Beliefs and Bubbles:
A structural model of cryptocurrency demand*

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Abstract

We study the role of investors' beliefs in the demand for cryptocurrencies. We develop a structural model of cryptocurrency demand with rich heterogeneity in investors' beliefs and demand elasticities and estimate it using a new investor-level survey obtained from a large trading company. We find that beliefs play an important role for investor demand and equilibrium prices. A counterfactual exercise shows that changing beliefs about the future value of cryptocurrencies from positive to negative for 25% of investors leads to a decrease in the price of Bitcoin by more than $1,500, or 15% of the original value, during the peak in January 2018.

PRELIMINARY AND INCOMPLETE

COMMENTS WELCOME

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1 Introduction

As new financial assets, cryptocurrencies have exhibited extreme volatility in recent times. 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.[1] The patterns of price and volumes in Figure 1 resemble previous episodes such as the 2001 Dotcom bubble (Hong and Stein, 2007). What is less known are what are the dynamics of investors beliefs during similar episodes and their quantitative importance.

In this paper we shed light on the role of beliefs for asset demand using the cryptocurrency industry as a laboratory. Most notably, we address the following question: what is the role of investors' beliefs in driving the rise and fall of the price of Bitcoin and other cryptocurrencies? To answer this question, we build a tractable structural demand model of cryptocurrency demand with rich heterogeneity in investors' beliefs and demand elasticities. We estimate the model using two new surveys on *individual-level* cryptocurrency holdings and expectations. We then use our model to address counterfactual questions. In particular, we show that changing beliefs about the future value of cryptocurrencies from positive to negative for 25% of investors leads to a decrease in the price of Bitcoin by more than $1,500, or 15% of the original value, during the peak in January 2018.

We exploit two new survey datasets that capture the joint behavior of beliefs and choices for US consumers and worldwide investors. The first one is the Survey of Consumer Payment Choice (SCPC). This is a public dataset collected by the Federal Reserve Bank of Boston and the Federal Reserve Bank of Atlanta that provides a comprehensive picture of the payment behavior of U.S. consumers. Most importantly for our analysis, starting in 2015 the survey added a series of questions about cryptocurrency usage as a payment tool. The second survey is a proprietary dataset from a trading platform that asks investors about their current cryptocurrency holdings as well as their expectations about the future evolution of

[1] The correlation between price and volume is 0.89.

these assets.

We begin our analysis with a series of reduced-form regressions to study the role of beliefs for cryptocurrency choice. First, we find that individuals 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%. Second, we find that 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 relative to the mean, while individuals that expect prices to decrease have an almost 30% lower number of cryptocurrencies. Finally, investors are also asked to report about the possibility of cryptocurrencies becoming mainstream and the potential for specific cryptocurrencies to become successful in the long term. Investors thinking that Bitcoin will never become mainstream are about 3 percentage points less likely to hold Bitcoin and hold a 20% percent lower number of cryptocurrencies. The belief that an additional cryptocurrency will be successful is associated with a 32 percentage points higher probability of holding Bitcoin and a 27% higher average number of cryptocurrencies in the portfolio.

Motivated by the reduced-form evidence about the effects of beliefs on demand, we build a tractable model of demand for the top ten cryptocurrencies featuring heterogeneous investors who differ in their beliefs and demand elasticities. We follow Koijen and Yogo (2019) so that our cryptocurrencies portfolio choice model implies a characteristics-based demand system. This approach is very suited to our context in which investors with different levels of wealth, risk-preferences and sophistication participate in a new market with an increasing number of products.[2] In our model, investors have a fixed amount of wealth and choose to allocate it

[2]We do not model the process through which new coins are supplied to the market (see Cong et al. (2019)). The assumption that supply is exogenous is supported by the nature of the proof-of-work protocol (Nakamoto et al., 2008), which follows a predetermined production schedule.

among different cryptocurrencies or invest it in an outside option, which captures all other investment opportunities. Under the assumption of downward sloping demand—which we fail to reject empirically—the equilibrium price of each cryptocurrency is unique and can be computed by aggregating across investors' demands.

We estimate the model via GMM on our trading platform dataset. Following the industrial organization literature on differentiated product demand (Berry et al., 1995; Nevo, 2001), we assume that characteristics other than prices are exogenous. To account for correlation between the endogenous price and unobserved demand shocks, we leverage two unique features of our data. First, since we observe holdings for many different cryptocurrencies, we include cryptocurrency fixed effects to capture unobservable time-invariant differences across cryptocurrencies. Second, we include investor beliefs in the demand system. 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. Therefore, we are able to control for time-varying, currency-specific factors, which further addresses endogeneity concerns. We find that: 1) investor demand is significantly decreasing in price, although the effects are not significant within cryptocurrencies; 2) investors that expect prices to increase in the short term are significantly more likely to demand cryptocurrencies, while an expected decrease in prices does not have a significant effect on demand; 3) investors who think cryptocurrencies are never going to be mainstream have a significantly lower demand for cryptocurrencies; 4) disagreement among investors on the future potential of specific cryptocurrencies generates significant and large differences in investors demand.

With the estimated model, we study the role of beliefs for equilibrium prices. In our first counterfactual simulation, we change investor beliefs and compute the resulting equilibrium prices and holdings. To implement the change in beliefs, we randomly pick 25% of the investors who have negative (positive) expectations and change their expectations to positive (negative). When we make short-term expectations more negative, we find that the price of Bitcoin would have dropped by more than \$1,500 to approximately \$9,000 from the peak in January 2018 at \$11,000 (a decline of about 15%). We perform a similar exercise to study the equilibrium impact of long-term expectations. Specifically, when we increase the fraction of investors thinking that cryptocurrencies will never become mainstream, we find that the equilibrium price of Bitcoin decreases by more than $2,000, or almost 20%. We also find heterogeneity in equilibrium price adjustments both across currencies within wave and across waves within currencies.

In our second counterfactual simulation, we study the role of expectations on portfolio allocation. When we make long-term expectations more negative, we find that investors shift about $230 toward cash. Zcash, litecoin and monero experience the largest decline in percentage terms, dropping by around 13% on average, while ripple seems more resilient with only about a 7% drop. As we make investors more skeptic about the potential of Bitcoin, the median Bitcoin holding decreases from $1,200 to approximately $1,100 (a 10% drop), with largest substitution toward dash and bitcoin-cash.

Literature review. Our work contributes to the literature on beliefs, portfolio choice and asset prices (Piazzesi and Schneider, 2009; Kaplan et al., 2017; Giglio et al., 2019). Our approach is mostly related to the framework proposed by Koijen and Yogo (2019). We build on their work and add beliefs in the indirect utility to understand their effects on price elasticities and on equilibrium prices. Most notably we study the role of beliefs of heterogenous investors for explaining the large increase in cryptocurrency prices during the end of 2017 and their subsequent decline during 2018. Thus our paper is also related to the literature studying bubbles determinants and dynamics (Scheinkman and Xiong, 2003; Adam et al., 2017; Barberis et al., 2018). Finally, we contribute to the growing literature on cryptocurrency markets. Our paper is mostly related to recent papers which have studied 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). We contribute to this literature by providing new detailed investors-level data on cryptocurrency holdings and beliefs and by developing a tractable structural model which we estimate with micro-data and use for counterfactual analysis.

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

2 Data and Facts

2.1 Data

Our analysis combines three main data sources. First, we use public available data on cryptocurrency prices and volumes from Coinmarketcap.[3] The website reports daily data on prices, volumes and circulating supply for several cryptocurrencies. Second, we use the Survey of Consumer Payment Choice (SCPC), which is a collaborative project of the Federal Reserve Bank of Boston and the Federal Reserve Bank of Atlanta. This second source is also public and provides a comprehensive understanding of the payment behavior of U.S. consumers. Most importantly for our analysis, since 2015 the survey added a series of questions about cryptocurrencies to understand their usage as a payment tool. Third, we obtained proprietary data from a trading platform about investors' holdings of cryptocurrencies as well as their expectations about these assets. This data comes from surveys that the trading platform has conducted every six months since January 2018. We have access to the two surveys from 2018, which involved about 5,500 investors.

Table 1 shows the main variables used in the analysis. Panel A shows the information from Coinmarketcap. We show the price for the ten cryptocurrencies which are included in the surveys as well as a price index for the next top 90 cryptocurrencies. period covered by the surveys, the average price of Bitcoin is about \$9,000, ranging from about \$7,000 to almost \$12,000. The other two major cryptocurrencies, Ethereum and Ripple, have a lower price, averaging \$750 and \$0.80, respectively. We also show two macro variables (the S&P

[3]The data can be downloaded at https://coinmarketcap.com.

500 and the Libor) which we include as controls in our analysis.

Panel B of Table 1 shows the main variables we use from the SCPC in the years 2015 to 2018. The average age is 50 years old, but some respondents are as young as 18 years old. The average income if approximately \$75,000, ranging from zero to \$1.2 million. . In the remainder of Panel B we report the key questions about cryptocurrencies. In the full sample, about 50% of respondents say that they have heard of Bitcoin, but only about 70 respondents report owning Bitcoin. This is approximately 1.2% of the respondent that are aware of Bitcoin. Among the small fraction that own Bitcoin there is a large variation in the amount they hold, from 0 to almost 6 million . The survey asks how familiar people are with Bitcoin in 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").

Most importantly for our analysis, the SCPC survey asks a series of questions about the expected value of Bitcoin over different horizons: week, month and year. The answer is a category from one (decrease a lot) to five (increase a lot). The majority of respondents think the price would stay the same, but this fraction decreases from almost 80% for the week horizon to around 50% for the year horizon. On average respondents seem to expect a decrease in prices rather than an increase, but there is substantial heterogeneity across households and horizons. For the week horizon, the decrease is 5 percentage points more common than the increase. This difference goes down to 3 percentage points for the monthly horizon and to 1 percentage point for the yearly horizon.

