The Review of Asset Pricing Studies

Investors' Beliefs and Cryptocurrency Prices

Matteo Benetton
Haas School of Business, University of California, Berkeley

Giovanni Compiani
Booth School of Business, University of Chicago

We explore the impact of investors' beliefs on cryptocurrency demand and prices using new individual-level survey data and a structural characteristics-based demand model with differentiated cryptocurrencies and heterogeneous investors. We show that younger individuals with lower incomes are more optimistic about the future value of cryptocurrencies, as are late investors. We identify the model combining observable beliefs with an instrumental variable strategy that exploits variation in the production of different cryptocurrencies. Counterfactual analyses quantify the impact on portfolio allocations and equilibrium prices of (i) (regulating) entry of late optimistic investors, and (ii) growing concerns among investors about the sustainability of energy-intensive proof-of-work cryptocurrencies. (*JEL*: D84, G11, G41)

Received: April 19, 2022; Editorial decision: August 19, 2023

Editor: Clemens Sialm
Authors have furnished an Internet Appendix, which is available on the Oxford University Press Web site next to the link to the final published paper online.

Beliefs play an important role in explaining economic outcomes, such as firms' real investments (Coibion, Gorodnichenko, and Kumar 2018 2019; Gennaioli, Ma, and Shleifer 2016), consumers' housing choices (Bailey et al. 2019; Kaplan, Mitman, and Violante 2020; Piazzesi and Schneider 2009), and investors' portfolio allocations (Giglio et al. 2021; Greenwood and Shleifer 2014; Vissing-Jørgensen 2003). Understanding to what extent beliefs affect allocations and prices is particularly relevant in the case of new financial assets, for which substantial variability in

We thank the Editor and two anonymous referees, Nick Barberis, Will Cong, Nicolae Garleanu, Amir Kermani, Ralph Koijen, Jiasun Li, Ye Li, Yukun Liu, Matteo Maggiori, Alexander MacKay, Christine Parlour, Johannes Stroebel, Chad Syverson, Aleh Tsyvinski, Annette Vissing-Jørgensen, Wei Xiong, and seminar participants at numerous conferences and seminars for helpful comments. Tianyu Han, Haoliang Jiang, Aiting Kuang, Jiarui Su, Anthony Adam Sy, and Zheng Zhang provided excellent research assistance. Benetton and Compiani gratefully acknowledge support from the Berkeley Haas Blockchain Initiative. All remaining errors are our own. Send correspondence to Matteo Benetton, benetton@berkeley.edu.

The Review of Asset Pricing Studies 14 (2024) 197–236

https://doi.org/10.1093/rapstu/raad015 Advance Access publication 8 January 2024

beliefs over time and across investors could lead to large price movements, including bubbles.[1]

In this paper, we explore the role of investors' beliefs as they affect portfolio allocations and asset prices, using the cryptocurrency industry as a laboratory. We leverage new survey data on both investors' beliefs and holdings and a unique feature of the cryptocurrency production process to estimate a characteristics-based demand system à la Koijen and Yogo (2019). We then use the estimated structural model to quantify the impact on portfolio allocations and equilibrium prices of (i) (regulating) entry of late optimistic investors, and (ii) growing concerns among investors about the sustainability of energy-intensive proof-of-work cryptocurrencies.

Anecdotal evidence suggests that entry of late and perhaps overly optimistic investors, "fear of missing out," and contagious social dynamics may have contributed to the rampant increase in cryptocurrency prices and extreme volatility in recent times (Liu and Tsyvinski 2021; Liu, Tsyvinski, and Wu 2022).[2] Figure 1 shows that the fraction of individuals in the United States who are aware of Bitcoin has increased in recent years, going from 45% in 2015 to almost 70% by the end of 2018. The increase mainly took place between 2017 and 2018, when the price of Bitcoin spiked and the asset class received widespread press coverage.[3] Panel (b) of Figure 1 shows that the fraction of individuals expecting the Bitcoin price to increase rose from around 17% in the fall of 2015 to approximately 27% in the fall of 2017, then declined slightly in 2018 following a rapid drop in cryptocurrency prices. While the debate about the benefits and costs of cryptocurrencies is still open, it is undeniable that this asset class has become an integral part of both retail and institutional investors' consideration sets, and an important area for regulatory scrutiny and possible intervention.[4]

---

1 A number of papers have explored the links between heterogeneous investors' beliefs and bubbles theoretically (Adam, Beutel, and Marcet 2017; Barberis et al. 2015, 2018; Barberis, Shleifer, and Vishny 1998; Scheinkman and Xiong 2003). On the empirical side, previous works have looked at beliefs and asset prices during the South Sea bubble (Temin and Voth 2004), the dot-com mania (Brunnermeier and Nagel 2004; Ofek and Richardson 2003), and the U.S. housing boom (Burnside, Eichenbaum, and Rebelo 2016; Cheng, Raina, and Xiong 2014; Fostel and Geanakoplos 2012; Hong and Sraer 2013; Kaplan, Mitman, and Violante 2020). Gennaioli and Shleifer (2020) provide a recent review of the related literature.

2 See, for example, N. Popper, "As Bitcoin scrapes $10,000, an investment boom like no other," *New York Times*, November 27, 2017, and L. MacLellan, "Why did bitcoin's price surge more than 200% this year?" *Quartz*, December 24, 2020. The same forces, together with a larger involvement of institutional investors, are likely behind the recent rapid growth of the cryptocurrency market, which reached a market capitalization of approximately $750 billion at the end of 2020.

3 The investing platform Robinhood started allowing retail investors to trade cryptocurrencies on their apps in 2018 (see E. Cheng, "Stock trading app Robinhood to launch bitcoin, ethereum trading in five states," *CNBC*, January 15, 2018). More recently, Christine Brown, Robinhood's head of cryptocurrency operations, revealed that in the first quarter of 2021, 9.5 million of its customers traded cryptocurrencies via the company's platform (see M. Azevedo, "Crypto trading on Robinhood spiked to 9.5M customers in first quarter," *Tech Crunch*, April 8, 2021).

4 As an example of the prominent role that the cryptocurrency market has reached for society at large, the IRS has added a cryptocurrency question to Form 1040 for 2020 (see see J. J. Roberts, "The IRS is adding a cryptocurrency question to Form 1040 for 2020," *Fortune*, September 28, 2020), and financial authorities such as the Securities and Exchange Commission and the Commodity Futures Trading Commission are considering regulation to protect investors in the crypto market (see G. Silverman, "US regulators signal bigger role in cryptocurrencies market," *Financial Times*, May 30, 2021). Outside the United States, research by the Financial Conduct Authority estimates that 2.3 million of adults in

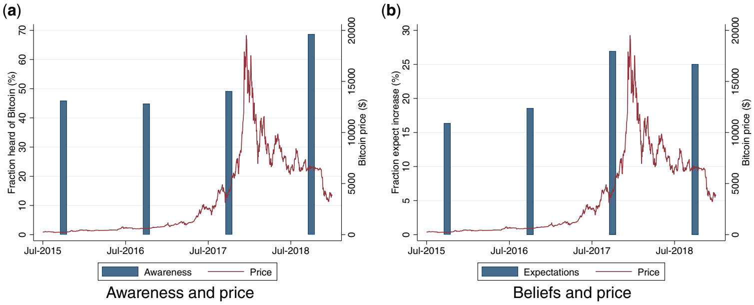

Figure 1
Crypto mania: Awareness and beliefs
The figure shows the daily price of Bitcoin in 2015–18. Data on the price of Bitcoin come from https://coinmarketcap.com. Panel (a) shows the fraction of people that say they have heard of Bitcoin (Awareness). Panel (b) shows the fraction of people, among those saying that they have heard of Bitcoin, who think that the price of Bitcoin is going to increase in the next year (Expectations). The awareness and beliefs measures come from the Survey of Consumer Payment Choice (SCPC). We use the waves from 2015 to 2018. The awareness measure is computed using all individuals responding to the survey. The beliefs measure is computed using the individuals that say they have heard of Bitcoin and appear in all waves.

We begin our analysis with a series of reduced-form regressions to study the drivers of beliefs about future cryptocurrency prices, and the role of beliefs for cryptocurrency investment choices. Our analysis covers investors surveyed by a trading company, as well as consumers—that is, a representative sample of the general population. We obtain three main stylized facts. First, we find that younger consumers with lower incomes and assets, as well as late investors, tend to be substantially more optimistic about future cryptocurrency prices. Second, we document a large dispersion in beliefs across both consumers and investors that is not explained by observable demographics, consistent with previous evidence on more traditional asset classes (Giglio et al. 2021; Kuchler and Zafar 2019; Malmendier and Nagel 2011). The (pseudo) R^2 using different measures of beliefs as a dependent variable is never above 0.05 for consumers and 0.25 for investors. Third, we find that, for both consumers and investors, optimistic beliefs have a positive effect on the probability of holding cryptocurrencies, controlling for demographics and other determinants of demand. In particular, short-term investors' optimism about the future value of cryptocurrencies is associated with (i) a higher probability of holding cryptocurrencies, and (ii) investors holding more distinct cryptocurrencies in larger amounts, conditional on holding at least one.

Motivated by the reduced-form evidence about the drivers of beliefs and the effects of beliefs on portfolio choices, we build a flexible, yet tractable, model of demand for cryptocurrencies. We follow Koijen and Yogo (2019) to derive a characteristics-based demand system from the cryptocurrency portfolio choice problem. In the model, investors have a fixed amount of wealth and choose to

the United Kingdom now hold cryptoassets (see R. Steiner, "Ownership of cryptos is an alternative to mainstream investments, according to research by U.K. regulators," *MarketWatch*, June 18, 2021).

allocate it among different cryptocurrencies or invest it in an outside option, which captures all other investment opportunities. Investors' choices depend on observable cryptocurrency characteristics (e.g., the protocol used to validate transactions and the currency's market capitalization), observable investor beliefs as elicited by the survey, and unobservable shocks.[5] A standard market-clearing condition closes the model. Under the assumption of downward-sloping demand—which we fail to reject empirically—the equilibrium price of each cryptocurrency is unique and can be computed as the solution to a fixed point problem.

We estimate the model on our trading platform dataset. A key challenge in estimating demand functions is that any unobservables affecting demand will also be correlated with prices due to the simultaneity of supply and demand. Thus, prices are likely to be econometrically endogenous (Berry, Levinsohn, and Pakes 1995). We address this in two ways. First, data on beliefs capture factors such as sentiment and disagreement across investors, which would otherwise be subsumed by the error terms and thus possibly contribute to the issue of price endogeneity. For example, if investors become more optimistic on Bitcoin, the demand for Bitcoin shifts out and therefore the Bitcoin price rises in equilibrium. This correlation creates a textbook endogeneity problem if investor optimism belongs in the error term; specifically, since the correlation between optimism and price is positive, we would expect an upward bias on the price elasticities. If instead data on beliefs are available and thus investor optimism is (at least partially) controlled for, the issue is mitigated. Our data captures beliefs on (i) the evolution of the entire asset class of cryptocurrencies, both in the short term and in the long term; and (ii) the potential of each individual cryptocurrency. By including these observed beliefs in the demand system, we are able to control for a substantial part of the time-varying, cryptocurrency-specific factors that affect a given investor's demand. Indeed, we find that the estimated own-price elasticities are less negative when beliefs are not included in the demand system relative to when they are, which is consistent with the expected upward bias.[6]

Second, we use an instrumental variable strategy to address the potential correlation between prices and unobservable demand shocks not captured by the beliefs data. Specifically, we construct supply-side instruments for prices by leveraging a unique feature of the asset class under consideration, the predetermined and

[5] Foley, Karlsen, and Putniņš (2019) find that a large fraction of Bitcoin users are involved in illegal activities. While we think this is unlikely to be the case for respondents in our survey, our demand system is well suited to flexibly capturing investor preferences for characteristics such as anonymity.

[6] While our identification strategy controls for several investor demographics and cryptocurrency characteristics, residual variation in unobservable demand that is correlated with beliefs could result in endogeneity of beliefs and thus bias our estimates. For instance, a policy change or news story could affect both investors' beliefs and their portfolio choices. Persistence in beliefs over time—which has been documented for other asset classes by recent studies (Egan, MacKay, and Yang 2022; Giglio et al. 2021)—could alleviate this concern, but we cannot fully test this hypothesis with our repeated cross-sections of investors. Incorporating a more structural model of beliefs formation in an asset demand system and accounting for beliefs endogeneity with a richer set of instruments could be interesting avenues for future research, as recently emphasized by Brunnermeier et al. (2021).

exogenous production process of proof-of-work cryptocurrencies (sometimes referred to as "mining").[7] Proof-of-work cryptocurrencies (including Bitcoin, Ethereum,[8] and many others) follow a protocol whereby a new coin is minted (or "mined") whenever a new block of transactions is added to the currency blockchain. This process is predetermined—thus satisfying the exogeneity condition required of instruments; further, the supply varies both across different cryptocurrencies and over time, yielding strong first-stage regressions. This instrument is based on the standard economic intuition that variables shifting supply—and notably the availability of different products (Conlon and Mortimer 2013)—should help identify the demand curve.[9]

With the estimated model in hand, we conduct several counterfactual analyses to study how changes in investors' beliefs affect equilibrium prices and allocations. First, we perform two counterfactual simulations that limit the widespread adoption of cryptocurrencies by banning the entry of late—and, in our sample, more optimistic—investors in the market.[10] In one exercise, we take all investors who bought their first cryptocurrency in 2018 (the last year in our data) and replace their short-term beliefs by sampling at random from the population of investors who did not invest in cryptocurrencies. This allows us to study how the composition of the investor pool affects equilibrium cryptocurrency prices while leaving the number of investors unchanged. In the second scenario, we simply ban the entry of late investors, by removing without replacement all investors who bought their first cryptocurrency in 2018. This captures the full effect of restricting entry. Comparing the two counterfactuals allows us to separately quantify the effect of changing investors' beliefs and the effect of reducing market size.

We estimate an elasticity of cryptocurrency prices to late investors' short-term beliefs of about 0.3, with significant heterogeneity across cryptocurrencies. Our counterfactual shows that the entry of late optimistic investors played an important role in the increase of cryptocurrency prices at the end of 2017 and beginning of 2018. Banning late investors leads to an average decline in the value of

7 In the context of demand for financial assets, Koijen and Yogo (2019) propose an instrument that exploits variation in the investment universe across investors and the size of potential investors across assets.

8 Technically, Ethereum is the name of the blockchain platform and Ether is the name of its native cryptocurrency. In this paper, we refer to both as Ethereum, with the interpretation being clear based on the context. We do the same for other similar cases, such as Ripple whose native currency is XRP.

