Investors' Beliefs and Cryptocurrency Prices*

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Abstract

We explore the impact of investors' beliefs on cryptocurrency demand and prices using three new individual-level surveys. We find that younger individuals with lower income and education are more optimistic about the future value of cryptocurrencies, as are late investors. We then estimate the cryptocurrency demand functions using a structural model with rich heterogeneity in investors' beliefs and preferences. To identify the model, we combine observable beliefs with an instrumental variable strategy that exploits variation in the production of different cryptocurrencies. Counterfactual analyses show that: i) entry of late optimistic investors increased the price of cryptocurrencies on average by about 38% during the boom in January 2018; ii) growing concerns among investors about the sustainability of energy-intensive Proof-of-Work cryptocurrencies lead to portfolio reallocations toward non Proof-of-Work cryptocurrencies and alternative investment opportunities, with Bitcoin and Ethereum experiencing the largest losses.

JEL codes: D84, G11, G41.

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1 Introduction

Beliefs play an important role in explaining economic outcomes, such as firms' real investments (Gennaioli et al., 2016; Coibion et al., 2018, 2019), consumers' housing choices (Piazzesi and Schneider, 2009; Kaplan et al., 2017; Bailey et al., 2019), and investors' portfolio allocations (Vissing-Jørgensen, 2003; Greenwood and Shleifer, 2014; Giglio et al., 2019). Understanding to what extent beliefs affect allocations and prices is particularly relevant in the case of new financial assets, for which substantial variability in 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 for portfolio allocations and asset prices using the cryptocurrency industry as a laboratory. As new financial assets, cryptocurrencies have exhibited extreme volatility in recent times (Liu and Tsyvinski, 2018; Liu et al., 2019).[2] We focus on the period between the end of 2017 and the beginning of 2018, when the entry of late and perhaps overly optimistic investors, "fear of missing out," and contagious social dynamics may have contributed to a rampant increase in cryptocurrency prices. For example, the investing platform Robinhood started allowing retail investors to trade cryptocurrencies on their apps during our sample period.[3,4] 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

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

[2]Figure A1 in Appendix A shows the price of Bitcoin, which increased from about $2,000 to almost $20,000 in the space of six months between July and December 2017, only to drop below $5,000 in the following six months. Similarly, the volume of Bitcoin transactions spiked and then plummeted. The correlation between price and volume is 0.89. The correlation in the changes between price and volume is almost 0.7.

[3]See https://www.cnbc.com/2018/01/25/stock-trading-app-robinhood-to-roll-out-bitcoin-ethereum-trading.html.

[4]Similarly, (overly) optimistic beliefs about house prices played an important role in the housing boom of the early 2000s in the U.S. (Cheng et al., 2014; Burnside et al., 2016; Kaplan et al., 2017).

billion at the end of 2020. While the debate about the benefits and costs of cryptocurrencies is still open, is it undeniable that this asset class has become an integral part of both retail and institutional investors consideration set, and an important area for regulatory scrutiny and possible intervention.[5]

The key contribution of this paper is the estimation of a demand system for cryptocurrencies that allows for a *quantification* of the role of heterogeneous investors' entry and beliefs for equilibrium prices. To this end, we use three surveys that capture beliefs and choices for both consumers and investors. The first one is the Survey of Consumer Payment Choice (SCPC), collected by the Federal Reserve Banks of Atlanta and Boston, which provides data on beliefs about future prices and holdings of cryptocurrencies for a representative sample of U.S. consumers. The second dataset, the 2018 ING International Survey on Mobile Banking, complements the first one by covering Europe and Australia, in addition to the U.S. The third and main dataset is a survey run by a U.S. trading platform, which focuses on investors worldwide. Relative to the first two, this survey targets individuals with an interest in new investment opportunities. As such, they are more likely to be representative of the population of investors who play a role in determining the market equilibrium and we simply call them "investors" throughout the paper.[6]

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. We obtain three main stylized facts. First, we find that consumers that

[5] As an example of the prominent role that the cryptocurrency market has reached for the society at large, the IRS has added a cryptocurrency question to Form 1040 for 2020 (See: https://fortune.com/2020/09/28/the-irs-is-adding-a-cryptocurrency-question-to-form-1040-for-2020/).

[6] 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 cryptocurrencies investors is very limited. However, anecdotal evidence during the period we analyze point to an important role of new retail investors which are well represented in our survey (See for example https://www.nytimes.com/2017/11/27/technology/bitcoin-price-10000.html and https://qz.com/1949850/why-investors-say-bitcoins-2020-surge-is-not-like-2017s/). An important role for investor sentiment in explaining price fluctuations and returns is also supported by both theoretical work (Sockin and Xiong, 2018; Cong et al., 2020), and empirical work based on aggregate data (Liu and Tsyvinski, 2018; Liu et al., 2019). Hence our results could be informative about the behavior of some of the marginal retail investors who were behind the large price movements during the sample period. Our survey asks investors when they bought their first cryptocurrency allowing us to identify early adopter and late entrants. We discuss in details our data in Section 2.

are younger and have lower income and assets are more likely to be more optimistic about future cryptocurrency prices. Lower levels of education and having a part-time job are also associated with more optimistic beliefs. In addition, we find that those who bought later among the trading company respondents tend to be substantially more optimistic. This is consistent with the fact that cryptocurrency prices—and the buzz associated with it—spiked in the months leading up to the survey.

Second, we document large dispersion in beliefs across both consumers and investors that is not explained by observable demographics, consistent with previous evidence from more traditional assets (Malmendier and Nagel, 2011; Kuchler and Zafar, 2019; Giglio et al., 2019). The (pseudo) R^2 using different measures of beliefs as dependent variable is never above 0.05 for consumers and 0.25 for investors. Third, we find that, for both consumers and investors, positive beliefs have a positive effect on the probability of holding cryptocurrencies, controlling for demographics and other determinants of demand (e.g., usage as a payment tool). Most notably, short-term investors' optimism about the future value of cryptocurrencies is associated with: i) a higher probability of holding crytocurrencies, and ii) investors holding more distinct crytocurrencies in larger amounts, conditional on holding.

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 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.[7] A standard market clearing condition closes the model. Under the assumption of downward-sloping demand—which we fail to reject empirically—

[7]Foley et al. (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.

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 et al., 1995). We leverage on our beliefs data to address this endogeneity concern. 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, currency-specific factors that affect a given investor's demand. This is in contrast to the more common setting in which data on beliefs are not available and thus investor beliefs are subsumed by the error term in the demand equation, thus exacerbating endogeneity concerns.[8]

Additionally, 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 exogenous production process of proof-of-work cryptocurrencies (sometimes referred to as "mining").[9] Proof-of-work cryptocurrencies (including Bitcoin, Ethereum 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

[8]Beliefs themselves can be endogenous and correlated with unobservable shocks affecting demand. Our identification strategy controls for several household demographics and cryptocurrency characteristics, however residual variation in unobservable demand that is correlated with variation in beliefs may still affect our estimates. Giglio et al. (2019) document large and *persistent* heterogeneity in beliefs, which supports our choice to abstract away from endogeneity of non-price characteristics which tend to vary at a frequency lower than prices. Incorporating a more structural model of beliefs formation in an asset demand system or accounting for beliefs endogeneity with a richer set of instruments could be interesting avenues for future research, as also emphasized by Brunnermeier et al. (2021).

[9]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.

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.[10]

Our estimates of the characteristics-based demand system illustrate two important advantages of including data on beliefs in structural demand models. First, we find that including beliefs in the demand system is important for correcting the upward bias in the estimates of the price coefficient. In this sense, data on beliefs are complementary to standard instrumental variable strategies in addressing endogeneity concerns when estimating demand. Second, data on beliefs capture important factors such as sentiment and disagreement across investors, which would otherwise be subsumed by the error terms. In this sense, including data on beliefs in the demand system has the potential to improve the fit of the model.[11]

With the estimated model in hand, we perform several counterfactual analyses to study how changes in investors' beliefs impact 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.[12] In one exercise, we remove all investors who bought their first cryptocurrency in 2018 (the last year in our data), and replace them 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 entry of late investors, by

[10]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) (Liu et al., 2019; Irresberger et al., 2020; Shams, 2020). While Bitcoin have maintained the lion share of the market, during the last 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/).

[11]Koijen and Yogo (2019) find that unobservable shocks ("latent demand") explain a large fraction of the variance of stock returns and interpret it as reflecting sentiment and disagreement among investors.

[12]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." For a recent debate on the application of regulatory sandbox in the cryptocurrency industry see: https://blog.liquid.com/what-is-a-regulatory-sandbox-and-how-does-it-apply-to-crypto.

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 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 cryptocurrencies by about 38%, of which 15% is due to changes in investors' beliefs.

Finally, we perform a counterfactual simulation 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 whoever solves a complex mathematical problem first. Several recent papers emphasize how this leads to a huge computational burden and thus substantial energy costs, which suggests that the PoW protocol might not be sustainable in the long run (De Vries, 2018; Budish, 2018; Benetton et al., 2019; Chiu and Koeppl, 2019; Saleh, 2019). Therefore, our counterfactual simulation can be viewed as a way to assess how prices and allocations would respond if investors became more aware of the inherent limitations of PoW currencies.[13] We find that, on average, equilibrium cryptocurrency prices decrease by around 12%, with Bitcoin and Ethereum experiencing the largest absolute and relative decline. On the other hand, the price of Ripple—a non-PoW currency—increases by around 6%.

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; Sockin

[13]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 `https://www.vox.com/recode/2021/5/18/22441831/elon-musk-bitcoin-dogecoin-crypto-prices-tesla` and `https://www.coindesk.com/elon-musk-says-tesla-is-suspending-bitcoin-payments-over-environmental-concerns`).

and Xiong, 2018; Biais et al., 2018; Schilling and Uhlig, 2019; Fernández-Villaverde and Sanches, 2019). On the empirical side, recent works have explored the characteristics of cryptocurrency investors (Hasso et al., 2019; Lammer et al., 2019) and the dynamics of cryptocurrency prices (Cheah and Fry, 2015; Corbet et al., 2018; Gandal et al., 2018; Liu and Tsyvinski, 2018; Liu et al., 2019; Griffin and Shams, 2019; Hu et al., 2019; Makarov and Schoar, 2019).

