Buy, Buy, Bye! The Role of Learning and Beliefs in Exiting from the Bitcoin Market*

Daniela Balutel Jorge Vásquez Marcel Voia

January 1, 2026

Abstract

We build and test a theoretical model of Bitcoin adoption and unadoption in which beliefs about Bitcoin's long-run survival and heterogeneous learning rates drive entry, exit, and re-entry decisions. The model implies ranked belief distributions across never owners, owners, and past owners, and describes how these distributions and the associated ownership shares evolve over time. Using 2017–2019 data from the Bank of Canada's Bitcoin Omnibus Survey and a sequential logit model with control functions, the empirical belief distributions, which are a key determinant of both entry and exit, align with the model: owners are the most optimistic, never owners the most pessimistic, and past owners lie in between, with past owners becoming more optimistic over time. A composite crypto-financial literacy (CFL) index plays a context-dependent role, as high-CFL individuals are less likely to exit during downturns but more likely to exit when market conditions improve, while medium and low CFL individuals are less likely to enter yet more inclined to exit. Counterfactual simulations that shift the population distribution of CFL upward show that higher CFL increases both current and past ownership, especially among respondents with strong survival beliefs, highlighting a complementarity between literacy and optimism in shaping the Bitcoin adoption lifecycle.

JEL codes: D83, O33, E41,

*Balutel: MITACS Postdoctoral Fellow, York University, Department of Economics & Currency Department, Bank of Canada, dbalutel@yorku.ca; Vásquez: Department of Economics, Smith College, jvasquez@smith.edu; Voia: Laboratoire d'Économie d'Orléans, Université d' Orléans, marcel.voia@univ-orleans.fr and University of Bucharest.

We thank Hiroshi Fujiki, Kim P. Huynh, Alex Shcherbakov and other members of the Economic Research and Analysis team in the Currency Department at the Bank of Canada for their valuable feedback; in addition to Joann Jasiak, Henry Kim, Badi Baltagi and Jan Ondrich for their comments and support. We also thank participants from the following seminars/institutions: York University Economics Seminar, National Bank of Romania, the Canadian Economics Association 2022, the CBDC Econ Working Group at the Bank of Canada, ERMAS 2022, New York Camp Econometrics. We would like to acknowledge Colette Stoeber for providing editorial assistance. The views presented are those of the authors and not necessarily those of the Bank of Canada. All errors are our own. Please do not cite or circulate

1 Introduction

Bitcoin's inception in 2009 marked the emergence of a decentralized digital currency that was intended to challenge traditional fiat systems Nakamoto (2008). Advertised as competitor for real currency, Bitcoin represented a new type of financial innovation. Consistent with new technology adoption patterns, its early stages featured low uptake followed by volatile growth and decline phases Halaburda et al. (2022), raising fundamental questions about the drivers of market entry and the overlooked phenomenon of exit.

While in a prior paper we examined Bitcoin adoption (BUY) through beliefs and network effects Balutel et al. (2022), this paper's novelty lies in modeling both entry and unadoption (BYE!) within a unified sequential framework. Building on Balutel et al. (2022), we develop a continuous-time model where agents are categorized as never owners, current owners, or past owners. The model is based on a sequence of decisions. First, never owners decide whether to adopt Bitcoin and become owners; otherwise they remain never owners. After adoption, in each subsequent period agents decide whether to stay owners or unadopt and become past owners. Beliefs about Bitcoin's long-term survival are updated based on signals, which can be positive (e.g., increased merchant acceptability) or negative (e.g., scams, cyberattacks). The theoretical model provides three key results that contribute to our understanding of Bitcoin adoption and disadoption dynamics.

First, belief distributions rank by ownership status (owners > past owners > never owners) via first-order stochastic dominance when learning rates satisfy $G_t^{y,o} \preceq G_t^{y,p} \preceq G_t^{y,n}$ (Proposition 2). Simulations show that owners hold more optimistic beliefs than past owners, who are generally more optimistic than never owners, explaining persistent ownership patterns and entry barriers.

Second, belief evolution within each status depends on the relative elasticities of the cumulative distribution function of learning rates with respect to time and the learning rate itself: $E_t G_t \gtrless E_\rho G_t$ (Proposition 3). This provides a framework for how beliefs shift over time, potentially altering ownership patterns.

Third, ownership dynamics emerge from entry, exit, and re-entry flows between states (never owners, owners, past owners), solving the initial value problem for the joint distribution of ownership status over time (Proposition 4). This theoretical model captures the Bitcoin adoption lifecycle.

As a second contribution, we use these theoretical predictions to find direct empirical validation using Bank of Canada's Bitcoin Omnibus Survey (BTCOS) data from 2017–2019. This data allows us to uniquely measure past owners, which overcome limitations in other data Henry et al. (2020); Balutel et al. (2023b). Our empirical analysis shows that indeed owners exhibit most optimistic beliefs, past owners intermediate (and increasingly optimistic over time), never owners most pessimistic. Next, unlike portfolio models Benetton and Compiani (2024); Fujiki (2021), our sequential logit model explicitly tests entry-exit dynamics.

The empirical strategy addresses belief endogeneity, which is central to theoretical selection, via two-stage control functions with exclusion restrictions. First-stage belief regressions incorporate Bitcoin ATMs (for entry, per Balutel et al. (2022)), regional cyber incidents, and survey day (for exit), satisfying relevance and exogeneity tests. Second-stage sequential logit estimates disentangle causal belief effects on transitions, with optimistic beliefs drive entry/re-entry, while pessimism prompts exit. As covariates we include demographics and crypto-financial literacy (CFL), constructed from Balutel et al. (2023a) indices to proxy heterogeneous learning rates and to address gender gaps in ownership.

CFL measure emerges as measure that is context-dependent. In particular, high-CFL agents exit less during downturns but more in upturns (risk management/capitalizing), while low/medium CFL reduces entry and accelerates exit.To deal with CFL endogeneity, we use counterfactuals, which are designed to isolately shift population distribution CFL upward[1]. This approach help use to understand the effect of increasing the joint dimension of CFL, while keeping everything else constant. The analysis is revealing that higher CFL boosts ownership especially among strong believers (with 5–10% gains), while is increasing the probability of exit for low believers (with 8-15%). Heterogeneity analysis by CFL and market conditions further documents how learning capacity amplifies belief-driven dynamics.

These contributions advance adoption literature Stix (2021); Henry et al. (2018, 2019a, 2020); Balutel et al. (2024), extend financial literacy research Bucher-Koenen et al. (2024), and inform crypto/CBDC policy by quantifying churn drivers absent in prior work Alvarez et al. (2023); Catalini and Tucker (2017).

The paper proceeds as follows. Section 2 presents the theoretical model. Section 3 describes BTCOS data. Section 4 details empirical strategy. Section 5 reports results. Section 6 concludes

2 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-

[1]The ljoint levels of crypto and financial literacy are not high in Canada, see....

mass of agents I.[2] In any time period $t > 0$, each agent $i \in I$ is either a *never owner* ($i \in \mathcal{N}_t$), *owner* ($i \in \mathcal{O}_t$), or *past owner* ($i \in \mathcal{P}_t$). That is, $I = \mathcal{N}_t \cup \mathcal{O}_t \cup \mathcal{P}_t$ for all t. Thus, at time t, each agent i has an observed ownership *status* $s_t \in \mathcal{S} = \{n, o, p, \}$. In addition, each agent i belongs to an observable *category* $y \in \mathcal{Y} = \{y_1, \ldots, y_K\}$ with $y_k \in \mathbb{R}^N$ for $k = 1, \ldots, K$. 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, as an example, an agent with category y and status s_t may represent a never 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.[3] 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).[4] 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.[5] As it is standard in the learning literature, we assume "conclusive" news, meaning that observing news leads agents to fully believe that the technology is either good or bad.[6] Consequently, we focus on the 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

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

[3] Our survey allows us to directly measure agents' beliefs regarding these two events; see Section 3.

[4] 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).

[5] 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.

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

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:

$$\dot{\xi}_{ys\lambda t} = \xi_{ys\lambda t}(1 - \xi_{ys\lambda t})\lambda, \quad \xi_{ys\lambda 0} = \bar{\xi}_0, \tag{2.1}$$

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 (2.1), 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:*

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

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: $G_t(\lambda|y, o) \le G_t(\lambda|y, p) \le G_t(\lambda|y, n)$ for all $\lambda \in \mathbb{R}$. Then, the conditional distribution of beliefs satisfies:*

$$\mathbb{P}_t(\xi_{\lambda t} \le \xi | y, o) \le \mathbb{P}_t(\xi_{\lambda t} \le \xi | y, p) \le \mathbb{P}_t(\xi_{\lambda t} \le \xi | y, n) \quad \forall \xi \in (0, 1). \tag{2.2}$$

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 2.

- insert Figure 2 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.[7] 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:

$$B(\xi_{ys\lambda t}, y) \geq u_{it}. \tag{2.3}$$

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:

$$\mathbb{P}(a_{it} = 1|\xi_{ys\lambda t}, y) = F(B(\xi_{ys\lambda t}, y)). \tag{2.4}$$

We interpret (2.4) as follows. Fix a time period t. If agent i is a current owner, i.e., $s_i = o$, then (2.4) describes the probability that i *stays* in the bitcoin market. However, if inequality (2.3) is reversed, then:

$$\mathbb{P}(a_{it} = 0|\xi_{ys\lambda t}, y) = 1 - F(B(\xi_{ys\lambda t}, y)) \tag{2.5}$$

captures the agent i's probability of *exit*. Similarly, if agent i is a potential new owner, $s_i = n$, then (2.4) reflects the agent i's probability of *entry*. Finally, for past owners, or $s_i = p$, expression (2.4) 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 $\sum_{s \in \mathcal{S}} \mu^t_{ys} = q_y$

[7] This flow payoff may be influenced by other variables that are not modelled, such as prices (see, e.g., Athey et al. (2016)). Importantly, our data allow us to directly measure beliefs; thus, it is likely that these beliefs already contain other relevant information (e.g., prices) for decision making. This allows us to isolate the belief channel, which is our main goal.

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:

$$\dot{\mu}^t_{yo} = \rho^t_{on}(y)\mu^t_{yn} + \rho^t_{op}(y)\mu^t_{yp} - \rho^t_{po}(y)\mu^t_{yo} \tag{2.6}$$

$$\dot{\mu}^t_{yp} = \rho^t_{po}(y)\mu^t_{yo} - \rho^t_{op}(y)\mu^t_{yp} \tag{2.7}$$

$$\dot{\mu}^t_{yn} = -\rho^t_{on}(y)\mu^t_{yn} \tag{2.8}$$

for all $y \in \mathcal{Y}$. The transition probabilities can be found using (2.1), (2.4), and (2.5):

$$\rho^t_{on}(y) = \int_\Lambda F(B(\xi_{yn\lambda t}, y))g(\lambda|n, y)d\lambda \tag{2.9}$$

$$\rho^t_{op}(y) = \int_\Lambda F(B(\xi_{yp\lambda t}, y))g(\lambda|p, y)d\lambda \tag{2.10}$$

$$\rho^t_{po}(y) = \int_\Lambda [1 - F(B(\xi_{yo\lambda t}, y))]g(\lambda|o, y)d\lambda \tag{2.11}$$

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 (2.6). 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 (2.7) and (2.8) are found analogously; for example, the change in the number of past adopters is the difference between exit and re-entry flows (see Figure 1).

- insert Figure 1 here. -

The model is solved by a process $(\mu^t : t \geq 0)$ obeying (2.6)–(2.8), given beliefs $(\xi_{ys\lambda t})_{t \geq 0}$ solving (2.1) 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 (2.1) with initial condition $\bar{\xi}_0$. Next, we rewrite the transition probabilities (2.9)–(2.11) by plugging the unique solution to (2.1). Finally, we show that the resulting dynamical system (2.6)–(2.8) is well-behaved, and thus it has a unique solution.

3 The Bitcoin Omnibus Survey Data

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

In the next few subsections, we discuss survey design of the survey, the demographic profile, motivations for exiting the Bitcoin market, a measure of crypto and financial literacy, and respondent beliefs about the expected survival of Bitcoin.

3.1 Survey design

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.

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

- insert Figure 4 here -

Bitcoin ownership has increased slowly over time. Past ownership is negatively correlated with the Bitcoin price, it increase as the price falls.

3.2 Demographic profile

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.

- insert Table 1 here -

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. These descriptive statistics indicate that owners and past owners of Bitcoin are likely to be a selected sample. Therefore, we need to be careful not to assign any causality based on tabular correlations.