9 Our identification strategy shares with some recent papers the advantage of looking at many cryptocurrencies jointly, rather than focusing only on the most popular one (i.e., Bitcoin) (Irresberger, John, and Saleh 2020; Liu, Tsyvinski, and Wu 2022; Shams 2020). While Bitcoin has maintained the lion's share of the market, during the past seven years the cryptocurrency market has witnessed a rapid introduction of new assets. Specifically, the number of cryptocurrencies listed on the Coinmarketcap website has increased from 7 in April 2013 to more than 2,300 in January 2020 (see https://coinmarketcap.com/all/views/all/).

10 Regulators around the world have discussed the introduction of "regulatory sandboxes" to promote the introduction of new financial products, while at the same time managing risks, preserving stability, and protecting consumers. Jenik and Lauer (2017) define a regulatory sandbox as "a framework set up by a financial sector regulator to allow small scale, live testing of innovations by private firms in a controlled environment."

cryptocurrencies by about 38%, of which 15% is due to the direct effect of late investors' optimism.[11]

Finally, we perform two counterfactual simulations to quantify the impact of investors becoming more pessimistic about the long-term potential of proof-of-work (PoW) cryptocurrencies. The PoW protocol assigns the right to validate a new block of transactions to whomever solves a complex mathematical problem first. Several recent papers emphasize how this leads to a huge computational burden and thus substantial energy costs, which is exacerbated by the rise of mining pools (Cong, He, and Li 2021), suggesting that the PoW protocol might not be sustainable in the long run (Benetton, Compiani, and Morse 2023; Budish 2018; Chiu and Koeppl 2019; De Vries 2018; Saleh 2021). Similar concerns are behind the decision of Ethereum to switch from PoW to proof-of-stake (PoS), a less energy-intensive validation protocol.

We first assess how prices and allocations would respond if investors became more aware of the inherent limitations of PoW currencies.[12] We find that, on average, equilibrium cryptocurrency prices decrease by around 12%, with Bitcoin (BTC) and Ethereum (ETH) experiencing the largest absolute and relative declines. On the other hand, the price of Ripple—a non-PoW currency—increases by around 6%. Finally, we use our demand model to study the effect of Ethereum abandoning the PoW protocol on investors' portfolios and equilibrium prices. In particular, we calibrate the change in beliefs needed to generate an increase in the price of ETH similar to that observed in the data after the announcement. To obtain a 22% increase in the price of ETH, our model requires around 15% of investors to become more long-term optimistic about that specific cryptocurrency. As a result, the median investor allocates about \$50 more to ETH (a 13% increase) at the expense of other cryptocurrencies, which experience a decline in price by about 0.7%. Overall, our analysis shows that a persistent change in investors' preferences toward more sustainable assets can lead to reallocation away from energy-consuming cryptocurrencies, with a large impact on equilibrium prices.

1. Related Literature

Our work is related to the growing literature studying various aspects of the cryptocurrency industry. A series of recent theoretical papers have studied speculative dynamics, multiple equilibria, and optimal design (Athey et al. 2016; Fernández-Villaverde and Sanches 2019; Schilling and Uhlig 2019; Sockin and Xiong 2018). On the empirical side, recent works have explored the dynamics of

11 With extrapolative investors' beliefs (Barberis et al. 2015; Da, Huang, and Jin 2021; Kuchler and Zafar 2019), our estimate of the relative effect of beliefs would represent a lower bound, as increases in prices would lead to increases in optimism, which would then further fuel demand.

12 Elon Musk's popular tweets about the environmental impact of Bitcoin mining and transactions provide a recent real-world example of our counterfactual exercise (see R. Molla, "When Elon Musk tweets, crypto prices move," *Vox*, June 14, 2021, and Z. Seward and D. Nelson, "Elon Musk says Tesla is suspending bitcoin payments over environmental concerns," *CoinDesk*, May 8, 2023).

cryptocurrency prices (Chea and Fry 2015; Corbet, Lucey, and Yarovaya 2018; Gandal et al. 2018; Griffin and Shams 2020; Hu, Parlour, and Rajan 2019; Li, Shin, and Wang 2020; Liu and Tsyvinski 2021; Liu, Tsyvinski, and Wu 2022; Makarov and Schoar 2020) and—to a more limited extent due to data availability constraints—the characteristics of cryptocurrency investors (Bonaparte 2021; Chan et al. 2020; Hasso, Pelster, and Breitmayer 2019; Lammer, Hanspal, and Hackethal 2019). Biais et al. (2023) and Han and Makarov (2021) combine theoretical models with exchange-level data to study how cryptocurrency prices are affected by transaction costs and benefits and boundedly rational investors' speculation, respectively.

We contribute to this growing literature in two main ways. First, we analyze new detailed individual-level data on both cryptocurrency holdings and beliefs for representative samples of U.S. and worldwide consumers as well as for a large sample of cryptocurrency investors. Second, we estimate a tractable structural model of cryptocurrency demand, with differentiated cryptocurrencies and heterogeneous investors, which we then use to shed light on the importance of including beliefs in the demand system and to perform counterfactual analyses. Our demand-based approach is particularly valuable for the cryptocurrency market, where tokens are highly heterogeneous and perform different functions, and the lack of cash flows makes the use of traditional valuation models problematic (Cong, He, and Tang 2022; Cong, Li, and Wang 2021; Cong and Xiao 2021).[13]

Thus, our work is related to the growing literature applying structural tools from empirical industrial organization to study financial markets, like deposits (Egan, Hortaçsu, and Matvos 2017; Xiao 2020), corporate loans (Crawford, Pavanini, and Schivardi 2018), mortgages (Allen, Clark, and Houde 2019; Benetton 2021; Buchak et al. 2018; Robles-Garcia 2019), credit cards (Nelson 2018), and insurance (Koijen and Yogo 2016). Within this literature, our work is closely related to Koijen and Yogo (2019), Koijen, Richmond, and Yogo (2020) and Egan, MacKay, and Yang (2022). Koijen and Yogo (2019) develop an equilibrium asset pricing model where investors' portfolio allocations are a function of their heterogeneous preferences for asset characteristics; Egan, MacKay, and Yang (2022) also adopt a characteristics-based demand estimation framework and apply it to exchange-traded funds to recover investors' expectations.

We apply the Koijen and Yogo (2019) framework to the cryptocurrency market and expand it in two main directions. We include the survey measures of investors' beliefs in the demand system and show that the resulting price elasticities are consistent with beliefs partially addressing the issue of price endogeneity. Further, by leveraging features of the cryptocurrency production process, we propose a supply-side instrumental variable approach to tackle remaining endogeneity concerns.

[13] Our approach can also be applied to the valuation of nonfungible tokens, provided one can find good supply-side instruments.

Finally, given our focus on the sharp increase in cryptocurrency prices in 2017 and the subsequent steep decline in 2018, our paper is also related to the literature studying empirically the role of investors' sentiments and beliefs for bubbles (see, e.g., Brunnermeier and Nagel 2004; Xiong and Yu 2011; Hong and Sraer 2013; Cheng, Raina, and Xiong 2014). We provide new evidence on heterogeneity in beliefs and holdings across both consumers and investors for an asset class—-cryptocurrencies—that could be prone to bubbles. Moreover, we use rich micro-data to estimate a flexible, yet tractable, model of demand for cryptocurrencies to quantify the role of heterogeneous expectations and disagreement for equilibrium price dynamics. To do so, we follow a growing literature that leverages survey data to investigate the role of expectations in financial markets. While survey data—including ours—have well-known limitations, they are typically the only source of information on expectations and thus play an increasingly important role in the study of financial markets (Brunnermeier et al. 2021; Giglio et al. 2021; Liu et al. 2022).

2. Data

2.1 Sources

Our analysis combines several data sources. First, we collect publicly available data from the CoinMarketCap website (https://coinmarketcap.com) and the Blockchain website (https://www.blockchain.com). These websites report daily information on prices, volumes, market capitalization, and circulating supply for several cryptocurrencies. The data have been employed in recent empirical work on cryptocurrencies, such as Liu and Tsyvinski (2021), Griffin and Shams (2020), and Hu, Parlour, and Rajan (2019), among others.

Next, we leverage three surveys about consumers' and investors' beliefs and holdings.[14] For our main analysis, we obtained proprietary data from a trading platform about investors' holdings of cryptocurrencies as well as their expectations about these assets. The data come from the Cryptocurrency and Blockchain Consumer and Investor Survey that the platform runs twice a year. The trading platform invited investors to participate in an online poll, maintaining anonymity of all survey responses and disabling online IP tracking. In this paper, we analyze two waves of this survey conducted in January–February 2018 and July–August 2018, respectively.[15] The first survey contains about 2,500 responses, whereas the second survey contains about 3,000 responses. While the platform's clients are spread across the world, the majority come from North America (65%), followed by Asia (24%), and South America and Europe (5%). The data do not link the identity of respondents across the survey waves, so we treat the two datasets as repeated cross-sections.

[14] In Internet Appendix D, we report the exact questions from the surveys that we use in our analysis.

[15] The trading platform has since been acquired and has unfortunately discontinued the survey.

To compare our survey respondents to the general population, we analyzed two additional surveys. First, we use the Survey of Consumer Payment Choice (SCPC), which is a collaborative project of the Federal Reserve Banks of Boston and Atlanta. The surveys have been conducted annually since 2009 with the aim to "gain a comprehensive understanding of the payment behavior of U.S. consumers" and have a longitudinal panel component. Importantly for our purposes, from 2015 onward, the survey added a series of questions about cryptocurrencies to understand their usage as a payment and investment tool.[16] Thus, we focus on the waves from 2015 to 2018. The total number of respondents in each wave is around 3,000, of which about a third is present in all waves since 2015.

Second, we obtained access to the 2018 ING International Survey on Mobile Banking. The purpose of the survey is to "gain a better understanding of how people around the globe spend, save, invest and feel about money." The survey we analyze was conducted by Ipsos—a multinational market research and consulting firm—between March 26 and April 6, 2018. The total sample comprises almost 15,000 respondents across Europe, the United States, and Australia. About 1,000 individuals were surveyed in each country and the sampling procedure reflects the gender and age distributions within each country.

2.2 Summary statistics

Table 1 shows the main variables we use from the surveys of the anonymous trading company. Approximately half of the respondents are 30 years old or younger, and about 68% of them have an income below $100,000. About 65% of respondents are based in North America, and about 10% are individual accredited investors. Almost all respondents have heard of cryptocurrencies, and about 55% hold at least one. Importantly, the surveys do not focus only on Bitcoin, but ask about holdings of other cryptocurrencies as well. Conditional on having invested in at least one cryptocurrency, the average respondent invests in almost three cryptocurrencies, and some investors hold a diversified portfolio including all the main cryptocurrencies that we consider.[17] The average investor in cryptocurrencies has about $40,000 invested in the asset class, but there is substantial heterogeneity going from $500 to more than $1 million.[18] About 40% of investors in cryptocurrencies bought their first in 2018—that is, after the large price increase in December 2017 and January 2018.

---

[16] Before 2015, the SCPC was conducted using the Rand Corporation's American Life Panel (ALP), while since 2015 the SCPC has been conducted using the Understanding America Study (UAS).

[17] Following the question in the survey, we focus on Bitcoin, Ethereum, Litecoin, Ripple, Zcash, Dash, Monero, and Bitcoin Cash. The survey also considers additional smaller currencies (Bytecoin and Swiftcoin), which we do not use in the analysis.

[18] To compute the amount invested, we take the midpoint of the following intervals among which respondents had to choose: < $1,000; $1,000 – $10,000; $10,000 – $100,000; $100,000 – $1,000,000; >$1,000,000. For the last category we take the lower bound. Unfortunately, the survey does not ask investors how much they invest in each specific cryptocurrency. When taking the model to the data, we combine the answer on the number of cryptocurrencies in the portfolio and the total amount invested to compute the portfolio weights.

Table 1
Summary statistics: Investors' survey

	Observations	Mean	Std. dev.	Minimum	Median	Maximum
Demographics:						
Age $\leq$ 30	4,647	0.50	0.50	0.00	0.00	1.00
Income $\leq$ \$100K	4,647	0.68	0.47	0.00	1.00	1.00
Outside US	4,647	0.36	0.48	0.00	0.00	1.00
Accredited investor	4,647	0.09	0.29	0.00	0.00	1.00
Cryptocurrency questions (general):						
Awareness	4,647	0.97	0.16	0.00	1.00	1.00
Holding (at least one crypto)	4,647	0.56	0.50	0.00	1.00	1.00
Holding (number of cryptos)	2,580	2.68	2.11	1.00	2.00	9.00
Holding ($,000)	2,580	39.51	134.21	0.50	5.50	1,000.00
Late buyers (2018)	2,580	0.39	0.49	0.00	0.00	1.00
Cryptocurrency questions (beliefs):						
Increase	4,647	0.62	0.49	0.00	1.00	1.00
Decrease	4,647	0.24	0.43	0.00	0.00	1.00
Never mainstream	4,647	0.08	0.28	0.00	0.00	1.00
High potential	41,823	0.24	0.42	0.00	0.00	1.00

Summary statistics for the main variables we use from the trading company survey. *Accredited investor* is a dummy for accredited investors of the trading company. *Awareness* is a dummy equal to one if the investor is aware of cryptocurrencies. *Holding (at least one crypto)* is a dummy equal to one if the investor holds at least one cryptocurrency. *Holding (number of cryptos)* is the number of cryptocurrencies an investor holds. The maximum of this variable is nine, as we focus on the eight largest cryptocurrencies in our sample (Bitcoin, Ethereum, Ripple, Litecoin, Bitcoin Cash, Zcash, Dash, and Monero), and group all other less popular cryptocurrencies in the composite cryptocurrency. *Holding ($,000)* is the total amount invested in cryptocurrencies by each investor. *Late buyer* is a dummy equal to one if the investor purchased her first cryptocurrency after 2017. *Increase (decrease)* is a dummy equal to one if the investor says the price is going to increase (decrease) by the end of the current year. *Never mainstream* is a dummy equal to one if the investor thinks cryptocurrencies are never going to be widely adopted. *High potential* is a dummy equal to one if the investor thinks a specific cryptocurrency has the potential to be successful.

Turning to the questions on expectations, more than 60% of respondents believe that the price of cryptocurrencies is going to increase over the course of the following year, while about 25% think the price is going to decrease, and only about 8% believe that cryptocurrencies are never going to be mainstream. In around 25% of all investor-cryptocurrency pairs, the investor thinks that that specific cryptocurrency has long-term potential.

2.3 Comparison of surveys and representativeness

The main advantage of our survey data is that we have information on both investors' holdings of and beliefs about cryptocurrencies. The main limitation is that our coverage relative to the universe of cryptocurrency investors is limited. While this requires us to assume that the representativeness of the survey stays constant in our counterfactual analysis, the survey still represents a valuable source of information relative to more aggregated data.[19] For example, existing work in industrial organization highlights the value of incorporating rich data from

[19] We discuss in detail in Section 4 how we scale up our portfolio choices when we solve for equilibrium prices in the baseline and counterfactual analyses.

