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The Role of Beliefs in Entering and Exiting the Bitcoin Market

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Abstract

Cryptoassets, such as Bitcoin, represent a new type of financial technology that has grown substantially in recent years in terms of market size. Previous research has documented the characteristics and motivations of early Bitcoin adopters, but less work has been done studying those who choose to exit the Bitcoin market. We develop a theoretical model of both entry and exit to the Bitcoin market, the dynamics of which are driven by agents' beliefs about Bitcoin's survival. We connect the model to micro-level data from Canada, allowing us to empirically test the role of beliefs in transitioning to past ownership. Using a control function approach with appropriate exclusion restrictions, we estimate the effects of beliefs while controlling both for selection into or out of Bitcoin ownership and for possible simultaneity. We find evidence that beliefs are significant predictors of exit, while the size and direction of these effects differ across time and ownership status.

Topics: Bank notes; Digital currencies and fintech; Econometric and statistical methods
JEL codes: D83, O33, E41

Résumé

Les cryptoactifs, comme le bitcoin, représentent un nouveau type de technologie financière ayant connu une croissance importante au cours des dernières années pour ce qui est de la taille du marché. Les caractéristiques et les motivations des premiers adeptes du bitcoin ont déjà fait l'objet de recherches, mais les études réalisées sur les personnes qui choisissent de sortir du marché du bitcoin sont moins nombreuses. Nous élaborons un modèle théorique d'entrée sur le marché du bitcoin et de sortie du marché, dont la dynamique repose sur les croyances des agents au sujet de la survie du bitcoin. Nous appliquons le modèle à des données microéconomiques canadiennes, ce qui nous permet de tester empiriquement le rôle des croyances dans les décisions de sortir du marché. À l'aide d'une fonction de contrôle reposant sur des restrictions d'exclusion appropriées, nous estimons les effets des croyances tout en tenant compte des effets de sélection (dans le marché du bitcoin ou hors de celui-ci) et d'une possible simultanéité. Il apparaît que les croyances sont des prédicteurs significatifs de sortie du marché, alors que l'importance et l'orientation de ces effets varient selon la période et le statut de détenteur.

Sujets : Billets de banque, Monnaies numériques et technologies financières, Méthodes économétriques et statistiques

Codes JEL : D83, O33, E41

1 Introduction

The economics of digital currencies—both private and public—is an increasingly important area of research and policy (Chiu and Keister, 2022). The first and most well-known private digital currency (or cryptocurrency) was Bitcoin, which was originally designed to facilitate decentralized, pseudonymous transactions on the Internet and also to serve as a form of electronic money not issued or controlled by governments (Nakamoto, 2008; Böhme et al., 2015).[1] Since Bitcoin's inception, an entire ecosystem has grown up around it, including the creation of thousands of other cryptocurrencies as well as innovations such as stablecoins, decentralized finance (Defi), smart contracts, and more. Being the first mover in this space, Bitcoin still retained about a 50% share of the cryptocurrency market in 2023, representing a market capitalization of over $500 billion (USD). However, its price volatility has prevented it from fulfilling key functions of money, such as maintaining a store of value or becoming a widely accepted medium of exchange. This has resulted in many coming to view Bitcoin as a type of risky asset; hence the common use of the term "cryptoasset" (versus cryptocurrency).

The interest of central banks in the rapid expansion of cryptoassets can be largely attributed to two main factors. First, cryptoasset markets are becoming more integrated with the traditional financial system, raising financial stability concerns (e.g., Macklem et al., 2022).[2] Second, the potential for cryptocurrencies to be widely used as a means of payment could have implications for the monetary sovereignty of countries and, in turn, for conducting monetary policy. Offering public digital currencies—better known as central bank digital currencies, or CBDCs—is a possible response to these concerns (see Lane (2020, 2021) or Bank of Israel (2023)).[3] While only a handful of existing CBDCs are currently in operation, over half of surveyed central banks from 81 countries report active development of or experimentation with CBDC (Kosse and Mattei, 2022).

Whether or not cryptoassets, such as Bitcoin, will become widely adopted and used depends on their rates of entry and exit (i.e., "adoption" and "disadoption"). This paper makes both theoretical and empirical contributions to help better understand these phenomena. First, we develop a tractable dynamic model of Bitcoin entry and exit, wherein agents' decisions are determined by their beliefs about Bitcoin survival, their outside option, and their ownership status. Next, we use detailed micro-level data from the Bank of Canada's Bitcoin Omnibus Surveys (BTCOS) to test the model's predictions. The data allows us to

[1] Biais et al. (2023) and Halaburda et al. (2022) offer recent overviews of the economics of cryptocurrencies.

[2] On January 10, 2024, the Securities Exchange Commission in the US approved the offering of Bitcoin exchange traded funds (ETFs), allowing mainstream investors exposure to Bitcoin's price while avoiding risks of owning it directly. Another example of integration with the traditional financial system is stablecoins: digital tokens that are supposedly backed by the purchase and holding of risk-free or low-risk assets.

[3] See Ahnert et al. (2022) and Auer et al. (2022) for a review of the economics literature on CBDC.

identify past owners—namely, those who previously owned Bitcoin but currently do not—and individuals' beliefs about how likely they think it is that Bitcoin will survive in the future. This information is crucial to bring the model to the data. We show that beliefs are a key driver of individuals' decisions around both entry and exit.

We develop a tractable dynamic model, in which, at any point in time, an agent belongs to one of three distinct groups: *owners*, who own Bitcoin in the current period; *past owners*, who have prior ownership experience; and *never owners*, who have yet to acquire Bitcoin for the first time. Each agent chooses whether or not to own Bitcoin in the next period, which allows agents to move across ownership categories over time. This allows us to capture exit, entry, and re-entry rates. The agents' decision problem is clouded by uncertainty; in particular, all agents are uncertain whether Bitcoin will survive or not in the future, and they update their beliefs via Bayes' rule by observing the evolution of a signal ("news"). We introduce heterogeneity in the speed of learning not only between different types of owners but also within each status across time. All else equal, agents with more optimistic beliefs are more likely to enter or re-enter the Bitcoin market, while agents with more pessimistic beliefs are more prone to exit or stay out of the market. We find that if owners learn faster than past owners, and past owners ones learn faster than never owners, then the cross-sectional distribution of beliefs across these groups is similarly ranked, matching key features of the data.

Our theoretical model is inherently dynamic, while our empirical data comes from repeated cross-sections. Thus, to validate our theoretical findings, we examine discrete dynamics by analyzing conditional probabilities computed across these repeated cross-sections. The empirical analysis is divided into two distinct stages, which are aligned with our identification strategy. First, we delve into demographic factors and cryptocurrency knowledge, assessing their influence on the development of either negative or positive beliefs about the future long-term survival of Bitcoin. The analysis reveals distinctive patterns in the factors influencing beliefs about Bitcoin survival across owners, past owners, and never owners.

Second, we focus specifically on drivers of exit by carefully controlling for both selection (various factors that may cause people to exit/disadopt) and the endogeneity of beliefs (the effect of beliefs on exit, as well as the effect of exit on beliefs). In estimating the effect of beliefs on exit, we use the estimated residual from the first stage model of beliefs as a correction term. The repeated cross-sectional nature of our available data does not allow us to precisely match the dynamic transitions described by the theoretical model; however, we gain insights by using econometric techniques. Using a multinomial choice model, we treat ownership status as a static choice in order to directly compare owners with past owners and never owners. We do this to test the theoretical predictions about the role of ranking in beliefs on decisions to own or exit the Bitcoin market. Additionally, a sequential logit model allows us to consider the transition from being a never owner to being a current owner and then to being a past owner. This sequential model is used to examine the cross-sectional dynamics of entry and exit and to study how changes in beliefs impact entry and exit.[4]

We find that beliefs have a significant effect on exit, but that the sizes and directions of effects differ across years and ownership status. A decrease in beliefs—i.e., individuals becoming more pessimistic about the survival of Bitcoin—increases the probability of exiting from the Bitcoin market. Among past owners, we observe a right shift in their belief distribution as time goes on, indicating the development of more optimistic beliefs over time. Higher beliefs are associated with a higher share of past owners re-entering the Bitcoin market. Controlling for selection and the endogeneity of beliefs strengthens the effect of beliefs on the probability of exit. Finally, we find that individuals' combined cryptocurrency knowledge and financial literacy (Balutel et al., 2024) also play an important role in entry and exit; in particular, investors with higher levels of such knowledge are better able to navigate price volatility in terms of their entry and exit rates. The results of our analyses can be useful to better understand not only the overall adoption and un-adoption process of Bitcoin but, more generally, the role of beliefs in the adoption and usage of new technologies.

The paper is structured as follows. We briefly review the literature in Section 2, and set up the model in Section 3. We discuss the data in Section 4 and methodology in Section 5. We present our empirical results in Section 6. Finally, we conclude in Section 7. Mathematical proofs, figures, and tables are available in the Appendices.

2 Literature Review

Our paper contributes to the growing literature on the economics of cryptocurrencies (e.g., Biais et al., 2023) by providing a nuanced empirical exploration of the role of beliefs in the entry to and exit from the Bitcoin market. In general, beliefs have been shown to be important for technology adoption. Rogers (2010) provides a high-level framework (the "s-curve" model) for the diffusion/adoption process of new technologies, in which early adoption is driven by individuals who like to experiment or who have strong beliefs about future usage. In addition, a growing literature documents that in the case of Bitcoin, early Bitcoin owners tend to be young, single, computer literate, male, and with high education and income (Divakaruni and Zimmerman, 2023; Henry et al., 2018, 2019a; Schuh and Shy, 2016; Fujiki,

[4] In both choice models, we address the endogeneity of beliefs on both ownership and past ownership. Our methodology allows for endogeneity corrections using two control functions and their interactions; see Imbens and Wooldridge (2009) for the case of multinomial and ordered responses.

2020).

Stix (2021) provides evidence that early Bitcoin owners have strong beliefs about its advantages relative to more conventional payment methods, whereas Fujiki (2021) argues that some Bitcoin owners use it primarily as an investment product to leverage its volatility or because of limited access to more traditional investment tools such as brokerages.

A growing literature addresses motivations for exiting or un-adopting Bitcoin or similar new technologies. Catalini and Tucker (2017) conducted an experiment wherein they gave Bitcoin to MIT undergraduates but varied the timing in the following way: those who were (a priori) more likely to be early adopters in the absence of the intervention received the Bitcoin later than their peers. They found that this caused these "natural early adopters" to actually reject the technology, especially in cases where the delay was visible to their peers, resulting in a loss of social status. The rejection by these early adopters had spillover effects that slowed the rate of adoption overall. Chi and Yang (2011) studied adoption of Twitter and found that the success (or lack thereof) of previous adopters influenced the rate of adoption.[5] That is, potential new adopters learn from the experience of those who adopt before them, and observing negative experiences can impede diffusion.

Choi and Liang (2023) study a dynamic monetary economy in which agents learn about a new asset and decide whether to adopt it or not. They examine the role of information on the price of the asset. Balutel et al. (2022b) also develop a learning model with entry to empirically examine the role of beliefs in the early stage of Bitcoin ownership in Canada. They find that optimistic beliefs about Bitcoin survival, as well as belonging to a large network of people that own Bitcoin, have positive and significant effects on ownership.

By contrast, in this paper, we consider three distinct ownership categories to capture not only entry but also *exit* rates. Furthermore, we distinguish between entry and *re-entry*, reflecting that the dynamics or motivations of adoption may be different for those who are newly entering the market than for those who have some previous experience. An analogous novel contribution in the field of labor economics is provided by Krusell et al. (2011), who jointly model labor force participation in addition to employment and unemployment, allowing for transitions between all three states.

[5] They refer to "past adopters," but this term has a different meaning in the current paper. In our paper, a past adopter refers specifically to someone who previously owned Bitcoin but currently does not. In Chi and Yang (2011), a past adopter means anyone who has already adopted Twitter at a given point in time.

3 A Model of Ownership and Beliefs

The goal of this section is to develop a tractable stylized model of entry and exit that allows us to guide our empirical strategy. The model focuses on beliefs and ownership dynamics.

Agents. We consider a continuous time model of Bitcoin adoption with a constant unit-mass of agents I.[6] In any time period $t > 0$, each agent $i \in I$ is either a *never owner* ($i \in \mathcal{N}_t$), *past owner* ($i \in \mathcal{P}_t$), or *current owner* ($i \in \mathcal{O}_t$). That is, $I = \mathcal{N}_t \cup \mathcal{P}_t \cup \mathcal{O}_t$ for all t. Thus, at time t, each agent i has an observed ownership *status* $s_t \in \mathcal{S} = \{n, p, o\}$. In addition, each agent i belongs to an observable *category* $y \in \mathcal{Y} = \{y_1, \dots, y_K\}$ with $y_k \in \mathbb{R}^N$ for $k = 1, \dots, K$. The mass of agents with category y is $q_y \in [0, 1]$ with $\sum_{y \in \mathcal{Y}} q_y = 1$. These categories reflect observable demographic characteristics that may influence adoption behaviors and beliefs. For instance, y may include attributes such as gender, age, education level, income level, and region. Thus, an agent with category y and status s_t may represent a potential new owner in time t who is male, lives in Ontario, is aged 18–34, has an income between \$50,000 and \$100,000, and has post-secondary education.

Beliefs and learning. Agents are uncertain whether Bitcoin will survive in the future. This uncertainty impacts agents' decisions on whether to own Bitcoin. We consider two hidden states of the world $\theta \in \{0, 1\}$, where $\theta = 1$ reflects a *stable* (or, "good") technology, and $\theta = 0$ an *unstable* (or, "bad") one. At time $t = 0$, all agents hold a common prior $\bar{\xi}_0 \in (0, 1)$ that the technology is stable. Naturally, a stable system would lead Bitcoin to survive in the long run or to become a robust method of payment; by contrast, an unstable technology would eventually exhibit failures, which may impact agents' beliefs and, thereby, their adoption decisions.[7] Agents update their beliefs by observing the evolution of a private signal, which is aimed to represent information seen by agents in the form of either "good news" (e.g., merchant acceptability, number of Bitcoin ATMs) or "bad news" (e.g., scams, stolen funds, cyberattacks, loss of access to wallet, crashes).[8] We assume that these news events are correlated with the hidden type of the underlying technology; in particular, these events arrive at a random time that is exponentially distributed.[9] As it is standard in the learning literature, we assume "conclusive" news,[10] meaning that observing news leads agents to fully believe that the technology is either good or bad. Consequently, we focus on the

[6] We fix a probability space $(I, \mathcal{I}, \mathbb{P})$ and assume that all functions defined on I are measurable.

[7] Our survey allows us to directly measure agents' beliefs regarding these two events; see Section 4.

[8] Recently, Uhlig (2022) documents that the stablecoin Terra UST, which remained close to \$1 USD since its introduction (November 2020), lost more than 75% of its value in roughly two weeks (May 9–15, 2022), leading to the erasure of more than \$50 billion USD or 90% in market value; see also Liu et al. (2023).

[9] Technically, we consider a learning model in which agents update their beliefs by observing events that follow a Poisson process with unknown arrival rate. See Hörner and Skrzypacz (2017) for a recent survey.

[10] For an exception, see, e.g., Keller and Rady (2010).

belief and ownership dynamics that emerge conditional on not observing news, i.e., when agents remain uncertain about the quality of the technology.

Given $\theta \in \{0,1\}$, we assume that agents learn at different rates $\tilde{\lambda}_\theta \in \Lambda \subseteq \mathbb{R}_+$. In particular, given θ, an agent with parameter $\tilde{\lambda}_\theta$ observes news at rate $\tilde{\lambda}_\theta$ (i.e., news follows a Poisson process with arrival rate $\tilde{\lambda}_\theta$). Let us define $\lambda = \tilde{\lambda}_0 - \tilde{\lambda}_1 \in \mathbb{R}$. An agent is fully characterized by a triplet, or *type* (y, s, λ). Given (y, s), we assume that, at time t, λ is distributed according to a cumulative distribution function (CDF) $G_t(\cdot|y, s)$ with density $g_t(\cdot|y, s)$. An agent with type (y, s, λ) holds (posterior) beliefs $\xi_{ys\lambda t} := \mathbb{P}_t(\theta = 1|y, s, \lambda)$. Using Bayes' rule, Appendix A shows that, given no news, the evolution of beliefs for an agent with type (y, s, λ) obeys:

$$\dot{\xi}_{ys\lambda t} = \xi_{ys\lambda t}(1 - \xi_{ys\lambda t})\lambda, \quad \xi_{ys\lambda 0} = \bar{\xi}_0, \tag{3.1}$$

where "dot" variables denote the time derivatives. Notice that the rate of change of beliefs, $\dot{\xi}_{ys\lambda t}$, is positive for $\lambda > 0$ but negative for $\lambda < 0$. This means that for an agent who expects good news to arrive faster than bad news, i.e., $\lambda < 0$, beliefs decrease over time in the absence of news, whereas the opposite happens when $\lambda > 0$. This reflects that agents can become either optimistic or pessimistic over time in the absence of news, depending on the sign of their learning parameter $\lambda \in \mathbb{R}$.

By using (3.1), we can determine the conditional distribution of beliefs in the population of interest, as we show next.

Proposition 1 *Given category $y \in \mathcal{Y}$ and ownership status $s \in \mathcal{S}$, the cumulative distribution of beliefs at time $t > 0$ is given by:*

$$\mathbb{P}_t(\xi_{ys\lambda t} \leq \xi | s, y) = G_t\left(t^{-1} \log\left(\frac{\xi}{1-\xi} \cdot \frac{1-\bar{\xi}_0}{\bar{\xi}_0}\right) \middle| s, y\right) \quad \forall \xi \in (0,1).$$

Using Proposition 1, we examine how the conditional distribution of beliefs depends on the ownership status of agents.