Finally, Panel C of Table 1 shows the main variables we use from the surveys of an anonymous trading company. Almost 70% of respondents are based in the U.S and about 10% are customers of the trading company. Almost all respondents have heard of Bitcoin and about 40% hold them. Interestingly, the surveys do not only focus 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 eleven cryptocurrencies. About 20% of the respondents declare to be professional investors in cryptocurrencies and around 18% invest for speculative motives. About 21% of investors in cryptocurrencies bought their first cryptocurrency in 2017 or later. Turning to the questions on expectations, more than 60% of respondents believe the price of Bitcoin is going to increase over the course of the year, whereas only about 8% believe that cryptocurrencies are never going to be mainstream.

Before turning to the empirical analysis, in Table 2 we compare our two different survey datasets along a few variables of interest. For comparability, we focus on the SCPC survey from 2018. Respondent in the trading company surveyx have a similar median income to SCPC respondents, but higher average income. This is consistent with the trading company targeting richer investor relative to the more nationally representative sample in the SCPC. In terms of age, respondents in the trading company surveys are younger than SCPC respondents by approximately 18 years, which is consistent with cryptocurrency investors being on average younger. Almost all investors surveyed by the trading company have heard of Bitcoin, as compared to about 70% of SCPC respondents. Regarding holdings, the two surveys also exhibit substantial differences. About 40% of people surveyed by the trading company invest in Bitcoin, while this is the case for about 1% of SCPC respondents. Finally, we compare expectations about the future value of Bitcoin. Only about 13% of the trading company survey respondents think the price of Bitcoin is going to stay the same, while the vast majority of SCPC survey respondents opt for this neutral option. 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 about 10 of SCPC survey respondent. Finally, 22% of trading company survey respondents think the price is going to decrease, while this is the case for about 15% of SCPC survey respondents. All in all, investors from the trading company survey tend to be more optimistic about the future evolution of the Bitcoin price relative to the SCPC respondents.

2.2 Reduced-form Evidence

In this section we present descriptive evidence on the role of beliefs in driving cryptocurrency demand. First, we describe patterns in investor expectations about future Bitcoin prices. Panel (a) of Figure 2 shows the fraction of people who have heard of Bitcoin in the SCPC. In 2015 around 45% of survey respondent have heard of Bitcoin. This fraction increases to almost 50% before the Bitcoin surge at the end of 2017 and by fall 2018 almost 70% say they are aware of Bitcoin. Panel (b) of Figure 2 shows the fraction of people who have heard of bitcoin and think that its price is going to increase in the next year. In 2015 and 2016 around 17% of respondents think the price of Bitcoin is going to increase in the next year. This fraction jumps to more than 25% in the months leading to the Bitcoin peak at the end of 2017 and then decline to around 23% as the price of Bitcoin decreases throughout 2018.

Next, we perform a series of reduced-form regressions to shed some light on the role of expectations in driving cryptocurrency demand and motivate the structural approach in the next section. Specifically, we consider the following specification:

$$y_{ijt} = \alpha + \beta_1 E_{it}[P_{j,t+h}] + \beta_2 E_{it}[F_j] + \gamma X_{ijt} + \epsilon_{ijt}$$

where y_{ijt} is the outcome of interest for individual i (e.g. whether i holds Bitcoin in her portfolio) and cryptocurrency j in period t; $E_{it}[P_{j,t+h}]$ is the expectation by individual i in period t about the future price in periods $t+h$ of cryptocurrency j; $E_{it}[F_j]$ is the expectation by individual i in period t about the fundamental value of cryptocurrency j; and γX_{ijt} are individual demographics and time and cryptocurrency controls. Our coefficients of interest are β_1 and β_2, which capture the impact of expectations on future prices and the fundamental value of cryptocurrencies on investor demand.

Table 3 shows the results from regression (1) for the SCPC survey. The dependent variable is a dummy equal to one if the individuals holds Bitcoin. In columns (1) to (4) we look at the full sample. Columns (1) to (3) show the expectations at different horizons: week, month and year, respectively. Respondents that expect an increase in the price of Bitcoin are more likely to own Bitcoin. The effects are statistically significant and large in magnitude. Positive expectations on future prices are associated with a 2 percentage point higher probability to own Bitcoin. Given an unconditional probability of 1%, this represent a twofold increase. Moreover, the effects are remarkably stable across different horizons. In column (4) of Table 3 we estimate a version of (1) with all expectations at different horizons included simultaneously. We find that individuals that expect an increase (decrease) over the next year (month) are more (less) likely to own Bitcoin. Individuals that expect prices to increase in the following year have a 1.5 percentage point higher probability to own Bitcoin, while individuals that expect prices to decrease in the next month have a 1.8 percentage point lower probability to own Bitcoin. We also find that individual that expect Bitcoin price to decline in the next week are more likely to own Bitcoin. This result may seem surprising, but it is consistent with the fact that individuals may be buying Bitcoin when the price is going down (hence the positive correlation with the expected weekly decrease) with the expectation that it will increase in the next year (hence the positive correlation with the expected yearly increase).

In columns (5) to (8) of Table 3 we show the estimates of regression (1) for only the 2018 wave of SCPC. Despite the lower number of observations, we find a positive and marginally significant correlation between weekly/monthly expected increases in prices and the probability of owning Bitcoin and a strongly significant correlated for yearly expectations. When we estimate the model with all the different horizons together, we again find that individuals that expect an increase (decrease) over the next year (month) are more (less) likely to own Bitcoin. The results for 2018 are even stronger in magnitude. Individuals that expect price to increase in the following year have a 3 percentage point higher probability to own Bitcoin, while individuals that expect price to decrease in the next month have a 2.2 percentage point lower probability to own Bitcoin. As with the full sample, an expected decline in the price of Bitcoin in the following week is associated to a higher probability of owning Bitcoin.

While our interest is in the effect of expectations on Bitcoin demand, the coefficients on a few covariates are also interesting. Female and older individuals are less likely own Bitcoin. We do not find that higher income or assets are associated with a higher probability of owning Bitcoin.

Next, we turn to the surveys conducted by the trading company. Table 4 shows the estimates of regression (1). In columns (1) to (4) the dependent variable is again a dummy equal to one if the individuals holds Bitcoin. 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. Individuals that expect prices to increase in the following year have a 6 percentage point higher probability to own Bitcoin, while individuals that expect prices to decrease have a 4 percentage point lower probability to own Bitcoin. Given an unconditional probability of about 15 percentage points, these effects translate into a 40 (28)% increase (decrease).

In column (2) we control for a set of demographics and additional covariates. We find that the role of expectations is statistically significant and, while the point estimates are lower, the magnitudes are still large. In column (3) we introduce a variable to capture the "fundamental" value of Bitcoin in the form a dummy equal to one if the individual thinks that Bitcoin is never going to become mainstream. As expected, a negative opinion about the long-term success of Bitcoin is associated with a lower probability of holding Bitcoin. Individuals thinking that Bitcoin will never become mainstream are about 3 percentage points less likely to hold Bitcoin. The effect of short-term expected price appreciation is barely affected, while both the significance and magnitude of the short-term expected price depreciation decrease. In column (4) of Table 4 we include an additional variable capturing the number of cryptocurrency that the investor thinks are going to be promising. We find that the belief that an extra cryptocurrency will be successful is associated with a 32 percentage point increase in the probability of holding bitcoin.

Finally, in columns (5) to (8) of Table 4 we study the effect of expectations on the "intensive" margin. The dependent variable is now the number of cryptocurrencies that individuals invest in. Column (1), we find that individuals that expect an increase (decrease) in cryptocurrency prices over the following year are more (less) likely to own many cryptocurrencies. The effect is strongly significant and large in magnitude. Investors that 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, but the magnitudes decline. In column (8) of Table 4 we control for the measure of long-term potential. Respondents thinking that cryptocurrencies will never become mainstream have a 20% lower number of cryptocurrencies, while thinking that cryptocurrencies have potential is associated with an increase in the number of cryptocurrencies by about 27%.

3 Model

Our descriptive results from Section 2 suggest that expectations about the future play an important role in driving cryptocurrency demand. In this Section we develop a simple model of demand for cryptocurrencies and equilibrium prices with heterogeneous investors and differentiated cryptocurrencies. Our model is closely related to Koijen and Yogo (2019), which provides a general framework for assets demand.

3.1 Cryptocurrency Supply

There are N cryptocurrencies in circulation indexed by $n = 1, ..., N$. We define $S_t(n)$ as the supply at time t of cryptocurrency n (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 possible additional 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.[4] Given the pre-determined structure of the production process, we argue that the increase in supply of existing cryptocurrencies is not first-order for the study of short-term boom-bust price dynamics, which is the object of our analysis. The introduction of new cryptocurrencies could be an interesting dimension

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

to explore in a richer model with entry and exit, but our analysis is constrained by the fact that the surveys we use only cover cryptocurrencies with the highest market shares.

The market capitalization of cryptocurrency n at time t is given by $ME_t(n) = P_t(n) \times S_t(n)$, where $P_t(n)$ is the unit price of cryptocurrency n in U.S. dollars. Given that $S_t(n)$ is fixed, only $P_t(n)$ is endogenous in our model. The gross return of holding cryptocurrency n is simply given by $R_t(n) = P_t(n)/P_{t-1}(n)$, as there is no dividends payment associated to holding cryptocurrencies. However, cryptocurrencies differ along other dimensions that investors possibly value. For example, cryptocurrencies can be used as means of payments with different easiness, 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 an algorithm called proof-of-work, while other currencies rely on a proof-of-stake algorithm (Bentov et al., 2016; Budish, 2018; Saleh, 2019). We collect the different characteristics of cryptocurrency n at time t into a vector $X_t(n)$. To fully capture unobservable characteristics that differ across cryptocurrencies, but are common across investors and time-invariant, we include cryptocurrency fixed effects $\delta(n)$.

3.2 Demand

The demand for cryptocurrencies comes from $i = 1, ..., I$ investors. Each investor i in period t is endowed an amount of wealth $A_{i,t}$. Investors choose how to allocate their wealth across the N 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 $R_t(0)$.