We contribute to this growing literature in two main ways. First, we analyze new detailed *investor-level* data on cryptocurrency holdings and beliefs for representative samples of US and worldwide consumers as well as for a large selected sample of cryptocurrency investors. Second, we estimate a tractable structural model of cryptocurrency demand, which we then use to shed light on the importance of including beliefs in the demand system and to perform counterfactual analyses. Thus, our work is related to the growing literature applying structural tools from empirical industrial organization to study financial markets, like deposits (Egan et al., 2017; Xiao, 2019), corporate loans (Crawford et al., 2018), mortgages (Allen et al., 2019; Benetton, 2018; 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 et al. (2020) and Egan et al. (2020). 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 et al. (2020) 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 make two main contributions. We include the survey measures of investors' beliefs in the demand system and show that: 1) the resulting price elasticities are consistent with beliefs partially addressing the issue of price endogeneity; and 2) the role of unobservables in explaining the cross-sectional variance of (log) returns is significantly reduced.

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' sentiment and beliefs for bubbles (see, e.g., Brunnermeier and Nagel (2004), Xiong and Yu (2011), Hong and Sraer (2013) and Cheng et al. (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 (Giglio et al., 2019).

Overview. The remainder of the paper is organized as follows. Section 2 describes the data sources and Section 3 provides reduced-form evidence on expectations and cryptocurrency demand. Section 4 describes the structural model. Section 5 details the estimation approach and presents the results. Section 6 shows the counterfactual simulations and Section 7 concludes.

2 Data

2.1 Sources

Our analysis combines several data sources. First, we collect publicly available data on cryptocurrencies from https://coinmarketcap.com and 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 (2018), Griffin and Shams (2019) and Hu et al. (2019), among others.

Next, we leverage three surveys about consumers' and investors' beliefs and holdings.[14] 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. In particular, they include questions about adoption and usage of nine payment instruments and about respondents' preferences for characteristics like security, cost, and convenience. 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.[15] Thus, in this paper 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 in this paper was conducted by Ipsos—a multinational market research and consulting firm—between March 26th and April 6th 2018. The total sample comprises almost 15,000 respondents across Europe, the U.S. and Australia. About 1,000 individuals were surveyed in each country and the sampling procedure reflects the gender and age distributions within each country.

Third, we obtained proprietary data from a trading platform about investors' holdings of cryptocurrencies as well as their expectations about these assets. The data comes from the Cryptocurrency and Blockchain Consumer and Investor Surveys that the platform runs twice times a year to understand the change in investors' views about cryptocurrencies and Blockchain and digital currencies. 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 these surveys conducted in January-February 2018 and July-August 2018, respectively.[16] The first survey contains about 2,500 responses, while

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

[15] 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).

[16] The trading platform has since the survey we employ in this analysis being acquired and unfortunately

the second survey contains about 3,000 responses. While the platform's clientele is spread across the world, the majority comes from North America (65%), followed by Asia (24%), and South America and Europe (5%). The data does not link the identity of respondents across the survey waves, so we treat the two datasets as repeated cross-sections.

2.2 Summary statistics

Table 1 shows the main variables from the two surveys on consumers. Panel A of Table 1 shows the main variables we use from the SCPC in the years 2015 to 2018. The average age is 50 years old, but some respondents are as young as 18 years old. The average annual gross income is approximately \$75,000, ranging from \$2,500 to \$750,000. About 43% of respondents are male and 47% have an education level below the Bachelor. About 50% of respondents say that they have heard of cryptocurrencies, but only about 1% of the respondent that are aware of cryptocurrencies report owning them. The survey also asks how familiar people are with cryptocurrencies on a scale from one (not at all familiar) to five (extremely familiar). There is quite a lot of variation in the data, with an average of about 1.6 (close to "slightly familiar"). Of the approximately 100 respondents who ever owned cryptocurrencies only about 10% report to have used them as a means of payment. Finally, the majority of respondents think the price will not vary much. On average, respondents seem to expect a decrease in prices rather than an increase, but there is substantial heterogeneity across households.

Panel B of Table 1 shows the summary statistics from the ING survey. The average age is 45 years old and the average net monthly income is €2,400. About half of the respondents are male, approximately 65% have an education level below a bachelor's degree, and 23% are unemployed, self-employed or in a part-time job. On average about 65% of respondents are aware of cryptocurrencies. Almost 9% owned them in 2018 and about 20% expect to own them in the future. With respect to beliefs, about one third of respondents expect cryptocurrencies to increase in value over the next year, while 27% expect them to decrease

it has discontinued the survey.

Table 1: Summary statistics: Consumers' Surveys

Panel A: U.S. consumers (SCPC)

	Observations	Mean	Std. Dev.	Minimum	Median	Maximum
Demographics:						
Age	11,084	50.57	15.12	18.00	51.00	100.00
Income (dollars)	10,970	72,878.87	70,776.87	2,500.00	55,000.00	750,000.00
Male	11,085	0.43	0.50	0.00	0.00	1.00
Education (Below Bachelor)	11,085	0.47	0.50	0.00	0.00	1.00
Asset ≤20K	10,844	0.51	0.50	0.00	1.00	1.00
Cryptocurrency questions (general):						
Awareness	11,030	0.53	0.50	0.00	1.00	1.00
Holding	5,841	0.01	0.11	0.00	0.00	1.00
Familiarity	5,843	1.59	0.86	1.00	1.00	5.00
Usage for transaction	113	0.12	0.33	0.00	0.00	1.00
Cryptocurrency questions (beliefs):						
Increase	5,797	0.25	0.43	0.00	0.00	1.00
Decrease	5,797	0.26	0.44	0.00	0.00	1.00

Panel B: Worldwide consumers (ING)

	Observations	Mean	Std. Dev.	Minimum	Median	Maximum
Demographics:						
Age	14,828	45.08	15.59	18.00	45.00	99.00
Income (euros)	13,245	2,368.99	1,905.37	0.00	1,750.00	9,000.00
Male	14,828	0.49	0.50	0.00	0.00	1.00
Education (Below Bachelor)	14,828	0.64	0.48	0.00	1.00	1.00
Non-standard employment	14,828	0.23	0.42	0.00	0.00	1.00
Cryptocurrency questions (general):						
Awareness	14,828	0.65	0.48	0.00	1.00	1.00
Holding	14,828	0.09	0.28	0.00	0.00	1.00
Holding (expected)	14,828	0.22	0.42	0.00	0.00	1.00
Cryptocurrency questions (beliefs):						
Increase	9,949	0.31	0.46	0.00	0.00	1.00
Decrease	9,949	0.27	0.44	0.00	0.00	1.00

Note: Summary statistics for the main variables used in the analysis. Panel A shows the main variables from the Survey of Consumer Payment Choice (SCPC) in the years 2015 to 2018. "Aware of cryptocurrencies" is the fraction of respondents who say they have heard of cryptocurrencies relative to the full sample. "Own cryptocurrencies" is the fraction owning cryptocurrencies among the respondents who say they have heard of them. "How familiar" is an index going from 1 (not at all familiar) to 5 (extremely familiar). "Used cryptocurrencies in transaction" is a dummy equal to one if the respondent used cryptocurrencies in a transaction. Week, month and year increase (decrease) are dummies equal to one if the individual expects the price of Bitcoin to increase (decrease) in the next week, month and year. Panel B shows the main variables from the ING International Survey. "Employment" is a dummy equal to one if the individual is self-employed, part-time or unemployed. "Aware of cryptocurrencies" is the fraction of respondents who say they have heard of cryptocurrencies relative to the full sample. "Own cryptocurrencies" is the fraction owning cryptocurrencies relative to the full sample.

in value.

Table 2 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 lower or equal to $100 thousands. About 65% of respondents are based in the North America and about 10% are individual accredited investors. Almost all respondents have heard of cryptocurrencies and about 55% hold at least one. Interestingly, 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 with all the main cryptocurrencies that we consider.[17] The average investor in cryptocurrency has on average about $40 thousands in cryptocurrencies, and there is a wide range going from $500 to more than $1 million.[18] About 40% of investors in cryptocurrencies bought their first in 2018, during - after the large price increase in December 2017 and January 2018.

Turning to the questions on expectations, more than 60% of respondents believe the price of cryptocurrencies is going to increase over the course of the 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 specific cryptocurrency has long-term potential.

Finally, in Table A1 of Appendix A we compare our different surveys on a few variables that are common across them. For comparability, we focus on respondents from North America in 2018. Overall, the sample surveyed by the trading company is tilted toward younger respondents that are much more likely to invest in cryptocurrencies and tend to be

[17] Following the question in the survey we consider separately: Bitcoin, Ethereum, Litecoin, Ripple, Zcash, Dash, Monero and Bitcoin Cash. We group Swiftcoin and Bytecoin with other minor cryptocurrencies that investors seldom mention in the open field of the question: "Other (please specify)".

