Investors' Beliefs and Asset Prices:

A Structural Model of Cryptocurrency Demand*

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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 amount of energy required for the production of the different cryptocurrencies. We find that beliefs explain a large fraction of the cross-sectional variance of returns. A counterfactual exercise shows that banning entry of late investors leads to a decrease in the price of Bitcoin by about $3,500, or approximately 30% of the price during the boom in January 2018. Late investors' optimism alone can explain about a third of the decline.

JEL codes: D84, G11, G41.

Keywords: Beliefs, Demand system, Cryptocurrencies, Surveys, Sentiment, Retail investors.

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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 affects 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 as well as potential 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). Figure 1 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.[2] The entry of late and perhaps overly optimistic investors, "fear of missing out," and contagious social dynamics may have contributed to the rampant growth of the cryptocurrency market, which reached a market capitalization of over \$300 billion in November 2017.[3]

The key contribution of this paper is the estimation of a demand system for cryptocur-

[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 US housing boom (Fostel and Geanakoplos, 2012; Hong and Sraer, 2013; Cheng et al., 2014). Gennaioli and Shleifer (2020) provides a recent review of the related literature.

[2]The correlation between price and volume is 0.89. The correlation in the changes between price and volume is almost 0.7 (see Figure A1 in Appendix A).

[3]Similarly, (overly) optimistic beliefs about house prices played an important role in the housing boom of the early 2000s in the US (Cheng et al., 2014; Burnside et al., 2016; Kaplan et al., 2017). The fact that companies such as Robinhood started allowing retail investors to trade cryptocurrencies on their apps during the period we study suggests that new investors may have played a role (see https://www.cnbc.com/2018/01/25/stock-trading-app-robinhood-to-roll-out-bitcoin-ethereum-trading.html).

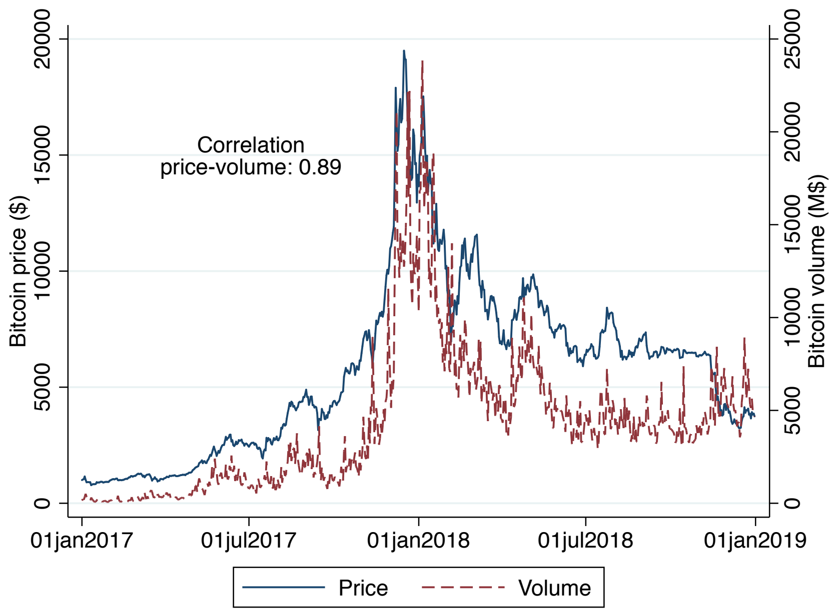

Figure 1: Bitcoin Mania?

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

rencies that allows for a *quantification* of the role of heterogeneous investors' beliefs for equilibrium price dynamics. To investigate the role of beliefs, 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 the future value and holdings of cryptocurrencies for a representative sample of US consumers. The second dataset, the 2018 ING International Survey on Mobile Banking, complements the first by covering Europe and Australia, in addition to the US. The third and main dataset is a survey run by a US 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.

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 find that consumers that 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.

We then explore the effect of beliefs on the demand for cryptocurrencies. We find that, for both consumers and investors, positive beliefs have a strong positive effect on the probability of holding cryptocurrencies, controlling for demographics and other determinants of demand (e.g. usage as a payment tool). US consumers that expect prices to increase are two percentage points more likely to own Bitcoin, which is approximately a twofold increase relative to an unconditional probability of 1%. Investors expecting an increase (decrease) in cryptocurrency prices are more (less) likely both to hold Bitcoin and to have a portfolio with many cryptocurrencies. The effects are statistically significant and large in magnitude. Along the "extensive" margin, investors that expect prices to increase (decrease) in the following year are six (four) percentage points more (less) likely to own Bitcoin. Along the "intensive" margin, investors that expect prices to increase in the following year have a 40% higher number of cryptocurrencies in their portfolio relative to the mean, while individuals that expect prices to decrease have an almost 30% lower number of cryptocurrencies.

Motivated by the reduced-form evidence about 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.[4] A standard market clearing condition closes the model. Under the assumption of

[4] Foley et al. (2019) find that a large fraction of Bitcoin users are involved in illegal activity. While we think this is unlikely to be the case for respondents in our survey, our demand system is well-suited to flexibly

downward-sloping demand—which we fail to reject empirically—the equilibrium price of each cryptocurrency is unique and can be computed by aggregating across investors' demands.

We estimate the model on our trading platform dataset. A key challenge in estimating demand functions is that, in equilibrium, some of the determinants of demand—notably price—are likely to be correlated with unobservables and are thus likely to be econometrically endogenous (Berry et al., 1995). We address this in two ways. First, 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.

Second, we use an instrumental variable strategy to address the potential correlation between prices and unobservable demand shocks not captured by the beliefs data. 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. In contrast, in this paper we leverage a unique feature of the asset class under consideration. Specifically, we use data on the production process of cryptocurrencies (sometimes referred to as "mining") to construct supply-side instruments for prices. This is based on the standard economic intuition that variables shifting supply should help identify the demand curve. Mining a cryptocurrency requires two main inputs: electricity and computer power. Our instrument combines time-series variation in quoted prices on Amazon for general hardware components used for mining with cross-sectional variation in mining difficulty of different cryptocurrencies.[5]

capture investor preferences for characteristics such as anonymity.

[5]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

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, controlling for beliefs reduces the quantitative importance of the unobservable shocks that are needed to rationalize the observed data. Specifically, a decomposition of the cross-sectional variance of cryptocurrency returns shows that including beliefs reduces the contribution of the unobservables from 70% to less than 10%. This large decline suggests that data on beliefs substantially improve the fit of the model by capturing important factors such as sentiment and disagreement across investors.

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.[6] 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 remaining population of investors. 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 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.

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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/).

[6] 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.

We find that changing the composition of investors decreases the price of Bitcoin by about $1,000 dollars, or approximately 9% of the original value, during the January 2018 boom. The full restriction on entry of late buyers leads to a decrease in the price of Bitcoin by about $3,500, or approximately 30% of the price during the boom. Thus, about one third of the decline in the price of Bitcoin is due to investors' beliefs and two thirds to the direct effect of entry on market size. We also find heterogeneity in equilibrium price adjustments both across currencies and over time. Overall, late investors' optimism alone can explain about 40% of the predicted decline in cryptocurrency prices.

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. PoW is a protocol for validating new transactions that is used by several top cryptocurrencies, including Bitcoin and Ethereum. 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. We find that, on average, equilibrium cryptocurrency prices decrease by around 11%, 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 5%.

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 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. First, 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. Second, by leveraging features of the cryptocurrency production process, we propose a supply-side instrumental variable approach to tackle remaining endogeneity concerns.

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), 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

Our analysis combines several data sources. 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 papers, such as Liu and Tsyvinski (2018), Griffin and Shams (2019) and Hu et al. (2019), among others.

Next, we contribute to the empirical analysis of cryptocurrency markets by leveraging three surveys about consumers' and investors' beliefs and holdings.[7] 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

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

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.[8] 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 US 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 multiple 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. The first survey contains about 2,500 responses, while 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.

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

[8] 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).

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 and time horizons.

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 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. The average respondent invests in 1.5 cryptocurrencies, and some investors hold a diversified portfolio with all the cryptocurrencies that we consider. About 35% of

Table 1: Summary statistics: Consumers' Surveys

	count	mean	sd	min	median	max
Panel A: US Consumers (SCPC)						
Demographics						
Age	11,084	50.6	15.1	18	51	100
Income ($)	10,970	72,878	70,776	2,500	55,000	750,000
Male	11,085	0.43	0.50	0	0	1
Education (Below Bachelor)	11,085	0.47	0.50	0	0	1
Asset $\leq$ 20K	10,844	0.51	0.50	0	1	1
Cryptocurrency questions (general)						
Aware of Cryptocurrencies	11,030	0.53	0.50	0	1	1
Own Cryptocurrencies	5,841	0.01	0.11	0	0	1
How familiar with Cryptocurrencies	5,843	1.59	0.86	1	1	5
Used Cryptocurrencies in transaction	113	0.12	0.33	0	0	1
Cryptocurrency questions (beliefs)						
Week Increase	5,789	0.08	0.27	0	0	1
Week Decrease	5,789	0.13	0.34	0	0	1
Month Increase	5,793	0.15	0.35	0	0	1
Month Decrease	5,793	0.18	0.38	0	0	1
Year Increase	5,797	0.25	0.43	0	0	1
Year Decrease	5,797	0.26	0.44	0	0	1
Panel B: Worldwide Consumers (ING)						
Demographics						
Age	14,828	45.1	15.6	18	45	99
Income (€)	13,245	2,369	1,905	0	1,750	9,000
Male	14,828	0.49	0.50	0	0	1
Education (Below Bachelor)	14,828	0.64	0.48	0	1	1
Employment	14,828	0.23	0.42	0	0	1
Cryptocurrencies questions (general)						
Aware of Cryptocurrencies	14,828	0.65	0.48	0	1	1
Own Cryptocurrencies	14,828	0.09	0.28	0	0	1
Expect to own	14,828	0.22	0.42	0	0	1
Cryptocurrencies questions (beliefs)						
Year increase	9,949	0.31	0.46	0	0	1
Year decrease	9,949	0.27	0.44	0	0	1

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.

Table 2: Summary statistics: Investors' Survey

	count	mean	sd	min	p50	max
Demographics						
Age	4,539	32.9	11.3	16	24	70
Income ($)	4,568	85,223	59,719	50,000	50,000	300,000
Age ≤ 30	4,568	0.50	0.50	0	1	1
Income $\leq 100K$	4,568	0.68	0.47	0	1	1
Outside US	4,568	0.36	0.48	0	0	1
Accredited investor	4,568	0.10	0.30	0	0	1
Cryptocurrency questions (general)						
Aware of crypto	4,568	0.99	0.10	0	1	1
Invest in at least one crypto	4,568	0.56	0.50	0	1	1
Number of cryptocurrencies	4,568	1.50	2.07	0	1	10
Early buyer (Before 2018)	4,568	0.35	0.48	0	0	1
Late buyer (2018)	4,568	0.22	0.42	0	0	1
Cryptocurrency questions (beliefs)						
Price increase	4,568	0.62	0.49	0	1	1
Price decrease	4,568	0.24	0.43	0	0	1
Never mainstream	4,568	0.08	0.28	0	0	1
Currency Potential	45,680	0.21	0.41	0	0	1

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 US, "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 crytocurrency 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.

investors in cryptocurrencies bought their first cryptocurrency before 2018, while 22% only bought their first cryptocurrency in 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 20% of all investor-cryptocurrency pairs, the investor thinks that specific cryptocurrency has long-term potential.

Before turning to the empirical analysis, in Table A1 of Appendix A we compare our different surveys along a few variables of interest. For comparability, we focus on North America in 2018. The survey of the trading company is tilted toward a younger population. About half of the respondents are younger than 30 years old, while the corresponding figures in the ING and SCPC surveys are 22% and 8%, respectively. Almost all individuals surveyed by the trading company have heard of Bitcoin, as compared to about 70% of SCPC and 57% of ING respondents. Regarding holdings, the surveys also exhibit some differences. About 47% of individuals surveyed by the trading company invest in cryptocurrencies, versus only 2% of SCPC and 8% of ING respondents.

