Bitcoin Experimentation in Canada: Adoption and Beliefs[*]

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Abstract

In the last few years, there has been a growing discussion on digital currencies; in particular, Bitcoin. Yet, empirical studies on Bitcoin adoption and experimentation are limited. In this paper, we develop a tractable model of Bitcoin experimentation which we then take to the data. Agents are uncertain about the quality of the underlying technology and update their beliefs by observing the survival of Bitcoin, which is affected by current and past levels of adoption. The model predicts that the path of adoption and agents' beliefs are both S-shaped over time, and that learning saturates earlier than adoption. We use unique data from the Bitcoin Omnibus Survey (BTCOS), which provides information on agents' adoption choices and beliefs about the medium- to long-term survival of Bitcoin in Canada. We find pieces of evidence consistent with the model. In particular, we find that for most individuals their speed of learning is currently decreasing, indicating that Bitcoin learning is in an advanced, or saturated, stage. However, the speed of Bitcoin adoption is not globally increasing, suggesting that Bitcoin experimentation is still in its infancy for some individuals.

Keywords: Bitcoin, adoption, experimentation, learning

JEL codes: D83, O33

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1 Introduction

It is becoming increasingly important to understand what determines the adoption and usage of private digital currencies. If private digital currencies become more widely adopted, they may impact the banking sector and interfere with the core functions of central banks (e.g., monetary policy). In the last few years, there has been an explosion of so-called "crypto-currencies," with more than 740 available. These currencies are revolutionizing the business model of online transactions. Among them, Bitcoin is the leader, enjoying the highest market cap and volume, as well as much more mainstream media attention.[1]

Bitcoin is a decentralized electronic fiat money with floating value that allows agents to make peer-to-peer payments and transactions without needing a trusted third party (Nakamoto, 2008; Böhme et al., 2015). This technological innovation has sparked interest from different academic fields, ranging from computer science to economics and finance; see Halaburda and Haeringer (2018) for a recent survey. Still, there is no consensus on whether this new technology will *survive* or not (Budish, 2018). Bitcoin and digital currencies appear to be in a nascent stage, where the transactional motive is small relative to the store-of-value one (Fung et al., 2017). This suggests that individuals are still experimenting with Bitcoin and learning its potential benefits and costs. But, how advanced is Bitcoin experimentation? And how advanced is the individuals' learning about this new technology? Because of data limitations, these questions remain unanswered.

The small but growing literature on digital currencies is largely silent about these issues. Some papers focus on the effects of delaying early adopters on the diffusion of Bitcoin (Catalini and Tucker, 2017), whereas others focus on the determinants of the Bitcoin exchange rate, usage, and speculation (Bolt and van Oordt, 2016; Athey et al., 2016). However, because of the lack of micro-data on agents' beliefs about Bitcoin survival, empirical studies that focus on Bitcoin adoption and learning remain somewhat limited.

In this paper, we provide a theoretical and empirical analysis of Bitcoin adoption and learning. We use unique data from the Bitcoin Omnibus Survey (BTCOS), which is a nationally representative survey of Canadians that includes questions related to Bitcoin, as well as demographic information. Crucially, the BTCOS provides us with information on agents' adoption decisions, and also on their beliefs about the medium- to long-term survival of Bitcoin, as well as expected future adoption. The data uncovers a novel relationship between Bitcoin adoption and agents' beliefs about its survival, which motivates our economic analysis. Specifically, Figure 1 shows that agents' beliefs about Bitcoin survival differs significantly when adoption is either positive or

[1] In 2017, Bitcoin's value increased rapidly, hitting historical records. Astonishingly, the price of one Bitcoin on January 01, 2017 was around US $1000, and it spiked at around US $19000 on December 16, 2017 (Source: `www.coindesk.com`). Likewise, the number of Google searches on Bitcoin has also been steadily increasing.

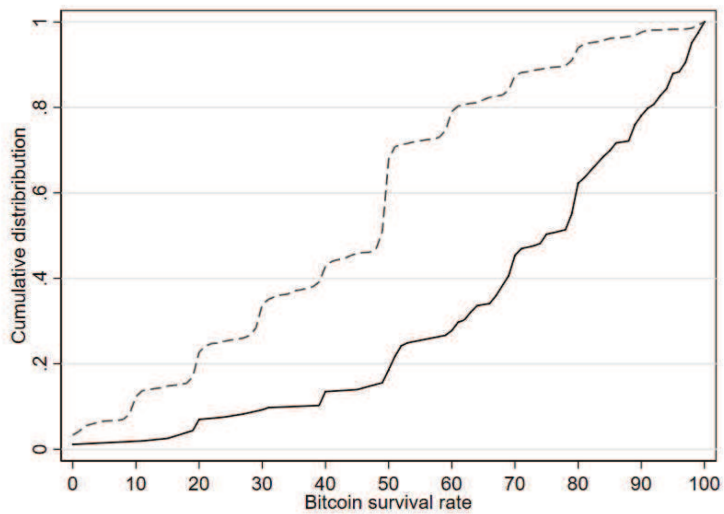

Figure 1: **The Survival Rate and Adoption.** The dashed line represents the expected survival rate cumulative distribution function conditional on no adoption, whereas the solid line is the same conditional on strictly positive adoption. The two distributions are statistically different. The figure shows that the agents' beliefs about Bitcoin survival is affected by adoption.

zero.[2] Specifically, *Bitcoin adopters are on average more optimistic about Bitcoin survival than non-adopters*.[3] This evidence indicates that Bitcoin experimentation may fuel agents beliefs about Bitcoin which, in turn, may impact future adoption. In other words, beliefs appear to be endogenous to the adoption level, and thus these two processes are likely to reinforce one another.

So motivated, we develop a simple dynamic model of Bitcoin adoption, in which agents' beliefs evolve over time depending on their adoption patterns. There is a continuum of risk-neutral agents that at every period chooses whether to adopt Bitcoin. Agents have heterogeneous adoption costs, and are symmetrically uncertain about the Bitcoin technology *quality*, which can be either good or bad. It is common knowledge that a good technology always survives, but a bad one can break down with a positive chance.[4] Thus, the *survival* of Bitcoin provides a noisy signal of its quality. Next, to capture the interplay between agents' adoption and learning, we assume that a bad technology is more likely to fail when more people adopt it. This allows us to capture market experimentation in reduced-form. Starting from a common prior *belief* that the technology is good, agents update their beliefs by observing the survival of Bitcoin. Survival fuels adoption, which in turn speeds up individuals' learning.[5] Thus, adoption and survival rates reinforce one another and

[2] Both cumulative distributions are significantly different. Differences are deemed statistically significant if the p-value from the Epps-Singleton two-sample test falls below the threshold of 0.05, i.e., a 95% significance level.

[3] The conditional mean of the survival rate is greater for adopters (70%) than for non-adopters (43%).

[4] In other words, we consider an experimentation model with a two-armed bandit whose risky arm yields failures according to a Poisson process (Keller and Rady, 2015). Its arrival rate is unknown to the agents.

[5] The speed of learning is endogenous, as in the experimentation literature in small markets (Bolton and Harris, 1999; Keller et al., 2005) and in large ones (Bergemann and Välimäki, 1997; Frick and Ishii, 2016).

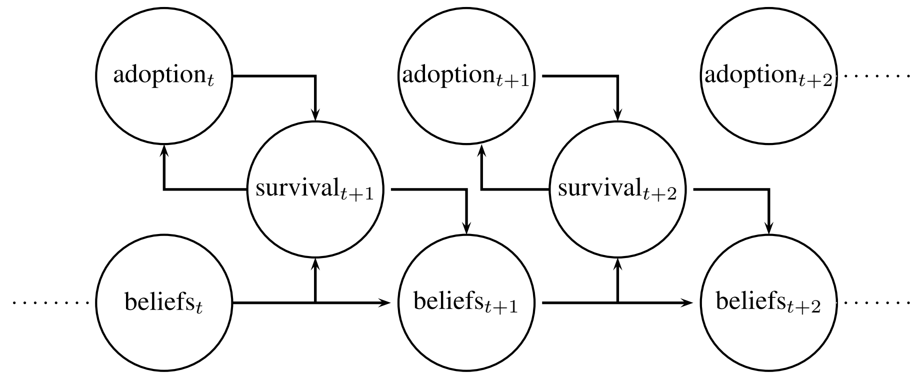

Figure 2: **The Dynamics of Adoption, Beliefs, and Survival.** Starting from a common prior belief in period t that the technology is good, current adoption and beliefs affect the survival of Bitcoin, which in turn affect the individual decision to adopt Bitcoin. The survival rate and current beliefs then influence beliefs in the next period, and so on.

are jointly determined. Figure 2 depicts the dynamics of adoption, beliefs, and survival.