[18] We compute the amount invested taking the middle point of the following categories for the amount invested in cryptocurrencies: $< \$1,000$, $\$1,000 - \$10,000$, $\$10,000 - \$100,000$, $\$100,000 - \$1,000,000$, $> \$1,000,000$. For the last category we take the lower bound. Unfortunately the survey does not ask to investors how much they invest in each specific cryptocurrency they invest to. 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 2: 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

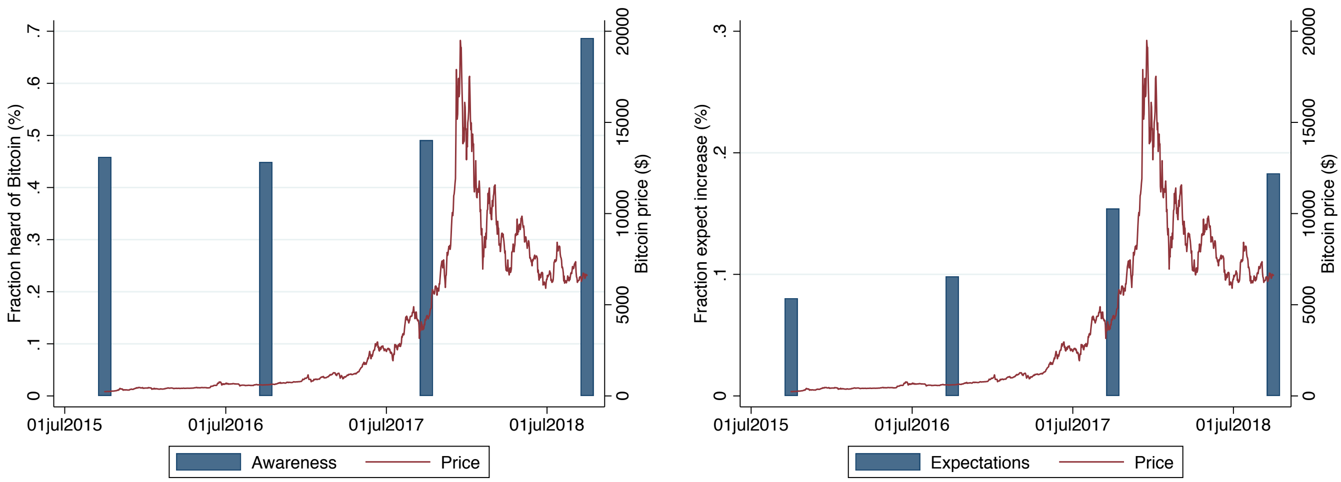
Note: Summary statistics for the main variables we use from the trading company survey. Demographics are age and income, "outside US" is a dummy for investors outside the U.S., "investor" is a dummy for accredited investors of the trading company. We observe a categorical variables for both age (< 18, $18-30$, $30-45$, $45-60$,> 60) and income ($< \$100K$, $\$100K-\$150K$,$\$150K-\$200K$, $\$200K-\$300K$,$> \$300K$). We define the continuous version taking the midpoint in each category, and 70 years and \$300K for the highest category of age and income, respectively. "Aware of crypto" is a dummy equal to one if the investor is aware of cryptocurrencies; "invest in at least one crypto" is a dummy equal to one if the investor holds at least one cryptocurrency; "number of cryptocurrencies" is the sum of cryptocurrencies an investor hold; "early (late) buyer" is a dummy equal to one is the investor purchased her first cryptocurrency before (after) 2017. "Price increase (decrease)" is a dummy equal to one is 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; "currency potential" is a dummy equal to one if the investor thinks a specific cryptocurrency has the potential to be successful.

somewhat more optimistic about the future of the asset class.

3 Reduced-form Evidence on Beliefs and Demand

3.1 Consumers Survey

In this section we describe our beliefs data in more detail and present some evidence on both the drivers of beliefs and the impact of beliefs on demand for cryptocurrencies. We begin by describing two aggregate patterns in the cryptocurrency industry in the last five years using our survey of US consumers. First, Panel (a) of Figure 1 shows that the fraction of US consumers who are aware of Bitcoin has increased over time, going from 45% in 2015



(a) Awareness and price

(b) Beliefs and price

Figure 1: Crypto Mania: Awareness and beliefs

Note: The figure shows the daily price Bitcoin in 2015-2018. Data on the price of Bitcoin comes from Coinmarketcap. 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 they have heard of Bitcoin, that think the price of Bitcoin is going to increase in the next year ("beliefs"). The awareness and beliefs measures come from the Survey of Consumer Payment Choice (SCPC). We use the waves 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.

to almost 70% by the end of 2018. The increase has mainly taken place between 2017 and 2018, when the price of Bitcoin spiked and the industry received widespread press coverage.

Second, Panel (b) of Figure 1 shows the dynamics over time of consumers' beliefs about the future price of Bitcoin. We plot the fraction of consumers expecting the price of Bitcoin to increase in the next year. This fraction increases from around 17% in Fall 2015 to approximately 27% in Fall 2017 to then decline slightly in 2018 following the rapid drop in the price of Bitcoin.

We now explore what factors drive differences in beliefs across individuals in our data. We estimate the following ordered logit model:

$$B_{ict} = OrdLogit\left(\beta D_i + \gamma_t + \gamma_c + \epsilon_{ict}\right), \tag{1}$$

where B_{ict} are the beliefs of individual i living in country c in period t; D_i are demographics characteristics of individual i; γ_t and γ_c are time and country fixed effects; and ϵ_{ict} captures unobservable determinants of beliefs.

Table 3 shows the results for our two consumer surveys. Columns (1) show the results from the survey of US consumer payments. The dependent variables is the consumers' response to a question about the future price of Bitcoin.[19] We find that consumers with lower income and assets tend to be more optimistic about the future value of Bitcoin, as do younger consumers. The result are significant and large in magnitude. All else equal, younger and lower income consumers are 18% and 34% more likely to expect an increase in the price of Bitcoin than the combined alternatives of no change or price decrease. Lower education levels are also associated with more optimistic beliefs, but the results are noisy. Finally, and perhaps surprisingly, we find that men tend to be less optimistic than women.

Column (4) of Table 3 shows the results from the 2018 ING worldwide survey. The dependent variable is the consumers' response to a question about the value of cryptocurrencies in the next 12 months.[20] As with the survey of US consumer payments, we find that the most important predictor of beliefs is age. Younger people are significantly more optimistic about the future value of cryptocurrencies. In addition, consumers without a bachelor's degree are significantly more optimistic about the future value of cryptocurrencies, and we find again that men tend to be less optimistic. Interestingly, respondents who are unemployed, self-employed or in a part-time job tend to have more positive beliefs.

We now present descriptive evidence on the role of beliefs in driving cryptocurrency demand.

$$y_{ict} = \alpha B_{ict} + \beta D_i + \gamma_t + \gamma_c + \epsilon_{ict}, \tag{2}$$

where y_{ict} denotes investor i's demand outcome in country c at time t; B_{ict} represents her beliefs; D_i are individual demographics; and γ_t and γ_c are time and country fixed effects,

[19] The variable can take five values: 1 (decrease a lot), 2 (decrease some), 3 (stay about the same), 4 (increase some), and 5 (increase a lot).

[20] The variable can take five values: 1 (decrease a lot), 2 (decrease some), 3 (stay about the same), 4 (increase some), and 5 (increase a lot).

Table 3: Beliefs and Holdings: Consumer Surveys

	SCPC			ING	
	(1) Beliefs	(2) Demand	(3) Demand	(4) Beliefs	(5) Demand
Beliefs:					
Increase		0.022***	0.007*		0.197***
		(0.004)	(0.004)		(0.008)
Decrease		0.002	0.003		-0.031***
		(0.004)	(0.004)		(0.008)
Increase × High familiarity			0.060***		
			(0.018)		
Decrease × High familiarity			-0.058***		
			(0.019)		
Demographics:					
Low income	0.139**	-0.005	-0.002	0.021	-0.030***
	(0.060)	(0.003)	(0.003)	(0.048)	(0.008)
Age ≤ 45	0.263**	0.014***	0.006	0.604***	0.020***
	(0.109)	(0.005)	(0.005)	(0.049)	(0.008)
Male	-0.156***	0.005*	0.001	-0.096**	0.054***
	(0.051)	(0.003)	(0.003)	(0.038)	(0.006)
Education (Below bachelor)	0.011	-0.002	-0.001	0.026	-0.028***
	(0.053)	(0.003)	(0.003)	(0.041)	(0.007)
Asset ≤ 20K	0.239***	0.000	0.000		
	(0.053)	(0.003)	(0.003)		
Non-standard employment				0.125***	0.005
				(0.046)	(0.008)
Year f.e.	Yes	Yes	Yes	No	No
Country f.e.	No	No	No	Yes	Yes
Mean Y	-0.01	0.01	0.01	0.04	0.13
SD Y	0.71	0.11	0.11	0.76	0.33
Pseudo R2	0.01			0.03	
Adjusted R2		0.01	0.07		0.11
Observations	5,706	5,706	5,706	9,949	9,949

Note: Estimates of coefficients from model (1). Columns (1) to (3) shows the results from the U.S. Survey of Consumer Payment Choice. The dependent variable is the consumers' response to a question about the future value of Bitcoin at different horizons. The horizons are next week, next month and next year. The variable can take five values: 1 (decrease a lot), 2 (decrease some), 3 (stay about the same), 4 (increase some), and 5 (increase a lot). In column (4), the dependent variables is the consumers' response to a question about the future value of digital currencies in the next 12 months.

respectively. We are especially interested in the coefficient α, which captures the impact of beliefs on investor demand, conditional on demographics.

Columns (2) and (3) of Table 3 shows the results for the SCPC. US consumers that expect an increase in the price of Bitcoin are more likely to own Bitcoin. The effects are statistically significant and large in magnitude. Positive expectations on future prices are associated with a 2 percentage point higher probability to own Bitcoin. Given a low unconditional probability of holding Bitcoin ($\approx 1\%$), optimistic beliefs lead to a twofold increase in holdings. However, the effects are smaller relative to the standard deviation. We find that moving from neutral to optimist increases the holdings by about 0.19 standard deviations. Additionally, in column (3) we study the heterogeneity in the effect of beliefs on holdings based on the level of familiarity with cryptocurrencies. We find that the consumers with a higher familiarity are significantly more likely to act based on their beliefs, consistent with previous work suggesting that individuals who are more confident in their own beliefs are more likely to trade on them (Odean, 1999; Barber and Odean, 2001; Giglio et al., 2019).