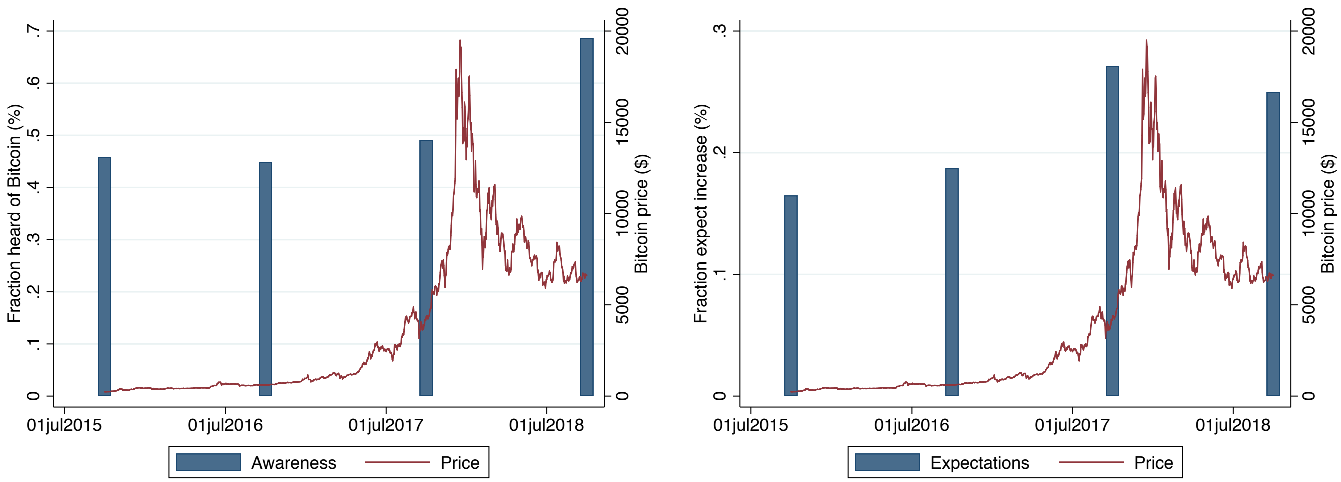
Finally, we compare expectations about the future value of cryptocurrencies. About 57% of the trading company survey respondents think the price of Bitcoin is going to increase in the next year, while this is the case for only 28% of SCPC and 33% of ING respondents. Finally, 28% of trading company survey respondents think the price is going to decrease; the corresponding figures for the SCPC and ING surveys are 30% and 24%, respectively. All in all, 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 somewhat more optimistic about the future of the asset class.

3 Reduced-form Evidence on Beliefs and Demand

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 investor demand for cryptocurrencies.[9] We begin by describing two aggregate patterns in the cryptocurrency industry in the last five years. First, Panel (a) of Figure 2 shows that the fraction of US consumers who are aware of Bitcoin has increased over time, going from 45% in 2015 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 2 shows the dynamics over time of consumers' beliefs about

[9]In Appendix C, we report the exact questions in each survey.



(a) Awareness and price

(b) Beliefs and price

Figure 2: Crypto Mania: Awareness and expectations

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 ("expectation"). The awareness and expectation 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 expectation measure is computed using the individuals that say they have heard of Bitcoin and appear in all waves.

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.

3.1 Drivers of Beliefs

We now explore what factors drive differences in beliefs across individuals in our data. We begin with the consumer surveys and estimate the following ordered probit model:

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

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 first two surveys. Columns (1) to (3) 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 at different horizons.[10] We find that consumers with lower income and assets tend to be more optimistic about the future value of Bitcoin at all horizons, as do younger consumers. The result are significant and large in magnitude. Lower education levels are also associated with more optimistic beliefs, but the results are noisy. Finally, we find that, perhaps surprisingly, 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. 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.

Next, we look at our main survey of investors from the trading platform. Columns (1) and (2) of Table 4 show the estimates of equation (1). In column (1), the dependent variable is 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. 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.

In column (2), we estimate the same specification using now as dependent variable a

[10] The horizons are next week, next month and next year. The variable takes five values: 1 (decrease a lot), 2 (decrease some), 3 (stay about the same), 4 (increase some), and 5 (increase a lot).

Table 3: DRIVERS OF BELIEFS: CONSUMER SURVEYS

	SCPC			ING
	Week	Month	Year	Year
	(1)	(2)	(3)	(4)
Low income	0.064*	0.083**	0.081**	0.012
	(0.038)	(0.035)	(0.033)	(0.027)
Age $\leq$ 45	0.170***	0.215***	0.185***	0.361***
	(0.035)	(0.032)	(0.031)	(0.021)
Education (Below Bachelor)	0.030	0.021	0.024	0.045**
	(0.037)	(0.033)	(0.030)	(0.023)
Male	-0.046	-0.036	-0.073**	-0.057***
	(0.034)	(0.031)	(0.029)	(0.022)
Asset $\leq$ 20K	0.036	0.097***	0.109***	
	(0.036)	(0.033)	(0.030)	
Self-employed, part-time, unemployed				0.074***
				(0.026)
Year fixed effects	Yes	Yes	Yes	No
Country fixed effects	No	No	No	Yes
Pseudo R^2	0.01	0.01	0.01	0.03
Observations	5,699	5,703	5,706	9,949

Note: Estimates of coefficients from model (1). Columns (1) to (3) shows the results from the US 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.

dummy equal to one if the investor thinks that cryptocurrencies will become mainstream, which we view as a measure of long-term beliefs. Again, younger investors and individuals who invested in cryptocurrencies tend to 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:

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

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 charac-

Table 4: Drivers of Beliefs: Investor survey

	Short-term Beliefs (1)	Long-term Beliefs (2)	Currency Potential (3)	Currency Potential (4)
Income $\leq 100K$	0.001	-0.129	0.013	0.012
	(0.048)	(0.081)	(0.020)	(0.021)
Age ≤ 30	0.158***	-0.007	0.033*	0.033*
	(0.041)	(0.062)	(0.018)	(0.018)
Outside US	0.236***	0.462***	-0.009	-0.009
	(0.045)	(0.079)	(0.019)	(0.019)
Early buyer (Before 2018)	0.398***	0.498***	0.270***	0.351***
	(0.048)	(0.078)	(0.022)	(0.026)
Late buyer (2018)	0.570***	0.422***	0.312***	0.280***
	(0.053)	(0.082)	(0.023)	(0.029)
Early buyer (2018) × Top 3				-0.194***
				(0.037)
Late buyer (2018) × Top 3				0.086**
				(0.042)
Macro controls	Yes	Yes	Yes	Yes
Other investor controls	Yes	Yes	Yes	Yes
Wave fixed effects	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Currency fixed effects	No	No	Yes	Yes
Pseudo R^2	0.03	0.09	0.27	0.27
Observations	4,182	4,182	45,680	45,680

Note: Estimates of coefficients from model (1) in columns (1) to (2), and model (2) 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. Macroeconomic controls are the logarithm of the S&P 500 and the 3-Month London Interbank Offered Rate (LIBOR).

teristics 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 cannot capture. The pseudo-R^2 in Table 3 is always below 0.05. In Table 4, the pseudo-R^2 increases to about 0.30 in columns (3) and (4) due to the inclusion of the currency fixed effect. This suggests that including demographic variables in the cryptocurrency demand system is not sufficient to control for differences in beliefs across investors. Motivated by this observation, we include both beliefs and demographics as explanatory variables in the descriptive regressions of the next section as well as in the structural model of Section 4.

3.2 Beliefs and Demand

We now present descriptive evidence on the role of beliefs in driving cryptocurrency demand. We begin by looking at the time series of investors' first investment in cryptocurrencies. Figure 3 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 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 2 and 3 show that the months leading up to the end of 2017 were characterized by a rise in cryptocurrency prices,[11] widespread awareness and optimism about this asset class across the general public, and an increase in investors' demand.

Next, we perform a series of reduced-form regressions to motivate the structural approach in the next section. We focus on two main outcome variables: (i) a dummy variable for whether an investor holds Bitcoin—the first and most popular cryptocurrency—which captures the "extensive margin"; and (ii) the number of cryptocurrencies that investors hold in their portfolio, which captures the "intensive margin". We estimate the following

[11]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).

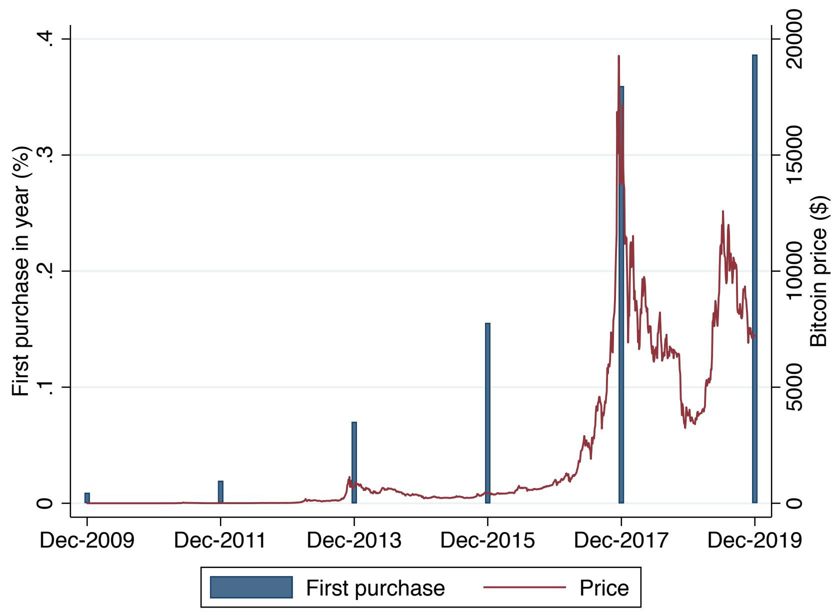


Figure 3: FIRST PURCHASE

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.

specification:

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

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

Table 5 shows the results from regression (3) for the investor survey.[12] First, we look at the "extensive" margin in columns (1) to (3). Column (1) shows the unconditional effect of expecting the price of cryptocurrencies to increase or decrease over the rest of the year. We find that individuals 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.

[12]Table A2 in Appendix A shows the result of estimating equation (3) on our consumer surveys. The results about beliefs are qualitatively similar. Regarding demographics, with find that younger male consumers are significantly more likely to own cryptocurrencies in both surveys.

Table 5: Beliefs and Demand: Investor Survey

	Whether Invest in Bitcoin			Number of Currencies		
	(1)	(2)	(3)	(4)	(5)	(6)
Short-term beliefs:						
Price increase	0.129***	0.126***	0.105***	0.652***	0.606***	0.557***
	(0.021)	(0.021)	(0.021)	(0.094)	(0.089)	(0.089)
Price decrease	-0.108***	-0.076***	-0.049**	-0.435***	-0.257**	-0.195*
	(0.024)	(0.024)	(0.024)	(0.107)	(0.101)	(0.101)
Long-term beliefs:						
Never mainstream			-0.076***			-0.397***
			(0.026)			(0.112)
Currency Potential			0.193***			0.269***
			(0.017)			(0.073)
Demographics:						
Income $\leq 100K$		-0.050***	-0.060***		-0.708***	-0.716***
		(0.017)	(0.017)		(0.071)	(0.071)
Age ≤ 30		0.106***	0.109***		0.500***	0.505***
		(0.015)	(0.015)		(0.063)	(0.063)
Outside US		0.074***	0.078***		0.442***	0.433***
		(0.016)	(0.016)		(0.069)	(0.069)
Macro controls	No	Yes	Yes	No	Yes	Yes
Other investor controls	No	Yes	Yes	No	Yes	Yes
Wave f.e.	No	Yes	Yes	No	Yes	Yes
Mean Dep. Var.	0.46	0.46	0.46	1.55	1.55	1.55
SD Dep. Var.	0.50	0.50	0.50	2.19	2.19	2.19
R^2	0.04	0.09	0.12	0.05	0.17	0.17
Observations	4,568	4,568	4,568	4,568	4,568	4,568

Note: Estimates of coefficients from model (3). 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).

Individuals that expect prices to increase in the following year have a 13 percentage-points higher probability to own Bitcoin, while individuals that expect prices to decrease have a 10 percentage-points lower probability of owning Bitcoin. Given an unconditional probability of about 46%, these effects translate into an approximately 28% and 23% increase and decrease, respectively.

In column (2) we control for a set of demographics and additional covariates. We find that the effect of beliefs on demand is still statistically significant. The point estimate for the increase dummy is almost unaffected, while the coefficient on the decrease dummy decreases in magnitude but remains significant. This result echoes our analysis of the drivers of beliefs in Section 3.1. While investors' demographics and beliefs are correlated, the latter have an independent impact on investment choices. This motivates our structural model and counterfactual exercises in which we assess how changes in beliefs affect investor holdings and thus equilibrium prices.

