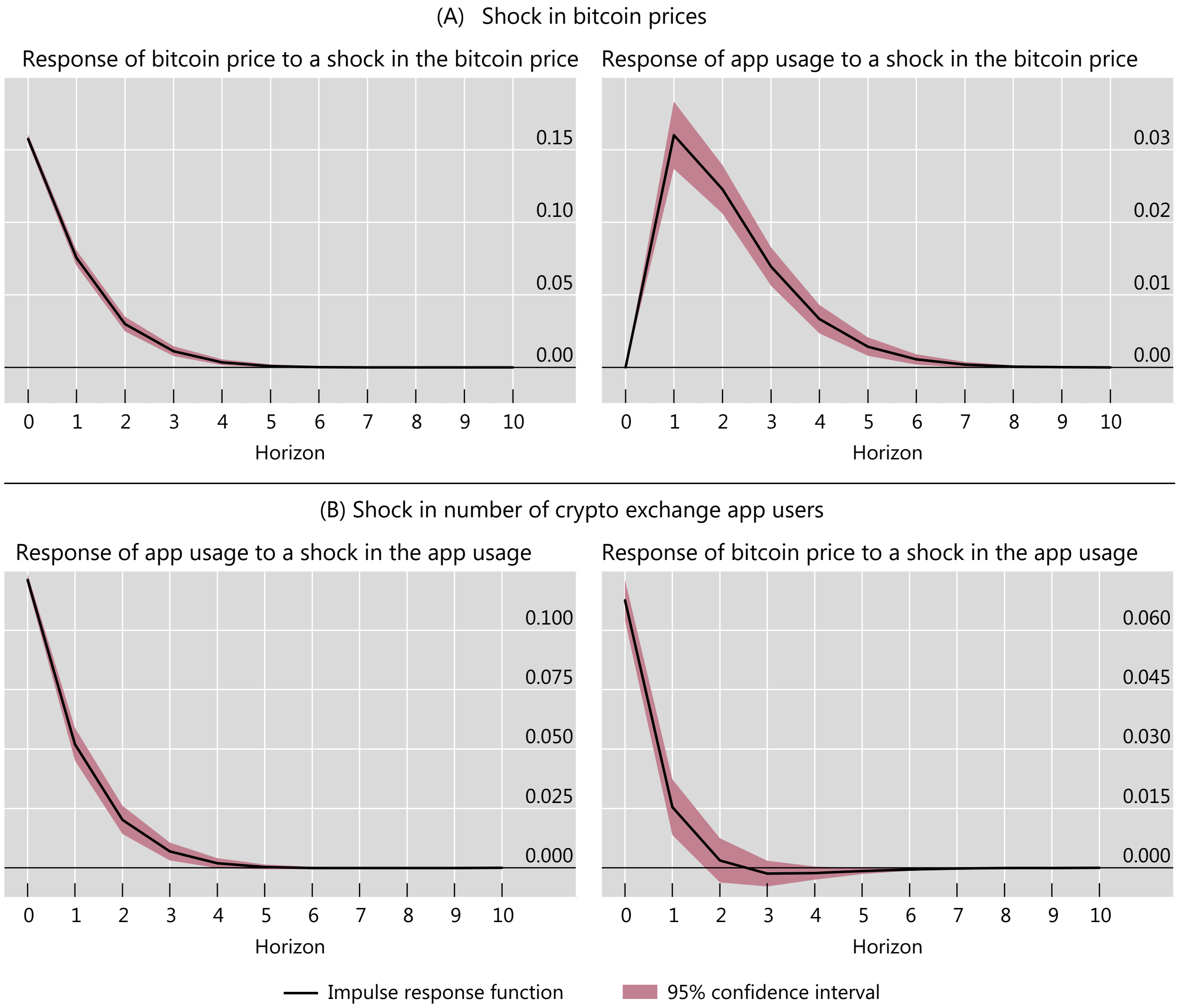
Graph 11 shows the dynamic responses to exogenous shock to the Bitcoin price (panel A) and to the number of crypto exchange app user (panel B). We use a standard

17 Unit root Phillips–Perron tests for all variables show that the null hypothesis that variables contain unit roots is always rejected. The results for the unit root Phillips–Perron tests for all variables in first differences are shown in Table A2 in the Appendix. Figure A1 in the appendix shows that our PVAR is stable because all the moduli of the companion matrix are smaller than one and the roots of the companion matrix are all inside the unit circle.

