Bitcoin Adoption and Beliefs in Canada[*]

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Abstract

There has been a growing discussion on digital currencies in the last few years, particularly Bitcoin. Nevertheless, research studies on Bitcoin adoption and experimentation are limited. In this paper, we develop a tractable model of Bitcoin experimentation in which agents are uncertain about the quality of the underlying technology and update their beliefs by observing the survival of Bitcoin. The model determines how adoption decisions depend on: (1) network effects; (2) own learning effects; and (3) social learning effects. We test the theoretical model's findings using unique data from the Bank of Canada's Bitcoin Omnibus Survey.

After accounting for the endogeneity of beliefs, we find that both network effects and own learning effects significantly impact Bitcoin adoption; however, we find no evidence on social learning effects. In particular, a one percentage point increase in the network size increases the probability of adoption by 0.96 percentage points, whereas a one percentage point increase in Bitcoin survival beliefs increases the probability of adoption by 0.17 percentage points. Our results suggest that network effects and individual experimentation were key drivers of Bitcoin adoption in 2017.

Keywords: Bitcoin adoption, network externalities, information externalities

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 central banks' core functions (e.g., monetary policy).[1] In the last few years, there has been an explosion of so-called "crypto-currencies," with more than 740 available. Bitcoin is the leader among them, enjoying the highest market cap and volume, as well as significant mainstream media attention.[2]

Bitcoin is a decentralized electronic fiat money with a 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. Recent evidence indicates that Bitcoin is in an early stage of diffusion: surveys conducted worldwide put estimates of Bitcoin ownership in the range of 1.5% to 5% (Stix, 2019; Henry et al., 2018; Authority, 2019; Hundtofte et al., 2019). Still, there is no consensus on whether this new technology will *survive* or not in the future.[3] It appears that individuals are still experimenting with Bitcoin and learning Bitcoin's potential benefits and costs. While the benefits of using Bitcoin are likely to depend on traditional *network effects* (i.e., how many others use Bitcoin), the cost of using Bitcoin is likely determined by the quality of this technology — which is unknown but can be gradually learned from both *individual experimentation* and *market experimentation*. A natural question then follows: How much Bitcoin adoption is explained by these three forces? The main contribution of this paper is to address this question.

The small but growing literature on digital currencies is largely silent about this question. 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 motives (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 adop-

[1] Indeed, Central banks worldwide are taking Bitcoin and other private digital currencies seriously, as evidenced in part by research and policy initiatives geared towards Central Bank Digital Currency — a digital form of cash aimed at competing with private counterparts. The Deputy Governor of the Bank of Canada states "Let's go back to the two scenarios I presented earlier that could warrant the launch of a CBDC. The first is where the use of physical cash is reduced or eliminated altogether. The second is where private cryptocurrencies make serious inroads [...]" Tim Lane's speech on 25 February 2020, source: `https://www.bankofcanada.ca/2020/02/money-payments-digital-age/`.

[2] 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.

[3] Budish (2018), e.g., argues that if Bitcoin were to achieve a broad level of acceptance/success as a digital currency, this would only result in certain economic incentives becoming strong enough that would effectively cause the system to collapse.

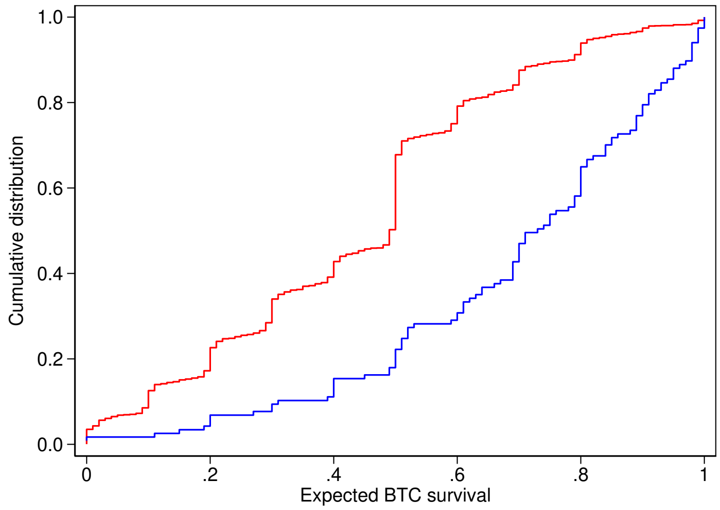

Figure 1: **Expected Bitcoin Survival and Adoption.** The graph shows the expected likelihood of survival of Bitcoin in 15 years, as reported by respondents to the 2017 Bitcoin Omnibus Survey. The red line represents the cumulative distribution function conditional on no adoption of Bitcoin, whereas the blue line is the same conditional on positive adoption. The two distributions are statistically different. The figure shows that the agents' beliefs about Bitcoin survival is affected by adoption.

tion and experimentation remain somewhat limited.

In this paper, we provide a theoretical and empirical analysis of Bitcoin adoption that takes into account the three forces mentioned above: (1) network effects; (2) individual learning effects; and (3) social learning effects.[4] Our analysis leverages a unique data from the Bitcoin Omnibus Survey (BTCOS). The BTCOS was commissioned in late 2016 by the Bank of Canada to gather information on the awareness and use of Bitcoin among Canadians; it has been conducted annually since then (Henry et al., 2017, 2018, 2019a, 2020). Data from the 2017 BTCOS uncovers a novel relationship between Bitcoin adoption and agents' beliefs about its survival. As seen in Figure 1, agents' beliefs about Bitcoin survival differs significantly when adoption is either positive or zero. In particular, Bitcoin adopters are on average more optimistic about Bitcoin survival than non-adopters.[5] This evidence suggests that Bitcoin experimentation may fuel agents' beliefs about Bitcoin which, in turn, may impact future adoption.