The model predicts sensible relationships between the adoption rate and beliefs. First, the adoption rate and beliefs are S-shaped over time.[6] Next, low adoption costs are associated with high beliefs and adoption at any period. Finally, learning saturates earlier than adoption, meaning that agents' learning reaches an advanced phase earlier than the level of adoption does.

We use the BTCOS to test the model predictions. The data allow us to observe (i) adoption in 2016 and 2017; (ii) survival beliefs from 2017 to 2032 (15-year survival) and; (iii) *expected* adoption in 2032. We exploit the structure of the model to construct the adoption and belief paths. This allows us to have a measure of "past, present, and future" adoption and beliefs. Because many testable implications of the model rely on the S-shape curvature of the adoption and belief paths, we test for convexity and concavity, and thereby shed light on the adoption and learning phases for the Canadian population. We find that, for most Canadians, learning is in an advanced phase, where the speed of learning is decreasing, or the belief path is a concave function of time. However, Bitcoin experimentation is not globally advanced. Indeed, for older people, Bitcoin experimentation is mainly in an initial phase, where the speed of adoption is increasing, or the adoption path is a convex function of time. The reverse holds for young people. This finding suggests that young people reach the saturation phase earlier than old ones. In addition, we also find that young people are associated with more adoption and with more optimistic beliefs about Bitcoin, which indicates that young people face lower adoption costs. Thus, our analysis suggests that lowering barriers to adopt may trigger adoption and learning disproportionately, given the

[6]The S-shaped adoption curve is a well-documented finding in the diffusion literature (Mansfield, 1968; Gort and Klepper, 1982; Rogers, 2010). Some theories suggest that gradual adoption is purely driven by heterogenous preferences in the population, i.e., that some are naturally early or late adopters (David, 1969). However, other theories suggest that adoption is driven by a process of contagion, social influence, and social learning; see Young (2009) and references therein.

mutual reinforcement of these two processes.

We set up the model in §2, and discuss the data and methodology in §3. We test the model implications in §4. Finally, we conclude in §5. Omitted proofs are available in the Appendix.

2 A Model Bitcoin Adoption and Learning

The goal of this section is to develop a tractable model that allows us to interpret the data. Time is discrete and infinite $t = 1, 2, \ldots, \infty$. There is a unit-mass continuum of risk-neutral *potential adopters* with the same demographic *type*. Since identical agents may choose to experiment or not with Bitcoin, depending on some unobserved characteristic, we assume that agents have heterogeneous *adoption costs* $c \in [0, \bar{c}]$ which, for simplicity, are uniformly distributed with $\bar{c} > 1$. Thus, within a demographic type, the *average adoption cost* is $\bar{c}/2 > 0$. Now, to compare adoption rates between demographic types, we assume that each type is characterized by its average adoption cost. Naturally, adoption costs *rise* if $\bar{c}$ rises.

Because Bitcoin is not backed by a central authority, adopting or using Bitcoin is, fundamentally, risky. We assume that there is an event in which this payment technology does not survive from one period to the next one. Intuitively, Bitcoin survival may depend on a number of variables, such as reliability, convenience, security, congestion management, etc. These attributes are hard to assess without experimentation by the market. For simplicity, we assume that all these attributes can be summarized into an unknown binary Bitcoin *quality* variable that can be either *good* or *bad*.

The chance that Bitcoin survives depends on its unknown quality and its adoption rate. In particular, we assume, for simplicity, that a good technology always succeeds, but a bad one is more likely to fail when more people adopt it. Specifically, if the adoption rate in period t is A_t and the technology is bad, then the *failure chance* in period t is $\Phi(A_t) \equiv \varphi + \phi A_t$, where $\varphi, \phi > 0$ and $\varphi + \phi < 1$.[7] Thus, detecting the unknown Bitcoin quality is more likely if more people adopt it, as the chance of failure increases in adoption. This allows us to capture (in reduced-form) market experimentation (see, e.g., Bergemann and Välimäki, 1997). For some intuition, think of security breaches and congestion management — two issues that are prevalent in Bitcoin (Gandal et al., 2018). In the first case, hackers may target their attacks to the Bitcoin network depending on how many people use Bitcoin; these attacks are more successful when the technology is bad.[8] In the second one, we could imagine that network congestion is also more likely to lead to a system

[7]Because $\varphi > 0$, agents can still learn from exogenous sources even if there is no adoption, as in Frick and Ishii (2016). They consider a model with a continuum of homogeneous agents, in which each agent faces a stopping problem: when to adopt. They focus on understanding how the nature of learning — namely, whether it is via "good" or "bad" news — affects adoption patterns.

[8]Budish (2018) discusses potential collapse scenarios that Bitcoin may face in the future.

failure when the technology is not good.[9]

At the initial period, agents hold a prior belief probability $\bar{\xi}_1 \in (0,1)$ that the quality of Bitcoin is good, and thus that it will survive into the next period. At later periods, agents use all *available information up to time* t, denoted by $\mathcal{F}_t$, to update their beliefs using Bayes' Rule. There are two possible histories. In one, Bitcoin fails and agents perfectly learn that its quality is bad. In the other, Bitcoin survives and agents remain uncertain about its quality. Let us call ξ_{t+1} the *no-failure posterior* probability that Bitcoin is good. Then, by Bayes' rule:

$$\xi_{t+1} = \frac{\xi_t}{\xi_t + (1-\xi_t)(1-\Phi(A_t))}. \tag{1}$$

The denominator in (1) is the Bitcoin *survival chance between periods* t *and* $t+1$, and is denoted by $\sigma_{t\to t+1}$. The actual survival chance of Bitcoin depends fundamentally on its quality. Yet, because this quality is unobservable, agents *believe* that with probability $\sigma_{t\to t+1}$ Bitcoin survives an extra period. Thus, different agents may hold different beliefs about the survival of Bitcoin.

As Figure 2 shows, posterior beliefs ξ_{t+1} are fixed by adoption A_t and beliefs ξ_t today. Also, notice that higher beliefs ξ_t translate into higher no-failure posterior beliefs: $\partial\xi_{t+1}/\partial\xi_t > 0$. Likewise, more current adoption raises posterior beliefs: $\partial\xi_{t+1}/\partial A_t > 0$. For if more people adopt in period t and Bitcoin survives, then it is more likely that the technology is good. Finally, observe that agents are more optimistic about Bitcoin as time goes, given no failures — namely, $\xi_{t+1} > \xi_t$.

Next, we iteratively apply Bayes rule to express beliefs in future periods as a function of current beliefs and the observed adoption path. This will be useful to link the theory and data in §3. Take any period t, a positive integer $\Delta \geq 1$, and an adoption path $(A_{t+j})_{j=0}^{\Delta-1}$. One can show that posterior $\xi_{t+\Delta}$ obeys:

$$\xi_{t+\Delta} = \frac{\xi_t}{\xi_t + (1-\xi_t)\prod_{j=0}^{\Delta-1}(1-\Phi(A_{t+j}))}. \tag{2}$$

As before, the denominator in (2) is the survival chance between periods t and $t+\Delta$, i.e., $\sigma_{t\to t+\Delta}$.

In each period, agents choose whether to adopt Bitcoin. Adoption is desirable only if the Bitcoin system survives into the next period (e.g., think that a transaction with Bitcoin takes one period to be completed). Given beliefs ξ_t and a (conjectured) adoption rate A_t, agents with per-period costs c adopt iff the per-period benefits, which are normalized to one, are greater than the costs, namely,

$$\xi_t + (1-\xi_t)(1-\Phi(A_t)) - c \geq 0. \tag{3}$$

That is, *agents adopt Bitcoin when the survival rate is high enough, or their adoption costs are*

[9] See Huberman et al. (2017) for a model of Bitcoin congestion and queues, and Chiu and Koeppl (2017) for the trade-offs between individual and market transactions and their effects on delay.

low enough.[10] Let us call $a^*(\xi_t, A_t, c) \in \{0, 1\}$ the optimal individual adoption function when beliefs are ξ_t, adoption is A_t, and costs are c, with the interpretation that $a^*(\xi_t, A_t, c) = 1$ means "adopt" Bitcoin. As depicted in Figure 2, the survival rate of Bitcoin reinforces adoption, and thus beliefs and adoption must be jointly determined in equilibrium.

In equilibrium, the adoption rate in any period t must be consistent with the agents' conjecture, i.e.:

$$A_t^* = \int_0^{\bar{c}} [a_t^*(\xi_t, A_t^*, c)/\bar{c}] dc = [\xi_t + (1 - \xi_t)(1 - \Phi(A_t^*))]/\bar{c}. \tag{4}$$

Solving for A_t^* yields an adoption function $\mathcal{A} : [0, 1] \mapsto \mathbb{R}$, which is given by:

$$\mathcal{A}(\xi) \equiv \frac{\xi + (1 - \xi)(1 - \varphi)}{\bar{c} + (1 - \xi)\phi}. \tag{5}$$

Appendix A.1 shows that, as agents become more optimistic, adoption rises at increasing rates — namely, the adoption function is strictly increasing and strictly convex, $\mathcal{A}' > 0, \mathcal{A}'' > 0$.