18 The choice of the deterministic component (constant versus trend) has been verified by testing the joint hypothesis of both the rank order and the deterministic component (so-called Pantula principle). The number of lags (p) has been set equal to 1 based on model-selection criteria by Andrews and Lu (2001).

Cholesky decomposition and order the Bitcoin price as the last variable.[19] This implies that the Bitcoin price reacts contemporaneously to all variables included in the PVAR. At the same time, we consider the app users as second last variable in the Cholesky decomposition, implying that they react contemporaneously to all variables except the Bitcoin price. The complete ordering of the variables is reported in vector z_t.

Impulse response functions to Bitcoin price and number of crypto exchange users Graph 11



The graphs show the impulse response functions for a shock in the monthly change in bitcoin price (top panels) or in the monthly number of crypto exchange apps active users (bottom panels). The other variables included in the PVAR model are the monthly changes in the country-level equity market price, equity market turnover and the global policy uncertainty index.

Sources: CryptoCompare; Sensor Tower; authors' calculations.

[19] Because the ordering of the variable is likely to affect orthogonalised impulse response functions (IRFs) and the interpretation of the results, we follow the theory and order the variable of interest last so they reacts to all variables within one month. This choice is in line with the PVAR literature that analyses the effectiveness of monetary policy shocks using VAR models. Confidence intervals are calculated using Monte Carlo simulation with p-value bands of 90%. The results do not change when altering the order of the variables in the Cholesky decomposition.

The results in panel A suggest that the number of app users respond strongly to a Bitcoin price shock. In case of a 15-percentage point increase in Bitcoin prices (corresponding to a one standard deviation shock), the number of crypto exchange app users increases by 3 percentage points on impact and continues to significantly increase for seven months after the shock.

A similar effect is detected in case of an exogenous shock to the number of users of the crypto exchange. A 12-percentage point increase in the number of crypto exchange app users (corresponding to one standard deviation shock) raises the Bitcoin price immediately by 6 percentage points. The effect continues to be significant for one month with a further 1.5 percentage point increase in the Bitcoin price. It vanishes after two months.

Similar results are obtained when using formal Granger tests (see Table A3 in the appendix). We find strong evidence (at the 99% confidence level) that Bitcoin price changes Granger-cause an increase in new crypto exchange app users, and vice versa.

Bitcoin distributional data[1]

Table 7

Percent change in	Holding size			
	Small	Medium	Whale	Humpback
	(I)	(II)	(III)	(IV)
Bitcoin price	0.006***	0.002***	–0.000	–0.024***
	(0.002)	(0.001)	(0.001)	(0.008)
Global economic policy	0.006	0.003	0.000	–0.017
uncertainty index[2]	(0.004)	(0.003)	(0.004)	(0.019)
Gold price	–0.014	0.008*	–0.012*	–0.017
	(0.011)	(0.005)	(0.007)	(0.036)
CBOE VIX index	–0.001	–0.000	0.000	–0.000
	(0.001)	(0.000)	(0.001)	(0.005)
Number of observations	3784	3784	3784	3782
R-squared	0.005	0.004	0.001	0.004

t-statistic calculated with robust standard errors in brackets; ***/**/* indicates statistical significance at the 1/5/10% level.

[1] All the variables correspond to the percent change in the specific variable. The dependent variable corresponds to the number of BTC held in addresses with balance less than 1 BTC (small), 1–1000 BTC (medium), 1000–100,000 BTC (whale) and more than 100,000 BTC (humpback). Winsorised at the 1.5th and 98.5th percentiles. [2] Standardised to a mean of zero and a standard deviation of one.

Sources: Baker et al (2016); CryptoCompare; Datastream; authors' calculations.