3.3 Motivations for exiting the Bitcoin market

The BTCOS asks past owners their main reason for no longer owning Bitcoin, see Table 4. These descriptive statistics provide us some self-reported motivations on why some respondents exited the Bitcoin market

- 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 5.

- insert Figure 5 here -

3.4 Measures of crypto and financial literacy

Besides demographic characteristics, we collect data on respondents knowledge of crypto and financial concepts. These measures are important since they are correlated with demographic characteristics but also may include unobservable factors such as confidence, see Bucher-Koenen et al. (2024) who show that certain demographics are less confident about financial concepts and are more likely to answer "don't know" to questions.

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 (2011). Based on responses to these questions, we categorize individuals as having low, medium, or high crypto and financial literacy. We build on the methodology of Balutel et al. (2023a) to construct these categories. Table 1 shows that both owners and past owners tend to have high crypto literacy but low financial literacy.

Balutel et al. (2023a) analyze these measures separately, examine how they relate to Bitcoin ownership and whether gender and other demographic differences are present. Balutel et al. (2023a) create a composite index of crypto and financial literacy (CFL) by combining these two indices. We categorize these financial literacy scores based on the research by Lusardi and Mitchell (2011). Kass-Hanna et al. (2022) construct a composite index for digital and financial literacy (DFL). They argue that traditional financial literacy needs to be redefined to include digital literacy. They find that this composite index of both digital and financial literacy are pivotal factors in shaping positive financial behaviors and ensuring long-term financial security for individuals. In our case, digital literacy is measured as crypto literacy.

The CFL index is then a composite of crypto and financial litearcy. 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 taking the category of crypto knowledge (low, medium, or high) based on responses to the three Bitcoin knowledge questions. In 2019, the CFL low category includes combinations of low-low and medium-low crypto knowledge and financial literacy. The medium category include combinations of medium-medium and high-low crypto knowledge and financial literacy. The high CFL category includes combinations of high-medium and high-high score crypto knowledge and financial literacy.

- insert Table 2 here -

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.

4 Empirical Strategy and Econometric Methodology

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

First, 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 non-parametrically identify the rankings in the distributions of beliefs across ownership status using tests of stochastic dominance and Epps-Singleton Two-Sample Empirical Characteristic Function Test.

Second, 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 as a nonparametric test the Epps-Singleton Two-Sample Empirical Characteristic Function and parametrically using a sequential choice model 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.

Third, we examine the Bitcoin past adopters. To build an empirical model for past ownership, it is important 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 (Eq. 2.5). 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.

Finally, Proposition 4 examines the overall dynamics of entry and exit given evolving beliefs, showing how agents transition across ownership states (Figure 1). 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 again 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.

4.1 Beliefs (expected survival of Bitcoin) dynamics

4.1.1 Between group dynamics

Building upon the theoretical hierarchy of beliefs across different ownership groups (Proposition 2) – current owners exhibiting the strongest beliefs in Bitcoin's survival, followed by past owners, and then never-owners we do the same test empirically by representing the empirical distribution function of the three groups over time.

$$\mathbb{P}_t(\widehat{\xi_{\lambda t} \leq \xi}|y,o) \geq \mathbb{P}_t(\widehat{\xi_{\lambda t} \leq \xi}|y,p) \geq \mathbb{P}_t(\widehat{\xi_{\lambda t} \leq \xi}|y,n) \quad \forall \xi \in (0,1), \tag{4.1}$$

where $\mathbb{P}_t(\widehat{\xi_{\lambda t} \leq \xi}|y,o)$ is the EDF for Bitcoin owners, $\mathbb{P}_t(\widehat{\xi_{\lambda t} \leq \xi}|y,p)$ is the EDF for Bitcoin owners and $\mathbb{P}_t(\widehat{\xi_{\lambda t} \leq \xi}|y,p)$ is the EDF for never owners.

To test between-ownership dynamics of the belief distribution, we use as a nonparametric test the Epps-Singleton Two-Sample Empirical Characteristic Function and parametrically we estimate separately the models of beliefs for never owners, Bitcoin owners, and Bitcoin past owners:

$$\xi_{it,g} = \delta X_{it,g} + u_{it}, \tag{4.2}$$

where $\xi_{it,g}$ are the beliefs about Bitcoin survival in 15 years for the group $g = n, o, p$, with $n =$ never owner, $o =$ Bitcoin owner and $p =$ past owner, while $X_{it,g}$ group specific demographics and additional group specific shifters in beliefs[8]

[8] For owners additional shifter are Bitcoin ATM growths, while for past owners are cyber incidents, additionally the day of the survey completion is also consider a potential explanatory variable for beliefs.

4.1.2 Within group dynamics

Proposition 3 suggests that the belief distribution, conditional on ownership status, can change over time due to the learning of individuals and the availability of information. To test within-ownership dynamics of the belief distribution, we use as a nonparametric test the Epps-Singleton Two-Sample Empirical Characteristic Function and parametrically using a sequential choice model over the three-year period 2017–2019 (see section 4.3).

4.2 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 2 to the data (see equation (2.5)). 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, 2015). 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:

$$\xi_{it} = \delta X_{it} + \gamma_1 Z_{1,jt} + \gamma_2 Z_{2,it} + u_{it}, \tag{4.3}$$

   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 $Z_{1,jt}$ and $Z_{2,it}$ 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:

$$e^*_{it} = \beta_0 + \beta_1 \xi_{it} + \beta_c X_{it} + \theta \widehat{u}_{it} + \varepsilon_{it}, \tag{4.4}$$

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 past ownership—is modeled via a logistic probability model:

$$\Pr(e_{it} = 1 | \xi_{ist}, X_{ist}, \widehat{u}_{it}) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 \xi_{it} + \beta_c X_{it} + \theta \widehat{u}_{it})}}. \tag{4.5}$$

Incidents faced by current owners may impact their beliefs about Bitcoin's survival. Figure 8 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 8 here -

This motivates the use of cybersecurity incidents as exclusion restriction. Additionally, we consider the day that a respondent took the survey as an additional exclusion restriction.

Table 5 provides an overview of the dynamics of cyber security incidents at the regional level.[9]

- insert Table 5 here -

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 9 provides a graphical representation of this relationship.

- insert Figure 9 here -

[9] 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.

The use of cybersecurity incidents and survey timing as exclusion restrictions in our analysis of Bitcoin ownership dynamics is well-justified by their influence on beliefs about Bitcoin's survival. Böhme et al. (2015) highlight operational risks which could threaten Bitcoin's security and technical platform. For example, a 51 percent attack in which a group of miners could seize control of the system. These attacks would lead to chaos and undermine trust in Bitcoin. Another form of attack is a denial of service attacks which bring the system to a standstill. Therefore, these cybersecurity incidents could serve as significant events that can alter individuals' perceptions of Bitcoin's reliability and security. These incidences may affect beliefs without directly influencing past ownership decisions. Our analysis shows a positive correlation between cybersecurity incidents and beliefs about Bitcoin survival (0.156), while demonstrating no correlation with past ownership (-0.016). 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. This supports the validity of using these incidents as instruments, as they impact beliefs but do not dictate ownership status.

Additionally, the timing of survey responses can be also important for understanding belief formation. Respondents who participate promptly may be more engaged with current events and market conditions, leading to stronger beliefs about Bitcoin's future viability. Choi and Liang (2023) emphasize that timely information significantly influences decision-making processes and belief formation in financial contexts. Our approach acknowledges this dynamic, suggesting that prompt respondents are likely to be more informed and thus hold stronger beliefs. By demonstrating that our exclusion instruments are correlated with beliefs while remaining independent of past ownership, we provide a strong theoretical and empirical basis for their validity in our identification mechanism.

The first-stage regression results demonstrate the negative correlations between the two exclusion restrictions and beliefs (Section 5.1). 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).

Additionally, to test the two exclusion restriction jointly, we apply an adjusted Wald test with F$(24, 5733)$=20.79 or p-value of 0.00 which suggests that the two exclusion restrictions are jointly significant in the first stage.

4.3 Sequential Choice Model

To test Proposition 2, which suggests that the ranking of beliefs about Bitcoin survival depends on the agents' learning rates, which differ for owners, past owners, and never owners, Proposition 3, which suggests that the belief distribution, conditional on an ownership status, can change over time because of individuals' learning and the availability of information and Proposition 4, which considers the solution of the overall dynamics of entry and exit, showing the agents' transition across ownership states, we propose a sequential choice model. That said, our last 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, we propose a sequential model of choices. From an empirical perspective, this leads us to consider a sequential choice model. 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. The suggested 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.

- insert Figure 10 here -

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[10]:

$$\mathbb{P}_{N,A\{a,e\}}(\xi_{it}, X_{it}) = \mathbb{P}_{A|N}(\xi_{it}, X_{it})\mathbb{P}_{e|A}(\xi_{it}, X_{it})\mathbb{P}_{e}(\xi_{it}, X_{it}), \tag{4.6}$$

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.

As with the model of past owners, we include a *decision specific* correction term (CF) to account for the endogeneity of beliefs influencing individuals' decisions. Given our assump-

[10]The sequential model is a generalization of the multinomial model; see Flores et al. (2019).

tion that beliefs are driving people's choices, we employ the CF used in the model of exit described in Section 4.2, and also a CF specific to an entry model, following Balutel et al. (2022).[11]

The transformed sequential model turns to:

$$\mathbb{P}_{N,A\{a,e\}}(\xi_{it}, \widehat{u}_{sit}, X_{it}) = \mathbb{P}_{A|N}(\xi_{it}, \widehat{u}_{sit}, X_{it})\mathbb{P}_{e|A}(\xi_{it}, \widehat{u}_{sit}, X_{it})\mathbb{P}_{e}(\xi_{it}, \widehat{u}_{sit}, X_{it}). \tag{4.7}$$

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.

4.4 Counterfactual Analysis: Testing the Role of Crypto-Financial Literacy in Entry-Exit Dynamics in the Bitcoin market

To further investigate the impact of crypto-financial literacy (CFL) on Bitcoin market dynamics and address its potential endogeneity associated with the entry and exit in the Bitcoin market, we conducted a series of counterfactual analyses. These analyses aim to isolate the effect of CFL on entry and exit decisions while controlling for other factors that could influence Bitcoin ownership.

The potential endogeneity of the CFL index may arise from several sources. Firstly, individuals who are more interested in cryptocurrencies may be more likely to seek out information and educate themselves about them, thus increasing their CFL scores. In contrast, those with higher CFL scores may be more inclined to participate in the Bitcoin market. This bidirectional relationship hampers the determination of the causal effect of CFL on Bitcoin market participation decisions. Although we initially considered CFL only as a control variable relative to our theoretical specification, we found that CFL is also an important driver on participation in the Bitcoin market; therefore, by building counterfacuals that change CFL in isolation to the other variables in the model, we want to understand how it relates to the changes in the beliefs about Bitcoin survival for both entry and exit in the Bitcoin market.

Counterfactual simulations allow us to explore how changes in the distribution of CFL levels across the population could affect the dynamics of entry and exit. We consider three scenarios in our analysis: a baseline one using the original distribution of CFL levels observed

[11] 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, see (Imbens and Wooldridge, 2009).

in our sample, a scenario where we increase the proportion of individuals with medium and high CFL by 20%, and another scenario with a 40% increase in medium and high CFL individuals.

For Ownership Probability Model:

$$\Pr(o_{it} = 1|\xi_{it,o}) = F(\beta_0 + \beta_b\xi_{it,o} + \beta_f CFL^c_{it,o} + \beta_c X_{it,o} + \theta\widehat{u}_{it,o}).$$

For Past Ownership Probability Model:

$$\Pr(p_{it} = 1|\xi_{it,p}) = F(\beta_0 + \beta_b\xi_{it,p} + \beta_f CFL^c_{it,p} + \beta_c X_{it,p} + \theta\widehat{u}_{it,p})$$

Our simulation process involves several steps to isolate the effect of changing the population's CFL distribution on Bitcoin market dynamics. First, we estimate baseline probabilities of Bitcoin ownership and past ownership using the original CFL distribution. We then recalculate these probabilities using the adjusted CFL distributions from the two alternative scenarios. Finally, we compare outcomes across all three scenarios while keeping the CFL index levels constant. This approach allows us to control for other factors that might influence ownership decisions and focus specifically on the impact of CFL distribution changes and isolate the interaction of the CFL with unobservables, which will reduce the impact of the unobservable on the role of CFL on the entry/exit probabilities, therefore eliminating the potential endogeneity of CFL.