So motivated, we develop a simple dynamic model of Bitcoin adoption, in which agents' beliefs and adoption patterns are jointly determined. There is a continuum of risk-neutral agents that at

[4] See, e.g., Goolsbee and Klenow (2002); Moretti (2011); Fafchamps et al. (2020) for other studies of adoption with network and/or information externalities in different economic contexts.

[5] Other survey evidence shows that beliefs about the future potential of Bitcoin may play an important role for early adopters. For example, an Austrian survey revealed that owners believe cryptocurrencies provide relative benefits in terms of making payments, compared with conventional payment methods (Stix, 2019). However, only 50% of these owners report having used digital currencies to make a payment. The implies that these owners believe that Bitcoin and other digital currencies will have benefits in the future.

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. Agents benefit from a big network regardless of the technology's quality. However, the cost of using Bitcoin naturally depends on technological grounds. In our learning process, it is common knowledge that a good technology always survives, but a bad one can break down with a positive chance and, in such event, agents would incur in a loss.[6] Thus, the *survival* of Bitcoin provides a noisy signal of its quality. Next, to simply capture social learning effects, we assume that a bad technology is more likely to fail when more people adopt it. 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.[7]

The model predicts a positive relationship between the adoption rate and beliefs. In particular, it determines how individual adoption behavior depends on network effects, individual experimentation, social learning, and adoption costs. We then take these predictions to the data. The main empirical challenge is the potential simultaneity between the Bitcoin adoption and beliefs: individuals with high beliefs are more likely to adopt and, conversely, individuals who adopt are more likely to have high beliefs. To address this potential simultaneity, we consider an identification strategy based on a two-stage control function approach (Wooldridge, 2015). In the first stage, we estimate Bitcoin beliefs as a function of observed demographic characteristics and, crucially, an exclusion restriction captured by the *regional growth in Bitcoin ATMs*. The exclusion restriction comes from the supply side, which arguably is correlated with past Bitcoin adoption but not with current adoption. We further consider another identification mechanism that builds on the potential difference in functional forms of the two-stage outcomes (Escanciano et al., 2016). In our paper, this difference is driven by a nonlinear age effect. Altogether, in the second stage, we use the residual from the first stage as a control function to correct for the endogeneity problem.

The empirical results suggest that both network effects and own learning effects are important driving forces of Bitcoin adoption. However, we find no evidence that social learning has a significant effect on individual adoption. Our results show that a one percentage point increase in the network size raises the probability of Bitcoin adoption by 0.79 percentage points, whereas a one percentage point increase in Bitcoin survival beliefs raises the chance of Bitcoin adoption by 0.17 percentage points. These results suggest that both network effects and individual experimentation were driving the adoption of Bitcoin in 2017.

Finally, we find that age — a proxy for adoption costs — has a significant negative impact on adoption and beliefs, with young people being associated with both more adoption and more

[6] 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.

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

optimistic beliefs about the survival of Bitcoin.[8] Specifically, our results indicate that a one year increase in age lowers the probability of adoption by 0.03 percentage points. These results are consistent with our theoretical model, as old individuals are more likely to face high adoption costs.

We set up the model in §2, and discuss the data in §3 and methodology in §4. We test the model implications in §5. Finally, we conclude in §6. Omitted proofs are available in the Appendix.

2 A Model Bitcoin Adoption and Learning

This section aims to develop a tractable stylized model that allows us to motivate the empirical analysis. Time is discrete and infinite $t = 1, 2, \ldots, \infty$. There is a unit-mass continuum of risk-neutral *potential adopters*. Since identical agents may choose to experiment or not with Bitcoin, depending on some unobserved characteristic, we assume that agents have heterogeneous *adoption costs* $c \in [0, 1]$, which are uniformly distributed.[9]

Since Bitcoin is not backed by a central authority, adopting or using Bitcoin is, fundamentally, risky. For simplicity, we assume that this technology's *quality* is unknown and can be summarized into a binary variable that can be either *good* or *bad*. Intuitively, the quality of this payment technology may depend on a number of variables, such as reliability, convenience, security, congestion management, etc. These attributes are hard to assess without individual experimentation.

Next, we introduce a learning process.[10] In every period, there is a chance that the technology fails, depending on its inherent quality. For simplicity, we assume 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 $\varphi + \phi < 1$.[11] This specification is aimed to simply reflect *individual learning effects* (captured by φ) and *information externalities* (captured by ϕA_t). That is, an individual can learn the quality of the technology not only via her experimentation, but also via the experimentation of others (see, e.g., Bergemann and Välimäki, 1997). Consequently, detecting the unknown Bitcoin quality is more likely if more people adopt it, as the chance of failure increases conditional on the technology being bad. In the context of the mode, the notion of "failure" is not to depict a situation in which the technology disappears, but rather to illustrate

[8]Early adopters are typically young leaving in urban areas, are educated and socially active (Rogers, 2010).

[9]The model has some elements in common with Vásquez and Nield (2019).

[10]Specifically, we consider an experimentation model with a two-armed bandit whose risky arm yields failures according to a Poisson process with an unknown arrival; see, e.g., Keller and Rady (2015). However, unlike that literature, in this paper, experimentation takes place in a *large* market (Bergemann and Välimäki, 1997).

[11]Frick and Ishii (2016) examine an innovation adoption model in which agents learn from exogenous and endogeneous sources. 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.