Column (3) adds our two measures of long-term beliefs as explanatory variables. The effect of short-term beliefs declines in magnitude but the point estimates continue to be statistically significant and economically relevant. As expected, 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.

Second, we explore the "intensive margin" in columns columns (4) to (6) of Table 5. The dependent variable is now the number of cryptocurrencies in an investor's portfolio. On average, investors hold one and a half cryptocurrencies, with a standard deviation slightly higher than two. In column (1), investors who expect price to increase in the following year have a 40% higher number of cryptocurrencies relative to the mean, while investors that expect price to decrease have an almost 30% lower number of cryptocurrencies in their portfolios. Once we include additional controls, the coefficients remain statistically significant and the magnitudes remain large. Column (6) shows that long-term beliefs also impact the extensive margin: respondents thinking that cryptocurrencies will never become mainstream have a 40% lower number of cryptocurrencies, while thinking that Bitcoin has potential is associated with an increase in the number of cryptocurrencies held by about 25%.

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).[13] Further, investors outside the US 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.[14]

Overall, our analysis of 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) about 40% of the investors in cryptocurrencies in 2018 entered the market for the first time in 2018; and 3) positive short-term and long-term beliefs about the future value of cryptocurrencies are associated with a higher probability of holding crytocurrencies and with holding a larger number of crytocurrencies in the portfolio.

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

[13]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).

[14]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/).

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 cryptocurrencies in circulation indexed by $j = 1, ..., J$. 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.[15] 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.[16]

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 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. 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.

The market capitalization of cryptocurrency j at time t is given by $MC_{jt} = P_{jt}S_{jt}$, where

[15] 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.

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

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, and we will propose an instrumental variable strategy to address this. 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). We collect the different characteristics of cryptocurrency j at time t into a vector X_{jt}.[17]

4.2 Demand

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

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

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

Investor wealth evolves according to the following intertemporal budget constraint:

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

[17]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.

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 one-factor structure and that expected returns are a function of the cryptocurrency own characteristics.

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

We specify the portfolio weights as follows:

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

where mc_{jt} is the logarithm of market capitalization of cryptocurrency j at time t, X_{jt} captures other observable characteristics of cryptocurrency j, 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.

We estimate the demand parameters from (8) using the generalized method-of-moments. 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.[18] Also, the inclusion of investors' demographics D_i and beliefs B_{ij} in the demand function allows for flexible substitution patterns across assets. 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. In our main specification, X_{jt} is simply a dummy for whether the currency follows the PoW algorithm or not. Given that the consensus protocol for a currency is rarely changed,[19] it seems reasonable to treat this as a fixed, exogenous characteristic.

Turning to prices, even if the price of cryptocurrencies could arguably be treated as exogenous from the point of view of an individual (small) investor, 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 equity. 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

$$E\left[\epsilon_{ijt}|mc_{jt}, X_{jt}, D_i\right] = E\left(\epsilon_{ijt}\right) = 1. \tag{9}$$

[18] 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 the investors together.

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

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.[20]

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

$$E\left[\epsilon_{ijt}|mc_{jt}, X_{jt}, D_i, B_{ij}\right] = 1. \tag{10}$$

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

Second, we propose a supply-side instrumental variable strategy to deal with any remaining endogeneity concerns. Our instrument is based on differences across cryptocurrencies and over time in the cost of producing new coins. Most of the cryptocurrencies in our data follow the PoW protocol, whereby new coins are generated whenever a new block of transactions is validated. Validating new transactions ("mining") involves employing huge amounts of computational power to solve complex mathematical problems. As a result, mining requires two main inputs: electricity and computer hardware.[21] We combine data on these two inputs to create our instrument.

Figure 4 displays the two key sources of variation.[22] Panel (a) shows the ranking of cryptocurrencies based on the cross-sectional variation in the energy required for mining. For each currency, the measure is constructed by taking the average over time of a mining

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

[21] For more discussion of the production process of cryptocurrencies, see Hayes (2017) and Cong et al. (2019), among others.

[22] In Appendix B, we discuss more in details the data sources and procedure to compute our instrument.

difficulty measure, which is available from https://coinmetrics.io. The most energy-intensive is Bitcoin, while Ripple—a non-Proof-of-Work currency—is the least energy-intensive.

Panel (b) of Figure 4 shows the time-series variation in the price of graphic cards by Micro-Star International (MSI) on Amazon.com. These graphic cards can be used for mining cryptocurrencies, but are employed more widely (e.g. for gaming). We chose this type of cards over hardware that is specifically designed for mining (e.g., the ASUS B250 mining expert motherboard), since the price of the latter is more likely to be correlated with unobservable determinants of cryptocurrency prices (and thus market equity). In other words, one can more convincingly argue that the price of general-purpose graphic cards is driven by exogenous factors (e.g., input prices, demand from gamers) and is therefore a valid instrument. Indeed, panel (b) of Figure 4 shows that, while the price of general-purpose graphic cards did increase following the Bitcoin boom at the end of 2017, the two price time series exhibit substantial independent variation.[23]

Our first-stage regression is then given by:

$$mc_{jt} = \psi \log(\mathit{Energy\ intensity}_j \times \mathit{Price\ of\ graphic\ card}_t) + \tau X_{jt} + \epsilon_{jt}, \tag{11}$$

where $\mathit{Energy\ intensity}_j$ is the energy-intensity ranking of cryptocurrencies and $\mathit{Price\ of\ graphic\ cards}_t$ is the price of the general-purpose graphic cards on Amazon. With this instrumental variable in hand, the exogeneity restriction needed to identify the model becomes:

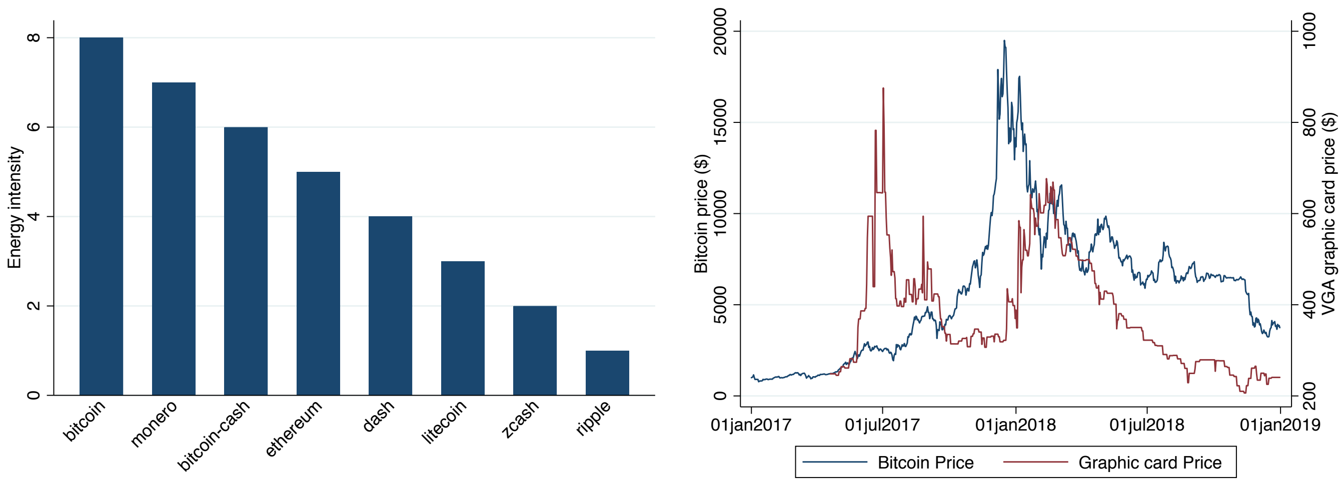
$$E\left[\epsilon_{ijt} | Z_{jt}, X_{jt}, D_i, B_{ij}\right] = 1. \tag{12}$$

where Z_{jt} is our supply-side instrument and all other variables are as in equation (10).

In the next section, we will present results for each of these identifying restrictions. In all cases, 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.[24]

[23] On the contrary, we found that the price of mining-specific graphic cards tracked the evolution of Bitcoin price almost perfectly in the sample period, which further suggests that it is likely to be endogenous. We discuss this further in Appendix B.

[24] There are two complications arising from limitations in the survey data. First, because we do not



(a) Energy Intensity

(b) Price of Hardware

Figure 4: Supply-side instruments

Note: Panel (a) shows a measure of energy intensity for the main cryptocurrencies in our sample. For each cryptocurrency, the measure is constructed by taking the average over time of a mining difficulty measure, which is available from https://coinmetrics.io. Panel (b) shows the price of Bitcoin and the price on Amazon of graphic cards by Micro-Star International (MSI).

Finally, as a robustness check, we also estimate the model with a full set of cryptocurrency fixed effects to capture unobservable time-invariant differences across cryptocurrencies. The exogeneity restriction required for identification of the model becomes:

$$E\left[\epsilon_{ijt}|Z_{jt}, X_{jt}, D_i, \delta_j\right] = 1, \tag{13}$$

where δ_j are cryptocurrencies fixed effects. The advantage of including these fixed effects is that they control for any time-invariant features of cryptocurrencies that are not captured by the PoW dummy and investors' beliefs. On the other hand, this reduces the variation available for identification of currency characteristics—notably market capitalization—especially given our relatively short time. For this reason, we decided to take the model in equation (12) as the baseline. We report the estimates with currency fixed effects as a robustness

observe investor's wealth but only their income bracket, we use the estimate in Emmons and Ricketts (2017) to impute wealth by multiplying income by 6.6. Second, we only observe the total amount each individual invests in cryptocurrencies, but not how that amount is allocated across currencies. To compute the currency-specific weights in the data, we assume that each investor allocates her cryptocurrency budget across the various currencies she hold based on the market shares in our sample.

check in Appendix A.

5.2 Results

5.2.1 Estimated Demand System

Table 6 shows the estimates of the structural demand parameters. In column (1) we report the estimates of the model based on the most restrictive exogeneity condition (9) which does not leverage instrumental variables nor observed investor beliefs. The fact that the coefficient on log market equity 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 approximately -0.40. 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.

In column (2) of Table 6, we include our measures of investor beliefs in the demand system. The coefficient on market equity remains significant and consistent with downward-sloping demand. Interestingly, the point estimate decreases, pushing the price elasticity of demand up to about -0.60. This is consistent with the fact that optimistic (pessimistic) beliefs are positively (negatively) 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, but the effect is imprecisely estimated. Turning to 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 also large. Finally, 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

Table 6: Structural Demand Parameters

	Baseline		IV	
	(1)	(2)	(3)	(4)
Characteristics:				
Log market capitalization	0.644***	0.476***	0.330***	0.198***
	(0.0340)	(0.0369)	(0.0387)	(0.0578)
Proof-of-Work	1.210***	0.869***	1.075***	0.686***
	(0.140)	(0.165)	(0.142)	(0.172)
Short-term beliefs:				
Price decrease		0.0387		0.231
		(0.287)		(0.256)
Price increase		0.305		0.403**
		(0.240)		(0.200)
Long-term beliefs:				
Never mainstream		-1.503***		-1.491***
		(0.344)		(0.305)
Currency Potential		1.632***		1.984***
		(0.114)		(0.127)
Macro controls	Yes	Yes	Yes	Yes
Investor controls	Yes	Yes	Yes	Yes
Average Own-Price Elasticity	-0.43	-0.60	-0.71	-0.84
Cragg-Donald Wald F statistic			34	34
Observations	41,112	41,112	41,112	41,112

Note: Estimates of the structural demand parameters from the model of Section 4. Columns (1) and (2) refer to the baseline model that does not instruments for prices. Columns (3) and (4) show the results for the model that instruments for prices using supply-side shifters. "Price increase (decrease)" is a dummy equal to one if the respondent expects the price of Bitcoin to increase (decrease) 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. "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 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).

this measure of long-term optimism is significant and about five times larger than that for short-term optimistic beliefs.

Column (3) and (4) of Table 6 show estimates that leverage the instrumental variable strategy we discussed in Section 5.1. Before discussing the demand estimates, we briefly comment on the first stage results, which can be found in Table A3 of Appendix A. We estimate equation (11) both in our survey period and in a longer time series. In both cases, we find a positive significant effect of our cost-shifter on market equity. The first stage $F-$statistic is around 60 in the larger sample, and above 30 in the survey sample.