By conducting these counterfactual analyses, we aim to gain insights into how improvements in crypto-financial literacy across the population could potentially affect Bitcoin market participation. A relevant exercise here is to look at the interplay between CFL, individual beliefs, and Bitcoin market participation.

This will help us understand how the role of the beliefs about Bitcoin survival are related to the CFL index providing a better understanding of the relationship between financial literacy and cryptocurrency market dynamics.

- insert Table 6 here -

5 Results

We present our results following the order outlined in Section 4.

- insert Figure 6 here -

and applying the Epps-Singleton Two-Sample Empirical Characteristic Function Test.

- insert Table 6 here -

Therefore, in the context of this ranking, an increase in beliefs over time among past owners may further suggest some agents will re-enter the Bitcoin market.

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 6), we see that the ranking of beliefs is preserved over the period under investigation.

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 7). 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 7 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.

and applying the Epps-Singleton Two-Sample Empirical Characteristic Function Test.

- insert Table 6 here -

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 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.[12] We also examine what drives negative or positive changes in beliefs for Bitcoin owners, past owners, and never owners.

[12] 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 6) 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.

Next, inspired by Proposition 2, we estimate a sequential choice 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 again the 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.

5.1 Drivers of Changes in Bitcoin Survival Beliefs

Table 9 presents the results of analyzing the factors affecting beliefs about Bitcoin survival (current owners, past owners and never owners).

- insert Table 9 here -

Empirically, we find that current owners exhibit more optimistic beliefs about Bitcoin's long-term survival compared to other groups, aligning with the model's prediction that higher beliefs are associated with ownership. This finding is consistent with Stix (2021), who provided evidence that early Bitcoin owners have strong beliefs about its advantages relative to conventional payment methods. However, certain factors negatively impact current owners' beliefs. Being in a relationship (-7.38 percentage points) and having children (-8.78 percentage points) are associated with more pessimistic views about Bitcoin's future among current owners. This contrasts with previous findings by Divakaruni and Zimmerman (2024), who found that early Bitcoin adopters tend to be single. Interestingly, current owners who correctly understand that Bitcoin is not government-backed also have more negative beliefs (-9.26 percentage points). This suggests that greater knowledge about Bitcoin's decentralized nature may lead to more cautious outlooks among those who currently own it, potentially reflecting a more nuanced understanding of the risks associated with an unstable technology. This aligns with Fujiki (2021) argument that some Bitcoin owners use it primarily as an investment product, leveraging its volatility.

For past owners, we found distinct patterns in their beliefs and characteristics, that is also a novel contribution to the literature which has primarily focused on adoption rather than exit. Middle-aged (35-54) past owners tend to have more positive beliefs about Bitcoin's survival (+9.95 percentage points) compared to younger individuals. This contrasts with previous findings by Schuh and Shy (2016) and Fujiki (2020), who found that younger individuals were more likely to be early adopters. Within the model's framework, this could be interpreted as this age group having a higher beliefs, possibly due to different learning rates or experiences with the technology. Past owners in the middle-income bracket (30k-69k) have significantly more negative beliefs (-17.71 percentage points), which the model might explain through different learning rates or exposure to different signals across income groups. Notably, past owners with children have more positive beliefs (+13.84 percentage points), contrasting with current owners. The study also found that past owners in 2019 had more positive beliefs (+13.5 percentage points) compared to 2017, indicating improving perceptions over time.

For never-owners we found different patterns in their beliefs compared to the other two groups. Age and education play significant roles, with older age groups and higher education levels associated with more negative beliefs about Bitcoin's survival. This aligns with previous findings by (Henry et al., 2018, 2019b) and Schuh and Shy (2016) that early Bitcoin adopters tend to be younger and more educated, suggesting that older and less educated individuals who have never owned Bitcoin are generally more skeptical about its future, potentially having lower beliefs in the model's terms. However, never owners who are not single have more positive beliefs (+2.74 percentage points), contrasting with current owners and previous literature findings. Interestingly, among never owners, correct understanding of Bitcoin's public ledger technology is associated with more positive beliefs (+6.1 percentage points). This aligns with the model's concept of learning and supports the findings of Balutel et al. (2022) on the importance of cryptocurrency knowledge in adoption decisions. The study also found that never owners in both 2018 and 2019 had more negative beliefs compared to 2017, suggesting growing skepticism among non-owners over time. This could be interpreted in the model as never owners receiving more negative signals or having different learning rates compared to the other groups, and relates to Catalini and Tucker (2017) findings on how delays in adoption can lead to rejection of the technology.

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, compared with those that bolster such beliefs. Consequently, when exploring new technologies, it is important to discern which factors are responsible for altering consumers' beliefs and how these changes impact the adoption of these innovations. Our findings underscore the complexity of belief formation and its impact on Bitcoin adoption and disadoption. The heterogeneity in belief formation across different ownership groups aligns with the model's prediction of varying learning rates. For instance, the positive shift in belief distribution among past owners over time suggests that their experiences may lead to more optimistic outlooks, potentially influencing re-entry decisions.The results also highlight the importance of cryptocurrency knowledge and financial literacy in navigating the volatile Bitcoin market.

This finding supports previous research by Balutel et al. (2022) on the role of knowledge in early Bitcoin adoption, extending it to exit decisions as well. It suggests that educational initiatives about cryptocurrency and financial concepts could play a significant role in shaping market participation.

5.2 Past Bitcoin Owners

As outlined in Section 4.2, we estimate a reduced form model for past owners that identifies exits from the Bitcoin market in two stages. Table 10 shows the results of the first stage.

- insert Table 10 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.

The first stage results presented in Table 10 provide valuable insights about the role of the exclusion restrictions, namely cyber incidents and day of survey, which are important for the identification for the second stage estimation. Both exclusion restrictions demonstrate significant power in shaping beliefs about Bitcoin survival, aligning with previous research on the impact of external factors on cryptocurrency perceptions[13].

Cyber incidents, measured through incident rates across different time periods, show varying but significant impacts on beliefs. This suggests that periods with higher rates of cryptocurrency-related cyber attacks are associated with more pessimistic views about Bitcoin's future, highlighting the importance of security perceptions in shaping beliefs. These findings are consistent with research by Böhme et al. (2015), who emphasized the critical role of security in the adoption and perception of cryptocurrencies. Additionally, the work of Auer and Tercero-Lucas (2022) on the impact of adverse events on cryptocurrency markets supports the relevance of using cyber incidents as an instrument for beliefs. The day of survey also proves to be a relevant instrument, with later days of the survey showing substantial negative effects on beliefs[14]. These findings suggest that the timing of the survey can significantly influence respondents' outlook on Bitcoin, possibly due to day-specific factors such as market events, news cycles, or even psychological factors related to different days of the week. This aligns with research by Kosba et al. (2016) on the impact of timing and information flow on cryptocurrency market dynamics. Furthermore, the use of survey timing as an

[13] The adjusted Wald testF-test: F(24, 5733) = 20.79, Prob ¿ F = 0.0000, for joint significance, suggests that the two exclusion restrictions are jointly significant in the first stage.

[14] Results for Day 7, Day 10 , Day 11,, and Day 12 show large negative and significant impacts on beliefs about Bitcoin survival

instrument is supported by econometric literature, such as Das et al. (2003), who discuss the validity of time-based instruments in addressing endogeneity issues in cross-sectional studies. The strength and significance of these exclusion restrictions validate their use in addressing potential endogeneity issues in the main analysis, allowing for a more accurate estimation of the effect of beliefs on Bitcoin ownership decisions in the second stage.

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 as a correction term for selection into a past owner and endogeneity of beliefs the residual from the first stage regression. Table 11 presents the results of the second stage.

insert Table 11 here -

The main result from this exercise is that controlling for selection strengthens the effect of beliefs on the probability of exiting. This finding aligns with the concept of investor sentiment in financial markets, as noted by Baker and Wurgler (2007). The strong negative relationship between beliefs about Bitcoin survival and exit probability is consistent with their observation that investor sentiment plays a crucial role in investment decisions, particularly in speculative assets. The marginal effect of beliefs about Bitcoin survival is significant, with a coefficient of -0.018 in the pooled model with control function (CF), indicating that a one-unit increase in belief reduces the probability of exit by 1.8 percentage points. The impact of selection is stronger for 2018, relative to 2019 and 2017; see Figure 11.

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 theoretical predictions, which suggest that the probability of exiting from the Bitcoin market changes as beliefs change over time as stronger beliefs reduce the probability of exiting. This dynamic echoes findings from Barberis et al. (1998) on how investor sentiment affects asset prices and investment behavior.

insert Figure 11 here -

Having lower education and being from one of the Atlantic provinces also drive exit. The relationship between education and exit probability supports broader literature on financial literacy and investment decisions. The lower exit probability associated with higher education aligns with findings by Lusardi and Mitchell (2014) that higher education is linked to better financial decision-making and risk management. The marginal effect for university education shows a significant reduction in exit probability by 17.3 percentage points when controlling for CF, highlighting its protective effect against disadoption.

Some demographic effects were different in 2019 compared with 2018 and 2017; for example, being younger, being unemployed, or having higher Crypto and Financial Literacy increases the exit probability. The varying effects of unemployment on exit behavior, particularly the strong positive association in 2019, highlight Bitcoin's potential role as a "buffer stock" for some investors. This aligns with Carroll and Samwick (1998) precautionary savings motive, suggesting economic shocks may force liquidation of crypto assets during financial stress. The marginal effect for unemployment indicates an increase in exit probability by 36.7 percentage points in 2019 when controlling for CF, underscoring its significant impact during economic downturns.

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 improvement over a model having only a constant term.[15] A visual representation of this decomposition is presented in Figure 12.

insert Figure 12 here -

The decomposition underscores beliefs' important role, notably in 2018 when there was a surge in exits. Also, it highlights CFL's significance and CF's importance, especially in 2018 and 2019. The fact that CF does not improve the model in 2017 reflects low exit rates during a period when Bitcoin's price was historically high. Thus, demographic characteristics were more relevant in 2017 but decreased in relevance from 2018 to 2019. This shift in financial literacy's effect from reducing exit probabilities in earlier years to increasing them later might indicate financially literate individuals were better at timing market conditions or reassessing investment strategies, similar to Grinblatt and Keloharju (2001) observations in stock markets. The phenomenon of disadoption (becoming a past owner), often referred to as "technology failures," is common early during new technology adoption (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 technology diffusion. Thus, regaining their trust becomes

[15]Practically we measure our choice variables' contribution to 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).

imperative as highlighted by Xin Xu and Tam (2017). This aligns with Gruber (1996) "smart money" concept discussed in mutual fund markets where more sophisticated investors quickly react to new information and market conditions. In Bitcoin's context, it may indicate early adopters who were potentially more speculative or less informed were more likely to exit as markets evolved and new information became available.

From central banks' viewpoint, understanding Bitcoin disadopters' characteristics is crucial if successfully introducing CBDCs is their goal. Risks leading to digital private currency disadoption like Bitcoin may bear similarities to those associated with CBDC adoption; hence understanding disadoption behavior is paramount. These findings underscore beliefs', demographics', and market conditions' complex interplay shaping Bitcoin investment behavior while highlighting economic and psychological factors' importance understanding cryptocurrency market dynamics extends investment exit behavior understanding into this novel asset class.

Next, we estimate a sequential choice model, which provide valuable insights into the dynamics of Bitcoin adoption and disadoption, aligning with and extending existing literature on technology adoption and investment behavior.

5.3 Sequential Model of Choices

To test the predictions about the ranking of beliefs and their dynamics over time on the probability of being a Bitcoin owner. Conditional on being an owner what is the probability of becoming a past owner? We first consider a non-parametric approach and then we estimate a sequential logit model.

Figure 6 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.[16] 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.

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

The assertion that owners exhibit faster learning rates than past owners, who in turn learn faster than never owners, is supported by the notion that prior experience with an asset can enhance one's understanding and adaptability to its dynamics. For instance, Choi and Liang (2023) highlight how agents in a dynamic monetary economy adjust their beliefs based on their experiences with an asset, suggesting that those with prior ownership are likely to have refined their learning processes compared to those without such experience. This aligns with our findings that the distribution of beliefs for owners first-order stochastically dominates (FOSD) that of past owners, indicating a structured progression in belief formation influenced by ownership history.

Moreover, the role of learning in shaping investors' beliefs is further substantiated by the work of Balutel et al. (2022), which emphasizes that individuals' beliefs about Bitcoin survival are significantly impacted by their social networks and prior experiences. This supports our Proposition 3, which posits that changes in beliefs among investors are the result of continuous learning processes. While quantifying these dynamics empirically presents challenges, the theoretical framework established in these studies provides a compelling basis for understanding how learning rates differ across ownership categories. Thus, we acknowledge the need for further empirical investigation into these learning mechanisms while reinforcing that our theoretical assertions are grounded in established economic principles regarding belief formation and investor behavior.