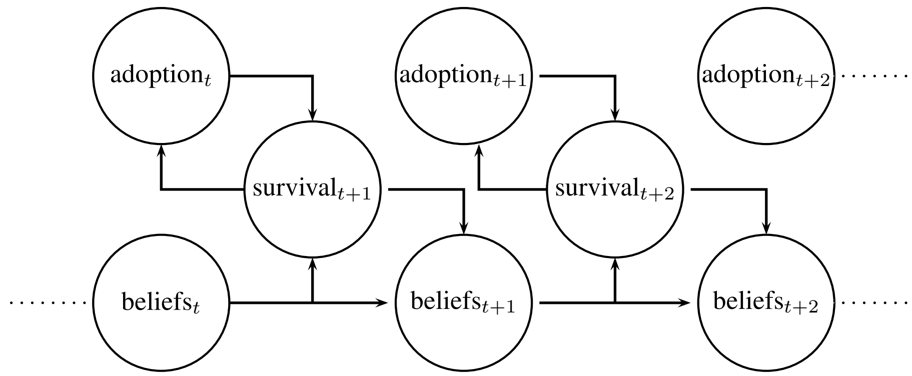

Figure 2: **The Dynamics of Adoption, Beliefs, and Survival.** Starting from a common prior belief in period t that the technology is good, current adoption and beliefs affect the survival of Bitcoin, which in turn affect the individual decision to adopt Bitcoin. The survival rate and current beliefs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

that Bitcoin could have some inherent technological issues that may persist over time.

For some intuition, think of security breaches and congestion management — two issues that are pervasive 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.[12] In the second one, we could imagine that network congestion is also more likely to lead to a system failure when the technology is not good.[13]

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 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; this reflects a "breakdown" event. In the other, Bitcoin survives and agents remain uncertain, but more optimistic, about its quality.[14] 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 chance that the technology does not fail between periods t and $t + 1$.

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: $\partial \xi_{t+1}/\partial A_t > 0$. If more people adopt in period t and Bitcoin survives, then it is more likely that the technology is good. Finally, observe

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

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

[14] Of course, this is just a technical simplification. For instance, if a good technology were also able to fail but at a lower rate than a bad one, observing a failure would lead to inconclusive news. More importantly, beliefs would still update upwards in absence of news, as in our stylized model. Clearly, incorporating such learning process would overcomplicate the model without bringing additional economic insights.

that agents are more optimistic about Bitcoin as time goes, given no failures — namely, $\xi_{t+1} > \xi_t$.

In each period, each potential adopter choose whether to adopt Bitcoin. Of course, adoption is more attractive if the Bitcoin system is not expected to fail within the next period (e.g., think that a transaction with Bitcoin takes one period to be completed). If Bitcoin fails, agents face a loss, which is normalized to one, but could still choose to adopt depending of the network size. Indeed, regardless of the quality of technology, individuals benefit from a big "network", and so the benefit of using Bitcoin is increasing in how many other individuals are already using Bitcoin, capturing standard *network effects*. Assume that this benefit is linear in the mass of adopters, $B(A_t) \equiv b + (1-b)A_t$, with $b \in [\varphi, 1-\phi]$.[15] This reflects that the benefits of using bitcoin depend on external and internal sources. All told, given beliefs ξ_t and adoption rate A_t, a potential adopter with adoption cost c *adopts* if and only if,

$$\underbrace{B(A_t)}_{\text{benefit}} - \underbrace{\Phi(A_t)(1-\xi_t)}_{\text{expected cost}} \geq c. \tag{2}$$

Agents adopt Bitcoin when both the failure rate and their adoption costs are low enough. Formally, let us call $a_{i,t} \in \{0,1\}$ the individual *adoption best-reply in period* t, given beliefs ξ_t and total adoption A_t, with the interpretation that $a_{i,t} = 1$ means "adopt" Bitcoin. Thus, $a_{i,t} = 1$ if and only if expression (2) holds. Also, call $y_{i,t} \equiv \mathbb{P}(a_{i,t} = 1 | \xi_t, A_t)$ the *probability of individual adoption in period* t, given beliefs ξ_t and total adoption A_t. Then,

Lemma 2.1. *There exist constants* $(\beta_0, \beta_1, \beta_2, \beta_3) \in \mathbb{R}^4_+$ *such that:*

$$y_{i,t} = \beta_0 + \beta_1 A_t + \beta_2 \xi_t + \beta_3 A_t \xi_t, \tag{3}$$

where $\beta_0 = b - \varphi$, $\beta_1 = 1 - \phi - b$, $\beta_2 = \varphi$, *and* $\beta_3 = \phi$.

Equation (3) is the fundamental equation that motivates our empirical exercise in §4. It captures three economic forces driving individual adoption: 1) Network externalities (β_1); 2) Individual learning effects (β_2); and 3) Information externalities (β_3). To see this, notice that a one unit increment in the network size A_t or in beliefs ξ_t have both a *direct and indirect effect* on the individual probability of adoption $y_{i,t}$:

$$\frac{\partial y_{i,t}}{\partial A_t} = \underbrace{\beta_1}_{\text{direct effect}} + \underbrace{\beta_3 \xi_t}_{\text{indirect effect}} \quad \text{and} \quad \frac{\partial y_{i,t}}{\partial \xi_t} = \underbrace{\beta_2}_{\text{direct effect}} + \underbrace{\beta_3 A_t.}_{\text{indirect effect}} \tag{4}$$

The indirect effect arises from social learning motives: an increase in the network size speeds up learning, thereby influencing adoption. Likewise, an increase in beliefs ξ_t leads to more adoption

[15] Restricting the domain of b is simply to prevent irrelevant corner solutions.

which, in turn, reinforces the learning process. The magnitude of this nonlinear indirect effect is regulated by β_3, which is equal to ϕ by Lemma 2.1. Thus, it is clear that if individuals did not learn from others, namely, $\phi = 0$, then $\beta_3 = 0$ and thus the indirect effects would vanish. In such case, β_1 and β_2 would only reflect standard network and own learning effects, respectively. Altogether, parameters $\beta_1, \beta_2, \beta_3$ allow us to identify whether and how much agents' adoption decisions are driven by traditional network benefits and social learning, respectively.