The demand parameters estimated using the instrumental variable strategy exhibit interesting patterns. First, comparing column (1) to column (3) and column (2) to column (4) shows that instrumenting for prices increases the magnitude of the estimated elasticities. This is consistent with the fact that the instrument helps correct for the bias arising from the simultaneity of demand and supply. Second, comparing columns (3) and (4) shows that the price elasticities further increase to about -0.85 when we control for beliefs, just like in the model without instruments. We further note that the coefficients on beliefs are large and statistically significant even when we instrument for price, reinforcing the conclusion that our measures of beliefs do affect demand. Column (4), which combines the instrument for price and the controls for investor beliefs, is our preferred specification and we will use it for the counterfactual simulations in Section 6.

5.2.2 Decomposition, Robustness, and Fit

The demand estimates from Table 6 show that beliefs have a significant effect on investor demand. To better quantify the importance of investor beliefs, we perform a decomposition of the variance of cryptocurrency returns along the lines of Koijen and Yogo (2019). Specifically, we decompose the cross-sectional variance of cryptocurrency returns into four main components: supply of cryptocurrencies (e.g., number of bitcoins in circulation), investors' wealth, investors' beliefs, and "latent demand," i.e. the unobservables denoted ϵ_{ijt} in our model.

Let $g_j(S_t, A_t, B_t, \epsilon_t)$ be the implicit function defining the equilibrium price for cryptocurrency j when the supply of the various cryptocurrencies is given by the vector S_t, and the wealth levels, beliefs and latent demand for the investors in the market are given by the vectors A_t, B_t, ϵ_t, respectively. The log returns for currency j from time t to $t + 1$ can then be written as follows:

$$r_{j,t+1} = \log \frac{P_{j,t+1}}{P_{j,t}} = r_{j,t+1}(S) + r_{j,t+1}(A) + r_{j,t+1}(B) + r_{j,t+1}(\epsilon), \tag{14}$$

where

$$\begin{aligned} r_{j,t+1}(S) &= g_j(S_{t+1}, A_t, B_t, \epsilon_t) - g_j(S_t, A_t, B_t, \epsilon_t) \\ r_{j,t+1}(A) &= g_j(S_{t+1}, A_{t+1}, B_t, \epsilon_t) - g_j(S_{t+1}, A_t, B_t, \epsilon_t) \\ r_{j,t+1}(B) &= g_j(S_{t+1}, A_{t+1}, B_{t+1}, \epsilon_t) - g_j(S_{t+1}, A_{t+1}, B_t, \epsilon_t) \\ r_{j,t+1}(\epsilon) &= g_j(S_{t+1}, A_{t+1}, B_{t+1}, \epsilon_{t+1}) - g_j(S_{t+1}, A_{t+1}, B_{t+1}, \epsilon_t). \end{aligned} \tag{15}$$

Letting $r_{t+1} = [r_{1,t+1}, \ldots, r_{J,t+1}]'$ and similarly for each of the quantities in (15), we can decompose the cross-sectional variance of log returns as

$$\mathrm{Var}(\mathbf{r}_{t+1}) = \mathrm{Cov}(r_{t+1}(S), r_{t+1}) + \mathrm{Cov}(r_{t+1}(A), r_{t+1}) + \mathrm{Cov}(r_{t+1}(B), r_{t+1}) + \mathrm{Cov}(r_{t+1}(\epsilon), r_{t+1}). \tag{16}$$

We use our model to compute each of the terms in (16). We take the baseline period t to be January 2018 (the first of the investor survey) and consider a counterfactual period $t+1$ in which the supply of Bitcoin as well as investors' wealth levels, beliefs and latent demand are all changed by the same percentage.[25]

Table 7 shows the results of the decomposition when the percentage change is set to 5% and 50%.[26] Columns (1) and (2) are based on the estimates from equation column (3) of Table 6, which does not exploit the information on beliefs. On the supply side, variation in the number of Bitcoins in circulation accounts for about 10% of the total variance of returns. On the demand side, investors' wealth explains 20%. Consistent with Koijen and Yogo (2019)'s results for stock returns, we find that latent demand accounts for the lion's share of the cross-sectional variation of cryptocurrency returns, explaining about 70%.

[25]Specifically, denoting the percentage by π%, we increase the supply of Bitcoin, wealth levels and latent demand values by π%. Regarding beliefs, we make investors more optimistic by (i) switching the short-term expectations of π% investors from negative/neutral to positive, and (ii) switching π% investors from not thinking that Bitcoin has long-term potential to holding that view.

[26]The results are robust to varying the magnitude of the change (in addition to the two reported, we simulated 10%, 25%, and 75% changes).

Table 7: Variance Decomposition of Cryptocurrency Returns

	Without beliefs		With beliefs	
	Δ5%	Δ50%	Δ5%	Δ50%
	(1)	(2)	(3)	(4)
Supply:				
Number of Bitcoin in circulation	10%	9%	10%	10%
Demand:				
Investors wealth	20%	19%	2%	2%
Latent demand	70%	72%	9%	6%
Short-term beliefs			9%	9%
Long-term beliefs			70%	73%

Note: Decomposition of the cross-sectional variance of cryptocurrency returns into supply- and demand-side effects. Columns (1) and (2) use the estimates from column (3) of Table 6, while columns (3) and (4) use the estimates from column (4) of Table 6. The values denote the relative contribution of different factors following a change from the baseline period t in January 2018 (the first wave of the investor survey) to a counterfactual period $t+1$ in which the supply of Bitcoin as well as investors' wealth levels, beliefs and latent demand are all changed by the same percentage (5% in columns (1) and (3) and 50% in columns (2) and (4)).

Next, in columns (3) and (4) of Table 7, we explore the role of sentiment and disagreement using the estimates from column (4) of Table 6, which includes the information on investor beliefs. The importance of the supply of Bitcoin is unaffected. However, on the demand side, the inclusion of investors' beliefs reduces the relative importance of both investors' wealth (which declines to about 2%) and latent demand (which decreases to about 7-8%). Short-term beliefs account for almost 10%, while long-term beliefs are now the main driver, explaining around 70% of the total variance. The fact that the explanatory power of latent demand substantially declines once we control for investors' beliefs suggests that including beliefs in the demand system helps control for factors such as sentiment and disagreement which would otherwise be absorbed in latent demand.[27]

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 include time fixed effects to control for all macroeconomic factors that are common across cryptocurrencies and

[27] While our quantitative results are limited to the specific period and industry we study, quantifying the importance of investors' beliefs for the cross-section of stock returns in asset-demand systems more generally could be an interesting area for future research.

investors and may drive cryptocurrency demand. Second, we include cryptocurrency fixed effects, thus capturing all time-invariant differences across cryptocurrencies in characteristics that can affect investors' demand. As shown in Table A4, both the results including time fixed effects and those with cryptocurrency fixed effects are similar to our main estimates in column (4) of Table 6. The main difference is that with the inclusion of cryptocurrency fixed effects, the price coefficient is imprecisely estimated, as we have limited variation over time within currency. In order to allow for additional heterogeneity across investors, we also estimate our model shown in column (4) of Table 6 separately for different age and income groups. Table A5 shows the results. The point estimates exhibit some variation across demographics, but are not statistically different.

Finally, Figure A4 shows the portfolio weights in our data and the ones predicted by the model. Our model slightly underestimates the demand for Bitcoin and Ripple and tends to underestimate the demand for the remaining cryptocurrencies, but overall it captures the patterns observed in the data well.

6 Counterfactual Analyses

With the estimated model (column (4) of Table 6), 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, late investors who bought their first cryptocurrency in 2018 tend to be more optimistic about the future value of cryptocurrencies. However, given the subsequent price dynamics throughout 2018, it is likely that these late optimistic investors experienced potentially large losses from their investment in cryptocurrencies.[28] Distortions in beliefs, "fear of missing out," and contagious social dynamics may have affected the evolution of cryptocurrency prices.[29] 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.[30]

In the first scenario, we remove all investors who bought their first cryptocurrency in 2018 or later, and replace them by sampling at random from the remaining population of investors. This allows us to study how the composition of the investor pool affects equilibrium cryptocurrency prices. In the second scenario, we simply ban entry of late investors, by removing all investors who bought their first cryptocurrency in 2018 or later without replacing them. This captures the full effect of restricting entry. Comparing of the two counterfactuals allows us to separately quantify the effect of investor selection and the effect of reducing market size.

Table 8 shows summary statistics for investor characteristics and beliefs in the baseline and counterfactual scenarios. While demographic variables are unchanged, investors tend to be slightly more pessimistic as one moves from the baseline to the "ban and replace" scenario and from the latter to the "ban without replacement" scenario.

[28]Unfortunately, we only observe a snapshot of investors' holdings which prevents us from computing *realized* gains and losses from *actual* trading behavior over time. However, we can compute the *potential* gains and losses from selling cryptocurrencies for the average investor at each point in time after the first purchase. Figure A6 reports these potential gains and losses in dollar and as a percentage of the initial investment in Bitcoin for two groups of investors: investors who bought their first Bitcoin in 2016-2017, and investors who bought their first Bitcoin in 2018. The former had the potential to make large capital gains averaging $4,000 (or almost 2,000 times the initial investment) if they sold their Bitcoin portfolio in 2018. In the same time period, late investors who bought their first currency in January 2018 could have lost on average around $300 (or about 50% of their original investment).

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

[30]Figure 2 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.

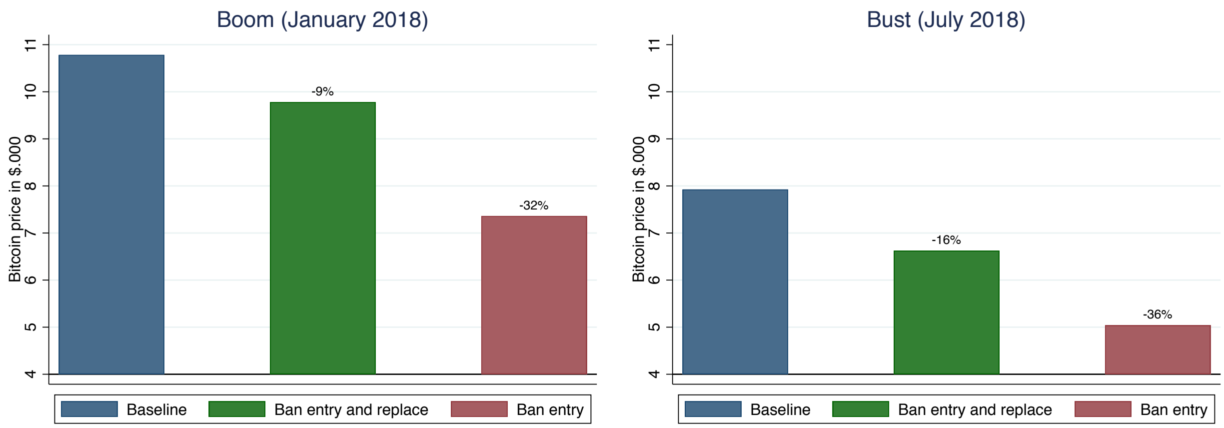
Table 8: Counterfactual Characteristics

	Boom (January 2018)			Bust (July 2018)		
	Baseline	Ban entry and replace	Ban entry	Baseline	Ban entry and replace	Ban entry
	(1)	(2)	(3)	(4)	(5)	(6)
Number of investors	2,047	2,047	1,646	2,521	2,521	1,911
Investor Characteristics:						
Age < 30	0.50	0.50	0.50	0.49	0.49	0.49
Income $< 100K$	0.73	0.73	0.73	0.63	0.63	0.63
Short-term beliefs:						
Positive short	0.63	0.60	0.60	0.61	0.59	0.58
Negative short	0.26	0.29	0.30	0.23	0.24	0.25
Long-term beliefs:						
Never mainstream	0.09	0.10	0.10	0.08	0.09	0.09
Potential top 3	0.46	0.45	0.45	0.47	0.45	0.44
Potential all others	0.10	0.10	0.10	0.10	0.10	0.10

Note: The table reports the number of investors and the average of several variables in the baseline and two counterfactual scenarios. The "ban entry and replace" counterfactual removes all investors who bought their first cryptocurrency in 2018 or later, and replaces them by sampling at random from the remaining population of investors. The "ban entry" counterfactual simply bans entry of late investors by removing all investors who bought their first cryptocurrency in 2018 or later without replacing them. The first three columns refer to the first wave in January 2018, while the last three columns refer to the second wave in July 2018. "Number of investors" is the total number of survey respondents. Investors characteristics are a dummy for whether an investor is 30 years old or younger and with an income below $100,000. "Positive (negative) short" are the fraction of investors who believe the price of cryptocurrencies are going to increase (decrease) over the course of the year. "Never mainstream" is the fraction of investors who think that cryptocurrencies will never become mainstream. "Potential top 3" is the fraction of investors who think that Bitcoin, Ethereum or Ripple have the potential to be successful. "Potential all others" is the fraction of investors who think that cryptocurrencies other than Bitcoin, Ethereum and Ripple have the potential to be successful.