Table 2
Comparison: Investors and consumers

	Trading company		SCPC		ING	
	Count	Mean	Count	Mean	Count	Mean
Demographics:						
Age $\leq$ 30	2,956	0.42	3,153	0.08	1,008	0.22
Income $\leq$ \$100K	2,956	0.76	3,149	0.77		
Cryptocurrency questions (general):						
Awareness	2,956	0.97	3,149	0.69	1,008	0.57
Holding	2,956	0.46	2,163	0.02	1,008	0.08
Cryptocurrency questions (beliefs):						
Increase	2,956	0.58	2,143	0.28	606	0.33
Decrease	2,956	0.27	2,143	0.30	606	0.24

Summary statistics for the three surveys used in the reduced-form analysis. For comparability, we focus on 2018 and North America. Specifically, for the Survey of Consumer Payment Choice (SCPC), we only use the 2018 wave. For the ING International Survey on Mobile Banking, we focus only on the United States. For the trading company survey, we focus only on North America. The variables are as defined in Table 1 of the main text and Table 8 in Internet Appendix C.

consumer surveys in identifying demand systems (Berry, Levinsohn, and Pakes 2004; Grieco, Murry, and Yurukoglu 2021).[20]

To give a better characterization of the investors in our sample, we compare our trading company survey with the two consumer surveys, which also contain information about both holdings and expectations (we discuss these in more detail in Internet Appendix C). For comparability, we focus on respondents from North America in 2018. Table 2 shows the results. The trading company survey is tilted toward a younger population. About 40% of the respondents are younger than 30 years old, while the corresponding figures in the SCPC and ING surveys are 8% and 22%, respectively. The fraction of respondents with an income below \$100,000 is similar in the trading company and SCPC surveys. Combining the results on age and income suggests that our trading company respondents are younger and richer than the average consumer, conditional on age.

Almost all individuals surveyed by the trading company have heard of Bitcoin, as compared to about 70% of SCPC and 57% of ING respondents. Regarding holdings, about 46% of individuals surveyed by the trading company invest in cryptocurrencies, versus only 2% of SCPC and 8% of ING respondents. With respect to beliefs, about 58% of the trading company survey respondents think the price of Bitcoin is going to increase in the next year, while this is the case for only 28% of SCPC and 33% of ING respondents.

Overall, cryptocurrency investors from our main survey tend to be young and optimistic, and have a portfolio with about 2.5 cryptocurrencies. This characterization of the average cryptocurrency investor is in line with recent work using data from cryptocurrency exchanges. For example, Chan et al. (2020) use data from a medium-sized cryptocurrency exchange in Asia and find

20 Berry, Levinsohn, and Pakes (2004) use second-choice data from a survey of car buyers to obtain precise estimates of the substitution patterns in a demand system for passenger vehicles.

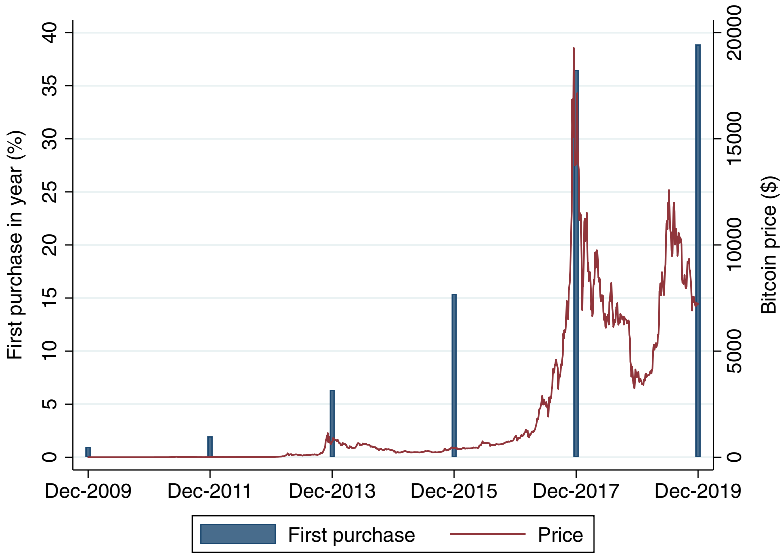

Figure 2
First purchase
The figure shows the daily price of Bitcoin in 2010–19. Data on the price of Bitcoin come from https://coinmarketcap.com. Each vertical bar shows the fraction of investors who purchased their first cryptocurrency in the two years before the vertical bar relative to the total number of investors who purchase cryptocurrency at any point in time.

that the average retail cryptocurrency investor is a 27-year-old male who holds 2.1 cryptocurrencies.

Finally, investors in the trading platform survey are asked when they bought their first cryptocurrency, which allows us to identify early adopters and late entrants. Figure 2 shows the breakdown of investors who bought a cryptocurrency by year of first purchase. While Bitcoin has been available since 2009, only about 30% of investors who bought a cryptocurrency did so before 2017, and almost 40% did so in 2018. Taken together, Figures 1 and 2 suggest that the months leading up to the end of 2017 were characterized by a rise in cryptocurrency prices,[21] widespread awareness and optimism about this asset class across the general public, and an increase in investors' demand. Hence, our survey represents well the new (marginal) young retail investors whose optimism may have contributed to the large price movements during the sample period, in line with anecdotal evidence,[22] theoretical work (Cong, Li, and Wang 2021; Sockin and Xiong 2018), and empirical work based on aggregate data (Han and Makarov 2021; Liu and Tsyvinski 2021; Liu, Tsyvinski, and Wu 2022).

[21] While we focus on Bitcoin prices in the plots, all other major cryptocurrencies followed a very similar trend in prices (see Figure 2 in Internet Appendix A).

[22] See, for example, N. Popper, "As Bitcoin scrapes $10,000, an investment boom like no other," *New York Times*, November 27, 2017.

Table 3
Drivers of beliefs: Investor survey

	Short-term optimism	Long-term optimism	High potential	
	(1)	(2)	(3)	(4)
Demographics:				
Income $\leq$ \$100K	0.007	–0.206***	0.036*	0.035*
	(0.043)	(0.074)	(0.020)	(0.020)
Age $\leq$ 30	0.144***	0.017	0.017	0.017
	(0.038)	(0.058)	(0.018)	(0.019)
Outside US	0.209***	0.533***	–0.031	–0.031
	(0.041)	(0.072)	(0.019)	(0.019)
Accredited investor	0.073	0.145	0.144***	0.144***
	(0.068)	(0.115)	(0.035)	(0.035)
Other variables:				
Early buyer	0.374***	0.555***	0.285***	0.341***
	(0.044)	(0.073)	(0.022)	(0.026)
Early buyer $\times$ Top3				–0.131***
				(0.036)
Late buyer	0.556***	0.477***	0.334***	0.274***
	(0.050)	(0.078)	(0.023)	(0.029)
Late buyer $\times$ Top3				0.144***
				(0.041)
Wave f.e.	Yes	Yes	Yes	Yes
Cryptocurrency f.e.	No	No	Yes	Yes
Mean Y	0.38	0.92	0.24	0.24
SD Y	0.85	0.28	0.42	0.42
Pseudo R^2	0.03	0.08	0.25	0.25
Observations	4,647	4,647	41,823	41,823

Estimates of coefficients from Equation (1) in columns (1) to (2), and Equation (2) in columns (3) and (4). *Short-term optimism* is the investors' response to a question about the value of cryptocurrencies over the course of 2018. *Long-term optimism* is a dummy equal to one if the investor thinks that cryptocurrencies will become mainstream. *High potential* is a dummy equal to one if the investor thinks a specific cryptocurrency has the potential to be successful. *Accredited investor* is a dummy for accredited investors of the trading company. *Early (late) buyer* is a dummy equal to one if the investor purchased her first cryptocurrency up to (after) 2017. *Top 3* is a dummy for Bitcoin, Ethereum, and Ripple. *$p < .1$, **$p < .05$, ***$p < .01$.

3. Reduced-Form Evidence on Beliefs and Demand

In this section, we study both the drivers of beliefs and the impact of beliefs on demand for cryptocurrencies using our main survey of investors from the trading platform. We conduct a similar analysis using the two surveys of consumers. For brevity, we report and discuss the results for consumers in Internet Appendix C and summarize the results at the end of this section.

3.1 Drivers of beliefs

We begin by exploring which factors drive differences in beliefs across investors in our data. We estimate the following ordered logit model:

$$B_{it} = OrdLogit(\beta D_i + \gamma_t + \epsilon_{it}), \tag{1}$$

where B_{it} are the beliefs of investor i in survey wave t; D_i are demographic characteristics of investor i (age, income, and country of residence); γ_t are wave fixed effects; and ϵ_{it} captures unobservable determinants of beliefs.

Table 3 shows the results. Column (1) shows the estimates of Equation (1) where the dependent variable is the investors' response to a question about the trend in value of cryptocurrencies in 2018 (the options are "Decrease," "Stay the same," and "Increase"), which we view as a measure of short-term beliefs. We find that younger investors have more optimistic beliefs, but we do not find significant differences in terms of income. Further, investors who invested in cryptocurrencies tend to be more optimistic than those who did not. In addition to that, investors who first invested in cryptocurrencies after 2017 are relatively more optimistic than investors who entered the market earlier.

In column (2), we estimate a logit specification now using as dependent variable a dummy equal to one if the investor thinks that cryptocurrencies will become mainstream, which we view as a measure of long-term beliefs. Interestingly, lower-income investors tend to be less optimistic about the long-term prospect of cryptocurrencies. Similar to the result in column (1) for short-term beliefs, investors who invested in cryptocurrencies tend to be more optimistic than those who do not hold any cryptocurrencies. However, in contrast to short-term beliefs, we find that early and late buyers have similar long-term beliefs.

Finally, in columns (3) and (4), we consider a question in the survey asking investors to list the cryptocurrencies, if any, that they think have long-term potential. We estimate the following probit model:

$$B_{ijt} = Probit(\beta D_i + \alpha D_i \times X_j + \gamma_t + \gamma_c + \gamma_j + \epsilon_{ijct}), \quad (2)$$

where B_{ijt} is a dummy equal to one for each currency j that is mentioned by investor i in survey wave t; D_i are demographic characteristics of individual i; X_j are characteristics of cryptocurrency j; γ_t and γ_j are wave and cryptocurrency fixed effects, respectively.

First, we confirm that having invested in cryptocurrencies is associated with more optimistic beliefs. Second, we exploit the fact that B_{ijt} now varies not just in the cross-section of investors but also across cryptocurrencies, to consider the effect of currency characteristics X_j on beliefs. In particular, in column (4), we find that late buyers tend to be especially optimistic about the top three cryptocurrencies (Bitcoin, Ethereum, and Ripple), whereas early buyers exhibit the opposite pattern. This is consistent with the possibility that late buyers might be more influenced by the buzz surrounding the top cryptocurrencies (perhaps the only ones they are aware of) relative to earlier investors who may have a deeper understanding of the market.

As a final remark, we note that there is a lot of variation in beliefs that our limited demographics are not able to capture. In Table 3, the pseudo-R^2 does not increase above 0.25 even with the inclusion of cryptocurrency fixed effects. In Table 9 in the Internet Appendix, which looks at the determinants of beliefs for consumers, the pseudo-R^2 is always below 0.05. This result is in line with recent work by Giglio et al. (2021) and suggests that including demographic variables in the cryptocurrency demand system is not sufficient to control for differences in beliefs across investors.[23] Motivated by this observation, we include both beliefs and demographics as explanatory variables in the structural model of Section 4.[24]

3.2 Beliefs and demand

We perform a series of reduced-form regressions to document the relationship between beliefs and cryptocurrency holdings. We consider the regression

$$y_{it} = \alpha B_{it} + \beta D_i + \gamma_t + \epsilon_{it}, \tag{3}$$

where y_{it} denotes investor i's demand outcome in survey wave t; B_{it} represents her beliefs; D_i are individual demographics; and γ_t are wave fixed effects. We are especially interested in the coefficient α, which captures the impact of beliefs on investor demand, conditional on demographics.

We present the results for several outcome variables y_{it}: (i) a dummy variable for whether an investor holds Bitcoin—the first and most popular cryptocurrency; (ii) the number of cryptocurrencies that investors hold in their portfolio; (iii) the total amount in dollars invested in cryptocurrencies; and (iv) the share of the investor's wealth invested in cryptocurrencies.[25] Table 4 shows the results.

First, we look at the "extensive" margin in columns (1) to (2). We find that investors who expect an increase (decrease) during the course of the year are more (less) likely to own Bitcoin. The effects are strongly significant and large in magnitude. Individuals who expect prices to increase in the following year have a 10-percentage-point higher probability to own Bitcoin, while individuals who expect prices to decrease have about a 4-percentage-point lower probability of owning Bitcoin. Given an unconditional probability of about 45%, these effects translate into a 24% increase and a 9% decrease, respectively. These results echo our analysis of the drivers of beliefs in Table 3. While investors' demographics and beliefs are correlated, the latter have an independent impact on investment choices. Long-term beliefs about the success of cryptocurrencies and the potential of Bitcoin also have a significant effect on the probability of holding Bitcoin.

Are the effects of beliefs on cryptocurrency holdings reasonable? To answer this question, in column (2) of Table 4 we compute the fraction of investors' wealth that is invested in cryptocurrencies. We find that moving from neutral to optimistic about the future value of cryptocurrencies increases the crypto share by about 0.8,

---

[23] Using detailed data on investors from a survey administered by Vanguard, Giglio et al. (2021) show that beliefs are characterized by large and persistent individual heterogeneity, and that demographic characteristics explain only a small portion of why some individuals are optimistic and some are pessimistic (Fact 3 in their paper).

[24] In Internet Appendix A, we show additional decompositions of the variation in our beliefs measures and their correlation with aggregate proxies of attention used in previous work.

[25] In our data, we do not observe investors' wealth, but only their income brackets. Therefore, we use estimates in the literature of the wealth-to-income ratio to compute investors' wealth from their income (Emmons and Ricketts 2017; Piketty and Zucman 2014). In the structural estimation, we assume a wealth-to-income ratio of 6 as the baseline, and test the robustness of our results to a range of wealth-to-income ratios from 3 to 7. While the level of the crypto share is by construction sensitive to the chosen wealth-to-income ratio, the estimated structural parameters are remarkably stable. The intuition is that their identification comes mainly from cross-sectional variation across investors and cryptocurrencies.