To close the model, we introduce a simple adoption process to capture the gradual nature of innovation diffusion. Motivated by the well-known Bass model (Bass, 1969), we posit that the number of new adopters is proportional to the numbers of individuals who have not adopted yet $1 - A_t$. Precisely, starting with an initial mass of adopters $A_1 = \bar{A}_1 \in (0, 1)$, the evolution of adoption obeys:

$$A_{t+1} = A_t + y_{i,t}(1 - A_t). \tag{5}$$

The model is solved by a joint adoption-belief process $(A_t, \xi_t)_{t=1}^{\infty}$ obeying (1) and (5), given (3), and initial conditions $A_1 = \bar{A}_1$ and $\xi_1 = \bar{\xi}_1$.[16]

Proposition 1. *(i) There exists a unique solution $(A_t, \xi_t)_{t=1}^{\infty}$ to the initial value problem; this solution is increasing over time. (ii) Suppose that adoption costs fall such that c is distributed uniformly on $[0, \bar{c}]$, with $\bar{c} < 1$. Then, the adoption path A_t and beliefs ξ_t strictly increase for all time $t > 1$.*

Appendix A.2 proves the existence and uniqueness. To see this, consider Figure 2. Conditional upon survival, only one path exists: Given initial beliefs $\bar{\xi}_1$ and adoption $\bar{A}_1$, there is only a single solution for belief ξ_2 and adoption A_2, given (1) and (5), respectively. These, in turn, determine beliefs and adoption ξ_3 and A_3, by the same logic, and so on. The top-left panel of Figure 3 depicts the path of adoption and beliefs. We next discuss some testable implications of the model briefly.

First, the joint process (A_t, ξ_t) is increasing over time: as the technology keeps surviving, agents become more optimistic about its quality, leading to more adoption. As seen in the top-right panel of Figure 3, this implies that individual probability of adoption $y_{i,t}$ is positively related to beliefs ξ_t and also to network size A_t.

Second, Appendix A.3 shows that a decrease in adoption costs raises adoption and beliefs at all non-trivial time periods — as depicted in the bottom-left panel of Figure 3. By Lemma 2.1, it follows that individual probability of adoption $y_{i,t}$ rises as adoption cost falls. Intuitively, when adoption costs fall, individuals are more likely to adopt at any non-trivial belief ξ_t, leading to more aggregate adoption A_t. This leads to a higher (no-failure) posterior beliefs, because not observing a breakdown provides stronger evidence that the technology is good when there is more adoption, leading to more individual adoption and so on. Altogether, starting from similar initial

[16]Notice that along the solution path, agents' adoption decisions are optimal at any instant t and determined by the aggregate variables (A_t, ξ_t). Thus, our solution notion coincides with a Markovian equilibrium.