We perform our exercise both in the first wave of our survey in January 2018 (the "boom" period) and in the second wave in July 2018 (the "bust" period). Figure 5 shows the counterfactual equilibrium price of Bitcoin in the different scenarios. First, we show the baseline price predicted by the model at the observed level of beliefs and characteristics. This represents an additional test of the goodness of fit of our model. We predict that the price of Bitcoin in January 2018 was around $10,800, which is close to the observed average price ($10,600).[31] In July 2018, the baseline price predicted by our model is down to about

[31]In January 2018, the average price of Bitcoin was around $13,000. We obtain a lower number due to



(a) Boom (b) Bust

Figure 5: Late buyers, optimistic beliefs and Bitcoin Prices
Note: The figure shows the equilibrium price of Bitcoin in three different scenarios in January 2018 (panel (a)) and July 2018 (panel (b)). The blue bar (first from left in each panel) represents the baseline scenario predicted by our model in Section 4. The "ban entry and replace" counterfactual (second bars from left) removes all investors who bought their first cryptocurrency in 2018 or later and replaces them by sampling at random from the remaining population of investors. The "ban entry" counterfactual (third bars from left) simply bans entry of late investors by removing all investors who bought their first cryptocurrency in 2018 or later without replacing them. Prices are in thousands of US dollars. The numbers above the bars are changes as a percentage of the initial price.

$8,000, consistent with the decline in the observed price which averaged $8,100 that month.[32]

Second, we report prices for the scenario where late buyers are replaced. In the boom, we find that changing the composition of investors decreases the price of Bitcoin by about $1,000 dollars, or approximately 9% of the original value. This is consistent with the fact that, as mentioned above, investors tend to be more pessimistic in the "ban and replace" scenario, paired with the large effects of beliefs on demand we documented in Section 5.2.

Third, Panel (a) of Figure 5 shows that preventing entry of late buyers would decrease the price of Bitcoin by about $3,500 dollars, or approximately 30% of the original value. This large effect is driven by two channels: (i) a change in composition towards more pessimistic

the fact that most survey responses were in the second half of January and the first few days of February 2018.

[32]Because our surveys do not cover the universe of cryptocurrency investors, we need to scale the demand predicted by the model in the sample in order to compute equilibrium quantities. To do so, we calculate what fraction of each currency's market capitalization is held by the investors in our sample and use it as the scaling factor. This procedure is valid as long as our counterfactuals do not affect the representativeness of our sample.

investors, similar to the first counterfactual; and (ii) the fact that the market shrinks. Specifically, banning late buyers decreases the number of potential investors from about 2,000 to about 1,600, as shown in Table 8. Thus, comparing the "ban and replace" counterfactual to the "ban without replacement" exercise allows us to decompose the effect of investor selection from the effect of reducing market size. We find that about one third of the decline in Bitcoin price is due to investor beliefs and the remaining two thirds to the direct effect on market size.

When we repeat the same exercise in the second wave in July 2018 (the "bust" period), we find that changing investor composition alone leads to a larger percentage decline in the price of Bitcoin relative to the boom (around 16%). Given that the full effect of restricting entry is about 36% of the baseline value in July 2018, in the bust period. approximately 45% of the decline is due to investor beliefs and the remaining 55% to the direct effect on market size.

Finally, while we have so far focused on the price of Bitcoin, our model allows us to compute equilibrium prices for all cryptocurrencies in the investors' choice set. Panel A of Table 9 shows the equilibrium prices for all cryptocurrencies in our sample in the baseline and counterfactual scenarios for the boom period.[33]

Replacing optimistic late buyers with less optimistic investors decreases the equilibrium price of cryptocurrency by about 15% on average. However, there is a lot of variation across cryptocurrencies in the effect of investor selection and beliefs. For example, the equilibrium prices of litecoin and dash decrease by less than 7%, while the prices of Ripple and Ethereum decline by around 20%. As expected, fully banning entry has a stronger effect for all cryptocurrencies, with prices declining by about 36% on average.

In column (8) of Table 9, we compute the decline in price in the first counterfactual relative to the decline in the second counterfactual. This highlights how the effect of investor composition and beliefs relative to the total effect varies across currencies. On average, about 40% of the decline is due to investor beliefs and 60% to the direct effect on market

[33]Table A6 in Appendix A repeats the same analysis for the second wave.

Table 9: Counterfactual Equilibrium Prices in the Boom

	Baseline	Ban entry and replace			Ban entry			Decomposition
	$	$	Δ$	Δ%	$	Δ$	Δ%	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
By cryptocurrency:								
Bitcoin	10785.24	9782.06	-1003.18	-9.30	7362.95	-3422.29	-31.73	0.29
Bitcoin-cash	1623.52	1405.98	-217.55	-13.40	1060.61	-562.92	-34.67	0.39
Dash	721.11	673.17	-47.95	-6.65	503.01	-218.11	-30.25	0.22
Ethereum	1071.65	876.57	-195.08	-18.20	661.82	-409.83	-38.24	0.48
Litecoin	177.80	168.17	-9.63	-5.42	126.56	-51.24	-28.82	0.19
Monero	296.82	256.84	-39.98	-13.47	192.63	-104.19	-35.10	0.38
Ripple	1.16	0.91	-0.24	-21.12	0.68	-0.48	-41.26	0.51
Zcash	447.42	408.73	-38.69	-8.65	308.67	-138.75	-31.01	0.28
Average				-15.46			-36.56	0.39

Note: Equilibrium prices for all main cryptocurrencies in our sample in the baseline and two counterfactual scenarios. Baseline is the January 2018 wave (the "boom" period). The "ban entry and replace" counterfactual removes all investors who bought their first cryptocurrency in 2018 or later and replaces them by sampling at random from the remaining population of investors. The "ban entry" counterfactual simply bans entry of late investors by removing all investors who bought their first cryptocurrency in 2018 or later without replacing them. Prices are in US dollars, changes are in US dollars, and percentages are relative to the baseline prices.

size. Again, we find substantial heterogeneity across currencies. For instance, while changes in investor beliefs contribute to around 50% of the total effect for Ripple and Ethereum, the corresponding figure is much lower for other smaller currencies, such as Litecoin and Dash. This heterogeneity across currencies is consistent with the reduced-form evidence from column (4) of Table 4, in which we find that late buyers tend to be especially optimistic about the top three cryptocurrencies (Bitcoin, Ethereum and Ripple). Our structural model shows that the optimism of late buyers for the top cryptocurrencies (perhaps the only ones they are aware of) could account for a large fraction of their price increase during the boom at the end of 2017.

To summarize, we find that the entry of late optimistic investors played an important in the increase of cryptocurrency prices at the end of 2017 and beginning of 2018. Removing investors who bought their first cryptocurrency from 2018 onward leads to an average decline in the value of cryptocurrencies by more than 30%. 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, which we find explains about one third of the total decline in prices for Bitcoin.

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 equilibrium prices and investors' portfolio allocations. Specifically, we simulate the market equilibrium when investor long-term beliefs about PoW currencies become more negative. As mentioned above, PoW is increasingly viewed as an unsustainable protocol and so our counterfactual exercise speaks to how the market would react if investors became more aware of its limitations.[34]

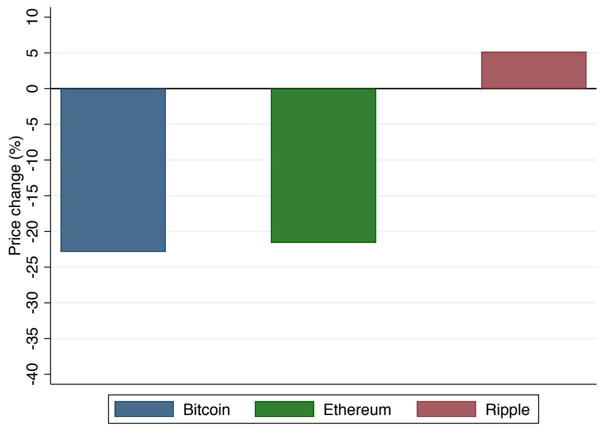
Figure 6 shows the changes in equilibrium prices and allocations for the three largest cryptocurrencies in the market: Bitcoin and Ethereum, which are based on the PoW protocol, and Ripple, which has a different, less energy-intensive consensus protocol. Panel (a) shows percentage changes in equilibrium prices when we make 25% of investors more pessimistic about PoW.[35] The prices of both Bitcoin and Ethereum decline by more than 20%, while Ripple's price increases by approximately 5%. Panel (b) of Figure 6 shows the changes in investor portfolio allocations. The median investor reduces her holdings of Bitcoin and Ethereum by about 10% and 35%, respectively, whereas holdings of Ripple increase by slightly more than 1%.

Table 10 shows equilibrium prices and allocations for all main cryptocurrencies in our sample in the boom period.[36] The average decrease in equilibrium cryptocurrency prices is around 11%, with Bitcoin and Ethereum experience the largest absolute and percentage declines. Among other cryptocurrencies based on the PoW consensus protocol, Litecoin,

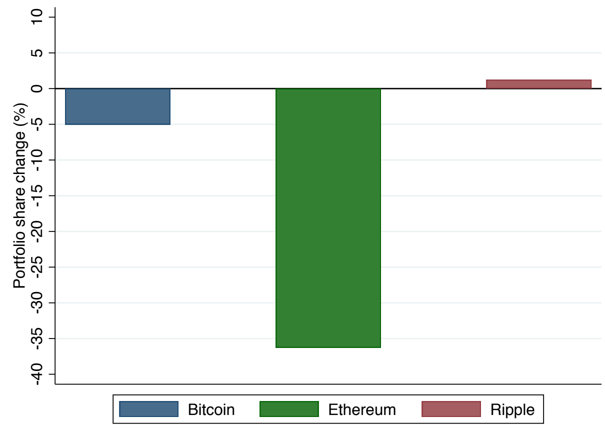
[34] Irresberger et al. (2020) offer an exhaustive discussions of advantages and limitations of different consensus protocols.

[35] 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.

[36] Table A7 in Appendix A replicates the same analysis for the second wave.



(a) Prices



(b) Portfolio Allocations

Figure 6: Energy Sustainability and Cryptocurrency Prices - Allocations
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. 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.

Dash, Zcash and Monero experience a large decline in their equilibrium prices, whereas Bitcoin-cash is the least affected PoW cryptocurrency.

Columns (5) to (8) of Table 10 analyze portfolio allocations of the median investor. In the baseline, the median investor has about $1,600 invested in cryptocurrencies, which is about 0.5% of their total wealth. Approximately $600 are invested in Bitcoin, or slightly less than 40% of the total amount invested in cryptocurrencies. The other cryptocurrencies with the highest shares in investors portfolio are Ethereum (almost 30%) and Litecoin (about 12%).

In the counterfactual, a decline in the expected sustainability of PoW cryptcurrencies leads the median investor to reduce her holdings of those currencies, while Ripple experiences a modest increase. Investors shift only about $30 dollar away from Bitcoin, despite the largest drop in price, while Ethereum and Litecoin experience the largest outflows (around $170 and $90, or 36% and 47% of the initial holdings, respectively). Investors' holdings of Dash, Zcash and Monero decline by a smaller amount in both absolute and percentage terms. Overall, the median investor shifts about $350 previously invested in cryptocurrencies to other investment opportunities.