Proposition 2 *Suppose that the conditional distributions are ranked in the first-order stochastic dominance sense at time t: $G_t(\lambda|y, o) \leq G_t(\lambda|y, p) \leq G_t(\lambda|y, n)$ for all $\lambda \in \mathbb{R}$. Then, the conditional distribution of beliefs satisfies:*

$$\mathbb{P}_t(\xi_{\lambda t} \leq \xi | y, o) \leq \mathbb{P}_t(\xi_{\lambda t} \leq \xi | y, p) \leq \mathbb{P}_t(\xi_{\lambda t} \leq \xi | y, n) \quad \forall \xi \in (0,1). \tag{3.2}$$

Intuitively, Proposition 2 asserts that, conditional on y, if at time t owners learn stochastically faster than past owners, and past owners learn stochastically faster than never owners, then their cumulative distribution of beliefs are ranked at time t. In other words, the conditional distributions do not cross, as seen in Figure 1.

- insert Figure 1 here. -

Our next result examines how the conditional distribution of beliefs changes over time for a given ownership status and category y. Let us define the log-likelihood odds as:

$$\ell(\xi) := \log\left(\frac{\xi}{1-\xi}\cdot\frac{1-\bar{\xi}_0}{\bar{\xi}_0}\right)$$

and the elasticity operator as $\mathcal{E}_x(h) := \partial\log(h)/\partial\log(x)$ for $x \mapsto h$ differentiable.

Proposition 3 *The conditional distribution of beliefs $\mathbb{P}_t(\xi_{ys\lambda t} \leq \xi|s,y)$ increases in time t if and only if the CDF of learning rates λ satisfies $\mathcal{E}_t(G_t) \geq \mathcal{E}_\lambda(G_t)$ for $\tilde{\lambda} = \ell(\xi)/t \in \mathbb{R}$.*

To see why Proposition 3 is true, consider $\mathbb{P}_t(\xi_{ys\lambda t} \leq \xi|s,y) = G_t(\ell(\xi)/t|s,y)$ as in Proposition 1. Then, the conditional distribution of beliefs increase over time when:

$$\frac{d}{dt}G_t\left(\frac{\ell(\xi)}{t}\,\middle|\,s,y\right) = -g_t\left(\frac{\ell(\xi)}{t}\,\middle|\,s,y\right)\frac{\ell(\xi)}{t^2} + \frac{\partial G_t}{\partial t}\left(\frac{\ell(\xi)}{t}\,\middle|\,s,y\right) \geq 0.$$

Now, let $\tilde{\lambda} = \ell(\xi)/t \in \mathbb{R}$ and rewrite the above inequality as:

$$\frac{\partial G_t(\tilde{\lambda}|s,y)}{\partial t} \geq \frac{\partial G_t(\tilde{\lambda}|s,y)}{\partial \lambda}\frac{\tilde{\lambda}}{t} \iff \mathcal{E}_t(G_t) \geq \mathcal{E}_\lambda(G_t).$$

From here we see that the cumulative distribution of beliefs, given ownership status and category, may increase, decrease, or remain constant over time, depending on the respective elasticities of $G_t(\cdot|s,y)$ in time t and in learning rate λ. These reflect the byproduct of two effects. To illustrate this point, consider beliefs $\xi > \bar{\xi}_0$ (the analysis is analogous in the opposite case) so that $\ell(\xi) > 0$. On one hand, as t increases, the chance that beliefs are at most ξ decreases. On the other hand, the conditional distribution over learning rates λ may also change over time increases as consequence of changes in the supply of information. If, for instance, G_t increases over time (i.e., low λ becomes more likely in the population of interest), then this effect would push the conditional distribution of beliefs to increase over time. All in all, the final effect would depend on the relative strength of these potentially confronting forces, encapsulated in the elasticities. Agents with ownership status s can become either more or less optimistic as time goes on, depending on how the distribution of learning rates evolve over time. Observe also that if G_t was time-invariant, then as time goes on, we should expect the CDF of beliefs to rotate about the prior $\bar{\xi}_0$, meaning that beliefs are more dispersed around the prior at any time period. However, this is not what we observe in the data, where the CDF for owners appears to shift in the FOSD over time, while the CDF for past owners remains relatively constant. This suggests that a plausible explanation for this phenomenon is that the CDF of learning rates may vary over time.

Payoffs and optimal behavior. We now specify the agents' payoffs and their corresponding optimal behavior. Each agent i has a random *reservation utility* $u_{it} \in \mathbb{R}$ (e.g., an alternative investment opportunity), which is distributed according to an atomless CDF $F(\cdot)$ that is independent of (y, s, λ). We assume that F is continuously differentiable. Agents trade-off the payoff to own bitcoin against their reservation utility. Consider agent i with type (y, s, λ). We assume that the *payoff to owning bitcoin* for an agent with category y and beliefs ξ is given by a function $B(\xi, y) \in \mathbb{R}$, which may depend on demographic variables. Our data allow us to directly measure beliefs, and this is important because these beliefs likely already contain other relevant information (e.g., prices) for decision making. This allows us to isolate the belief channel, which is our main goal. We assume that, for each y, $B(\cdot, y)$ is increasing and continuously differentiable. This captures that agents who are more optimistic (in the sense of having higher beliefs) are more prone to owning bitcoin in any given period. More precisely, given an agent with beliefs $\xi_{ys\lambda t}$ and reservation utility u_{it}, owning bitcoin between $[t, t + dt)$ is optimal if and only if:

$$B(\xi_{ys\lambda t}, y) \geq u_{it}. \tag{3.3}$$

Conversely, an agent prefers not to own bitcoin if the inequality above is reversed. Let us call $a_{it} \in \{0, 1\}$ the ownership decision in period t of agent i, with the interpretation that $a_{it} = 1$ means owns Bitcoin. Then, for an agent with beliefs $\xi_{ys\lambda t}$, the probability of owning Bitcoin in period t (or, between $[t, t + dt)$) is given by:

$$\mathbb{P}(a_{it} = 1|\xi_{ys\lambda t}, y) = F(B(\xi_{ys\lambda t}, y)). \tag{3.4}$$

We interpret (3.4) as follows. Fix a time period t. If agent i is a current owner, i.e., $s_i = o$, then (3.4) describes the probability that i *stays* in the bitcoin market. However, if inequality (3.3) is reversed, then:

$$\mathbb{P}(a_{it} = 0|\xi_{ys\lambda t}, y) = 1 - F(B(\xi_{ys\lambda t}, y)) \tag{3.5}$$

captures the agent i's probability of *exit*. Similarly, if agent i is a potential new owner, $s_i = n$, then (3.4) reflects the agent i's probability of *entry*. Finally, for past owners, or $s_i = p$, expression (3.4) captures the agent i's probability of *re-entry*. Altogether, agents with more optimistic beliefs are more likely to enter or re-enter the Bitcoin market, while agents with more pessimistic beliefs are more prone to exit or stay out of the market.

Ownership dynamics. Let us denote $\mu^t := (\mu^t_{ys}) \in \mathbb{R}^{\mathcal{Y}\times\mathcal{S}}$ as the joint distribution between category y and ownership s in period t, with $\mu^t_{ys} \geq 0$ for all y, s and $\sum_{s\in\mathcal{S}} \mu^t_{ys} = q_y$ for all $y \in \mathcal{Y}$. We now specify how this joint distribution evolves over time. Motivated by the well-known Bass model (Bass, 1969), we introduce a gradual adoption/disadoption process. To this end, for each ownership s, we compute the total entry and exit flows to and from a given ownership state at any period. Let us call $\rho^t_{\tilde{s}s}(y)$ the chance that an agent with category y migrates from s to $\tilde{s}$ between $[t, t+dt)$. Then, μ^t obeys the following dynamics:

$$\dot{\mu}^t_{yo} = \rho^t_{on}(y)\mu^t_{yn} + \rho^t_{op}(y)\mu^t_{yp} - \rho^t_{po}(y)\mu^t_{yo} \tag{3.6}$$

$$\dot{\mu}^t_{yp} = \rho^t_{po}(y)\mu^t_{yo} - \rho^t_{op}(y)\mu^t_{yp} \tag{3.7}$$

$$\dot{\mu}^t_{yn} = -\rho^t_{on}(y)\mu^t_{yn} \tag{3.8}$$

for all $y \in \mathcal{Y}$. The transition probabilities can be found using (3.1), (3.4), and (3.5):

$$\rho^t_{on}(y) = \int_\Lambda F(B(\xi_{yn\lambda t}, y))g(\lambda|n, y)d\lambda \tag{3.9}$$

$$\rho^t_{op}(y) = \int_\Lambda F(B(\xi_{yp\lambda t}, y))g(\lambda|p, y)d\lambda \tag{3.10}$$

$$\rho^t_{po}(y) = \int_\Lambda [1 - F(B(\xi_{yo\lambda t}, y))]g(\lambda|o, y)d\lambda \tag{3.11}$$

Consider agents with category y at time t. As previously discussed, these agents can be either owners, past owners, or never owners. This is captured by the joint distribution μ^t_{ys}, which represents the mass of agents with category y and ownership status s. To understand how this joint distribution evolves over time, consider current owners. With probability $g(\lambda|o, y)$, a current owner learns at rate λ and thus chooses to exit with chance $1 - F(B(\xi_{yo\lambda t}), y)$. Consequently, the average exit rate from owners with category y is given by $\rho^t_{po}(y)$, as seen in (3.6). In contrast, never owners or past owners with category y could choose to become owners. By the same logic, this happens at average entry rates of $\rho^t_{on}(y)$ and $\rho^t_{op}(y)$, respectively. Equations (3.7) and (3.8) are found analogously; for example, the change in the number of past adopters is the difference between exit and re-entry flows (see Figure 2).

The model is solved by a process $(\mu^t : t \geq 0)$ obeying (3.6)–(3.8), given beliefs $(\xi_{ys\lambda t})_{t\geq 0}$ solving (3.1) for $y \in \mathcal{Y}, \lambda \in \Lambda, s \in \mathcal{S}$, and initial conditions $\mu^0 = \bar{\mu}^0 \in \mathbb{R}^{\mathcal{Y}\times\mathcal{S}}$ and common prior $\xi_{ys\lambda 0} = \bar{\xi}_0 \in (0, 1)$ for all y, λ, s. Having solved the initial value problem (IVP), the total measure of agents with ownership status s evolves according to $t \mapsto \sum_{y\in\mathcal{Y}} \mu^t_{ys}$.

Proposition 4 *There exists a unique solution to the initial value problem.*

In Appendix A, we solve the model in two steps. First, for each type (y, s, λ) we find the unique solution to (3.1) with initial condition $\bar{\xi}_0$. Next, we rewrite the transition probabilities (3.9)–(3.11) by plugging the unique solution to (3.1). Finally, we show that the resulting dynamical system (3.6)–(3.8) is well-behaved, and thus it has a unique solution.

- insert Figure 2 here. -

4 The Bitcoin Omnibus Survey Data

We use data from the Bank of Canada's Bitcoin Omnibus Survey (BTCOS) from years 2017, 2018 and 2019. The survey was first conducted in late 2016 with the purpose of serving as a monitoring tool, obtaining basic measurements of Bitcoin awareness and ownership among the Canadian population; see Henry et al. (2020); Balutel et al. (2023) for further details.

Respondents to the BTCOS are recruited via an online panel managed by the research firm Ipsos, and they complete the survey in an online format. The core components of the survey are as follows: awareness of Bitcoin; ownership/past ownership of Bitcoin; amount of Bitcoin holdings; reasons for ownership/non-ownership. As the survey has evolved over time, its scope has broadened based on a demand for more detailed information about the motivation of Bitcoin owners and their usage behavior. As a result, the BTCOS also gathers information on beliefs about the future adoption/survival of Bitcoin; financial knowledge and knowledge of Bitcoin features; price expectations; use of Bitcoin for payments or person-to-person transfers; ownership of other cryptocurrencies; and cash holdings. In addition to content questions, respondents are also asked to provide demographic information, such as age, gender, and marital status. Sampling for the survey is conducted to meet quota targets based on age, gender, and region. Once the sample is collected, the Bank of Canada conducts a calibration procedure to ensure that the sample is representative of the adult Canadian population along a variety of dimensions; see Henry et al. (2019b).

Figure 3 shows the overall dynamics of Bitcoin awareness, ownership, and past ownership.

- insert Figure 3 here -

Note that while current Bitcoin ownership has increased slowly over time, the level of past Bitcoin owners has a non-monotone trend: exits increase as the price of Bitcoin falls.

Table 1 shows the distribution of demographic variables associated to respondents from the 2017–2019 BTCOS. The sample sizes by survey year are 2,623 in 2017, 1,987 in 2018, and

1,987 in 2019. Of those who completed the survey, we identified 117 Bitcoin owners in 2017, 99 in 2018, and 89 in 2019. There were 37 past owners in 2017, 45 in 2018, and 50 in 2019. The first column of each year shows the percentage of respondents in each category who own Bitcoin, while the second column of each year reports the percentage of respondents in each category who previously owned Bitcoin but no longer do (past owners). We use these individual-level characteristics as control variables in our empirical analysis. The results show that across years, both Bitcoin owners and past owners are more likely to be male, young, with a university degree or high income.

- insert Table 1 here -

Besides demographic characteristics, our empirical model also controls for individuals' crypto and financial literacy. Henry et al. (2018) developed three questions to measure specific Bitcoin knowledge and broad cryptoasset knowledge. Financial literacy is measured by the "Big Three" questions of Lusardi and Mitchell (2011a). Based on responses to these questions, we categorize individuals as having low, medium, or high crypto and financial literacy.[11] Table 1 shows that both current and past Bitcoin owners tend to have high crypto literacy but low financial literacy.

In our empirical model, we jointly account for both crypto and financial literacy.[12] Given the small share of past owners in the data, this approach aims to reduce the dimensionality of our model specification, enhancing the stability of our results. Specifically, we create a composite index of crypto and financial literacy (CFL) by combining the two indices. For the CFL low category, we consider all combinations of low-low and low-medium financial literacy and crypto knowledge scores. For the medium category, we include combinations of medium-medium and low-high scores. Lastly, for the high category, we incorporate combinations of medium-high and high-high scores.[13] Thus, we get an index of CFL with counts for never owners, current owners, and past Bitcoin owners, as shown in Table 2.[14]

- insert Table 2 here -

[11] We build on the methodology of Balutel et al. (2022a) to construct these categories.

[12] In contrast, Balutel et al. (2024) analyze these measures separately, examining how they relate to Bitcoin ownership and whether gender differences are present.

[13] Simplifying versions of literacy scores can be found in Lusardi and Mitchell (2011b). Also, Kass-Hanna et al. (2022) construct a composite index for digital and financial literacy (DFL) with the purpose of showing that both financial and digital literacy are pivotal factors in shaping positive financial behaviors and ensuring long-term financial security for individuals.

[14] The financial literacy questions were not yet included in the BTCOS in 2017; 2018 was the first year they were introduced in the survey instrument. Therefore, the CFL category for 2017 is constructed by simply taking the category of crypto knowledge (low, medium, or high) based on responses to the three Bitcoin knowledge questions.

Table 3 shows population weighted average scores for the new index of CFL by owners, past owners, and never owners.

- insert Table 3 here -

Notice that current Bitcoin owners generally exhibit higher overall CFL scores compared with both never owners and past owners. The exception is for the year 2019, where past owners have the highest score. A noteworthy dip in the overall CFL score for past Bitcoin owners occurred in 2018, coinciding with the peak in exits during that year. Furthermore, the CFL score for past owners displays more variability than that of current or never owners. We see an observable improvement over time in the overall CFL score for never owners. Current owners experience a more pronounced decline in 2019 compared with the preceding years. These findings will be examined and discussed further in our subsequent conditional analysis.

Examining self-reported motivations for exiting the Bitcoin market suggests that past owners are likely to be a selected sample. The BTCOS asks past owners their main reason for no longer owning Bitcoin (see Table 4).

- insert Table 4 here -

According to Table 4, the main determinants that drive individuals to exit the Bitcoin market are the price volatility, Bitcoin not being easy to acquire/use, beliefs that the system will not survive and the use of alternative digital currencies. Indeed, at the time of the surveys from 2017 to 2019, Bitcoin's price passed through different phases of volatility, from a (then) all-time high, to a low point, followed by a period of relatively stable prices, as seen in Figure 4.

- insert Figure 4 here -

Finally, the key variable of interest linking our model with the data is beliefs about the future of survival of Bitcoin. On a scale of 1 to 100, respondents are asked how likely they think it is that Bitcoin will survive in the next 15 years. Looking at the dynamics of beliefs across ownership status (Figure 5), we see that the ranking of beliefs is preserved over the period under investigation.

- insert Figure 5 here -

The distributional representation shows that past owners exhibit the most changes in beliefs over time. The gap between the distribution of beliefs of owners and never owners stays constant, yet past owners get closer in beliefs to owners in 2019—especially for individuals at the bottom of the belief distribution. To better see these dynamics over time, we also look at within group dynamics of the distribution of beliefs (Figure 6). After 2017, the distribution of beliefs for never owners decreased—they became more pessimistic after the negative price shock at the end of 2017—and stayed stable for 2018 and 2019.

- insert Figure 6 here -

The distribution of owners did not change significantly over the three-year period, which may owe to the slow/constant adoption rate. The within group dynamics also highlight the changes in beliefs for past owners, especially in 2019, suggesting that they became more optimistic.

5 Empirical Strategy and Econometric Methodology

Motivated by the theoretical model, we build an empirical strategy in four steps.

First, we examine the *exits* from the Bitcoin market, centering on past owners. To build an empirical model for past ownership, it is crucial to understand the mechanism that drives individuals out of the market. Our key assumption, motivated by the theoretical model, is that (1) exit is driven by changes in beliefs about the future survival of Bitcoin; and (2) this change in beliefs owes to individuals' learning. Intuitively, some Bitcoin owners may be more affected than others by reported incidents such as price crashes, scamming and hacking, data breaches, and lost wallets. There may also be financial reasons to exit (e.g., selling holdings to cash out for profits), which can be seen as changes in the individuals' outside options.