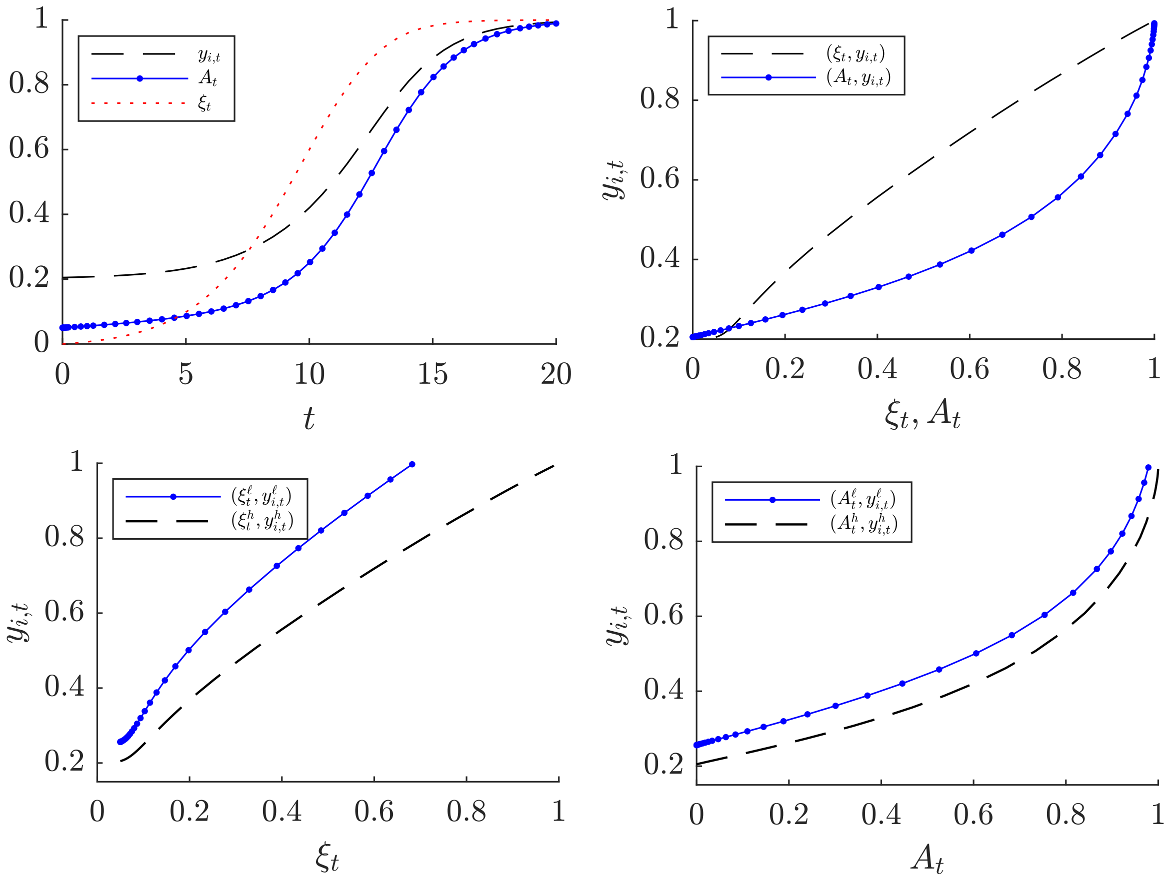

Figure 3: **Adoption and Beliefs.** All panels assume $\phi = 0.5$, $\varphi = 0.1$; $b = 0.1$. The bottom panels consider a reduction in the adoption cost uniform distribution, from $c_\ell \sim \mathcal{U}[0,1]$ to $c_h \sim \mathcal{U}[0,0.8]$.

conditions, agents with lower adoption costs not only adopt more but are more optimistic about Bitcoin, leading to cross-sectional differences across agents over time.

3 The Bitcoin Omnibus Survey Data

3.1 Overview of the data set

We use data from the Bank of Canada's Bitcoin Omnibus Survey (BTCOS). First conducted in late 2016, the purpose of the BTCOS was originally to serve as a monitoring tool, obtaining basic measurements of Bitcoin awareness and ownership among the Canadian population.

Respondents to the BTCOS are recruited via an online panel managed by the research firm Ipsos, and complete the online format survey. The survey's core components are 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 Bitcoin owners' motivation and their usage behavior. Our analysis relies mostly on the 2017 BTCOS, wherein the following questions were added to the core components: beliefs about the future adoption/survival of Bitcoin; knowledge of Bitcoin features; price expectations; use of Bitcoin for payments or person-to-person transfers; ownership of other cryptocurrencies; cash holdings.

In 2017, 2,623 Canadians completed the BTCOS, of which 117 self-identified as Bitcoin owners. In addition to content questions, respondents are also asked to provide demographic information, see Table 1.

- insert Table 1 here -

Most of these questions are required of the respondent to answer in order for the survey to be considered complete (thereby receiving incentives); however, certain questions such as employment and income are deemed sensitive, and hence there is missing data present. 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 an in-depth calibration procedure to ensure that the sample is representative of the adult Canadian population along with a variety of dimensions (see Henry et al. (2019b) for details).

3.2 Bitcoin Adoption and Beliefs

Each respondent who indicates that they are aware of Bitcoin answers the question: "Do you currently have or own any Bitcoin?" A respondent is deemed a Bitcoin adopter if they answer "Yes" to this question; those who have not heard of Bitcoin are considered non-adopters.[17] Table 2 shows the adoption rates of Bitcoin in 2016 and 2017, both overall and by several demographic categories such as region, gender, and age. Adoption is noticeably higher among younger Canadians (aged 18-34 years old) with 11.1% self-reporting as Bitcoin owners in 2017, compared with just 3.2% of those aged 35-54 and only 0.5% among those over 55. Adoption is also higher among males versus females (6.6% versus 2.1% in 2017). Regional variation is less stark, but adoption is higher in British Columbia and Quebec, and lowest in the Atlantic provinces.

- insert Table 2 here -

We use some of these characteristics to construct a network measure A_t in order to capture network effects. In particular, we use the answer "My friends own Bitcoin" from the question "Please

[17]The first question of the BTCOS asks simply "Have you heard of Bitcoin?" In 2016, 62% of Canadians indicated the were aware of Bitcoin; this increased to 83% in 2017.

tell us your main reason for owning Bitcoin," and we correlate it with the observed characteristics of the respondents. Specifically, the dominant characteristics, namely, region and age, are used to construct a *local network* variable for each respondent in 2017 by assigning the level of adoption for age categories within their region for the year 2016 respondents. This allows us to proxy for A_t in the model.

Finally, respondents who are aware of Bitcoin answer the question: "How likely do you think it is that the Bitcoin system will survive or fail in the next 15 years?" A sliding scale from 0 to 100 is presented to the respondent, where 0 means they think that Bitcoin will certainly fail, while 100 means they think that Bitcoin will certainly survive. To proxy for beliefs ξ_t, the answer to this question is divided by 100 and interpreted as a probability. The mean is 0.45 and the median 0.5.

4 Empirical Strategy and Econometric Methodology

The theoretical model in §2 translates on testing whether and, if so, how much Bitcoin adoption depends on: (1) network externalities; (2) own learning effects; (3) social learning effects; and (4) adoption cost. Because individual adoption a_{it} is a binary variable, equation (3) in Lemma 2.1 suggests the following empirical specification:

$$a_{it} = \mathbb{P}(\beta_0 + \beta_1 A_{it} + \beta_2 \xi_{it} + \beta_3 \xi_{it} A_{it} + \beta_4 Age_i + \beta_c X_i + \beta_r R_j) + \epsilon_{it}, \tag{6}$$

where a_{it} is a dummy for Bitcoin adoption of individual i at the time of the evaluation, and ϵ_{it} is a logistically distributed error. Let us make a few observations regarding specification (6). First, as discussed in §3, A_{it} reflects the network size of individual i at time t, whereas ξ_{it} measures beliefs of individual i at time t about the survival of Bitcoin. Also, as highlighted in §2, the non-linear term $\xi_{it} A_{it}$ captures information externalities or social learning forces. Finally, the control variables X_i include demographic characteristics about respondent i at the time of the evaluation, namely, gender, income, employment, education, number of kids in household, marital status, and household grocery shopping responsibilities. The controls R_j are regional dummies.