An *equilibrium* is a sequence $(a_t^*, \xi_t, A_t^*)_{t=1}^{\infty}$ solving (1), (3), and (4), with $\xi_1 = \bar{\xi}_1$. As illustrated in Figure 2, conditional upon survival, only one equilibrium path exists: Given beliefs $\bar{\xi}_1$, there is only a single solution for adoption, namely, $A_1^* = \mathcal{A}(\bar{\xi}_1)$. This solution and $\bar{\xi}_1$ uniquely determine posterior beliefs ξ_2 via (1). These beliefs then determine $A_2^* = \mathcal{A}(\xi_2)$ via (4)-(5), which together with ξ_2 determine ξ_3 via (1), and so on. Altogether, *there exists a unique equilibrium path*.

We now turn to the testable implications of the model. First, we center on how current beliefs impact current adoption. The model predicts that adoption A_t^* depends positively on beliefs in that period ξ_t, because $\partial\mathcal{A}/\partial\xi > 0$ and $A_t^* = \mathcal{A}(\xi_t)$. Second, Appendix A.2 shows that, conditional upon survival, *the path of adoption is increasing and S-shaped*. Thus, the initial experimentation phase is determined by the curve's inflection point. Let us define the *speed of adoption* as the rate of change of adoption. We say that Bitcoin experimentation is in an *initial* (or, alternatively, *advanced*) phase if the speed of adoption is increasing (or, decreasing) in time. In other words, the convexity and concavity of the adoption S-curve identify initial and advanced experimentation phases, respectively. Third, along the same line, Appendix A.2 shows that *the belief path ξ_t is also S-shaped*. Thus, an analogous characterization for beliefs applies. We say that learning is in an *initial* (or, *advanced*) phase if the speed of learning is increasing (or, decreasing) in time. Fourth, Appendix A.3 shows that *learning saturates earlier than adoption* in the sense that the inflection point of the belief curve precedes that of the adoption curve.

Finally, observe that variations in beliefs and adoption patterns are driven by variations in the average adoption cost $\bar{c}/2$. Indeed, a change in $\bar{c}$ impacts adoption, which in turn changes beliefs, and thus adoption etc. Hence, types with the same prior beliefs may hold different posterior beliefs

[10] Athey et al. (2016) explore a related model with a similar decision rule, where the speed of learning is exogenous.

provided their average costs differ. Moreover, notice from (4) that if the average adoption cost $\bar{c}$ falls, the adoption rate A_t^* and beliefs ξ_t rise in every period. This means that types with lower costs adopt more (higher A_t^*) and are more optimistic (higher ξ_t), and thus they transition to advanced phases of learning and experimentation earlier than high-cost types.

In summary, the implications of the model are the following:

Predictions. *(a) There is a positive relation between adoption A_t^* and beliefs ξ_t.*

(b) Adoption increases over time, conditional upon survival.

(c) Adoption follows an S-shaped path. In the initial phase, it is expected to increase at an accelerating rate, while it increases at a decelerating rate in the advanced phase.

(d) Beliefs also follow an S-shaped path. In the initial phase, beliefs increase at an accelerating rate, while it increases at a decelerating rate in the advanced phase.

(e) Learning saturates earlier than adoption.

(f) If the average adoption cost falls, then adoption and beliefs increase in every period.

3 Data and Methodology

Overview. We use data from the BTCOS to test the model predictions. The data consist of three waves. Waves 1 and 2 were both conducted in late 2016, resulting in a sample size of $N = 1,997$ Canadians aged 18 or older. Wave 3 of the BTCOS was conducted a year later (from December 13, 2017 to January 9, 2018), yielding a sample size $N = 2,632$.[11] In all waves, we use standard weighting and imputation methods to ensure that the results are representative of the Canadian population. Table 1 provides a summary statistics of the data.[12] Because few individuals responded to both surveys, we analyze the data as a repeated cross-section, as we explain shortly.

[11] Wave 3 of the BTCOS was sampled in a similar way to waves 1 and 2, using an online omnibus survey. In wave 3, 115 people had also responded to a previous wave. Of these 115 people, 33 also responded in wave 1, and 82 in wave 2. The majority of responses (82%) were collected on December 13, 2017.

[12] See Henry et al. (2018, 2019) for more information and description of these data sets.

Table 1: **Summary Statistics**

	Age					High	High
	Mean	Median	Female	Employment	Awareness	Propensity	Knowledge
Wave 1	47.6	48	51.3%	55.0%	62.0%	22.4%	1.4%
Wave 2	48.0	49	51.6%	55.3%	65.7%	27.7%	10.9%
Wave 1 and 2	47.8	49	51.4%	55.2%	63.9%	25.2%	6.3%
Wave 3	48.0	49	51.4%	55.8%	85.8%	36.7%	19.1%

Notes: Weighted results are based on post-stratification by region, age, and gender in 2016. Table shows the percentage of each wave with the specified attribute. Employment shows the proportion of individuals who are part-time, full-time, or self employed. High propensity refers to the proportion of individuals who are identified as having a higher likelihood to adopt or use Bitcoin. Table 3 has additional information on the construction of this variable. High knowledge refers to the proportion of individuals who correctly answered three or more skill testing questions about Bitcoin. Additional information on the construction of this variable can be found in Table 4.

The data not only contains demographic information, but also information about Bitcoin knowledge and adoption propensity. *Propensity to adopt* is a variable indicating whether an individual has high or low bias to adopting Bitcoin. We construct this indicator as follows. The BTCOS asks, "What is your primary reason for owning or not owning Bitcoin?" Individuals who note that their reason for adopting is a unique feature of Bitcoin (e.g., "the ability to make anonymous payments") are categorized as having a high propensity to adopt. Likewise, those who identify a key feature of Bitcoin as being their reason for choosing not to adopt (e.g., "I am concerned about lack of oversight from regulatory bodies") are categorized as having a low propensity, see Table 2.

Table 2: **Propensity to Adopt**

Main reason for not owning Bitcoin		Wave 1/2	Wave 3
I do not understand/know enough about the technology	H	337	671
It is not widely accepted as a method of payment	H	91	119
The value of Bitcoin varies too much	H	39	110
I use alternative digital currencies (e.g., Ethereum, etc)	H	4	5
My current payment methods meet all my needs	L	395	473
I do not trust a private currency that is not backed by the central government	L	150	213
I do not believe the Bitcoin system will survive in the future	L	-	157
It is not easy to acquire/use	L	69	112
I am concerned about cyber theft	L	58	86
I am concerned about lack of oversight from regulatory bodies	L	47	78
Other	-	24	84
Main reason for owning Bitcoin			
I am interested in new technologies	H	17	16
It uses secure blockchain technology to prevent loss and fruad	H	6	3
It is a cost saving technology	H	-	6
It allows me to make payments anonymously	H	4	5
I do not trust the goverment or the Canadian dollar	H	2	3
I do not trust banks	H	2	2
It is an investment	L	6	61
My friends own Bitcoin	L	-	17
I use it to buy goods and services on the internet	L	4	9
I use it to buy goods and services in physical stores	L	8	3
I use it to make remittances or other international payments	L	6	1
Other	-	3	3

Notes: H denotes high propensity; L denotes low propensity. A dash denotes that the choice was not provided in waves 1 and 2 of the BTCOS. Propensity to adopt Bitcoin is identified based on a respondent's viewpoint of unique attributes of Bitcoin. For example, within respondents who have adopted Bitcoin, high propensity individuals view unique attributes of Bitcoin as the primary reason for adoption, while low propensity individuals selected non-unique Bitcoin features as the primary reason for adoption. Within non-adopters, low propensity individuals select specific aspects of Bitcoin as the primary negative reason. Non-adopters who cite lack of acceptance, knowledge, price variance, or ownership of other digital currencies are identified as high propensity. Individuals who select "other" and provide a written response are sorted into these categories based on these guidelines.