Finally, columns (5) of Table 3 reports the estimates of equation (2) for the ING survey. Consumers expecting a price increase are 19 percentage point more likely to own Bitcoin, while consumers expecting a decrease are about 3 percent points less likely to own Bitcoin. Given an unconditional probability of 13%, the effect of positive (negative) beliefs is approximately an increase (decrease) by 150% (-25%) in the probability of owning Bitcoin.

While our interest is in the effect of expectations on Bitcoin demand, the coefficients on a few covariates are also interesting. Younger male consumers are significantly more likely to own cryptocurrencies in both surveys. Despite having more optimistic beliefs on average, lower income and education consumer are less likely to own cryptocurrencies once we control for beliefs.

3.2 Investors Survey

In this section we study both the drivers of beliefs and the impact of beliefs on demand for cryptocurrencies on our main survey of investors from the trading platform. We begin by looking at the time series of investors' first investment in cryptocurrencies. Figure 2 shows the breakdown of investors who bought a cryptocurrency by years of first purchase. While Bitcoin has been available since 2009, only about 30% of investors who bought a cryptocurrency

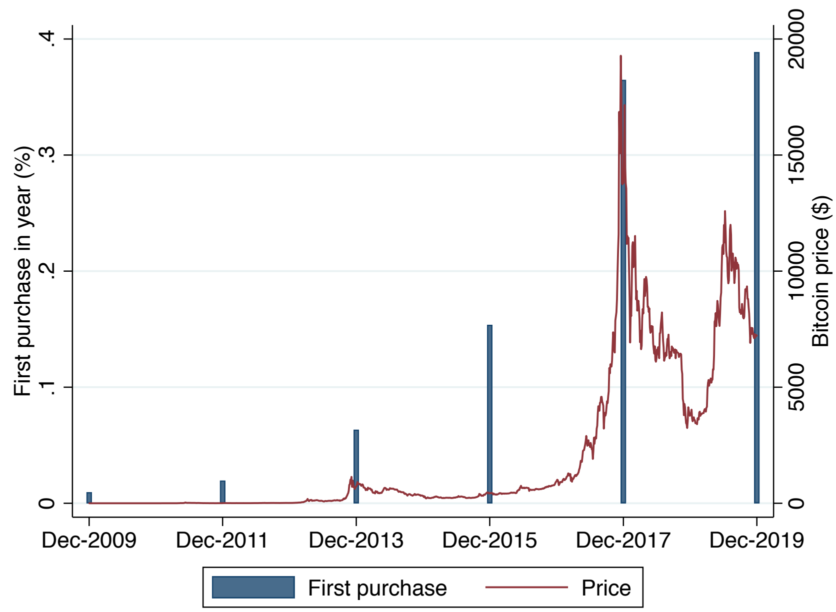


Figure 2: First Purchase

Note: The figure shows the daily price of Bitcoin in 2010-2018. Data on the price of Bitcoin comes from Coinmarketcap. Each vertical bar shows the fraction of investors who purchased their first cryptocurrency in the two years before the vertical bar.

did so before 2017. The majority of investors bought their first cryptocurrency from 2016 onward, with almost 40% them investing in the crypto market for the first time only in 2018. Taken together, Figures 1 and 2 show 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.

Table 4 shows the results on the determinants of investors' beliefs. Column (1) shows the estimates of equation (1) with the consumers' response to a question about the trend in value of cryptocurrencies in 2018, which we view as a measure of short-term beliefs, as dependent variable. We confirm our previous result that younger consumers 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.

[21]While we focus on Bitcoin prices in the plots, all other major cryptocurrencies followed a very similar trend in prices (see Figure A2 in Appendix A).

Table 4: Drivers of Beliefs: Investor survey

	Short-term Beliefs	Long-term Beliefs	High Potential	
	(1)	(2)	(3)	(4)
Demographics:				
Income ≤ \$100K	0.007	-0.206***	0.036*	0.035*
	(0.043)	(0.074)	(0.020)	(0.020)
Age ≤ 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 × 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 × 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 R2	0.03	0.08	0.25	0.25
Observations	4,647	4,647	41,823	41,823

Note: Estimates of coefficients from model (1) in columns (1) to (2), and model (3) in columns (3) and (4).“Short-term beliefs” is the investors’ response to a question about the value of cryptocurrencies over the course of 2018. “Long-term beliefs” is a dummy equal to one if investors think that cryptocurrencies will become mainstream. “Currency potential” is a dummy equal to one if the investor thinks a specific cryptocurrency has the potential to be successful.

In column (2), we estimate a logit specification using now 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. Interesting, lower income investors tend to be less optimistic about the long-term prospect of cryptocurrencies. Similarly to the result in column (1) for short-term beliefs, investors who invested in cryptocurrencies tend be more optimistic. 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:

$$B_{ijct} = Probit\left(\beta D_i + \alpha D_i \times X_j + \gamma_t + \gamma_c + \gamma_j + \epsilon_{ijct}\right), \tag{3}$$

where B_{ijct} is a dummy equal to one for each currency j that is mentioned by investor i in survey wave t in country c; D_i are demographics characteristics of individual i; X_j are characteristics of cryptocurrency j; γ_t, γ_c and γ_j are time, country and cryptocurrency fixed effects, respectively. First, we confirm that being young and having invested in cryptocurrencies is associated with more optimistic beliefs.

Second, we exploit the fact that B_{ijct} 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 is not able to capture. The pseudo-R^2 in Table 3 is always below 0.05. In Table 4, the pseudo-R^2 does not increase above 0.25 even with the inclusion of the cryptocurrency fixed effects. This result is in line with recent work by Giglio et al. (2019), and suggests that including demographic variables in the cryptocurrency demand system is not sufficient to control for differences in beliefs across investors.[22] Motivated by this observation, we include both beliefs and demographics as explanatory variables in the structural model of Section 4.

[22]Using detailed data on investors from a survey administered by Vanguard, Giglio et al. (2019) show that beliefs are characterized by large and persistent individual heterogeneity, and that demographic characteristics explain only a small part of why some individuals are optimistic and some are pessimistic (Fact 3 in their paper).

Next, we perform a series of reduced-form regressions to motivate the structural approach in the next section. Similarly to the analysis of consumers, we estimate equation (2). However, given the richness of the investor survey we now present the results for several outcome variables: (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 investors wealth invested in cryptocurrencies.[23] Table 5 shows the results.

First, we look at the "extensive" margin in columns (1) to (2). Column (1) shows the effect of expecting the price of cryptocurrencies to increase or decrease over the rest of the year, controlling for demographics and additional covariates. We find that investors that 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 that expect prices to increase in the following year have a 10 percentage-points higher probability to own Bitcoin, while individuals that expect prices to decrease have about a 4 percentage-points lower probability of owning Bitcoin. Given an unconditional probability of about 45%, these effects translate into an approximately 24% and 9% increase and decrease, respectively. These results echo our analysis of the drivers of beliefs in Table 4. 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. A negative opinion about the long-term success of cryptocurrencies is associated with a lower probability of holding Bitcoin. Individuals thinking that cryptocurrencies will never become mainstream are about 8 percentage points less likely to hold Bitcoin. We find that the belief that Bitcoin will be successful is associated with an almost 20 percentage-points increase in the probability of holding Bitcoin, which correspond to more than a 40% increase relative to the mean.

Are the effect of beliefs on cryptocurrency holdings reasonable? To answer this question, in column (2) of 5 we compute the fraction of investors' wealth that is invested in

[23] In our data we do not observe investor's wealth, but only their income bracket. Therefore we use the estimate in Emmons and Ricketts (2017) to impute wealth by multiplying income by 6.6.

Table 5: 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 R2	0.12	0.09	0.21	0.12	0.09
Observations	4,647	4,647	2,580	2,580	2,580

Note: Estimates of coefficients from model (2). Columns (1) to (4) report the results from the full sample. Macroeconomic controls are the logarithm of the S&P 500 and the 3-Month London Interbank Offered Rate (LIBOR).

cryptocurrencies. We find that moving from neutral to optimist about the future value of cryptocurrencies increase the crypto share by about 0.8, which corresponds to about 35% relative to the mean equity share and 0.10 standard deviations. While our results is not directly comparable to Giglio et al. (2019) as we do not have a continuous measure of expectations the magnitude of the effect relative to the standard deviation has a similar order of magnitude.[24] Additionally, a large effect of short-term optimistic beliefs on holding in a volatile market such as the cryptocurrencies is consistent with gambling preferences as a potential motive behind (excessive) trading, as documented by Liu et al. (2021) for Chinese retail investors.

Second, we explore the "intensive margin" in columns columns (3) to (5) of Table 5. The dependent variable in columns (3) is the number of cryptocurrencies in an investor's portfolio. 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 price to increase in the following year have a 13% higher number of cryptocurrencies relative to the mean, while investors that expect price to decrease are not statistically different from investors who expect the price to stay the same. Column (3) also shows that a larger number of cryptocurrencies with high potential is associated with an increase in the number of cryptocurrencies held by about 24% relative to the mean, while thinking that cryptocurrencies will never become mainstream has no effect on the number of cryptocurrencies in the portfolio.

In column (4) we shows the results using the total amount invested in cryptocurrencies as dependent variable. Conditional on having at least one cryptocurrency, investors hold on average \$40 thousands in cryptocurrencies, with a lot of variation across investors as we already documented in Table 2. Optimistic investors who expect price to increase in the following year have about \$18 thousands more invested in cryptocurrencies, which is approximately 45% more than investors with less optimistic beliefs relative to mean amount invested. Negative short-term beliefs, 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 use again the share invested in crypto as dependent variable, but now focusing on investors with positive holdings. We find that moving from neutral to optimist about the future value of cryptocurrencies increase the crypto share by about 1.4 among investors who hold cryptocurrencies, which corresponds to an increase by about 35%

[24] Giglio et al. (2019) find that a one-standard-deviation increase in expected 1-year stock returns is associated with a 0.16 standard deviation increase in equity shares.

relative to the mean. The effect of moving from neutral to optimist account for about 0.14 of the standard deviation in the crypto share.