Next, the sequential choice model provides a comprehensive framework for analyzing the factors influencing an individual's status as a never owner, current owner, or past owner of Bitcoin. This approach allows us to investigate the dynamics of moving from being a never owner to becoming an owner, and subsequently from being a current owner to becoming a past owner (Figure 1). This sequential analysis aligns with the technology adoption lifecycle model proposed by Rogers (2010), which describes the adoption of innovations as a process occurring in stages.

We estimate a sequential logit model, in which a never owner can become an owner, who can then become a past owner. Table 17 in the appendix B shows the results of this exercise. The sequential model reveals a nuanced role of beliefs in the ownership process. Notably, beliefs play opposite roles for owners and past owners. An increase in beliefs raises the chances of becoming and remaining an owner, while decreasing the likelihood of transitioning to past ownership. This finding aligns with the theoretical predictions of our model and provides empirical support for the hypothesis that belief formation is a crucial driver in Bitcoin adoption and retention decisions. This is consistent with the work of Baker and Wurgler (2007) on investor sentiment in financial markets, highlighting the importance of beliefs in investment decisions, particularly for speculative assets like Bitcoin.

Additionally, when we account for the endogeneity of beliefs via control functions, 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, see Table 12.

- insert Table 12 here -

The control function (CF) linked to the beliefs of past owners plays a pivotal role in driving the outcomes. The model with two CFs amplifies the significance of beliefs for current owners, although it does not exhibit a comparable enhancement for past owners when compared with the single CF model. This finding underscores the importance of accounting for belief endogeneity in understanding ownership transitions, a point emphasized by Villas-Boas and Winer (1999) in their work on endogeneity in brand choice models.

The sequential model provides 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. Figure 14 depicts a visual representation of this decomposition.

- insert Figure 14 here -

The impact of our choice variables on the likelihood ratio show that 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. These temporal shifts in factor importance align with the findings of Greenwood and Shleifer (2014) on the evolving role of expectations in asset pricing and investment behavior.

The sequential choice model proves particularly effective in addressing the potential simultaneity issue that links individuals' beliefs to both entry and exit decisions. This approach resolves an important timing challenge that is absent when analyzing entry and exit in isolation, a point emphasized byHowell et al. (2020) in their study of Initial Coin Offerings and cryptocurrency token sales.

Table 13 provides a summary of the role of the relevant variables for the the analyzed models outlined in Section4 (past ownership and sequential choices):

- insert Table 13 here -

Beliefs exert the greatest influence in 2018 for past ownership probability, and in 2019 for 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.

In Figure 15 we look at the the role of beliefs in Bitcoin market entry and exit decisions.

- insert Figure 15 here -

The S-shaped curve for Bitcoin ownership and inverted S-shaped curve for past adopters demonstrate a nuanced relationship between beliefs and market behavior. For entry, the S-shaped curve indicates that as beliefs about Bitcoin's future become more positive, the probability of entering the market increases non-linearly. At low belief levels, the entry probability remains relatively low and increases slowly. However, there's a critical belief threshold (about 50%) where the entry probability begins to rise more rapidly, creating the characteristic S-shape. This suggests that a certain level of optimism about Bitcoin's future is necessary before individuals are likely to enter the market. Conversely, the inverted S-shaped curve for exiting probabilities shows that as beliefs become more positive, the likelihood of exiting the Bitcoin market decreases non-linearly. At high belief levels, the exit probability is low and decreases slowly. As beliefs become less positive, there's a point where the exit probability begins to increase more rapidly, forming the inverted S-shape. This indicates that individuals are more likely to remain in the market as long as their beliefs stay above a certain threshold, but once beliefs drop below this level, the probability of exit increases sharply.

These findings align with our theoretical model, which posits that agents with more optimistic beliefs are more likely to enter or re-enter the Bitcoin market, while those with more pessimistic beliefs are more prone to exit or stay out of the market. The S and inverted-S curves provide empirical support for this theoretical prediction, highlighting the imprtant role that beliefs play in shaping Bitcoin market dynamics.

5.4 Crypto and Financial Literacy

Our empirical analyses indicate that beliefs play the most important role in both entry and exit decisions in the Bitcoin market. But, we also uncover that crypto-financial literacy (CFL) has strong predictive power, contributing to the financial literacy literature.[17]

The effect of CFL on market exit decisions appears to be context-dependent. During market downturns, such as in 2018, individuals with high CFL show a lower likelihood of exiting. Conversely, during market improvements like in 2019, high CFL individuals are more likely to exit. This suggests that those with high CFL may be better equipped to manage Bitcoin market risks while also potentially capitalizing on market recoveries. Interestingly, individuals with medium CFL exhibit a similar pattern: they are less likely to enter the Bitcoin market but more inclined to exit, particularly evident in the 2019 results. The sequential model reinforces these observed patterns in the probability of becoming a past owner.

To further explore the impact of digital and financial literacy on Bitcoin ownership, we constructed counterfactual scenarios based on the logistic model estimates. The baseline probabilities were derived from the original model, while the adjusted lines represent simulated scenarios where literacy levels were increased by 20% and 40% respectively. The results are presented in Figure 16:

- insert Figure 16 here -

The counterfactual analysis of digital and financial literacy's impact on Bitcoin ownership yields several important insights. Firstly, higher levels of literacy are consistently associated with increased probabilities of both current and past Bitcoin ownership across all belief levels, highlighting the fundamental role of financial knowledge in cryptocurrency adoption. Secondly, the impact of literacy exhibits non-linear effects, with a 40% increase in literacy having a larger influence compared to a 20% increase. This suggests that substantial improvements in literacy may be necessary to significantly alter ownership patterns. Thirdly, the effect of increased literacy is more pronounced for individuals with higher beliefs about Bitcoin's future, indicating a complementarity between literacy and optimism. This synergy implies that educational efforts may be particularly effective when targeted at those already inclined towards cryptocurrency. Lastly, the impact of literacy on past ownership mirrors its

[17] Balutel et al. (2023a) 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. (2024). 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.

effect on current ownership, suggesting that literacy not only influences current adoption, but also increases the likelihood of past experimentation with Bitcoin. This finding underscores the influence of financial literacy on individuals' willingness to engage with novel financial technologies over time.

These findings contribute significantly to the financial literacy literature by demonstrating the complex relationship between crypto-financial literacy (CFL) and Bitcoin market behavior. The study reveals that CFL not only influences initial adoption but also impacts exit decisions and past experimentation with Bitcoin. This nuanced understanding of how financial literacy affects cryptocurrency participation across different market conditions and belief levels extends our knowledge of how financial education shapes participation in novel financial technologies.

5.5 Sensitivity Analysis: Role of Unobserved Heterogeneity

The sensitivity analysis presented in Table 15, evaluates the impact of unobserved heterogeneity (UH) on Bitcoin adoption and exit dynamics, using the sequential logit model framework. Following the methodology of Buis (2011), the analysis explores how adjustments to UH influence the estimated effect of beliefs about Bitcoin's survival probability ($E(Survival)$) across different ownership transitions.

- insert Table 15 here -

The benchmark model, labeled as "No CF," excludes control functions (CF) for endogeneity. In this model, $E(Survival)$ significantly affects transitions between ownership states: it positively influences transitions from "never owner" (n) to either "owner" (o) or "past owner" (p), and negatively impacts transitions from "owner" to "past owner." Introducing UH adjustments, such as $UH(9,0)$ or $UH(9,-5)$, amplifies the magnitude of $E(Survival)$'s effects, particularly for transitions from $n \rightarrow \{o,p\}$, while maintaining stability in the direction of effects. These results suggest that unobserved factors play a larger role in initial adoption decisions compared to exit dynamics.

The inclusion of CF further stabilizes the results, addressing endogeneity and improving reliability of the results. Notably, increasing UH beyond initial adjustments yields stable outcomes, reinforcing the robustness of these findings. Temporal differences across 2017–2019 highlight variations in $E(Survival)$'s effects, reflecting changing market conditions and external shocks.

These findings align with the theoretical framework and empirical results. The need for substantial UH adjustments in early adoption stages supports the notion that initial adoption involves greater uncertainty and variability in individual learning rates. By contrast, exit decisions appear less sensitive to unobserved factors. The inclusion of CF mirrors the paper's two-stage modeling approach, where residuals from belief regressions are incorporated into sequential logit models to address endogeneity.

Overall, this analysis underscores the importance of accounting for unobserved heterogeneity and endogeneity when modeling Bitcoin adoption dynamics. It highlights that beliefs about survival probabilities remain a key determinant of ownership transitions, while unobserved factors play a more significant role during early adoption phases. These insights have practical implications for stabilizing Bitcoin adoption through interventions such as improving financial literacy or addressing security concerns.

6 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 reveals significant variations in the impact of beliefs on ownership across time and by ownership status. Consistent with our theoretical predictions, a decrease in beliefs predicts a higher likelihood of exiting the Bitcoin market. Importantly, we find that beliefs about Bitcoin's survival have become more optimistic for past owners over time, suggesting the potential for market re-entry.

The impact of beliefs on ownership decisions has strengthened over time, as evidenced by our sequential model. By 2019, beliefs had become almost as impactful as all demographic variables combined in explaining ownership choices. This underscores the growing importance of perceptions and expectations in driving Bitcoin market dynamics.

The role of CFL emerges as an important factor in shaping the Bitcoin market. Our likelihood ratio decompositions for sequential models highlight the changing importance of CFL over time, with higher relevance in 2017 and 2019. This suggests that financially literate individuals may be better equipped to navigate price volatility and make informed decisions about Bitcoin ownership. 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 (Alvarez 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.

References

Alvarez, F., D. Argente, , and D. Van Patten (2023): "Are cryptocurrencies currencies? Bitcoin as legal tender in El Salvador," *Science*, 382.

Athey, S., I. Parashkevov, V. Sarukkai, and J. Xia (2016): "Bitcoin Pricing, Adoption, and Usage: Theory and Evidence," *Stanford University Graduate School of Businesss Research Paper*.

Auer, R. and D. Tercero-Lucas (2022): "Distrust or speculation? The socioeconomic drivers of U.S. cryptocurrency investments," *Journal of Financial Stability*, 62, 101066.

Baker, M. and J. Wurgler (2007): "Investor Sentiment in the Stock Market," *Journal of Economic Perspectives*, 21, 129–152.

Balutel, D., W. Engert, C. S. Henry, K. P. Huynh, D. Rusu, and M. Voia (2023a): "Crypto and Financial Literacy of Cryptoassets Owners Versus Non-Owners: The Role of Gender Differences," *Journal of Financial Literacy and Welbeing*, 1, 514–540.

Balutel, D., W. Engert, C. S. Henry, K. P. Huynh, and M. C. Voia (2024): "Explaining Bitcoin ownership in Canada: Trends from 2016 to 2021," *Canadian Journal of Economics*, 57, 777–798.

Balutel, D., M.-H. Felt, G. Nicholls, and M.-C. Voia (2023b): "Bitcoin awareness, ownership and use: 2016–20," *Applied Economics*, 1–26.

Balutel, D., C. Henry, J. Vásquez, and M. Voia (2022): "Bitcoin Adoption and Beliefs in Canada," *Canadian Journal of Economics*, 55, 1729–1761.

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

Bass, F. M. (1969): "A new product growth for model consumer durables," *Management Science*, 15, 215–227.

Benetton, M. and G. Compiani (2024): "Investors' Beliefs and Cryptocurrency Prices," *The Review of Asset Pricing Studies*, 14, 197–236.

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

Bucher-Koenen, T., R. Alessie, A. Lusardi, and M. van Rooij (2024): "Fearless Woman: Financial Literacy and Stock Market Participation," *Management Science*, 0, null.

Carroll, C. D. and A. A. Samwick (1998): "How Important is Precautionary Saving?" *The Review of Economics and Statistics*, 80, 410–419.

Catalini, C. and C. Tucker (2017): "When early adopters don't adopt," *Science*, 357, 135–136.

Choi, M. and F. Liang (2023): "Learning and money adoption," *Journal of Political Economy*, 131.

Danaf, M., C. A. Guevara, and M. Ben-Akiva (2023): "A control-function correction for endogeneity in random coefficients models: The case of choice-based recommender systems," *Journal of Choice Modelling*, 46, 100399.

Divakaruni, A. and P. Zimmerman (2024): "Uncovering Retail Trading in Bitcoin: The Impact of COVID-19 Stimulus Checks," *Management Science*, 70, 2066–2085.

