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Crypto trading and Bitcoin prices: evidence from a new database of retail adoption

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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 publicly available database 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 entry of new users, in particular among more risk-seeking segments of the population. Moreover, we find that when prices rise larger holders sell, likely making a return at retail users' expense. We confirm these findings by exploiting an exogenous decline in the Bitcoin price during the social unrest in Kazakhstan in early 2022.

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Keywords: Bitcoin, cryptocurrencies, cryptoassets, regulation, decentralised finance, DeFi, retail investment.

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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 (Blandin et al (2021), de Best (2022)).

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 still largely self-referential and oftentimes does not finance real-world investments (Aramonte et al (2022)).

Why then 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 (Auer and Tercero-Lucas (2022), FCA (2021)). As they fluctuate widely in value and can sustain only a limited volume of transactions (Boissay et al (2022)), cryptocurrencies have also not proven useful to date for payments in real transactions 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.[1]

In this paper, we shed further light on the role of speculative and safe haven considerations as drivers of cryptocurrency adoption. For this, we assemble a novel cross-country database on retail downloads and the use of crypto exchange apps at daily frequency for 95 countries over 2015 to 2022.[2] We first use the database to establish a series of stylised facts on crypto adoption across countries and over time. We then provide novel evidence on the relationship between the use of crypto trading apps, the Bitcoin price as well as other macroeconomic variables in a global context.

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 (eg equity price indices or stock market turnover), global uncertainty or observable and unobservable country characteristics. In particular, the price of Bitcoin remains the most important factor in explaining adoption when we control for global uncertainty or volatility, suggesting that explanations based on Bitcoin as a safe haven fall short of explaining adoption. 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 highly significant effect on the number

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

2 The data can be downloaded here: https://www.bis.org/publ/work1049.htm.

of new users. It also explains the lion's share of the variation in the entry of new users. These results suggest that an increase in the price of Bitcoin leads to new users entering the crypto system.

A concern for our estimation is that the entry of new users could itself lead to price increases, potentially leading to reverse causality. To address this issue, we focus on a specific episode of an exogenous shock to the price of Bitcoin: the social unrest in Kazakhstan in early 2022. In the wake of China's crackdown on Bitcoin mining in 2021, Kazakhstan became one of the worlds' most important countries for mining Bitcoin. However, mining activity in Kazakhstan was severely disrupted in January 2022, when rising fuel prices led to deadly riots. In consequence, the Bitcoin price fell by almost 20% between late December and early January. The reason is that lower mining capacity implies higher transaction costs due to higher fees. Importantly, the decline in the global price of Bitcoin was largely independent of changes in the number of users in other countries. Excluding users in Kazakhstan from the sample, we find that the exogenous change in the Bitcoin price during the episode had a strong and significant dampening effect on the entry of new users – confirming our main result that the Bitcoin price affects investor entry.[3]

To further support our results and interpretation, we analyse 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. We also find that young male users are more sensitive to changes in the price of Bitcoin than female users and older men. These patterns are consistent with a speculative motive arising from feedback trading considerations, ie users being drawn to the crypto ecosystem by rising Bitcoin prices – rather than a dislike for traditional banks, the search for a store of value or distrust in public institutions. Our findings for a large number of countries expand upon results obtained for Germany (Hackethal et al (2021)) and the US (Purisainen and Toczynski (2022)).

Our second main finding is that smaller users are buying Bitcoin when prices increase, while the largest holders (so-called whales) are selling. We combine our data on app users with complementary data from the Bitcoin blockchain to assess changes in holdings based on the total holdings of the wallet. The uncovered patterns suggest that larger holders are making a return at the smaller users' expense. This result is consistent with recent evidence on the Terra/Luna crash and FTX bankruptcy (Liu et al (2023), Cornelli et al (2023)).

And third, based on our novel cross-country data and adoption patterns, we perform simulations and find that, at the time of writing, about three-quarters of users had likely lost money on their investments in cryptocurrencies. We first estimate the distribution of the number of users downloading crypto exchange apps at different levels of the Bitcoin price. We find that 73% of users downloaded their app when the price of Bitcoin was above $20,000 – above the price of Bitcoin in October 2022. Second, assuming that each new user bought $100 of Bitcoin in the month of the first app download and in each subsequent month, our computation shows that over 75% of users would have lost money. The median investor would have lost 48% of their total $900 in funds invested.

3 As an additional test for causality we estimate a panel vector autoregression (PVAR) model, tackling endogeneity issues by means of a Cholesky decomposition, which orders the Bitcoin price last. For more details see Appendix B.

Our results have relevance for policy discussions on the regulation of cryptocurrencies for consumer and investor protection, as well as to ensure financial stability. In particular, they raise concerns that individual decisions are backward-looking and that many retail investors are not fully informed about the risks or volatility of the crypto sector. As recent events have made clear, rising interest rates and other shocks can lead to a large fall in the prices of Bitcoin and other crypto-assets, as the dynamics that buoyed the market move into reverse. In light of our findings that retail investors tend to lose out during such episodes, policy that aims at protecting investors from losses in the crypto space seems necessary.

Our paper makes two contributions to the emerging literature on crypto-currency adoption.

First, we construct a novel and publicly available database on cryptocurrency adoption for a large number of countries and show that retail investors enter the market when the Bitcoin price increases. Our results on investor entry and exit, obtained with data from a large number of apps, are consistent with Kogan et at (2023), who focus on the trading behaviour of crypto investors. In a sample of 200,000 retail traders on crypto exchange eToro, they show that crypto traders follow a momentum-like strategy in cryptocurrencies, even when they are contrarian in stocks and gold. We also 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).[4] Moreover, our results could imply that entry of retail investors could further fuel price increases, as established in Benetton and Compinai (2022).

Second, our result that larger investors sell to smaller investors as prices rise suggests that sophisticated investors are able to profit at the expense of retail investors in crypto. They echo findings in Liu et al (2023) for the Terra/Luna collapse, as well as in Cornelli et al (2023) for the FTX bankruptcy. In particular, Liu et al (2023) use data from the Terra blockchain and find that wealthier and more sophisticated investors ran first and experience smaller losses, while smaller investors ran later and experienced larger losses. Our results for a large sample of countries generalise these findings to periods outside of dramatic shocks in the crypto space. Even in calmer times, larger investors appear to cash out at the expense of smaller investors.

The paper is organised as follows. Section 2 introduces our dataset, provides a number of novel stylised facts on crypto adoption across countries and preforms simulations to assess to what extent investors have gained or lost money in crypto. Section 3 discusses our empirical strategy and presents the key empirical findings on crypto app use and Bitcoin prices. Section 4 exploits a shock episode to obtain exogenous variation in the price of Bitcoin and reports results that support a causal interpretation of our findings. Finally, Section 5 concludes.

4 Our results also relate to and build on work that seeks 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).

2. Data description

Our data on the adoption of crypto apps come from Sensor Tower, a proprietary app intelligence data provider. Sensor Tower collects data on various app statistics for apps from the Apple and the Google Play store, among which downloads and active use. 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)). 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 to June 2022. To select the sample of apps, we rely on the list of crypto exchanges from the CCData (formerly 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 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 CCData, a leading source of data on cryptocurrency prices.[5] In addition to the price and volume data, CCData, 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

[5] 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.[6] Finally, we obtain measures of risk aversion at the country level from Rieger et al (2015).

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. Table A1 in the appendix provides further details.

Descriptive statistics

Table 1

	No observations	Mean	Standard deviation	Min	Max
Panel A: Crypto adoption analysis					
Monthly average daily active users	6,677	83,419	309,128	0.32	5,983,340
Bitcoin price	6,677	14,912	17,519	236.51	62,080
MSCI equity index price[1]	5,260	4,380	35,600	0.00	396,000
Stock market turnover[2]	4,701	328	1,450	0	21,500
Gold price	6,677	1,486.57	274.08	1,076.11	1,993.31
Global economic policy uncertainty index	6,677	222.01	67.57	101.50	430.26
FX standard deviation	6,270	1.66	99.17	0	7,853
CPI, yoy change	6,538	340.34	8,354	–100	344,510
Panel B: country characteristics analysis					
Monthly average daily active users	4,575	109,763	364,275	0.34	5,983,340
Bitcoin price	4,575	14,273	17,322	236.51	62,080
Commercial bank branches per 100k adults	4,409	19.54	11.64	3.45	67.51
Regulatory quality	4,575	0.83	0.78	–0.92	2.26
Control of corruption	4,575	0.67	0.97	–0.95	2.28
Male population below 35	4,492	14.72	4.47	9.90	37.82
Remittance received, % of GDP	4,088	1.45	2.26	0	10.49

[1] Country-specific MSCI equity index price, in local currency. Reported in millions, in regressions in actual values. [2] Based on the country specific Datastream equity index, in local currency. Reported in billions, in regressions in thousands.

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

[6] 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.