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

$$\max_{w_{i,t}(n)} E_{i,t}\left[\log(A_{i,T})\right]. \tag{1}$$

Investor wealth evolves according to the following intertemporal budget constraint:

$$A_{i,t+1} = A_{i,t} \left[(1 - \sum_n w_{i,t}(n)) R_{t+1}(0) + \sum_n w_{i,t}(n) R_{t+1}(n) \right] \tag{2}$$

Investors also face short-sale constraints:

$$w_{i,t}(n) \geq 0; w_{i,t}(n) < 1 \tag{3}$$

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. Given the data available to us, we allow investors to have heterogeneous beliefs on future returns. We also allow investors to disagree on the fundamental value of cryptocurrency n. Unlike Koijen and Yogo (2019), we also include *observable* investor i beliefs on expected returns and perception of cryptocurrency n's "quality." Finally, different investors can forms beliefs based on unobservable (to the econometrician) characteristics of different cryptocurrencies. We capture this residual heterogeneity in the error term $\epsilon_{i,t}(n)$, which we assume to be positive as we do not observe negative positions in our data.

Given these assumptions, investor i cares about cryptocurrency n observable returns and characteristics, observable beliefs on future returns and adoption prospects, and unobservable characteristics. The share of wealth investor in relative to the outside option is given by:

$$\frac{w_{i,t}(n)}{w_{i,t}(0)} = \delta_{i,t}(n) = \exp\left\{\alpha_i me_t(n) + \beta_i X_t(n) + \gamma_i exp_{i,t}(n)\right\} \epsilon_{i,t}(n), \tag{4}$$

where $me_t(n)$ if the logarithm of market equity, $X_t(n)$ are cryptocurrency n observable characteristics, $exp_{i,t}(n)$ are investor i expectations about returns and quality of cryptocurrency n, $\epsilon_{i,t}(n)$ is latent demand.

To recap, we have several sources of heterogeneity in demand: first, demand elasticity to price (α_i); second, observable differences in beliefs ($exp_{i,t}(n)$); third, elasticity to beliefs (γ_i); fourth, latent demand ($\epsilon_{i,t}(n)$).

3.3 Equilibrium

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

$$ME_t(n) = \sum_{i=1}^{I} A_{i,t} w_{i,t}(n), \tag{5}$$

where demand by investor i for cryptocurrency n is obtained by multiplying investor i's portfolio weight by his wealth $A_{i,t}w_{i,t}(n)$. Under the assumption of downward sloping demand ($\alpha_i < 1$ for all investors), Koijen and Yogo (2019) show that the equilibrium is unique. In the counterfactual analysis of Section 5, we solve for the equilibrium market equity using (5). The price of cryptocurrency is then computed as $P_t(n) = \frac{ME_t(n)}{S_t(n)}$.

4 Estimation and Results

4.1 Estimation

We estimate the preference parameters of investors from equation (4) using GMM. In the baseline model, we pool all investors together, but we also re-estimate the model separately for different demographics groups in the Appendix.[5] We first estimate the effect of price (via market equity) on demand with the following identifying condition:

$$E\left[\epsilon_{i,t}(n) | me_t(n), X_t(n)\right] = 1, \tag{6}$$

where $me_t(n)$ if the logarithm of market equity, $X_t(n)$ are cryptocurrency n observable characteristics. Following the industrial organization literature on differentiated product demand (Berry et al., 1995; Nevo, 2001), we assume that characteristics other than prices

[5]Koijen and Yogo (2019) estimate the their model for each investor at each date when investors have more than 1,000 strictly positive holdings. In our setting we have a cross section of 10 cryptocurrencies for most of which holding are equal to zero, which force us to pool our investors together.

are exogenous.

Even if the price of cryptocurrencies could be treated as exogenous from the point of view of the individual investor, unobservable common factors (e.g. "quality") can affect all investors simultaneously thus shifting demand and biasing the coefficient on prices. To account for unobservable time-invariant differences across cryptocurrencies we estimate our demand model with a full set of cryptocurrencies fixed effects. The conditional exclusion restriction then becomes:

$$E\left[\epsilon_{i,t}(n)|me_t(n), X_t(n), \delta(n)\right] = 1, \tag{7}$$

where $\delta(n)$ are cryptocurrencies fixed effects. While our exclusion restriction in equation (7) controls for factors that are common across investors and can be correlated with prices, there can still be common *shocks* to different cryptocurrencies (captured in the error term $\epsilon_{i,t}(n)$) that affect their demand and are correlated with prices. One traditional approach to address this residual price endogeneity is to instrument prices with exogenous supply side shifters. In our case, a natural candidate would be the price of electricity as it represents the main input for mining proof-of-work-based cryptocurrencies. However, Liu and Tsyvinski (2018) found insignificant effects of electricity prices on cryptocurrency returns in the time-series. To tackle this issue, we leverage the information about beliefs in our data to further enrich the demand model. Common trends in expectations across investors can help capture common shocks, thus lowering concerns about unobservable correlation of latent demand with the endogenous price. Our final exclusion restriction is then given by:

$$E\left[\epsilon_{i,t}(n)|me_t(n), X_t(n), \delta(n), exp_i(n)\right] = 1, \tag{8}$$

where $exp_i(n)$ captures investor i's expectations about cryptocurrency n.[6] Defining the vector of all structural demand parameters $\theta = (\alpha, \beta, \delta, \gamma)$, the empirical moments following

[6]As we discussed in Section 2 some of our expectation measures vary at the level of investor i, but are common across cryptocurrencies, while other measures such as potential vary jointly across investor i and cryptocurrencies n.

orthogonality condition (8) are given by:

$$g(\theta) \equiv \sum_{i=1}^{I} \sum_{n=1}^{N} Z_{it}(n) \left[\frac{\frac{w_{i,t}(n)}{w_{i,t}(0)}}{\frac{w_{i,t}(n)(\theta)}{w_{i,t}(0)(\theta)}} - 1 \right], \tag{9}$$

where $\frac{w_{i,t}(n)}{w_{i,t}(0)}$ is the observed fraction invested by investors i in cryptocurrency n relative to the outside option, while $\frac{w_{i,t}(n)(\theta)}{w_{i,t}(0)(\theta)}$ is the predicted fraction from equation (4). We sum across all cryptocurrencies $n = 1, ..., N$ and across all investors $i = 1, ..., I$. Our instruments $Z_{it}(n)$ are the logarithm of market equity, fixed effects for each cryptocurrencies, expectations variables, and interaction of them. The GMM estimator is:

$$\hat{\theta} = \arg\min_{\theta} g(\theta)' W^{-1} g(\theta), \tag{10}$$

where the weighting matrix is the inverse of the covariance matrix.

4.2 Results

Table 5 shows the estimated structural demand parameters. In column (1) we report the estimates of the model without expectations. The point estimate on log market equity $\alpha = 0.175 < 1$ is consistent with downward sloping demand and thus uniqueness of the equilibrium. The coefficient is precisely estimated. We also find that investors seem to have a strong and significant preference for proof-of-work type of cryptocurrencies.

In column (2) of Table 5 we include several measures capturing investors expectations. The coefficient on market equity remains significant and consistent with downward sloping demand. Interestingly, the point estimate increases, thus controlling for expectations makes investors less elastic to price.

We look at how consumers expect cryptocurrencies to perform both in the short term and in the long term. A first question asks investors about the expected value of cryptocurrencies in the remaining part of the year. As expected, investors that believe the value is increasing (decreasing) are more (less) likely to demand cryptocurrencies. A second question asks investors about the year when cryptocurrencies are going to become mainstream. 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. The point estimate on the never mainstream dummy is about three times larger than the point estimates for the price decrease dummy. Finally, we include a dummy that captures investor perceptions of cryptocurrencies potential. This dummy varies both across investors and across cryptocurrencies. We find a significant and strong increase in investor demand associated with the belief that that specific cryptocurrency has potential. The point estimate on the cryptocurrency potential dummy is about four times larger than the point estimates for the price increase dummy. Notice that the coefficient on proof-of-work declines by more than 50% as we include controls for investor beliefs.

Column (3) and (4) of Table 5 include cryptocurrencies fixed effects, thus capturing all time-invariant differences across cryptocurrencies in characteristics that can affect investors' demand. Once we include them, the price coefficient becomes negative but loses significance. The change in magnitude is consistent with the coefficient on price being upward biased due to the simultaneity of demand and supply. In column (4) we report the parameters of our main specification with both cryptocurrencies fixed effects and controls for expectations.[7] The price coefficient is now higher, but still significantly below one, implying demand is downward-sloping. While the introduction of the fixed effects makes our price coefficient not significant, we have enough variation in the cross section of investors and over time to identify the role of beliefs in driving demand. Investors that believe the value is increasing are significantly more likely to demand cryptocurrencies, while the effects of a decrease in value are not significant. The point estimate on the never mainstream dummy is still large and significant. Finally, even within cryptocurrency we have enough disagreement among investors to estimate a significant and large in magnitude effect of the cryptocurrency potential dummy on investors' demand.

While we use investors' demographics and other characteristics as controls, their coeffi-

[7]Given our model is over-identified we perform a J-test and we find that we cannot reject the model .

cients are also of interest. We find that richer investors have a significantly higher demand for cryptocurrencies, while older investors have a significantly lower demand. If we consider cryptocurrencies as fairly new investment products, the result that richer and younger investors are the early adopters of these new products is consistent with previous literature studying technology adoption (see for example Foster and Rosenzweig (2010) for a review). In addition, relatively older people may have more direct experience of losses (for example 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).

Investors outside the US have a significantly higher demand for cryptocurrencies.[8] The countries with the largest demand relative to the number of investors from that country are Asia and South America. This evidence is consistent with Asia, and especially China, being a hub for cryptocurrencies mining and perhaps investments and with some Latin American countries having high appetite for cryptocurrencies given political turmoil and high instability of their national currencies.[9] Both the self-reported accredited and institutional investor types and speculative motives lead to a higher demand for cryptocurrencies. The positive effect of the accredited-institutional investor dummy may capture factors such as self-confidence, which may play a disproportionately high role when prices and trading volumes are high (Odean, 1999; Barber and Odean, 2001). Finally, we do not find significant differences between early adopters and investors who purchased their first cryptocurrency later.