D'Haultfœuille, X., S. Hoderlein, and Y. Sasaki (2021): "Testing and relaxing the exclusion restriction in the control function approach," *Journal of Econometrics*, 105075.

Flores, A., G. Berbeglia, and P. Van Hentenryck (2019): "Assortment optimization under the Sequential Multinomial Logit Model," *European Journal of Operational Research*, 273, 1052–1064.

Forum Research Inc. (2023): "Digital Canadian Dollar Public Consultation: Report," Link to report.

Fujiki, H. (2020): "Who adopts crypto assets in Japan? Evidence from the 2019 financial literacy survey," *Journal of the Japanese and International Economies*, 58, 101107.

——— (2021): "Crypto asset ownership, financial literacy, and investment experience," *Applied Economics*, 53, 4560–4581.

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

Grinblatt, M. and M. Keloharju (2001): "What Makes Investors Trade?" *Journal of Finance*, 56, 589–616.

Gruber, M. J. (1996): "Another Puzzle: The Growth in Actively Managed Mutual Funds," *"The Journal of Finance"*, 51, 783–810.

Halaburda, H., G. Haeringer, J. Gans, and N. Gandal (2022): "The microeconomics of cryptocurrencies," *Journal of Economic Literature*, 60, 971–1013.

Heckman, J. J. and R. Robb (1985): "Alternative methods for evaluating the impact of interventions: An overview," *Journal of Econometrics*, 30(1–2), 239–267.

Henry, C. S., W. Engert, A. Sutton-Lalani, S. Hernandez, D. McVanel, and K. P. Huynh (2024): "Unmet payment needs and a central bank digital currency," *Journal of Digital Banking*, 8, 311–337.

Henry, C. S., K. P. Huynh, and G. Nicholls (2018): "Bitcoin awareness and usage in Canada," *Journal of Digital Banking*, 2, 311–337.

——— (2019a): "Bitcoin Awareness and Usage in Canada: An Update," *The Journal of Investing*, 28, 21–31.

Henry, C. S., K. P. Huynh, G. Nicholls, and M. W. Nicholson (2019b): "2018 Bitcoin Omnibus Survey: Awareness and Usage," *Bank of Canada Staff Discussion Paper*, 2019-10.

——— (2020): "Benchmarking Bitcoin Adoption in Canada: Awareness, Ownership and Usage in 2018," *Ledger*, 5.

Hogan, J., K. Lemon, and B. Libai (2003): "What Is the True Value of a Lost Customer?" *Journal of Service Research - J SERV RES*, 5, 196–208.

Hörner, J. and A. Skrzypacz (2017): *Learning, Experimentation, and Information Design*, Cambridge University Press, vol. 1 of *Econometric Society Monographs*, 63–98.

Hosmer, D. W., S. Lemeshow, and R. X. Sturdivant (2013): *Applied Logistic Regression*, Wiley Series in Probability and Statistics, John Wiley & Sons, Inc.

Howell, S. T., M. Niessner, and D. Yermack (2020): "Initial Coin Offerings: Financing Growth with Cryptocurrency Token Sales," *The Review of Financial Studies*, 33, 3925–3974.

Imbens, G. and J. Wooldridge (2009): "Cemmap Lecture Notes 14: Control Function and Related Methods," Cemmap, UCL.

Kass-Hanna, J., A. C. Lyons, and F. Liu (2022): "Building Financial Resilience Through Financial and Digital Literacy in South Asia and Sub-Saharan Africa," *Emerging Markets Review*, 51, 100846.

Keller, G. and S. Rady (2010): "Strategic experimentation with Poisson bandits," *Theoretical Economics*, 5, 275–311.

Kosba, A., A. Miller, E. Shi, Z. Wen, and C. Papamanthou (2016): "Hawk: The blockchain model of cryptography and privacy-preserving smart contracts," in *2016 IEEE symposium on security and privacy (SP)*, IEEE, 839–858.

Liu, J., I. Makarov, and A. Schoar (2023): "Anatomy of a Run: The Terra Luna Crash," Working Paper 31160, National Bureau of Economic Research.

Lusardi, A. and O. S. Mitchell (2011): "Financial literacy around the world: an overview," *Journal of Pension Economics and Finance*, 10, 497–508.

——— (2014): "The Economic Importance of Financial Literacy: Theory and Evidence," *Journal of Economic Literature*, 52, 5–44.

Lyons, A. and J. Kass-Hanna (2021): "A Methodological Overview to Defining and Measuring "Digital" Financial Literacy," *Financial Planning Review*, 4, 1–19.

Nakamoto, S. (2008): "Bitcoin: A peer-to-peer electronic cash system," *mimeo*.

Orcutt, M. (2023): "What's next for China's digital currency?" Link to article, MIT Technology Review.

Rogers, E. M. (2010): *Diffusion of innovations*, Simon and Schuster.

Sandholm, W. H. (2010): *Population games and evolutionary dynamics*, MIT Press.

Schuh, S. and O. Shy (2016): "US consumers' adoption and use of Bitcoin and other virtual currencies," in *DeNederlandsche Bank, Conference entitled "Retail payments: mapping out the road ahead"*.

Stix, H. (2021): "Ownership and Purchase Intention of Crypto-assets: survey results," *Empirica*, 48, 65–99.

Teschl, G. (2012): *Ordinary differential equations and dynamical systems*, vol. 140, American Mathematical Society.

Uhlig, H. (2022): "A Luna-tic Stablecoin Crash," NBER Working Papers 30256, National Bureau of Economic Research.

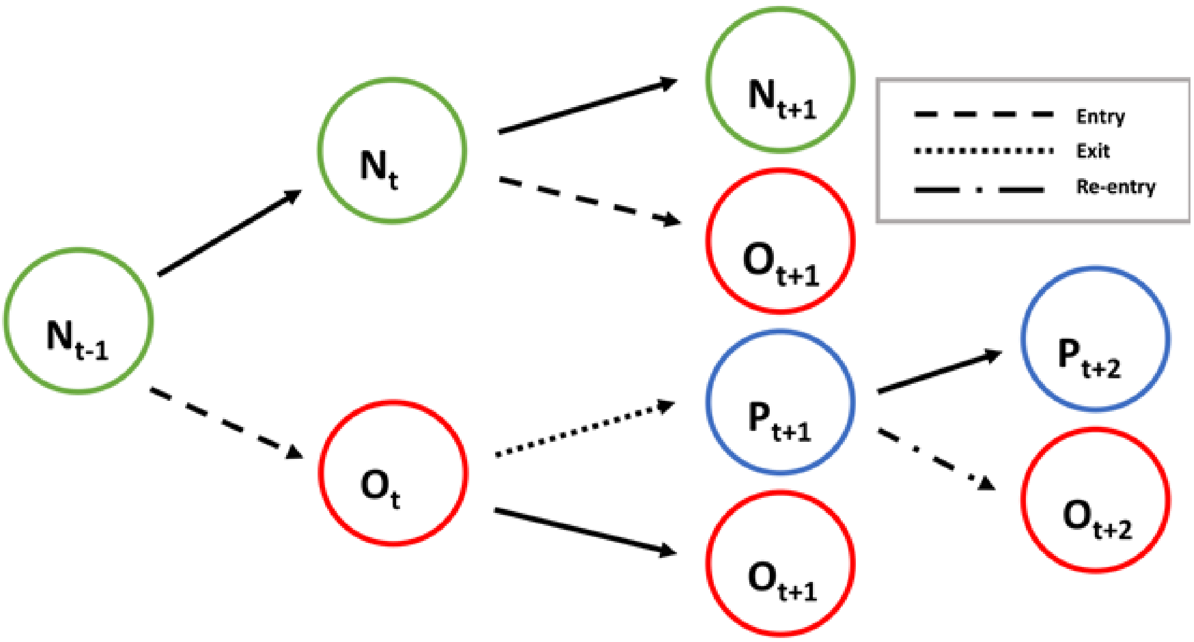
Villas-Boas, J. M. and R. S. Winer (1999): "Endogeneity in Brand Choice Models," *Management Science*, 45, 1324–1338.

Wooldridge, J. (2015): "Control Function Methods in Applied Econometrics," *Journal of Human Resources*, 50, 420–445.

Xin Xu, J. Y. T. and K. Y. Tam (2017): "Winning Back Technology Disadopters: Testing a Technology Readoption Model in the Context of Mobile Internet Services," *Journal of Management Information Systems*, 34, 102–140.

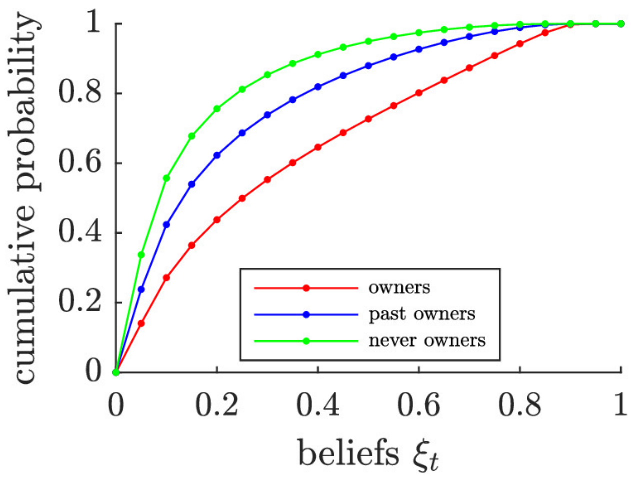
Figures

Figure 1: **Model diagram**

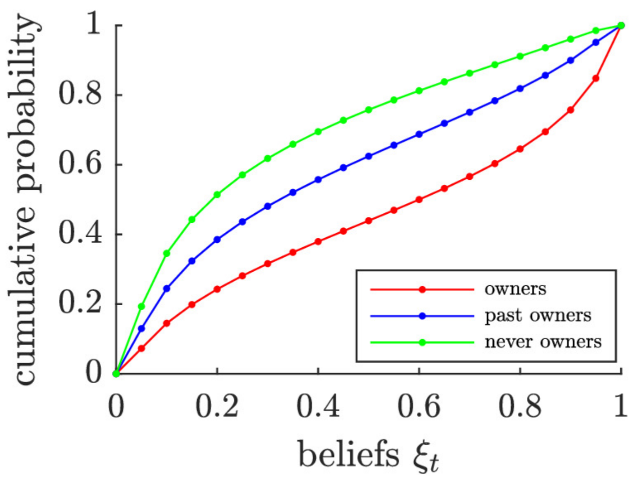


Note: Schematic of the possible transitions captured by the theoretical model.