2.1 Stylised facts on global crypto adoption

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 about 120,000 to more than 32.5 million per day. During the rapid price increases in late 2017 and early 2021, alone, around 105 and 511 million new monthly active app users joined. As of mid-2022, there were a total of about 700 million instances of monthly active use in our global sample, and a cumulative total of 565 million crypto exchange app downloads over the full sample period.[7]

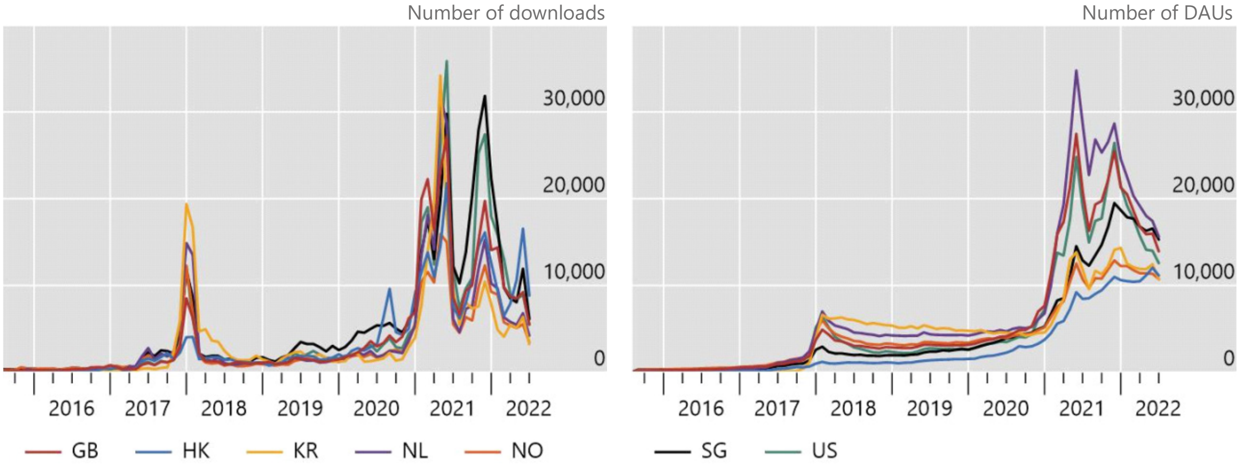
Several countries registered monthly downloads of crypto exchange apps exceeding 15,000 per 100,000 inhabitants with a peak of more than 35,000 (Graph 1, left-hand panel). Daily active users of these apps exceeded 10,000 per 100,000 inhabitants on average, with a peak of about 35,000 (right-hand panel). The group of top downloading jurisdictions comprises 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.

Adoption of crypto exchange apps over time

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.

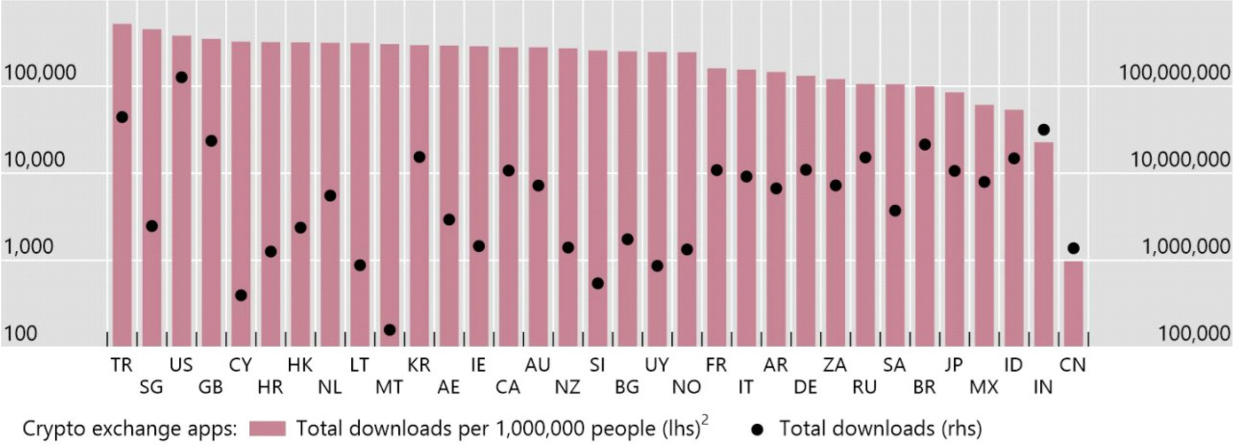
Sources: Sensor Tower; World Bank; authors' calculations.

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 (Graphs 2 and 3). It is lowest in China and in India, where legal restrictions likely prevent greater retail adoption.

[7] 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



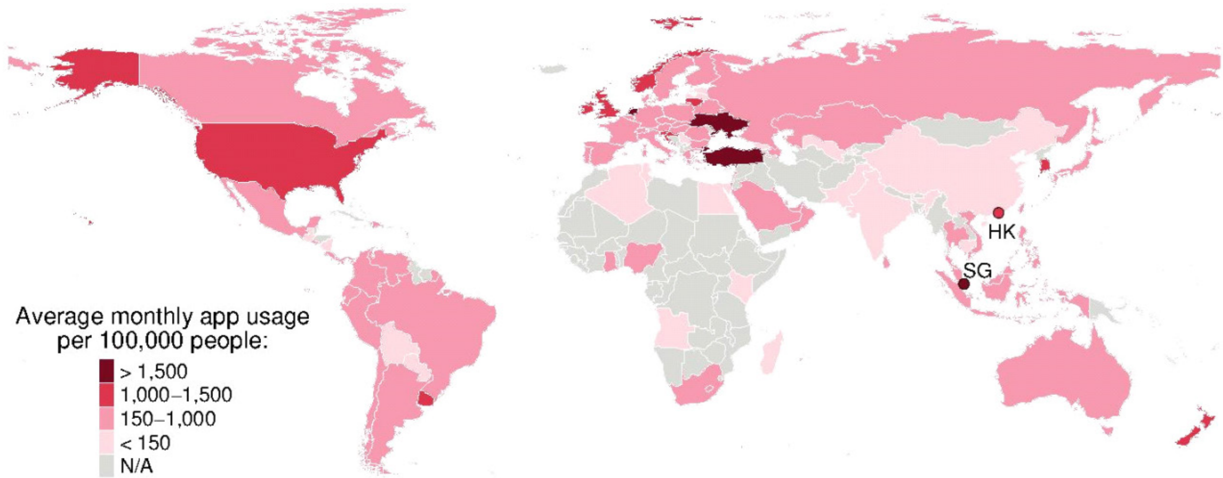
AE = United Arab Emirates, AR = Argentina, AU = Australia, BG = Bulgaria, BR = Brazil, CA = Canada, CN = China, CY = Cyprus, DE = Germany, FR = France, GB = United Kingdom, HK = Hong Kong SAR, HR = Croatia, ID = Indonesia, IE = Ireland, IN = India, IT = Italy, JP = Japan, KR = Korea, LT = Lithuania, 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



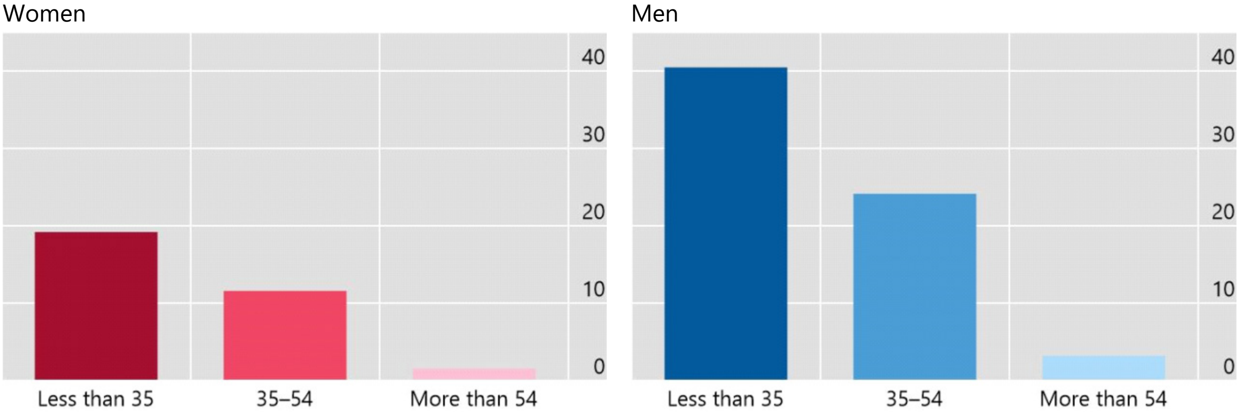
The use of this map does not constitute, and should not be construed as constituting, an expression of a position by the BIS regarding the legal status of, or sovereignty of any territory or its authorities, to the delimitation of international frontiers and boundaries and/or to the name and designation 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. This compares to 26% of young men in the general population in the countries in our sample. 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.

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.