Table 4
Beliefs and demand: Investor survey

	Full Sample		Investors with positive holdings		
	(1) Invest in Bitcoin	(2) Crypto share (%)	(3) Number of crypto	(4) Amount ($,000)	(5) Crypto share (%)
Beliefs (short-term):					
Price increase	0.106***	0.815**	0.340***	18.278**	1.425**
	(0.021)	(0.330)	(0.114)	(7.661)	(0.595)
Price decrease	–0.042*	0.059	–0.081	7.820	0.972
	(0.023)	(0.374)	(0.139)	(9.292)	(0.721)
Beliefs (long-term):					
Never mainstream	–0.081***	–0.573	–0.107	–3.331	–0.710
	(0.026)	(0.416)	(0.191)	(12.801)	(0.993)
High potential (dummy)	0.202***				
	(0.016)				
High potential (number)		0.301***	0.637***	–0.435	0.122
		(0.090)	(0.031)	(2.072)	(0.161)
Demographics:					
Income $\leq$ $100K	–0.081***	–3.489***	–0.553***	–69.318***	–4.555***
	(0.016)	(0.255)	(0.081)	(5.409)	(0.420)
Age $\leq$ 30	0.117***	0.525**	0.295***	0.782	0.194
	(0.014)	(0.231)	(0.081)	(5.410)	(0.420)
Outside US	0.101***	0.149	0.374***	–7.275	–0.494
	(0.015)	(0.246)	(0.081)	(5.441)	(0.422)
Accredited investor	0.175***	3.534***	0.845***	78.450***	4.617***
	(0.026)	(0.414)	(0.130)	(8.712)	(0.676)
Wave f.e.	Yes	Yes	Yes	Yes	Yes
Mean Y	0.45	2.13	2.68	39.51	3.83
SD Y	0.50	7.83	2.11	134.21	10.20
Adjusted R^2	0.12	0.09	0.21	0.12	0.09
Observations	4,647	4,647	2,580	2,580	2,580

Estimates of coefficients from Equation (3). Columns (1) and (2) report the results from the full sample. Columns (3) to (5) report the results from the sample of investors with positive holdings of cryptocurrencies. *Price increase (decrease)* is a dummy equal to one if the investor says the price is going to increase (decrease) by the end of the current year. *Never mainstream* is a dummy equal to one if the investor thinks cryptocurrencies are never going to be widely adopted. *High potential (dummy)* is a dummy equal to one if the investor thinks a specific cryptocurrency has the potential to be successful. *High potential (number)* is the number of cryptocurrencies the investor thinks have the potential to be successful. *Accredited investor* is a dummy for accredited investors of the trading company.
$*p < .1$, $**p < .05$, $***p < .01$.

which corresponds to about 35% of the average crypto share or 0.10 standard deviations. While our results are not directly comparable to those of Giglio et al. (2021)—since that paper uses a continuous measure of expectations, whereas ours are discrete—the effect relative to the standard deviation has a similar order of magnitude.[26] Additionally, a large effect of short-term optimistic beliefs on holdings in a volatile market such as cryptocurrencies is consistent with gambling preferences as a potential motive behind (excessive) trading, as documented by Liu et al. (2022) for Chinese retail investors.

[26] Giglio et al. (2021) find that a one-standard-deviation increase in expected one-year stock returns is associated with a 0.16-standard-deviation increase in equity shares.

Second, we explore the "intensive" margin in columns (3) to (5) of Table 4. Conditional on having at least one cryptocurrency, investors hold on average 2.7 cryptocurrencies, with a standard deviation slightly higher than two. Investors who expect prices to increase in the following year have a 13% higher number of cryptocurrencies relative to the mean, while investors who expect prices to decrease are not statistically different from investors who expect the price to stay the same. Column (4) shows that, conditional on having at least one cryptocurrency, investors hold \$40,000 in cryptocurrencies on average, with a lot of variation across investors, as already documented in Table 1. Investors who expect prices to increase in the following year have an extra \$18,000 invested in cryptocurrencies relative to more pessimistic investors, which is approximately 45% relative to the mean amount invested. Negative short-term and long-term beliefs do not seem to play an important role for the amount invested in cryptocurrencies, conditional on investing. Finally, in column (5) we find that moving from neutral to optimistic about the future value of cryptocurrencies increases the crypto share by about 1.4 percentage points among investors who hold cryptocurrencies, which corresponds to an increase of about 35% relative to the mean crypto share, or 0.14 standard deviations.

While our interest is in the effect of beliefs on cryptocurrency demand, the coefficients on investor demographics are also interesting. We find that investors with lower incomes have a significantly lower demand for cryptocurrencies, while younger investors have a significantly higher demand. Because cryptocurrencies are a relatively new asset class, the result that higher-income, younger investors are among the early adopters of these new products is consistent with previous literature on technology adoption (see, for example, Foster and Rosenzweig 2010 for a review). In addition, relatively older people may have more direct experience of losses (e.g., from the global financial crisis of 2008) relative to younger investors, thus making them more risk averse and skeptical of investing in cryptocurrencies (Malmendier and Nagel 2011).[27] Further, investors outside the United States have a significantly higher demand for cryptocurrencies. The countries with the largest demand relative to the number of investors from that country are in Asia and South America. This is consistent with Asia, and especially China, being a hub for cryptocurrency mining and with investors from Latin American countries having high appetites for cryptocurrencies, given the relative instability of their national currencies due to political turmoil.[28]

Overall, our analysis of investors' beliefs and demand, paired with a similar analysis for consumers in Internet Appendix C, yields three main stylized facts: (1)

27 Our result that younger individuals are more likely to hold Bitcoin is consistent with previous evidence. For example, a 2015 survey from CoinDesk finds that about 60% of Bitcoin users are below 34 years old ("New CoinDesk report reveals who really uses bitcoin," *CoinDesk*, June 10, 2015).

28 Regarding China, see Rauchs et al. (2018) and Benetton, Compiani, and Morse (2023), among others. Brazil and Argentina are among the early adopters of cryptocurrencies. The founder of Solidus Capital, a hedge fund, was reported to say, "Latin America is very volatile. Cryptos are turning into a new haven for these families" (see J. Dargan, "Love in the time of bitcoin: Latin America and cryptocurrency," *Hackernoon*, June 4, 2019).

young consumers and late investors are more likely to have more optimistic beliefs about the future of cryptocurrencies; (2) there is a lot of dispersion in beliefs across consumers and investors that is not explained by observable demographics; and (3) short-term optimism about the future value of cryptocurrencies is associated with (i) a higher probability of holding cryptocurrencies and (ii) a larger number of cryptocurrencies and amount invested, conditional on holding at least one cryptocurrency. These facts motivate our structural model and counterfactual exercises in which we assess how changes in beliefs affect investor holdings and prices in equilibrium.

4. A Structural Model of Cryptocurrencies

The descriptive results from Section 3 suggest that beliefs about the future play an important role in driving cryptocurrency demand and that late investors entered the market with more optimistic beliefs than incumbent investors. In this section, we develop a simple model of demand for cryptocurrencies with heterogeneous investors and differentiated cryptocurrencies to quantify the role of beliefs and the impact of entry by new optimistic investors on equilibrium prices. Our model builds on the general framework for estimating asset demand proposed by Koijen and Yogo (2019), with a few differences. First, we include the observed measures of beliefs from the investor survey in the demand system. Second, to handle price endogeneity, we propose an instrumental variable strategy that is based on variation in the production of different cryptocurrencies.

4.1 Supply

There are J_t cryptocurrencies in circulation in period t indexed by $j = 1, \dots, J_t$. We define S_{jt} as the supply at time t of cryptocurrency j (for example, the number of Bitcoins in circulation). We focus on an economy with a predetermined supply of cryptocurrencies. Thus, we abstract from two real-world complexities of the cryptocurrency industry: first, the endogenous production of existing cryptocurrency (e.g., the mining of Bitcoin) and, second, the introduction of new cryptocurrencies.[29]

Regarding the first point, most cryptocurrencies follow a predetermined production process. For example, Figure 6 in Internet Appendix B shows that while the price of Bitcoin displays high volatility, the number of Bitcoins in circulation grows based on a predetermined schedule. Thus, we argue that the endogenous increase in supply of existing cryptocurrencies is not first-order for the study of short-term price dynamics—which is the object of our analysis—and treat the

[29] Production of cryptocurrencies has been studied in previous work (see Cong, He, and Li 2021 and Schilling and Uhlig 2019 among others). We also do not consider possible endogenous decreases in the supply of coins due to "burning," which we think is not a first-order issue in the period and for the currencies we focus on.

supply of cryptocurrencies as exogenous.[30] The introduction of new cryptocurrencies could be an interesting dimension to explore in a richer model that features entry and exit on the supply side, but our analysis is constrained by the fact that the surveys we use cover only the top cryptocurrencies in terms of market shares.

The market capitalization of cryptocurrency j at time t is given by $MC_{jt} = P_{jt}S_{jt}$, where P_{jt} is the unit price of cryptocurrency j in U.S. dollars. As discussed above, we treat S_{jt} as exogenous, but allow P_{jt} to be endogenous in our model. The expected gain from holding cryptocurrency j is given by P_{jt+1}/P_{jt}.

Additionally, cryptocurrencies differ along other dimensions that investors possibly value. For example, cryptocurrencies can be used as means of payments with different ease of use, diffusion, and privacy properties (Böhme et al. 2015; Goldfeder et al. 2018). Another important characteristic is the consensus algorithm used to validate transactions. For example, Bitcoin uses the proof-of-work protocol, while other currencies rely on different algorithms, such as proof-of-stake (Bentov, Gabizon, and Mizrahi 2016; Budish 2018; Saleh 2021). Finally, previous work has identified additional factors, such as volatility and momentum, varying both across cryptocurrencies and over time as important determinants of cross-sectional expected returns in the cryptocurrency market (Liu, Tsyvinski, and Wu 2022). We collect the different characteristics of cryptocurrency j at time t into the vector X_{jt}.

4.2 Demand

The demand for cryptocurrencies in each period t comes from $i = 1, \ldots, I_t$ investors. Each investor i in period t is endowed with an amount of wealth A_{it}. Investors choose how to allocate their wealth across the J cryptocurrencies and an outside asset, denoted by 0. The outside asset represents all of the alternative investment opportunities not captured by the model (such as cash, equity, or bonds). The gross return from investing in the outside option is defined as R_{0t+1}.

Investors choose the fraction of wealth to invest in each cryptocurrency (w_{ijt}) to maximize expected log utility over terminal wealth at date T:

$$\max_{w_{ijt}} E_{it}[\log(A_{iT})]. \tag{4}$$

Investor wealth evolves according to the following intertemporal budget constraint:

$$A_{it+1} = A_{it}\left[\left(1 - \sum_{j=1}^{J} w_{ijt}\right)R_{0t+1} + \sum_{j=1}^{J} w_{ijt}R_{jt+1}\right]. \tag{5}$$

Investors also face short-sale constraints:

[30] In Section 5.1 we discuss how we exploit the predetermined production process of proof-of-work cryptocurrencies as a supply-side shifter to identify our demand system.

$$w_{ijt} \geq 0; w_{ijt} < 1. \tag{6}$$

Following Koijen and Yogo (2019), we assume that returns have a factor structure and that expected returns are a function of the cryptocurrencies' own characteristics. Under this assumption, the optimal portfolio depends on cryptocurrencies' characteristics (e.g., market capitalization, consensus protocol, and beta) and latent demand (e.g., unobserved cryptocurrency characteristics and investor-specific demand shifters). Specifically, we assume the following functional form for portfolio weights:

$$\frac{w_{ijt}}{w_{i0t}} = \exp\{\alpha mc_{jt} + \beta X_{jt} + \gamma B_{ij} + \lambda D_i\}\epsilon_{ijt}, \tag{7}$$

where mc_{jt} is the logarithm of market capitalization of cryptocurrency j at time t; X_{jt} captures other observable characteristics of cryptocurrency j (a dummy for proof-of-work cryptocurrencies, beta, and momentum); B_{ij} denotes investor i's belief about cryptocurrency j; D_i are investor i's demographics; and ϵ_{ijt} captures any unobserved factors affecting demand—for example, how convenient the cryptocurrency is as a means of payment for a given investor (the "convenience yield" in the model of Sockin and Xiong 2018). Thus, the expression in Equation (7) is consistent with the idea that investors' decisions might be driven by the expected capital gain from the different cryptocurrencies as well as the possibility of using them for payment purposes.[31]

Equation (7) and the budget constraint imply that the weight on cryptocurrency j is given by:

$$w_{ijt} = \frac{\exp\{\alpha mc_{jt} + \beta X_{jt} + \gamma B_{ij} + \lambda D_i\}\epsilon_{ijt}}{1 + \sum_{k=1}^{J} \exp\{\alpha mc_{kt} + \beta X_{kt} + \gamma B_{ik} + \lambda D_i\}\epsilon_{ikt}}, \tag{8}$$

and the portfolio weight on the outside asset is:

$$w_{i0t} = \frac{1}{1 + \sum_{k=1}^{J} \exp\{\alpha mc_{kt} + \beta X_{kt} + \gamma B_{ik} + \lambda D_i\}\epsilon_{ikt}}. \tag{9}$$

This specification for the portfolio weights is the same as in Koijen and Yogo (2019), except that we also include the observable measures of beliefs from the investor survey as explanatory variables.

[31] Unfortunately, we do not have payment data, and our investor survey does not contain a question that allows us to isolate the use of cryptocurrencies as a means of payment. However, we estimate a version of Equation (7) in which we also include a measure of the expected adoption of blockchain technology in the company where the respondent works, as an imperfect proxy of the convenience yield. We thank Wei Xiong for this suggestion.

4.3 Equilibrium

To close the model, we write the market-clearing condition for each cryptocurrency. The equilibrium market capitalization for cryptocurrency j is obtained by summing the demand for cryptocurrency j across all investors, as follows:

$$MC_{jt} = \sum_{i=1}^{I} A_{it} w_{ijt}, \tag{10}$$

where demand by investor i for cryptocurrency j is obtained by multiplying investor i's portfolio weight w_{ijt} by his wealth A_{it}. Under the assumption of downward-sloping demand, Koijen and Yogo (2019) show that the equilibrium is unique.

In the counterfactual analysis of Section 6, we obtain the equilibrium prices by solving the fixed-point equation in (10). Since our data cover only a subsample of the universe of investors, we need to appropriately scale up the right-hand side of Equation (10) in the counterfactuals. Specifically, for each cryptocurrency and each wave, we compute the factor that, when multiplied by the holdings of that currency in the data, yields its market capitalization at that time. Then, we use these same factors to scale up the right-hand side of Equation (10) when solving for prices in the counterfactual simulations.

5. Estimation and Results

5.1 Identification and estimation

When taking the model to the data, we set $J = 9$, corresponding to the largest cryptocurrencies in terms of market capitalization (among those in our data) and a composite option capturing all remaining cryptocurrencies.[32] We estimate the demand parameters from Equation (7) using the generalized method of moments. The parameters are estimated by matching the ratio of weights $\frac{w_{ijt}}{w_{i0t}}$ given by Equation (7) to the corresponding quantity in the data across investors and currencies. In the baseline model, we pool all investors together, but we also reestimate the model separately for different groups based on demographics.[33] The inclusion of investors' demographics D_i and beliefs B_{ij} in the demand function allows for flexible substitution patterns across assets. For example, two investors with the same demographic characteristics and demand shocks ϵ_{ijt} will typically have different portfolio weights (and different demand elasticities) if their beliefs are different.