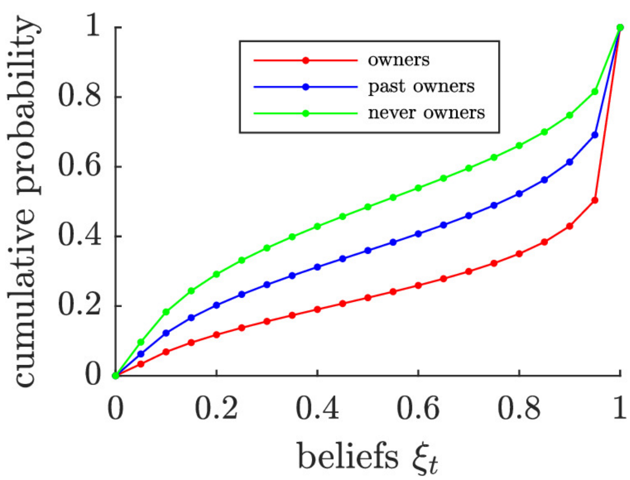
Figure 2: **Simulated belief dynamics**



(a) Low



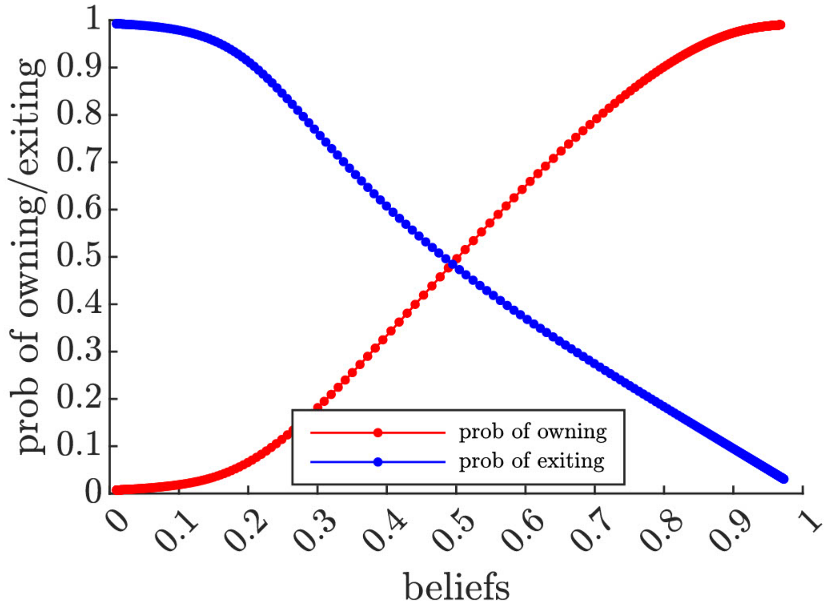
(b) Medium



(c) High

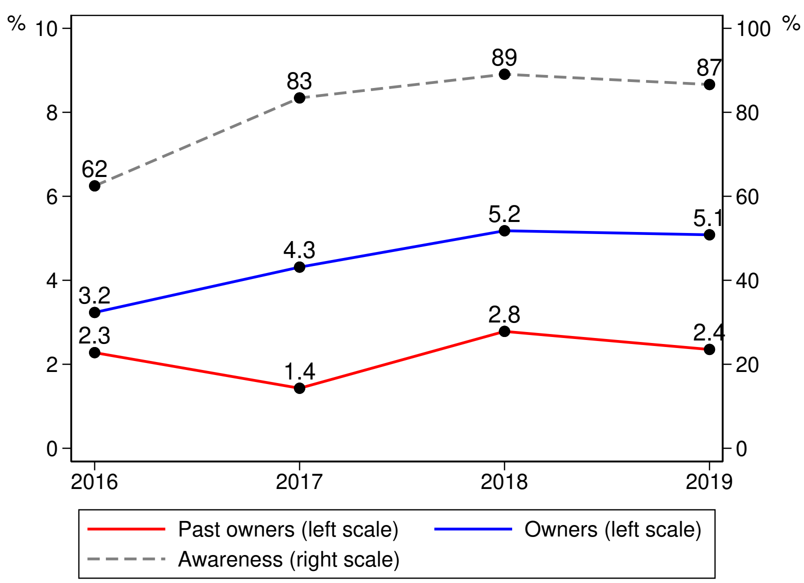
Note: Evolution of CDFs as individuals' beliefs evolve as predicted from the theoretical model. Figure assumes owners learn (stochastically) faster than past owners, and past owners faster than never owners.

Figure 3: $\Pr(own = 1|Beliefs)$ **and** $\Pr(pastown = 1|Beliefs)$



Note: Evolution of $\Pr(own = 1|Beliefs)$ - red and $\Pr(pastown = 1|Beliefs)$ - blue.

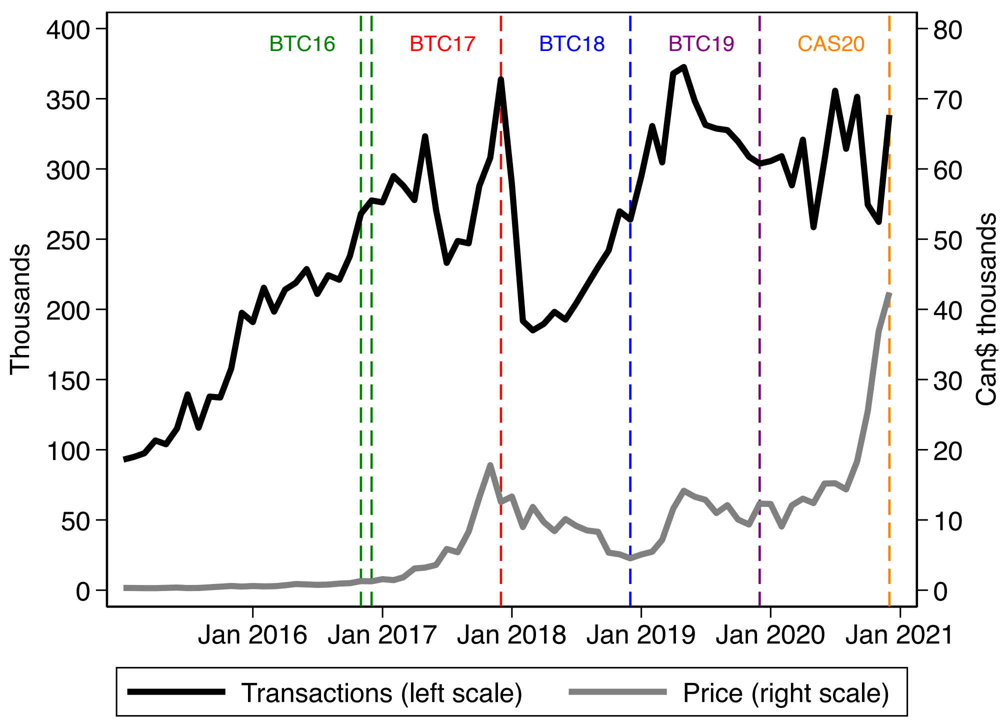
Figure 4: **Bitcoin awareness and ownership 2016–19**



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

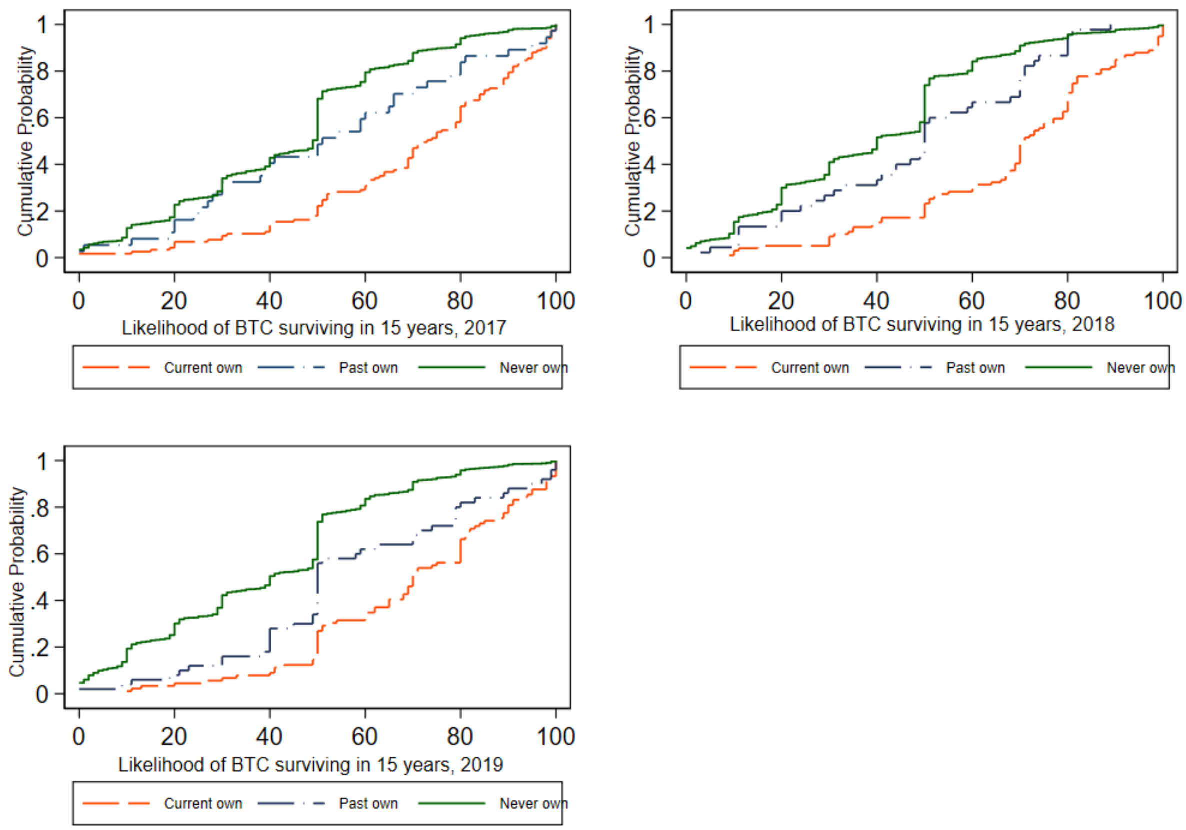
This figure plots yearly estimates of the share of Canadians who were aware of Bitcoin, who owned Bitcoin, and who exited from 2016 to 2019. Estimates from 2016 to 2019 are from the Bitcoin Omnibus Survey. For ease of presentation, ownership and past-ownership is scaled from 0% to 10% (left scale), while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

Figure 5: **Price and volume of Bitcoin at the time of BTCOS surveys**



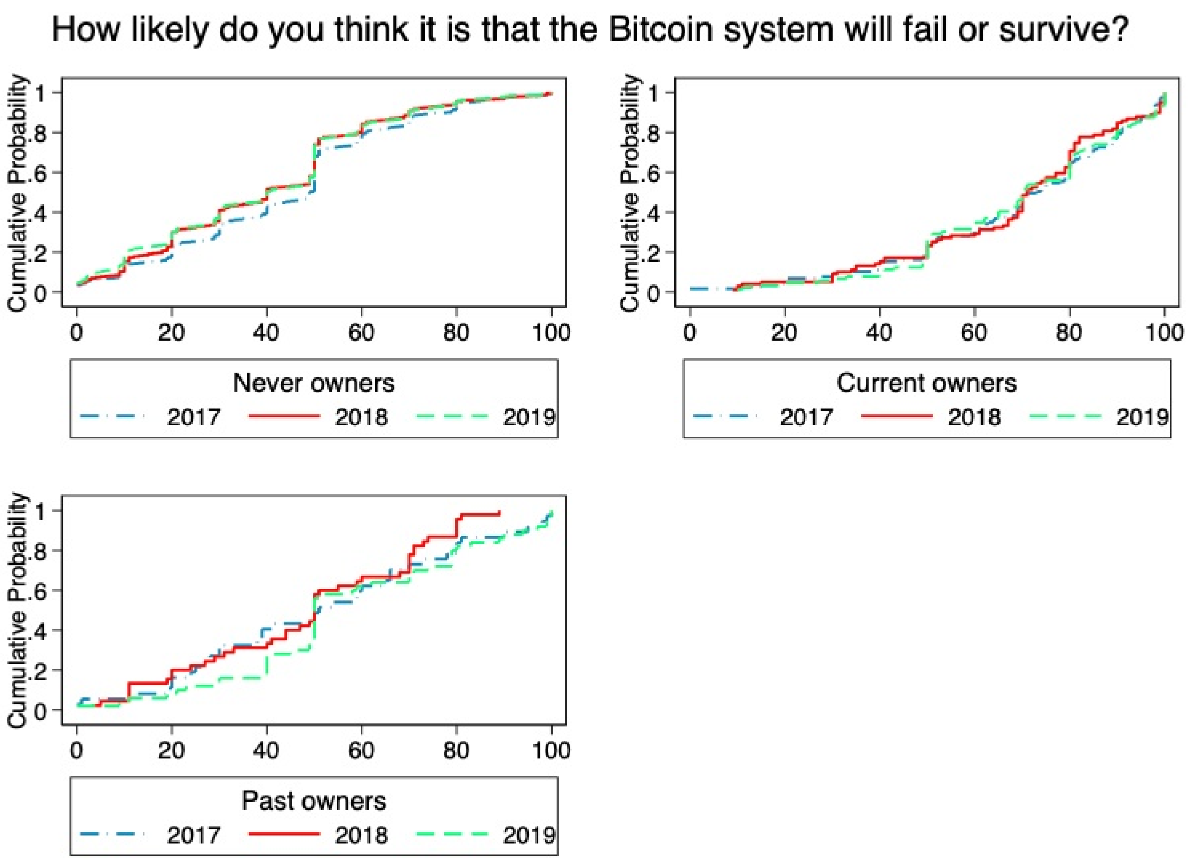
Note: This figure plots the number of transactions conducted on the Bitcoin network (left scale) as well as the price of Bitcoin in Canadian dollars (right scale), showing dates when various Bank of Canada surveys measuring Bitcoin were conducted. Green vertical lines indicate the first iteration of 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 6: **Expected survival rate of Bitcoin in 15 years: Between group dynamics of beliefs ξ_{it}:**



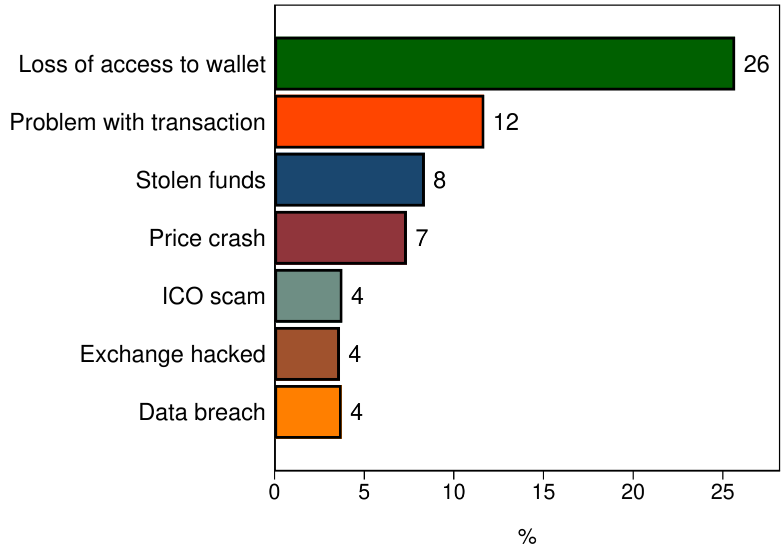
Note: Question from the BTCOS: *"How likely do you think it is that the Bitcoin system will survive for the next 15 years?"* Respondents answered on a scale of 0 to 100.