We also categorize individuals according to their Bitcoin literacy. Waves 2 and 3 include five true or false questions. We construct a *knowledge score* variable to measure performance on this question. For individuals in waves 2 and 3, we assign *pass* if they got at least 3 questions correct, and *fail* otherwise; see Table 3 for further information.[13]

Table 3: **Knowledge Score**

		Wave 1	Wave 2	Wave 3
1.	Bitcoin allows for direct transactions between two parties, without a third party involved. (True)	–	53	51
2.	The total supply of Bitcoin is fixed. (True)	–	15	21
3.	All Bitcoin transactions are recorded on a distributed ledger that is publicly accessible. (True)	–	17	19
4.	Bitcoin is backed by the government. (False)	–	50	59
5.	Bitcoin transactions take place instantaneously. (False)	–	5	–
6.	The security (i.e., immutability) of the Bitcoin system relies solely on cryptography. (False)	–	–	4
	Mean score	0.89	0.92	1.33
	Median	0.91	0	1

Notes: This table provides the proportion of individuals who correctly answered each of the true or false knowledge questions. The correct answer for each is given in brackets. People who are not aware of Bitcoin are assumed to have a knowledge score of 0. The wording of question 4 changed from wave 2 to wave 3 of the survey; wave 2 wording was as follows: "Bitcoin is similar to other national currencies, such as the euro or peso, that are backed by the government." Wave 1 of the survey did not include knowledge questions. Responses are imputed using respondent results from wave 2. The imputation procedure allows for non-integer numbers.

Finally, to analyze the data as a pseudo-panel, we generate cohorts, or "types," based on this information. We use binary variables to identify type membership, ensuring to have at least 10 observations for each type. To prevent cohorts with small sample sizes, we exclude employment as a type dimension for individuals with high knowledge scores. The first column of Table 4 provides an overview of the types that we consider in our analysis.

Adoption. We observe the adoption choices of individuals in every wave, and identify period 1 with waves 1 and 2 (2016 respondents), and period 2 with wave 3 (2017-18 respondents). The BTCOS asks, "Do you currently have or own any Bitcoin?" Respondents can answer "Yes" or "No." This question allow us to construct the adoption rates A_t^* in periods one and two for each demographic type.[14] Due to the repeated cross sectional nature of the data, we are unable to match

[13] As noted in Henry et al. (2018), true or false knowledge questions were not included in wave 1 of the BTCOS. The pass or fail rate of wave 1 respondents was imputed based on the knowledge score of wave 2 respondents. Mean value imputation was conducted, matching wave 1 and wave 2 respondents on age, gender, income, employment and ownership characteristics. Individuals who are not aware of Bitcoin are assumed to "fail" the knowledge questions.

[14] This question was answered only by those who responded "Yes" to "Have you heard of Bitcoin?" We assume that individuals who have not heard of Bitcoin do not own Bitcoin.

an individual's adoption in period 1 to their adoption in period 2, and vice-versa. Thus, as detailed earlier, we generate a pseudo-panel by aggregating respondents into types. We then consider a nonparametric approach and examine the evolution of the average mean across time periods for each type, assuming that the dimensions used to generate types correctly describe adoption in period 1 of individuals sampled in period 2.

Many testable implications of the model rely on the curvature of the adoption and belief paths, which require observations for at least three time periods. As explained earlier, from the data we observe adoption in periods 1 and 2. We construct an approximation of *future adoption* and *beliefs* using novel information from the BTCOS, wave 3.

To this end, we exploit two key questions from the survey. The first question extracts information about individuals' medium- to long-run beliefs about the survival of Bitcoin. Respondents are asked: "How likely do you think it is that the Bitcoin system will fail or survive in the next 15 years?" Using a sliding scale, respondents choose from [0,100], with 0 representing "certain fail" and 100 "certain survival." From our previous analysis in §2, the answer to this question is precisely the expected survival chance between periods two and seventeen (i.e., 15 years from period 2), namely, $\mathbb{E}[\sigma_{2\to17}|\mathcal{F}_2]$, where $\mathcal{F}_2$ is all the information available to agents in period 2. Similarly, the second question asked: "What percentage of Canadians do you predict will be using Bitcoin 15 years from now?" Individuals use a sliding scale where 0 means "no Canadians will be using Bitcoin" and 100 means "all Canadians will be using Bitcoin".[15] We assume the answer to this question corresponds to the expected adoption rate in period 17 conditional on survival, i.e., $\mathbb{E}[A^*_{17}|\text{survival}, \mathcal{F}_t]$. Since there is no adoption if Bitcoin fails, it follows that,

$$\hat{A}^*_{17} \equiv \mathbb{E}[A^*_{17}|\mathcal{F}_2] = \mathbb{E}[A^*_{17}|\text{survival}, \mathcal{F}_2] \cdot \mathbb{E}[\sigma_{2\to17}|\mathcal{F}_2]. \tag{6}$$

These approximations allow us to approximate *future adoption* $\hat{A}^*_{17}$ using current information.

Beliefs. We construct past, present, and future beliefs ξ_t. This step is more involved. In what follows, we set $\varphi = 0.2$ and $\phi = 0.3$, so that the conditional failure chance (when the technology is of bad quality) equals $\Phi(A_t) = 0.5$ whenever there is full adoption ($A_t = 1$).

As previously discussed, we observe in the data $\mathbb{E}[\sigma_{2\to17}|\mathcal{F}_2]$, which, by (2), is equal to:

$$\xi_2 + (1-\xi_2)\mathbb{E}\left[\prod_{j=0}^{14}(1-\Phi(A^*_{2+j})) \,\middle|\, \mathcal{F}_2\right].$$

We need an approximation for the above bracketed term. To this end, first notice that the belief process is martingale, i.e., $\mathbb{E}[\xi_{t+1}|\mathcal{F}_t] = \xi_t$. Next, because the adoption function $\mathcal{A}(\xi_t)$ is convex in ξ_t and the equilibrium adoption obeys $A^*_t = \mathcal{A}(\xi_t)$, the adoption process is a submartingale

[15] The average response of this question is 33% and above current adoption in Canada (5.8%).

$\mathbb{E}[A^*_{t+1}|\mathcal{F}_t] \geq A^*_t$, by Jensen's inequality; see Theorem 5.2.3 in Durrett (2010). In words, adoption stochastically increases over time. Using this observation and a generalized version of Holder's inequality (Cheung, 2001), Lemma A.1 shows that *there exists an affine function* $\Gamma(\cdot)$ *such that*:

$$\mathbb{E}\left[\prod_{j=0}^{14}(1-\Phi(A^*_{2+j}))\;\Big|\;\mathcal{F}_2\right] \leq \prod_{j=0}^{14}\Gamma(A^*_2)^{\frac{1}{15}}. \tag{7}$$

Bound (7) allows us to approximate the conditional survival rate of Bitcoin between periods two and seventeen, which in turn allows us to approximate beliefs at period 2. Specifically, we let beliefs ξ_2 solve $\mathbb{E}[\sigma_{2\to 15}|\mathcal{F}_2] = \xi_2 + (1-\xi_2)\prod_{j=0}^{14}\Gamma(A^*_2)^{\frac{1}{15}}$, and thus:

$$\xi_2 = \frac{\mathbb{E}[\sigma_{2\to 15}|\mathcal{F}_2] - \prod_{j=0}^{14}\Gamma(A^*_2)^{\frac{1}{15}}}{1-\prod_{j=0}^{14}\Gamma(A^*_2)^{\frac{1}{15}}}. \tag{8}$$

Notice that this method *underestimate* the actual beliefs agents hold in period 2. Nevertheless, Appendix A.5 shows that if the approximated belief path is concave, then the actual belief path must be concave too. That is, when learning is advanced for the approximated path, then it is also advanced for actual belief path. Thus, working with approximated beliefs does not affect our results qualitatively, provided learning is at an advanced stage, which is what we empirically found.

Next, we recover beliefs in period one ξ_1 using adoption in period one and formula (1) inversely:

$$\xi_1 = \frac{\xi_2(1-\Phi(A_1))}{1-\xi_2\Phi(A_1)}. \tag{9}$$

Finally, we approximate future beliefs in period 17. For this, we use again the fact that beliefs are stochastically constant over time, i.e, $\mathbb{E}[\xi_{t+1}|\mathcal{F}_t] = \xi_t$. Thus, from Bayes' rule (1), we can derive beliefs in the next period ξ_3 using current beliefs ξ_2 and adoption A_2. So assuming Bitcoin will survive one more period (i.e, over 2018), we have an estimate $\hat{\xi}_{17} \equiv \mathbb{E}[\xi_{17}|\mathcal{F}_3] = \xi_3$, where:

$$\xi_3 = \frac{\xi_2}{\xi_2 + (1-\xi_2)(1-\Phi(A_2))}. \tag{10}$$

All told, the data allow us to construct beliefs $(\xi_1, \xi_2, \hat{\xi}_{17})$ and adoption rates $(A^*_1, A^*_2, \hat{A}^*_{17})$. We use this constructed data to examine the stage of adoption and learning in the population. It is important to observe that we are not imposing a positive relationship between A_t and ξ_t in the construction of these variables.[16]

[16] Indeed, from equation (9), one may think that — holding beliefs ξ_2 constant — adoption A_1 and beliefs ξ_1 should be negatively related. This reasoning is misleading, since adoption A_1 is correlated with beliefs ξ_2 by Bayes' rule (1).