As discussed in Section 3, we observe: (i) the number and identity of cryptocurrencies that investors hold in their portfolios; (ii) the total dollar amount invested

32 Specifically, we focus on the eight largest cryptocurrencies in our sample (Bitcoin, Ethereum, Ripple, Litecoin, Bitcoin Cash, Zcash, Dash, and Monero), and group all other cryptocurrencies in the composite cryptocurrency.

33 Koijen and Yogo (2019) estimate the model for each investor in each period when investors have more than 1,000 strictly positive holdings. In contrast, we have a cross section of nine cryptocurrencies for most of which holdings are equal to zero, which requires us to pool investors together.

in cryptocurrencies. However, we do not know how that amount is allocated across the various cryptocurrencies in the portfolio of each investor. In our baseline model, we compute the currency-specific weights w_{ijt} by assuming that each investor allocates her cryptocurrency budget across the various currencies she holds based on the market shares in our sample (i.e., the fraction of investors holding any given cryptocurrency).[34] Given that this assumption affects the variation in our dependent variable, we test the robustness of our results to different imputation rules. In particular, we also consider a rule where all cryptocurrencies in the portfolio receive equal weights and one where the weights are proportional to the market shares in the investor's demographic group.

Following the industrial organization literature on demand for differentiated products (Berry, Levinsohn, and Pakes 1995; Nevo 2001), we assume that characteristics other than prices, X_{jt}, are exogenous. For example, X_{jt} includes a dummy for whether the currency follows the PoW protocol or not. Given that the consensus protocol for a currency is rarely changed,[35] it seems reasonable to treat this as a fixed, exogenous characteristic. Other characteristics include performance indicators such as market beta and momentum; for these, the assumption is that they are mean-independent of the factors affecting demand that are not captured by the other observable currency characteristics, demographics, and beliefs.

Cryptocurrency prices could arguably be treated as exogenous from the point of view of an individual (small) investor, as is the case in our data. However, even with atomistic investors, unobservable factors affecting choices for all investors (e.g., the inherent quality or media buzz surrounding a given currency) could shift aggregate demand and thus lead to bias in the estimated coefficient on market capitalization. This is the standard challenge in estimating a demand system from quantities and prices that are simultaneously determined in the market equilibrium. More formally, the simultaneity between prices and quantities could lead to violations of the restriction

$$E[\epsilon_{ijt}|mc_{jt}, X_{jt}, D_i] = E(\epsilon_{ijt}) = 1. \tag{11}$$

The first equality is the substantive part of this restriction, and it is violated if price—and thus market capitalization—is correlated with the unobservable determinants of demand.[36]

To account for the endogeneity of prices we take two main steps. First, we leverage the fact that in our data we observe measures of investor beliefs on both

[34] For example, Bitcoin is held by 43% of investors, Ethereum by 22%, and Ripple by 13%. Suppose that investor A holds only Bitcoin, Ethereum, and Ripple in her cryptocurrency portfolio; then, we compute her weights as $0.55 = \frac{43}{43+22+13}$ for Bitcoin, $0.28 = \frac{22}{43+22+13}$ for Ethereum, and $0.17 = \frac{13}{43+22+13}$ for Ripple (and zero for all other cryptocurrencies). Next, suppose that investor B only holds Bitcoin and Ethereum; then, we compute her weights as $0.66 = \frac{43}{43+22}$ for Bitcoin and $0.34 = \frac{22}{43+22}$ for Ethereum (and zero for all other cryptocurrencies). Finally, if investor C only holds Bitcoin in her portfolio, we will assign a weight of 1 to Bitcoin and zero to all other cryptocurrencies.

[35] For instance, Ethereum has been rumored to switch from PoW to proof-of-stake for years, but that has not happened to date.

[36] Setting the mean of ϵ_{ijt} to 1 is a normalization without loss of generality.

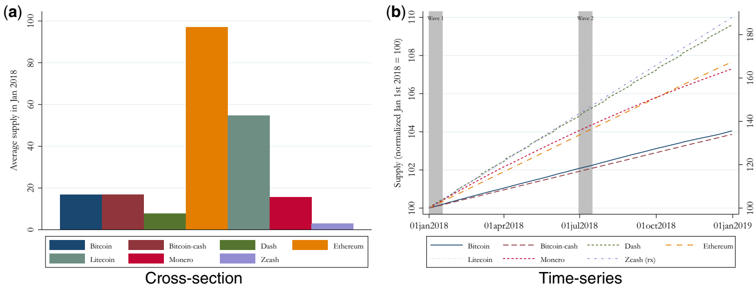

Figure 3
Supply-side instruments
Panel (a) shows the average supply in January 2018 for the seven PoW cryptocurrencies in our sample. For each currency, the measure is constructed by taking the average of the daily supply in January, which is available from the Coin Metrics website (https://coinmetrics.io). The supply is given by the sum of all native units ever created and visible on the ledger (i.e., issued) at the end of the day. Panel (b) of Figure 3 shows the time-series variation in supply in 2018. To account for the differences in scale across currencies, we normalize the supply on January 1, 2018, to 100.

the short-term price evolution and the long-term potential of cryptocurrencies. We argue that these beliefs capture an important portion of the time-varying aggregate shocks that affect investor choices. Absent data on beliefs, these shocks would enter the unobservable error term ϵ_{ijt}, but in our setting we are able to control for them. Our exogeneity restriction then becomes:

$$E[\epsilon_{ijt}|mc_{jt}, X_{jt}, D_i, B_{ij}] = 1. \tag{12}$$

Including beliefs has the dual advantage of allowing flexibility in substitution patterns across investors, as well as controlling for some of the otherwise unobservable determinants of demand that could be correlated with prices.

Second, we propose a supply-side instrumental variable strategy to tackle possible remaining endogeneity concerns for prices. Our instrument is based on differences across cryptocurrencies and over time in the production of new coins. Most of the cryptocurrencies in our data follow the PoW protocol (Ripple is the only notable exception), whereby new coins are generated (or "mined") whenever a new block of transactions is validated. The frequency with which a new coin is mined is a predetermined feature of each cryptocurrency's protocol, thus satisfying the exogeneity restriction. Further, changes in supply affect the currencies' market capitalization, which ensures relevance of the instrument. The intuition behind this instrumental variable strategy is standard: exogenous changes in supply help identify demand.[37] In our context, the production process of cryptocurrencies provides the desired exogenous variation.[38]

---

[37] For example, Conlon and Mortimer (2013) show that stockouts provide helpful identifying variation.

[38] A potential threat to our identifying assumption is the presence of schemes, such as crypto airdrops, which can alter the circulating supply in a way that could be correlated with unobservable demand determinants. Ideally, we would like to directly control for crypto airdrops, but data on these events are not available in a consistent way for the period we study. However, the primary reason for crypto airdrops is to promote a blockchain startup, project, or service, by dropping tokens automatically into the wallets of users who own a specific coin (e.g., Bitcoin or Ethereum). Hence, crypto airdrops

Figure 3 displays the two key sources of variation in our instrumental variable. Panel (a) shows the average supply in January 2018 for the seven PoW cryptocurrencies in our sample. For each currency, the measure is constructed by taking the average of the daily supply in January, which is available from the Coin Metrics website (https://coinmetrics.io).[39] We can see that there is substantial heterogeneity in the levels of supply across currencies. Panel (b) of Figure 3 shows the time-series variation in 2018. To account for differences in scale across currencies, we normalize the supply on January 1, 2018, to 100. The supply of all PoW currencies follows a predetermined trajectory, but the slopes differ across currencies, which provides additional identifying variation.

More formally, our first-stage regression is given by:

$$mc_{jt} = \psi \log(supply_{jt}) + \tau X_{jt} + \epsilon_{jt}, \tag{13}$$

where $supply_{jt}$ is the number of coins in circulation for currency j at time t, and X_{jt} are the same controls used in the demand estimation equation (7). With this instrumental variable in hand, the exogeneity restriction needed to identify the model becomes:

$$E[\epsilon_{ijt} | Z_{jt}, X_{jt}, D_i, B_{ij}] = 1, \tag{14}$$

where Z_{jt} is our supply-side instrument and all other variables are as in Equation (12).

We conclude the discussion of identification by noting that our focus is on endogeneity of prices and we treat beliefs as exogenous to the model. In particular, when considering our counterfactual exercises, we quantify the effects that exogenously given changes in investor beliefs have on equilibrium prices and holdings. The model does not capture the possibility that beliefs may endogenously readjust as a consequence of the changes in prices. This choice is motivated by two main considerations. First, not modeling the fact that beliefs might in turn react to changes in prices is likely to either (i) underestimate the role of beliefs in driving asset demand, if beliefs are extrapolative (Barberis et al. 2015; Da, Huang, and Jin 2021; Kuchler and Zafar 2019); or (ii) not have much of an impact on the estimates, if beliefs are persistent over time (Egan, MacKay, and Yang 2022; Giglio et al. 2021). Therefore, if anything, we interpret our estimates of the effect of beliefs on demand as a lower bound on the true impact. Second, our choice is in line with the demand estimation literature in industrial organization, which has mostly focused on price endogeneity as the first-order issue and has emphasized the theoretical and

are less likely to matter for the large cryptocurrencies that we focus on in our estimation. Indeed, popular historical airdrops involved cryptocurrencies that are not in our sample, and websites tracking current airdrops show newer cryptocurrencies with lower market capitalization (https://airdrops.io/). We also abstract in our analysis from changes in prices due to inflated reporting of volumes coming from wash trading (Aloosh and Li 2019; Cong et al. 2023). A thorough analysis of wash trading regulation could be an interesting avenue for future research.

[39] The supply is given by the sum of all native units ever created and visible on the ledger (i.e., issued) at the end of the day.

Table 5
Structural demand parameters

	(1)	(2)	(3)	(4)
Characteristics:				
Market capitalization	0.655***	0.599***	0.599***	0.439***
	(0.082)	(0.087)	(0.086)	(0.098)
Proof-of-work	0.824***	0.739***	0.697***	0.521***
	(0.153)	(0.159)	(0.161)	(0.176)
Beta	2.214***	2.371***	2.493***	1.992***
	(0.230)	(0.258)	(0.263)	(0.278)
Four-week momentum	0.169	0.244	0.246	0.046
	(0.227)	(0.244)	(0.236)	(0.290)
Beliefs:				
Price increase		0.617***	0.444***	0.300*
		(0.165)	(0.166)	(0.171)
Never mainstream			−1.664***	−1.497***
			(0.321)	(0.363)
High potential				1.516***
				(0.143)
Average own-price elasticity	−0.36	−0.41	−0.41	−0.57
Macroeconomic controls	Yes	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes
Observations	41,823	41,823	41,823	41,823

Estimates of the structural demand parameters from the model of Section 4. *Beta* is based on cryptocurrency market excess return following Liu, Tsyvinski, and Wu (2022). *Price increase* is a dummy equal to one if the respondent expects the price of Bitcoin to increase over the course of the year. *Never mainstream* is a dummy equal to one if the investor thinks cryptocurrencies are never going to be widely adopted. *High potential* is a dummy equal to one if the investor thinks a given currency has the potential to be successful in the long term. *Demographic controls* are dummies for age, income, country of residence, and a dummy for whether the investor is a customer of the trading company. *Macroeconomic controls* are the logarithm of the S&P 500 and the three-month London Interbank Offered Rate (LIBOR). Standard errors are clustered at the investor level.
$^{*}p < .1$, $^{**}p < .05$, $^{***}p < .01$.

computational challenges associated with endogenizing nonprice characteristics as well.[40]

5.2 Results

5.2.1 Main estimates. Table 5 shows the estimates of the structural demand parameters. All columns report the estimates based on the "weaker" exclusion restriction in Equation (14). Before discussing the demand estimates, we briefly comment on the first-stage results, which can be found in Table 3 of Internet Appendix B. We estimate Equation (13) both in our survey period and in a longer time series, which includes not only the dates that overlap with our survey, but all data points from 2018. In both cases, we find a positive and highly significant effect of (log-)supply on (log-)market capitalization. Given that our endogenous variable within market capitalization is price, we also estimate Equation (13) using cryptocurrency (log-)price as the dependent variable. Consistent with the intuition that an outward shift of the supply curve lowers equilibrium prices, we find a negative and highly significant effect of (log-)supply on (log-)prices. The first-stage *F*-statistic is

[40] A paper in which both prices and other characteristics are endogenous is Fan (2013).

more than 200 (20) in the survey sample using market capitalization (price) as the dependent variable.

In column (1) of Table 5, we do not control for investors' beliefs and find a coefficient on log market capitalization of about 0.65. The fact that this coefficient is smaller than one guarantees that demand is downward-sloping and the equilibrium is unique (Koijen and Yogo 2019). The coefficient is precisely estimated, and the associated average own-price elasticity is –0.36. In addition, we find that investors have a strong and significant preference for PoW cryptocurrencies, which is consistent with the fact that many of the oldest and most popular currencies are based on PoW protocols. We also find a positive, statistically significant, and large coefficient on the cryptocurrency beta, while the effect of momentum is not significant and small in magnitude. A positive beta suggests that investors tend to prefer cryptocurrencies that have a higher volatility in comparison to the overall volatility in the cryptocurrency market.[41]

In column (2) of Table 5, we include our measures of short-term investor beliefs in the demand system.[42] The coefficient on market capitalization remains significant and consistent with downward-sloping demand. Interestingly, the point estimate decreases, pushing the price elasticity of demand up to –0.41. This is consistent with the fact that optimistic beliefs are positively correlated with both price and demand, and therefore omitting them from the model leads to upwards bias on the price elasticities (in absolute value). Thus, including beliefs in the demand system appears to help address the issue of price endogeneity. We also find that expectations play a significant role for investor demand. Specifically, investors who believe that the value of cryptocurrencies will increase in the next year are more likely to demand cryptocurrencies, and the effect is precisely estimated.

Next, column (3) of Table 5 adds long-term expectations. We find that investors who think cryptocurrencies are never going to be mainstream have a significantly lower demand for cryptocurrencies. Finally column (4) of Table 5 includes the cryptocurrency-specific dummy about long-run potential. Investors believing that a given cryptocurrency has potential in the long run tend to hold more of that currency in their portfolios. Again, the effect of this measure of long-term optimism is significant. Under the assumption that beliefs about long-run potential capture some form of expected future "cash flows" from crypto assets, our results are consistent with models where variation in prices is explained by investors' expectations on dividend growth, rather than just investors' time-varying discount rates (Barberis et al. 2015; Campbell and Shiller 1988; Cochrane 2011; De La O

41 Following Liu, Tsyvinski, and Wu (2022), we estimate beta by regressing the cryptocurrency-specific excess return on the cryptocurrency excess market return. The latter is constructed as the difference between the cryptocurrency market index return, and the risk-free rate measured by the one-month Treasury bill rate.