Figure 7: **Bitcoin expected survival rate in 15 years: Within group dynamics of beliefs ξ_{it}:**



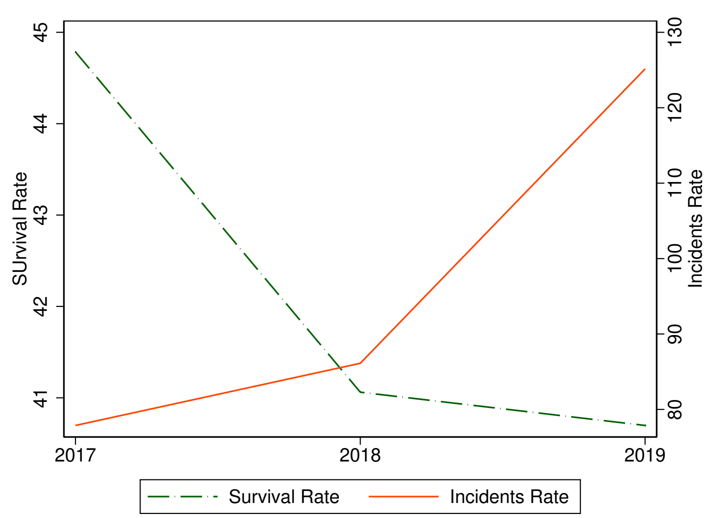
Note: Question from the BTCOS: *"How likely do you think it is that the Bitcoin system will survive for the next 15 years?"* Respondents answered on a scale of 0 to 100.

Figure 8: **Selection out of the Bitcoin market: Cryptocurrency risks and loss incidents faced by past Bitcoin owners, 2019**



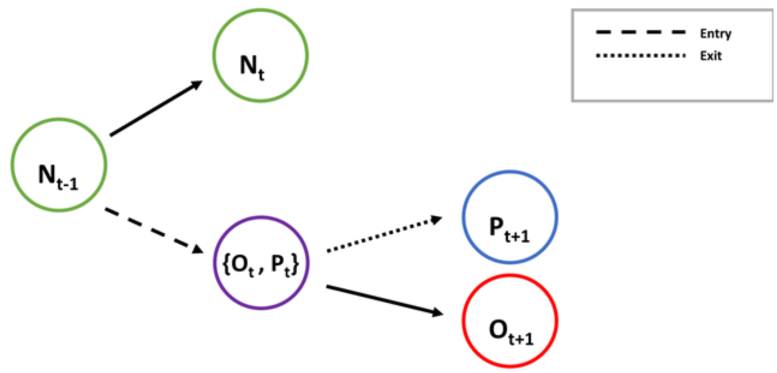
Note: This figure reports the percentages of cryptocurrency past owners who experienced any of the indicated incidents in 2019 BTCOS. The sample consists of 50 Canadians aged 18 and over who indicated owning Bitcoin in the past, but not at the time of the survey. All estimates are calculated using survey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

Figure 9: **Expected survival rate of Bitcoin (ξ_{it}) and cyber incidents rate (Z_{jt})**



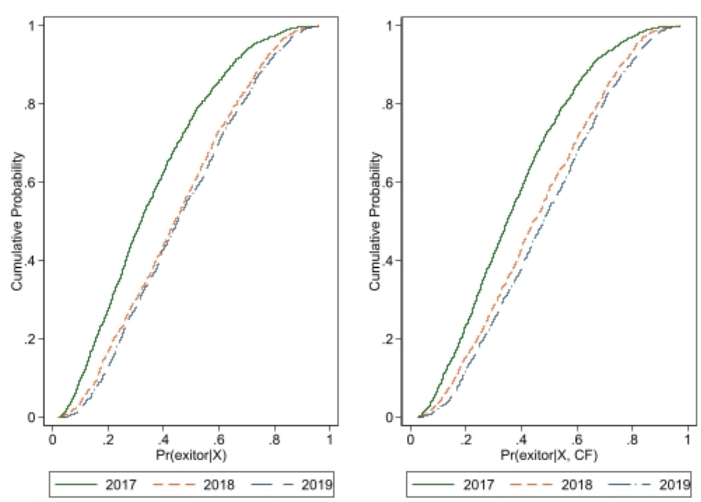
Source: BTCOS and CANSIM

Figure 10: **Sequential nature ownership and past ownership - modelling the latent state**



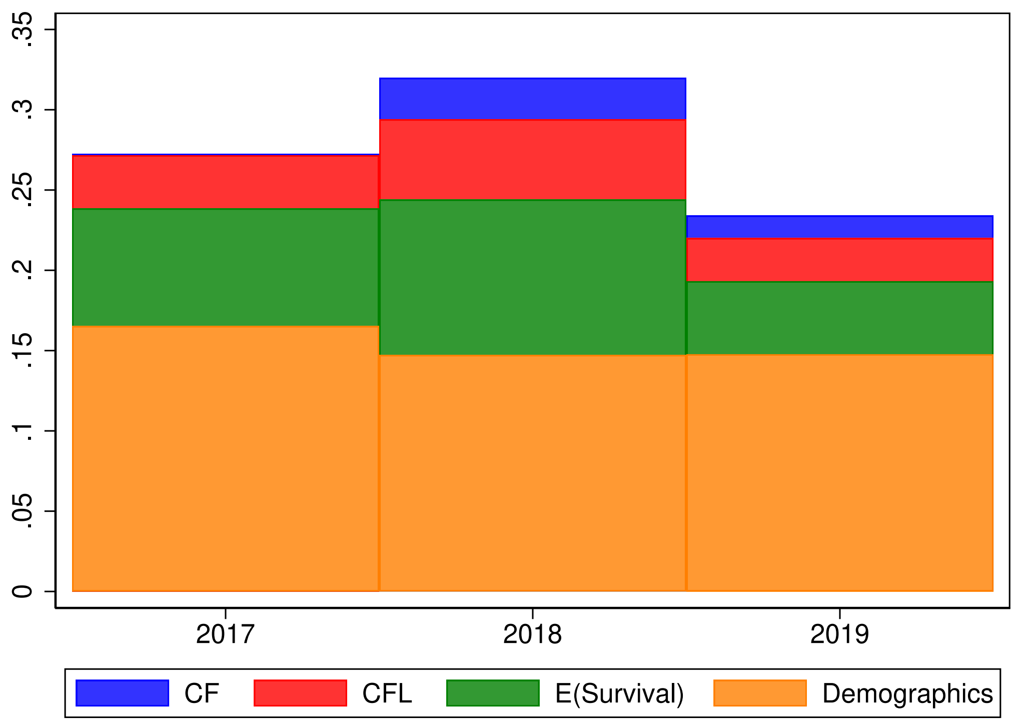
Note: Schematic of the transitions captured by the sequential model.

Figure 11: **Probability of exiting: 2017–19, without and with CF**



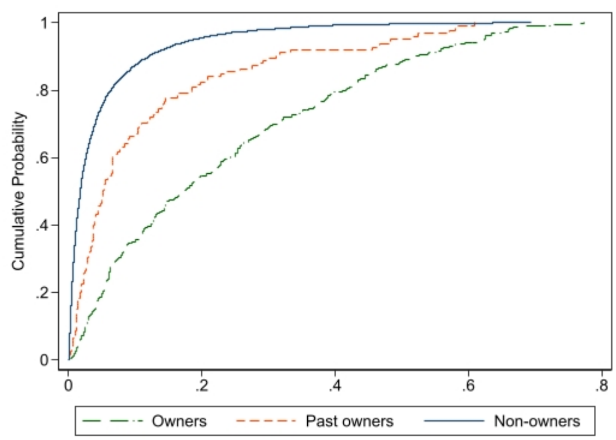
Note: All estimates are calculated using survey weights.

Figure 12: **Likelihood ratios (Pseudo-R^2) contributions: Probability of being a past owner**



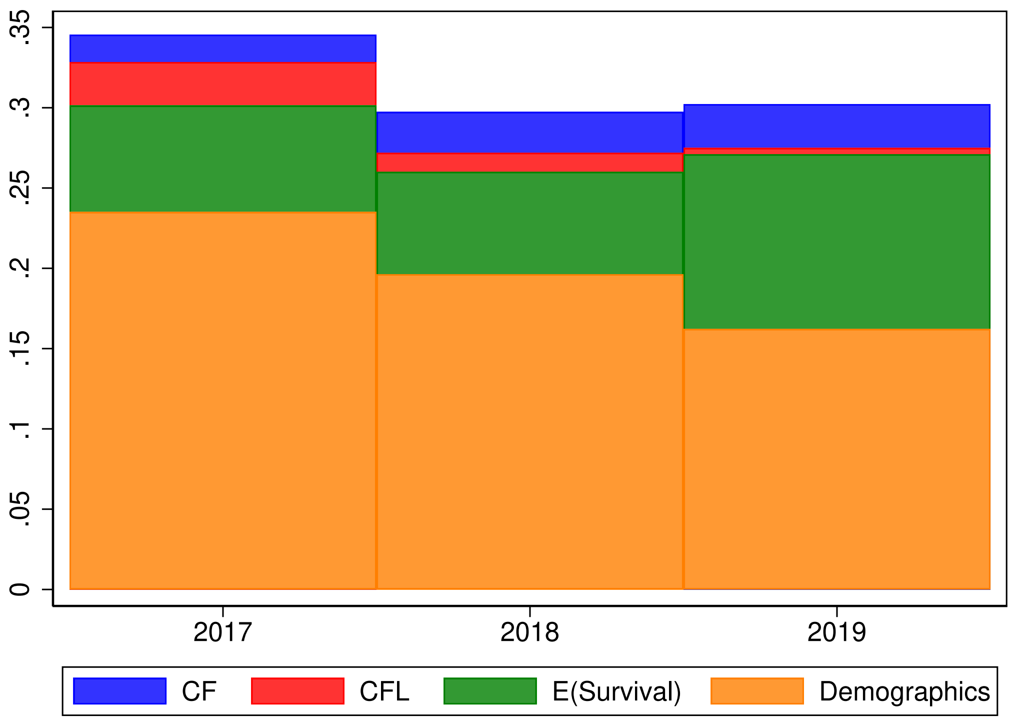
Note: The following coding is used for measuring the $Pseudo-R^2 = 1 - \frac{Log-likelihood(Model)}{Log-Likelihood(Constant)} - \lambda\frac{df}{N-1}$ contribution (Hosmer et al., 2013) for the probability of being a Bitcoin past owner: CF = control function contribution to the probability, CFL = crypto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

Figure 13: **Probability of being an owner and past owner relative to never owner**



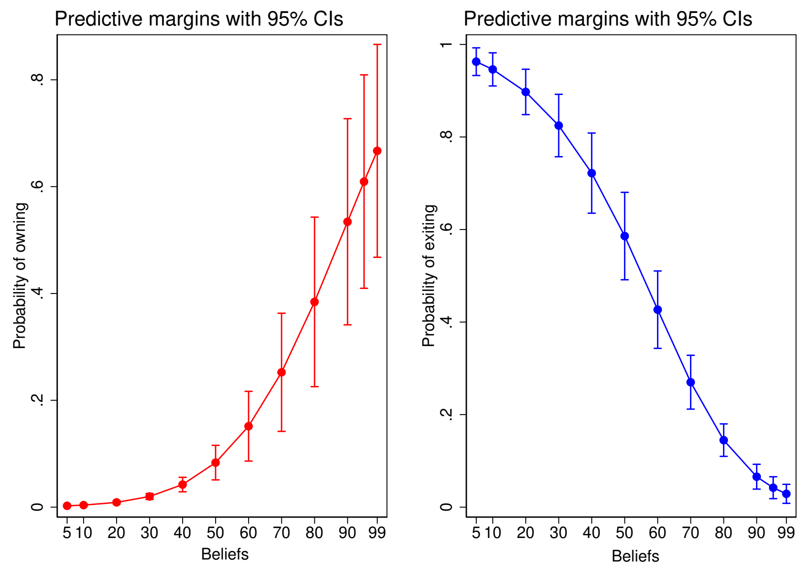
Note: All estimates are calculated using survey weights.