Behaviour by larger vs smaller investors

The supply of Bitcoin is fixed by protocol, with a maximum global supply of 21 million.[20] This raises the question: if retail investors tend to enter the market when prices rise, who is exiting, ie selling their Bitocins? Complementary data from the Bitcoin blockchain allow us to assess changes in holdings based on the total holdings of the wallet. We can assess small and medium Bitcoin holders (those with less than 1 and

[20] As the network nears this threshold, block rewards are periodically reduced by half – or "halving". It has been argued that as block rewards approach zero, payments security will decrease (Auer (2019)).

between 1 and 1000 Bitcoin, respectively), and compare these with so-called "whales", and the even larger "humpbacks", who own wallets in excess of 100,000 Bitcoin.

Table 7 shows that in periods of price increases, small Bitcoin holdings tend to increase, while especially the largest Bitcoin holders – the humpbacks – tend to sell. This, again, is consistent with a market sustained by new entrants, allowing early investors and insiders to cash out at their expense.[21]

5. Conclusion

Our analysis has shown that, around the world, Bitcoin price increases have been tied to greater entry by retail investors. In particular, with data over 2015–22, we show that users are more likely to make active use of crypto exchange apps in months after a rise in the price of Bitcoin. This is particularly true for young men, who tend to have a higher risk tolerance than women and older users. They are also higher for users with an Android device, who tend to have lower incomes than iOS users. These findings hold when controlling for a range of global and country-specific factors. They are stronger in countries with higher bank branch density or adoption of digital payments, and weaker regulatory quality. An analysis of two unanticipated shocks that led to a fall in the price of Bitcoin, in May 2021 and January 2022, suggests that the relationship can be interpreted as causal. Further, in a panel VAR, price increases Granger-cause new entry, but new entry does not Granger-cause price increases.

Our findings shed light on the motivation for retail investors to enter crypto markets. They support the notion that, by and large, investors view cryptocurrencies as a speculative investment (a "gamble") rather than a means of payment for real economic transactions. They also raise concerns around consumer protection: if users are driven primarily by backward-looking price movements, are they fully prepared for the potential consequences of a price correction? Our estimations that 73-81% of global investors have likely lost money on their crypto investment, and that larger investors ("humpbacks") have tended to sell when smaller investors are buying, may give grounds for deeper investigation of claims that crypto will "democratise" the financial system.

Without attempting to predict future market developments, our study does raise questions about the implications of greater crypto adoption for the economy and consumer welfare. As recent developments have shown, if interest rates rise and global risk appetite suddenly wanes, the overall market could dry up. If, following price declines, retail investors make losses and exit the market, there is the potential for self-reinforcing dynamics. For authorities tasked with consumer protection and financial stability, a deeper understanding of these scenarios and the associated knock-on effects would be constructive.

[21] This is one channel by which crypto trading may redistribute wealth to insiders, along with broader rents in the crypto and decentralised finance sector (Makarov and Schoar (2022)).

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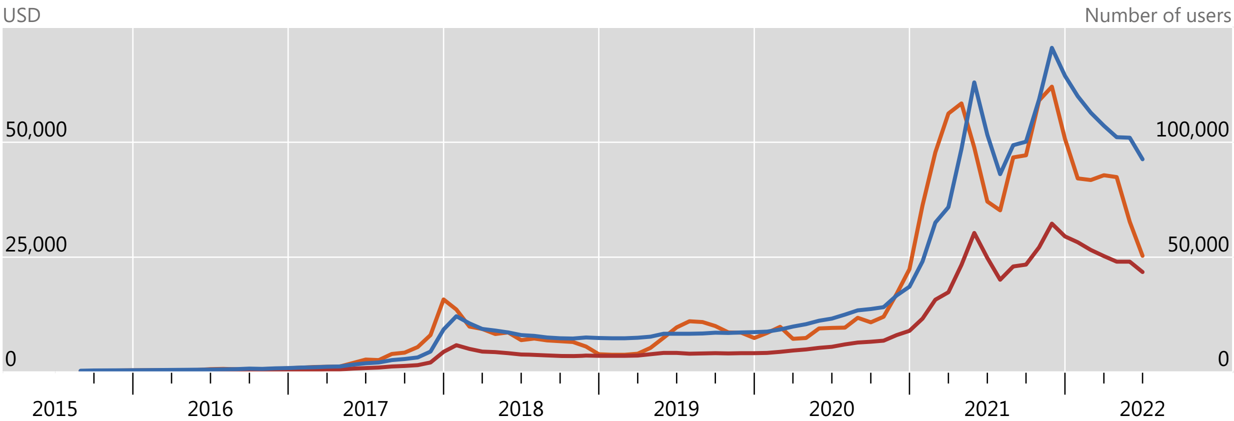
Appendix