42 The reduced-form results in Table 4 show that short-term optimism (i.e., expecting a price increase) has a positive and statistically significant effect on demand, while short-term pessimism (i.e., expecting a price decrease) turns out not to be significant. Accordingly, we omit the price decrease dummy from our baseline specification. Table 5 in the Internet Appendix shows the results when we include the price decrease dummy.

Table 6
Structural demand parameters: Heterogeneity

	By income		By age		By period	
	(1) ≤ \$100K	(2) > \$100K	(3) ≤ 30	(4) > 30	(5) Boom	(6) Bust
Characteristics:						
Market capitalization	0.575***	0.164	0.266**	0.720***	0.359**	0.456***
	(0.136)	(0.127)	(0.105)	(0.123)	(0.148)	(0.092)
Proof-of-work	0.567**	0.482***	0.618***	0.462*	0.216	0.726***
	(0.235)	(0.155)	(0.179)	(0.264)	(0.234)	(0.224)
Beta	2.215***	1.897***	1.718***	4.414***	1.923***	2.800***
	(0.333)	(0.527)	(0.378)	(0.648)	(0.297)	(0.643)
Four-week momentum	–0.594**	1.115**	0.773**	–1.031***	–0.034	–0.299
	(0.233)	(0.489)	(0.392)	(0.280)	(0.300)	(0.948)
Beliefs:						
Price increase	0.489**	0.296	0.214	0.499**	0.630**	0.180
	(0.234)	(0.225)	(0.220)	(0.246)	(0.262)	(0.220)
Never mainstream	–1.263***	–1.741***	–1.388***	–2.185***	–0.696	–2.299***
	(0.451)	(0.490)	(0.420)	(0.464)	(0.544)	(0.322)
High potential	1.483***	1.577***	1.550***	1.484***	1.813***	1.428***
	(0.167)	(0.176)	(0.146)	(0.197)	(0.196)	(0.160)
Average own-price elasticity	–0.46	–0.83	–0.75	–0.29	–0.65	–0.55
Macroeconomic controls	Yes	Yes	Yes	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,422	13,401	20,907	20,916	19,134	22,689

Estimates of the structural demand parameters from the model of Section 4. Columns (1) and (2) show the estimates splitting the full sample by income; columns (3) and (4) show the estimates splitting the full sample by age; columns (5) and (6) show the estimates for the boom (January 2018) and bust (July 2018) periods, respectively. *Beta* is based on cryptocurrency market excess return following Liu, Tsyvinski, and Wu (2022). *Price increase* is a dummy equal to one if the respondent expects the price of Bitcoin to increase over the course of the year. *Never mainstream* is an indicator equal to one if the investor thinks cryptocurrencies are never going to be widely adopted. *High potential* is a dummy equal to one if the investor thinks a given currency has the potential to be successful in the long term. *Demographic controls* are dummies for age, income, country of residence, and if the investor is a customer of the trading company. *Macroeconomic controls* are the logarithm of the S&P 500 and the three-month London Interbank Offered Rate (LIBOR). Standard errors are clustered at the investor level.
$^{*}p < .1$, $^{**}p < .05$, $^{***}p < .01$.

and Myers 2021). Even if one of the key features of the majority of cryptocurrencies is the absence of current cash flows, investors might expect future cash flows coming, for example, from user adoption and network effects. In addition, including the measure capturing long-run potential further reduces the point estimate of the coefficient on market capitalization. As a result, the average price elasticity of demand becomes –0.57. This is consistent with the idea that controlling for currency-specific beliefs further helps to address the issue of price endogeneity.

5.2.2 Heterogeneity. We now discuss the results from several heterogeneity analyses. First, we estimate the model in column (4) of Table 5 separately for different income groups. Columns (1) and (2) in Table 6 show the results. The point estimates exhibit some variation across income. Lower-income investors tend to be less elastic to prices. The price elasticity of demand is about –0.46 for low-income investors and almost twice as large for high-income investors. Additionally, lower-income investors are more responsive to short-term beliefs and somewhat less responsive to long-term beliefs relative to high-income investors.

Columns (3) and (4) in Table 6 show the results by age. Young investors tend to be more elastic to prices than older investors. The price elasticity of demand is approximately –0.75 for young investors and only about –0.30 for older investors. On the other hand, older investors are more responsive to both positive short-term beliefs and negative long-term beliefs than younger investors.

Finally, columns (5) and (6) of Table 6 report the estimates for the boom (January 2018) and bust (July 2018) periods, respectively. Overall, the coefficients on characteristics are qualitatively similar in the two periods, with a small loss of precision in some cases due to the lower number of observations relative to the pooled estimation strategy. The price elasticity of demand is approximately –0.65 in the boom period and –0.55 in the bust period. Comparing the parameters on beliefs in the two periods, some interesting patterns emerge. First, in the boom period, the coefficient on short-term price increase is approximately 0.63, which is twice as large as the baseline pooled estimate of 0.31. In contrast, in the bust period, the coefficient on short-term price increase is smaller, at 0.18, and not statistically significant. Second, in the boom period, the dummy for investors who think cryptocurrencies are never going to be mainstream is not significant and low in magnitude. On the other hand, thinking that cryptocurrencies are never going to be mainstream has a large effect in the bust period, with a point estimate that is about twice as large as the baseline estimate. This pattern is consistent with existing work on the role of beliefs for trading and asset prices (Füllbrunn et al. 2022; Haruvy, Lahav, and Noussair 2007; Hong and Stein 2007).

5.2.3 Robustness and fit. Before turning to our beliefs counterfactuals, we briefly describe some of the additional analyses that we have run to assess the robustness and fit of the model. Internet Appendix B reports the results.

First, we estimate the model shown in column (4) of Table 5 using a different allocation rule for the amount invested across cryptocurrencies, which affects our dependent variable. Column (1) of Table 4 in the Internet Appendix shows the results using weights based on market shares in different demographic groups, while column (2) shows the results using equal weights. The results are qualitatively similar to our baseline specification.

Second, we estimate the model shown in column (4) of Table 5 using different assumptions on the wealth-to-income ratio. Columns (3) to (6) of Table 4 in the Internet Appendix show the results. The coefficients on both cryptocurrency characteristics and investors' beliefs are remarkably stable across a wide range of wealth-to-income ratios that have been identified in the literature (Emmons and Ricketts 2017; Piketty and Zucman 2014).

Third, Table 5 of the Internet Appendix reports the results of several robustness checks with additional control variables. We show that our results are robust to the inclusion of: (i) a dummy for negative short-term beliefs, (ii) a dummy for whether

Table 7
Late buyers, optimistic beliefs, and cryptocurrency prices

	Baseline	Counterfactual: Beliefs only						Counterfactual: No entry			
		Only short-term beliefs		Late buyer from 2018		Late buyer from 2016		Late buyer from 2018		Late buyer from 2016	
	Level (1)	Level (2)	Δ % (3)	Level (4)	Δ % (5)	Level (6)	Δ % (7)	Level (8)	Δ % (9)	Level (10)	Δ % (11)
Panel A: Market size and beliefs											
Number of investors	4,647	4,647	0.0%	4,647	0.0%	4,647	0.0%	3,636	–21.8%	2,687	–42.2%
Short-term price increase	63%	59%	–7.2%	59%	–7.2%	56%	–11.2%	60%	–5.6%	57%	–10.7%
Never mainstream	9%	9%	0.0%	11%	19.4%	12%	34.5%	10%	13.0%	12%	27.6%
Panel B: Cryptocurrency Prices											
bitcoin	10869	10611	–2.4%	10277	–5.4%	9516	–12.4%	7004	–35.6%	2857	–73.7%
bitcoin-cash	1662	1633	–1.8%	1577	–5.1%	1483	–10.7%	1040	–37.4%	468	–71.8%
dash	727	716	–1.5%	692	–4.8%	640	–11.9%	461	–36.5%	184	–74.7%
ethereum	1089	1066	–2.1%	1025	–5.9%	958	–12.1%	638	–41.4%	264	–75.7%
litecoin	178	174	–2.6%	168	–5.7%	155	–13.0%	114	–35.9%	40	–77.7%
monero	298	290	–2.5%	280	–5.9%	258	–13.3%	181	–39.4%	70	–76.5%
ripple	1.16	1.13	–3.2%	1.08	–7.2%	1.00	–14.0%	0.65	–44.0%	0.27	–76.8%
zcash	451	443	–1.9%	428	–5.1%	400	–11.3%	295	–34.7%	123	–72.7%
Average			–2.2%		–5.6%		–12.3%		–38.1%		–75.0%

The table shows the results from the baseline and five counterfactual analyses for the first wave of our survey in January 2018 (the "boom" period). Panel A shows the number of investors, the fraction of investors that believe the price of cryptocurrencies is going to increase, and the fraction of investors that believe cryptocurrencies will never become mainstream. Panel B shows the equilibrium prices for all cryptocurrencies in our sample and the average across them. Column (1) is the baseline; columns (2) and (3) show the scenario in which we replace only the short-term beliefs of late investors (from 2018 onward) with short-term beliefs of nonbuyers; columns (4) and (5) show the counterfactual in which we replace all beliefs of late investors with the beliefs of nonbuyers; columns (6) and (7) do the same as columns (4) and (5) but defining late investors as anyone who bought their first cryptocurrency from 2016 onward; columns (8) and (9) show the baseline no-entry counterfactual in which we ban entry of late investors, by removing all investors who bought their first cryptocurrency in 2018 or later without replacing them; and columns (10) and (11) show the no-entry counterfactual in which we ban entry of all investors who bought their first cryptocurrency from 2016 onward.

the company at which the investor works plans to introduce blockchain technology in its operations in the following two years, (iii) a dummy for the survey wave, and (iv) a measure of the age of different cryptocurrencies. We also estimate the demand system excluding the only non-proof-of-work cryptocurrency in our sample (Ripple), including additional interactions of the different beliefs measures, and including the cryptocurrency potential of other currencies. The results are similar to our baseline model.

Fourth, we include proxies for aggregate investor attention and sentiment, as well as network effects, in our demand model. We construct two proxies for investor attention following Liu and Tsyvinski (2021). Specifically, we look at the deviation of Google searches for the word "Bitcoin" in a given week compared to the average of those in the preceding four weeks (to measure attention in general) and the ratio between Google searches for the phrase "Bitcoin hack" and searches for the word "Bitcoin" (to measure negative attention). Next, a growing literature has emphasized the importance of network effects for user adoption and cryptocurrencies valuation (Biais et al. 2023; Cong, Li, and Wang 2021; Pagnotta and Buraschi 2018; Sockin and Xiong 2018). To address this, we follow the empirical approach in Liu, Tsyvinski, and Wu (2022) and compute the weekly changes in logged active and new addresses as a measure of the network's growth. We match these measures to the dates our survey was conducted and estimate the demand model with these additional controls. Table 6 of the Internet Appendix shows that our baseline coefficients are robust to the inclusion of aggregate measures capturing average investor attention and network effects.

Finally, we perform the following out-of-sample exercise to study the model fit. We randomly select 80% of our investors, estimate the model on that subsample, and compute the model-predicted weights for the remaining 20% of the sample. As shown in Table 7 of the Internet Appendix, the estimates are quantitatively similar to those obtained using the full sample. Interestingly, the correlation between the model-predicted weights and those in the holdout data increases by about 11% going from the model in column (1) to that in column (4) of Table 5, which suggests that including our measures of beliefs in the demand system improves the fit of the model.

6. Counterfactual Analyses

With the estimated model in hand, we study the role of investors' entry and beliefs for equilibrium prices and allocations. In our first set of counterfactual simulations, we investigate the effect of beliefs by computing the market equilibrium in the scenario where late optimistic buyers are prevented from investing in cryptocurrencies. In a second counterfactual simulation, which is motivated by environmental concerns about the high energy intensity of the PoW protocol, we make the currency-specific expectations about PoW currencies more pessimistic and quantify the substitution patterns toward other cryptocurrencies and alternative investment opportunities.[43]

6.1 The role of late optimistic buyers

As we have shown in Section 3, investors who bought their first cryptocurrency late (i.e., in 2018) tend to be more optimistic about the future value of cryptocurrencies. This may have been driven partly by "fear of missing out" and contagious social dynamics.[44] In this section, we explore the quantitative importance of late investors' beliefs by considering two counterfactual scenarios in which we limit the widespread adoption of cryptocurrencies by banning the entry of late optimistic investors in the market.[45]

[43] Our counterfactuals are based on the estimated parameters of Section 5.2. As always, one should not use these estimates to perform quantitative counterfactuals in contexts that are very different from that captured by our sample. For example, if the pool of investors and their financial sophistication has substantially changed since our sample period, then one should use caution before extrapolating our estimates to the present time.

[44] Similarly, (overly) optimistic beliefs about house prices played an important role in the housing boom of the early 2000s in the United States (Burnside, Eichenbaum, and Rebelo 2016; Cheng, Raina, and Xiong 2014; Kaplan, Mitman, and Violante 2020).

[45] Figure 3 in the Internet Appendix shows that the rise and fall in prices corresponded to an increase in the number of unique addresses used on the Bitcoin blockchain. Unfortunately, it is not possible to distinguish from this data whether an

Figure 4
Late buyers, optimistic beliefs, and cryptocurrency prices
The figure shows the average percentage changes relative to the baseline for the first wave of our survey in January 2018 (the "boom" period) for two counterfactuals. In the first counterfactual ("Beliefs only"), we remove all investors who bought their first cryptocurrency in 2018 or later, and replace their beliefs by sampling at random from the population of nonbuyers. In the second counterfactual ("No entry"), we simply ban entry of late investors by removing all investors who bought their first cryptocurrency in 2018 or later without replacing them. *Number of investors* refers to the change in the total number of potential investors in the cryptocurrency market. *Short-term positive beliefs* refers to the change in the fraction of investors reporting an expected increase in the value of cryptocurrencies in the following year. *Portfolio allocation* refers to the average change in the amount invested in the cryptocurrencies in our sample. *Cryptocurrency prices* refers to the average change in the price for the cryptocurrencies in our sample. All bars are changes as a percentage of the relative value in the baseline.

Using the estimates in column (3) of Table 5, we construct two main counterfactuals. In the first counterfactual, we remove all investors who bought their first cryptocurrency in 2018 and replace their beliefs by sampling at random from the population of nonbuyers. This allows us to isolate the effect of late investors' beliefs on equilibrium cryptocurrency prices. In the second counterfactual, we altogether ban entry of late investors, by removing all investors who bought their first cryptocurrency in 2018 without replacing them. This captures the full effect of a regulation that restricts entry into the market, for example by requiring to be registered as a qualified investor in order to buy a new security. Comparing the two counterfactuals allows us to separately quantify the effect of investors' beliefs and the effect of a regulation restricting entry.