Table 4: **Types, Adoption, Beliefs, and Convexity Tests**

	Wave 1 and 2		Wave 3						Convexity test	
Type	N	A_1^*	N	A_2^*	$\hat{A}_{17}^*$	ξ_1	ξ_2	$\hat{\xi}_{17}$	A	ξ
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
YMULF	53	0.00	61	0.04	0.13	0.31	0.36	0.42	-0.03	-0.04
YMUHF	33	0.00	41	0.04	0.24	0.49	0.54	0.60	-0.02	-0.05
YMELF	261	0.05	170	0.12	0.19	0.40	0.46	0.52	-0.06	-0.05
YMEHF	86	0.03	125	0.07	0.24	0.48	0.54	0.60	-0.03	-0.05
YMLP	23	0.30	139	0.35	0.28	0.45	0.53	0.62	[-0.05]	-0.07
YMHP	23	0.54	64	0.18	0.28	0.47	0.58	0.65	[0.34]	-0.10
YFULF	124	0.02	119	0.03	0.18	0.37	0.43	0.49	-0.01	-0.05
YFUHF	38	0.08	75	0.00	0.23	0.46	0.53	0.58	0.09	-0.06
YFELF	247	0.01	234	0.02	0.19	0.40	0.45	0.51	0.00	-0.05
YFEHF	91	0.06	214	0.03	0.22	0.43	0.49	0.55	[0.04]	-0.05
YFLP	18	0.11	54	0.19	0.26	0.45	0.52	0.59	-0.07	-0.06
YFHP	13	0.21	42	0.08	0.30	0.53	0.61	0.67	[0.14]	-0.07
OMULF	195	0.01	194	0.00	0.09	0.29	0.34	0.39	[0.01]	-0.04
OMUHF	54	0.03	93	0.00	0.14	0.38	0.43	0.49	[0.04]	-0.05
OMELF	146	0.00	139	0.01	0.11	0.31	0.36	0.41	0.00	-0.04
OMEHF	41	0.00	66	0.00	0.16	0.37	0.42	0.48	0.01	-0.05
OMLP	19	0.06	85	0.08	0.14	0.36	0.42	0.48	-0.01	-0.05
OFULF	233	0.00	245	0.00	0.13	0.32	0.37	0.43	0.01	-0.04
OFUHF	60	0.00	106	0.00	0.20	0.41	0.47	0.52	0.01	-0.05
OFELF	165	0.00	159	0.03	0.16	0.37	0.42	0.48	-0.02	-0.05
OFEHF	51	0.00	101	0.00	0.17	0.37	0.42	0.48	0.01	-0.05
OFLP	11	0.00	43	0.03	0.13	0.35	0.40	0.46	-0.03	-0.05
OHP	12	0.06	63	0.02	0.20	0.46	0.52	0.58	[0.05]	-0.05
Overall	**1,970**	**0.029**	**2,545**	**0.054**	**0.184**	**0.394**	**0.451**	**0.512**	**−0.015**	**−0.050**
S.E.									(−0.016, −0.013)	(−0.051, −0.049)

Notes: Weighted results are based on post-stratification by region, age, and gender in 2016. Type represents the different cohorts generated. The characteristics of the cohort can be identified by the five letter code, as follows: Y represents respondents who are less than 48 years old, O otherwise; M represents male, F otherwise; E represents employed, U otherwise; H represents high propensity to adopt Bitcoin, L otherwise; and P represents correctly answered at least three out of five knowledge questions, F otherwise. Additional information on the construction of the propensity to adopt and the knowledge variable can be found in Tables 3 and 4, respectively. Columns denoting the adoption rate (A_t^*) show the proportion of each cohort that adopts Bitcoin in period t, and also the approximated future adoption rate for each cohort, $\hat{A}_{17}^*$. ξ_t represents the mean beliefs held by each type for period t. The convexity test shows whether the paths of adoption (A) or beliefs (ξ) are concave (negative test) or convex (positive test). Parenthesized terms in column (9) represents cohorts for whom adoption is non-monotone, invalidating the convexity test.

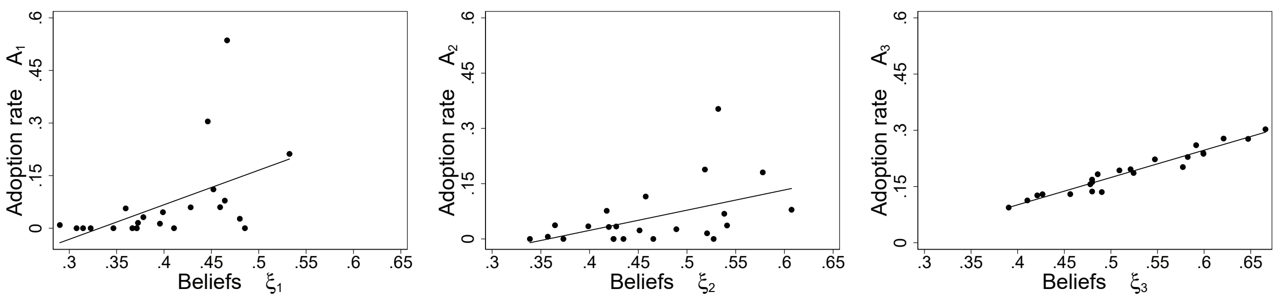

Figure 3: **Adoption and Beliefs.** For all time periods considered (past, present, and future), adoption and beliefs about Bitcoin technology are positively related. Since beliefs ξ_t increase over time, the realizations of ξ_t are high when t is high. The correlation is 0.50 between A_1^* and ξ_1, 0.48 between A_2^* and ξ_2, and 0.97 between $\hat{A}_{17}$ and $\hat{\xi}_{17}$. The latter correlation is high by construction, see our discussion in §4-A.

4 Testing the Model Predictions

A. Adoption and Beliefs. The model predicts that agents adopt more when the survival rate of Bitcoin rises. Since the Bitcoin survival rate rises as beliefs that the technology is good rises, we should observe that adoption A_t^* positively relates to beliefs ξ_t in any time period t. As seen in Figure 3, adoption and beliefs are positively correlated. The right panel of Figure 3 shows a very close relationship between future adoption and future beliefs. This is indeed owed to the construction of the variables. For to construct $\hat{A}_{17}^*$ and $\hat{\xi}_{17}$ we use the expected survival rate and beliefs ξ_2, respectively (see equations (6) and (10)). But, as seen in equation (9), we use the expected survival rate to construct ξ_2. This explains why $\hat{A}_{17}^*$ and $\hat{\xi}_{17}$ are almost perfectly correlated. Hence, we use only the left and middle panels of Figure 3 to validate the model.

B-C. Adoption and the Speed of Adoption. The model also predicts that adoption should be increasing over time. The reason is that a longer survival of Bitcoin provides a stronger signal that its quality is good, reinforcing adoption and therefore future beliefs. From Table 4 we see that, at the aggregate level, *adoption increases over time*. Adoption is $A_1^* = 2.9\%$ in period 1 (year 2016), is $A_2^* = 5.4\%$ in period 2 (year 2017), and is expected to be $\hat{A}_{17}^* = 18.4\%$ in period 17 (year 2032). On average, individuals forecast more Bitcoin adoption for the next 15 years. Also, as seen in Figure 4, at the type level, the adoption path is increasing for 15 out of 23 demographic types. Thus, the data appears to be consistent with the model in the majority of the cases.