While our interest is in the effect of beliefs on Bitcoin demand, the coefficients on investor demographics are also interesting. We find that investors with lower income have a significantly lower demand for cryptocurrencies, while younger investors have a significantly higher demand. Because cryptocurrencies are a relatively new investment products, 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).[25] Further, investors outside the U.S. 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 appetite for cryptocurrencies given the relative instability of their national currencies due to political turmoil.[26]

Overall, our analysis of consumers' and investors' beliefs and demand yields three main stylized facts: 1) unsophisticated 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)

[25]Our result that younger individual are more likely to old 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 (https://www.coindesk.com/new-coindesk-report-reveals-who-really-uses-bitcoin).

[26]Regarding China, see Rauchs et al. (2018) and Benetton et al. (2019), 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 https://hackernoon.com/love-in-the-time-of-bitcoin-latin-america-and-cryptocurrency-42d60cc4c177). Finally, the recent ING survey on European, US and Australian customers that we use in this paper finds that about 9, 8 and 7 percent of them currently own cryptocurrencies, respectively (see https://think.ing.com/reports/cracking-the-code-on-cryptocurrency/).

a higher probability of holding cryptocurrencies, and ii) a larger number of cryptocurrencies and amount invested, conditional on holding. These facts motivate our structural model and counterfactual exercises in which we assess how changes in beliefs affect investor holdings and thus equilibrium prices.

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 of new optimistic investors on equilibrium prices. Our model is closely related to the general framework for estimating asset demand proposed by Koijen and Yogo (2019).

4.1 Supply

There are J_t cryptocurrencies in circulation in period t indexed by $j = 1, ..., J_t$. 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 endowment economy with a fixed supply of cryptocurrencies. Thus, we abstract from two real-world complexities of the cryptocurrency industry: first, the endogenous production of existing cryptocurrency (e.g., mining of Bitcoin) and, second, the introduction of new cryptocurrencies.[27]

Regarding the first point, most cryptocurrencies follow a predetermined production process. For example, Figure A3 in Appendix A shows that while the price of Bitcoin displays high volatility, the number of Bitcoins in circulation grows based on a predetermined generation algorithm. Thus, we argue that the endogenous increase in supply of existing

[27]Production of cryptocurrencies has been studied in previous work (see Cong et al. (2019) and Schilling and Uhlig (2019) among others).

cryptocurrencies is not first-order for the study of short-term price dynamics—which is the object of our analysis—and treat the supply of cryptocurrencies as exogenous.[28] The introduction of new cryptocurrencies could be an interesting dimension to explore in a richer model that featured entry and exit on the supply side, but our analysis is constrained by the fact that the surveys we use only cover the top cryptocurrencies in terms of market shares and investors beliefs.

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. Given that S_{jt} is exogenous, only P_{jt} is 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 et al., 2016; Budish, 2018; Saleh, 2019). 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 cryptocurrencies expected returns (Liu et al., 2019). We collect the different characteristics of cryptocurrency j at time t into a vector X_{jt}.[29]

4.2 Demand

The demand for cryptocurrencies in each period t comes from $i = 1, ..., I_t$ 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

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

[29] To fully capture unobservable characteristics that differ across cryptocurrencies, but are common across investors and time-invariant, we also include cryptocurrency fixed effects in a robustness analysis in Appendix A.

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:

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

Investor wealth evolves according to the following intertemporal budget constraint:

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

Investors also face short-sale constraints:

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

Following Koijen and Yogo (2019), we assume that returns have a 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, beta) and latent demand (e.g., unobserved characteristics and investors demand shifters).

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 demand for cryptocurrency j across all investors, as follows:

$$MC_{jt} = \sum_{i=1}^{I} A_{it}w_{ijt}, \tag{7}$$

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 solve for the equilibrium market capitalization using (7). The price of cryptocurrency is then computed as $P_{jt} = \frac{MC_{jt}}{S_{jt}}$.

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 the data) and a composite option capturing all remaining cryptocurrencies.[30]

We assume the following functional form for portfolio weights when taking the model outlined in Section 4 to the data:

$$\frac{w_{ijt}}{w_{i0t}} = \exp\left\{\alpha mc_{jt} + \beta X_{jt} + \gamma B_{ij} + \lambda D_i\right\} \epsilon_{ijt}, \tag{8}$$

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—e.g. 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 (8) 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.

[30] Specifically, we focus on the eight largest cryptocurrencies in our sample (Bitcoin, Ethereum, Ripple, Litecoin, Bitcoin Cash, Zcash, Dash, and Monero), and group Swftcoin and Bytecoin together with other less popular cryptocurrencies in the composite cryptocurrency.

Equation (8) and the budget constraint imply that the weight on cryptocurrency j is given by:

$$w_{ijt} = \frac{\exp\left\{\alpha mc_{jt} + \beta X_{jt} + \gamma B_{ij} + \lambda D_i\right\} \epsilon_{ijt}}{1 + \sum_{k=1}^{9} \exp\left\{\alpha mc_{kt} + \beta X_{kt} + \gamma B_{ik} + \lambda D_i\right\} \epsilon_{ikt}}, \tag{9}$$

and the portfolio weight on the outside asset (e.g., cash) is:

$$w_{i0t} = \frac{1}{1 + \sum_{k=1}^{9} \exp\left\{\alpha mc_{kt} + \beta X_{kt} + \gamma B_{ik} + \lambda D_i\right\} \epsilon_{ikt}}. \tag{10}$$

We estimate the demand parameters from (8) using the generalized method-of-moments. The parameters are estimated by matching the ratio of weights $\frac{w_{ijt}}{w_{i0t}}$ given by equation (8) to the corresponding quantity in the data across investors and currencies. In the baseline model, we pool all investors together, but we also re-estimate the model separately for different groups based on demographics in Appendix A.[31] 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_{it} will typically have different portfolio weights (and different demand elasticities) if their beliefs are different.

As discussed in Section 3.2, we observe: i) the number and identity of cryptocurrencies that investors hold in their portfolio; ii) the total dollar amount invested in cryptocurrencies. However, we do not know how that amount is allocated across all the cryptocurrencies in the investor portfolio. 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 hold based on the market shares in our sample. Given that this assumption affects the variation in our dependent variable, we test the robustness of our results to different allocation rules. In particular, we also consider an allocation where all cryptocurrencies in the portfolio receive equal weights and one where the weights are proportional to the market

[31] Koijen and Yogo (2019) estimate the their 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.

shares in the investor's demographics group.

Following the industrial organization literature on demand for differentiated products (Berry et al., 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 algorithm or not. Given that the consensus protocol for a currency is rarely changed,[32] 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

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

The first equality is the substantive part of this restriction and it could be violated if price—and thus market capitalization—is correlated with the unobservable determinants of demand.[33]

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 the short term price evolution and the long-term potential of cryptocurrencies. We argue that these beliefs cap-

[32]For instance, Ethereum has been rumored to switch from PoW to Proof-of-Stake for years, but that has not happened to date.

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

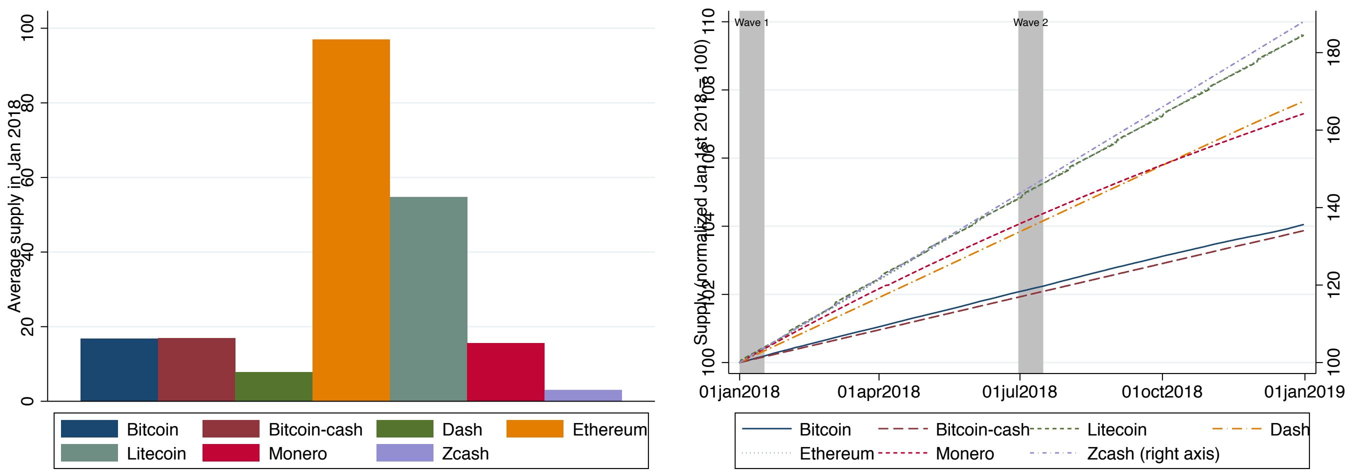
ture an important portion of the time-varying aggregate shocks that affect investor choices. Absent data on beliefs, these shocks would enter the unobservable error term ϵ_{ijt}, but in our setting we are able to control for them. Our exogeneity restriction then becomes:

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

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. Beliefs themselves could be endogenous and correlated with unobservable shocks affecting demand. With extrapolative expectations, one possibility could be to use past cryptocurrency prices as instruments for current investor beliefs. However, such instruments would likely have limited power in explaining variation in the cross-section of investors, given the substantial and persistent heterogeneity documented in the literature (Giglio et al., 2019). For these reasons we decided to abstract from endogeneity in beliefs in our analysis. This is in line with the evolution of the demand estimation literature in industrial organization, which first focused on price endogeneity alone and only more recently has started dealing with endogeneity of non-price variables.