This pattern is consistent with the findings of surveys on cryptocurrency and fintech use; here, too, young men are overrepresented (Auer and Tercero-Lucas (2022); Chen et al (2023)).[8]

2.2 Simulating returns on crypto investments

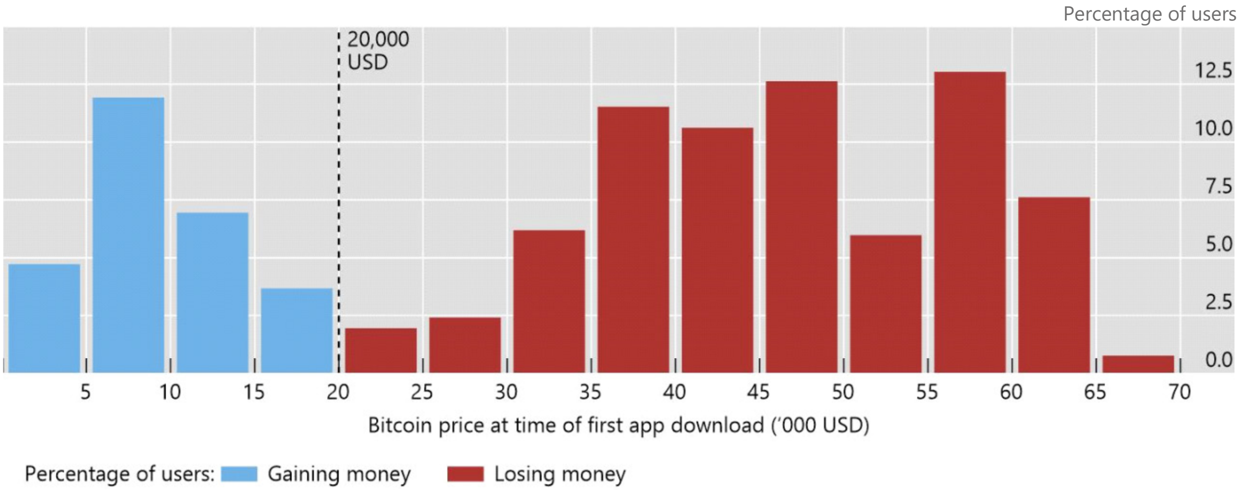
While our database does not contain information on the actual performance of crypto currency investments of individuals, we can perform simulations to obtain an estimate.

First, we estimate the distribution of the number of users downloading crypto exchange apps at different levels of the Bitcoin price. We find that 73% of 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.

[8] This finding also mirrors those 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



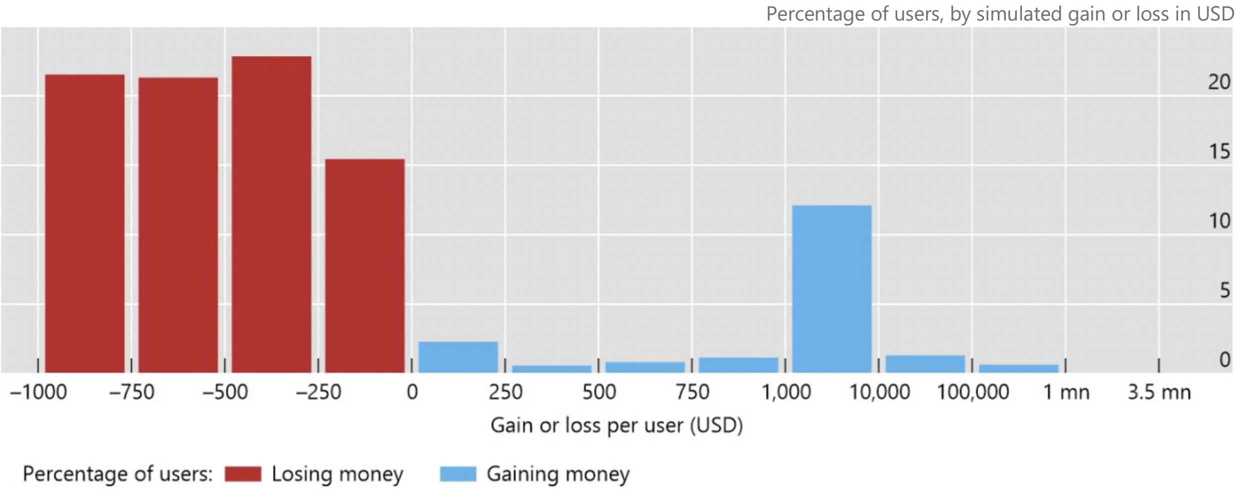
The graph shows a histogram of the share of daily downloads of crypto-exchange apps by Bitcoin price at the time of first download. Estimations of losses or gains assume that the users purchased bitcoin on the same daily they downloaded the crypto-exchange app.

Sources: CCData; 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 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, over three-quarters of users have lost money Graph 6



Sources: CCData; Sensor Tower; authors' calculations.

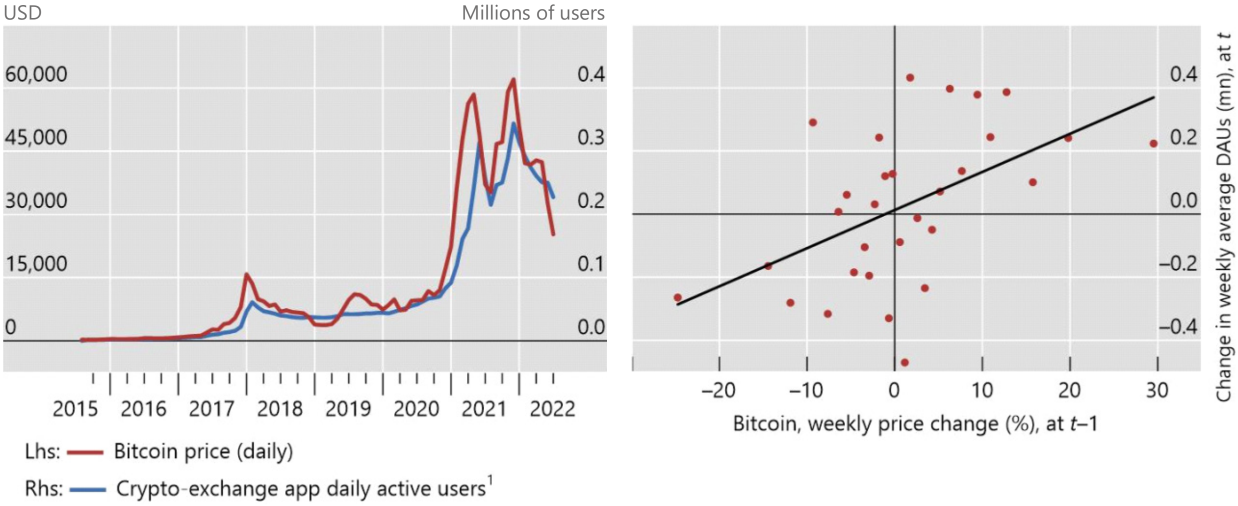
Taken together these findings suggest that the vast majority of Bitcoin investors has lost money, with the exception of a few players who made substantial large gains.

3. Empirical analysis

Bitcoin prices and user numbers have moved in lockstep, with a correlation coefficient of more than 0.9 in the time series (Graph 7, left-hand panel), but the relationship is not fully contemporaneous. An increase in user numbers has generally lagged rises in prices.[9] A scatterplot confirms these patterns: weekly changes in users are positively correlated with past changes in Bitcoin prices (right-hand panel). This lagged relationship could suggest that users enter the system attracted by high prices and in the expectation that prices continue to rise. In what follows, we examine these patterns in greater detail.

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

Daily active users increase as Bitcoin price trends higher | Inflows of users are correlated with price increases[2]



[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 at the country-month level.

Sources: CCData; Sensor Tower; authors' calculations.

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

$$\ln{(DAUs)_{i,t}} = \beta * \ln{(BTC)_t} + \gamma * X_{i,t} + \theta_i + \varepsilon_{i,t} \qquad (1)$$

The dependent variable is the log of the monthly average number of daily active users (DAU) in jurisdiction i and month t. It is obtained by summing the daily numbers of daily active users of all apps at the country level each day and then taking a monthly average. The main independent variable is the Bitcoin price in month t in logs. We choose the maximum, rather than the average, as it generally attracts the greatest attention of investors. We include a set of macro-economic control variables (at the country-time or time level) discussed in more detail below. Further, in each specification we include country fixed effects to account for any observable and unobservable time-invariant country characteristics. For example, these fixed effects account for the level of development or country size.

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

Table 2 shows that an increase in the Bitcoin price is associated with a significant increase in the number of new users. In column (I), a one percent increase in the Bitcoin price is associated with an increase in the monthly average number of daily active users by 1.1%. The estimated coefficient is significant at the 1% level. To see whether this correlation is driven by other financial or country-specific conditions, we control for various factors in columns (II)–(V). When controlling for countries' stock market returns (column II) or turnover (column III), the global gold price (column IV), or global economic policy uncertainty, countries' FX volatility and countries' CPI inflation (column V), the coefficient on the Bitcoin price remains highly significant and similar in economic magnitude. In the most stringent specification in column (V), a one percent increase in the Bitcoin price is associated with an increase in new users by 0.91%.[10]

Note that the positive correlation between the CPI and the number of users in column (V) is consistent with Aiello et al (2023), who show that higher expected inflation increases crypto investing.

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					0.556***
uncertainty index					(0.041)
FX standard deviation					–0.041
					(0.028)
CPI, yoy change					0.037***
					(0.003)
Number of observations	6,677	5,260	4,701	4,701	4,516
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; CCData; Datastream; Refinitiv Eikon; Sensor Tower; national data; authors' calculations.

[10] As a robustness check we run the specification from column (I) on the sample of 4,516 observations from column (V). The results are similar (ie coefficient of 1.04, and significant at the 1% level) to the ones from column I suggesting that we can consistently trace the decrease in the coefficient size of the natural logarithm of the price of bitcoin to the introduction of controls.