The model implies that the positive parameters β_1 and β_2 capture direct network effects and own learning effects. Both effects can be indirectly reinforced via social learning, reflected by coefficient β_3, as seen in expression (4). Adoption cost is captured by β_4, the coefficient on age, as older individuals are more likely to have higher adoption costs. Our empirical specification will test these predictions and the importance of these effects for individual Bitcoin adoption in 2017.

4.1 Identification

A simultaneity problem arises because an increase in Bitcoin survival beliefs may increase adoption of Bitcoin, which, in turn, can further reinforce the beliefs about survival. Consequently, ignoring this issue would most likely bias the estimates on beliefs about Bitcoin survival *downward*. As a byproduct, network effects may also be underestimated.

We propose to break this simultaneity using a control function that uses a two-stage modeling approach. This approach has technical advantages compared to other methods, given the nonlinear nature of our empirical model (Wooldridge, 2011). First, other two-stage approaches that, e.g., mirror 2SLS, are not suitable for nonlinear models. Also, the CF approach allows for a simpler test of endogeneity via a Wald test. Finally, one can easily compute standard errors via Bootstrap.

In the first stage, we model the beliefs as a function of observed demographic characteristics, the nonlinear age effect, and an additional exclusion restriction: *the growth in Bitcoin ATMs*.[18] The nonlinearity of age can be justified as an identification mechanism as there is a difference in functional form between the two-stage outcomes; this difference is driven by age. Using results in Escanciano et al. (2016), the nonlinearity condition required for identification is satisfied here, and thus age squared can provide an additional identification mechanism.

Table 3 presents the regional growth in Bitcoin ATMs over 2016–2017. We collected data on Bitcoin ATMs in Canada for 2016 and 2017 at the city level from a website called "Coin ATM Radar" (`https://coinatmradar.com/`), using Wayback Machine, a digital archive of the World Wide Web. We then aggregated this information at the the regional level, as seen in Table 3.

Notice that there is no uniform growth on Bitcoin ATMs over different cities in Canada; in some cities, we see ATM closures (e.g., Surrey and Whistler in BC) or no change (e.g., Maple Ridge in BC; North Bay and Sault Ste, Marie in Ontario; Red Deer in Alberta or Gatineau in Quebec). These observations suggest that, while adoption increased substantially (in fact, doubled) in Canada between 2016 and 2017 (Henry et al., 2017), the regional change in Bitcoin ATMs does not follow a similar path — at least from a contemporaneous perspective.

- insert Table 3 here -

Our exclusion restriction comes from the supply side. Intuitively, Bitcoin ATMs' suppliers provide this service *after* observing an increase in Bitcoin demand. Indeed, an individual cannot

[18]Bitcoin ATMs are easy to use and have similar functions compared to a regular ATM, namely, it allows users to exchange their digital currency credits for cash and vice-versa. Bitcoin ATMs accept cards and some accept cash too. Although the internet is used for transactions, customers are not linked to their bank accounts but rather to a crypto-exchange. In 2013, Canada became the first country in the world to open a Bitcoin ATM. Since then, numerous Bitcoin ATM providers have entered in Canada.

affect ATM's placement; however, ATM providers could locate them in places where they have seen many Bitcoin adopters. Also, installing and running a Bitcoin ATM is costly,[19] presumably leading suppliers to carefully choose their location based on previous observed levels of adoption. Thus, Bitcoin ATM network size does not reflect current adoption but previous levels of adoption.[20]

On the other hand, an increase in the Bitcoin ATM network surely affects current beliefs about Bitcoin survival, as installing a Bitcoin ATM provides public information that the technology is becoming more prevalent. This signaling channel is indeed credible because it demands upfront technological investments in the area from the providers. Altogether, our exclusion restriction meets the properties needed to address the simultaneity of Bitcoin adoption and beliefs.[21]

To formally check if ATMs' growth is a valid exclusion restriction, we compute the regional correlation between the growth in ATMs, growth in Bitcoin adoption, and Bitcoin survival beliefs; see Table 4. As previously argued, the regional growth in Bitcoin ATMs is not correlated with the regional growth in Bitcoin Adoption; however, it is indeed correlated with its expected survival.

- insert Table 4 here -

We use the nonlinearity of age and the exclusion restriction as an identification mechanism to uncover the true effect of beliefs on individual adoption decisions. The proposed identification mechanism is based on a two-stage control function (CF) approach (Heckman and Robb, 1985), because of the probabilistic nature of our model (binary dependent variable). In the first stage, Bitcoin belief ξ_{it} is projected on the exclusion restriction and a set of observed characteristics at an individual and regional level:

$$\xi_{it} = \alpha_0 + \alpha_1 \Delta ATM_{jt} + \alpha_2 Age + \alpha_3 Age^2 + \alpha_c X_i + \alpha_r R_j + u_{it}, \tag{7}$$

where ΔATM_{jt} is the growth in Bitcoin ATMs in region j at time t, and u_{it} is an error term.