Second, Proposition 2 suggests that the ranking of beliefs about Bitcoin survival depends on the agents' learning rates, which differ for owners, past owners, and never owners. That is, the theory indicates that the ranking of beliefs across individuals is affected by the probability that an individual is a Bitcoin owner, past owner, or never owner. Moreover, the beliefs of Bitcoin owners first-order stochastic dominates (FOSD) the beliefs of the past owners which, in turn, FOSD the beliefs of never owners. To test this, we consider two avenues. First, we non-parametrically identify the rankings in the distributions of beliefs across ownership status using tests of stochastic dominance. Second, we propose a conditional multinomial choice model, in which we compare the role of beliefs on the probability of being a current owner or past owner relative to being a never owner. We test whether Bitcoin owners have, on average, the strongest beliefs about Bitcoin survival, while never owners have the weakest.

Third, Proposition 3 suggests that the belief distribution, conditional on an ownership status, can change over time because of individuals' learning and the availability of information. To test within-ownership dynamics of the belief distribution, we use the same multinomial choice model each year over the three-year period 2017–2019. A decrease in the distance of beliefs between owners and past owners and between owners and never owners will most likely increase entry or re-entry; while an increase in the distance of beliefs between owners and past owners or never owners will most likely reduce participation in the market.

Finally, Proposition 4 examines the overall dynamics of entry and exit given evolving beliefs, showing how agents transition across ownership states (Figure 2). This motivates us to examine how the transitions across ownership status depend on the agents' beliefs. In particular, we are interested in understanding the joint transitions from a never owner to a current Bitcoin owner and from a current owner to a past Bitcoin owner. From an empirical perspective, this lends itself to using a sequential choice model, in which a never owner may become a Bitcoin owner while an owner can choose to exit and thus become a past owner.

5.1 An Empirical Model for Past Owners

Focusing on the beliefs channel, we build a reduced-form model for past owners to bring the theory model in Section 3 to the data (see equation (3.5)). To properly model exit behavior from the Bitcoin market, we must address two key challenges: endogeneity and selection bias.

First, endogeneity arises due to the simultaneous relationship between beliefs about Bitcoin's survival and the decision to exit the market. If beliefs about Bitcoin's survival decrease, this can increase the number of exits from the market. These exits, in turn, can further influence individuals' beliefs about Bitcoin's prospects. Second, the selection of exiting may be prompted by various factors, such as responding to price crashes, encountering scams, or strategically choosing to sell holdings and cash out for profits. To correct for these issues, we use a control function (CF) approach (Heckman and Robb, 1985; Wooldridge, 2011). In particular, our empirical model identifies exit from the Bitcoin market in two stages.

In the first stage, we model agents' beliefs as a function of demographic characteristics, crypto knowledge, and exclusion restrictions. The exclusion restrictions explain variation in beliefs about Bitcoin survival but do not directly impact exits in a given time period. In the second stage, we estimate the probability of becoming a past Bitcoin owner using Bitcoin owners as a benchmark, while accounting for the non-random exit. Specifically, as we show next, the model specification includes (besides demographic characteristics and crypto and financial literacy) a correction term—namely, the residual from the first stage regression.

1. First stage—Model of Beliefs:

$$\xi_{it} = \delta X_{it} + \gamma Z_{it} + u_{it}, \tag{5.1}$$

where ξ_{it} is the belief of individual i at time t, X_{it} are individual level observable characteristics (age, gender, education, income, labor status, Bitcoin knowledge); and Z_{it} are exclusion restrictions (explained below).

2. Second Stage—Model of Exit: Let the latent variable e^*_{it} define the latent utility of exit from the Bitcoin market, which is positive for those who exit from the Bitcoin market and negative for Bitcoin owners. In this case, someone who exits is observed if $e^*_{it} > 0$, which can be represented by the observed outcome $e_{it} = \mathbf{1}(e^*_{it} > 0) = 1$ if $e^*_{it} > 0$, and 0 otherwise. Given the latent utility model:

$$e^*_{it} = \beta_0 + \beta_1 \xi_{it} + \beta_c X_{it} + \theta \widehat{u}_{it} + \varepsilon_{it}, \tag{5.2}$$

where $\widehat{u}_{it}$ is the CF derived from the first stage and ε_{it} is the unobserved error variable that follows a logistic distribution. The observed outcome e_{it}—which is individual i's observed exit choice at time t, with the interpretation that $e_{it} = 1$ denotes exits—is modeled via a logistic probability model:

$$\Pr(e_{it} = 1 | \xi_{ist}, X_{ist}, \widehat{u}_{it}) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 \xi_{it} + \beta_c X_{it} + \theta \widehat{u}_{it})}}. \tag{5.3}$$

Incidents faced by current owners may impact their beliefs about Bitcoin's survival. Figure 7 provides a graphical representation of the different types of incidents faced by past Bitcoin owners (e.g., loss of wallet access, transaction problems, hacking, scamming, and stolen funds). Some of these incidents may have a stronger role in affecting beliefs (e.g., hacking or scamming) than others (e.g., volatility) and thus the selection out of the Bitcoin market.

- insert Figure 7 here -

This motivates the use of two exclusion restrictions for identification. First, we use (general) cyber security incidents faced by Canadians during the period 2016–19. Table 5 provides an overview of the dynamics of cyber security incidents at the regional level.[15]

- insert Table 5 here -

[15] The types of cyber incidents, aggregated in our measure, are described by Statistics Canada; see https://open.canada.ca/data/en/dataset/2d4b6fdf-d0ac-4da0-97fd-0482fec5c294.

To justify that the measure of cyber incidents is a valid exclusion restriction, we examine how the overall regional variation in cyber incidents correlates with the beliefs about Bitcoin's survival. Figure 8 provides a graphical representation of this relationship.

- insert Figure 8 here -

Furthermore, the correlation between our exclusion restriction (total cyber incidents at the regional-level)—which is denoted by Z_{jt}—and the residuals from the model for exit are close to 0 (precisely, -0.02). This suggests no time t direct impact on exiting probability. The no direct-timing effect can be justified by the fact that the overall regional time t incidents are measured and reported at the end of the year, while the past adoption refers to individuals who are not in the Bitcoin market at the time period t.

The second proposed exclusion restriction is the day that a respondent took the survey. We justify this choice because people who respond promptly may have a greater interest in the survey's content and stronger beliefs about Bitcoin. Conversely, as the waiting time to complete the survey increases, the correlation with beliefs tends to decrease.

The first-stage regression results will demonstrate the negative correlations between the two exclusion restrictions and beliefs (Section 6.1). Additionally, to check the validity of our exclusion restrictions, we check whether $E(e_{it}|\xi_{it}, Z_{it}) = E(e_{it}|\xi_{it})$; see Appendix B. The results of these regressions show that the two exclusion restrictions affect the probability of exit, not directly but through their influence on beliefs. This confirms the validity of our exclusion restrictions. Furthermore, utilizing two different exclusion restrictions also helps to identify causal effects, even if the exclusion restrictions are not strong (D'Haultfœuille et al., 2021).

5.2 Multinomial Choice Model

Having understood how beliefs impact exits, we now turn to examine how beliefs are influenced by an individual's ownership status. The conditional analysis allows us to see if the observed unconditional rankings are preserved after accounting for various other factors.[16] Additionally, we employ a multinomial choice model to examine within-ownership dynamics in the distribution of beliefs over the three-year period from 2017 to 2019. A decrease in the disparity of beliefs between owners and past owners, as well as between owners and individuals who have never owned Bitcoin, is likely to encourage more entry or re-entry into the

[16] We also check whether the unconditional rankings of beliefs for Bitcoin owners, past owners, and never owners are statistically significant using tests of stochastic dominance. We find that the beliefs about Bitcoin survival for Bitcoin owners FOSD the beliefs of both past owners and never owners, while the beliefs of past owners FOSD the beliefs of never owners.

market. Conversely, an increase in the disparity of beliefs between owners and past owners or never owners is likely to reduce participation in the Bitcoin market.

Specifically, given beliefs, demographic characteristics, and CFL, we posit that the probability that an individual has a particular ownership status is given by:

$$\mathbb{P}(S_{it} = s|\xi_{ist}, X_{ist}) = \frac{e^{\beta_0+\beta_1\xi_{ist}+\beta_c X_{ist}}}{1+\sum_{s=1}^{3} e^{\beta_0+\beta_1\xi_{ist}+\beta_c X_{ist}}}, \tag{5.4}$$

where S_{it} is an indicator for the ownership state $s \in \{1, 2, 3\}$ of an individual i at time t, where $s = 1$ denotes a never owner, $s = 2$ an owner, and $s = 3$ a past owner. ξ_{ist} represents respondent i's beliefs at time t about Bitcoin survival, given ownership status s; whereas X_{ist} is a set of individual characteristics for respondent i in period t, given ownership status s.

As with the model of exit, we include a *decision specific* correction term (CF) to account for the endogeneity of beliefs influencing individuals' decisions. Given our assumption that beliefs are driving people's choices, we employ the CF used in the model of exit described in Section 5.1, and also a CF specific to an entry model, following Balutel et al. (2022b).[17] In the second-stage regression, the transformed multinomial choice model becomes:

$$\mathbb{P}(S_{it} = s|\xi_{ist}, X_{ist}) = \frac{e^{\beta_0+\beta_1\xi_{ist}+\theta_s\widehat{u_s}_{it}+\beta_c X_{ist}}}{1+\sum_{s=1}^{3} e^{\beta_0+\beta_1\xi_{ist}+\theta\widehat{u}_{it}+\beta_c X_{ist}}}. \tag{5.5}$$

5.3 Sequential Choice Model

The multinomial choice model may suffer from some shortcomings linked with the exchangeability of the choices. Using a model that allows for a sequence of choices is also appropriate, especially as we can empirically study Proposition 4, which considers the solution of the overall dynamics of entry and exit, showing the agents' transition across ownership states. We should notice that, because our data is repeated cross-sectional, as opposed to panel, data, we do not directly observe the transitions between ownership categories. That said, our specific interest lies in understanding the joint transitions from being a never owner to a current Bitcoin owner, and from being a current owner to a past Bitcoin owner. From an empirical perspective, this leads us to consider a sequential choice model. This approach could also address the simultaneity between the formation of beliefs about Bitcoin survival and both entry and exit decisions. Given a sequence of entry and exit, we differentiate between the beliefs formed by Bitcoin owners and past owners, respectively. Thus, the model addresses a timing issue that is not directly solved by examining entry and exit separately.

[17] Proposed CF corrections in a multinomial setting was suggested by Imbens and Wooldridge (2009). Also, dealing with endogeneity via CF for these types of nonlinear models was explored by Danaf et al. (2023). In our case, we use two CFs and their interactions for greater flexibility (Imbens and Wooldridge, 2009).

To understand the influence of beliefs on the stability of these entry and exit dynamics in the Bitcoin market over time, we propose estimating a sequential logit model of entry and exit. In practice, given the available data, we approximate the sequence of transitions as follows: a never owner can become an *adopter* (i.e., a current owner), who can then transition to a past owner[18]:

$$\mathbb{P}_{N,A\{a,e\}}(\xi_{it}, X_{it}) = \mathbb{P}_{A|N}(\xi_{it}, X_{it})\mathbb{P}_{e|A}(\xi_{it}, X_{it})\mathbb{P}_{e}(\xi_{it}, X_{it}), \tag{5.6}$$

where $\mathbb{P}_{A|N}(\xi_{it}, X_{it})$ is the probability of becoming a Bitcoin adopter—which includes both current and past Bitcoin owners—conditional on beliefs about Bitcoin survival and demographic characteristics; $\mathbb{P}_{e|A}(\xi_{it}, X_{it})$ is the probability of becoming a past Bitcoin owner given that an individual was a Bitcoin adopter, conditional on beliefs and demographic variables; and $\mathbb{P}_{e}(\xi_{it}, X_{it})$ is the marginal probability of becoming a past Bitcoin owner.

We check the stability of the dynamics of entry and exit using this sequential model approach. In particular, we focus on the role that beliefs play in entry and exit from the Bitcoin market. Of course, we add choice specific correction terms (CFs) to address the selection into entry and exit driven by the beliefs about Bitcoin survival. The transformed sequential model turns to:

$$\mathbb{P}_{N,A\{a,e\}}(\xi_{it}, \widehat{u}_{sit}, X_{it}) = \mathbb{P}_{A|N}(\xi_{it}, \widehat{u}_{sit}, X_{it})\mathbb{P}_{e|A}(\xi_{it}, \widehat{u}_{sit}, X_{it})\mathbb{P}_{e}(\xi_{it}, \widehat{u}_{sit}, X_{it}). \tag{5.7}$$

The estimation method relies on maximum likelihood estimation applied to a sequential logit model. The introduction of CFs correction within a sequential logit framework can also be considered a methodological contribution to nonlinear models of this nature and is based on the suggestion of Imbens and Wooldridge (2009) for multinomial models.

Having presented our empirical strategy above, Table 6 summarizes how we assess various predictions or assumptions of the model using the available data.

- insert Table 6 here -

6 Results

We present our results following the order outlined in Section 5. First, we study how demographic factors and cryptocurrency knowledge impact individuals' beliefs regarding Bitcoin survival. The goal is to gain a deeper understanding of belief formation within the three relevant ownership categories: owners, past owners, and never owners. Second, we present the

[18] The sequential model is a generalization of the multinomial model; see Flores et al. (2018).

results for selection out from the Bitcoin market (the probability of becoming a past Bitcoin owner), focusing on the role of beliefs driving this selection.[19] We also examine what drives negative or positive changes in beliefs for Bitcoin owners, past owners, and never owners.

Next, inspired by Proposition 2, we estimate a multinomial probability model to study how beliefs are affected by the probability of being a Bitcoin owner, a past owner, and a never owner. We also test the within-ownership dynamics in the distribution of beliefs (at the average level) over the three-year period 2017–19. Finally, we use a sequential choice model to address a timing problem that cannot be solved by examining entry and exit separately. This allows us to show that agents' transition across ownership states changes over time in response to changes in beliefs, as highlighted in Proposition 4.

6.1 Drivers of Changes in Bitcoin Survival Beliefs

Table 7 presents the results of analyzing the factors affecting beliefs about Bitcoin survival.

The results show differences across the role of demographics and other controls in shaping people's beliefs. Specifically, age, education, and Bitcoin knowledge have a negative impact on the beliefs of individuals who have never owned Bitcoin. Additionally, relative to the year 2017, beliefs about Bitcoin survival among never owners were negatively affected in 2018 and 2019. Among past owners, only income exhibited a negative influence on their beliefs; whereas among current owners, being in a relationship, having children, and answering correctly the question about whether Bitcoin is government-backed had negative effects on their beliefs. In contrast, within the subgroup of never owners, positive effects were observed for being in a relationship and possessing Bitcoin knowledge, especially in relation to the use of public ledger technology by Bitcoin. For past owners, age, absence of children, and the year 2019 had a positive impact on their beliefs.

- insert Table 7 here -

These results emphasize that the formation of beliefs is heterogeneous across Bitcoin owners, past owners, and never owners. It is important to highlight that a greater number of demographic factors exert a negative influence on beliefs concerning Bitcoin survival,

[19] We focus primarily on examining the impact of changes in beliefs on driving the exit. It is challenging to separate the influence of changes in beliefs from changes in outside options based on the available data. The lack of information regarding the reasons for exit further complicates this analysis. While we acknowledge that changes in beliefs may not be the sole factor triggering exits, we have observed notable differences in beliefs between current Bitcoin owners and past owners (refer to Figure 5) across various belief dimensions. Consequently, these differences in beliefs contribute significantly to the observed exits. It is worth noting that, within the time frame of our data collection, the outside option—specifically, price fluctuations—did not exhibit significant predictive power for exits in our model.

compared with those that bolster such beliefs. Consequently, when exploring new technologies, it becomes crucial to discern which factors are responsible for altering consumers' beliefs and how these changes impact the adoption of these innovations. As emphasized by Gerli et al. (2022), in the context of smart technologies, the design of policies must address both cognitive and emotional barriers to technology adoption. This underscores the need for decision-makers to move beyond the simplistic assumption that enhancing digital skills among potential users easily translates into increased adoption and implementation of new technologies (such as CBDC).

6.2 Past Bitcoin Owners

As outlined in Section 5.1, we estimate a reduced form model for past owners that identifies exits from the Bitcoin market in two stages. Table 8 shows the results of the first stage.

- insert Table 8 here -

The first stage results show the relevance of our two exclusion restrictions. We also check the validity of the two instruments by testing whether $E(Y|X,Z) = E(Y|X)$. Appendix B shows that $E(\widehat{Y|X,Z}) = E(\widehat{Y|X})$, suggesting that our exclusion restrictions are indeed valid.

In the second stage, we estimate the probability of becoming a past Bitcoin owner, using owners as a benchmark. Besides demographic characteristics and crypto-financial literacy (CFL), we include a correction term—the residual from the first stage regression— to account for selection from the Bitcoin market. Table 9 presents the results of the second stage.

- insert Table 9 here -

The main result from this exercise is that controlling for selection strengthens the effect of beliefs on the probability of exiting. The impact of selection is stronger for 2018, relative to 2019 and 2017; see Figure 9. The higher negative impact of the beliefs in 2018 is driven by the high negative shock in the price of Bitcoin. The lowest impact of the change in beliefs is in 2017, which is associated with the dynamics of price observed in that year (high positive shock on the Bitcoin price). Also, after the decline in price at the beginning of 2018, which led to the highest proportion of exits (2.8%) in 2019, the price stabilized and the exits declined (to 2.4%). These results are in line with the theoretical predictions, which suggest that the probability of exiting from the Bitcoin market changes as beliefs change over time—stronger beliefs reduce the probability of exiting.

- insert Figure 9 here -

Having lower education and being from one of the Atlantic provinces also drive exit. Some demographic effects were different in 2019 compared with 2018 and 2017; for example, being younger, being unemployed, or having higher CFL increases the exit probability.

Finally, we can summarize the results of the model via a likelihood ratio decomposition based on distinct groupings of variables. In particular, we group demographic characteristics together and then examine improvements to the model obtained by adding beliefs, CFL score, and the control function CF. The likelihood ratio calculation enhances our comprehension of each group's contribution to the likelihood of being a past owner by quantifying the improvement over the model having only a constant term.[20] A visual representation of this decomposition is presented in Figure 10.