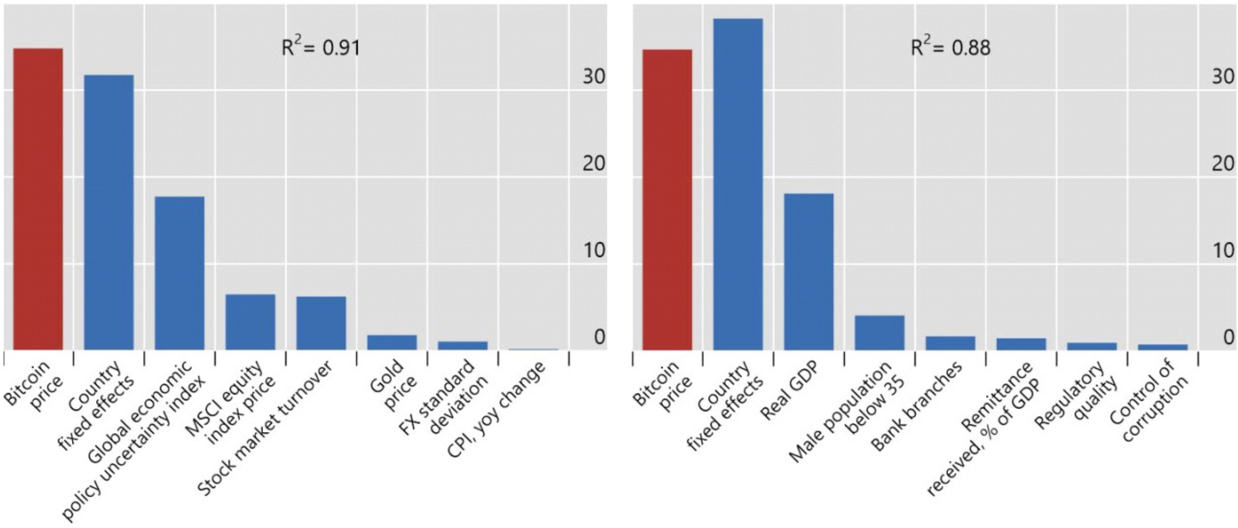
All in all, these findings suggest that the relation between daily active users and the Bitcoin price is not fully explained by other observable macro-factors.[11]

Moreover, the Bitcoin explains the lion's share of the overall variation in entry of new users across countries and time. Graph 8, panel (a) plots the results from a Shapley decomposition of the R-squared of Equation (1). The Bitcoin price explains almost 35% of the overall variation in the entry of new users, followed by time-invariant country-level unobservables, captured through country fixed effects, with slightly more than 30%. All other time-varying factors combined explain the residual 35%.

Shapley decompositions

In per cent — Graph 8

Time-varying macro controls — Country characteristics



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, the CPI, the regulatory quality, the control of corruption, and country fixed effects is applied the natural logarithm. For the left-hand panel, the underlying regression correspond to table 2, column (V). For the right-hand panel the underlying regression is based on data in yearly frequency, as most of the country-level indicators are not available in higher frequency. The dependent variable corresponds to the yearly average of the number of daily active users of crypto exchange apps. The independent variables correspond to the number of bank branches per 100,000 adults, real GDP, regulatory quality, control of corruption, male population below 35, remittances received as percentage of GDP and a set of country-level dummies.

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

3.1 Differences by user 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

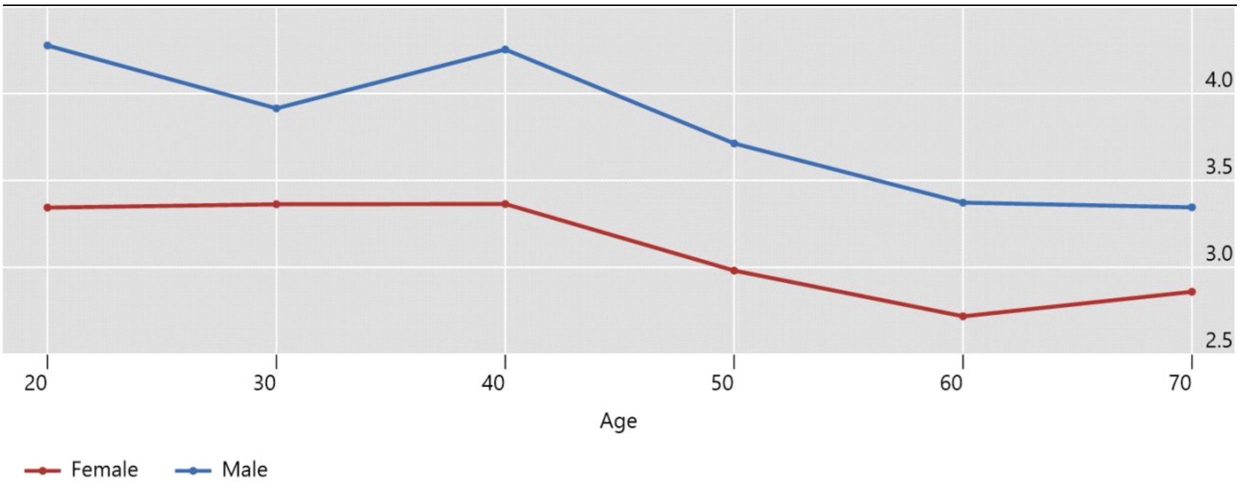
[11] In additional robustness tests, we control for the *network factors* identified in Liu and Tsyvinski (2021), namely number of wallets, number of active addresses, number of transactions, number of payments, and the first principal component of these four measures. Overall, our results are robust after controlling for these network factors (unreported).

shows that younger men are more willing to take financial risks than both women and older male respondents (Graph 9). Similar findings have been reported in other contexts (see, for example, Borghans et al, 2009; Arano et al, 2010).[12]

Investigating to what extent the relationship between price development and new users differs across demographic groups could hence offer additional insights on its drivers. 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 among US consumers

Index, 1 (lowest willingness)–7 (highest willingness) Graph 9



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 use the number of new users among different population subgroups as dependent variable. Since the breakdown among subgroups is only available at the app and not the country level, we aggregate our data to the monthly level. The dependent variables correspond to the simple average of the country-level monthly average number of active users of crypto exchange apps for each gender-age bucket.

Table 3, columns I–IV show that young men have a higher sensitivity to changes in the Bitcoin price than older men or women of any age. The coefficient on the Bitcoin price is 1.5 times larger for young men (column I) compared to older men (column II), and more than two (three) times as large relative to women below (above) age 35 (columns III and IV). Yet the relationship remains significant at the 1% level for all population groups even after controlling for the local stock market price and turnover, gold price, the global economic policy uncertainty index, exchange rate standard deviation and the year-on-year change in CPI.

12 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 trust and the use of fintech by gender, with implications for use and adoption (Armantier et al, 2021; Chen et al, 2023; Doerr et al, 2023).

To further shed light on the importance of risk-aversion, columns V and VI report results of panel regressions on country-month level data (see Equation (1)). The dependent variable corresponds to the natural logarithm of the monthly average of daily active users. We control for the standard deviation of the exchange rate, the year-on-year change in CPI, the natural logarithm of the local stock market price and turnover, gold price, and the global economic policy uncertainty index, and country-level unobservables through the inclusion of country fixed-effects. The coefficients of interest correspond to the interaction terms between the natural logarithm of the price of bitcoin and indicators of risk aversion at the country-level as derived by Rigier et al. (2015).

Results show that that adoption is lower in more risk-averse countries for a given increase in the Bitcoin price. These findings lend further support to the argument 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.

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

	Monthly average number of users[1]				Ln(monthly average daily active users)	
	Male below 35	Male above 35	Female below 35	Female above 35		
	(I)	(II)	(III)	(IV)	(V)	(VI)
Bitcoin price	1.505***	0.979***	0.707***	0.467***		
	(0.398)	(0.263)	(0.183)	(0.125)		
Ln(Bitcoin price)					0.910***	0.974***
					(0.028)	(0.036)
Risk aversion (losses)[2]*					–0.015***	
ln(Bitcoin price)					(0.001)	
Risk aversion (gains)[2]*						–0.066**
ln(Bitcoin price)						(0.033)
Number of observations	83	83	83	83	3,557	3,557
R-squared	0.910	0.911	0.915	0.910	0.905	0.898

***/**/* indicates statistical significance at the 1/5/10% level. Regressions in columns I–IV include the local stock market price and turnover, gold price, the global economic policy uncertainty index, exchange rate standard deviation and the year-on-year change in CPI as controls; robust standard errors in brackets. Panel regressions with country fixed effects in columns V–VI include the natural logarithm of the local stock market price and turnover, gold price, and the global economic policy uncertainty index, in addition to the exchange rate standard deviation and the year-on-year change in CPI as controls; standard errors clustered by time in brackets.

[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. [2] Risk aversion measures correspond to the relative risk premiums (RRP) from Rieger et al (2015). RRP losses (gains) correspond to the country-level median value based on lotteries with a negative (positive) expected value. Negative values for the RRPs indicate risk seeking.

Sources: Baker et al (2016); Rieger et al (2015); CCData; World Bank; Datastream; Refinitiv Eikon; Sensor Tower; national data; authors' calculations.