In the Appendix we report several robustness checks and heterogeneity analysis which we only briefly discuss here. We estimate our main model reported in column (4) of Table 5

[8]The shares in our data for different continents are: North America 65 percent; Asia 24 percent, South America 5 percent; Europe 5 percent, Africa 1 percent, Australia less than 0.5 percent.

[9]For China see Rauchs et al. (2018) and Benetton et al. (2019), among others. For South America, Brazil and Argentina are among the early adopters of cryptocurrencies and the founder of hedge the fund Solidus Capital is 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, a recent survey by ING on European, US and Australian customers find that about 9, 8 and 7 percent of them respectively currently own cryptocurrencies (see https://think.ing.com/reports/cracking-the-code-on-cryptocurrency/.

separately for different investors demographics. Further, we add time fixed effects to capture all macro factors that are common across cryptocurrencies and investors and may drive cryptocurrency demand.

5 Counterfactuals

With the estimated model, we study the role of beliefs for equilibrium prices and allocations. In our first counterfactual simulation, we change the fraction of investor with optimistic beliefs about the future price of cryptocurrencies to understand the role they played in the increase of the price of Bitcoin towards the end of 2017. In our second counterfactual simulation, we change the currency-specific expectations about the future prospect of Bitcoin to understand substitution patterns toward other cryptocurrencies and alternative investment opportunities.

5.1 Optimistic beliefs on cryptocurrencies prices and bubbles

With the estimated model we study the role of expectations for the equilibrium Bitcoin price. Figure 3 shows the counterfactual equilibrium price of Bitcoin in difference scenarios using the data from the "boom" period in our data (January 2018). First, we show the baseline price predicted by the model at the observed level of expectations and characteristics. This represents an additional test of the goodness of fit of our model. We predict an equilibrium price of Bitcoin in January 2018 around \$10,800, which is close to the observed average price that month (\$10,600).

We begin by exploring the role of short-term beliefs. Our counterfactual exercise consists of three steps: First, we shock investors' beliefs from negative to positive and viceversa. Second, we recompute the investor-level portfolio shares. Third, we aggregate them to predict equilibrium market equity and equilibrium prices, keeping fixed investor wealth ($A_{i,t}$) and the supply of cryptocurrencies $S_t(n)$. We implement the shock in short-term beliefs by picking a random subset of 25 percent of investors who expect a decrease in cryptocurrencies value and by changing their beliefs about the future value of cryptocurrencies to positive. We find that the price of Bitcoin would have increase by approximately $400, which represents a 4% increase relative to the original price of Bitcoin. When we instead change 25% of investors who expect an increase in cryptocurrencies value to negative beliefs we find that the price would have dropped by more than $1,500 to approximately $9,000. This represents a decline of about 15% relative to the original value.

In Figure 3 we then explore the role of long-term beliefs about the possibility that cryptocurrencies will eventually become mainstream. In our investors sample during the boom period almost all respondents think cryptocurrencies will become mainstream at some point in the future, thus increasing further the share of optimist not surprisingly does not change equilibrium prices much. On the other hand, when we randomly move 25% of investors to the group thinking cryptocurrencies may never become mainstream we find a large decrease in the equilibrium price of Bitcoin. The price declines now by more than $2,000, which represents an almost 20% drop relative to the initial price.

In Appendix 6 we report the results for the same exercise for the July 2018 wave, which we label the "bust" period. Interestingly we find that shocks to short-term beliefs play a more important role during the boom period, while shocks to long-term beliefs have stronger effects during the bust period.

In Figure 3 we focused on the price of Bitcoin, which is the market leader in the cryptocurrencies industry. Table 6 shows the equilibrium prices for all main cryptocurrencies in our sample in the baseline and the two counterfactual scenario when we randomly shock short- and long-term beliefs about the future value of cryptocurrencies from positive to negative for 25% of investors. Panel A shows the counterfactuals starting from the "boom" period in January 2018, while Panel B shows the counterfactuals starting from the "bust" period in July 2018. We find heterogeneity in equilibrium price adjustments both across currencies within wave and across waves within currencies. During the boom, shocking optimistic investors to have short-term negative beliefs on the future value of cryptocurrencies reduce prices of bitcoin-cash and ripple by less than 14%, while ethereum and zcash drop by more than 15.5%. While ripple is one of the currency least affected by the counterfactual change in expectations during the "boom", during the "burst" the same percentage change leads to a decline in the equilibrium price of Ripple of about 13.3%, which is the second largest decline among all cryptocurrencies. Finally, we find an additional dimension of heterogeneity in the effect of short-term relative to long-term beliefs in the boom relative to bust periods, which is consistent with the evidence for Bitcoin only from Figure 3. Short-term beliefs play a more important role during the boom than in the bus. The average decline from changing short-term beliefs of 25% of investors is 15 during the boom period, while about 11% during the bust period.[10] Long-term beliefs instead seem to matter relatively more in the bust than in the boom. The declines are 19% in boom and 21% in the bust.

5.2 Long-term potential and cryptocurrencies allocations

In a second set of counterfactuals, we look at allocations. We adopt a similar approach to that in the previous section. First, we study a "common" shock to all cryptocurrencies by randomly changing by 25% the fraction of investors to the group thinking cryptocurrencies may never become mainstream and study reallocation across cryptocurrencies and toward the outside option. Second, we study an "idiosyncratic" shock to Bitcoin only by randomly changing by 25% the fraction of investors to the group thinking Bitcoin has no potential to be successful in the long-term. Table 7 shows the equilibrium allocation for all main cryptocurrencies in our sample in the baseline and the two counterfactual scenarios just described. Panel A focuses on the boom period, while period B looks at the bust period.

In the baseline we find that the median investor has about $2,000 invested in cryptocurrencies, which is about 1% of their total wealth. Approximately $1,200 are invested in Bitcoin, which is around 60% of the total amount invested in cryptocurrencies. The other cryptocurrencies with the highest shares in investors portfolio are ethereum, litecoin, ripple and bitcoin-cash. Jointly with Bitcoin these four cryptocurrencies represent about 95% of the wealth invested in cryptocurrencies for the median investor. A common decline in the

[10] This calculation excludes bytecoin-bcn and swftcoin.

prospect cryptcurrencies will become mainstream lead to a decline in all cryptocurrencies holdings as investors shift about $230 toward cash. Zcash, litecoin and monero experience the largest decline in percentage terms, dropping by around 13% on average, while ripple seems to be very resilient dropping by only about 7%.

In the last three columns of Table 7 we study the effect of changing the potential for Bitcoin only, all else equal. We find that the fraction of Bitcoin declines by about 10% from $1,200 to approximately $1,100. The majority of money moves to cash. Within cryptocurrencies, the largest substitution in percentage terms is toward dash and bitcoin-cash.

6 Conclusions

In this paper we shed light on the role of beliefs for asset demand using the cryptocurrency industry as a laboratory. We build a tractable structural demand model of cryptocurrencies demand with rich heterogeneity in investors' beliefs and demand elasticities. We estimate the model using two new surveys on individual-level cryptocurrencies holdings and expectations. Our counterfactual exercise shows shows that changing beliefs about the future value of cryptocurrencies from positive to negative for 25 percent of investors lead to a decrease in the price of Bitcoin during the pick in January 2018 by more than $1,500, or 15 percent of the original value.

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Table 1: Summary statistics

	mean	sd	min	p50	max	count
Panel A: Coinmarketcap						
price bitcoin	9175.356	1597.553	6958.32	8616.13	11755.5	33
price ALT	1225.793	274.9466	862.779	1225.309	1655.78	33
price bitcoin_cash	1164.206	393.9468	692.63	1194.23	1767.58	33
price bytecoin_bcn	.0044641	.0018185	.002294	.004381	.007379	33
price dash	486.8342	249.9694	199.5	582.83	811.84	33
price ethereum	745.2773	297.7925	406.8	817.51	1246.7	33
price litecoin	133.2658	51.8061	73.38	150.1	230.51	33
price monero	217.96	86.15972	114.06	236.51	331.77	33
price ripple	.8300856	.3779874	.413776	.891992	1.4	33
price swftcoin	.0177473	.0138086	.00353	.017905	.043805	33
price zcash	334.1776	126.9467	176.54	383.86	509.27	33
sp500	2800.111	64.224	2643.85	2820.4	2872.87	33
libor	2.05308	.2747786	1.73918	1.90394	2.34856	33
Panel B: Survey of consumer payment system						
Demographics						
Age	50.56694	15.12256	18	51	100	11084
Income	73683.65	76171.56	0	55000	1250000	10915
Gender	1.2424	.7125513	0	1	2	11085
Highest level of education	11.20054	2.227846	1	11	16	11085
Homeowner	1.304565	.460244	1	1	2	10996
Net worth	155085.7	870805	0	20000	5.00e+07	10844
Bitcoin questions (general)						
Heard of bitcoin	.5297371	.4991375	0	1	1	11030
Own bitcoin	.0123267	.1103485	0	0	1	5841
How much Bitcoin	8.47e+08	6.94e+09	0	70	5.68e+10	67
How familiar with Bitcoin	1.592162	.8628195	1	1	5	5843
Used Bitcoin in transaction	1.345133	.873927	0	2	2	113
Bitcoin questions (expectations)						
Week Increase	.0789428	.2696728	0	0	1	5789
Week Same	.7913284	.4063943	0	1	1	5789
Week Decrease	.1297288	.3360338	0	0	1	5789
Month Increase	.1462109	.3533481	0	0	1	5793
Month Same	.6777145	.467392	0	1	1	5793
Month Decrease	.1760746	.3809165	0	0	1	5793
Year Increase	.2456443	.4305057	0	0	1	5797
Year Same	.4990512	.5000422	0	0	1	5797
Year Decrease	.2553045	.4360698	0	0	1	5797

	mean	sd	min	p50	max	count
Panel C: Trading Company						
Demographics						
Income: Rich	.3171164	.465399	0	0	1	5077
Age: Old	.1374828	.3443902	0	0	1	5077
Country: Outside US	.3439039	.4750563	0	0	1	5077
Investor	.1083317	.3108295	0	0	1	5077
Bitcoin questions (general)						
Total Choice	1.490053	2.172467	0	1	11	5077
Type: Professional	.2076029	.4056308	0	0	1	5077
speculative motive	.1812094	.3852295	0	0	1	5077
First Purchase: Late	.2115422	.4084421	0	0	1	5077
Bitcoin questions (expectations)						
Price increase	.6205844	.4852945	0	1	1	4586
Price decrease	.242041	.4283657	0	0	1	4586
Never mainstream	.0860745	.2805016	0	0	1	5077