Young male users enter mostly during periods of pronounced price swings

Graph A1



Simple average of the country-level monthly average of DAUs by age and gender. Based on active users of 45 crypto exchanges android and iOS apps.

Sources: CryptoCompare; Sensor Tower; authors' calculations.

App-level regressions: young vs old, male vs female, iOS vs Android users

Table A1

	Monthly average of daily active users: without app fixed effects					
	Male below 35	Male above 35	Female below 35	Female above 35	iOS	Android
	(I)	(II)	(III)	(IV)	(V)	(VI)
Bitcoin price	6.139***	2.244***	2.463***	0.816***	0.019**	0.074***
	(1.045)	(0.566)	(0.521)	(0.306)	(0.008)	(0.012)
App fixed effects	N	N	N	N	N	N
Number of observations	2594	2594	2594	2594	2594	2570
R-squared	0.014	0.005	0.007	0.002	0.001	0.019

	Monthly average of daily active users: with app fixed effects					
	Male below 35	Male above 35	Female below 35	Female above 35	iOS	Android
	(I)	(II)	(III)	(IV)	(V)	(VI)
Bitcoin price	6.501***	2.537***	2.594***	0.968***	0.028***	0.074***
	(0.878)	(0.509)	(0.464)	(0.290)	(0.008)	(0.009)
App fixed effects	Y	Y	Y	Y	Y	Y
Number of observations	2594	2594	2594	2594	2594	2570
R-squared	0.458	0.471	0.462	0.468	0.472	0.472

Robust standard errors in brackets; ***/**/* indicates statistical significance at the 1/5/10% level.

Sources: CryptoCompare; Sensor Tower; authors' calculations.

Unit root tests[1]

Table A2

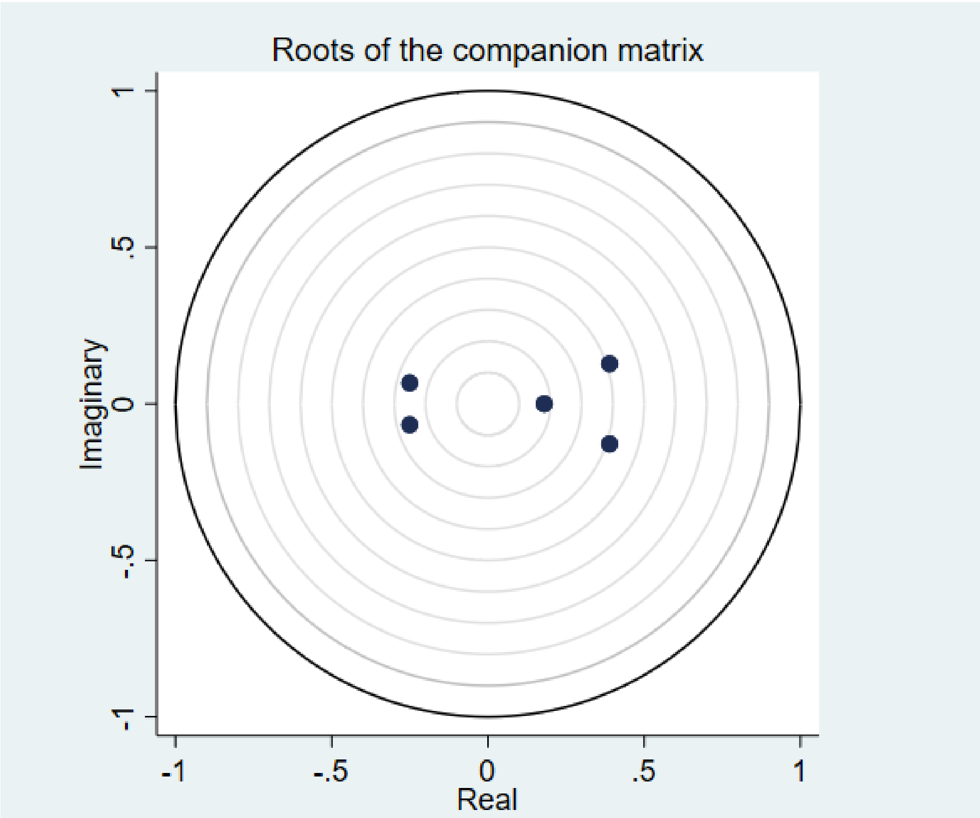
	Δ Ln(monthly average daily active users)		Δ Ln(bitcoin price)		Δ Ln(MSCI equity index price)[2]		Δ Ln(stock market turnover)[3]		Δ Ln(global economic policy uncertainty index)	
	Stat	P-value	Stat	P-value	Stat	P-value	Stat	P-value	Stat	P-value
Inverse chi-squared	2,839.09	0.00	3,365.14	0.00	4,052.00	0.00	4,158.90	0.00	6,395.97	0.00
Inverse normal	–48.22	0.00	–51.98	0.00	–59.30	0.00	–61.46	0.00	–75.75	0.00
Inverse logit *t*	–85.49	0.00	–95.23	0.00	–135.61	0.00	–149.51	0.00	–181.08	0.00
Modified inv chi-squared	145.72	0.00	162.88	0.00	237.44	0.00	263.04	0.00	318.36	0.00