3.2 Differences by country characteristics

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 in 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 ("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 (I) shows that the relationship is slightly stronger in countries with more bank branches, ie in countries with a better-developed traditional financial system.

Crypto adoption and institutional characteristics | Table 4

	Dependent variable: ln(monthly average daily active users)				
	(I)	(II)	(III)	(IV)	(V)
Ln(bitcoin price)	0.910***	1.047***	1.003***	0.666***	0.835***
	(0.016)	(0.014)	(0.013)	(0.086)	(0.013)
No commercial bank branches per 100k adults	0.016***				
	(0.006)				
No commercial bank branches per 100k adults*ln(bitcoin price)	0.001**				
	(0.001)				
Regulatory quality		1.268***			
		(0.112)			
Regulatory quality*ln(bitcoin price)		–0.158***			
		(0.009)			
Control of corruption			1.710***		
			(0.128)		
Control of corruption* ln(bitcoin price)			–0.127***		
			(0.007)		
Ln(male population below 35)				–2.404***	
				(0.274)	
Ln(male population below 35) * ln(bitcoin price)				0.090***	
				(0.031)	
Remittance received, % of GDP					–0.329***
					(0.059)
Remittance received, % of GDP * ln(bitcoin price)					0.054***
					(0.005)
Number of observations	4,409	4,575	4,575	4,492	4,088
R-squared	0.909	0.919	0.920	0.912	0.912

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, in addition to the exchange rate standard deviation and the year-on-year change in the CPI.

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

Columns (II) and (III) 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. Column (IV) shows that, consistent with the results from Table 3 and Graph 4, the relationship is more pronounced in countries with a higher male population below 35. Finally, column (V) shows the relationship between the Bitcoin price and user entry is stronger in countries with a higher inflow of remittances as a percentage of GDP.

Taken together, results in Tables 2, 3 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.

To contrast the relative importance of country-level factors, panel (b) in Graph 8 again shows how much of the variation in the entry of new users (measured with the R-squared) they can explain. To ensure an adequate comparison of the Bitcoin price with country-level indicators at yearly frequency, we aggregate the data in Equation (1) to the yearly level. The dependent variable thus corresponds to the natural logarithm of the yearly average of the number of daily active users of crypto exchange apps. The independent variables correspond to the natural logarithm of the Bitcoin price, the log of the number of bank branches per 100,000 adults, real GDP, and male population below 35, plus regulatory quality, control of corruption, remittances received as percentage of GDP and a set of country-level dummies. While the price of Bitcoin explains almost 35% of the total variation, time-varying country characteristics explain less than 30% overall. Consistent with results for time-series control variables in panel (a), 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.

4. Exploiting exogenous variation in the Bitcoin price

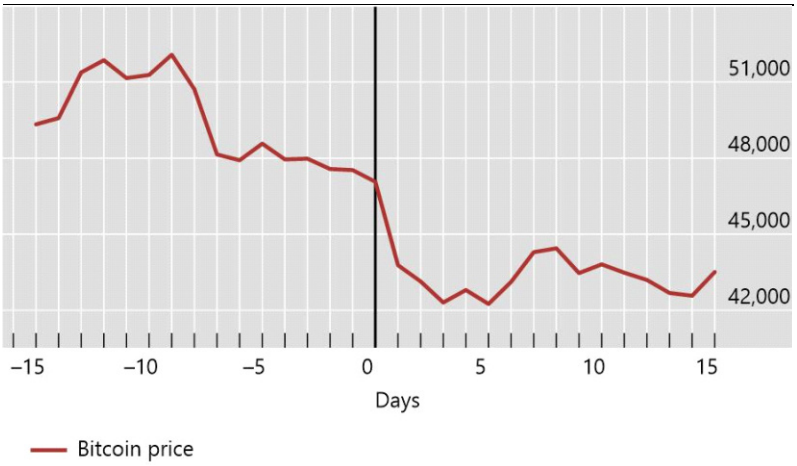
While our analysis so far suggests that new users are attracted by rising prices, the relationship between Bitcoin prices and the influx of new users could also operate in the other direction. As new users download apps and use their fiat money to buy Bitcoin, they might drive up the price of Bitcoin (Benetton and Compinai (2022)). While the patterns in Graph 1 suggest that user inflows tend to follow price increases with a lag of around two months, in what follows, we address the issue of reverse causality through an event study of an episode with an arguably exogenous change to the price of Bitcoin: the social unrest in Kazakhstan in 2022.

In May 2021, the Chinese government announced a crackdown on Bitcoin mining and trading in China. Since Chinese miners had been responsible for up to three-quarters of all mining at its peak, this policy move had a large and swift effect on Bitcoin mining capacity. Bitcoin mining equipment was subsequently exported from China and miners eventually set up shop in other countries with cheap and abundant energy supplies. One such location was neighbouring Kazakhstan, which had large, vacant warehouses and factories well-suited to house mining operations, as well as cheap energy from coal (70% of electricity production) and natural gas. In a few months, Kazakhstan became one of the worlds' most important countries for mining Bitcoin.

However, mining activity in Kazakhstan was severely disrupted in January 2022, when rising fuel prices led to deadly riots. In consequence, the Bitcoin price fell by about 15% between late December and early January, from over $48,000 to about $42,000, as shown in Graph 10, panel (a). The reason is that lower mining capacity implies higher transaction costs due to higher fees.

Kazakhstan unrest leads to a price drop

In US dollars Graph 10



The vertical line corresponds to January 5, 2022, the day on which, after social unrest in Kazakhstan broke out in response to higher gas prices, a "nation-scale internet blackout" occurred. The horizontal axis indicates the number of days around the event.

Sources: CCData.

We argue that during the days around the riot, the price of Bitcoin fell due to reasons unrelated to the adoption of crypto apps in countries other than Kazakhstan. We can hence exploit this episode as an exogenous shock to the price of Bitcoin and study its effect on daily active users.[13]

We thus estimate equation (1) but limit the sample period to the 15 days around the event window (5 January 2022). Table 5 reports the results. The main independent variable is a dummy with a value of one during the 15 days after the start of the riots and a value of zero in the 15 days prior. This dummy hence captures the global drop in the price of Bitcoin. Additionally, we control for the change in local stock market price and turnover, the price of gold and the VIX, and include a set of country-level dummies to capture the effect of unobservable country characteristics. To strengthen identification, we exclude the country in which the shock originated (ie Kazakhstan) from the sample.

[13] One remaining concern is that the drop in mining capacity could have repercussions on users based outside of 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-chain transactions which, in turn, would not be affected by such a structural change in a third country.

Event study: impact of exogenous shocks to Bitcoin prices on user numbers			Table 5
	Dependent variable: daily change in active users		
	(I)	(II)	(III)
Event dummy	–0.006***	–0.005**	–0.004**
	(0.002)	(0.002)	(0.002)
Daily change in MSCI equity index price[1]		0.587***	0.644***
		(0.102)	(0.098)
Daily change in stock market turnover[2,]		–0.011	–0.010
		(0.011)	(0.010)
Daily change in gold price		0.192	0.185
		(0.207)	(0.208)
Daily change in VIX		0.015	–0.006
		(0.024)	(0.013)
FX standard deviation		–0.002	–0.004
		(0.005)	(0.004)
Number of observations	932	932	897
R-squared	0.090	0.109	0.121

Standard errors clustered by country 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: CCData; Datastream; Refinitiv Eikon; Sensor Tower; national data; authors' calculations.

Results from Table 5 show that, across the different speciation's, the inflow of new users slows markedly following the event. The price drop of almost 15% reduced the inflow of new users by 6% in column (1). The estimated coefficient is significant at the 1% level. Adding macroeconomic control variable only leads to a modest decline in the coefficient in column (II). Finally, to further tighten identification column III excludes Kazakhstan's neighbouring countries from the analysis and yields similar results. This pattern suggests that the positive relationship between prices and users allows for a causal interpretation.[14]

5. Behaviour of large vs small investors

The supply of Bitcoin is fixed by protocol, with a maximum global supply of 21 million.[15] This raises the question: if retail investors tend to enter the market when prices rise, who is exiting, ie selling their Bitcoins? Complementary data from the Bitcoin blockchain allow us to assess changes in holdings based on the total holdings of the

[14] We provide additional evidence on the causal link between crypto trading and Bitcoin prices in Appendix B, where we perform a panel vector autoregression (PVAR) analysis on monthly data for 57 countries over the period October 2015 – April 2022.

[15] 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)).

wallet. We can assess small Bitcoin holders (those with less than 1 Bitcoin in their wallet), and compare these with so-called "whales", ie holders of large wallets.

Table 6 shows that in periods of price increases, small Bitcoin holdings tend to increase (ie small investors might *follow the trend*). The dependent variable in columns (I) and (III) corresponds to the natural logarithm of number of BTC held in addresses with balance less than 1 BTC (ie retail investors), in columns (II) and (IV) it corresponds to the coins in miners' accounts (ie large investors). In column (V) it corresponds to the *share* of the overall Bitcoin supply held in accounts with a balance below one BTC. There is a positive and statistically significant coefficient for the Bitcoin price in columns (I) and (III). Among the largest Bitcoin holders –the miners which belong to the whale category – there is a negative coefficient for the Bitcoin price in column (II) and (IV). The coefficients are highly significant from both a statistical and an economic point of view – a one percent increase in the price of Bitcoin corresponds to 42.1% increase and a 4.1% decrease in the number of Bitcoin held by small investors and miners, respectively. Our results are robust to the inclusion of controls for crypto exchange-inflows and outflows.[16]

Additionally, Table 6 sheds light on the behaviour of small investors and miners at times of heightened market volatility. The variable "*high volatility*" captures periods of higher fluctuations in the bitcoin price by taking a value of one when the daily Bitcoin price change is larger than two standard deviations in absolute value. The positive and statistically significant coefficient for the interaction term in column (III) indicates that small investors behave in a procyclical way by even more during times of higher volatility. On the other hand, the economically and statistically insignificant coefficient for the interaction term in column (IV) suggests that miners don't behave differently in times of higher market volatility than in normal times.