Figure 14: **Likelihood ratios (Pseudo-R^2) contributions: Sequential model of choices**



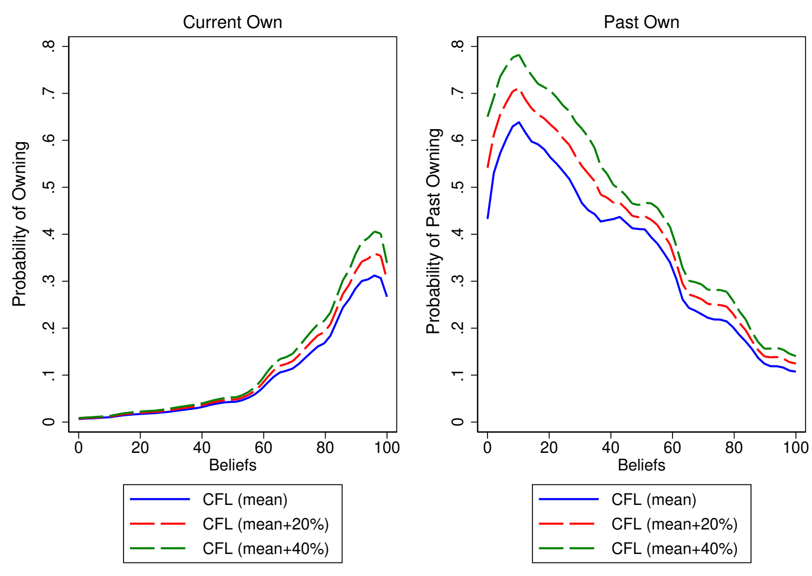
Note: The following coding is used for measuring the $Pseudo - R^2 = 1 - \frac{Log-likelihood(Model)}{Log-Likelihood(Constant)} - \lambda \frac{df}{N-1}$ contribution (Hosmer et al., 2013) for the probability of being a Bitcoin past owner: CF = control function contribution to the probability, CFL =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

Figure 15: **The changes on probability of being a Bitcoin owner versus past-owners as a function of Beliefs**



Note: The marginal changes in probabilities are computed using full support of the Beliefs.

Figure 16: **Predicted Ownership Probabilities by Beliefs and Literacy Levels**



Note: The graph shows predicted ownership probabilities—own (left) and past-own (right)—by beliefs (0-100) and literacy levels (CFL: low, medium, high). Baseline probabilities are derived from the logistic model, while adjusted lines simulate 20% and 40% increases in literacy. All estimates are survey-weighted.

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**

Never Owners				
CFL	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
Owners				
CFL	2017	2018	2019	Total
Low	27	33	34	94
Medium	58	28	21	107
High	32	38	34	104
Total	117	99	89	305
Past Owners				
CFL	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 (%)**

Never Owners	**mean**	**Obs**
2017	1.482	2,108
2018	1.718	1,688
2019	1.706	1,656
Owners	**mean**	**Obs**
2017	2.033	117
2018	2.019	99
2019	1.862	89
Past Owners	**mean**	**Obs**
2017	1.706	37
2018	1.624	45
2019	2.006	50

Note: This table provides the weighted means of CFL scores (low =1, med =2, high =3) 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 (%)**

Reasons	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

Source: Statistics Canada, formerly CANSIM 252-0096. The number of cybercrime incidents was aggregated across five regions.

Geography: Province or territory (2016-2019).

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

Model prediction / assumption	Empirical test
1] Ranking of beliefs by ownership type. *Model prediction / assumption* Assuming types have different speeds of learning, ranking of beliefs is preserved across time (Prop. 2; Eq. 4.1)	*Empirical test* Between groups distribution of beliefs (Fig. 6); Epps-Singleton Two-Sample Empirical Characteristic Function Test
2] Distribution of beliefs across time. *Model prediction / assumption* Conditional on a given ownership type, distribution of learning rates can increase, decrease or remain constant (Prop. 3)	*Empirical test* Compare relative size of marginal effects of beliefs by ownership type, across time (Fig 7; Tables 17–12). The results show that the role of beliefs can either increase or decrease, especially for past Bitcoin owners, depending on the volatility of the market. Epps-Singleton Two-Sample Empirical Characteristic Function Test
3] Beliefs drive exit from the Bitcoin market. *Model prediction / assumption* Probability of exit depends on level of beliefs and reservation utility (Eq. 2.5)	*Empirical test* Estimated coefficient on beliefs is negative and significant in second-stage model of exit (Eq. 4.4; Table 11), validating the prediction of the model.
4] Dynamics of transitioning between ownership states *Model prediction / assumption* There is a unique equilibrium solution to the dynamical system describing how the rates of ownership and past ownership evolve across time (Eq. 2.6–2.8; Prop. 4)	*Empirical test* Using a sequential logit model, jointly estimate the transition from never owner to Bitcoin adopter, and then from an adopter to past owner (Eq. 4.7; Tables 17–12). The results about the Bitcoin ownership and past ownership are in line with the predictions of the model.

Table 7: **Between groups (ownership type) ranking of beliefs over time**

Year	Group	Comparison	Obs	ES-test	P-value
2017	NO	O	2188	131.14	0
2017	NO	PO	2108	5.75	0.22
2017	O	PO	154	13.19	0.01
2018	NO	O	1742	179.84	0
2018	NO	PO	1688	18.33	0.001
2018	O	PO	144	30.65	0
2019	NO	O	1695	237.72	0
2019	NO	PO	1656	33.01	0
2019	O	PO	139	10.46	0.03

Table 8: **Within groups (time) ranking of beliefs over ownership type**

Adopter	Year	Comparison	Obs	ES-test	P-value
NO	2017	2018	3714	30.17	0
NO	2017	2019	3677	36.97	0
NO	2018	2019	3249	10.32	0.03
O	2017	2018	216	0.69	0.95
O	2017	2019	206	1.62	0.81
O	2018	2019	188	1.55	0.82
PO	2017	2018	82	5.04	0.28
PO	2017	2019	87	2.52	0.64
PO	2018	2019	95	10.80	0.02

Table 9: **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 dependent variable represents individuals' beliefs about Bitcoin's survival over the next 15 years. For the control variables, 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. All estimates are calculated using survey weights. Significance stars ***, **, and * represent 1%, 5%, and 10% significance, respectively.

Table 10: **First-stage model for beliefs about Bitcoin survival for the Past Owners, 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)
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

Standard errors in parentheses

*** p¡0.01, ** p¡0.05, * p¡0.1

Note: The dependent variable represents individuals' beliefs about Bitcoin's survival over the next 15 years. $Incident\_rate_{P,O,Q,A}$, 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. For the control variables, 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. All estimates are calculated using survey weights. Significance stars ***, **, and * represent 1%, 5%, and 10% significance, respectively.

Table 11: **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)
CFL: 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)
CFL: 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 dependent variable represents individuals' past ownership of Bitcoin. For the control variables, the base case is defined as: Male, Age 18–34, High School, Low Income, British Columbia, Employed. CFL = Financial and crypto literacy. The $\widehat{u}$ is the control function (CF) obtained as a residual from the first-stage regression in Table 10. The price of Bitcoin is defined as the opening price on the day the interview was conducted. All estimates are calculated using survey weights. Significance stars ***, **, and * represent 1%, 5% and, 10% significance, respectively.

Table 12: **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)
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)
Demographics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
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 sequences are based on two stages. In the first stage, the dependent variable is binary, with categories defined as 1 = never owned and 2 = current or past owner. In the second sequence, the dependent variable is also binary: 1 = current owner and 2 = past owner. For the control variables, the base case is Male, Age 18–34, High School, Low Income, Employed, No Kids, Single, British Columbia. The price of Bitcoin is defined as the opening price on the day the interview was conducted. The $\widehat{u}_{past}$ is the control function (CF) obtained as a residual from the first-stage regression in Table 10, while $\widehat{u}_{own}$ is obtained according to the methodology in Balutel et al. (2022). N = never owner, O = current owner, P = past owner, and CFL = Financial and crypto literacy. All estimates are calculated using survey weights. Significance stars ***, **, and * represent 1%, 5%, and 10% significance, respectively.

Table 13: **Likelihood ratio decompositions for empirical models**

Model	Year	Demographics	E(Survival)	CFL	CF
Logit (Table 11)	2017	0.17	0.24	0.27	0.27
Logit (Table 11)	2018	0.15	0.24	0.29	0.32
Logit (Table 11)	2019	0.15	0.19	0.22	0.23
Sequential Logit (Table 12)	2017	0.24	0.30	0.33	0.35
Sequential Logit (Table 12)	2018	0.20	0.26	0.27	0.30
Sequential Logit (Table 12)	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 Logit model is detailed in Table 11, the Sequential Logit model is shown in Table 12.

Table 14: **Total contribution for the transitions n to {o,p} and from o to p for E(Survival),CF and CFL**

Year	Variable	Total n to {o,p}	Contribution o to p
2017	E(Survival)	0.0115	0.009
2018	E(Survival)	0.0147	0.0125
2019	E(Survival)	0.0049	0.0027
2017	CF	0.0008	0.003
2018	CF	0.0062	0.0086
2019	CF	0.0005	0.001
2017	CFL	0.038	0.0442
2018	CFL	0.014	0.0248
2019	CFL	0.0094	0.0198

Notes: CF = control function contribution to the transition probability, CFL = crypto and financial literacy contribution to the transition probability, E(Survival) = Beliefs contribution to the transition probability.

Table 15: Sensitivity Analysis - Role of unobserved heterogeneity (UH)

Model	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
No CF	E(Survival)	0.030***	-0.032***	0.023***	-0.034***	0.214***	-0.176***	0.040***	-0.033***
		(0.003)	(0.006)	(0.005)	(0.011)	(0.050)	(0.035)	(0.005)	(0.012)
No CF, UH(9,0)	E(Survival)	0.139***	-0.032***	0.112***	-0.034***	0.138***	-0.048***	0.184***	-0.033***
		(0.016)	(0.006)	(0.021)	(0.011)	(0.032)	(0.011)	(0.023)	(0.012)
No CF, UH(9,-5)	E(Survival)	0.137***	-0.114***	0.109***	-0.096***	0.137***	-0.151***	0.179***	-0.128***
		(0.015)	(0.010)	(0.020)	(0.020)	(0.031)	(0.025)	(0.022)	(0.021)
With CF	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)
With CF, UH(1,1)	E(Survival)	0.164***	-0.097***	0.128***	-0.008	0.231***	-0.120*	0.164***	-0.174***
		(0.017)	(0.031)	(0.027)	(0.052)	(0.036)	(0.069)	(0.032)	(0.055)

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 (2.1). This differential equation admits a closed-form solution. Indeed, (2.1) 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 $x \in (0,1)$:

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

Consequently, if $G(\cdot|y,o) \leq G(\cdot|y,p) \leq G(\cdot|y,n)$ then it inequality (4.1) 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:

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

As a result:

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

This concludes the proof. □

A.3 Proof of Proposition 4

We will show that, for each category $y \in \mathcal{Y}$, the system (2.6)–(2.8) 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 (2.1), 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 (2.6)–(2.8) 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 16: **Appendix Empirical Section: Test of Validity of Exclusion restrictions: $H_0 : E(Y|X,Z) = E(Y|X)$.**

Marginal Effects VARIABLES	(1) $\widehat{E(Y\|X)}$	(2) $\widehat{E(Y\|X,Z)}$
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, $***p < 0.01, **p < 0.05, *p < 0.1$

Table 17: **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)
CFL: 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)
CFL: 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 sequences are based on two stages. In the first stage, the dependent variable is binary, with categories defined as 1 = never owned and 2 = current or past owner. In the second sequence, the dependent variable is also binary: 1 = current owner and 2 = past owner. For the control variables, 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. All estimates are calculated using survey weights. Significance stars ***, **, and * represent 1%, 5%, and 10% significance, respectively.