Next, to verify whether the speed of adoption is currently increasing, we drop demographic types for which adoption is not increasing in time (8 out of 23). We consider the following *convexity test*. This test consists in taking the weight $\zeta = 15/16$ so that the second period can be written as a convex combination between periods 1 and 17, namely, $2 = \zeta + (1 - \zeta)17$. Then, we explore whether the convex combination of adoption rates between the first and last periods is greater or less than the adoption rate in the second period. Because a convex function always lie below the

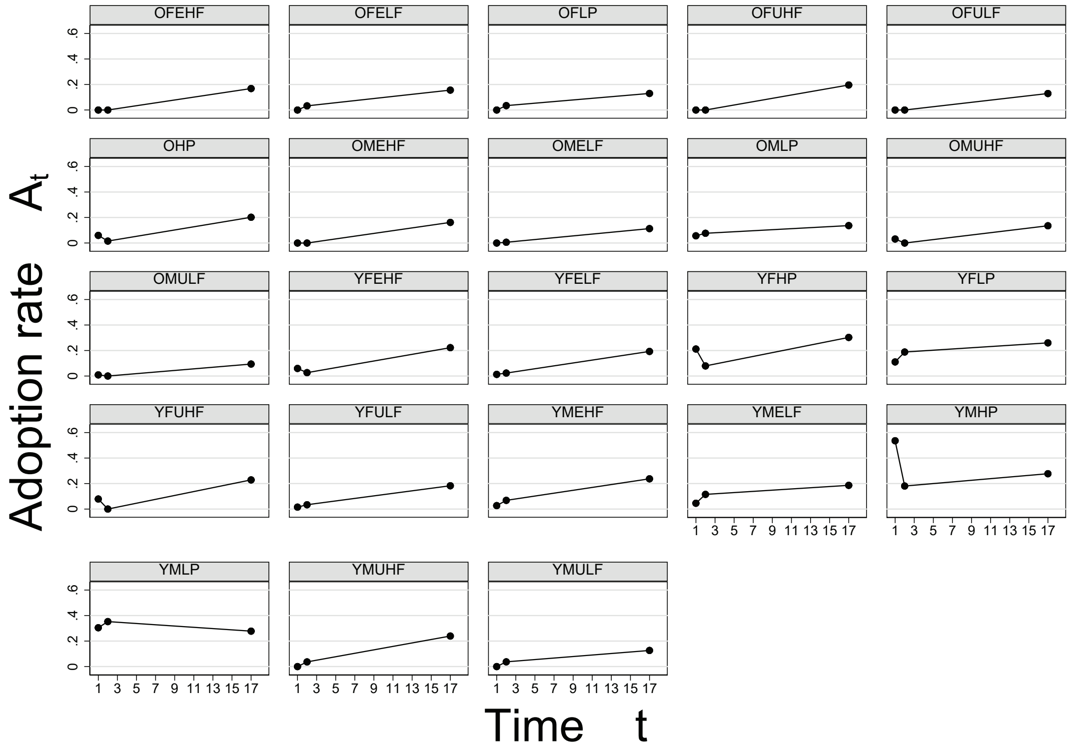

Figure 4: **The Adoption Path.** For most types, adoption rises in time. Within those types for which adoption is monotone, the speed of adoption is currently increasing (at $t = 2$) for some types, but is decreasing for others.

line segment between any two points, the speed of adoption is increasing in period 2 if and only if the difference $\zeta A_1^* + (1-\zeta)\hat{A}_{17}^* - A_2^* \geq 0$. Finally, as previously argued, since the model predicts that adoption is initially and eventually convex and concave in time (S-shaped path), respectively, the convexity test allows us to uncover how early or advanced Bitcoin experimentation is.

Column (9) of Table 4 shows the result of this convexity test. We observe that, for 6 out of 15 types, the speed of adoption is increasing (the difference is positive). However, for 9 out 15, the speed of adoption is decreasing (the difference is negative). Further exploration of Table 4 reveals that the speed of adoption is increasing and decreasing mainly for old and young adults, respectively. This is consistent with commonly held view that young people are usually more inclined to experiment with new technologies than older ones, and thus young people reach the saturation phase earlier. Altogether, *Bitcoin experimentation is not globally in its advanced phase*, even though more than 10 years have elapsed since its market introduction.

D. The Speed of Learning. Because of Bayes' rule (1) and since adoption reinforces learning, the path of beliefs ξ_t is increasing in time, as seen in Figure 5. According to Table 4, at the aggregate level, current beliefs ξ_2 are around 0.45. That is, individuals put slightly more weight on the event that Bitcoin is a bad technology and that it will eventually collapse. But, should we

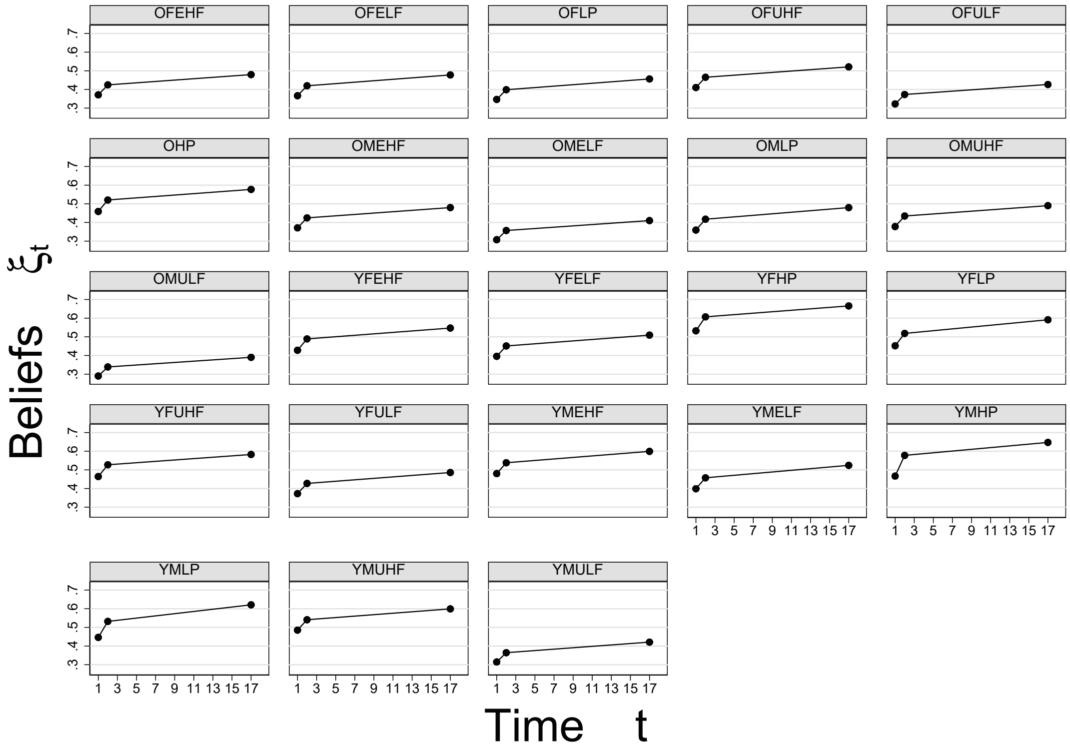

Figure 5: **The Belief Path.** For all types, the speed of learning is currently decreasing (at $t = 2$) (concave portion of the belief S-curve).

expect these beliefs to rapidly improve over time? Also, is individuals' learning "saturated"?

For this goal, we use our estimates of beliefs and adapt our previously used convexity test. Because the belief path is S-shaped, this exercise would shed light on whether the speed of learning is increasing or decreasing, and thereby how advanced learning is in the population. As before, consider the weight $\zeta = 15/16$. The speed of learning is currently decreasing if and only if the difference $\zeta\xi_1^* + (1-\zeta)\hat{\xi}_{17}^* - \xi_2^* \leq 0$. As argued in §A.5, if the speed of learning is decreasing for the approximated path $(\xi_1^*, \xi_2^*, \hat{\xi}_{17}^*)$, then it is also decreasing for the actual unobserved path.

Column (10) of Table 4 shows that for all types the convexity test is negative — namely, *Bitcoin learning is globally advanced*. This means that, conditional on the survival of Bitcoin, individual beliefs about the quality of Bitcoin should have small variations over time. Comparing this finding with that of adoption, see that the inflection point of beliefs unambiguously precedes that of adoption for those demographic types for which the speed of adoption is increasing, and so for those types we should expect greater increases in adoption relative to beliefs in the short-run.

Table 5: **The Effects of Adoption Costs**

Type	A_1^*	A_2^*	$\hat{A}_{17}^*$	ξ_1	ξ_2	$\hat{\xi}_{17}$
YFELF	0.01	0.02	0.2	0.4	0.45	0.51
OFELH	0	0.03	0.16	0.37	0.42	0.48
Difference	*0.01*	*-0.01*	*0.04*	*0.03*	*0.03*	*0.03*
S.E.	*(0.00,0.03)*	*(-0.06,0.05)*	*(-0.03,0.10)*	*(-0.06,0.11)*	*(-0.06,0.12)*	*(-0.06,0.13)*
YFULF	0.02	0.03	0.18	0.37	0.43	0.49
OFULF	0	0	0.13	0.33	0.38	0.43
Difference	*0.02*	*0.03*	*0.05*	*0.04*	*0.05*	*0.06*
S.E.	*(0.00,0.04)*	*(0.00,0.07)*	*(-0.01,0.12)*	*(-0.04,0.14)*	*(-0.04,0.15)*	*(-0.04,0.16)*
YMEHF	0.03	0.07	0.24	0.48	0.54	0.6
OMEHF	0	0	0.15	0.36	0.42	0.47
Difference	*0.03*	*0.07*	*0.09*	*0.12*	*0.12*	*0.13*
S.E.	*(0.00,0.05)*	*(0.02,0.12)*	*(0.00,0.15)*	*(0.01,0.21)*	*(0.01,0.22)*	*(0.01,0.23)*
YMELF	0.04	0.12	0.19	0.4	0.46	0.52
OMELF	0	0.01	0.11	0.31	0.36	0.41
Difference	*0.04*	*0.11*	*0.08*	*0.09*	*0.1*	*0.11*
S.E.	*(0.02,0.08)*	*(0.04,0.17)*	*(0.01,0.14)*	*(0.01,0.18)*	*(0.01,0.19)*	*(0.01,0.22)*
YMULF	0	0.04	0.12	0.31	0.36	0.41
OMULF	0.01	0	0.1	0.29	0.34	0.39
Difference	*-0.01*	*0.04*	*0.02*	*0.02*	*0.02*	*0.02*
S.E.	*(-0.03,0.00)*	*(0.00,0.11)*	*(-0.03,0.10)*	*(-0.07,0.12)*	*(-0.08,0.13)*	*(-0.08,0.15)*
YFLP	0.11	0.17	0.26	0.45	0.51	0.58
OFLP	0	0.03	0.13	0.35	0.4	0.46
Difference	*0.11*	*0.14*	*0.13*	*0.1*	*0.11*	*0.12*
S.E.	*(0.00,0.26)*	*(0.00,0.29)*	*(0.03,0.24)*	*(-0.02,0.23)*	*(-0.02,0.26)*	*(-0.02,0.29)*