Note: Summary statistics for the main variables used in the analysis. Panel A shows the information from Coinmarketcap. We shows the price for the ten cryptocurrencies which are included in the survey and the price of an alternative cryptocurrencies which is the average of the other 90 largest cryptocurrencies. We also shows the S&P 500 and the libor. Panel B shows the main variables from the Survey of Consumer Payment Choice (SCPC) in the years 2015 to 2018. Demographics are age, income, gender, education, home-ownership status and net worth. Heard of Bitcoin is the fraction of respondents who have heard of Bitcoin relative to the full sample, Own is the fraction owning Bitcoin relative to the respondents who have heard of, How much bitcoin is the amount of invested in Bitcoin in US $, how familiar is an index going from 1 (not at all familiar) to 5 (extremely familiar), used Bitcoin in transaction is a dummy equal to one if the respondent used Bitcoin in a transaction. Expectations at different horizons range from 1 (decrease a lot) to 5 (increase a lot). Panel C of shows 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 trading company customers. Total choice is the sum of cryptocurrencies investors hold, type professional is a dummy equal to one if the respondent report to be a professional investors in cryptocurrencies, speculative motive is a dummy equal to one if the respondent report to invest in cryptocurrencies for speculative motives, first purchase late is a dummy equal to one is the investor purchase the first crytocurrency after 2016. Price increase is a dummy equal to one is the investor respond the price is going to increase until the end of the current year, never mainstream is a dummy equal to one is the investor thinks cryptocurrencies are never going to be adopted.

Table 2: Comparison: SCPC and Trading Company

		Trading Company				SCPC				Difference
		Observations	Median	Mean	S.E.	Observations	Median	Mean	S.E.	
Demo	Income	5,077	50,000	85,936.58	868.7986	3,094	59,000	72,365.3	1,346.23	13,571.28***
	Age	5,031	37	33.30	0.163	3,153	53	51.90	0.268	-18.60***
BTC	% heard of	5,499	1	0.966	0.00245	3,149	1	0.687	0.00827	0.279***
	% holding	5,499	0	0.406	0.00662	3,149	0	0.0117	0.00192	0.394***
	Exp: Incr	5,008	1	0.568	0.00700	2,141	0	0.0920	0.00625	0.476***
	Exp: Same	5,008	0	0.126	0.00469	2,141	1	0.756	0.00929	-0.630***
	Exp: Decr	5,008	0	0.222	0.00587	2,141	0	0.152	0.00777	0.0694***

Note: Summary statistics for the two surveys. trading company reports the full sample of respondents. SCPC reports only the 2018 year. The variables are as defined in Table 1. For the expectations question for SCPC we group 1 (decrease a lot) and 2 (decrease some) into decrease, and 3 (increase some) and 4 (increase a lot).

Table 3: Expectations and Demand: SCPC

	All years				Only 2018			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Week Increase	0.0248**			0.00984	0.0234*			0.0104
	(0.0103)			(0.0126)	(0.0139)			(0.0165)
Week Decrease	0.00934*			0.0251***	0.0115			0.0337**
	(0.00531)			(0.00829)	(0.00915)			(0.0138)
Month Increase		0.0222***		0.00745		0.0178*		-0.00762
		(0.00794)		(0.0101)		(0.0103)		(0.0141)
Month Decrease		-0.00114		-0.0179***		-0.00535		-0.0221**
		(0.00353)		(0.00686)		(0.00627)		(0.0111)
Year Increase			0.0213***	0.0148***			0.0305***	0.0315***
			(0.00571)	(0.00554)			(0.00849)	(0.0106)
Year Decrease			0.00273	0.00237			0.000471	0.000268
			(0.00322)	(0.00526)			(0.00528)	(0.00831)
Age: Old	-0.0107**	-0.00955**	-0.00858**	-0.00878**	-0.0193***	-0.0184**	-0.0166**	-0.0170**
	(0.00437)	(0.00435)	(0.00429)	(0.00429)	(0.00719)	(0.00719)	(0.00715)	(0.00715)
Income: Rich	0.00430	0.00456	0.00413	0.00448	0.00739	0.00737	0.00749	0.00791
	(0.00474)	(0.00472)	(0.00472)	(0.00472)	(0.00780)	(0.00782)	(0.00779)	(0.00781)
Gender: Female	-0.00580	-0.00565	-0.00563	-0.00580	-0.0134**	-0.0138**	-0.0137**	-0.0142**
	(0.00361)	(0.00361)	(0.00358)	(0.00357)	(0.00576)	(0.00593)	(0.00583)	(0.00589)
Asset: More	0.000111	0.000363	0.000306	0.000914	0.00678	0.00755	0.00816	0.00836
	(0.00438)	(0.00438)	(0.00437)	(0.00439)	(0.00649)	(0.00656)	(0.00648)	(0.00647)
Constant	-0.422**	-0.426**	-0.442**	-0.414*	-2.819	-2.560	-2.763	-2.897
	(0.211)	(0.215)	(0.212)	(0.214)	(1.901)	(1.886)	(1.900)	(1.913)
y-mean	0.0125	0.0124	0.0124	0.0125	0.0171	0.0171	0.0171	0.0171
y-sd	0.111	0.111	0.111	0.111	0.130	0.130	0.130	0.130
R-Square	0.00881	0.00987	0.0110	0.0148	0.0130	0.0130	0.0205	0.0251
Observations	5699	5703	5706	5696	2105	2105	2107	2104

Note: Estimates of coefficients from model (1). Columns (1) to (4) report the results from the full sample. Columns (5) to (8) report the results from the 2018 survey. 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 expect the price of Bitcoin to increase (decrease) in the following week. Month increase (decrease) is a dummy equal to one if the respondent expect the price of Bitcoin to increase (decrease) in the following month. Year increase (decrease) is a dummy equal to one if the respondent expect the price of Bitcoin to increase (decrease) in the following year. Demographics controls are dummies for age, income, gender and assets.

Table 4: Expectations and Demand: Trading Company

	Whether Invest in Bitcoin				Number of Invested Currencies			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Price increase	0.0609***	0.0484***	0.0461***	0.0386***	0.670***	0.532***	0.508***	0.498***
	(0.00786)	(0.00699)	(0.00701)	(0.00664)	(0.0865)	(0.0769)	(0.0771)	(0.0764)
Price decrease	-0.0396***	-0.0201***	-0.0176**	-0.0111*	-0.435***	-0.221***	-0.193**	-0.185**
	(0.00785)	(0.00692)	(0.00694)	(0.00660)	(0.0863)	(0.0761)	(0.0763)	(0.0756)
Income: Rich		0.0617***	0.0611***	0.0600***		0.678***	0.672***	0.671***
		(0.00742)	(0.00741)	(0.00707)		(0.0816)	(0.0815)	(0.0809)
Age: Old		-0.0347***	-0.0348***	-0.0311***		-0.382***	-0.383***	-0.378***
		(0.00638)	(0.00638)	(0.00618)		(0.0702)	(0.0702)	(0.0697)
Country: Outside US		0.0412***	0.0396***	0.0405***		0.453***	0.436***	0.437***
		(0.00620)	(0.00619)	(0.00589)		(0.0682)	(0.0681)	(0.0676)
Type: Professional		0.0489***	0.0474***	0.0479***		0.538***	0.521***	0.522***
		(0.00875)	(0.00876)	(0.00833)		(0.0962)	(0.0964)	(0.0957)
speculative motive		0.0748***	0.0742***	0.0672***		0.823***	0.816***	0.807***
		(0.00837)	(0.00837)	(0.00792)		(0.0921)	(0.0920)	(0.0913)
Investor		0.0572***	0.0565***	0.0493***		0.629***	0.621***	0.612***
		(0.0114)	(0.0114)	(0.0107)		(0.126)	(0.125)	(0.124)
First Purchase: Late		0.0916***	0.0911***	0.0835***		1.008***	1.002***	0.992***
		(0.00762)	(0.00762)	(0.00729)		(0.0839)	(0.0839)	(0.0833)
log_sp500		0.545	0.549	0.573		5.994	6.040	6.071
		(0.526)	(0.525)	(0.471)		(5.784)	(5.778)	(5.689)
log_libor		0.103***	0.102***	0.105***		1.129***	1.126***	1.130***
		(0.0216)	(0.0216)	(0.0204)		(0.237)	(0.237)	(0.235)
Never mainstream			-0.0321***	-0.0154***			-0.353***	-0.331***
			(0.00525)	(0.00539)			(0.0578)	(0.0574)
Currencies Potential				0.322***				0.419***
				(0.00602)				(0.0247)
Constant	0.114***	-4.367	-4.395	-4.650	1.252***	-48.04	-48.34	-48.68
	(0.00670)	(4.169)	(4.165)	(3.737)	(0.0737)	(45.86)	(45.81)	(45.11)
y-mean	0.142	0.142	0.142	0.142	1.563	1.563	1.563	1.563
y-sd	0.349	0.349	0.349	0.349	2.208	2.208	2.208	2.208
R-Square	0.0155	0.0751	0.0757	0.210	0.0467	0.227	0.229	0.234
Observations	50446	50446	50446	50446	50446	50446	50446	50446

Note: Estimates of coefficients from model (1). In columns (1) to (4) the dependent variable is a dummy equal to one if the investor invest in Bitcoin. In columns (5) to (8) the dependent variable is the number of currencies investors hold. Price increase (decrease) is a dummy equal to one if the respondent expect the price of Bitcoin to increase (decrease) in the following year. Never mainstream is a dummy equal to one if the investor think cryptocurrencies are never going to be adopted. Currencies potential is a dummy equal to one if the investor think some specific currencies have 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 trading company customer, year of first purchase. Macroeconomic controls are the logarithm of the S&P 500 and the libor.