Second, we propose a supply-side instrumental variable strategy to tackle any 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.

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



(a) CROSS-SECTION

(b) TIME-SERIES

Figure 3: SUPPLY-SIDE INSTRUMENTS

Note: 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 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 to 100 on January 1st 2018.

January, which is available from https://coinmetrics.io.[34] We can see 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 the differences in scale across currencies, we normalize the supply to 100 on January 1st 2018. The supply of all PoW currencies follows a predetermined trajectory, but the slopes differ across currencies, which provides additional identifying variation.

Our first-stage regression is given by:

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

where $Supply_j$ is the number of coins in circulation; and X_{jt} are the same controls used in the demand estimation equation (8). With this instrumental variable in hand, the exogeneity

[34]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.

restriction needed to identify the model becomes:

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

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

5.2 Results

Table 6 shows the estimates of the structural demand parameters. All columns report the estimates based on the exclusion restriction given by (14). Column (1) shows the model without controlling for investors' belief. We find a coefficient on log market capitalization of about 0.65. The fact that the coefficient on log market capitalization is smaller than 1 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.[35]

In column (2) of Table 6, we include our measures of short-term investor beliefs in the demand system.[36] The coefficient on market capitalization remains significant and consistent with downward-sloping demand. Interestingly, the point estimate decreases, pushing the

[35]Following Liu et al. (2019), 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.

[36]The reduced-form results in Table 5 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 A2 in the Appendix shows the results that include the price decrease dummy.

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 6 adds long-term expectations. We find that investors who think cryptocurrencies are never going to be mainstream have a significantly lower demand for cryptocurrencies. The magnitude of the effect is large.

Finally column (4) of Table 6 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 and about five times larger than that for short-term optimistic beliefs. The inclusion of cryptocurrency-specific dummy about 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.

In Appendix A, we report additional robustness checks, heterogeneity analyses and measures of the fit of the model, which we only briefly discuss here. First, we estimate the model shown in column (4) of Table 6 using a different allocation rule for the amount invested across cryptocurrencies, which affects our dependent variable. Column (1) of Table A2 shows the results using weights based on market shares in different demographics groups, while column (2) shows the results using equal weights. We also estimate a version of the model including a dummy for negative short-term beliefs. The results are qualitatively similar to our baseline specification. Second, in order to allow for additional heterogeneity across investors, we also estimate the model in column (4) of Table 6 separately for different age and income groups. Table A3 shows the results. The point estimates exhibit some variation across demographics,

Table 6: 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
Macro controls	Yes	Yes	Yes	Yes
Demographics controls	Yes	Yes	Yes	Yes
Mean Y	41,823	41,823	41,823	41,823

Note: Estimates of the structural demand parameters from the model of Section 4. "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. Demographics controls are dummies for age, income, and country of residence. Additional individual-level controls include investor self-reported type, a dummy for whether the investor is a trading company customer, and year of first purchase. Macroeconomic controls are the logarithm of the S&P 500 and the 3-Month London Interbank Offered Rate (LIBOR).

but are not statistically different. Finally, Figure A4 compares the portfolio weights in our data to those predicted by the model in column (4). Our model slightly underestimates the demand for Bitcoin and Ripple and tends to overestimate the demand for the remaining cryptocurrencies, but overall it captures the patterns observed in the data well.

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 counterfactual simulation, we investigate the effect of beliefs in the cryptocurrency market by preventing late optimistic buyers from investing in cryptocurrencies. In a second counterfactual simulation, we make the currency-specific expectations about PoW currencies more pessimistic and quantify the substitution patterns toward other cryptocurrencies and alternative investment opportunities.

6.1 Late buyers, optimistic beliefs and cryptocurrency prices

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.[37] 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.[38]

Using the estimates in column (3) of Table 6 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 non-buyers. 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 restricting entry. Comparing the two counterfactuals allows us to separately quantify the effect of investors' beliefs and the effect of reducing market size.

[37]Similarly, (overly) optimistic beliefs about house prices played an important role in the housing boom of the early 2000s in the U.S. (Cheng et al., 2014; Burnside et al., 2016; Kaplan et al., 2017).

[38]Figure 1 in the 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 whether an address belongs to an existing investors opening a new account or to a new investor opening her first account. However, our survey data allows us to identify when individual investors bought their first cryptocurrency.

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 non-buyers, whereas in the second counterfactual we prevent late buyers from purchasing cryptocurrencies, which leads to a decline in the market size by about 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 on average by about 4% and cryptocurrency prices decline by more than 5% in equilibrium, keeping the market size constant. The combined change in beliefs and 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 non-buyers. 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 also 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 non-buyers. 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

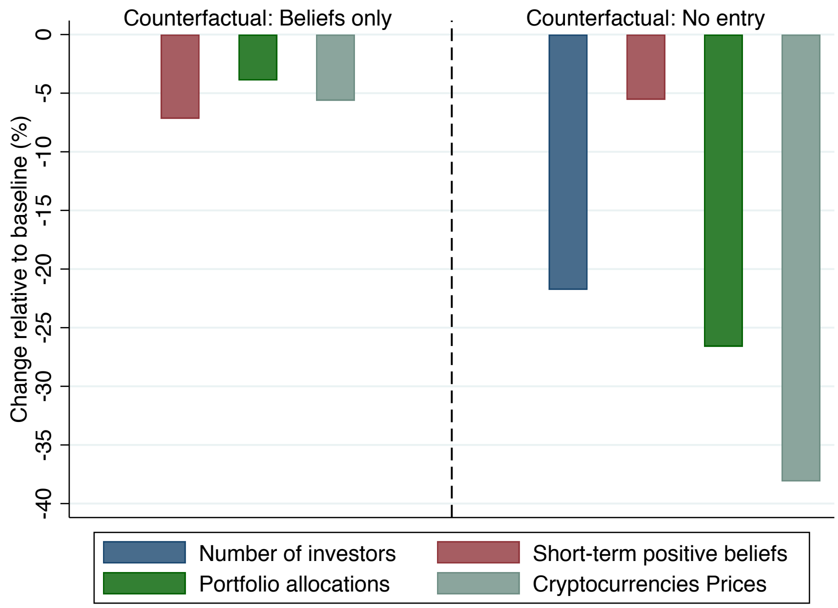


Figure 4: Late buyers, optimistic beliefs and cryptocurrency prices

Note: 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") remove all investors who bought their first cryptocurrency in 2018 or later, and replace their beliefs by sampling at random from the population of non-buyers. 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 is change in the total number of potential investors in the cryptocurrency market. Short-term positive beliefs in the change in the fraction of investors reporting an expected increase in the value of cryptocurrencies in the following year. Portfolio allocation is the average change in the amount in $ invested in the cryptocurrencies in our sample. Cryptocurrency prices is the average change in the price in $ in the cryptocurrencies in our sample. All bars are changes as a percentage of the relative value in the baseline.

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 decline 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 decrease 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, non-buyers tend to be more 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 non-buyers, 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 non-buyers.

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 2016-2017. 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.

Table 7: Late buyers, optimistic beliefs and cryptocurrency prices

	Baseline	Counterfactual: Beliefs Only						Counterfactual: No Entry			
		Only short term beliefs		Baseline		Late buyer from 2016		Baseline		Late buyer from 2016	
	Level	Level	Δ %	Level	Δ %	Level	Δ %	Level	Δ %	Level	Δ %
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(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%

Note: 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 cryptocurrency 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 with short-term beliefs of non-buyers; columns (4) and (5) show the baseline beliefs counterfactual in which we replace all beliefs of late investors with short-term beliefs of non-buyers; columns (6) and (7) show the beliefs counterfactual in which we replace all investors 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.

6.2 Energy sustainability and cryptocurrency allocations

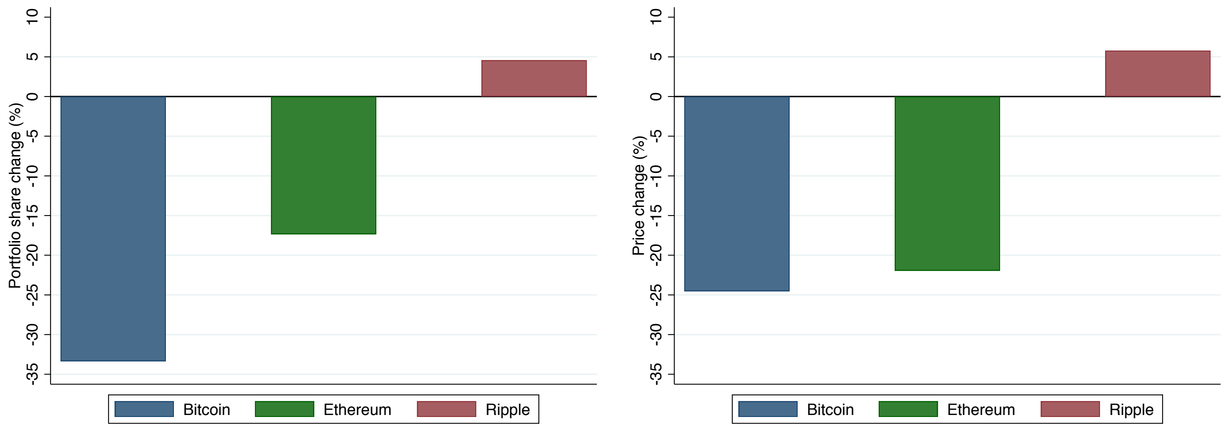
In a second set of counterfactuals, we study the role of long-term beliefs about specific cryptocurrencies for investors' portfolio allocations and equilibrium prices. Specifically, using the estimates in column (4) of Table 6, we simulate the market equilibrium when investor long-term beliefs about PoW currencies become more negative. As mentioned above, PoW is increasingly criticized due to its huge energy consumption and so our counterfactual exercise speaks to how the market would react if investors became more aware of its limitations.[39]

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.[40] The median investor reduces her 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 (3) report portfolio allocations for the median investor. In the baseline, the median investor has about $3,200 invested in cryptocurrencies, which is about 1% of their total wealth. Approximately $1,600 are invested in Bitcoin, which accounts for the lion's share at more than 70% of the total amount invested. The other cryptocurrencies with the highest shares in investors portfolio are Ethereum and Litecoin, corresponding to 13% and 6%, respectively.