We repeat the same analysis using the natural logarithm of the share of Bitcoin held in small accounts as dependent variables (column V) and we find consistent results. This evidence, again, is consistent with a market sustained by new entrants and unsophisticated investors, allowing early investors and insiders to cash out at their expense.[17]

One should note that these results are based on on-chain data. This is dictated by the absence of equivalent account balance information for off-chain data – ie crypto exchanges do not disclose statistics on the holdings based on the total holdings of their clients' wallet. However, the strong positive correlation between on- and off-chain trading volume, gives us confidence on claiming that our findings can reasonably be generalised.[18]

[16] Crypto exchanges hold large amounts of crypto on behalf of their clients, and might have to trade in response to clients buy- and sell-orders. The inclusion of this control addresses the concern that our results might be influenced by this specific trading behaviour.

[17] 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)).

[18] Depending on the data source used and the respective assumptions adopted to estimate the relevant metrics, we find a correlation between on- and off-chain trading volume for Bitcoin which ranges between 0.4 and 0.6 for the period 2020–February 2023.

Bitcoin distributional data

Table 6

Natural logarithm:	Holding size				Share of Bitcoin supply
	Retail investors[1]	Miners	Retail investors[1]	Miners	Retail investors[1]
	(I)	(II)	(III)	(IV)	(V)
Bitcoin price	0.421***	–0.041***	0.292***	–0.038***	0.236***
	(0.002)	(0.000)	(0.004)	(0.001)	(0.003)
Bitcoin price * high volatility[2]			0.023**	0.002	0.023***
			(0.010)	(0.002)	(0.009)
Other controls[3]	N	N	Y	Y	Y
Number of observations	3,787	3,787	3,787	3,787	3,787
R-squared	0.955	0.897	0.979	0.899	0.975

Robust standard errors in brackets; ***/**/* indicates statistical significance at the 1/5/10% level. All variables are expressed as natural logarithms and are winsorised at the 1.5th and 98.5th percentiles.

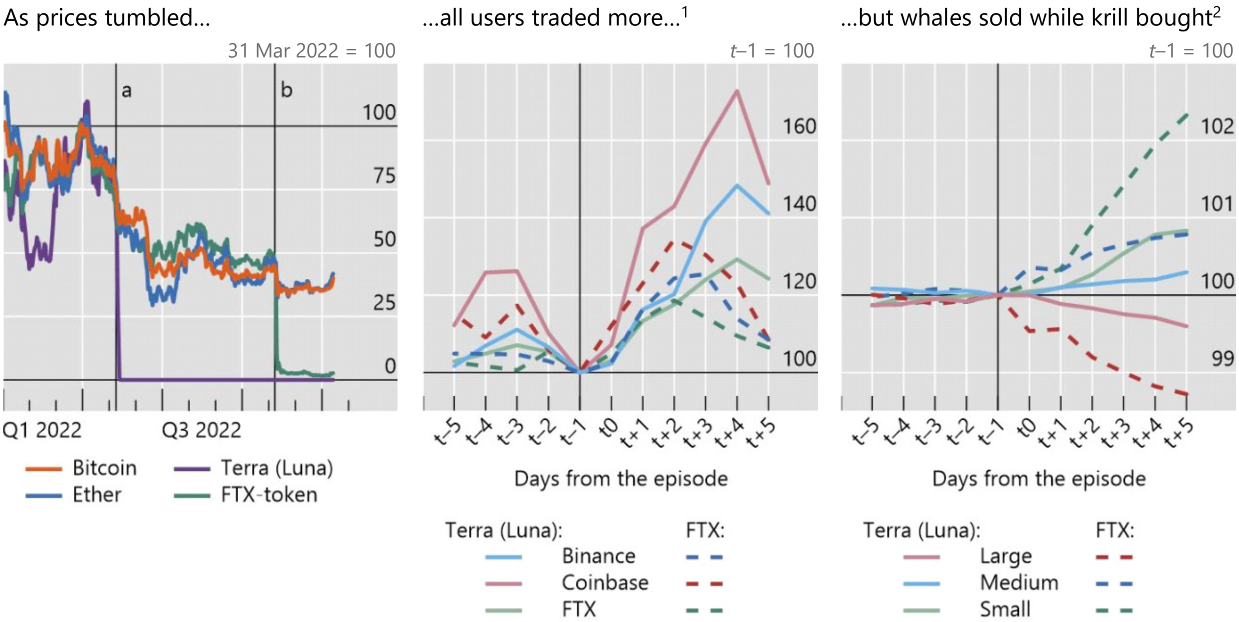
[1] Number of BTC held in addresses with balance less than 1 BTC. [2] High volatility corresponds to a dummy that takes value 1 when the bitcoin price change is more than 2 standard deviations in absolute value. [3] Regressions include the global economic policy uncertainty index, gold price, CBOE VIX index, crypto exchange-outflows and -inflows, and high volatility dummy as controls.

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

Our findings in Table 6 are consistent with results from Cornelli et al (2023) and Liu et al (2023). Cornelli et al (2023) provide descriptive evidence for two shock episodes in the crypto ecosystem – the Terra/Luna crash and the FTX bankruptcy. Graph 11 replicates their main findings. As cryptocurrency prices fell (Graph 11, left-hand panel), trading activity on major crypto exchanges increased markedly (centre panel) suggesting that users tried to adjust their portfolios away from owning tokens under stress towards other cryptoassets, including asset-backed stablecoins. However, owners of large wallets reduced their holdings of Bitcoin in the days after the episodes, probably cashing out at the expense of smaller retail holders. On the other hand, medium-sized holders, and even more so small retail holders, increased their holdings of Bitcoin.

Liu et at (2023) analyse the Terra/Luna crash with detailed data from the Terra blockchain and trading data from centralised exchanges. They show that the run on Terra was a by-product of growing concerns about the sustainability of the system. After few large holders of UST reduced their exposures, the run was in action as other large traders followed suit. Blockchain technology empowered investors with (almost) real-time monitoring tools of other's actions, which resulted in an acceleration of the run. Consistently with our findings, not everyone traded at the same time and/or in the same direction. Due to the complexity of the system, less sophisticated and poorer investors found themselves at greater informational disadvantage. This resulted in larger and more sophisticated investors running first and experiencing much smaller losses. Meanwhile small retail and less sophisticated investors ran later and suffered larger losses.

In stormy seas, "the whales eat the krill" Graph 11



[a] Terra USD and Luna collapse, 8 May 2022. [b] FTX collapse, 7 November 2022.

[1] Based on daily active users of cryptoexchange apps. [2] Based on the number of BTC held in addresses with balance less than 1 BTC (small), 1–1000 BTC (medium), and more than 1000 BTC (large).

Sources: Cornelli et al (2023); CoinGecko; IntoTheBlock; Sensor Tower.

6. Conclusion

Our analysis has shown that, around the world, Bitcoin price increases have been tied to greater entry by retail investors. Using a novel dataset on crypto app use over 2015–22, we show that users are more likely to make active use of crypto exchange apps in the 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. These findings hold when controlling for a range of global and country-specific factors. An analysis of an unanticipated shock that led to a fall in the price of Bitcoin in January 2022 suggests that the relationship can be interpreted as causal.

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. Furthermore, our findings show that as the Bitcoin price rises larger investors ("whales") tend to sell while smaller investors are buying. This evidence raises 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 procyclical trading behaviour characterising small investors, 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 hence 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.

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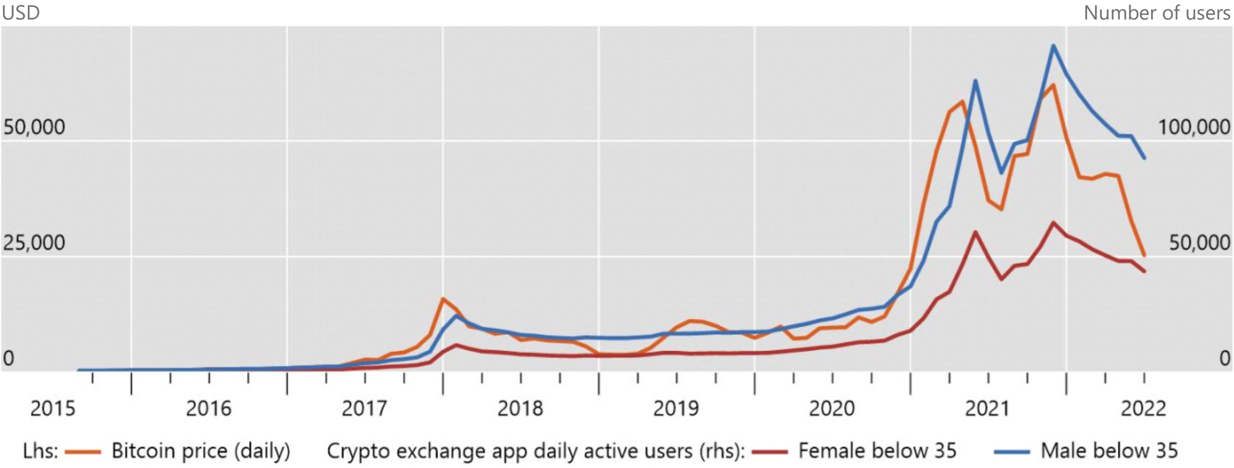
Appendix A: further tests

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: CCData; Sensor Tower; authors' calculations.