Table 5: Structural Demand Parameters

	Baseline		Fixed effects	
	(1)	(2)	(3)	(4)
Log market cap	0.175***	0.371***	-0.293	0.380
	(0.0519)	(0.0377)	(0.337)	(0.470)
Price decrease		-0.462*		-0.360
		(0.279)		(0.262)
Price increase		0.477**		0.649***
		(0.235)		(0.222)
Never mainstream		-1.349***		-1.182***
		(0.317)		(0.325)
Currencies Potential		1.973***		1.532***
		(0.118)		(0.0927)
Proof-of-work	1.842***	0.718***		
	(0.172)	(0.145)		
Income: Rich	2.535***	1.928***	2.001***	1.866***
	(0.189)	(0.179)	(0.196)	(0.184)
Age: Old	1.811**	-0.459*	-0.454*	-0.564**
	(0.822)	(0.263)	(0.273)	(0.276)
Country: Outside US	0.0765	0.716***	0.411**	0.632***
	(0.188)	(0.209)	(0.169)	(0.185)
Type: Professional	1.893***	1.999***	1.598***	1.821***
	(0.189)	(0.185)	(0.179)	(0.185)
Speculative motive	0.157	0.821***	0.868***	0.939***
	(0.171)	(0.183)	(0.158)	(0.171)
Investor	0.628***	1.222***	1.327***	1.348***
	(0.235)	(0.236)	(0.233)	(0.237)
First Purchase: Late	0.573***	0.121	0.255	0.102
	(0.184)	(0.192)	(0.178)	(0.178)
Cryptocurrencies f.e.	NO	NO	YES	YES
Macro controls	YES	YES	YES	YES
Observations	49215	49215	49215	49215

Note: Estimates of the structural demand parameters from the demand model of Section 3. Price increase (decrease) is a dummy equal to one if the respondent expect the price of Bitcoin to increase (decrease) in the following year. Never mainstream is a dummy equal to one if the investor think cryptocurrencies are never going to be adopted. Currencies potential is a dummy equal to one if the investor think some specific currencies have 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 trading company customer, year of first purchase. Columns (1) and (2) include a dummy for proof-of-work cryptocurrencies. Columns (3) and (4) include cryptocurrencies fixed effects. Macroeconomic controls are the logarithm of the S&P 500 and the libor.

Table 6: Counterfactual Equilibrium Prices with Negative Beliefs

	Baseline	Short term negative beliefs			Long term negative beliefs		
	$	$	Δ$	Δ%	$	Δ$	Δ%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Boom (January 2018)							
ALT	1,520.69	1,340.63	-180.06	-11.84	1,229.16	-291.53	-19.17
bitcoin	10,806.15	9,142.41	-1,663.74	-15.40	8,704.32	-2,101.83	-19.45
bitcoin-cash	1,635.14	1,416.22	-218.92	-13.39	1,344.41	-290.73	-17.78
bytecoin-bcn	0.01	0.01	0.00	0.00	0	-0.01	-100.00
dash	720.61	609.10	-111.51	-15.47	589.94	-130.67	-18.13
ethereum	1,077.01	908.71	-168.30	-15.63	872.97	-204.04	-18.95
litecoin	177.66	151.14	-26.52	-14.93	139.95	-37.71	-21.23
monero	296.03	250.45	-45.58	-15.40	243.36	-52.67	-17.79
ripple	1.15	0.99	-0.16	-13.91	0.94	-0.21	-18.26
swftcoin	0.03	0.02	-0.01	-33.33	0.02	-0.01	-33.33
zcash	447.52	377.74	-69.78	-15.59	355.94	-91.58	-20.46
Panel B: Bust (July 2018)							
ALT	990.33	884.08	-106.25	-10.73	816.28	-174.05	-17.57
bitcoin	7,935.94	6,926.10	-1,009.84	-12.72	6,360.47	-1,575.47	-19.85
bitcoin-cash	807.26	707.58	-99.68	-12.35	616.81	-190.45	-23.59
bytecoin-bcn	0	0	0.00	.	0	0.00	.
dash	241.51	211.73	-29.78	-12.33	186.56	-54.95	-22.75
ethereum	461.75	408.31	-53.44	-11.57	365.45	-96.30	-20.86
litecoin	84.05	73.11	-10.94	-13.02	66.66	-17.39	-20.69
monero	137.84	122.81	-15.03	-10.90	106.67	-31.17	-22.61
ripple	0.45	0.39	-0.06	-13.33	0.36	-0.09	-20.00
swftcoin	0.01	0.01	0.00	0.00	0	-0.01	-100.00
zcash	210.23	181.44	-28.79	-13.69	160.53	-49.70	-23.64

Note: Equilibrium prices for all main cryptocurrencies in our sample in the baseline and two counterfactual scenarios. Short-term negative beliefs randomly shock short-term beliefs about the future value of cryptocurrencies from positive to negative for 25 percent of investors. Long-term negative beliefs randomly shock long-term beliefs about the probability cryptocurrencies become mainstream from positive to negative for 25 percent of investors. Prices are in US dollars. Changes are in US dollars and percent of the initial price.

Table 7: COUNTERFACTUAL EQUILIBRIUM ALLOCATION WITH DIFFERENT POTENTIALS

	Baseline	Cryptocurrencies Never Mainstream			Bitcoin no potential		
	\$	\$	Δ\$	Δ%	\$	Δ\$	Δ%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Boom (January 2018)							
ALT	15.36	14.50	-0.87	-5.63	16.18	0.82	5.36
bitcoin	1231.51	1108.65	-122.86	-9.98	1106.83	-124.68	-10.12
bitcoin-cash	62.77	56.93	-5.84	-9.30	66.01	3.24	5.17
bytecoin-bcn	7.92	6.84	-1.08	-13.64	8.03	0.11	1.39
dash	27.27	24.51	-2.76	-10.11	28.92	1.65	6.05
ethereum	312.88	284.71	-28.17	-9.00	325.73	12.85	4.11
litecoin	236.44	206.28	-30.16	-12.76	239.23	2.79	1.18
monero	30.44	26.99	-3.45	-11.32	31.16	0.72	2.37
ripple	72.63	67.50	-5.13	-7.06	75.64	3.01	4.15
swftcoin	11.75	10.61	-1.13	-9.66	11.95	0.20	1.72
zcash	20.80	17.52	-3.29	-15.80	20.28	-0.52	-2.51
outside asset	329140.69	329369.93	229.24	0.07	329320.96	180.28	0.05
Panel B: Bust (July 2018)							
ALT	50.57	46.57	-3.99	-7.89	52.66	2.09	4.14
bitcoin	4241.46	3494.05	-747.42	-17.62	3384.17	-857.29	-20.21
bitcoin-cash	174.52	167.54	-6.98	-4.00	188.05	13.53	7.75
bytecoin-bcn	21.72	20.25	-1.47	-6.78	22.70	0.98	4.51
dash	64.85	60.68	-4.18	-6.44	67.43	2.58	3.97
ethereum	756.78	694.82	-61.96	-8.19	787.43	30.64	4.05
litecoin	603.76	554.00	-49.75	-8.24	637.12	33.37	5.53
monero	81.21	75.03	-6.18	-7.61	83.68	2.47	3.05
ripple	226.95	210.08	-16.87	-7.44	237.15	10.20	4.49
swftcoin	26.63	24.97	-1.66	-6.23	28.00	1.37	5.16
zcash	59.63	55.01	-4.62	-7.75	60.77	1.14	1.91
outside asset	328897.21	329203.48	306.27	0.09	329166.39	269.18	0.08

Note: Equilibrium allocations for all main cryptocurrencies in our sample and the outside option in the baseline and two counterfactual scenarios. Cryptocurrencies never mainstream randomly shock long-term beliefs about the probability cryptocurrencies become mainstream from positive to negative for 25 percent of investors. Bitcoin no potential randomly shock the beliefs about the potential for Bitcoin only from positive to negative for 25 percent of investors. Allocation are in US dollars. Changes are in US dollars and percent of the initial price.