- insert Figure 10 here -

The decomposition underscores the important role of beliefs, notably in 2018 when there was a surge in exits. Also, it highlights the significance of CFL and CF, especially in 2018 and 2019. The fact that the CF does not improve the model in 2017 reflects the low rate of exit during a period where the price of Bitcoin was at a historical high. Thus, demographic characteristics were more relevant in 2017, but decreased in relevance in 2018–2019.

The phenomenon of disadoption (becoming a past owner), often referred to as "technology failures," is a common occurrence in the early stages of adopting new technologies (e.g., Xin Xu and Tam, 2017). According to Hogan et al. (2003), disadopters represent a critical segment, as they are typically early adopters who can exert negative social influences, potentially fostering distrust and hindering the technology's diffusion. Thus, it becomes imperative to regain their trust, as highlighted by Xin Xu and Tam (2017). From the viewpoint of central banks, understanding the characteristics of Bitcoin disadopters is crucial if the goal is to successfully introduce a CBDC. The risks that lead to disadoption of digital private currency, such as Bitcoin, may bear similarities to those associated with CBDC adoption. Hence, understanding disadoption behavior is of paramount importance.

6.3 Multinomial Model of Ownership

To test the predictions about the ranking of beliefs and their dynamics over time on the probability of being a Bitcoin owner, past owner or a never owner, we first consider a non-parametric approach, and then we estimate a conditional multinomial probability model, in which the benchmark group is those who have never owned Bitcoin.

[20] Practically we measure the contribution of our choice variables on the log-likelihood ratios via a $Pseudo-R^2 = 1 - \frac{Log-likelihood(Model)}{Log-Likelihood(Constant)} - \lambda \frac{df}{N-1}$ measure (Hosmer et al., 2013).

Figure 5 plots the empirical CDF of respondents' beliefs about the expected survival of Bitcoin in the next 15 years for owners, past owners, and never owners, respectively. Notice that the CDFs do not intersect, and their ranking remains stable over time.

In particular, the distribution of beliefs for owners FOSD that of past owners, which, in turn, FOSD the distribution of beliefs for never owners.[21] These results are in line with the theoretical predictions (Proposition 2), indicating heterogeneous learning rates between and within ownership categories. We also see a shift in the distributions of beliefs to the right as time goes on, with the distribution of past owners moving the fastest towards that of owners. In 2017, past owners were closer in beliefs to the never owners, but then their beliefs became closer to those of current owners. This shift in the beliefs, especially for past owners, suggests temporal exits from the Bitcoin market rather than permanent ones.

Next, we estimate a conditional multinomial logit to test if this ranking is also preserved when we condition the choice probabilities on the demographic characteristics. Table 10 shows the results of the multinomial model, indicating that the ranking of beliefs on choice probabilities is preserved.

- insert Table 10 here -

The role of beliefs is stronger for owners than past owners, and both are positive on average, compared with never owners; moreover, their role is strengthened after controlling for belief endogeneity. As outlined in Section 5.2, to address endogeneity concerns regarding beliefs influencing both adoption and exit choices, we introduce two CFs (tailored for each choice) comprising residuals from modeling beliefs separately for owners and past owners, along with their interaction for greater flexibility (Imbens and Wooldridge, 2009). Table 11 presents the results with two CFs.

- insert Table 11 here -

Notably, the CF associated with past owners' beliefs drives the outcomes, reflecting the evolving nature of their beliefs over time compared to the more stable beliefs of current owners. The model with two CFs enhances the role of beliefs compared with the single CF model, demonstrating a substantial improvement over the model without endogeneity correction. The model estimates that the beliefs of never owners are more negative than those of past owners, which are smaller on average than of current Bitcoin owners (see Figure 11).

- insert Figure 11 here -

[21] A FOSD test based on Kolmogorov-Smirnov yielded a p-value of 0.

The relevant demographic characteristics for the choice probabilities relative to the benchmark (never owners) are gender and age, having a negative impact for owners and past owners; education, having a positive impact for owners; and unemployment and not in the labor force, with a negative impact for owners. Income has a negative impact for past owners.

As in the case of the probability of being a past owner, we also undertake a likelihood ratio decomposition of our multinomial model based on the same grouping of variables (beliefs, demographic characteristics, CFL score, and CFs). Figure 12 depicts a visual representation of this decomposition.

- insert Figure 12 here -

This highlights the increased importance of beliefs in the choice model over time. Despite only constituting a single variable, beliefs improve the likelihood ratio almost as much as all demographic variables combined in 2019. The importance of CFL is more pronounced in 2017 and declines over time, while the importance of selection (the role of the CF) increases over time. Demographic characteristics contribute less to the model relevance over time.

All in all, the results of this analysis hold significant importance, as they underscore a key determinant (beliefs) of choice probabilities among Bitcoin owners, past owners, and never owners. These findings also shed light on how variations in beliefs regarding Bitcoin's survival offer insights into these choice probabilities.

6.4 Sequential Model of Choices

We now turn to examine the joint transitions from being a never owner to becoming an owner, and from being a current owner to being a past owner (Figure 2). As outlined in Section 5.3, we estimate a sequential logit model, in which a never owner can become a current owner, who can then become a past owner. Table 12 shows the results of this exercise. Notice that beliefs play opposite roles for owners and past owners. Intuitively, an increase in beliefs raises the chances of owning, inducing owners to remain as owners and not exit. The results show that becoming an owner increases beliefs (positive effect), while becoming a past owner decreases beliefs (negative effect).

- insert Table 12 here -

Additionally, when we control for the endogeneity of beliefs, their role is strengthened in measuring the transition probabilities in the model. As before, to address endogeneity concerns regarding beliefs influencing both adoption and exit choices, we employ CFs in a two-step approach, as done for the multinomial choice model in Section 5.2; see Table 13.

- insert Table 13 here -

Similar to the multinomial choice model, the CF linked to the beliefs of past owners plays a pivotal role in driving the outcomes. While the model with two CFs amplifies the significance of beliefs for current owners, it does not exhibit a comparable enhancement for past owners when compared with the single CF model. Compared with the multinomial model, the sequential model provides more stable results in terms of demographics: gender and age impact the transition from being a never owner to being current owner, while income and employment status impact the transition from being an owner to being a past owner.

Our empirical results are in line with the theoretical predictions. Bitcoin owners are becoming more optimistic over time, while past owners' beliefs are moving closer to those of current owners. The results also emphasize that the distance in beliefs between a never owner and a new owner is stable over time, while it decreases over time as we move from an owner to a past owner, in which the distance decreases (especially between 2018 and 2019).

As a final analysis, we also undertake a likelihood ratio decomposition of our sequential choice model, as done in Section 6.3. Figure 13 depicts a visual representation of this decomposition.

- insert Figure 13 here -

The impact of our choice variables on the likelihood ratio aligns with the findings from the multinomial model (Section 6.3). Notably, the role of beliefs exhibits an increasing trend over time, while that of demographic variables shows a decreasing one. CFL demonstrates higher relevance in the years 2017 and 2019, while CF (measuring selection effect) is more relevant in 2018–19. The sequential choice model proves highly effective in addressing the potential simultaneity issue that links individuals' beliefs to both entry and exit decisions. By staggering entry and exit choices while differentiating between owners' and past owners' beliefs, the sequential approach resolves a crucial timing challenge that is absent when the analysis focuses on entry and exit in isolation.

Table 14 provides a summary of the role of the relevant variables for the three analyzed models outlined in Section5 (past ownership, multinomial choices, and sequential choices):

- insert Table 14 here -

Beliefs exert the greatest influence in 2018 for past ownership probability, and in 2019 for both the multinomial and sequential choice models. Correction terms addressing selection bias and belief endogeneity become more pertinent post-2017, particularly in 2018, when exit-related selection peaks. Crypto-financial literacy CFL has the most significant impact on the probability of being a past owner (particularly in 2018 amid the downturn in the Bitcoin market), while demographic factors seem to have a diminishing role in explaining ownership and transitions over time across all analyzed models.

Altogether, the sequential approach provides valuable insights into the dynamics of Bitcoin adoption, taking into account not only the formation of beliefs about Bitcoin's survival but also the demographic drivers of these decisions. Understanding these dynamics is not only appropriate to Bitcoin but also holds relevance for the adoption and disadoption of other digital currencies, including CBDCs.

6.5 Crypto and Financial Literacy

Our empirical analyses indicate that beliefs have an important role in the entry and exit to the Bitcoin market. As a byproduct, we also uncover that crypto-financial literacy CFL also seems to have a strong predictive power, thereby contributing to the financial literacy literature.[22] The effect of CFL on the decision to exit the market appears to depend on market conditions. Individuals with high CFL exhibit a decreased likelihood of exiting during downturns, such as in 2018. Conversely, the opposite holds during market improvements, like in 2019. This suggests that individuals with high CFL may be better equipped at managing the risks linked to Bitcoin market, while also potentially capitalizing on market recoveries, as evidenced by the positive effect of high CFL in 2019. It is noteworthy that individuals with medium CFL exhibit a similar correspondence: they are less likely to enter the Bitcoin market but more inclined to exit, particularly evident in the 2019 results. The sequential model reinforces the observed patterns in the probability of becoming a past owner.

7 Conclusion

We develop a model to study the dynamics of Bitcoin entry and exit. Agents make decisions based on their beliefs of Bitcoin's future viability and alternatives. We classify individuals into owners, past owners, and never owners, with varying learning rates, determining how their beliefs compare with each other across time and also how they evolve over time.

Our empirical analysis unveils significant variations in the impact of beliefs on ownership across time and by ownership status. A decrease in beliefs predicts a higher likelihood of

[22] Balutel et al. (2024) discuss the roles of crypto and financial literacy separately, in relation to Bitcoin ownership and with a specific focus on gender differences; see also Bucher-Koenen et al. (2021). Lyons and Kass-Hanna (2021) explore the intersection of digital literacy and financial literacy to show the pathways influencing financial behavior. Fujiki (2021) studies differences in financial literacy among crypto asset owners and non-owners, finding that owners who have investment experience with conventional risky financial assets demonstrate higher financial literacy compared with owners who lacked such investment experience.

exiting the Bitcoin market, aligning with our theoretical predictions. Beliefs about Bitcoin's survival has become more optimistic for past owners, suggesting there may be re-entry as time goes on. Also, individuals' combined financial literacy and cryptocurrency knowledge play an important role shaping the Bitcoin market. We also examine the impact of demographic factors and cryptocurrency knowledge on the the respective beliefs of owners, past owners, and never owners. Age, education, Bitcoin knowledge, incidents, and price negatively influence the beliefs of individuals who have never owned Bitcoin. In contrast, income, relationship status, and incidents play a negative role in shaping the beliefs of past owners, while for current owners, incidents have a stronger negative impact.

Our work has implications for understanding the introduction of a CBDC and how its adoption and use might evolve over time. New products that gain widespread adoption typically do so by following an s-curve process (Rogers, 2010). Henry et al. (2024) study whether the introduction of a CBDC may help address unmet payment needs in Canada, finding that the majority of consumers—who would be needed to drive the s-curve—have weak incentives to adopt, being well-served by existing payment methods. Real world implementations of CBDC, such as in China, bear out these predictions: the digital yuan has struggled to find a role in the Chinese payments market (Orcutt, 2023). Furthermore, attempting to overcome such barriers by offering financial incentives to on-board consumers can also be ineffective, as demonstrated by El Salvador's efforts to promote use of Bitcoin as a national currency (Argente et al., 2023). Our work suggests that the role of beliefs may be a missing element from the discussion about CBDC introduction. Incentivizing the use of a CBDC could help facilitate learning but may not sufficiently change underlying core beliefs of consumers. A public consultation by the Bank of Canada revealed that many respondents believe "the Bank of Canada should not be researching and building the capacity to issue a digital Canadian dollar," nor do they believe that "the Bank [...] will consider the public's feedback about a potential digital Canadian dollar" (Forum Research Inc., 2023). Addressing such beliefs should, therefore, be of first-order concern.

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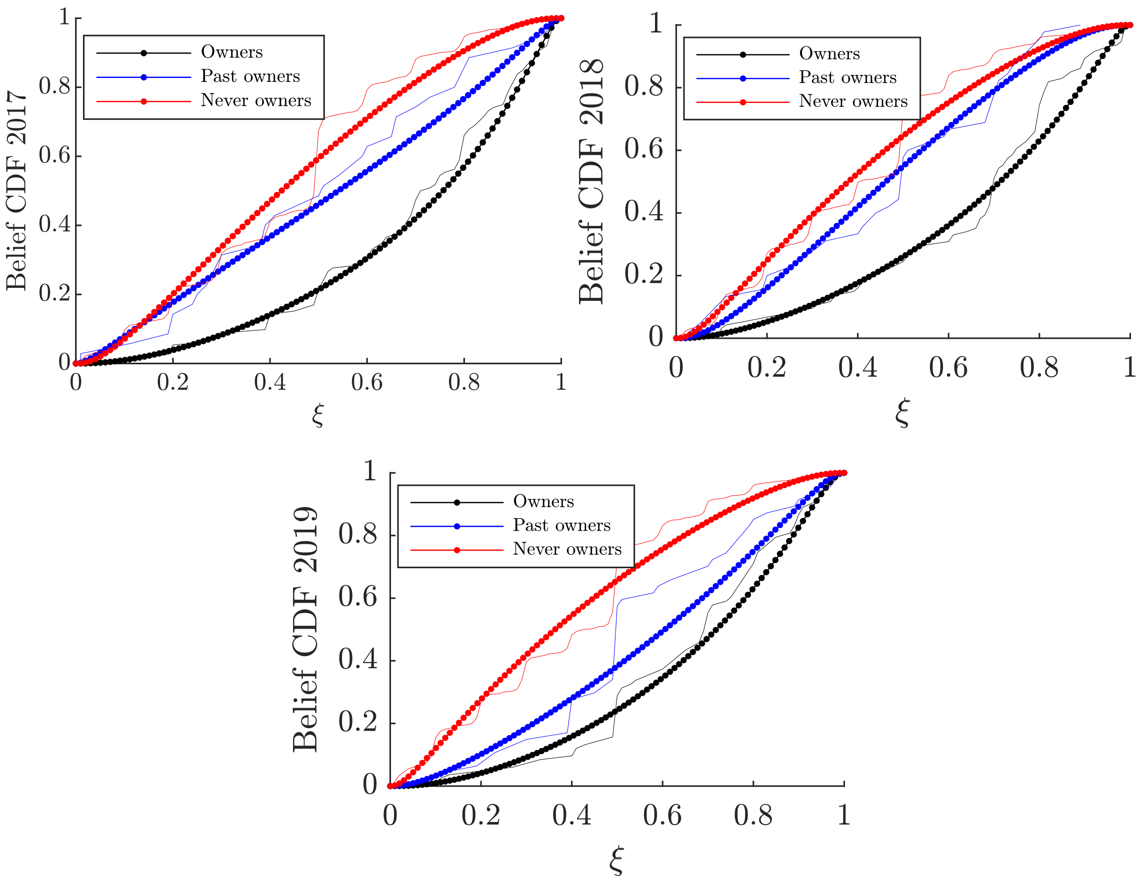
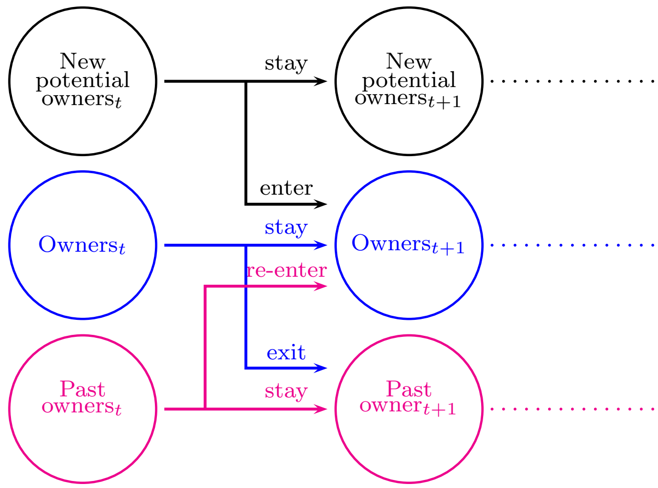
Figures

Figure 1: **Simulated belief dynamics**



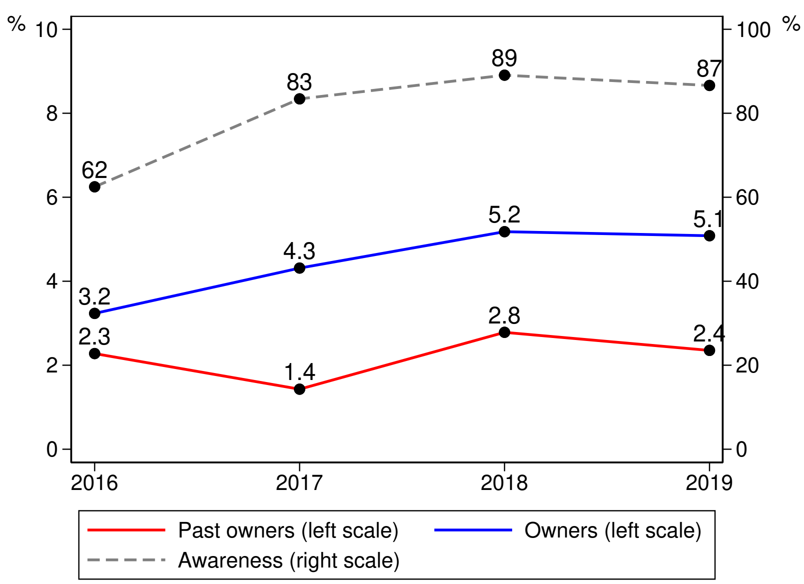
Note: Evolution of CDFs as individuals' beliefs evolve as predicted from the theoretical model. Figure assumes owners learn (stochastically) faster than past owners, and past owners faster than never owners.

Figure 2: **Model diagram**



Note: Schematic of the possible transitions captured by the theoretical model.