Descriptive statistics for additional regressions

Table A1

	No observations	Mean	Standard deviation	Min	Max
Panel A: risk aversion analysis					
Monthly average number of users[1]					
Male below 35	83	29,484	35,584	678	127,005
Male above 35	83	19,536	23,374	317	82,700
Female below 35	83	14,215	16,885	272	59,589
Female above 35	83	9,633	11,239	163	39,142
Bitcoin price	83	14,345	17,469	237	62,080
Monthly average daily active users	3,557	131,734	409,363	0.34	5,983,340
Bitcoin price	3,557	14,364	17,370	236.51	62,080
Risk aversion (losses)[2]	3,557	–1.64	7.79	–53.00	–0.17
Risk aversion (gains)[2]	3,557	0.71	0.11	0.44	0.93
Panel B: event study					
Daily change in active users	932	–0.01	0.05	–0.47	0.24
Event dummy	932	0.51	0.50	0	1.00
Daily change in MSCI equity index price[3]	932	0.001	0.01	–0.08	0.04
Daily change in stock market turnover[4]	932	0.005	0.14	–1.59	0.60
Daily change in gold price	932	0.001	0.01	–0.01	0.01
Daily change in VIX	932	0.01	0.08	–0.12	0.17
FX standard deviation	932	0.48	0.94	0	7.26
Panel C: Trading behaviour analysis					
Retail investors holdings size[5]	3,787	495,017	364,628	18,996	1,143,231
Miners holdings size	3,787	2,374,634	267,254	1,944,223	3,265,029
Share of bitcoin supply held by retail investors[5]	3,787	3.04	1.94	0.28	5.99
High volatility[6]	3,787	0.04	0.20	0	1
Bitcoin price	3,787	9,712	15,732	4.68	68,979
Global economic policy uncertainty index	3,787	188.95	72.73	86.29	430.26
Gold price	3,787	1,452	254.64	1,061	2,072

[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. [2] Risk aversion measures correspond to the relative risk premiums (RRP) from Rieger et al (2015). RRP losses (gains) correspond to the country-level median value based on lotteries with a negative (positive) expected value. Negative values for the RRPs indicate risk seeking. [3] Country-specific MSCI equity index price, in local currency. [4] Based on the country specific Datastream equity index, in local currency. [5] Number of BTC held in addresses with balance less than 1 BTC. [6] High volatility corresponds to a dummy that takes value 1 when the bitcoin price change is more than 2 standard deviations in absolute value.

Sources: Baker et al (2016); Rieger et al (2015); CCData; Datastream; IntoTheBlock; World Bank; Refinitiv Eikon; Sensor Tower; national data; authors' calculations.

Table A1 gives additional descriptive statistics for variables used in our analysis.

Table A2 shows that in periods of price increases, small Bitcoin holdings tend to increase – positive and statistically significant coefficient for the Bitcoin price percent change in column I – while especially the largest Bitcoin holders – the whales – tend to sell – negative and statistically significant coefficient for the Bitcoin price percent change in column I. Our results are robust to the inclusion of a control for crypto exchange outflows. Crypto exchanges hold large amounts of crypto on behalf of their clients, and might have to trade in response to clients' buy and sell orders. The inclusion of this control addresses the concern that our results might be influenced by this specific trading behaviour.

Bitcoin distributional data[1]

Table A2

	Holding size		
	Small	Medium	Whale
	(I)	(II)	(III)
Bitcoin price, % change	0.006***	0.002**	–0.002**
	(0.002)	(0.001)	(0.001)
Global economic policy	0.000	–0.000	0.000
uncertainty index[2], % change	(0.000)	(0.000)	(0.000)
Gold price, % change	–0.012	0.008*	–0.009**
	(0.011)	(0.004)	(0.004)
CBOE VIX index, % change	–0.001	–0.000	–0.000
	(0.001)	(0.000)	(0.000)
Ln(crytoexchange outflows)	–0.017***	–0.006***	–0.007***
	(0.002)	(0.001)	(0.001)
Number of observations	3786	3786	3786
R-squared	0.024	0.018	0.021

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), and more than 1000 BTC (whale). 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); CCData; Datastream; IntoTheBlock; authors' calculations.

Table A3 replicates the same analysis for Ether. Data from the Ethereum blockchain on the daily change in the amounts of ETH held by the three types of holders yields similar evidence as for Bitcoin – when the price of ETH increases, small and medium holders increase their holdings, whereas whales sell their coins.[19]

[19] The summary statics for the variables used in tables A2 and A3 are reported in table A1 in appendix A.

Ethereum distributional data[1] Table A3

	Holding size		
	Small	Medium	Whale
	(I)	(II)	(III)
Ether price, % change	0.014***	0.010***	–0.001***
	(0.004)	(0.002)	(0.000)
Global economic policy uncertainty index[2], % change	–0.001*	0.000	–0.000
	(0.001)	(0.000)	(0.000)
Gold price, % change	0.016	–0.009	0.001
	(0.027)	(0.014)	(0.001)
CBOE VIX index, % change	0.003	–0.000	0.000
	(0.003)	(0.001)	(0.000)
Ln(crytoexchange outflows)	–0.165***	–0.096***	–0.006***
	(0.016)	(0.007)	(0.001)
Number of observations	2532	2532	2532
R-squared	0.062	0.085	0.027

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 ETH held in addresses with balance less than 1 ETH (small), 1–1000 ETH (medium), and more than 1000 ETH (whale). 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); CCData; Datastream; IntoTheBlock; authors' calculations.

Results are very similar when we look at Bitcoin and additionally control for crypto exchange inflows, or we replace crypto exchange outflows with net flows (tables A4–A7). This evidence, again, is consistent with a market sustained by new entrants and unsophisticated investors, allowing early investors and insiders to cash out at their expense.[20]

[20] 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)).

Bitcoin distributional data[1]

Table A4

	Holding size		
	Small	Medium	Whale
	(I)	(II)	(III)
Bitcoin price, % change	0.006***	0.002**	–0.002**
	(0.002)	(0.001)	(0.001)
Global economic policy uncertainty index[2], % change	0.000	–0.000	0.000
	(0.000)	(0.000)	(0.000)
Gold price, % change	–0.012	0.008*	–0.009**
	(0.011)	(0.004)	(0.004)
CBOE VIX index, % change	–0.001	–0.000	–0.000
	(0.001)	(0.000)	(0.000)
Ln(crytoexchange outflows)	–0.020**	–0.011	0.002
	(0.010)	(0.008)	(0.006)
Ln(crytoexchange inflows)	0.003	0.005	–0.009
	(0.011)	(0.008)	(0.007)
Number of observations	3786	3786	3786
R-squared	0.024	0.018	0.023

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), and more than 1000 BTC (whale). Winsorised at the 2nd and 98th percentiles. [2] Standardised to a mean of zero and a standard deviation of one.

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

Bitcoin distributional data[1]

Table A5

	Holding size		
	Small	Medium	Whale
	(I)	(II)	(III)
Bitcoin price, % change	0.006***	0.002***	–0.002**
	(0.002)	(0.001)	(0.001)
Global economic policy uncertainty index[2], % change	0.000	–0.000	0.000
	(0.000)	(0.000)	(0.000)
Gold price, % change	–0.014	0.007*	–0.010**
	(0.011)	(0.005)	(0.005)
CBOE VIX index, % change	–0.001	–0.000	–0.000
	(0.001)	(0.000)	(0.000)
Crytoexchange net flows, in BTC mn	–0.105	–0.150	–0.495
	(1.198)	(0.480)	(0.553)
Number of observations	3786	3786	3786
R-squared	0.004	0.004	0.004

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), and more than 1000 BTC (whale). Winsorised at the 2nd and 98th percentiles. [2] Standardised to a mean of zero and a standard deviation of one.

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

Ethereum distributional data[1]

Table A6

	Holding size		
	Small	Medium	Whale
	(I)	(II)	(III)
Ether price, % change	0.013***	0.009***	–0.001***
	(0.004)	(0.002)	(0.000)
Global economic policy uncertainty index[2], % change	–0.001*	0.000	–0.000
	(0.001)	(0.000)	(0.000)
Gold price, % change	0.016	–0.009	0.002
	(0.027)	(0.014)	(0.001)
CBOE VIX index, % change	0.003	–0.000	0.000
	(0.003)	(0.001)	(0.000)
Ln(crytoexchange outflows)	–0.094*	0.050**	–0.014***
	(0.057)	(0.024)	(0.002)
Ln(crytoexchange inflows)	–0.076	–0.158***	0.009***
	(0.057)	(0.025)	(0.002)
Number of observations	2532	2532	2532
R-squared	0.063	0.108	0.033

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 ETH held in addresses with balance less than 1 ETH (small), 1–1000 ETH (medium), and more than 1000 ETH (whale). Winsorised at the 2nd and 98th percentiles. [2] Standardised to a mean of zero and a standard deviation of one.