Figure 4 shows the average percentage changes relative to the baseline for the first wave of our survey in January 2018 (the "boom" period). In the first counterfactual, the number of investors is unchanged, because we replace late investors with nonbuyers, whereas in the second counterfactual we prevent late buyers from purchasing cryptocurrencies, which leads to a decline in the market size by about

address belongs to an existing investor opening a new account or to a new investor opening her first account. However, our survey data allow us to identify when individual investors bought their first cryptocurrency.

22%. In both counterfactuals, the share of investors with short-term positive beliefs declines by about 5–7%. As a result of less optimistic beliefs, investors decrease their cryptocurrency holdings by about 4% on average and cryptocurrency prices decline by more than 5% in equilibrium, keeping the market size constant. The change in beliefs combined with the reduction in market size leads to a decline in the average investment in cryptocurrencies by more than 25% and a drop in equilibrium cryptocurrency prices by approximately 38%.

Figure 4 shows the average effects across cryptocurrencies, whereas in Table 7, we report a detailed breakdown across cryptocurrencies and the results of two additional counterfactuals. First, we simulate a counterfactual in which we replace only the short-term beliefs of late investors with short-term beliefs of nonbuyers. Second, we expand our definition of late investors by including all investors who bought their first cryptocurrency from 2016 onward (as opposed to 2018 in our baseline specification).

Panel A reports summary statistics for number of investors and beliefs in the baseline and counterfactual scenarios. Investors' demographics and views of cryptocurrency-specific potential are, by construction, unchanged in the counterfactual that only changes beliefs, while they are affected in the counterfactual in which we ban late investors. Panel B reports the prices for the eight individual cryptocurrencies in our sample and the average percentage changes across cryptocurrencies.

In columns (2) and (3) of Table 7, we report the results from the counterfactual in which we replace only the short-term beliefs of late investors with short-term beliefs of nonbuyers. This change leads to a decrease in the fraction of short-term optimists by four percentage points or 7.2% relative to a baseline of 63%. Lower optimism about the future value of cryptocurrencies leads to a decrease in equilibrium prices by 2.2% on average. Hence, we estimate an elasticity of cryptocurrency prices to late investors' short-term beliefs of about 0.3. This average elasticity masks heterogeneous effects across different cryptocurrencies. The same decline in investors' short-term optimism leads to a decrease in the price of Dash by 1.5%, while Ripple's price declines by more than twice as much.

In columns (4) and (5), we report the results for our baseline beliefs counterfactual in which investors not only become more pessimistic in the short term, but also in the long term (i.e., more likely to think that cryptocurrencies will not become mainstream). As a result, the price of Bitcoin decreases by about \$700 (5.4%), from \$10,900 to \$10,200. On average, cryptocurrency prices decline by about twice as much relative to the counterfactual in which we only change short-term positive beliefs. This result is consistent with the fact that, as mentioned above, nonbuyers tend to be overall more pessimistic, paired with the large effects of long-term beliefs on demand we documented in Section 5.2.

In columns (6) and (7), we expand our definition of late buyers to include all investors who bought their first cryptocurrency from 2016 onward. Specifically, we replace the beliefs of all investors who bought their first cryptocurrency after 2016 with the beliefs of nonbuyers, again keeping the number of investors unchanged. Panel A shows a larger decrease (increase) in the share of short-term optimists (long-term pessimists), which translates into larger declines in equilibrium cryptocurrency prices (panel B). For example, the price of Bitcoin now decreases by about \$1,400, from \$10,900 to \$9,500. On average, cryptocurrency prices decline by more than 12% as a result of the less optimistic beliefs of late investors relative to early investors and nonbuyers.

Finally, the last four columns of Table 7 show the results for the counterfactuals with no entry of late investors. Specifically, banning late buyers decreases the number of potential investors from about 4,600 to about 3,600, a 22% decline. As expected, fully banning entry has a stronger effect for all cryptocurrencies, with prices declining by about 38% on average. We find stronger effects for popular cryptocurrencies such as Ripple and Ethereum, which decline by more than 40%, while Bitcoin is less affected. Columns (10) and (11) implement a ban that also removes investors who bought their first cryptocurrency in 2016–17. In this case the market size declines by about 42%. On average, the combination of a smaller investor pool and more pessimistic beliefs reduces cryptocurrency prices by 75% in January 2018.

To summarize, we find that the entry of late optimistic investors played an important role in the increase of cryptocurrency prices at the end of 2017 and beginning of 2018. We estimate an elasticity of cryptocurrency prices to late investors' short-term beliefs of about 0.3. We also find that banning investors who bought their first cryptocurrency from 2018 (2016) onward leads to an average decline in the value of cryptocurrencies by about 38% (75%). This effect is driven by a decline in the number of potential buyers, but also by the fact that late buyers tend to be more optimistic relative to other investors. Comparing the counterfactuals in which we only change beliefs with the counterfactual where late investors are excluded altogether, we find that approximately 15% of the change in equilibrium prices is due to the direct effect of late investors' optimism.

6.2 The impact of environmental concerns on proof-of-work cryptocurrencies

In a second set of counterfactuals, we study the role of long-term beliefs about specific cryptocurrencies for investors' portfolio allocations and equilibrium prices. Specifically, using the estimates in column (4) of Table 5, we simulate the market equilibrium when investor long-term beliefs about PoW currencies become more negative. As mentioned earlier, PoW is increasingly criticized due to its huge energy consumption;[46] our counterfactual exercise speaks to how the market would react if investors became more aware of its limitations.

[46] Irresberger, John, and Saleh (2020) offer an exhaustive discussion of advantages and limitations of different consensus protocols. Recent swings in cryptocurrency prices have been associated to Elon Musk's popular tweets about the environmental impact of Bitcoin mining (see Molla, "When Elon Musk tweets, crypto prices move," and Seward and Nelson, "Elon Musk says Tesla is suspending Bitcoin payments over environmental concerns,").

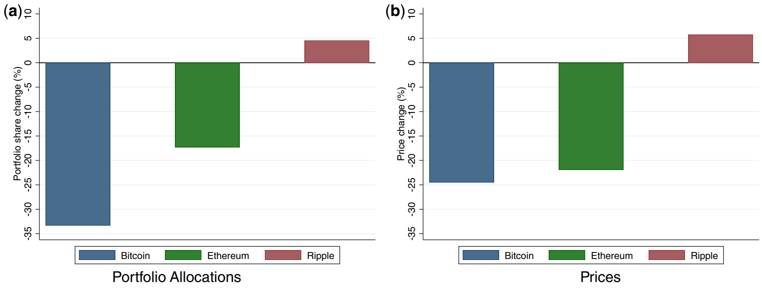

Figure 5
Energy sustainability and cryptocurrency allocations: Prices
The figure shows the percentage change in the equilibrium prices and median portfolio allocations for Bitcoin, Ethereum, and Ripple in a counterfactual scenario in which we make 25% of investors more pessimistic about PoW. We take 25% of the investors that list at least one PoW currency among those with long-term potential and consider the counterfactual scenario in which they do not list any PoW currency among those with potential. The values in the figure are changes as a percentage of the initial prices and portfolio allocations predicted by our model in the January 2018 baseline.

Table 8
Counterfactual equilibrium prices and portfolio allocations

	Baseline		Counterfactual: Green preferences				Counterfactual: ETH switch			
	Allocations	Prices	Allocations		Prices		Allocations		Prices	
	\$ (1)	\$ (2)	\$ (3)	Δ % (4)	\$ (5)	Δ % (6)	\$ (7)	Δ % (8)	\$ (9)	Δ % (10)
Bitcoin	2,387	10,869	1,590	–33.4%	8,202	–24.5%	2456	2.9%	10799	–0.6%
Bitcoin-cash	64	1,662	49	–23.6%	1,477	–11.1%	67	5.1%	1650	–0.7%
Dash	43	727	40	–5.2%	655	–9.8%	42	–1.3%	721	–0.8%
Ethereum	410	1,089	339	–17.3%	850	–21.9%	462	12.7%	1326	21.7%
Litecoin	184	178	116	–37.2%	146	–18.1%	187	1.3%	177	–0.7%
Monero	49	298	46	–5.2%	275	–7.7%	48	–2.3%	296	–0.8%
Ripple	78	1.16	82	4.6%	1.23	5.8%	79	0.9%	1.15	–0.8%
Zcash	24	451	23	–3.4%	411	–8.9%	24	0.1%	448	–0.8%
Average				–15.1%		–12.0%				
Outside option	328,285		329,056	0.23%			328,289	0.00%		

Equilibrium prices and median portfolio allocations for all main cryptocurrencies in our sample and the outside option in the baseline and two counterfactual scenarios. The baseline is January 2018 (the "boom" period). In the counterfactual "Green preferences," we take 25% of the investors that list at least one proof-of-work currency among those with long-term potential and consider the counterfactual scenario in which they do not list any proof-of-work currency among those with potential. In the counterfactual "ETH switch," we calibrate a 22% increase in the price of ETH in line with the one observed after the first public announcement of ETH switching to proof-of-stake on April 30, 2018. Prices and allocations are in U.S. dollars. Changes are in U.S. dollars or are expressed as percentages of the initial price.

Figure 5 shows the changes in equilibrium allocations and prices for the three largest cryptocurrencies in the market: Bitcoin and Ethereum, which are based on the PoW protocol, and Ripple, which has a different, less energy-intensive consensus protocol. Panel (a) of Figure 5 shows the changes in investor portfolio allocations when we make 25% of investors more pessimistic about PoW.[47] The median investor reduces her

[47] More precisely, we take 25% of the investors that list at least one PoW currency among those with long-term potential and consider the counterfactual scenario in which they do not list any PoW currency among those with potential.

holdings of Bitcoin and Ethereum by about 33% and 17%, respectively, whereas holdings of Ripple increase by almost 5%. Panel (b) shows percentage changes in equilibrium prices relative to the baseline. The prices of both Bitcoin and Ethereum decline by more than 20%, while Ripple's price increases by approximately 6%.

Table 8 shows portfolio allocations and equilibrium prices for all main cryptocurrencies in our sample in the boom period. Columns (1) to (2) report median portfolio allocations and prices for the baseline, whereas columns (3) to (6) report the same outcomes for the counterfactual in which investors become more negative on the expected sustainability of PoW cryptocurrencies. In the counterfactual, we find a reduction in the median holdings of PoW currencies, while Ripple experiences a modest increase. At the median, almost \$800 are shifted away from Bitcoin, which corresponds to a decline by a third. Litecoin experiences the largest percentage outflows declining by more than 35%, while holdings of Dash, Zcash, and Monero decline by a smaller amount in both absolute and percentage terms. Overall, cryptocurrency holdings decline by 15% on average.

Turning to prices, we find that on average, equilibrium cryptocurrency prices decrease by around 12%, with Bitcoin and Ethereum experiencing the largest absolute and percentage declines. For example, the price of Bitcoin decreases by about \$2,700 (25%), from \$10,900 to \$8,200. Among other cryptocurrencies based on the PoW consensus protocol, Litecoin also experiences a large decline, whereas Zcash and Monero are the least affected PoW cryptocurrencies. Overall, our counterfactual analysis shows that investors' concerns about the long-term sustainability of PoW cryptocurrencies lead to large portfolio reallocations and price adjustments: (i) away from the cryptocurrency market as a whole; and (ii) across cryptocurrencies with different characteristics and consensus protocols within the market.

Finally, we use our demand model to study the effect of Ethereum abandoning the PoW protocol on investors' portfolios and equilibrium prices, all else equal. After several years of discussion, Ethereum switched from the PoW protocol to a different protocol called proof-of-stake (PoS) on September 15, 2022. The left panel of Figure 7 in the Internet Appendix shows the price of ETH—and BTC as a benchmark—in the months before and after the merge. The price of ETH was trending down before the merge and continued doing so after it. Relative to BTC, the price of ETH experienced a differential drop by an additional 20% in the few days after the merge and stabilized thereafter. The lack of a price surge—potentially attributable to the change to a more sustainable protocol—is not surprising given that the move had already been announced publicly. For this reason, we also looked at the price evolution around the date of the first public announcement, which according to several sources dates back to April 30, 2018.[48] The right panel of Figure 7 in the Internet Appendix shows that the price of ETH was trending up before the announcement of the merge and continued doing so after it. Relative to BTC, the price of ETH experienced a differential increase by about 22% in the few

[48] See https://twitter.com/vitalikbuterin/status/991021062811930624?s=21 and https://www.reddit.com/r/ethereum/comments/8g1q55/comment/dy85pq0/?context=3.

days after the merge announcement, but the gap closed in the month after. While the (relative) price increase after the announcement might be consistent with investors' positive response to ETH moving to a more sustainable protocol, the rapid reversal and lack of a persistent effect could be explained by uncertainty on the credibility of this first announcement. Indeed, it took more than four years from this first announcement for ETH to implement the switch in practice.

With these considerations in mind, we calibrate the change in beliefs needed to generate an increase in the ETH price similar to that observed after the announcement. Columns (7) to (10) in Table 8 show the results. To obtain a 22% increase in the price of ETH, our model requires about 15% of investors becoming more long-term optimistic about that specific cryptocurrency. As a result, the median investor allocates about \$50 more to ETH (a 13% increase) and the equilibrium price rises from \$1,089 to \$1,326. The increase in the price of ETH comes at the expense of other cryptocurrencies, which experience a decline in price by about 0.7%. Overall, our analysis shows that a persistent change in investors' preferences toward more sustainable assets can lead to reallocation away from energy-consuming cryptocurrencies with a large impact on equilibrium prices.

7. Conclusion

In this paper, we study the role of investors' beliefs for cryptocurrency demand. Reduced-form evidence and a structural model of asset demand point to an important impact of beliefs on individuals' holdings of cryptocurrencies and their equilibrium prices. Notably, including observed beliefs in the demand system alleviates the issue of price endogeneity and opens up a set of (counterfactual) questions that could be answered using a demand-based asset pricing model. In our specific setting, we use the estimated model to simulate how the market prices would react to (i) (regulating) entry of late optimistic investors, and (ii) investors becoming more pessimistic about a large class of highly energy-intensive cryptocurrencies.

Our work could be extended with regards to both the data and the model. First, we relied only on information from surveys. While our surveys ask about both expectations and holdings, observing actual trading behavior for a panel of consumers and investors at a high frequency—along the lines of Giglio et al. (2021)—could allow one to identify an even richer model of cryptocurrency demand. For example, it might be possible to account for persistent heterogeneity in beliefs and preferences across individuals, as well as explore short-selling by pessimistic investors. Second, our model takes the number of cryptocurrencies in an investor's choice set as fixed. Given the increase in the number of cryptocurrencies over time (Cong et al. 2021), endogenizing the set of available cryptocurrencies through a model of entry could be a promising avenue for future research.