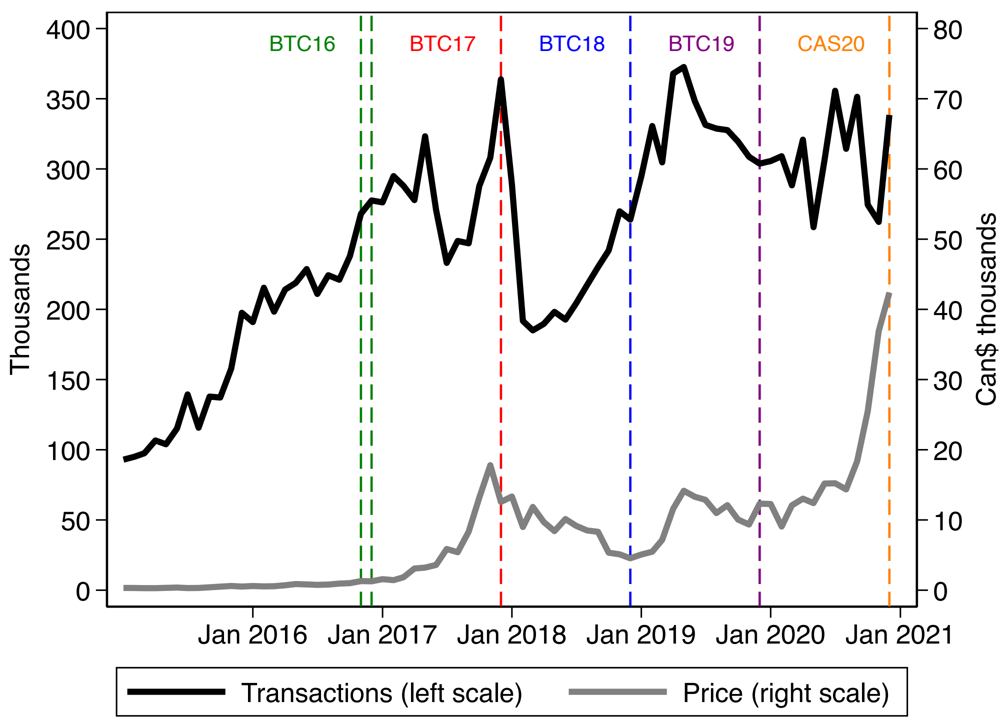
Figure 3: **Bitcoin awareness and ownership 2016–19**



Note: Estimates of average Bitcoin awareness, current ownership and past ownership in Canada.

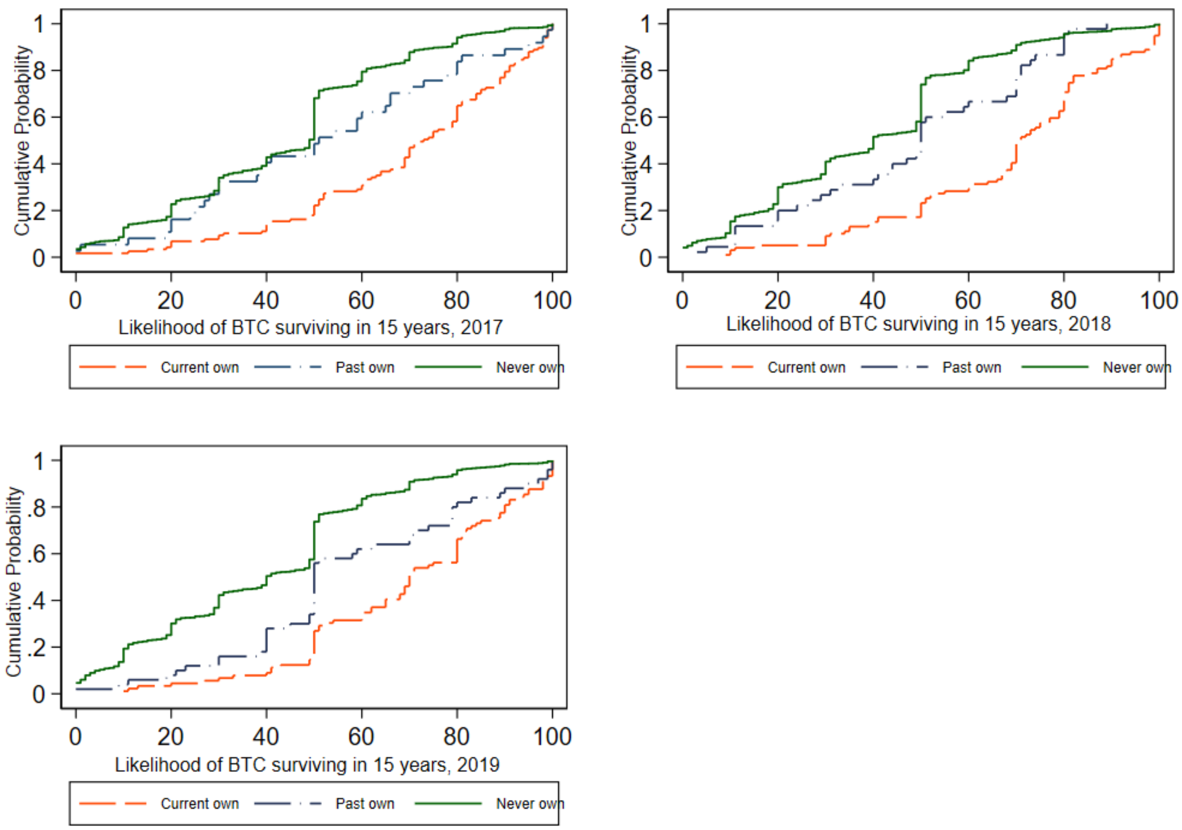
This figure plots yearly estimates of the share of Canadians who were aware of Bitcoin, who owned Bitcoin, and who exited from 2016 to 2019. Estimates from 2016 to 2019 are from the Bitcoin Omnibus Survey. For ease of presentation, ownership and past-ownership is scaled from 0% to 10% (left scale), while awareness is scaled from 0% to 100% (right scale).

Figure 4: **Price and volume of Bitcoin at the time of BTCOS surveys**



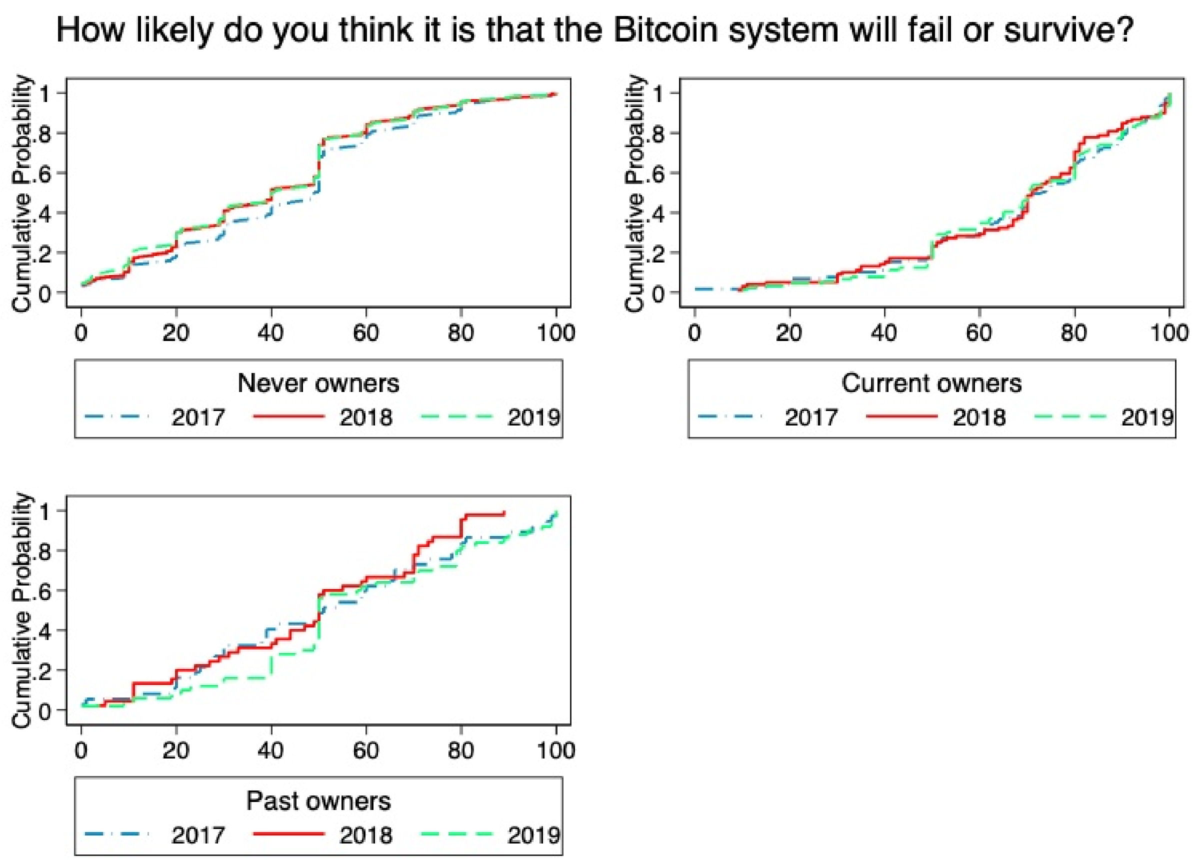
Note: This figure plots the number of transactions conducted on the Bitcoin network (left scale) as well as the price of Bitcoin in Canadian dollars (right scale), showing dates when various Bank of Canada surveys measuring Bitcoin were conducted. Green vertical lines indicate the first iteration of the Bank of Canada's Bitcoin Omnibus Survey (BTCOS), conducted initially as a pilot in two stages; the red vertical line indicates the 2017 BTCOS; the blue vertical line indicates the 2018 BTCOS; and the purple line indicates the 2019 BTCOS. The orange vertical line represents the Bank of Canada's Cash Alternative Survey (CAS) conducted in November 2020, which contained a limited number of questions about Bitcoin awareness and ownership.

Figure 5: **Expected survival rate of Bitcoin in 15 years: Between group dynamics of beliefs ξ_{it}:**



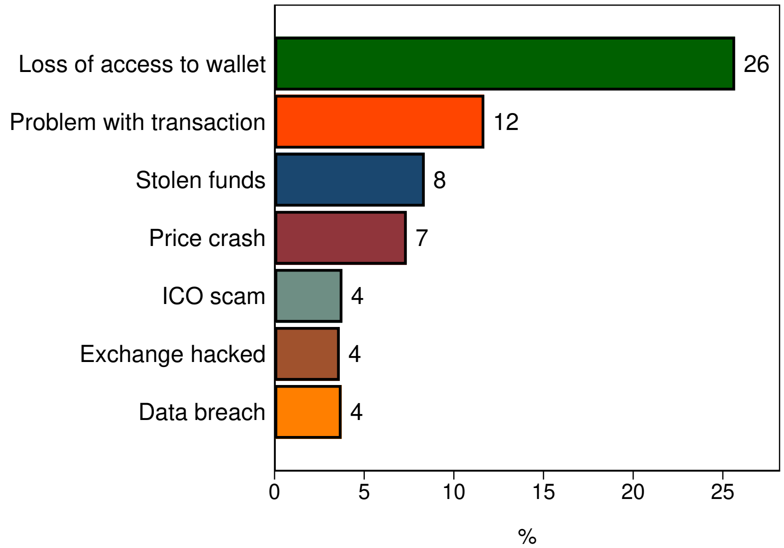
Note: Question from the BTCOS: *"How likely do you think it is that the Bitcoin system will survive for the next 15 years?"* Respondents answered on a scale of 0 to 100.

Figure 6: **Bitcoin expected survival rate in 15 years: Within group dynamics of beliefs ξ_{it}:**



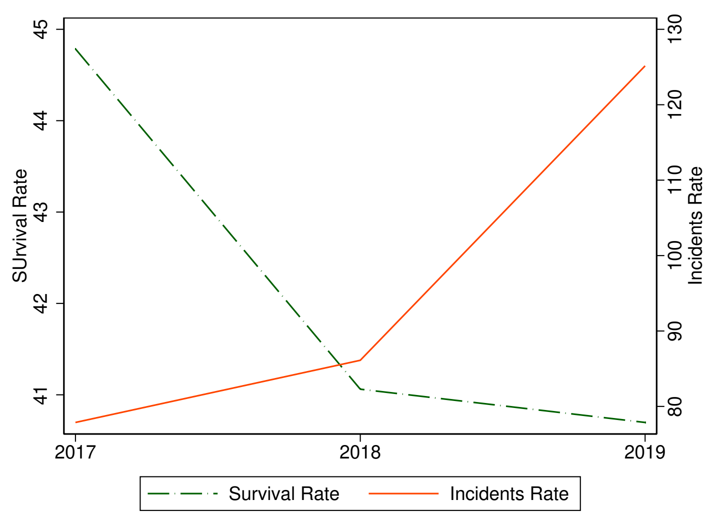
Note: Question from the BTCOS: *"How likely do you think it is that the Bitcoin system will survive for the next 15 years?"* Respondents answered on a scale of 0 to 100.

Figure 7: **Selection out of the Bitcoin market: Cryptocurrency risks and loss incidents faced by past Bitcoin owners, 2019**



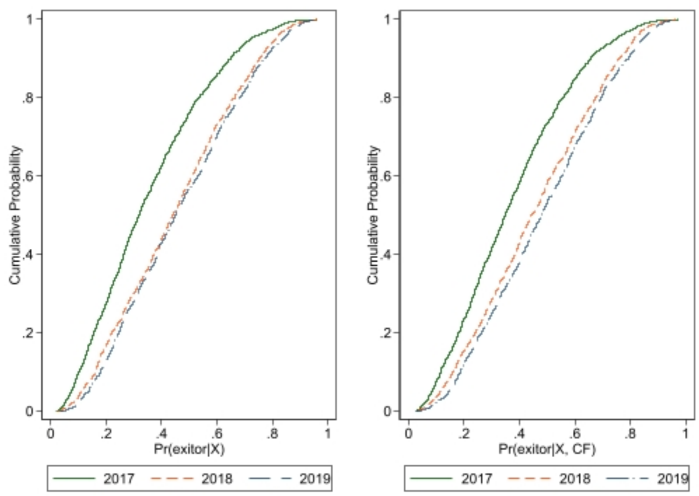
Note: This figure reports the percentages of cryptocurrency past owners who experienced any of the indicated incidents in 2019 BTCOS. The sample consists of 50 Canadians aged 18 and over who indicated owning Bitcoin in the past, but not at the time of the survey. All estimates are calculated using survey weights.

Figure 8: **Expected survival rate of Bitcoin (ξ_{it}) and cyber incidents rate (Z_{jt})**



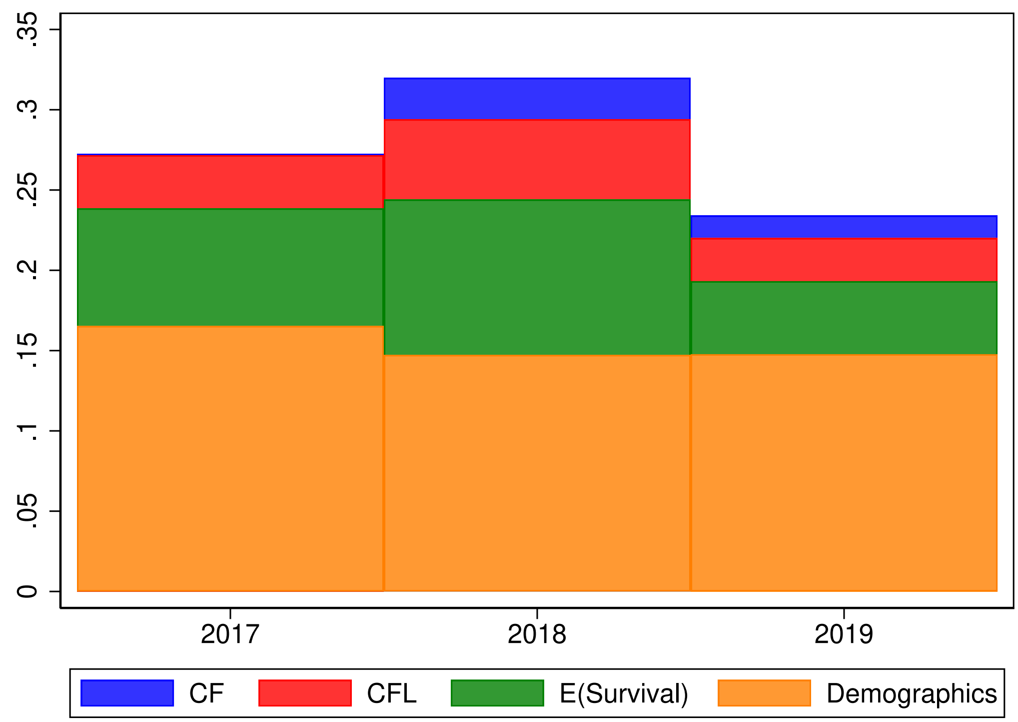
Source: BTCOS and CANSIM

Figure 9: **Probability of exiting: 2017–19, without and with CF**



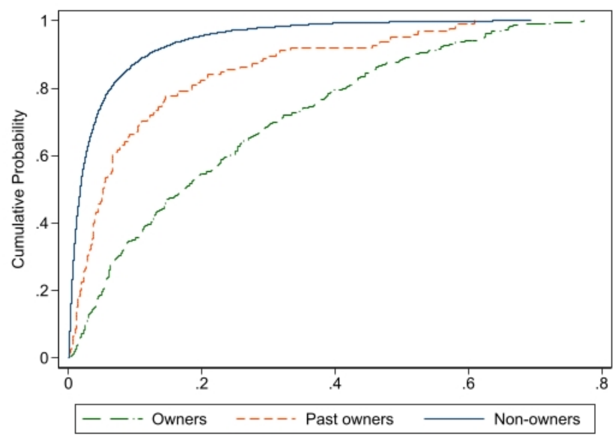
Note: All estimates are calculated using survey weights.