[39] Irresberger et al. (2020) offer an exhaustive discussions 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 `https://www.vox.com/recode/2021/5/18/22441831/elon-musk-bitcoin-dogecoin-crypto-prices-tesla` and `https://www.coindesk.com/elon-musk-says-tesla-is-suspending-bitcoin-payments-over-environmental-concerns`).

[40] 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.



(a) Portfolio Allocations

(b) Prices

Figure 5: Energy Sustainability and Cryptocurrency Allocations - Prices
Note: 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 using January 2018 as the baseline.

In the counterfactual, a decline in the expected sustainability of PoW cryptocurrencies leads the median investor to reduce her holdings of those currencies, while Ripple experiences a modest increase. The median investor shifts almost $800 dollar away from Bitcoin, which corresponds to a decline by about a third. Litecoin experiences the largest 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, as the median investor shifts about $950 previously invested in cryptocurrencies to the outside option (i.e., other investment opportunities).

Columns (4) to (6) of Table 8 show results for equilibrium prices. The average decrease in equilibrium cryptocurrency prices is 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.

Table 8: Counterfactual Equilibrium Prices and Portfolio Allocations

	Portfolio allocation			Prices		
	Baseline	Counterfactual		Baseline	Counterfactual	
	$	$	Δ %	$	$	Δ %
	(1)	(2)	(3)	(4)	(5)	(6)
bitcoin	2387	1590	-33.4%	10869	8202	-24.5%
bitcoin-cash	64	49	-23.6%	1662	1477	-11.1%
dash	43	40	-5.2%	727	655	-9.8%
ethereum	410	339	-17.3%	1089	850	-21.9%
litecoin	184	116	-37.2%	178	146	-18.1%
monero	49	46	-5.2%	298	275	-7.7%
ripple	78	82	4.6%	1.16	1.23	5.8%
zcash	24	23	-3.4%	451	411	-8.9%
Average			-15.1%			-12.0%
Outside option	328,285	329,056	0.23%			

Note: Equilibrium prices and median portfolio allocations for all main cryptocurrencies in our sample and the outside option in the baseline and a counterfactual scenario in which we make 25% of investors more pessimistic about PoW. Baseline is the January 2018 wave (the "boom" period). In the counterfactuals 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. Prices and allocations are in US dollars. Changes are in US dollars and percent of the initial price.

7 Conclusion

In this paper, we shed light on the role of beliefs for asset demand using the cryptocurrency industry as a laboratory. 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 substantially reduces the importance of the unobservables in explaining the cross-sectional variance of returns. We use the estimated model to simulate how the market prices would react to (i) a counterfactual change in the number and composition of 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 only relied 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. (2019)—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. Endogenizing the set of available cryptocurrencies through a model of entry could be a promising avenue for future research.

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APPENDICES

Appendix A provides supplementary figures and tables, including robustness checks and a model fit exercise. Appendix B reports the detailed questions about cryptocurrency holdings and beliefs from the three surveys that we use in our main analysis.

A Additional Figures and Tables

Table A1: Comparison: Investors and Consumers

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

Note: Summary statistics for the three surveys used in the reduced-form analysis. For comparability, we focus on 2018 and the 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 only focus on the U.S. For the trading company survey, we only focus on North America. The variables are as defined in Tables 1 and 2.

Table A2: Structural Demand Parameters: Robustness

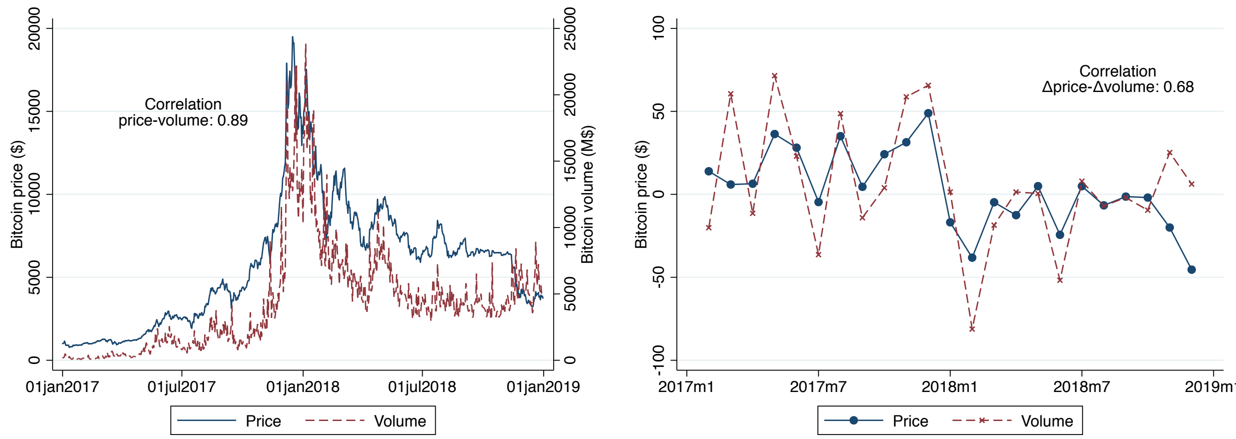
	Portfolio share		Additional controls
	(1) Weighted by group	(2) Equally weighted	(3)
Characteristics:			
Market capitalization	0.497***	0.274***	0.428***
	(0.108)	(0.085)	(0.097)
Proof-of-Work	0.552***	0.322**	0.517***
	(0.179)	(0.158)	(0.175)
Beta	2.194***	1.165***	2.015***
	(0.282)	(0.292)	(0.269)
Four-week momentum	-0.042	0.063	0.052
	(0.287)	(0.283)	(0.289)
Beliefs:			
Price Increase	0.321*	0.433***	0.338
	(0.178)	(0.156)	(0.238)
Price Decrease			0.067
			(0.293)
Never Mainstream	-1.443***	-1.593***	-1.494***
	(0.381)	(0.308)	(0.354)
High Potential	1.448***	1.600***	1.528***
	(0.156)	(0.128)	(0.142)
Macro controls	Yes	Yes	Yes
Demographics controls	Yes	Yes	Yes
Mean Y	41,823	41,823	41,823

Note: Estimates of the structural demand parameters from the model of Section 4. Column (1) includes week fixed effects. Column (2) includes currency fixed effects. "Price increase (decrease)" is a dummy equal to one if the respondent expects the price of Bitcoin to increase (decrease) in the following year. "Never mainstream" is a dummy equal to one if the investor thinks cryptocurrencies are never going to be adopted. "Currency potential" is a dummy equal to one if the investor thinks a given currency has the potential to be successful in the long term. Demographics controls are dummies for age, income, and country of residence. Additional individual-level controls include investor self-reported type, a dummy for whether the investor is a customer of the trading company, and year of first purchase. The macroeconomic controls are the logarithm of the S&P 500 and the 3-Month London Interbank Offered Rate (LIBOR).

Table A3: Structural Demand Parameters: By Demographics

	By income		By age	
	(1)	(2)	(3)	(4)
	$\leq$ \$100K	$>$ \$100K	$\leq$ 30	$>$ 30
Characteristics:				
Market capitalization	0.575***	0.164	0.266**	0.720***
	(0.136)	(0.127)	(0.105)	(0.123)
Proof-of-Work	0.567**	0.482***	0.618***	0.462*
	(0.235)	(0.155)	(0.179)	(0.264)
Beta	2.215***	1.897***	1.718***	4.414***
	(0.333)	(0.527)	(0.378)	(0.648)
Four-week momentum	-0.594**	1.115**	0.773**	-1.031***
	(0.233)	(0.489)	(0.392)	(0.280)
Beliefs:				
Price Increase	0.489**	0.296	0.214	0.499**
	(0.234)	(0.225)	(0.220)	(0.246)
Never Mainstream	-1.263***	-1.741***	-1.388***	-2.185***
	(0.451)	(0.490)	(0.420)	(0.464)
High Potential	1.483***	1.577***	1.550***	1.484***
	(0.167)	(0.176)	(0.146)	(0.197)
Macro controls	Yes	Yes	Yes	Yes
Demographics controls	Yes	Yes	Yes	Yes
Mean Y	28,422	13,401	20,907	20,916

Note: Estimates of the structural demand parameters from the model of Section 4. Columns (1) and (2) show the estimates splitting the full sample by age, while columns (3) and (4) show the estimates splitting the full sample by income. "Price increase (decrease)" is a dummy equal to one if the respondent expects the price of Bitcoin to increase (decrease) in the following year. "Never mainstream" is a dummy equal to one if the investor thinks cryptocurrencies are never going to be adopted. "Currency potential" is a dummy equal to one if the investor thinks a given cryptocurrency has the potential to be successful in the long term. Demographics controls are dummies for age, income, and country of residence. Additional individual-level controls include investor self-reported type, a dummy for whether the investor is a customer of the trading company, and year of first purchase. The macroeconomic controls are the logarithm of the S&P 500 and the 3-Month London Interbank Offered Rate (LIBOR).



(a) Levels (b) Δ

Figure A1: Crypto Mania: Prices and Volumes

Note: The left figure shows the daily price and transaction volume of Bitcoin in 2017-2018. The right figure shows the monthly price changes and monthly transaction volume changes of Bitcoin in 2017-2018. Data on the price of Bitcoin and transaction volumes comes from https://coinmarketcap.com.