References

Adam, K., J. Beutel, and A. Marcet. 2017. Stock price booms and expected capital gains. *American Economic Review* 107(8):2352–408.

Allen, J., R. Clark, and J.-F. Houde. 2019. Search frictions and market power in negotiated-price markets. *Journal of Political Economy* 127(4):1550–98.

Aloosh, A., and J. Li. 2019. Direct evidence of bitcoin wash trading. Available at SSRN 3362153.

Athey, S., I. Parashkevov, V. Sarukkai, and J. Xia. 2016. Bitcoin pricing, adoption, and usage: Theory and evidence. Technical Report.

Bailey, M., E. Dávila, T. Kuchler, and J. Stroebel. 2019. House price beliefs and mortgage leverage choice. *Review of Economic Studies* 86(6):2403–52.

Barberis, N., R. Greenwood, L. Jin, and A. Shleifer. 2015. X-CAPM: An extrapolative capital asset pricing model. *Journal of Financial Economics* 115(1):1–24.

———. 2018. Extrapolation and bubbles. *Journal of Financial Economics* 129(2):203–27.

Barberis, N., A. Shleifer, and R. Vishny. 1998. A model of investor sentiment. *Journal of Financial Economics* 49(3):307–43.

Benetton, M. 2021. Leverage regulation and market structure: A structural model of the U.K. mortgage market. *Journal of Finance* 76(6):2997–3053.

Benetton, M., G. Compiani, and A. Morse. 2023. When cryptomining comes to town: High electricity-use spillovers to the local economy. Technical Report, National Bureau of Economic Research.

Bentov, I., A. Gabizon, and A. Mizrahi. 2016. Cryptocurrencies without proof of work. *International Conference on Financial Cryptography and Data Security*, pp. 142–57. Heidelberg: Springer.

Berry, S., J. Levinsohn, and A. Pakes. 1995. Automobile prices in market equilibrium. *Econometrica: Journal of the Econometric Society*, 841–90.

———. 2004. Differentiated products demand systems from a combination of micro and macro data: The new car market. *Journal of Political Economy* 112(1):68–105.

Biais, B., C. Bisiere, M. Bouvard, C. Casamatta, and A. J. Menkveld. 2023. Equilibrium bitcoin pricing. *Journal of Finance* 78(2):967–1014.

Böhme, R., N. Christin, B. Edelman, and T. Moore. 2015. Bitcoin: Economics, technology, and governance. *Journal of Economic Perspectives* 29(2):213–38.

Bonaparte, Y. 2021. On the portfolio choice of crypto asset class: Meet the gentlemen investors. Available at SSRN 3829275.

Brunnermeier, M., E. Farhi, R. S. Koijen, A. Krishnamurthy, S. C. Ludvigson, H. Lustig, S. Nagel, and M. Piazzesi. 2021. Perspectives on the future of asset pricing. *Review of Financial Studies* 34(4): 2126–60.

Brunnermeier, M., and S. Nagel. 2004. Hedge funds and the technology bubble. *Journal of Finance* 59(5):2013–40.

Buchak, G., G. Matvos, T. Piskorski, and A. Seru. 2018. The limits of shadow banks. Technical Report, National Bureau of Economic Research.

Budish, E. 2018. The economic limits of bitcoin and the blockchain. Technical Report, National Bureau of Economic Research.

Burnside, C., M. Eichenbaum, and S. Rebelo. 2016. Understanding booms and busts in housing markets. *Journal of Political Economy* 124(4):1088–147.

Campbell, J. Y., and R. J. Shiller. 1988. Stock prices, earnings, and expected dividends. *Journal of Finance* 43(3):661–76.

Chan, Q., W. Ding, C. Lin, and A. G. Rossi. 2020. An inside look into cryptocurrency exchanges. Available at SSRN 3759062.

Chea, E.-T., and J. Fry. 2015. Speculative bubbles in bitcoin markets? An empirical investigation into the fundamental value of bitcoin. *Economic Letters* 130:32–36.

Cheng, I.-H., S. Raina, and W. Xiong. 2014. Wall Street and the housing bubble. *American Economic Review* 104(9):2797–2829.

Chiu, J., and T. V. Koeppl. 2019. Blockchain-based settlement for asset trading. *Review of Financial Studies* 32(5):1716–53.

Cochrane, J. H. 2011. Presidential address: Discount rates. *Journal of Finance* 66(4):1047–108.

Coibion, O., Y. Gorodnichenko, and S. Kumar. 2018. How do firms form their expectations? New survey evidence. *American Economic Review* 108(9):2671–2713.

Coibion, O., Y. Gorodnichenko, and T. Ropele. 2019. Inflation expectations and firm decisions: New causal evidence. *Quarterly Journal of Economics* 135(1):165–219.

Cong, L. W., Z. He, and J. Li. 2021. Decentralized mining in centralized pools. *Review of Financial Studies* 34(3):1191–235.

Cong, L. W., Z. He, and K. Tang. 2022. Staking, token pricing, and crypto carry. Available at SSRN 4059460.

Cong, L. W., G. A. Karolyi, K. Tang, and W. Zhao. 2021. Value premium, network adoption, and factor pricing of crypto assets. *Network Adoption, and Factor Pricing of Crypto Assets (December).*

Cong, L. W., X. Li, K. Tang, and Y. Yang. 2023. Crypto wash trading. *Management Science* 69(11):6427–54.

Cong, L. W., Y. Li, and N. Wang. 2021. Tokenomics: Dynamic adoption and valuation. *Review of Financial Studies* 34(3):1105–55.

Cong, L. W., and Y. Xiao. 2021. Categories and functions of crypto-tokens. *The Palgrave Handbook of FinTech and Blockchain*, pp. 267–84. Cham: Springer.

Conlon, C. T., and J. H. Mortimer. 2013. Demand estimation under incomplete product availability. *American Economic Journal: Microeconomics* 5(4):1–30.

Corbet, S., B. Lucey, and L. Yarovaya. 2018. Datestamping the bitcoin and ethereum bubbles. *Finance Research Letters* 26:81–88.

Crawford, G. S., N. Pavanini, and F. Schivardi. 2018. Asymmetric information and imperfect competition in lending markets. *American Economic Review* 108(7):1659–1701.

Da, Z., X. Huang, and L. J. Jin. 2021. Extrapolative beliefs in the cross-section: What can we learn from the crowds? *Journal of Financial Economics* 140(1):175–96.

De La O, R., and S. Myers. 2021. Subjective cash flow and discount rate expectations. *Journal of Finance* 76(3):1339–87.

De Vries, A. 2018. Bitcoin's growing energy problem, *Joule* 2(5):801–5.

Egan, M., A. Hortaçsu, and G. Matvos. 2017. Deposit competition and financial fragility: Evidence from the U.S. banking sector. *American Economic Review* 107(1):169–216.

Egan, M., A. MacKay, and H. Yang. 2022. Recovering investor expectations from demand for index funds. *Review of Economic Studies* 89(5):2559–99.

Emmons, W. R., and L. R. Ricketts. 2017. Household wealth is at a post–World War II high: Should we celebrate or worry? Technical Report, Federal Reserve Bank of St. Louis.

Fan, Y. 2013. Ownership consolidation and product characteristics: A study of the US daily newspaper market. *American Economic Review* 103(5):1598–1628.

Fernández-Villaverde, J., and D. Sanches. 2019. Can currency competition work? *Journal of Monetary Economics* 106:1–15.

Foley, S., J. R. Karlsen, and T. J. Putniņš. 2019. Sex, drugs, and bitcoin: How much illegal activity is financed through cryptocurrencies? *Review of Financial Studies* 32(5):1798–1853.

Fostel, A., and J. Geanakoplos. 2012. Trancing, CDS, and asset prices: How financial innovation can cause bubbles and crashes. *American Economic Journal: Macroeconomics* 4(1):190–225.

Foster, A. D., and M. R. Rosenzweig. 2010. Microeconomics of technology adoption. *Annual Review of Economics* 2(1):395–424.

Füllbrunn, S., C. Huber, C. Eckel, and U. Weitzel. 2022. Heterogeneity of beliefs and trading behavior: A reexamination. *Journal of Financial and Quantitative Analysis* 1–25.

Gandal, N., J. Hamrick, T. Moore, and T. Oberman. 2018. Price manipulation in the bitcoin ecosystem. *Journal of Monetary Economics* 95:86–96.

Gennaioli, N., Y. Ma, and A. Shleifer. 2016. Expectations and investment. *NBER Macroeconomics Annual* 30(1):379–431.

Gennaioli, N., and A. Shleifer. 2020. *A crisis of beliefs: Investor psychology and financial fragility*. Princeton, NJ: Princeton University Press.

Giglio, S., M. Maggiori, J. Stroebel, and S. Utkus. 2021. Five facts about beliefs and portfolios. *American Economic Review* 111(5):1481–522.

Goldfeder, S., H. Kalodner, D. Reisman, and A. Narayanan. 2018. When the cookie meets the blockchain: Privacy risks of web payments via cryptocurrencies. *Proceedings on Privacy Enhancing Technologies* 2018(4):179–99.

Greenwood, R., and A. Shleifer. 2014. Expectations of returns and expected returns. *Review of Financial Studies* 27(3):714–46.

Grieco, P. L., C. Murry, and A. Yurukoglu. 2021. The evolution of market power in the US auto industry. Technical Report, National Bureau of Economic Research.

Griffin, J. M., and A. Shams. 2020. Is bitcoin really untethered? *Journal of Finance* 75(4):1913–64.

Han, B. Y., and I. Makarov. 2021. Feedback trading and bubbles. Available at SSRN 3796200.

Haruvy, E., Y. Lahav, and C. N. Noussair. 2007. Traders' expectations in asset markets: Experimental evidence. *American Economic Review* 97(5):1901–20.

Hasso, T., M. Pelster, and B. Breitmayer. 2019. Who trades cryptocurrencies, how do they trade it, and how do they perform? Evidence from brokerage accounts. *Journal of Behavioral and Experimental Finance* 23:64–74.

Hong, H., and D. Sraer. 2013. Quiet bubbles. *Journal of Financial Economics* 110(3):596–606.

Hong, H., and J. C. Stein. 2007. Disagreement and the stock market. *Journal of Economic Perspectives* 21(2):109–28.

Hu, A. S., C. A. Parlour, and U. Rajan. 2019. Cryptocurrencies: Stylized facts on a new investible instrument. *Financial Management* 48(4):1049–68.

Irresberger, F., K. John, and F. Saleh. 2020. The public blockchain ecosystem: An empirical analysis. Available at SSRN 3592849.

Jenik, I., and K. Lauer. 2017. Regulatory sandboxes and financial inclusion. Working Paper, Washington D.C.: CGAP.

Kaplan, G., K. Mitman, and G. L. Violante. 2020. The housing boom and bust: Model meets evidence. *Journal of Political Economy* 128(9):3285–345.

Koijen, R. S., R. J. Richmond, and M. Yogo. 2020. Which investors matter for equity valuations and expected returns? Technical Report, National Bureau of Economic Research.

Koijen, R. S., and M. Yogo. 2016. Shadow insurance. *Econometrica* 84(3):1265–87.

———. 2019. A demand system approach to asset pricing. *Journal of Political Economy* 127(4):1475–515.

Kuchler, T., and B. Zafar. 2019. Personal experiences and expectations about aggregate outcomes. *Journal of Finance* 74(5):2491–542.

Lammer, D., T. Hanspal, and A. Hackethal. 2019. Who are the bitcoin investors? Evidence from indirect cryptocurrency investments. Working Paper No. 277, SAFE.

Li, T., D. Shin, and B. Wang. 2020. Cryptocurrency pump-and-dump schemes. Available at SSRN 3267041.

Liu, Y., Tsyvinski, A., Wu, X. 2022. Common risk factors in cryptocurrency. *Journal of Finance* 77(2):1133–77.

Liu, H., C. Peng, W. Xiong, and W. A. Xiong. 2022. Taming the bias zoo. *Journal of Financial Economics* 143(2):716–41.

Liu, Y., and A. Tsyvinski. 2021. Risks and returns of cryptocurrency. *Review of Financial Studies* 34(6):2689–727.

Markarov, I., and A. Schoar. 2020. Trading and arbitrage in cryptocurrency markets. *Journal of Financial Economics* 135(2):293–319.

Malmendier, U., and S. Nagel. 2011. Depression babies; Do macroeconomic experiences affect risk taking? *Quarterly Journal of Economics* 126(1):373–416.

Nelson, S. 2018. Private information and price regulation in the United States credit card market. Working Paper.

Nevo, A. 2001. Measuring market power in the ready-to-eat cereal industry. *Econometrica* 69(2):307–42.

Ofek, E., and M. Richardson. 2003. Dotcom mania: The rise and fall of internet stock prices. *Journal of Finance* 58(3):1113–37.

Pagnotta, E., and A. Buraschi. 2018. An equilibrium valuation of bitcoin and decentralized network assets. Available at SSRN 3142022.

Piazzesi, M., and M. Schneider. 2009. Momentum traders in the housing market: Survey evidence and a search model. *American Economic Review* 99(2):406–11.

Pikkety, T., and G. Zucman. 2014. Capital is back: Wealth-income ratios in rich countries, 1700–2010. *Quarterly Journal of Economics* 129(3):1255–310.

Rauchs, M., A. Blandin, K. Klein, G. Pieters, M. Recanatini, and B. Zhang. 2018. 2nd global cryptoasset benchmarking study. Available at SSRN 3306125.

Robles-Garcia, C. 2019. Competition and incentives in mortgage markets: The role of brokers. Working Paper.

Saleh, F. 2021. Blockchain without waste: Proof-of-stake. *Review of Financial Studies* 34(3):1156–90.

Scheinkman, J. A., and W. Xiong. 2003. Overconfidence and speculative bubbles. *Journal of Political Economy* 111(6):1183–220.

Schilling, L., and H. Uhlig. 2019. Some simple bitcoin economics. *Journal of Monetary Economics* 106:16–26.

Shams, A. 2020. The structure of cryptocurrency returns. Working Paper, Charles A. Dice Center.

Sockin, M., and W. Xiong. 2018. A model of cryptocurrencies. Unpublished manuscript, Princeton University.

Temin, P., and H.-J. Voth. 2004. Riding the South Sea bubble. *American Economic Review* 94(5):1654–68.

Vissing-Jørgensen, A. 2003. Perspectives on behavioral finance: Does "irrationality" disappear with wealth? Evidence from expectations and actions. *NBER Macroeconomics Annual* 18:139–94.

Xiao, K. 2020. Monetary transmission through shadow banks. *Review of Financial Studies* 33(6):2379–420.

Xiong, W., and J. Yu. 2011. The Chinese warrants bubble. *American Economic Review* 101(6):2723–53.