Table 10: COUNTERFACTUAL EQUILIBRIUM PRICES AND PORTFOLIO ALLOCATIONS

	Prices				Portfolio Allocations			
	Baseline	Counterfactual			Baseline	Counterfactual		
	$	$	Δ$	Δ%	$	$	Δ$	Δ%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
By cryptocurrency:								
Bitcoin	10785.24	8317.30	-2467.94	-22.88	598.08	567.91	-30.18	-5.05
Bitcoin-cash	1623.52	1502.08	-121.45	-7.48	81.35	73.03	-8.32	-10.22
Dash	721.11	620.97	-100.15	-13.89	56.18	54.33	-1.85	-3.29
Ethereum	1071.65	840.41	-231.24	-21.58	476.74	303.73	-173.01	-36.29
Litecoin	177.80	142.92	-34.89	-19.62	193.49	102.62	-90.86	-46.96
Monero	296.82	260.86	-35.96	-12.11	54.61	53.06	-1.55	-2.85
Ripple	1.16	1.22	0.06	5.14	39.17	39.66	0.49	1.25
Zcash	447.42	388.41	-59.00	-13.19	44.54	43.50	-1.04	-2.33
Others	1516.28	1570.55	54.27	3.58	34.06	34.30	0.24	0.70
Average				-11.04				-10.71
Non-crypto assets					329,092	329,449	357	0.11

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). 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.

References

Adam, K., A. Marcet, and J. Beutel (2017): "Stock price booms and expected capital gains," *American Economic Review*, 107, 2352–2408.

Allen, J., R. Clark, and J.-F. Houde (2019): "Search frictions and market power in negotiated-price markets," *Journal of Political Economy*, 127, 1550–1598.

Athey, S., I. Parashkevov, V. Sarukkai, and J. Xia (2016): "Bitcoin pricing, adoption, and usage: Theory and evidence," .

Bailey, M., E. Dávila, T. Kuchler, and J. Stroebel (2019): "House price beliefs and mortgage leverage choice," *The Review of Economic Studies*, 86, 2403–2452.

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

——— (2018): "Extrapolation and bubbles," *Journal of Financial Economics*, 129, 203–227.

Barberis, N., A. Shleifer, and R. Vishny (1998): "A model of investor sentiment," *Journal of financial economics*, 49, 307–343.

Benetton, M. (2018): "Leverage regulation and market structure: An empirical model of the uk mortgage market," *Available at SSRN 3247956*.

Benetton, M., G. Compiani, and A. Morse (2019): "Cryptomining: Local evidence from china and the us," Tech. rep., Working paper.

Bentov, I., A. Gabizon, and A. Mizrahi (2016): "Cryptocurrencies without proof of work," in *International Conference on Financial Cryptography and Data Security*, Springer, 142–157.

Berry, S., J. Levinsohn, and A. Pakes (1995): "Automobile prices in market equilibrium," *Econometrica: Journal of the Econometric Society*, 841–890.

Biais, B., C. Bisiere, M. Bouvard, C. Casamatta, and A. J. Menkveld (2018): "Equilibrium bitcoin pricing," *Available at SSRN 3261063*.

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

Brunnermeier, M. and S. Nagel (2004): "Hedge Funds and the Technology Bubble," *Journal of Finance*, 59, 2013–2040.

Buchak, G., G. Matvos, T. Piskorski, and A. Seru (2018): "The limits of shadow banks," Tech. rep., National Bureau of Economic Research.

Budish, E. (2018): "The economic limits of bitcoin and the blockchain," Tech. rep., National Bureau of Economic Research.

Burnside, C., M. Eichenbaum, and S. Rebelo (2016): "Understanding booms and busts in housing markets," *Journal of Political Economy*, 124, 1088–1147.

Cheah, E.-T. and J. Fry (2015): "Speculative bubbles in Bitcoin markets? An empirical investigation into the fundamental value of Bitcoin," *Economics Letters*, 130, 32–36.

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

Chiu, J. and T. V. Koeppl (2019): "Blockchain-based settlement for asset trading," *The Review of Financial Studies*, 32, 1716–1753.

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

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

Cong, L. W., Z. He, and J. Li (2019): "Decentralized mining in centralized pools," Tech. rep., National Bureau of Economic Research.

CORBET, S., B. LUCEY, AND L. YAROVAYA (2018): "Datestamping the Bitcoin and Ethereum bubbles," *Finance Research Letters*, 26, 81–88.

CRAWFORD, G. S., N. PAVANINI, AND F. SCHIVARDI (2018): "Asymmetric information and imperfect competition in lending markets," *American Economic Review*, 108, 1659–1701.

DE VRIES, A. (2018): "Bitcoin's growing energy problem," *Joule*, 2, 801–805.

EGAN, M., A. HORTAÇSU, AND G. MATVOS (2017): "Deposit competition and financial fragility: Evidence from the us banking sector," *American Economic Review*, 107, 169–216.

EGAN, M. L., A. MACKAY, AND H. YANG (2020): "Recovering Investor Expectations from Demand for Index Funds," Tech. rep., National Bureau of Economic Research.

EMMONS, W. R. AND L. R. RICKETTS (2017): "Household Wealth is at a Post-WW II High: Should We Celebrate or Worry?" Tech. rep., Federal Reserve Bank of St. Louis.

FERNÁNDEZ-VILLAVERDE, J. AND D. SANCHES (2019): "Can currency competition work?" *Journal of Monetary Economics*, 106, 1–15.

FOLEY, S., J. R. KARLSEN, AND T. J. PUTNIŅŠ (2019): "Sex, drugs, and bitcoin: How much illegal activity is financed through cryptocurrencies?" *The Review of Financial Studies*, 32, 1798–1853.

FOSTEL, A. AND J. GEANAKOPLOS (2012): "Tranching, CDS, and asset prices: How financial innovation can cause bubbles and crashes," *American Economic Journal: Macroeconomics*, 4, 190–225.

FOSTER, A. D. AND M. R. ROSENZWEIG (2010): "Microeconomics of technology adoption," *Annu. Rev. Econ.*, 2, 395–424.

GANDAL, N., J. HAMRICK, T. MOORE, AND T. OBERMAN (2018): "Price manipulation in the Bitcoin ecosystem," *Journal of Monetary Economics*, 95, 86–96.

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

Gennaioli, N. and A. Shleifer (2020): *A Crisis of Beliefs*, Princeton University Press.

Giglio, S., M. Maggiori, J. Stroebel, and S. Utkus (2019): "Five facts about beliefs and portfolios," Tech. rep., National Bureau of Economic Research.

Goldfeder, S., H. Kalodner, D. Reisman, and A. Narayanan (2018): "When the cookie meets the blockchain: Privacy risks of web payments via cryptocurrencies," *Proceedings on Privacy Enhancing Technologies*, 2018, 179–199.

Greenwood, R. and A. Shleifer (2014): "Expectations of returns and expected returns," *The Review of Financial Studies*, 27, 714–746.

Griffin, J. M. and A. Shams (2019): "Is bitcoin really un-tethered?" *Available at SSRN 3195066*.

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

Hayes, A. S. (2017): "Cryptocurrency value formation: An empirical study leading to a cost of production model for valuing bitcoin," *Telematics and Informatics*, 34, 1308–1321.

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

Hu, A. S., C. A. Parlour, and U. Rajan (2019): "Cryptocurrencies: Stylized facts on a new investible instrument," *Financial Management*, 48, 1049–1068.

Irresberger, F., K. John, and F. Saleh (2020): "The Public Blockchain Ecosystem: An Empirical Analysis," *Available at SSRN*.

Jenik, I. and K. Lauer (2017): "Regulatory sandboxes and financial inclusion," *Washington, DC: CGAP.*

Kaplan, G., K. Mitman, and G. L. Violante (2017): "The housing boom and bust: Model meets evidence," Tech. rep., National Bureau of Economic Research.

Koijen, R. S., R. J. Richmond, and M. Yogo (2020): "Which Investors Matter for Equity Valuations and Expected Returns?" Tech. rep., National Bureau of Economic Research.

Koijen, R. S. and M. Yogo (2016): "Shadow insurance," *Econometrica*, 84, 1265–1287.

——— (2019): "A demand system approach to asset pricing," *Journal of Political Economy*, 127, 1475–1515.

Lammer, D., T. Hanspal, and A. Hackethal (2019): "Who Are the Bitcoin Investors? Evidence from Indirect Cryptocurrency Investments," *Evidence from Indirect Cryptocurrency Investments (December 10, 2019).*

Liu, Y. and A. Tsyvinski (2018): "Risks and returns of cryptocurrency," Tech. rep., National Bureau of Economic Research.

Liu, Y., A. Tsyvinski, and X. Wu (2019): "Common risk factors in cryptocurrency," Tech. rep., National Bureau of Economic Research.

Makarov, I. and A. Schoar (2019): "Trading and arbitrage in cryptocurrency markets," *Journal of Financial Economics.*

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

Nelson, S. (2018): "Private information and price regulation in the us credit card market," *Unpublished Working Paper.*

Nevo, A. (2001): "Measuring market power in the ready-to-eat cereal industry," *Econometrica*, 69, 307–342.

Ofek, E. and M. Richardson (2003): "Dotcom mania: The rise and fall of internet stock prices," *The Journal of Finance*, 58, 1113–1137.

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

Rauchs, M., A. Blandin, K. Klein, G. Pieters, M. Recanatini, and B. Zhang (2018): "2nd Global Cryptoasset Benchmarking Study," .

Robles-Garcia, C. (2019): "Competition and incentives in mortgage markets: The role of brokers," Tech. rep., Working paper.

Saleh, F. (2019): "Blockchain without waste: Proof-of-stake," *Available at SSRN 3183935*.

Scheinkman, J. A. and W. Xiong (2003): "Overconfidence and speculative bubbles," *Journal of political Economy*, 111, 1183–1220.

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

Shams, A. (2020): "The Structure of Cryptocurrency Returns," *Charles A. Dice Center Working Paper*.

Sockin, M. and W. Xiong (2018): "A model of cryptocurrencies," *Unpublished manuscript, Princeton University*.

Temin, P. and H.-J. Voth (2004): "Riding the south sea bubble," *American Economic Review*, 94, 1654–1668.

Vissing-Jørgensen, A. (2003): "Perspectives on behavioral finance: Does" irrationality" disappear with wealth? Evidence from expectations and actions," *NBER macroeconomics annual*, 18, 139–194.

Xiao, K. (2019): "Monetary transmission through shadow banks," *Available at SSRN 3348424*.

APPENDICES

Appendix A provides supplementary figures and tables, including robustness checks and a model fit exercise. Appendix B discusses the data sources and the procedure we followed to construct our instrument for cryptocurrency prices. Appendix C 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	2,900	0.43
Cryptocurrency questions (general)						
Aware of crypto	3,149	0.69	1,008	0.57	2,900	0.99
Invest in at least one crypto	2,163	0.02	1,008	0.08	2,900	0.47
Cryptocurrency questions (beliefs)						
Price increase	2,143	0.28	606	0.33	2,900	0.57
Price decrease	2,143	0.30	606	0.24	2,900	0.28

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 US. For the trading company survey, we only focus on North America. The variables are as defined in Tables 1 and 2.

Table A2: Beliefs and Demand: Consumers surveys

	SCPC				ING
	Week	Month	Year	All	Year
	(1)	(2)	(3)	(4)	(5)
Beliefs:					
Week Increase	0.025***			0.010	
	(0.006)			(0.007)	
Week Decrease	0.009**			0.025***	
	(0.004)			(0.007)	
Month Increase		0.022***		0.007	
		(0.004)		(0.006)	
Month Decrease		-0.001		-0.018***	
		(0.004)		(0.007)	
Year Increase			0.021***	0.015***	0.191***
			(0.004)	(0.005)	(0.008)
Year Decrease			0.003	0.002	-0.032***
			(0.004)	(0.005)	(0.008)
Demographics:					
Low income	-0.004	-0.004	-0.004	-0.004	-0.029***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.008)
Age $\leq$ 45	0.010***	0.009***	0.008***	0.009***	0.043***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.007)
Education (Below Bachelor)	-0.003	-0.002	-0.002	-0.002	-0.024***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.007)
Male	0.006*	0.006*	0.006*	0.006*	0.054***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.006)
Asset $\leq$ 20K	0.000	-0.000	-0.000	-0.001	
	(0.003)	(0.003)	(0.003)	(0.003)	
Self-employed, part-time, unemployed					0.004
					(0.008)
Year fixed effects	Yes	Yes	Yes	Yes	No
Country fixed effects	No	No	No	No	Yes
Mean Dep. Var.	0.01	0.01	0.01	0.01	0.13
SD Dep. Var.	0.11	0.11	0.11	0.11	0.33
R^2	0.01	0.01	0.01	0.02	0.11
Observations	5,699	5,703	5,706	5,696	9,949

Note: Estimates of coefficients from model (3). Columns (1) to (4) report the results for SCPC. Columns (5) reports the results for ING. The dependent variable is a dummy equal to one if the individuals holds Bitcoin. "Week increase (decrease)" is a dummy equal to one if the respondent expects the price of Bitcoin to increase (decrease) in the following week. "Month increase (decrease)" is a dummy equal to one if the respondent expects the price of Bitcoin to increase (decrease) in the following month. "Year increase (decrease)" is a dummy equal to one if the respondent expects the price of Bitcoin to increase (decrease) in the following year.