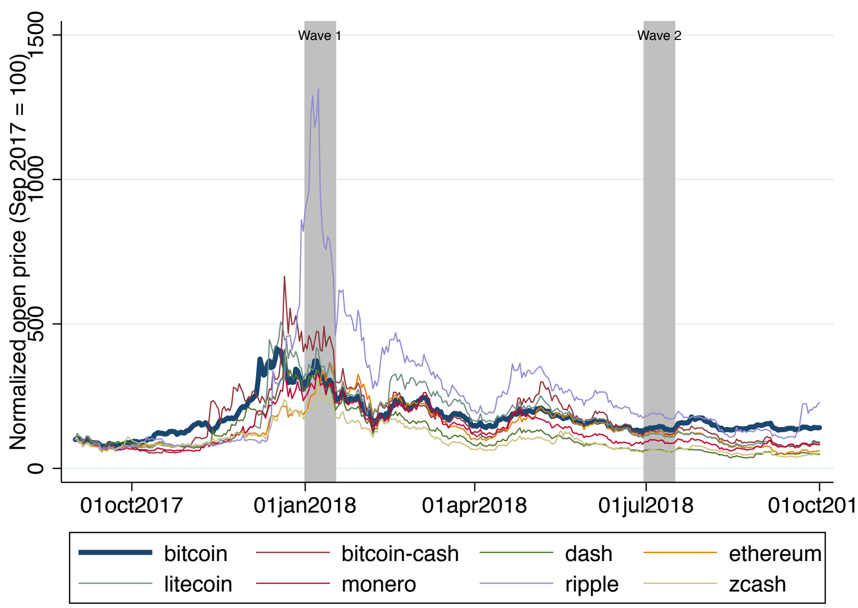


Figure A2: Cryptocurrency Price Variation

Note: The figure shows the daily prices for eight cryptocurrencies in 2017-2018. The cryptocurrencies are: bitcoin, bitcoin-cash, dash, ethereum, litecoin, monero, ripple, zcash. Data comes from https://coinmarketcap.com.

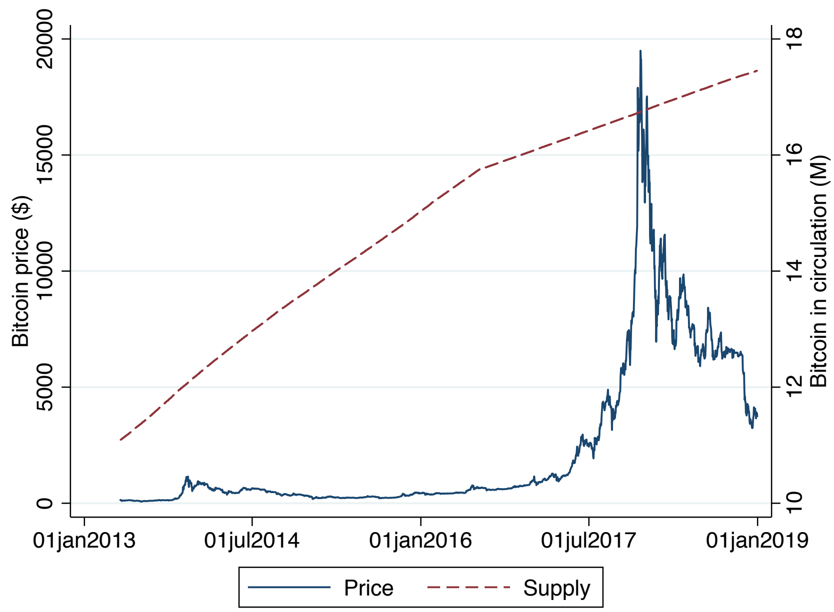


Figure A3: Bitcoin Price and Supply

Note: The figure shows the price of Bitcoin in US dollars and the number of Bitcoins in circulation. Data on the price of Bitcoin comes from https://coinmarketcap.com. Data on the number of Bitcoin in circulation comes from https://www.blockchain.com/charts.

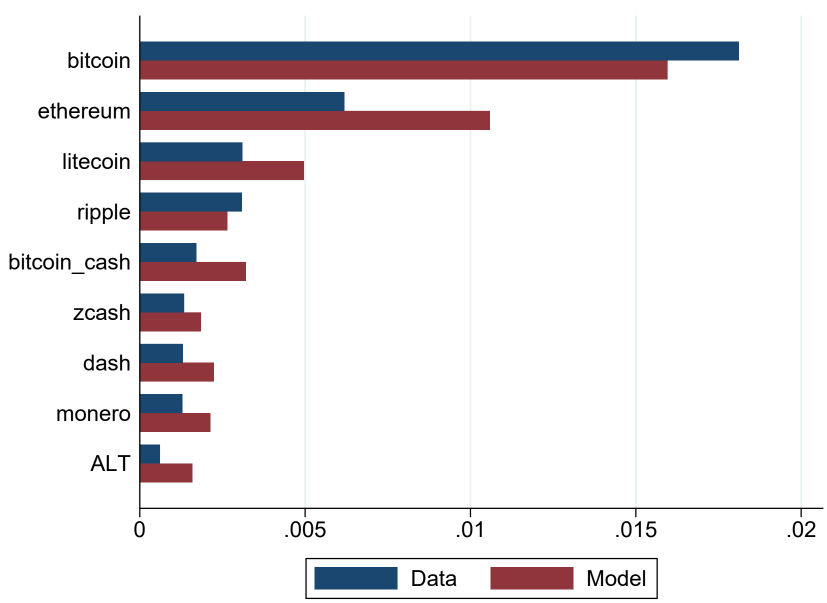


Figure A4: Model Fit

Note: The figure shows the average portfolio weights for the main cryptocurrencies in our sample and the composite cryptocurrency. For each cryptocurrency, we report the average in the data and that predicted by the model using the estimates in column (4) of Table 6.

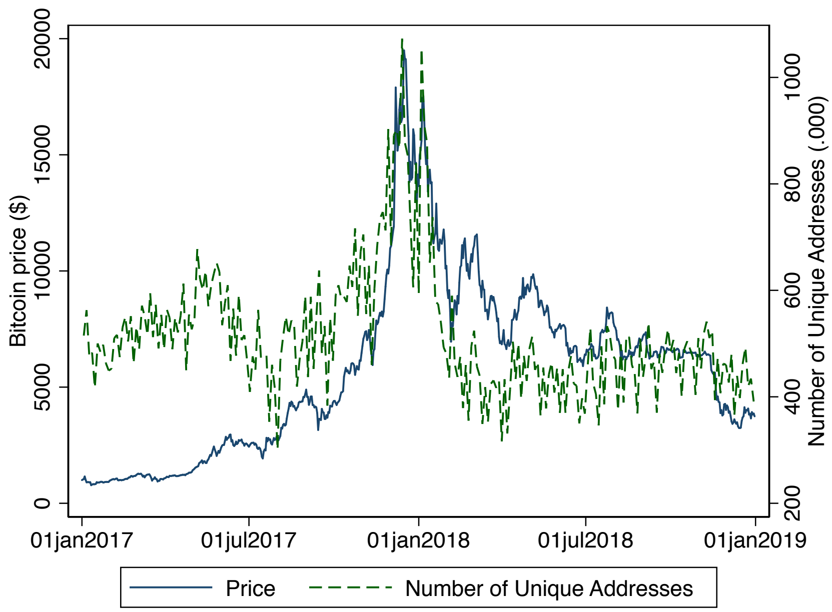


Figure A5: Investors' Entry

Note: The figure shows the daily price for Bitcoin and number of unique addresses used on the Bitcoin blockchain in 2017-2018. Data on the price of Bitcoin and transaction volumes comes from https://coinmarketcap.com. Data on addresses comes from https://www.blockchain.com/charts.

B Questions from Surveys

In this Appendix, we report the main questions from the the different surveys that we use in our analysis.

Survey of consumer payment system (SCPC).

- Question on beliefs: *How do you expect the value of one Bitcoin (BTC) to change over the following time periods?*

  Options: Decrease a lot, Decrease some, Stay about the same, Increase some, Increase a lot. The different horizons are next week, next month, next year.

- Question on holdings: *Do you have or own any of these virtual currencies?*

  Options: yes, no. The following currencies are available in the 2018 survey: Bitcoin, Bitcoin Cash, Ethereum, Ripple, Litecoin, Stellar, EOS.

ING - International Survey.

- Question on beliefs: *Please indicate how much you agree or disagree with the following statements: "I think the value of digital currencies - such as Bitcoins - will increase in the next 12 months?"*

  Options: Strongly agree, Agree, Neither agree or disagree, Disagree, Strongly disagree, I don't have an opinion.

- Question on holdings: *I own some cryptocurrency.*

  Options: yes, no.

Trading Company Investors Survey.

- Question on short-term beliefs: *How do you expect the values of cryptocurrencies to trend in 2018?*

  Options: Decrease, Stay the same, Increase, I don't know.

- Question on long-term beliefs: *How long do you think it would take for cryptocurrency to be accepted as mainstream?*

  Options: By end of 2020, By end of 2025, By end of 2030, It will never become mainstream, I don't know.

- Question on cryptocurrency potential: *Which currencies do you think have the potential to be successful in the long term? (SELECT TOP THREE)?*

  Options: Bitcoin, Ethereum, Litecoin, Ripple, Zcash, Dash, Monero, Swiftcoin, Bitcoin Cash, Bytecoin, None of the above, I don't know, Other (please specify).

- Question on holdings: *Which of the following cryptocurrencies do you own? (SELECT ALL THAT APPLY)*

  The following currencies are available in the survey: Bitcoin, Ethereum, Litecoin, Ripple, Zcash, Dash, Monero, Swiftcoin, Bitcoin Cash, Bytecoin, None of the above, Other (please specify).

- Question on holdings: *How much do you own in cryptocurrencies (approximate USD value today)?*

  Options: $< 1,000$, $1,000–10,000$, $10,000–100,000$, $100,000–1,000,0000$, $> 1,000,0000$.