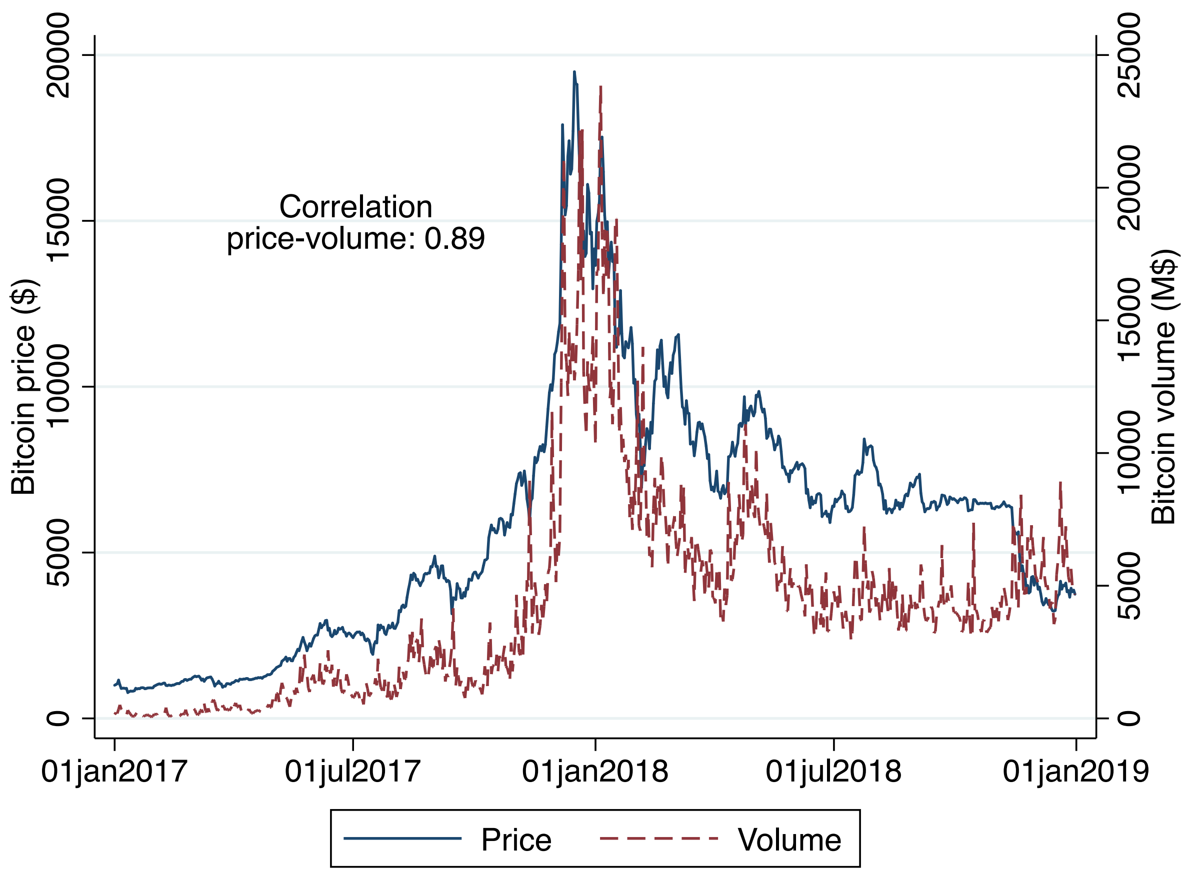

Figure 1: Crypto Mania: Prices and volumes

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 Coinmarketcap.

(a) Awareness and price

(b) Expectations 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 have heard of Bitcoin (awareness). Panel (b) shows the fraction of people who have heard of bitcoin that think the price of bitcoin is going to increase in the next year (expectation). The awareness and expectation measures comes 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 have heard of bitcoin and appear in all waves.

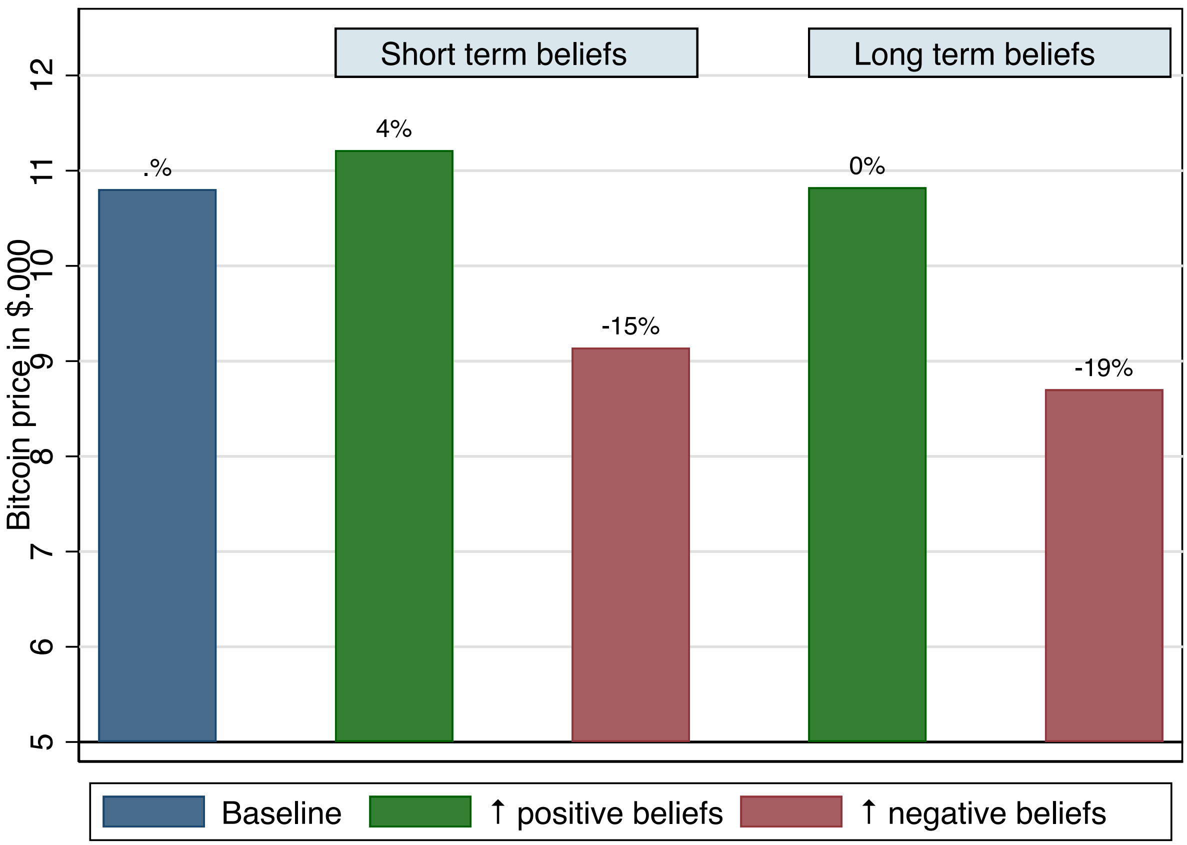

Figure 3: Counterfactual Expectations and Bitcoin Price: Boom

Note: The figure shows the equilibrium price of Bitcoin in five different scenarios for January 2018 wave (the "boom" period). The blue bar represents the baseline scenario predicted by our model in Section 3. Short-term beliefs randomly shock short-term beliefs about the future value of cryptocurrencies from negative (positive) to positive (negative) for 25 percent of investors. Long-term negative beliefs randomly shock long-term beliefs about the probability cryptocurrencies become mainstream from negative (positive) to positive (negative) for 25 percent of investors. The green bars represent the switch from negative to positive beliefs. The red bars represent the switch from positive to negative beliefs. Prices are in thousands of US dollars. The numbers in the figure are changes as percent of the initial price.

ADDITIONAL APPENDIX

Table A1: Structural Demand Parameters: By Demographics

	(1) Entire Sample	(2) Young	(3) Old	(4) Poor	(5) Rich
Market Cap (log)	0.402***	0.383***	0.810***	0.428***	0.398***
	(0.0379)	(0.0368)	(0.0872)	(0.0462)	(0.0381)
Price increase	0.579**	0.481**	1.543**	1.153***	-0.0650
	(0.229)	(0.236)	(0.676)	(0.311)	(0.352)
Price decrease	-0.317	-0.236	-1.231*	0.0679	-0.862**
	(0.275)	(0.283)	(0.675)	(0.381)	(0.398)
Never mainstream	-1.416***	-1.440***	-0.536	-1.104***	-2.177***
	(0.316)	(0.306)	(0.954)	(0.356)	(0.457)
Currencies Potential	1.922***	1.892***	1.907***	2.038***	1.755***
	(0.113)	(0.120)	(0.236)	(0.144)	(0.163)
Constant	9.627	-53.79	-90.74	97.19	-105.4
	(79.82)	(89.72)	(97.15)	(130.1)	(66.17)
Observations	49215	42948	6267	33282	15933

Note: Summary statistics for the main variables used in the analysis. Panel A reports the variable in the Product Sales Database. Panel B reports the variables from Moneyfacts. Panel C reports the variables from the Bank of England Funding for Lending Scheme Database.

Table A2: Structural Demand Parameters: Time fixed effects

	(1) Just ME	(2) Just short exp	(3) Just long exp	(4) Just potential	(5) Baseline
Market Cap (log)	0.511***				0.417***
	(0.0314)				(0.0358)
Price increase		0.900***			0.464*
		(0.181)			(0.238)
Price decrease		0.0251			-0.453*
		(0.224)			(0.273)
Never mainstream			-1.419***		-1.456***
			(0.329)		(0.314)
Currencies Potential				2.603***	1.973***
				(0.117)	(0.113)
Constant	-20.58***	-8.594***	-7.797***	-9.303***	-19.52***
	(0.854)	(0.233)	(0.187)	(0.250)	(0.922)
Observations	49215	50248	50248	50248	49215

Note: Summary statistics for the main variables used in the analysis. Panel A reports the variable in the Product Sales Database. Panel B reports the variables from Moneyfacts. Panel C reports the variables from the Bank of England Funding for Lending Scheme Database.