Figure 10: **Likelihood ratios (Pseudo-R^2) contributions: Probability of being a past owner**



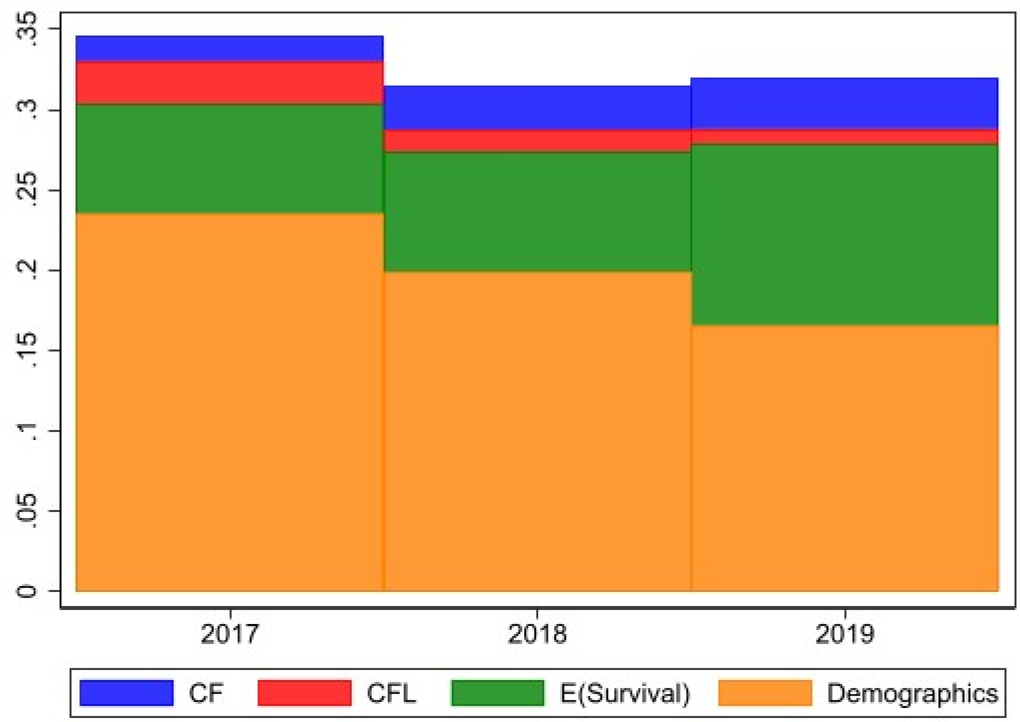
Note: The following coding is used for measuring the $Pseudo - R^2 = 1 - \frac{Log-likelihood(Model)}{Log-Likelihood(Constant)} - \lambda \frac{df}{N-1}$ contribution (Hosmer et al., 2013) for the probability of being a Bitcoin past owner: CF = control function contribution to the probability, CFL = crypto and financial literacy contribution to the probability, E(Survival) = Beliefs contribution to probability, Demographics = demographics contribution to the probability.

Figure 11: **Probability of being an owner and past owner relative to never owner**



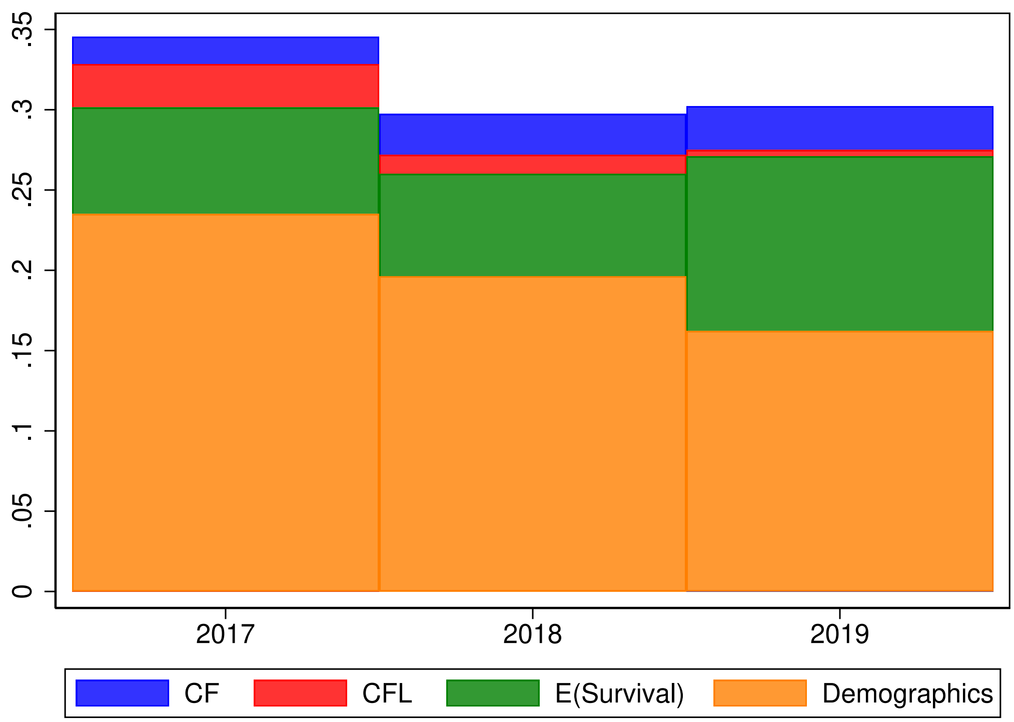
Note: All estimates are calculated using survey weights.

Figure 12: **Likelihood ratios (Pseudo-R^2) contributions: Multinomial model of choices**



Note: The following coding is used for measuring the $Pseudo - R^2 = 1 - \frac{Log-likelihood(Model)}{Log-Likelihood(Constant)} - \lambda \frac{df}{N-1}$ contribution (Hosmer et al., 2013) for the probability of being a Bitcoin past owner: CF = control function contribution to the probability, CFL = crypto and financial literacy contribution to the probability, E(Survival) = Beliefs contribution to probability, Demographics = demographics contribution to the probability.

Figure 13: **Likelihood ratios (Pseudo-R^2) contributions: Sequential model of choices**



Note: The following coding is used for measuring the $Pseudo - R^2 = 1 - \frac{Log-likelihood(Model)}{Log-Likelihood(Constant)} - \lambda \frac{df}{N-1}$ contribution (Hosmer et al., 2013) for the probability of being a Bitcoin past owner: CF = control function contribution to the probability, CFL = crypto and financial literacy contribution to the probability, E(Survival) = Beliefs contribution to probability, Demographics = demographics contribution to the probability.

Tables

Table 1: **Percentage of Canadians who own Bitcoin, and have owned Bitcoin between 2017 and 2019**

	2017		**2018**		**2019**	
	Current own	Past own	Current own	Past own	Current own	Past own
Overall	4.3	1.4	5.2	2.8	5.1	2.4
Male	6.6	2.2	6.7	4.2	8.1	3.3
Female	2.1	0.7	3.7	1.4	2.2	1.5
18–34	11.1	2.6	10.5	5.6	7.8	5.2
35–54	3.2	1.7	4.9	3.3	6.7	1.7
55+	0.5	0.4	1.7	0.3	1.7	1.0
High school or less	3.7	1.2	2.3	3.4	3.3	1.3
College / CEGEP / Trade	3.1	1.5	5.7	1.9	4.3	2.9
University	6.7	1.6	9.1	2.8	8.7	3.4
<30k	4.3	1.7	2.8	3.6	3.7	4.8
30k–69k	5.6	0.5	4.8	2.4	3.8	1.8
70k+	4.3	2.1	7.0	3.3	6.6	2.3
Employed	6.1	2.1	7.1	3.2	6.8	2.4
Unemployed	1.9	0.9	5.2	1.1	0.9	5.9
Not in labor force	1.5	0.4	1.9	2.1	2.3	1.9
B.C.	5.2	1.3	6.3	5.2	5.3	2.1
Prairies	4.1	0.8	6.0	3.3	3.9	2.2
Ontario	3.9	1.9	5.2	2.6	6.2	2.9
Quebec	5.1	1.2	4.6	1.2	4.4	1.4
Atlantic	3.1	1.5	2.8	2.8	3.8	4.0
Fin lit: Low			7.3	2.9	7.5	2.6
Fin lit: Medium			4.7	2.6	2.9	2.1
Fin lit: High			4.1	2.8	5.1	2.4
BTC knowledge: Low	2.3	1.4	1.8	3.6	2.7	1.3
Medium	6.5	1.6	9.1	1.6	7.1	3.9
High	22.6	4.7	27.8	6.6	32.2	10.2

Note: This table provides estimated percentages of Canadians that currently own Bitcoin (Col. 1, 3, 5) and have owned Bitcoin in the past (Col. 2, 4, 6). All estimates are calculated using survey weights.

Table 2: **Counts of crypto and financial literacy, 2017–19**

NO				
FCL	2017	2018	2019	Total
Low	1,196	746	744	2,686
Medium	793	589	586	1,968
High	119	353	326	798
Total	2,108	1,688	1,656	5,452
BO				
FCL	2017	2018	2019	Total
Low	27	33	34	94
Medium	58	28	21	107
High	32	38	34	104
Total	117	99	89	305
PO				
FCL	2017	2018	2019	Total
Low	15	24	16	55
Medium	12	14	22	48
High	10	7	12	29
Total	37	45	50	132

Note: This table provides the counts of CFL categories (low, medium, high) for Bitcoin owners (BO), past Bitcoin owners (PO) and never owners (NO).

Table 3: **Weighted means of crypto and financial literacy, 2017–19 (%)**

NO	**mean**	**Obs**
2017	1.482	2,108
2018	1.718	1,688
2019	1.706	1,656
BO	**mean**	**Obs**
2017	2.033	117
2018	2.019	99
2019	1.862	89
PO	**mean**	**Obs**
2017	1.706	37
2018	1.624	45
2019	2.006	50

Note: This table provides the weighted means of CFL scores for Bitcoin owners (BO), past Bitcoin owners (PO), and never owners (NO).

Table 4: **Main reasons for not owning Bitcoin stated by past owners, 2017–19 (%)**

	2017	2018	2019
I do not understand/know enough about the technology	21	11	8
It is not widely accepted as a method of payment	14	6	6
My current payment methods meet all my needs	3	5	12
The value of Bitcoin varies too much	12	17	18
It is not easy to acquire/use	28	17	14
I do not trust a private currency that is not backed by the central government		4	3
I am concerned about cyber theft	12	10	7
I am concerned about lack of oversight from regulatory bodies	2	10	3
I use alternative digital currencies instead (e.g. Etherium, Tether, Litecoin, etc)	0	0	13
I do not believe the Bitcoin system will survive in the future	9	15	13
Other	0	4	3

Note: This table provides the distribution of past owners responses to the question, “Please tell us your main reason for not owning any Bitcoin.” All estimates are calculated using survey weights.

Table 5: **Regional rate per 100,000 population of cyber incidents, 2016–19**

	2016	**2017**	**2018**	**2019**
B.C.	129	114	144	197
Prairies	73	81	105	121
Quebec	37	42	48	58
Ontario	70	80	75	130
Atlantic	85	104	132	167

Note: Source CANSIM 252-0096

Geography: Province or territory (2016-2019)

Table 6: **Connections between theoretical model of Bitcoin entry/exit and empirical analysis**

1] Beliefs drive exit from the Bitcoin market.	
Model prediction / assumption	*Empirical test*
Probability of exit depends on level of beliefs and reservation utility (Eq. 3.5)	Estimated coefficient on beliefs is negative and significant in second-stage model of exit (Eq. 5.2; Table 9), validating the prediction of the model.
2] Ranking of beliefs by ownership type.	
Model prediction / assumption	*Empirical test*
Assuming types have different speeds of learning, ranking of beliefs is preserved across time (Prop. 2; Eq. 3.2)	Non-parametric Kolmogrov-Smirnov of FOSD (Fig. 5); marginal effects of beliefs for owners/past owners is positive, relative to non-owners with the highest magnitude being associated to owners (Tables 10–11). The prediction of the model is also validated.
3] Distribution of beliefs across time.	
Model prediction / assumption	*Empirical test*
Conditional on a given ownership type, distribution of learning rates can increase, decrease or remain constant (Prop. 3)	Compare relative size of marignal effects of beliefs by ownership type, across time (Fig 6; Tables 10–11). The results show that the role of beliefs can either increase or decrease, especially for past Botcoin owners, depending on the volatility of the market.
4] Dynamics of transitioning between ownership states	
Model prediction / assumption	*Empirical test*
There is a unique equilibrium solution to the dynamical system describing how the rates of ownership and past ownership evolve across time (Eq. 3.6–3.8; Prop. 4)	Using a sequential logit model, jointly estimate the transition from never owner to Bitcoin adopter, and then from an adopter to past owner (Eq. 5.7; Tables 12–13). The results about the Bitcoin ownership and past ownership are in line with the predictions of the model.

Table 7: **Model for beliefs about Bitcoin survival by ownership status, 2017–19**

VARIABLES	Owners	Past Owners	Never Owners
Female	3.719	-4.283	-0.686
	(3.108)	(4.481)	(0.952)
Age: 35–54	3.715	9.948**	-6.567***
	(3.265)	(4.456)	(1.316)
Age: 55+	-1.115	-6.933	-9.401***
	(5.420)	(6.293)	(1.370)
College / CEGEP / Trade	6.463	7.532	-4.002***
	(4.502)	(5.195)	(1.170)
University	4.860	2.985	-6.047***
	(4.666)	(5.568)	(1.240)
Income: 30k–69k	0.404	-17.709**	-0.788
	(4.350)	(6.837)	(1.341)
Income: 70k+	1.069	-7.944	1.434
	(5.333)	(6.565)	(1.484)
Unemployed	-2.368	9.046	-0.765
	(8.057)	(6.890)	(2.143)
Not in labor force	0.029	6.307	-1.484
	(4.907)	(6.459)	(1.112)
Not single	-7.384*	-3.801	2.742***
	(4.365)	(5.640)	(1.050)
Kids	-8.780**	13.837**	2.318*
	(4.100)	(5.644)	(1.322)
BTC_fix supply_DK	-4.190	4.474	-3.926***
	(4.488)	(5.209)	(1.278)
BTC_fix supply_C	2.358	10.625**	-1.450
	(3.369)	(5.338)	(1.688)
BTC_pub_ledger_DK	-3.486	-2.690	-1.845
	(5.612)	(5.635)	(1.347)
BTC_pub_ledger_C	0.0320	6.006	6.094***
	(3.446)	(5.275)	(1.692)
BTC_gov_backed_DK	-11.289*	-1.051	-3.791
	(5.961)	(8.653)	(2.687)
BTC_gov_backed_C	-9.257**	7.604	-5.680**
	(4.027)	(8.004)	(2.651)
2018	-2.242	1.655	-3.658***
	(3.992)	(5.654)	(1.035)
2019	0.286	13.503**	-3.827***
	(4.044)	(5.512)	(1.077)
Constant	81.207***	41.852**	57.967***
	(11.303)	(16.572)	(4.020)
Observations	296	125	4,743
R-squared	0.093	0.353	0.081

Note: The base case is Male, Age 18–34, High School, Low Income, Employed, Single, Incorrect answer for Bitcoin knowledge questions (DK = "Don't know" answer, C = correct answer) and Year 2017. Significance stars ***, **, and * represent 1%, 5%, and 10% significance, respectively.

Table 8: **First-stage model for beliefs about Bitcoin survival, 2017–19**

VARIABLES	Pooled E(Survival)
Female	-0.660
	(0.912)
Age: 35–54	-6.285***
	(1.215)
Age: 55+	-9.983***
	(1.300)
College	-2.986***
	(1.124)
University	-4.785***
	(1.203)
30k–69k	-1.101
	(1.292)
70k+	0.961
	(1.432)
Unemployed	-0.478
	(1.999)
Not in labor force	-1.689
	(1.065)
Not single	1.707*
	(1.032)
Kids	2.009
	(1.228)
BTC_fix_supply_DK	-4.099***
	(1.234)
BTC_fix_supply_C	1.845
	(1.506)
BTC_pub_ledger_DK	-1.791
	(1.296)
BTC_pub_ledger_C	7.729***
	(1.535)
BTC_gov_backed_DK	-3.656
	(2.667)
BTC_gov_backed_C	-5.057*
	(2.614)
Incident_rate_P17	-1.786
	(2.686)
Incident_rate_O17	-2.919
	(2.913)
Incident_rate_Q17	-5.852**
	(2.300)
Incident_rate_A17	-1.844
	(1.808)
Incident_rate_P18	-5.354**
	(2.186)
Incident_rate_O18	-1.113
	(2.957)
Incident_rate_Q18	-8.496***
	(2.815)
Incident_rate_A18	-6.578***
	(2.163)
Incident_rate_P19	-9.466***
	(2.767)
Incident_rate_O19	-4.368*
	(2.555)
Incident_rate_Q19	-2.582
	(3.476)
Incident_rate_A19	-8.487***
	(2.728)
Incident_rate_A19	-2.463
	(3.317)
Incident_rate_A19	-4.618
	(3.423)
Day 2	-0.738
	(1.825)
Day 3	1.918
	(3.908)
Day 4	0.697
	(2.305)
Day 5	-0.643
	(2.389)
Day 6	0.372
	(2.229)
Day 7	-8.843***
	(2.983)
Day 8	-0.519
	(2.502)
Day 9	-2.098
	(4.768)
Day 10	-25.48***
	(3.812)
Day 11	-15.55***
	(2.739)
Day 12	-8.666***
	(2.104)
Day 13	-2.604
	(2.568)
Constant	61.57***
	(4.332)
Observations	5,164
R-squared	0.112

Note: $Incident\_rate_{P,O,Q,A}$, regional level cyber incidents for Prairies, Ontario, Quebec, Atlantic provinces. "Day 2" through "Day 12" are the subsequent days when the survey was administered or when participants answered the survey. The base case is Male, Age 18–34, High School, Low Income, Employed, Single, No kids, Incorrect answer for Bitcoin knowledge questions (DK = "Don't know" answer, C = correct answer), Day 1 of completing the survey. Significance stars ***, **, and * represent 1%, 5%, and 10% significance, respectively.