The residual from the first stage is subsequently used in the second stage as a CF. That is, the benchmark model in equation (6) is augmented with CF as follows:

$$a_{it} = \mathbb{P}(\beta_0 + \beta_1 A_{it} + \beta_2 \xi_{it} + \beta_3 \xi_{it} A_{it} + \beta_4 Age_i + \beta_c X_i + \beta_r R_j + \beta_{CF} \hat{u}_{it}) + \epsilon_{it}, \tag{8}$$

[19]These costs involves, e.g., the price of the machine, taxes, installation fees, legal costs, and operation costs. See `https://coinatmradar.com/blog/revenue-and-costs-of-running-a-bitcoin-atm/`.

[20]This is also consistent with rational forward-looking behavior from the suppliers' perspective, since expectation about future adoption given all available information today must be a function of adoption levels observed up to today. Consequently, the decision to install Bitcoin would not capture current Bitcoin adoption, but past adoption levels.

[21]Of course, other exclusion restrictions could have been considered such as the use of digital wallets. Importantly, according to Henry et al. (2018), new adopters were mostly young non-educated males with low financial literacy scores, making the use of Bitcoin ATMs appealing given its simplicity on converting cash to Bitcoin.

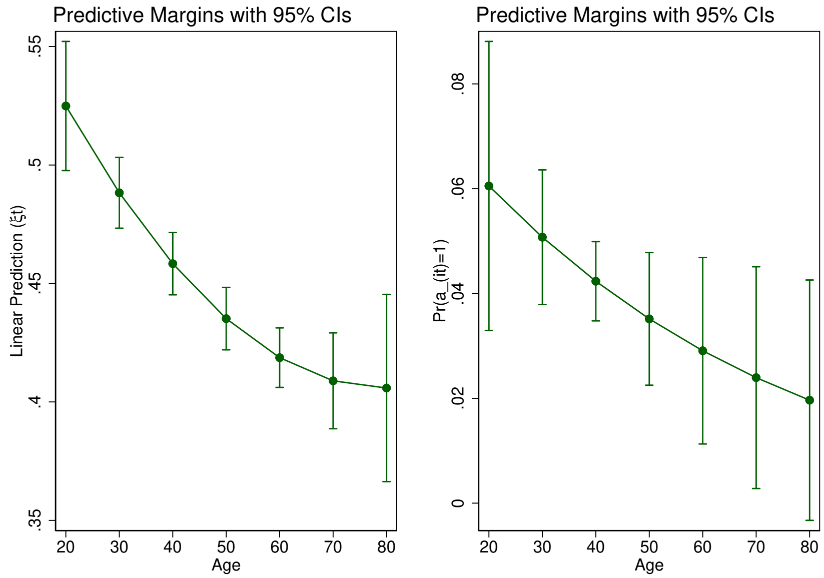

Figure 4: **Predictive Margins of Beliefs, Probability of Bitcoin Adoption by Age.**

where $\hat{u}_{it}$ is the control function obtained from first stage regression and used to control for endogenous selection. The probability of Bitcoin adoption is estimated via a logit based likelihood. Also, to account for low adoption rate at the evaluation time (about 5%), we estimate for robustness checks a penalized logistic based likelihood (Heinze and Schemper, 2002).

Before closing this section, we briefly discuss the role of Age^2 in equation (7). Observe the nonlinearity age effect on beliefs compared to that of adoption that is depicted in Figure 4. Motivated by Escanciano et al. (2016), we exploit this relative difference in curvature as an additional identification mechanism for the second stage model.[22]

5 Results

The discussion of our results follows the proposed stages of the identification. We start presenting the first stage results, estimated via OLS, which examines the agents' beliefs about Bitcoin survival. We then discuss the second stage results, estimated via a Logit model, which are related to individual Bitcoin adoption. The second stage results quantify how much Bitcoin adoption depends on network externalities, own learning effects, social learning effects, and adoption cost. These testable hypotheses are motivated by our theoretical model.

[22]This identification mechanism preserves natural features of the data but is not crucial for our main results.

5.1 Beliefs about Bitcoin survival

Table 5 shows the results of the first stage analysis. The first column displays the results without accounting for both regional growths in counts of Bitcoin ATMs and nonlinear age effects. The second column presents the results with such considerations only, whereas the third column shows the outcome for the full first-stage model.

- insert Table 5 here -

Notice from column (2) the significance of our identification mechanisms in explaining beliefs (F-stat is equal to 17.28). Both the growth in counts of Bitcoin ATMs by region and age squared are significant at the 5% and 1% levels, respectively. In particular, age effects are decreasing and convex (the coefficient for age is negative and significant, while that of age squared is positive and significant). This suggests that an older individual is less optimistic about the survival of Bitcoin at increasing rates, namely, the absolute belief divergence gets smaller as people become older. This is consistent with the theoretical model (Proposition 1) to the extent that older individuals face higher adoption costs. In general, the first stage results with and without the exclusion restrictions are similar, as seen in columns (1) and (3) in Table 5.

The regional growth in ATMs is positive and significant for Atlantic Provinces, Quebec and Ontario, relative to British Columbia. Thus, a relative increase in Bitcoin ATMs leads individuals to have more optimistic beliefs about Bitcoin survival, ceteris paribus. Interestingly, those without kids or that are not doing grocery shopping are more pessimistic about Bitcoin's survival than those with children or actively doing grocery shopping (c.f. Balutel et al., 2020). A plausible reason could be that individuals with no children or not actively doing grocery shopping may face tighter financial constraints, and so have greater adoption costs and lower beliefs (Proposition 1).[23]

Finally, respondents with higher education were more pessimistic about Bitcoin: the college and university variables show negative effects compared to the benchmark education category, high school. The rationale for this finding may be linked to the fact that Bitcoin was seen mostly as a speculative investment asset as the price was close to its historical peak in 2017. Thus, individuals with higher education may have seen this high price variation as a short-lived potential bubble rather than a long-term investment opportunity.