Table A3: First Stage

	Full sample	Survey sample
	(1)	(2)
log(Intensity × Hardware price)	0.453***	1.107***
	(0.059)	(0.161)
Macro controls	Yes	Yes
Wave f.e.	No	Yes
Cragg-Donald Wald F statistic	58	34
R^2	0.02	0.40
Observations	2,465	310

Note: First-stage estimates of equation (11) in the full sample and the survey sample. Each observation is a cryptocurrency-date pair. The full sample is all 2018, while the survey sample only includes the dates covered by the trading platform survey.

Table A4: STRUCTURAL DEMAND PARAMETERS: ROBUSTNESS

	Robustness	
	Time fixed effects	Currency fixed effects
	(1)	(2)
Characteristics:		
Log market capitalization	0.206***	-0.713
	(0.0549)	(7.870)
Proof-of-work	0.696***	
	(0.169)	
Short-term beliefs:		
Price decrease	0.173	0.106
	(0.259)	(0.320)
Price increase	0.392*	0.453**
	(0.206)	(0.227)
Long-term beliefs:		
Never mainstream	-1.501***	-1.247**
	(0.295)	(0.507)
Currency Potential	1.967***	1.459***
	(0.124)	(0.128)
Macro controls	Yes	Yes
Investor controls	Yes	Yes
Time fixed effects	Yes	No
Cryptocurrency fixed effects	No	Yes
Observations	41,112	41,112

Note: Estimates of the structural demand parameters from the model of Section 4 that instruments for prices. 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 whetehr 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 A5: Structural Demand Parameters: By Demographics

	By demographics			
	Age		Income	
	≤ 30	> 30	$\leq 100K$	$> 100K$
	(1)	(2)	(3)	(4)
Characteristics:				
Log market capitalization	0.0745	0.336***	0.245***	0.123
	(0.0614)	(0.0884)	(0.0679)	(0.0850)
Proof-of-work	0.809***	0.483*	0.677***	0.717***
	(0.199)	(0.258)	(0.205)	(0.227)
Short-term beliefs:				
Price decrease	0.468	-0.0194	0.523*	-0.146
	(0.350)	(0.343)	(0.309)	(0.411)
Price increase	0.379	0.500*	0.791***	0.0234
	(0.259)	(0.271)	(0.249)	(0.332)
Long-term beliefs:				
Never mainstream	-1.389***	-1.562***	-1.280***	-1.603***
	(0.310)	(0.491)	(0.351)	(0.581)
Currency Potential	2.067***	1.931***	2.063***	1.815***
	(0.137)	(0.193)	(0.149)	(0.200)
Macro controls	Yes	Yes	Yes	Yes
Investor controls	Yes	Yes	Yes	Yes
Observations	20,907	20,205	27,855	13,257

Note: Estimates of the structural demand parameters from the model of Section 4. All columns show the model using the instrumental variable approach. 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).

Table A6: Counterfactual Equilibrium Prices in July 2018

	Baseline	Ban entry and replace			Ban entry			Decomposition
	$	$	Δ$	Δ%	$	Δ$	Δ%	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
By cryptocurrency:								
bitcoin	7927.10	6626.45	-1300.65	-16.41	5041.03	-2886.07	-36.41	0.45
bitcoin-cash	803.69	695.06	-108.63	-13.52	529.47	-274.22	-34.12	0.40
dash	240.37	232.76	-7.61	-3.17	176.31	-64.06	-26.65	0.12
ethereum	458.99	375.98	-83.01	-18.09	285.72	-173.28	-37.75	0.48
litecoin	83.79	74.02	-9.76	-11.65	56.40	-27.38	-32.68	0.36
monero	137.08	126.21	-10.86	-7.93	96.21	-40.87	-29.82	0.27
ripple	0.45	0.36	-0.09	-19.86	0.27	-0.18	-39.21	0.51
zcash	209.29	170.40	-38.89	-18.58	128.77	-80.52	-38.47	0.48
Average				-13.47			-34.32	0.38

Note: Equilibrium prices for the main cryptocurrencies in our sample in the baseline of July 2018 and two counterfactual scenarios. The "ban entry and replace" counterfactual removes all investors who bought their first cryptocurrency in 2018 or later and replaces them by sampling at random from the remaining population of investors. The "ban entry" counterfactual simply bans entry of late investors by removing all investors who bought their first cryptocurrency in 2018 or later without replacing them. Prices are in US dollars, changes are in US dollars, and percentages are relative to the baseline prices.

Table A7: Counterfactual Equilibrium Prices and Portfolio Allocations in July 2018

	Prices				Portfolio Allocations			
	Baseline	Counterfactual			Baseline	Counterfactual		
	$	$	Δ$	Δ%	$	$	Δ$	Δ%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
By cryptocurrency:								
bitcoin	7927.10	6112.46	-1814.64	-22.89	1505.57	1277.91	-227.65	-15.12
bitcoin-cash	803.69	733.40	-70.29	-8.75	287.48	261.39	-26.09	-9.08
dash	240.37	219.38	-21.00	-8.74	166.27	140.23	-26.03	-15.66
ethereum	458.99	360.00	-99.00	-21.57	844.19	724.26	-119.93	-14.21
litecoin	83.79	69.38	-14.41	-17.20	469.44	380.10	-89.34	-19.03
monero	137.08	124.01	-13.07	-9.53	197.26	174.86	-22.40	-11.36
ripple	0.45	0.49	0.04	9.74	162.26	165.14	2.88	1.78
zcash	209.29	188.12	-21.17	-10.12	129.99	117.91	-12.09	-9.30
Others	987.18	1063.45	76.27	7.73	90.79	91.46	0.67	0.73
Average				-8.44				-9.89
Non-crypto assets					329,161	329,455	294	0.09

Note: Equilibrium prices and median portfolio allocations for the main cryptocurrencies in our sample and the outside option in the baseline (July 2018) and a counterfactual scenario in which we make 25% of investors more pessimistic about PoW. Prices and allocations are in US dollars, changes are in US dollars, and percentages are relative to the baseline prices.

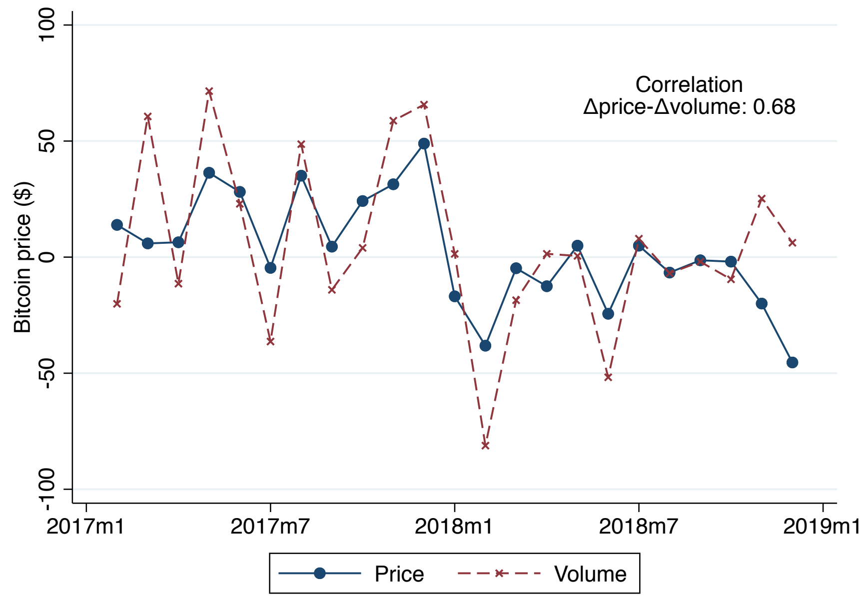


Figure A1: Crypto Mania: ΔPrices and ΔVolumes

Note: The 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.

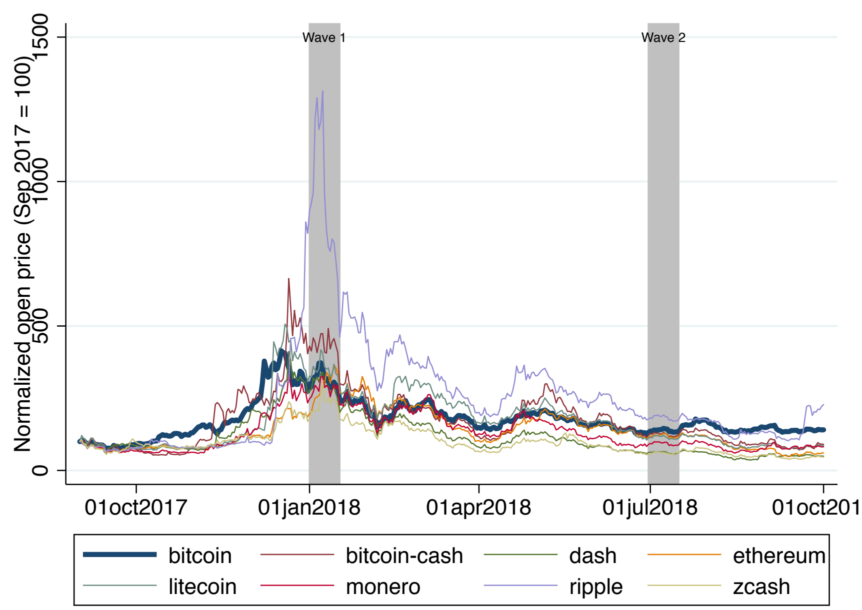


Figure A2: Cryptocurrency Price Variation

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.

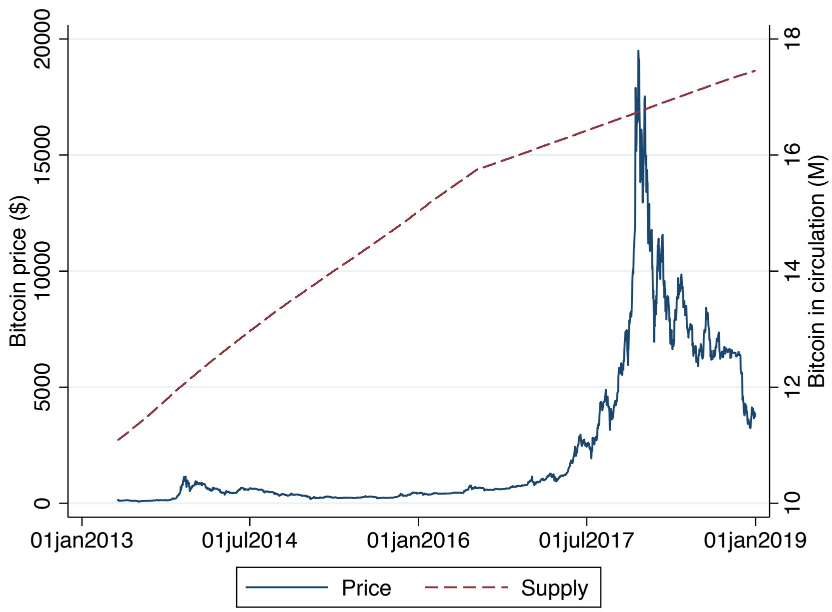


Figure A3: Bitcoin Price and Supply

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.