Note: Type represents the different cohorts generated. The characteristics of the cohort can be identified by the 5 letter code, as follows: Y represents respondents who are less than 48 years old, O otherwise; M represents male, F otherwise; E represents employed, U otherwise; H represents high propensity to adopt Bitcoin, L otherwise; P represents correctly answered at least three out of five knowledge questions, F otherwise. This table excludes all demographic types for which the adoption path is not increasing in time. It then compares the effect of age, or adoption costs, on adoption rates and beliefs in every period, fixing all other type characteristics.

E. Changing Adoption Costs. Another model prediction is that when adoption costs fall, adoption and beliefs increase in all periods. To test this prediction, we compare demographic types for which the only dimension that differs is *age*. Why age? Intuitively, older people are less inclined to innovate or learn how to use new technologies. They may find it too involved to set-up an account, learn how to use it, etc. Indeed, evidence from the Method of Payments surveys indicates that older people are on average more likely to stick to more conventional payment methods (Henry et al., 2015). This suggests that it is reasonable to conjecture that older individuals incur a higher cost of adopting a new payment method. Henceforth, we associate older individuals as incurring a higher average adoption cost. Notice that this exercise is formally equivalent to changing the average adoption cost $\bar{c}/2$, which affects the equilibrium determination via (4).

To compare adoption rates and beliefs across types, we exclude demographic types for which the adoption path is not monotone. This leaves us with five comparisons to perform, in which people are identical but differ in age only. Table 5 shows the adoption rates and beliefs for each relevant type. We notice that, for all cases but one, the data seems to be consistent with the theory — namely, *adoption and beliefs increase as age decreases*.

5 Concluding Remarks

Motivated by an empirical observation that Bitcoin adopters are more optimisitic about the survival of Bitcoin than non-adopters, this paper develops a simple model of Bitcoin/technology adoption with endogenous learning. The model delivers several testable predictions that we take to the data. We use the BTCOS survey, which contains information on Bitcoin usage and perceptions in Canada. We find pieces of evidence supporting the model. First, adoption increases as individuals become more optimistic about Bitcoin. Second, adoption rates increase over time for most demographic sectors. Third, individuals with lower adoption costs have higher adoption rates and are more optimistic about Bitcoin technology. Finally, using the data and structure of the model, we find that the speed of learning is globally decreasing in Canada; however, the speed of adoption is not. In other words, for some demographic segments (e.g., older people) the speed of adoption is increasing while that of learning is decreasing. This indicates that learning saturates earlier than adoption, which is consistent with the theoretical model.

As for future work, a structural estimation of the model parameters seems interesting, as this would allow us to reconstruct the paths of adoption and beliefs and perform counterfactual analysis.

A Appendix

A.1 The Adoption Function is Increasing and Convex

We differentiate (5) to see that:

$$\mathcal{A}'(\xi) = \frac{\bar{c}\varphi + \phi}{[\bar{c} + \phi(1-\xi)]^2} > 0 \quad \text{and} \quad \mathcal{A}''(\xi) = \frac{2\phi(\bar{c}\varphi + \phi)}{[\bar{c} + \phi(1-\xi)]^3} > 0.$$

As a result, adoption increases at increasing rates as individuals become more optimistic.

A.2 The Belief and Adoption Paths are S-shaped

I. BELIEFS. We now show that *the belief path is S-shaped*. To this end, consider two periods, namely, t and $t+dt$. Then, applying Bayes' rule (1), given A_t, yields a posterior belief:

$$\xi_{t+dt} = \frac{\xi_t}{\xi_t + (1-\xi_t)(1-\Phi(A_t)dt)} = \frac{\xi_t}{1-(1-\xi_t)\Phi(A_t)dt}.$$

Subtracting ξ_t and dividing both sides by dt we obtain:

$$\frac{\xi_{t+dt}-\xi_t}{dt} = \frac{\xi_t(1-\xi_t)\Phi(A_t)}{1-(1-\xi_t)\Phi(A_t)dt}.$$

Taking $dt \to 0$ yields the following law of motion, $\dot{\xi}_t = \xi_t(1-\xi_t)(\varphi + \phi A_t)$. Next, use that, in equilibrium, $A_t = \mathcal{A}(\xi_t)$, given (5), to get the equilibrium evolution of beliefs:

$$\dot{\xi}_t = \xi_t(1-\xi_t)(\varphi + \phi\mathcal{A}(\xi_t)) = \xi_t(1-\xi_t)\left(\frac{\bar{c}\varphi + \phi}{\bar{c} + (1-\xi_t)\phi}\right).$$

As discussed in the main text, $\dot{\xi}_t > 0$ as agents become more optimistic about the technology as time goes by, conditional on observing no failures. Now, define $h : [0,1] \mapsto \mathbb{R}$ as follows,

$$h(\xi) \equiv \xi(1-\xi)\left(\frac{\bar{c}\varphi + \phi}{\bar{c} + (1-\xi)\phi}\right).$$

By the Mean Value theorem, there exists $\hat{\xi} \in (0,1)$ such that $h'(\hat{\xi}) = 0$, because $h(0) = h(1) = 0$. Moreover, $h(\cdot)$ is strictly concave[17] and thus $\hat{\xi}$ is unique.

Finally, we argue that $\dot{\xi}_t$ is single peaked. Indeed, $\ddot{\xi}_t = h'(\xi_t)\dot{\xi}_t$, and so $\ddot{\xi}_t = 0$ if and only if $h'(\xi_t) = 0$ (as $\dot{\xi}_t > 0$). But, $h'(\cdot)$ vanishes only when beliefs $\xi_t = \hat{\xi}$. Because $\dot{\xi}_t > 0$, there exists a unique time $\hat{t} > 0$ for which $\xi_{\hat{t}} = \hat{\xi}$. That is, $\ddot{\xi}_t$ vanishes uniquely at time $t = \hat{t}$. Also, for $t \lesseqgtr \tilde{t}$, we have $\xi_t \lesseqgtr \hat{\xi}$, and so $\ddot{\xi}_t = h'(\xi_t)\dot{\xi}_t \gtreqless 0$. Altogether, $\dot{\xi}_t$ is single peaked or ξ_t is S-shaped. □

II. ADOPTION. We now show that *the adoption path is also S-shaped*. First, notice that adoption evolves according to, $\dot{A}_t = \mathcal{A}'(\xi_t)\dot{\xi}_t = \mathcal{A}'(\xi_t)h(\xi_t) \equiv g(\xi_t)$ where $g : [0,1] \mapsto \mathbb{R}$ obeys:

$$g(\xi) = \frac{(1-\xi)\xi(\phi + \bar{c}\varphi)^2}{(\bar{c} + \phi(1-\xi))^3}.$$

Following our previous logic, because $g(0) = g(1) = 0$ there exists $\tilde{\xi} \in (0,1)$ such that $g'(\tilde{\xi}) = 0$.

[17] Indeed, after some algebra, we see that $h''(\xi) = -\frac{2\bar{c}(\phi+\bar{c})(\phi+\bar{c}\varphi)}{(\bar{c}+\phi(1-\xi))^3} < 0$.