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

Ethereum distributional data[1] Table A7

	Holding size		
	Small	Medium	Whale
	(I)	(II)	(III)
Ether price, % change	0.012***	0.008***	–0.001***
	(0.004)	(0.002)	(0.000)
Global economic policy	–0.000	0.000	–0.000
uncertainty index[2], % change	(0.001)	(0.000)	(0.000)
Gold price, % change	0.010	–0.014	0.001
	(0.028)	(0.014)	(0.001)
CBOE VIX index, % change	0.003	0.000	–0.000
	(0.003)	(0.001)	(0.000)
Crytoexchange net flows, in	–0.208	–0.589***	0.087***
ETH mn	(0.187)	(0.099)	(0.011)
Number of observations	2532	2532	2532
R-squared	0.008	0.035	0.042

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 ETH held in addresses with balance less than 1 ETH (small), 1–1000 ETH (medium), and more than 1000 ETH (whale). Winsorised at the 2^{nd}h and 98^{th} percentiles. [2] Standardised to a mean of zero and a standard deviation of one.

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

Appendix B: 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.[21] Therefore the starting point of the multivariate analysis is:

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

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.[22]

Graph B1 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 Cholesky decomposition and order the Bitcoin price as the last variable. [23] 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.

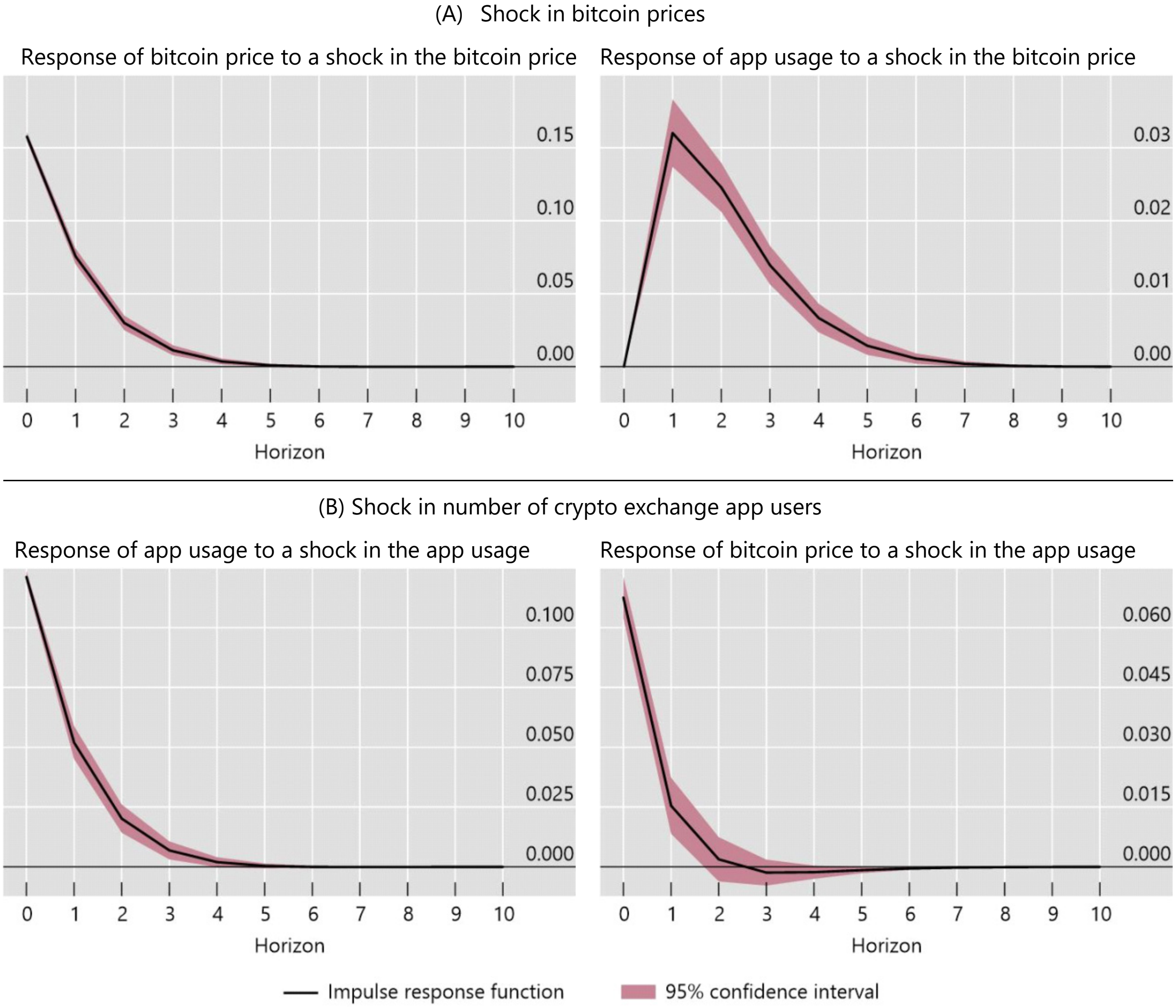
21 Unit root Phillips–Perron tests for all variables show that the null hypothesis that variables contain unit roots is always rejected. The results for the unit root Phillips–Perron tests for all variables in first differences are shown in Table B2 in the Appendix. Graph B2 in the appendix shows that 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.

22 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).

23 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.

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

Graph B1



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: CCData; Sensor Tower; authors' calculations.

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 B3 in the appendix). We find evidence (estimates are significant at the 1% level) that Bitcoin price changes Granger-cause an increase in new crypto exchange app users.

Unit root tests[1]

Table B2

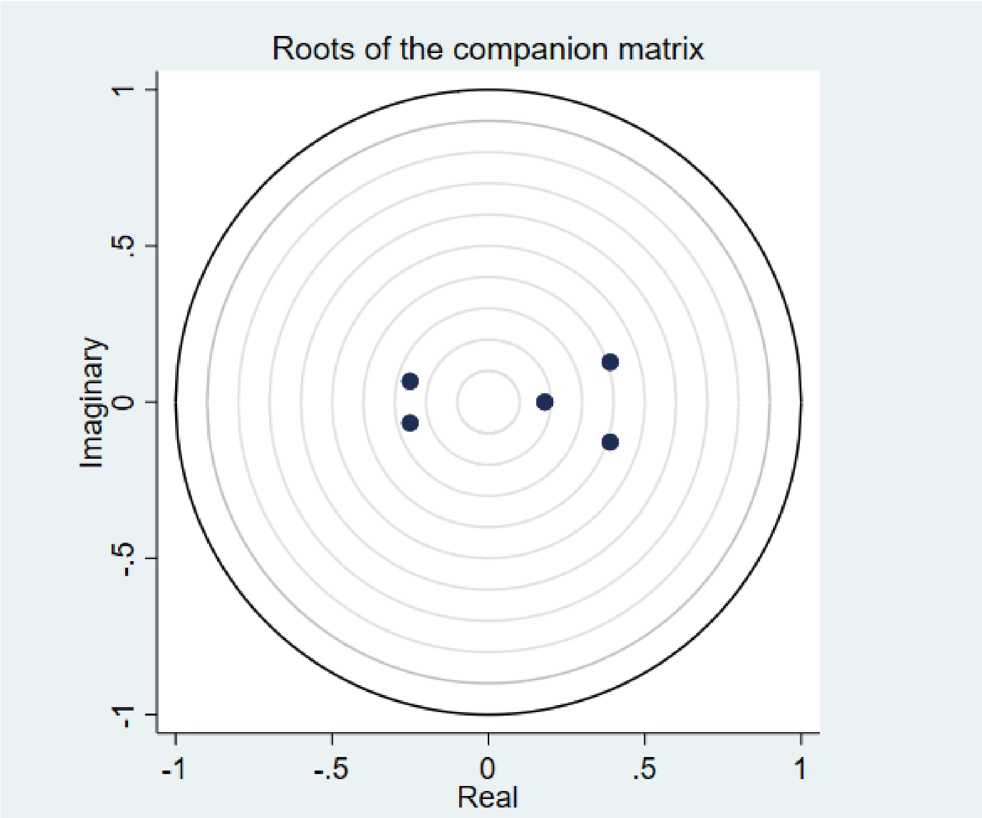
	Δ Ln(monthly average daily active users)		Δ Ln(bitcoin price)		Δ Ln(MSCI equity index price)[2]		Δ Ln(stock market turnover)[3]		Δ Ln(global economic policy uncertainty index)	
	Stat	P-value	Stat	P-value	Stat	P-value	Stat	P-value	Stat	P-value
Inverse chi-squared	2,839.09	0.00	3,365.14	0.00	4,052.00	0.00	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); CCData; Datastream; Refinitiv Eikon; Sensor Tower; authors' calculations.

Roots of the companion matrix

Graph B2



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

PVAR Granger test[1]

Table B3

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); CCData; Datastream; Refinitiv Eikon; Sensor Tower; authors' calculations.

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