[1] Based on Phillips–Perron tests. The null hypothesis is that all panels contain unit roots. The sample includes 57 countries over the period Oct 2015–Apr2022. Data winsorised at the 1st and 99th percentiles. [2] Country specific MSCI equity index price, in local currency. [3] Based on the country specific Datastream equity index, in local currency.

Sources: Baker et al (2016); CryptoCompare; Datastream; Refinitiv Eikon; Sensor Tower; authors' calculations.

Roots of the companion matrix

Graph A2



Source: Baker et al (2016); CryptoCompare; Datastream; Refinitiv Eikon; Sensor Tower; authors' calculations.

PVAR Granger test[1]

Table A3

Equation/ excluded	Δ Ln(monthly average daily active users)			Δ Ln(bitcoin price)			Δ Ln(MSCI equity index price)[2]			Δ Ln(stock market turnover)[3]			Δ Ln(global economic policy uncertainty index)		
	chi2	df	p-value	chi2	df	p-value	chi2	df	p-value	chi2	df	p-value	chi2	df	p-value
Δ Ln(monthly average daily active users)				32.92	1	**0.00**	17.93	1	0.00	0.34	1	0.559	73.00	1	0.00
Δ Ln(bitcoin price)	203.92	1	**0.00**				1.05	1	0.305	30.02	1	0.00	29.56	1	0.00
Δ Ln(MSCI equity index price)[2]	18.18	1	0.00	1.42	1	0.233			0.00	3.65	1	0.056	306.26	1	0.00
Δ Ln(stock market turnover)[3]	2.56	1	0.11	3.23	1	0.072	8.49	1	0.004				13.35	1	0.00
Δ Ln(global economic policy uncertainty index)	45.06	1	0.00	102.19	1	0.00	218.60	1	0.00	65.62	1	0.00			
All	265.49	4	0.00	152.65	4	0.00	241.96	4	0.00	136.84	4	0.00	368.16	4	0.00

The null hypothesis of the test is that the excluded variable does not Granger-cause the equation variable.

[1] The sample includes 57 countries over the period Oct 2015–Apr2022. Data winsorised at the 1st and 99th percentiles. [2] Country specific MSCI equity index price, in local currency. [3] Based on the country specific Datastream equity index, in local currency.

Sources: Baker et al (2016); CryptoCompare; Datastream; Refinitiv Eikon; Sensor Tower; authors' calculations.