Moreover, simple algebra allows us to determine that $\tilde{\xi}$ is unique. Indeed,

$$g'(\xi) = \frac{(\phi + \bar{c}\varphi)^2 \left(c(1-2\xi) + \phi\left(1-\xi^2\right)\right)}{(\bar{c} + \phi(1-\xi))^4}.$$

Thus, $g'(\xi) = 0$ if and only if $c(1-2\xi) + \phi(1-\xi^2) = 0$. But, this equation has a unique solution on $[0,1]$. Such solution is given by $\tilde{\xi} = (-c + \sqrt{\phi^2 + \bar{c}^2 + \bar{c}\phi})/\phi$. Finally, it is straightforward to see that $g'(0) > 0 > g'(1)$, and so $g'(\xi)$ must cross the horizontal axis from above, as $\tilde{\xi}$ is unique. Altogether, we conclude that $g(\cdot)$ is hump-shaped.

We now argue that A_t is S-shaped. To this end, we show that $\dot{A}_t$ is single-peaked. First, notice that $\ddot{A}_t = g'(\xi_t)\dot{\xi}_t$. Thus, since $\dot{\xi}_t > 0$, we have that $\ddot{A}_t = 0$ if and only if $g'(\xi_t) = 0$. But $g'(\xi_t) = 0$ when $\xi_t = \tilde{\xi}$, which happens uniquely at time $t = \tilde{t} > 0$ obeying $\xi_{\tilde{t}} = \tilde{\xi}$. In other words, $\ddot{A}_t$ vanishes only once at time $t = \tilde{t}$. For time $t \lesseqgtr \tilde{t}$, we have $\xi_t \lesseqgtr \tilde{\xi}$, and so $\ddot{A}_t = g'(\xi_t)\dot{\xi}_t \gtreqless 0$. All in all, this shows that $\dot{A}_t$ is single peaked or A_t is S-shaped in time t. □

A.3 Learning Saturates Earlier than Adoption

We now show that the inflection point of the belief path $t \mapsto \xi_t$ precedes that of the adoption path $t \mapsto A_t$. To this end, we examine the adoption path. By §A.2-II, the adoption path is described by $\dot{A}_t = \mathcal{A}'(\xi_t)\dot{\xi}_t$. Differentiating both sides with respect to time t, yields:

$$\ddot{A}_t = \mathcal{A}''(\xi_t)\dot{\xi}_t^2 + \mathcal{A}'(\xi_t)\ddot{\xi}_t.$$

Now, notice that when the belief path reaches its inflection point, i.e., $\ddot{\xi}_t = 0$, adoption obeys $\ddot{A}_t = \mathcal{A}''(\xi_t)\dot{\xi}_t^2 > 0$ as $\dot{\xi}_t > 0$ and $\mathcal{A}'' > 0$ by §A.1. In other words, when learning saturates ($\ddot{\xi}_t = 0$), adoption is still in its initial phase wherein $\ddot{A}_t > 0$. □

A.4 Approximating the Survival Rate

Lemma A.1. *The conditional Bitcoin survival rate from period 2 to 17, forecasted using current available information, obeys* $\mathbb{E}\left[\prod_{j=0}^{14}(1-\Phi(A_{2+j})) \;\middle|\; \mathcal{F}_2\right] \leq \prod_{j=0}^{14}\Gamma(A_2)^{\frac{1}{15}}$*, for some affine function* Γ.

Proof: Consider positive numbers $(p_j)_{j=0}^{14}$ such that $\sum_{j=0}^{14} 1/p_j = 1$. Then, using a generalized version of Holder's Inequality (Theorem 2.1 in Cheung (2001)) we have:

$$\mathbb{E}\left[\prod_{j=0}^{14}(1-\Phi(A_{2+j})) \;\middle|\; \mathcal{F}_2\right] \leq \prod_{j=0}^{14}\mathbb{E}\left[(1-\Phi(A_{2+j}))^{p_j} \;\middle|\; \mathcal{F}_2\right]^{\frac{1}{p_j}} \tag{11}$$

Now, for each $p_j > 1$, consider the auxiliary function $\Upsilon_{p_j}(A) \equiv [1-\Phi(A)]^{p_j}$ and a linear approximation around some $\bar{A}$ so that $\Upsilon_{p_j}(A) = \Upsilon_{p_j}(\bar{A}) + \Upsilon'_{p_j}(\bar{A})(A-\bar{A})$ with $\Upsilon'_{p_j} < 0$. Thus, the right expression in (11) is equal to:

$$\begin{aligned}\prod_{j=0}^{14} \mathbb{E}\left[\Upsilon_{p_j}(A_{2+j}) \,\middle|\, \mathcal{F}_2\right]^{\frac{1}{p_j}} &= \prod_{j=0}^{14}\left[\Upsilon_{p_j}(\bar{A}) + \Upsilon'_{p_j}(\bar{A})(\mathbb{E}(A_{2+j} \mid \mathcal{F}_2) - \bar{A})\right]^{\frac{1}{p_j}} \\ &\leq \prod_{j=0}^{14}\left[\Upsilon_{p_j}(\bar{A}) + \Upsilon'_{p_j}(\bar{A})(A_2 - \bar{A})\right]^{\frac{1}{p_j}}.\end{aligned}$$

The equality follows from the fact that the expectation is a linear operator, whereas the inequality follows from the Law of Iterated Expectations and the fact that $(A_t)_t$ is a submartingale, and thus $\mathbb{E}[A_{t+j}|\mathcal{F}_t] \geq A_t$ for all $j > 0$. □

Remark. Notice that the previous bound holds for any strictly positive vector $(p_j)_j$. For the computational part, for simplicity, we take $p_j = 15$ for all j. We also take $\bar{A}$ as the adoption rate in period 2 across all demographic types, namely, $\bar{A} = 0.054$ by Table 4.

A.5 The Actual Belief Process is Currently Concave

In this section, we show that if the approximated path of beliefs is concave, then the original path of beliefs is also concave. First, for any beliefs ξ_2 and adoption rates A_1, A_2, we can compute past beliefs ξ_1 and future beliefs $\hat{\xi}_{17}$, using equations (9) and (10), respectively. By the convexity test, given $\zeta = 15/16$, the belief path $(\xi_1, \xi_2, \hat{\xi}_{17})$ is concave if and only if:

$$\zeta\xi_1 + (1-\zeta)\hat{\xi}_{17} - \xi_2 = \zeta\frac{\xi_2(1-\Phi_1)}{1-\xi_2\Phi_1} + (1-\zeta)\frac{\xi_2}{1-(1-\xi_2)\Phi_2} - \xi_2 \leq 0, \tag{12}$$

where $\Phi_1 \equiv \Phi(A_1)$ and $\Phi_2 \equiv \Phi(A_2)$. As seen in Table 4, for all demographic types, the belief path is concave, i.e., the above inequality holds when $\xi_2 = \xi_2^*$, where ξ_2^* is given by equation (8).

Now, define the actual belief path as the one induced by the unobserved beliefs, say, $\tilde{\xi}_2$. We'll show that if inequality (12) obtains for $\xi_2 = \xi_2^*$, then it also obtains for $\xi_2 = \tilde{\xi}_2$. Consider (12) and divide it by ξ_2 and multiply it by $1 - \xi_2\Phi_1 > 0$ and $1-(1-\xi_2)\Phi_2 > 0$ to get an equivalent inequality $H(\xi_2) \leq 0$, where $H : [0,1] \mapsto \mathbb{R}$ obeys

$$H(\xi_2) \equiv \zeta(1-\Phi_1)(1-(1-\xi_2)\Phi_2) + (1-\zeta)(1-\xi_2\Phi_1) - (1-(1-\xi_2)\Phi_2)(1-\xi_2\Phi_1) \leq 0.$$

Doing some algebra allows us to simplify $H(\xi_2)$ and obtain:

$$H(\xi_2) = -\zeta\Phi_1 + (1-\xi_2)(1-\zeta(1-\Phi_1)) + \xi_2\Phi_1(\zeta-(1-\xi_2)\Phi_2).$$

It is easy to see that H is a quadratic and strictly convex function, $H'' < 0$. Also, H is initially positive and decreasing, $H(0) > 0 > H'(0)$, and vanishes at $\xi = 1$, $H(1) = 0$. From the data (Table 4), we know that $H(\xi_2^*) < 0$, which implies that (by continuity of H) there exists $\underline{\xi}_2 \in (0, \xi_2^*)$ such that $H(\underline{\xi}_2) = 0$. Thus, the two roots of H where it vanishes are $\xi_2 = \underline{\xi}_2$ and $\xi_2 = 1$. Thus, $H(\xi_2) \leq 0$ for $\xi_2 \in [\underline{\xi}_2, 1]$, as H is quadratic and strictly convex.

Finally, from inequality (7), it is easy to see that the approximated beliefs ξ_2^* is an underestimate of $\tilde{\xi}_2$ — namely, $\tilde{\xi}_2 \geq \xi_2^*$. Thus, if $H(\xi_2^*) < 0$, then we must have that $H(\tilde{\xi}_2) < 0$. This implies that the actual belief path (induced by $\xi_2 = \tilde{\xi}_2$) is concave too. □

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