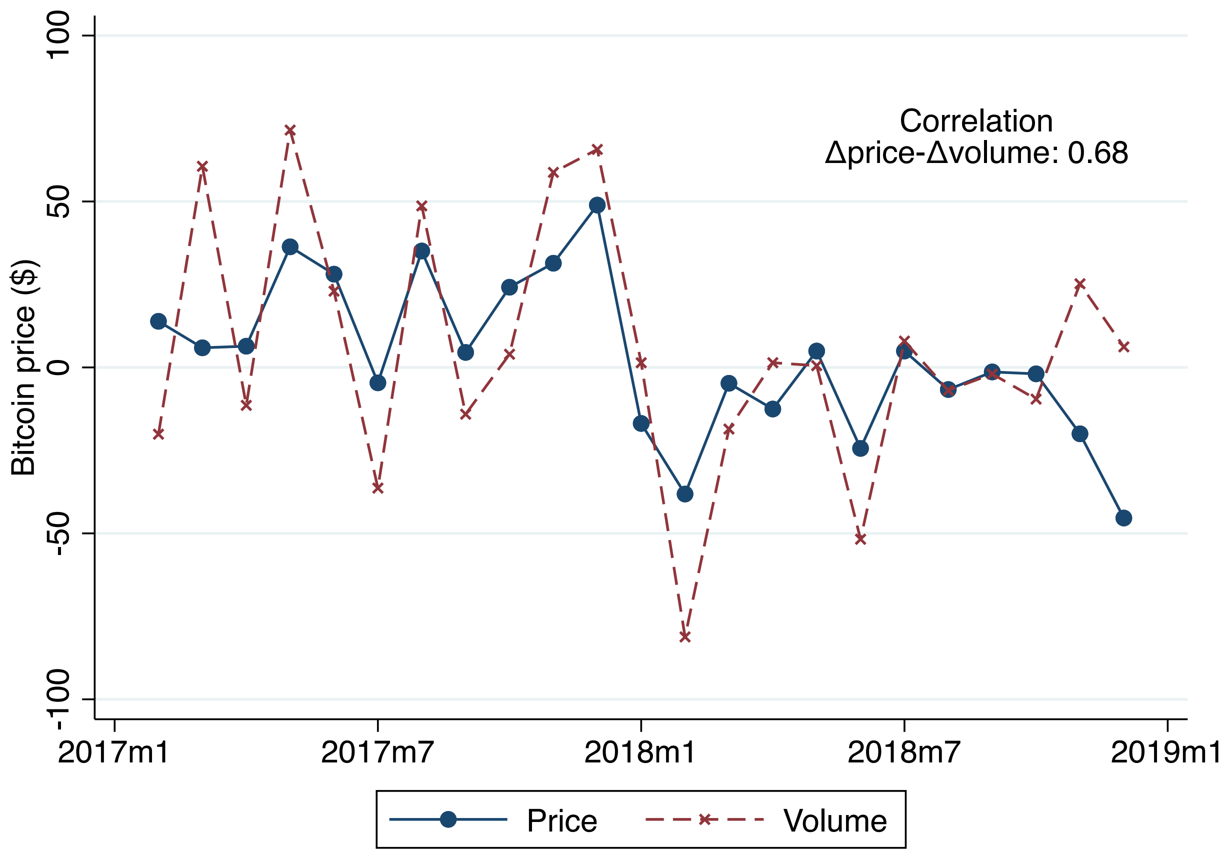

Figure A1: Crypto Mania: Δ Prices and volumes

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 Coinmarketcap.

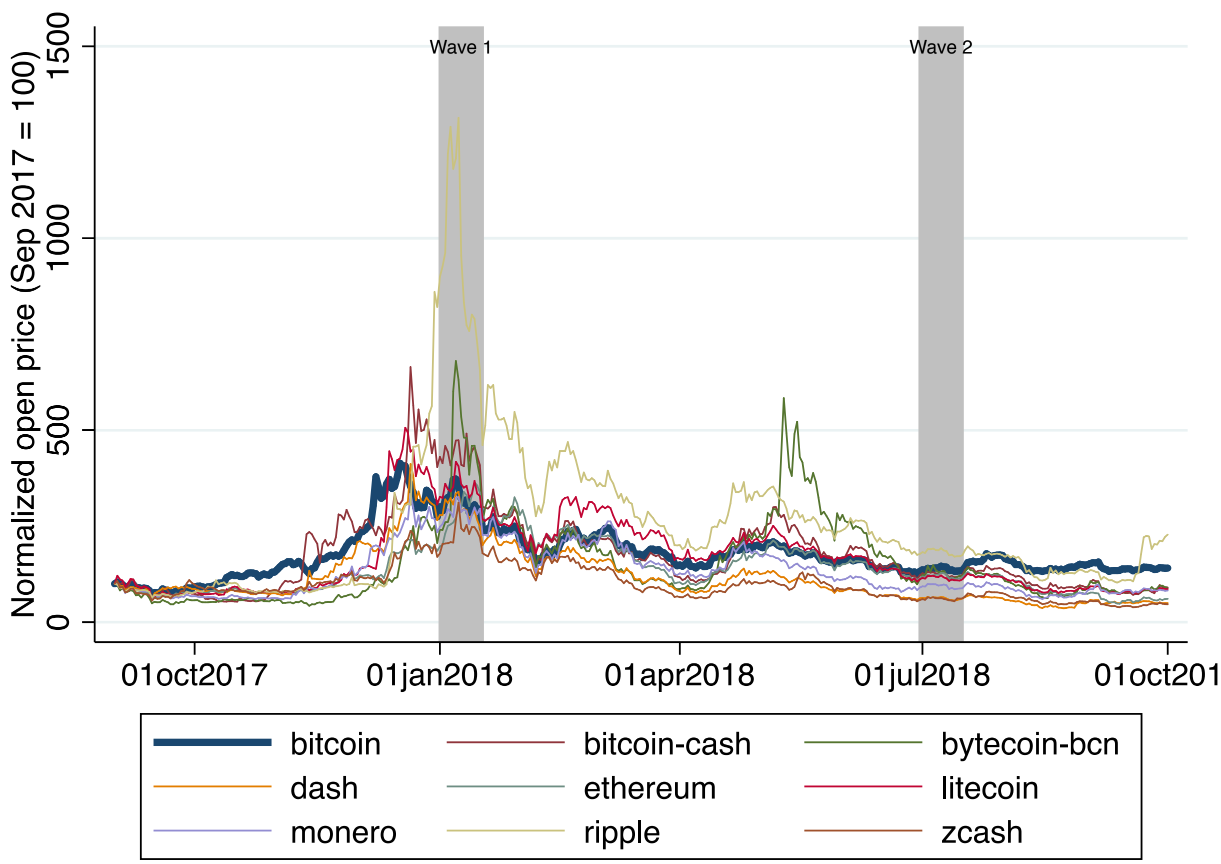

Figure A2: Cryptocurrencies Price Variation

Note: The figure shows the daily price for nine cryptocurrencies in 2017-2018. The cryptocurrencies included are: bitcoin, bitcoin-cash, bitcoin-bcn, dash, ethereum, litecoin, monero, ripple, zcash. Data comes from Coinmarketcap.

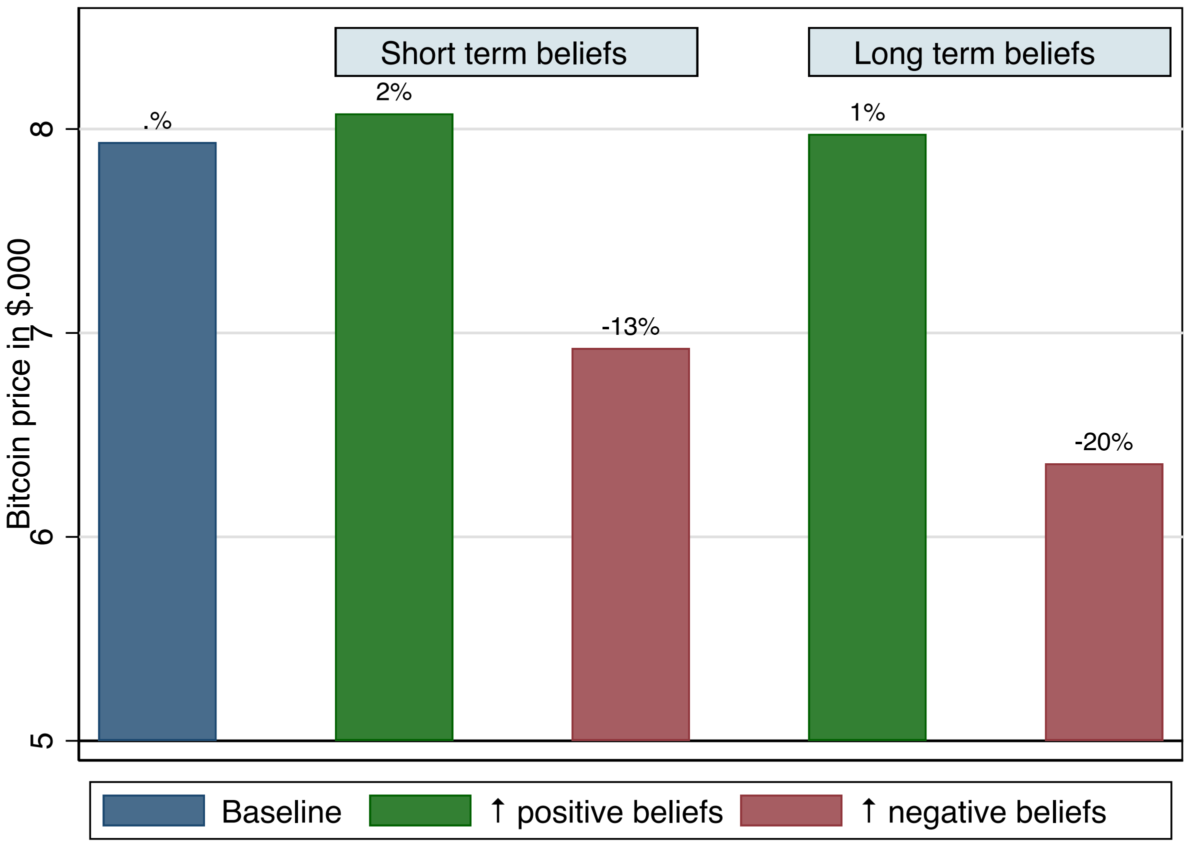

Figure A3: Counterfactual Expectations and Bitcoin Price: Bust

Note: The figure shows the equilibrium price of Bitcoin in five different scenarios for July 2018 wave (the "bust" period). The blue bar represents the baseline scenario predicted by our model in Section 3. Short-term beliefs randomly shock short-term beliefs about the future value of cryptocurrencies from negative (positive) to positive (negative) for 25 percent of investors. Long-term negative beliefs randomly shock long-term beliefs about the probability cryptocurrencies become mainstream from negative (positive) to positive (negative) for 25 percent of investors. The green bars represent the switch from negative to positive beliefs. The red bars represent the switch from positive to negative beliefs. Prices are in thousands of US dollars. The numbers in the figure are changes as percent of the initial price.