Table 9: **Marginal effects of the probability of being a Bitcoin past owner, without and with controlling for sample selection**

VARIABLES	Pool	Pool - CF	2017	2017 - CF	2018	2018 - CF	2019	2019 - CF
E(Survival)	-0.006***	-0.018***	-0.004***	-0.005	-0.006***	-0.023***	-0.005***	-0.020***
	(0.001)	(0.004)	(0.001)	(0.005)	(0.001)	(0.007)	(0.002)	(0.006)
$\widehat{u}$		0.013***		0.001		0.017**		0.016**
		(0.004)		(0.005)		(0.007)		(0.006)
Female	-0.011	-0.028	0.022	0.021	-0.043	-0.05	0.015	-0.013
	(0.051)	(0.050)	(0.072)	(0.073)	(0.080)	(0.084)	(0.084)	(0.085)
Age: 35–54	0.035	-0.045	0.086	0.076	0.166**	0.090	-0.166*	-0.275***
	(0.056)	(0.056)	(0.081)	(0.093)	(0.074)	(0.080)	(0.088)	(0.089)
Age: 55+	-0.042	-0.157	0.187	0.177	-0.205***	-0.283***	-0.169	-0.308***
	(0.094)	(0.099)	(0.168)	(0.177)	(0.072)	(0.065)	(0.125)	(0.116)
College	0.037	-0.017	0.060	0.055	-0.249**	-0.289**	0.161	0.095
	(0.076)	(0.078)	(0.100)	(0.104)	(0.117)	(0.118)	(0.111)	(0.116)
University	-0.108	-0.173**	-0.122	-0.128	-0.270**	-0.338**	-0.003	-0.073
	(0.078)	(0.082)	(0.085)	(0.094)	(0.129)	(0.133)	(0.103)	(0.113)
Income: 30k–69k	-0.114	-0.118	-0.207**	-0.206**	-0.022	-0.045	-0.178	-0.170
	(0.083)	(0.075)	(0.093)	(0.095)	(0.179)	(0.172)	(0.138)	(0.123)
Income: 70k+	-0.002	0.005	0.040	0.045	-0.057	-0.080	-0.087	-0.091
	(0.090)	(0.085)	(0.121)	(0.126)	(0.172)	(0.166)	(0.148)	(0.130)
Unemployed	0.193	0.137	-0.162**	-0.165**	-0.148	-0.158	0.494***	0.367**
	(0.140)	(0.118)	(0.081)	(0.081)	(0.181)	(0.170)	(0.154)	(0.162)
Not in labor force	0.092	0.043	-0.024	-0.027	0.071	0.027	0.101	0.015
	(0.078)	(0.073)	(0.090)	(0.090)	(0.114)	(0.101)	(0.126)	(0.112)
Kids	-0.002	0.040	-0.032	-0.027	-0.068	-0.004	-0.061	0.001
	(0.060)	(0.060)	(0.070)	(0.072)	(0.078)	(0.082)	(0.100)	(0.099)
Not single	0.016	0.044	-0.057	-0.052	-0.068	-0.032	0.015	0.061
	(0.059)	(0.056)	(0.079)	(0.083)	(0.098)	(0.088)	(0.100)	(0.095)
FCL: Medium	0.024	0.048	-0.132	-0.123	-0.058	-0.044	0.219**	0.231**
	(0.062)	(0.058)	(0.085)	(0.088)	(0.085)	(0.087)	(0.108)	(0.098)
FCL: High	-0.084	-0.012	-0.175*	-0.159	-0.282***	-0.206**	0.145	0.187**
	(0.064)	(0.064)	(0.094)	(0.120)	(0.092)	(0.096)	(0.094)	(0.089)
Price of Bitcoin	-0.020	-0.030	-0.042	-0.045	0.640*	0.523	-0.037	-0.047
	(0.040)	(0.040)	(0.030)	(0.035)	(0.385)	(0.388)	(0.109)	(0.107)
Province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes						
Observations	421	421	147	147	140	140	134	134

Note: The base case is Male, Age 18–34, High School, Low Income, British Columbia, Employed. CFL = Financial and crypto literacy. Significance stars ***, **, and * represent 1%, 5% and, 10% significance, respectively.

Table 10: **Multinomial choice model of entry and exit**

VARIABLES	Owner pooled	Past owner pooled	Owner 2017	Past owner 2017	Owner 2018	Past owner 2018	Owner 2019	Past owner 2019
E(Survival)	0.040***	0.010*	0.031***	0.004	0.043***	0.001	0.050***	0.023***
	(0.004)	(0.005)	(0.007)	(0.006)	(0.006)	(0.010)	(0.007)	(0.006)
Female	-0.838***	-1.140***	-1.148***	-1.567***	-0.694**	-1.575***	-1.118***	-0.498
	(0.175)	(0.269)	(0.330)	(0.468)	(0.290)	(0.509)	(0.342)	(0.413)
Age: 35–54	-0.794***	-0.849***	-1.405***	-0.808*	-1.151***	-0.770*	0.222	-1.075**
	(0.204)	(0.292)	(0.308)	(0.427)	(0.375)	(0.465)	(0.373)	(0.434)
Age: 55+	-1.750***	-2.117***	-2.770***	-1.363	-1.740***	-3.336***	-1.033**	-1.946***
	(0.270)	(0.557)	(0.614)	(1.129)	(0.520)	(1.249)	(0.432)	(0.511)
College	0.278	0.187	-0.417	-0.289	0.918*	-0.712	0.370	1.185**
	(0.284)	(0.356)	(0.388)	(0.834)	(0.516)	(0.536)	(0.511)	(0.519)
University	0.809***	0.098	0.279	-0.688	1.172**	-0.478	1.348***	1.158**
	(0.284)	(0.383)	(0.361)	(0.878)	(0.502)	(0.564)	(0.481)	(0.540)
Income: 30k–69k	0.0385	-0.663*	0.104	-1.665**	0.551	0.287	-0.361	-1.355***
	(0.290)	(0.339)	(0.416)	(0.658)	(0.662)	(0.622)	(0.489)	(0.482)
Income: 70k+	-0.334	-0.365	-0.675	-0.624	0.399	0.457	-0.560	-1.329***
	(0.308)	(0.374)	(0.456)	(0.588)	(0.633)	(0.734)	(0.514)	(0.443)
Unemployed	-0.682	0.099	-1.387	-0.907	0.525	-0.969	-2.107**	0.678
	(0.444)	(0.482)	(1.021)	(1.326)	(0.634)	(0.887)	(0.824)	(0.693)
Not in labor force	-0.385	0.175	-0.600	-1.121	-0.164	0.739	-0.461	0.374
	(0.238)	(0.334)	(0.507)	(0.781)	(0.424)	(0.467)	(0.382)	(0.408)
Kids	0.475**	0.606*	0.688**	0.863	1.029***	1.252**	-0.386	0.0967
	(0.234)	(0.317)	(0.313)	(0.598)	(0.348)	(0.496)	(0.440)	(0.516)
Not single	-0.177	0.128	-0.153	-0.579	-0.126	0.231	-0.412	0.288
	(0.214)	(0.294)	(0.316)	(0.447)	(0.325)	(0.567)	(0.359)	(0.429)
FCL: Medium	0.234	0.239	0.880***	-0.141	0.286	-0.160	-0.668*	1.068**
	(0.202)	(0.288)	(0.295)	(0.537)	(0.366)	(0.459)	(0.374)	(0.529)
FCL: High	1.009***	0.410	1.949***	1.110**	1.224***	-0.459	-0.0228	1.236**
	(0.247)	(0.325)	(0.446)	(0.541)	(0.394)	(0.619)	(0.351)	(0.580)
Price of Bitcoin	-1.013	-0.044**	0.174	-0.106	-1.758	-0.222	0.906**	1.234*
	(0.012)	(0.019)	(0.199)	(0.261)	(1.816)	(2.534)	(0.450)	(0.652)
Constant	-3.104***	-1.036***	-6.153	2.542	3.348	0.622	-11.523***	-15.945**
	(0.688)	(1.195)	(4.407)	(6.203)	(8.700)	(12.442)	(4.397)	(6.356)
Province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes						
Observations	5164	5164	1,992	1,992	1,582	1,582	1,590	1,590

Note: The base case is Male, Age 18–34, High School, Low Income, Employed, No Kids, Single, British Columbia. CFL = Financial and crypto literacy. The Price of Bitcoin is at the beginnings of the day of the interview. Significance stars ***, **, and * represent 1%, 5%, and 10% significance, respectively.

Table 11: **Multinomial choice model of entry and exit: Control for endogeneity of beliefs using 2 CF**

VARIABLES	Owner pooled	Past owner pooled	Owner 2017	Past owner 2017	Owner 2018	Past owner 2018	Owner 2019	Past owner 2019
E(Survival)	0.173***	0.087***	0.119***	0.102**	0.221***	0.164***	0.197***	0.031
	(0.017)	(0.024)	(0.025)	(0.046)	(0.033)	(0.043)	(0.035)	(0.045)
$\widehat{u}_{own}$	-0.011	-0.016	0.005	-0.042	-0.042	-0.184*	-0.028	-0.079*
	(0.013)	(0.019)	(0.043)	(0.044)	(0.053)	(0.094)	(0.034)	(0.046)
$\widehat{u}_{past}$	-0.129***	-0.066***	-0.096**	-0.070*	-0.143***	-0.020	-0.126***	-0.091*
	(0.018)	(0.022)	(0.039)	(0.038)	(0.047)	(0.072)	(0.034)	(0.051)
$\widehat{u}_{own} * \widehat{u}_{past}$	-0.000	-0.000	0.000	-0.000	-0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female	-0.737***	-1.101***	-0.927*	-1.738***	-0.705*	-2.219***	-0.957***	-0.054
	(0.194)	(0.316)	(0.425)	(0.597)	(0.424)	(0.740)	(0.381)	(0.425)
Age: 35–54	0.068	-0.396	-0.776*	-0.431	-0.281	-0.915	1.024**	-0.337
	(0.245)	(0.332)	(0.419)	(0.518)	(0.565)	(0.717)	(0.467)	(0.595)
Age: 55+	-0.201	-1.348**	-1.735**	-0.881	0.101	-3.046**	0.545	-0.999
	(0.328)	(0.641)	(0.744)	(1.130)	(0.672)	(1.205)	(0.592)	(0.819)
College	0.574*	0.299	-0.048	-0.328	0.875	-2.045*	0.624	2.123***
	(0.293)	(0.441)	(0.508)	(0.836)	(0.713)	(1.101)	(0.571)	(0.723)
University	1.299***	0.318	0.776*	-0.544	1.358**	-1.411	1.706***	1.938***
	(0.278)	(0.444)	(0.468)	(0.868)	(0.655)	(1.005)	(0.534)	(0.743)
Income: 30k–69k	0.185	-0.567	0.224	-1.619**	0.684	0.070	-0.282	-1.150**
	(0.302)	(0.352)	(0.448)	(0.637)	(0.687)	(0.686)	(0.469)	(0.498)
Income: 70k+	-0.452	-0.456	-0.707	-0.731	0.308	-0.150	-0.880*	-1.188***
	(0.305)	(0.376)	(0.497)	(0.601)	(0.665)	(0.771)	(0.466)	(0.442)
Unemployed	-0.589	0.247	-1.363	-0.613	0.382	-0.349	-1.895**	0.577
	(0.466)	(0.482)	(0.985)	(1.342)	(0.773)	(0.853)	(0.823)	(0.739)
Not in labor force	-0.084	0.304	-0.369	-0.900	-0.023	0.483	-0.512	0.698*
	(0.246)	(0.334)	(0.507)	(0.663)	(0.498)	(0.558)	(0.395)	(0.414)
Kids	0.170	0.521	0.453	1.005	0.876*	2.403***	-0.547	0.471
	(0.224)	(0.334)	(0.373)	(0.616)	(0.496)	(0.913)	(0.494)	(0.657)
Not single	-0.343*	0.073	-0.344	-0.519	-0.072	1.435	-0.389	-0.392
	(0.201)	(0.287)	(0.409)	(0.567)	(0.506)	(0.886)	(0.424)	(0.607)
FCL: Medium	-0.078	0.084	0.530	-0.505	-0.114	-0.263	-0.665*	1.073**
	(0.216)	(0.293)	(0.328)	(0.441)	(0.378)	(0.425)	(0.358)	(0.519)
FCL: High	0.174	-0.091	0.984**	0.112	0.174	-1.197**	-0.519	1.089*
	(0.264)	(0.371)	(0.460)	(0.612)	(0.448)	(0.598)	(0.394)	(0.620)
Price of Bitcoin	0.305	0.194	0.275	-0.028	-2.649	-3.225	0.667	1.080*
	(0.228)	(0.212)	(0.195)	(0.284)	(1.976)	(3.121)	(0.483)	(0.616)
Constant	-17.406***	-10.599***	-12.841**	-4.372	-1.660	3.364	-17.946***	-13.49*
	(5.277)	(5.081)	(4.953)	(7.996)	(9.000)	(12.517)	(4.841)	(7.091)
Province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes						
Observations	5164	5164	1,992	1,992	1,582	1,582	1,590	1,590

Note: The base case is Male, Age 18–34, High School, Low Income, Employed, No Kids, Single, British Columbia. FCL = Financial and crypto literacy. The Price of Bitcoin is at the beginnings of the day of the interview. Significance stars ***, **, and * represent 1%, 5%, and 10% significance, respectively.

Table 12: **Sequential model of choices of entry and exit**

VARIABLES	Pool n to {o,p}	Pool o to p	2017 n to {o,p}	2017 o to p	2018 n to {o,p}	2018 o to p	2019 n to {o,p}	2019 o to p
E(Survival)	0.030***	-0.032***	0.023***	-0.034***	0.027***	-0.048***	0.040***	-0.033***
	(0.003)	(0.006)	(0.005)	(0.011)	(0.006)	(0.011)	(0.005)	(0.012)
Female	-0.941***	-0.066	-1.281***	0.182	-0.974***	-0.322	-0.945***	0.098
	(0.155)	(0.296)	(0.283)	(0.591)	(0.287)	(0.600)	(0.279)	(0.545)
Age: 35–54	-0.809***	0.203	-1.235***	0.658	-1.040***	1.268**	-0.205	-1.055*
	(0.174)	(0.317)	(0.266)	(0.609)	(0.313)	(0.608)	(0.311)	(0.561)
Age: 55+	-1.888***	-0.261	-2.273***	1.315	-2.275***	-2.522**	-1.383***	-1.072
	(0.272)	(0.603)	(0.674)	(1.049)	(0.528)	(1.270)	(0.346)	(0.892)
College	0.245	0.197	-0.361	0.423	0.256	-1.676**	0.675	0.980
	(0.231)	(0.407)	(0.383)	(0.677)	(0.377)	(0.787)	(0.421)	(0.710)
University	0.581**	-0.639	0.0130	-1.034	0.468	-1.839**	1.261***	-0.0231
	(0.234)	(0.443)	(0.375)	(0.758)	(0.370)	(0.879)	(0.419)	(0.713)
Income: 30k–69k	-0.230	-0.698	-0.237	-1.932**	0.488	-0.159	-0.870**	-1.128
	(0.229)	(0.472)	(0.365)	(0.784)	(0.481)	(1.285)	(0.367)	(0.817)
Income: 70k+	-0.380	-0.00835	-0.639*	0.256	0.463	-0.419	-0.955***	-0.518
	(0.253)	(0.496)	(0.383)	(0.784)	(0.517)	(1.232)	(0.370)	(0.839)
Unemployed	-0.378	1.012	-1.298	-1.760	0.138	-1.221	-0.436	2.771***
	(0.342)	(0.688)	(0.862)	(1.318)	(0.520)	(1.736)	(0.616)	(1.010)
Not in labor force	-0.159	0.509	-0.809*	-0.196	0.243	0.499	-0.140	0.588
	(0.215)	(0.417)	(0.464)	(0.760)	(0.369)	(0.773)	(0.318)	(0.700)
Kids	0.0900	-0.0921	0.252	0.469	0.00159	0.511	0.190	-0.0999
	(0.180)	(0.342)	(0.254)	(0.633)	(0.336)	(0.742)	(0.302)	(0.643)
Not single	0.512**	-0.0131	0.710**	-0.262	1.088***	-0.512	-0.211	-0.391
	(0.199)	(0.350)	(0.288)	(0.572)	(0.329)	(0.603)	(0.384)	(0.644)
FCL: Medium	0.256	0.131	0.577**	-0.948	0.172	-0.410	-0.0720	1.392**
	(0.177)	(0.338)	(0.270)	(0.594)	(0.322)	(0.615)	(0.327)	(0.652)
FCL: High	0.833***	-0.502	1.667***	-1.328*	0.733**	-2.258***	0.366	0.976
	(0.200)	(0.394)	(0.375)	(0.783)	(0.321)	(0.855)	(0.323)	(0.622)
Price of Bitcoin	0.204	-0.118	0.114	-0.349	-1.144	4.836	1.010***	-2.236
	(0.166)	(0.230)	(0.163)	(0.264)	(1.580)	(3.016)	(0.383)	(0.701)
Constant	-6.709*	4.014	-3.333	10.378	3.114	-16.191	-11.883***	3.144
	(3.813)	(5.256)	(3.671)	(6.455)	(7.765)	(13.682)	(3.717)	(7.092)
Province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes						
Observations	5,164	5,164	1,992	1,992	1,582	1,582	1,590	1,590

Note: The base case is Male, Age 18–34, High School, Low Income, Employed, No Kids, Single, British Columbia. N = never owner, O = current owner, P = past owner and CFL = Financial and crypto literacy. Significance stars ***, **, and * represent 1%, 5%, and 10% significance, respectively.