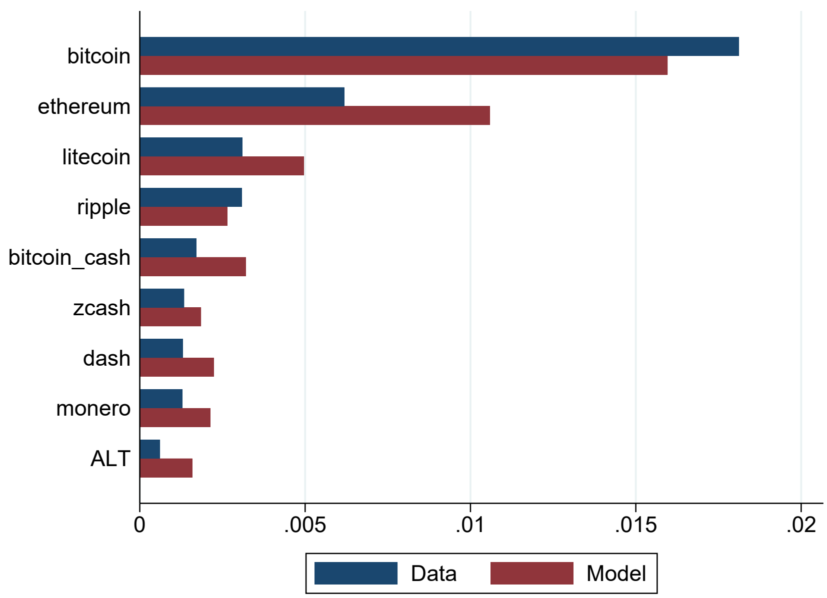


Figure A4: Model Fit

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.

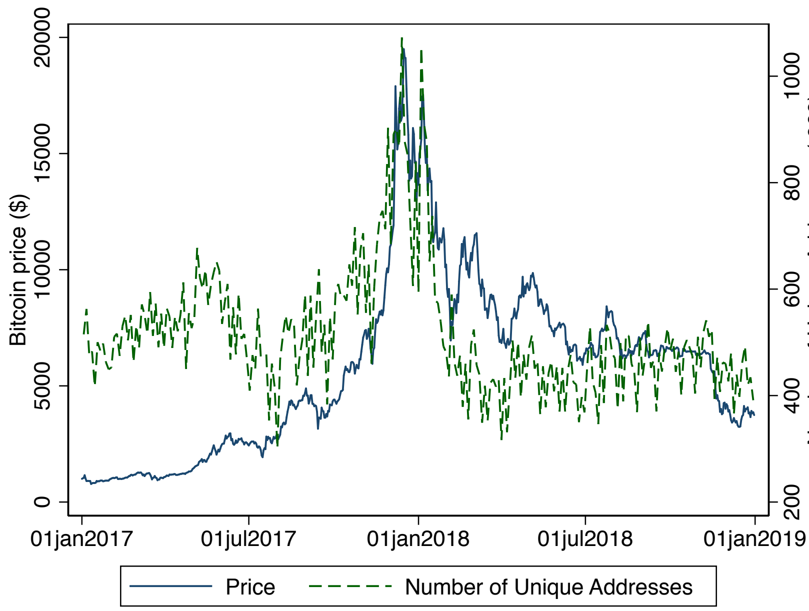
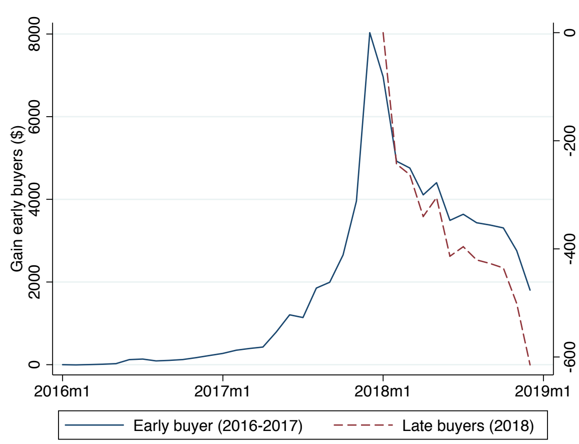
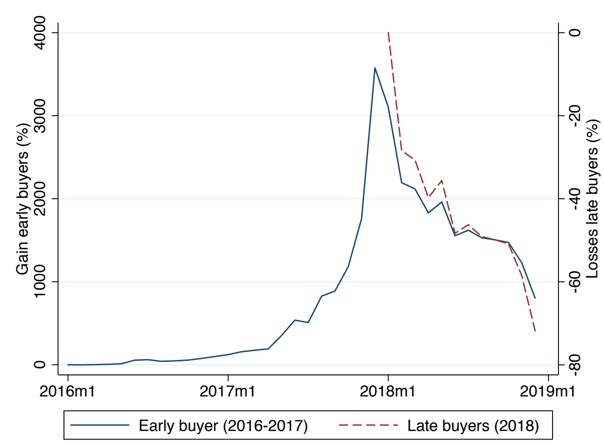


Figure A5: Investors' Entry

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.



(a) Levels



(b) Percentages

Figure A6: Investors' Gains and Losses

Note: The figure shows the potential gains and losses in dollar (panel (a)) and as a percentage of the initial investment (panel (b)) for Bitcoin for two groups of investors: investors who bought their first Bitcoin in 2016-2017, and investors who bought their first Bitcoin in 2018. For investors who bought their first Bitcoin in 2016-2017, we compute the number of Bitcoins in the portfolio by dividing the amount invested in Bitcoin by the average closing price in January 2016. For investors who bought their first Bitcoin in 2018, we compute the number of Bitcoins in the portfolio by dividing the amount invested in Bitcoin by the average closing price in January 2018. Hence, by construction, the gains-losses are equal to zero in January 2016 for investors who bought their first Bitcoin in 2016-2017, and equal to zero in January 2018 for investors who bought their first Bitcoin in 2018.

B Additional Details on the Instrument

In this Appendix, we discuss the data sources and the variables we used to calculate the instrument for cryptocurrency market capitalization. The instrument combines two sources of variation, which are displayed in Figure 4 in the main text: (i) cross-sectional variation in the energy required for mining the different cryptocurrencies, and (ii) time-series variation in the price of hardware used for mining cryptocurrencies. Our supply-side instrument builds on the intuition by Hayes (2017), who proposes a cost production model for valuing Bitcoin. On the one hand, additional computing power added to the global mining network will tend to increase the mining difficulty (in order to keep the rate at which new cryptocurrencies are mined stable), putting upward pressure on the price. On the other hand, increases in mining hardware efficiency due to technological progress or lower electricity prices will reduce marginal costs and prices.

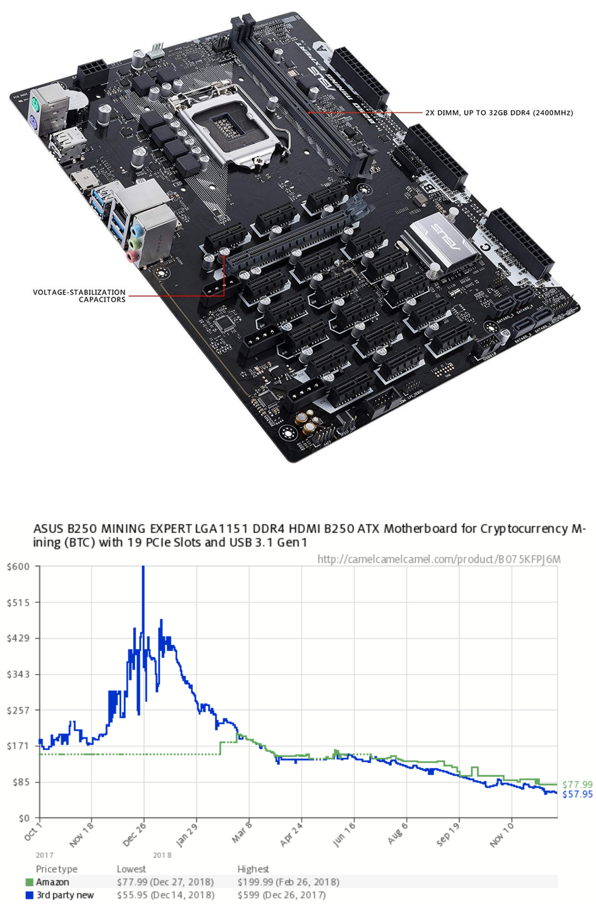
Energy intensity. We construct a measure of energy intensity for each cryptocurrency in our sample. First, we obtained data on hash rate and mining difficulty from https://coinmetrics.io. The hash rate is the speed at which computations are being completed across all miners in the network. Mining difficulty is the average difficulty of finding a hash that meets the protocol-designated requirement (e.g., the difficulty of adding a new block of transactions to the Bitcoin blockchain). Thus, we expect a positive correlation between hash rate and difficulty with electricity consumption. The advantage of our approach is that data on hash rate and difficulty are available for all Proof-of-Work cryptocurrencies, while data on energy consumption are hard to obtain as there is no central register with all active machines and the associated power consumption levels (see https://digiconomist.net/bitcoin-energy-consumption).

We construct the energy intensity score by multiplying the hash rate and mining difficulty for each cryptocurrency, and then taking logs. To get rid of time-series variation in difficulty or hash rate that is potentially correlated with omitted determinants of investors' demand, we average our intensity score over time and obtain a time-invariant ranking across Proof-of-

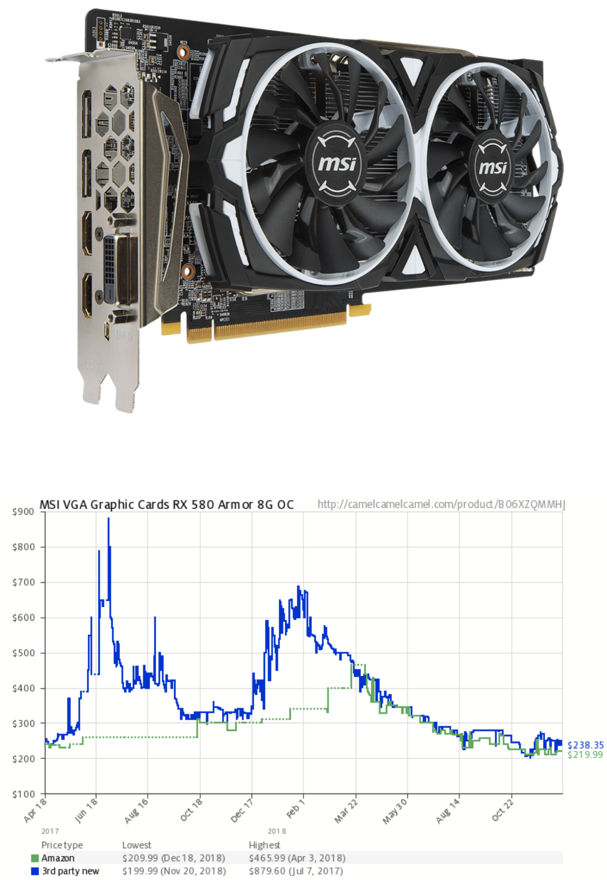
Work cryptocurrencies based on their consumption intensity. Finally, Ripple is based on a Proof-of-Stake consensus protocol which is entirely controlled by its creators, the US-based company Ripple Labs. Therefore, the energy consumption for mining activities should be much lower. Thus we treat Ripple as the least energy intensive cryptocurrency in our sample. The final ranking is shown in Figure 4 in the main text.

Price of hardware. We collect price data for several popular cryptocurrency mining hardware devices sold on Amazon (see https://www.anandtech.com/show/13747/prices-of-mining-hardware-drop). Panel (a) of Figure A7 refers to the B250 Mining Expert motherboard by ASUS, while panel (b) refers to a mainstream graphics card by Micro-Star International (MSI). To obtain a plot of the historical prices from the Amazon website, we use the Chrome extension Keepa. We then use a tool called "WebPlotDigitizer", available here https://automeris.io/WebPlotDigitizer/ to extract numerical values from the plot. We applied this method to a few test graphs generated by us and it performs well.

The price of mining-specific motherboards tracked the evolution of Bitcoin price almost perfectly in our sample period, which suggests that it is likely to be endogenous. The price of general-purpose graphic cards also increases following the Bitcoin boom at the end of 2017, but on can see that the two time series exhibit substantial independent variation. MSI general graphic cards can be used for mining cryptocurrencies, but are employed more widely (e.g., for gaming). Thus, we chose this type of graphic card over the mining-specific hardware, since the price of the latter is more likely to be correlated with unobservable determinants of cryptocurrency prices.



(a) Asus B250 Mining Expert Motherboard



(b) MSI's VGA Graphic Card

Figure A7: Hardware for Mining

Note: Panel (a) shows the B250 Mining Expert Motherboard by Asus and its price on Amazon. Panel (b) shows the MSI's VGA Graphic Card and its price on Amazon. "Third party new" is the lowest price by 3rd party seller on Amazon.

C 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: $< 1,000$, $1,000-10,000$, $10,000-100,000$, $100,000-1,000,0000$, $> 1,000,0000$.