Table 13: **Sequential model of choices of entry and exit: Control for endogeneity of beliefs using 2 CF**

VARIABLES	Pool n to {o,p}	Pool o to p	2017 n to {o,p}	2017 o to p	2018 n to {o,p}	2018 o to p	2019 n to {o,p}	2019 o to p
E(Survival)	0.144***	-0.104***	0.113***	-0.023	0.201***	-0.136*	0.147***	-0.173***
	(0.015)	(0.027)	(0.024)	(0.046)	(0.033)	(0.064)	(0.029)	(0.050)
$\widehat{u}_{own}$	-0.013	-0.014	-0.006	-0.119*	-0.086	-0.164*	-0.002	0.129**
	(0.012)	(0.023)	(0.034)	(0.064)	(0.061)	(0.089)	(0.029)	(0.058)
$\widehat{u}_{past}$	-0.107***	0.089***	-0.088***	0.090	-0.093**	0.260***	-0.116***	0.022
	(0.015)	(0.028)	(0.031)	(0.063)	(0.043)	(0.086)	(0.031)	(0.062)
$\widehat{u}_{own} * \widehat{u}_{past}$	-0.000	0.000	0.000	-0.001*	-0.000	0.0001	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female	-0.847***	-0.216	-1.144***	-0.338	-1.155***	-0.863	-0.679**	0.574
	(0.182)	(0.327)	(0.359)	(0.653)	(0.434)	(0.739)	(0.303)	(0.637)
Age: 35–54	-0.075	-0.348	-0.649*	-0.151	-0.445	0.024	0.579	-1.233*
	(0.210)	(0.364)	(0.356)	(0.797)	(0.481)	(0.803)	(0.408)	(0.702)
Age: 55+	-0.591*	-1.147	-1.367*	-0.065	-0.910	-5.421***	-0.000	-1.280
	(0.322)	(0.763)	(0.758)	(1.252)	(0.627)	(1.696)	(0.510)	(1.188)
College	0.479*	-0.227	0.109	-0.500	-0.141	-3.613***	1.116**	1.638*
	(0.261)	(0.474)	(0.462)	(0.843)	(0.682)	(1.236)	(0.472)	(0.887)
University	0.952***	-1.166**	0.408	-1.845*	0.305	-3.730***	1.724***	0.303
	(0.255)	(0.505)	(0.438)	(1.014)	(0.620)	(1.296)	(0.466)	(0.895)
Income: 30k–69k	-0.092	-0.790*	-0.133	-2.407***	0.536	-0.991	-0.740**	-0.580
	(0.243)	(0.446)	(0.389)	(0.866)	(0.541)	(1.178)	(0.372)	(0.760)
Income: 70k+	-0.484*	-0.017	-0.686*	0.235	0.233	-1.389	-1.104***	0.047
	(0.257)	(0.476)	(0.415)	(0.875)	(0.572)	(1.174)	(0.358)	(0.806)
Unemployed	-0.233	0.755	-1.237	-1.062	0.283	-1.386	-0.276	1.968**
	(0.361)	(0.609)	(0.846)	(1.319)	(0.574)	(2.311)	(0.688)	(0.959)
Not in labor force	0.077	0.213	-0.574	-0.211	0.306	-0.226	0.164	0.350
	(0.222)	(0.417)	(0.451)	(0.793)	(0.446)	(0.781)	(0.308)	(0.738)
Kids	0.299	0.370	0.552	0.760	1.323***	1.307	-0.499	-0.618
	(0.204)	(0.394)	(0.337)	(0.844)	(0.506)	(1.025)	(0.453)	(0.722)
Not single	-0.206	0.386	-0.391	0.409	0.377	0.842	-0.366	-0.162
	(0.180)	(0.378)	(0.333)	(0.908)	(0.489)	(0.948)	(0.378)	(0.681)
FCL: Medium	-0.002	0.327	0.208	-0.849	-0.150	0.281	-0.095	1.793**
	(0.190)	(0.342)	(0.281)	(0.560)	(0.329)	(0.695)	(0.320)	(0.671)
FCL: High	0.097	-0.055	0.664	-1.035	-0.229	-1.689**	-0.048	1.393**
	(0.229)	(0.388)	(0.405)	(0.905)	(0.373)	(0.825)	(0.360)	(0.682)
Price of Bitcoin	0.256	-0.175	0.207	-0.435	-2.626	1.923	0.844**	-0.469
	(0.173)	(0.241)	(0.165)	(0.338)	(2.078)	(3.826)	(0.397)	(0.706)
Constant	-14.102***	8.650	-10.007**	9.821	0.104	-1.268	-16.184***	13.557*
	(4.037)	(5.653)	(4.324)	(8.345)	(8.554)	(16.070)	(4.170)	(7.747)
Province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes						
Observations	5,164	5,164	1,992	1,992	1,582	1,582	1,590	1,590

Note: The base case is Male, Age 18–34, High School, Low Income, Employed, No Kids, Single, British Columbia. N = never owner, O = current owner, P = past owner, and CFL = Financial and crypto literacy. Significance stars ***, **, and * represent 1%, 5%, and 10% significance, respectively.

Table 14: **Likelihood ratio decompositions for empirical models**

Model	Year	Demographics	E(Survival)	CFL	CF
Logit	2017	0.17	0.24	0.27	0.27
Logit	2018	0.15	0.24	0.29	0.32
Logit	2019	0.15	0.19	0.22	0.23
Multinomial Logit	2017	0.22	0.29	0.31	0.33
Multinomial Logit	2018	0.18	0.26	0.27	0.29
Multinomial Logit	2019	0.15	0.26	0.27	0.29
Sequential Logit	2017	0.24	0.30	0.33	0.35
Sequential Logit	2018	0.20	0.26	0.27	0.30
Sequential Logit	2019	0.16	0.27	0.27	0.30

Notes: The following coding is used for measuring the transformed likelihood ratio using the $Pseudo - R^2 = 1 - \frac{Log-likelihood(Model)}{Log-Likelihood(Constant)} - \lambda \frac{df}{N-1}$ contribution for the probability of being a Bitcoin past owner: CF = control function contribution to the probability, CFL = crypto and financial literacy contribution to the probability, E(Survival) = Beliefs contribution to probability, Demographics = demographics contribution to the probability.

The role of beliefs in entering and exiting the Bitcoin market: Online Appendix

A Technical Details and Omitted Proofs

A.1 Proof of Proposition 1

Fix a type (y, s, λ), and consider equation (3.1). This differential equation admits a closed-form solution. Indeed, (3.1) can be written as:

$$\frac{d\xi_{ys\lambda t}}{\xi_{ys\lambda t}(1-\xi_{ys\lambda t})} = \lambda dt.$$

Integrating both sides between $[0, t]$, using that $\xi_{ys\lambda 0} = \bar{\xi}_0$, yields:

$$\log\left(\frac{\xi_{ys\lambda t}}{1-\xi_{ys\lambda t}} \cdot \frac{1-\bar{\xi}_0}{\bar{\xi}_0}\right) = \lambda t.$$

Then, we solve for $\xi_{ys\lambda t}$ to get:

$$\xi_{ys\lambda t} = \frac{\kappa_0 e^{\lambda t}}{1+\kappa_0 e^{\lambda t}}, \tag{A.1}$$

where $\kappa_0 \equiv \bar{\xi}_0/(1-\bar{\xi}_0)$. Next, we fix a time instant $t > 0$, and condition on ownership s and category y. The conditional probability that beliefs are less than or equal to x, with $x \in (0, 1)$:

$$\begin{aligned}
\mathbb{P}_t(\xi_{ys\lambda t} \leq x | s, y) &= \mathbb{P}_t\left(\frac{\kappa_0 e^{\lambda t}}{1+\kappa_0 e^{\lambda t}} \leq x\right) = \mathbb{P}_t\left(e^{\lambda t} \leq \left(\frac{x}{1-x}\right)\kappa_0^{-1}\right) \\
&= \mathbb{P}_t\left(\lambda \leq t^{-1}\log\left(\left(\frac{x}{1-x}\right)\kappa_0^{-1}\right)\right) = G\left(t^{-1}\log\left(\left(\frac{x}{1-x}\right)\kappa_0^{-1}\right)\Big| s, y\right).
\end{aligned}$$

Consequently, if $G(\cdot|y, o) \leq G(\cdot|y, p) \leq G(\cdot|y, n)$ then it inequality (3.2) holds. $\square$

A.2 Proof of Proposition 2

For each (s, y), define the cumulative distribution function of beliefs at time t as:

$$\tilde{G}_{syt}(x) \equiv G\left(t^{-1}\log\left(\left(\frac{x}{1-x}\right)\kappa_0^{-1}\right)\Big| s, y\right).$$

Also, define the cumulative distribution function of beliefs at time t conditional on $\{\lambda \geq 0\}$ and $\{\lambda \leq 0\}$, respectively, as:

$$\tilde{G}_{syt}(x|\lambda \geq 0) \qquad \text{and} \qquad \tilde{G}_{syt}(x|\lambda \leq 0).$$

These expressions represent the distribution of beliefs for agents who are impacted more and less by good news than bad news (i.e., $\lambda \leq 0$ and $\lambda \geq 0$) respectively.

Now consider two time instants, t_0, t_1 with $t_0 < t_1$. We separate into two cases.

- Case 1: Consider $x \geq \bar{\xi}_0$. Then, it is easy to see that,

  $$\log\left(\left(\frac{x}{1-x}\right)\kappa_0^{-1}\right) \geq 0.$$

  This implies that the distribution of beliefs can be written as:

  $$\tilde{G}_{syt}(x) = G(0|s,y) + \tilde{G}_{syt}(x|\lambda \geq 0)(1 - G(0|s,y)).$$

  Consequently, the difference between the belief CDFs across two time periods is:

  $$\tilde{G}_{syt_1}(x) - \tilde{G}_{syt_0}(x) = [\tilde{G}_{syt_1}(x|\lambda \geq 0) - \tilde{G}_{syt_0}(x|\lambda \geq 0)](1 - G(0|s,y)).$$

  Thus, we conclude that:

  $$\tilde{G}_{syt_1}(x) \geq \tilde{G}_{syt_0}(x) \iff \tilde{G}_{syt_1}(x|\lambda \geq 0) \geq \tilde{G}_{syt_0}(x|\lambda \geq 0).$$

- Case 2: Consider $x < \bar{\xi}_0$. Following the same steps as before, the distribution of beliefs now obeys:

  $$\tilde{G}_{syt}(x) = \tilde{G}_{syt}(x|\lambda \leq 0)G(0|s,y).$$

  Therefore:

  $$\tilde{G}_{syt_1}(x) - \tilde{G}_{syt_0}(x) = (\tilde{G}_{syt_1}(x|\lambda \leq 0) - \tilde{G}_{syt_0}(x|\lambda \leq 0))G(0|s,y).$$

  As a result:

  $$\tilde{G}_{syt_1}(x) \geq \tilde{G}_{syt_0}(x) \iff \tilde{G}_{syt_1}(x|\lambda \leq 0) \geq \tilde{G}_{syt_0}(x|\lambda \leq 0).$$

This concludes the proof. $\square$

A.3 Proof of Proposition 4

We will show that, for each category $y \in \mathcal{Y}$, the system (3.6)–(3.8) has a unique solution. To this end, fix $y \in \mathcal{Y}$. We'll use (A.1) to express the transition probabilities as a function of time explicitly. Specifically, we rewrite the transition probabilities as follows:

$$\begin{aligned}
\rho^t_{on}(y) &= \int_\Lambda F(B(\Xi(t,\lambda),y))g(\lambda|n,y)d\lambda \\
\rho^t_{op}(y) &= \int_\Lambda F(B(\Xi(t,\lambda),y))g(\lambda|p,y)d\lambda \\
\rho^t_{po}(y) &= \int_\Lambda [1 - F(B(\Xi(t,\lambda),y))]g(\lambda|o,y)d\lambda
\end{aligned}$$

where $t \mapsto \Xi(t,\lambda)$ is the unique solution to (3.1), given λ, i.e.:

$$\Xi(t,\lambda) := \frac{\kappa_0 e^{\lambda t}}{1+\kappa_0 e^{\lambda t}}, \quad \kappa_0 := \frac{\bar{\xi}_0}{1-\bar{\xi}_0}.$$

Notice that for each $y \in \mathcal{Y}$, functions $\rho^t_{on}(y), \rho^t_{op}(y), \rho^t_{po}(y)$ are continuously differentiable in time t, since we assumed that functions $g(\cdot|s,y), F(\cdot), B(\cdot,y)$ are continuously differentiable, and $\Xi(\cdot,\lambda)$ is clearly continuously differentiable.

Now, let us define $C := \{(\mu_{yo},\mu_{yp},\mu_{yn}) \in \mathbb{R}^3_+ : \sum_{s\in\mathcal{S}} \mu_{ys} = q_y\}$, and $V : C \times \mathbb{R} \to \mathbb{R}^3$ as:

$$V(\mu_{yo},\mu_{yp},\mu_{yn},t) := (\rho^t_{on}(y)\mu_{yn} + \rho^t_{op}(y)\mu_{yp} - \rho^t_{po}(y)\mu_{yo}, \rho^t_{po}(y)\mu_{yo} - \rho^t_{op}(y)\mu_{yp}, -\rho^t_{on}(y)\mu_{yn}).$$

Therefore, our system of ODEs (3.6)–(3.8) can be expressed as:

$$(\dot\mu_{yo},\dot\mu_{yp},\dot\mu_{yn}) = V(\mu_{yo},\mu_{yp},\mu_{yn},t), \quad (\mu^0_{yo},\mu^0_{yp},\mu^0_{yn}) = (0,0,q_y) \tag{A.2}$$

We will show that the this initial value problem (IVP) has a unique solution, and that this solution belongs to C for all time $t \geq 0$.

To this end, we extend $V(\cdot,t)$ to $\mathbb{R}^3$ by considering $\pi_C : \mathbb{R}^3 \to C$, namely, the closest projection onto the compact and convex set C. Call the extension $\bar{V} : \mathbb{R}^3 \times \mathbb{R} \to \mathbb{R}^3$, defined as $\bar{V}(\mu_{yo},\mu_{yp},\mu_{yn},t) = V(\pi_C(\mu_{yo},\mu_{yp},\mu_{yn}),t)$. Of course, $\bar{V}$ and V agree when $(\mu_{yo},\mu_{yp},\mu_{yn}) \in C$. Now, notice that V is locally Lipschitz continuous in $(\mu_{yo},\mu_{yp},\mu_{yn})$, and uniformly with respect to t, since the Jacobian matrix of V has as entries that are continuously differentiable functions; thus, $\bar{V}$ is locally Lipschitz continuous in $(\mu_{yo},\mu_{yp},\mu_{yn})$, and uniformly with respect to t. Therefore, the Picard-Lindelöf Theorem (Theorem 2.2 in Teschl (2012)) ensures the existence of a unique solution $t \in (-T,T) \mapsto (\mu^t_{yo},\mu^t_{yp},\mu^t_{yn}) \in \mathbb{R}^3$

to the following relaxed IVP:

$$(\dot{\mu}_{yo}, \dot{\mu}_{yp}, \dot{\mu}_{yn}) = \bar{V}(\mu_{yo}, \mu_{yp}, \mu_{yn}, t), \quad (\mu^0_{yo}, \mu^0_{yp}, \mu^0_{yn}) = (0, 0, q_y).$$

Next, we will show that, indeed, this solution $(\mu^t_{yo}, \mu^t_{yp}, \mu^t_{yn}) \in C$ for all $t \in (-T, T)$. To see this, we verify that, for each t and $(\mu_{yo}, \mu_{yp}, \mu_{yn}) \in C$, the vector of growth rates $V(\mu_{yo}, \mu_{yp}, \mu_{yn}, t)$ belongs to the tangent cone of C at the point $(\mu_{yo}, \mu_{yp}, \mu_{yn})$. Using Observation 4.4.3 in Sandholm (2010), this can be easily checked in this context, since the sum of growth rates $\sum_{s \in \mathcal{S}} \dot{\mu}^t_{ys} = 0$ for all t, implying that the mass of agents in y remains constant over time and equal to q_y; in addition, whenever $\mu^t_{ys} = 0$ for some s, we have $\dot{\mu}^t_{ys} \geq 0$, implying that the dynamics will lead $(\mu^t_{yo}, \mu^t_{yp}, \mu^t_{yn})$ to remain in C. Altogether, if the initial value $(\mu^0_{yo}, \mu^0_{yp}, \mu^0_{yn}) \in C$ then the solution to the relaxed IVP solves (A.2), i.e., $t \mapsto (\mu^t_{yo}, \mu^t_{yp}, \mu^t_{yn}) \in C$ for all $t \in (-T, T)$; see Theorem 4.A.5 in Sandholm (2010). This concludes the proof. $\square$

B Validity test of exclusion restriction

Table 15: **Appendix Empirical Section: Test of Validity of Exclusion restrictions: $E(Y|X,Z) = E(Y|X)$?**

Marginal Effects	(1)	(2)
VARIABLES	$\widehat{E(Y\|X)}$	$\widehat{E(Y\|X,Z)}$
E(Survival)	-0.006***	-0.006***
	(0.001)	(0.001)
48.incident_rate		-0.101
		(0.147)
58.incident_rate		0.049
		(0.179)
75.incident_rate		-0.013
		(0.125)
80.incident_rate		0.203
		(0.148)
81.incident_rate		-0.160
		(0.134)
104.incident_rate		0.089
		(0.158)
105.incident_rate		-0.016
		(0.139)
114.incident_rate		0.005
		(0.143)
121.incident_rate		0.026
		(0.186)
130.incident_rate		0.039
		(0.170)
132.incident_rate		0.205
		(0.220)
144.incident_rate		0.053
		(0.164)
167.incident_rate		0.340
		(0.217)
197.incident_rate		0.044
		(0.191)
2.day		0.176
		(0.107)
3.day		0.225
		(0.238)
4.day		0.023
		(0.149)
5.day		0.109
		(0.140)
6.day		0.140
		(0.132)
7.day		0.037
		(0.229)
8.day		0.169
		(0.164)
9.day		0.232
		(0.256)
Observations	437	431

Notes: Retained the significant demographics, $***p < 0.01, **p < 0.05, *p < 0.1$