The residual from this first stage estimation is further used as a control function in the second stage, which contains our main equation of interest.

[23] Balutel et al. (2020) find that individuals with kids who do grocery shopping are more likely to hold Bitcoin than those with no kids and do not do grocery shopping. They also find that Bitcoin owners who have kids and do grocery shopping hold more cash than Bitcoin holders who do not have kids and do not do grocery shopping.

5.2 Bitcoin adoption

As discussed in §4.1, modeling Bitcoin adoption requires addressing an endogeneity problem related to a key variable of interest, namely, beliefs about Bitcoin survival. Thus, we use CF as a correction term in the second stage. As argued in §4.1, CF approach allows for a simple endogeneity test via a Wald test. In particular, we reject a Null test of exogeneity as we obtain a value for the Wald test of 49.82 (with a p-value of 0). This validates our suggested endogeneity correction via CF. Table 6 presents the Logit results without CF in column (1) and with CF in column (2). We interact CF with all demographic characteristics to potentially capture further sources of selection for Bitcoin adoption. We then estimate the model with a Lasso Logit (Hastie et al., 2015).

The Lasso selected only one interaction, which is between the Prairies region and CF. One reason why Lasso selects this interaction is that the omitted benchmark category, i.e., the growth in Bitcoin ATMs in British Columbia, has a similar proportion of ATM growth as in Prairies. Therefore, the information from the omitted category may resurface via the interaction between CF and Prairies. In turn, after we introduce this interaction in the model, the network effect is amplified. This may owe to the fact that although the network level in Prairies is the smallest compared to other regions, it has one of the highest variations between network sizes across age cohorts (three times smaller network size for older than for the younger group). Thus, CF amplifies the effect of this variation in favour of the younger cohort (which is the driving force of the network effect), while CF attenuates the selected interaction effect. Indeed, the interaction becomes insignificant in the Logit model, although Lasso considered it relevant for the Bitcoin adoption model (8). The results of the Logit after Lasso selection are presented in Table 6, column (3).

Additionally, in columns (4) and (5) we add the penalized likelihood Logit results to account for low adoption rates, as discussed in 4.1. Column (4) presents the results with CF, whereas column (5) with the CF and the CF interaction. The results are similar in all specifications, except that network effects increase in importance when the CF interaction is accounted for.

- insert Table 6 here -

Across the board, it is clear that beliefs about the survival of Bitcoin are correlated with Bitcoin adoption. The coefficient on beliefs is significant at the 1% level in each of the considered models. Higher beliefs about Bitcoin survival are related to a greater likelihood of adopting Bitcoin. This effect is *amplified* after we control for endogeneity — the magnitude of the marginal effect is roughly three times greater. The control function variable is significant at 5% in both specifications (logit and penalized likelihood logit), indicating that the baseline models provide a biased estimate of the effect of beliefs on adoption. When CF is introduced, the strong correction of beliefs indicates that early Bitcoin adopters have already high beliefs about Bitcoin's future survival.

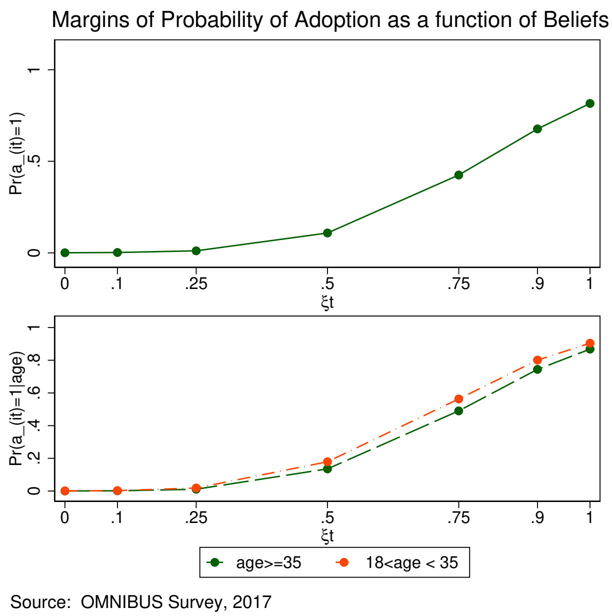

Figure 5: **The Marginal Effects of Probability of Bitcoin Adoption by Beliefs**

As of network effects, the relationship is positive and significant at the 10% level for the Logit models with and without control function, respectively. The model with CF interaction, selected by Lasso, amplifies the network effect and improves its significance. For the penalized likelihood Logit models there is a significance at the 10% level for both specifications (with both CF and CF interaction). The marginal effects coefficients (see Table 7) on the local network variable are positive and significant, showing a marginal change between the model without and with control function. The magnitude of the marginal effect changes when the CF interaction is added, indicating that a high Bitcoin adoption among peers is associated with high a propensity to adopt, as predicted by the theoretical model in §2.

- insert Table 7 here -

Altogether, our empirical results suggest that both network and own learning effects are important forces driving Bitcoin adoption. However, we see no evidence of social learning effects, as measured by the interaction term $A_{it}\xi_{it}$. Specifically, our analysis shows that a one percentage point increase in the network size raises the probability of Bitcoin adoption by 0.96 percentage points (for the model with both CF and CF interaction), whereas a one percentage point increase in Bitcoin survival beliefs increases the adoption chance by 0.17 percentage points. Also, we find that one year increase in age lowers the probability of adoption by 0.03 percentage points. This may

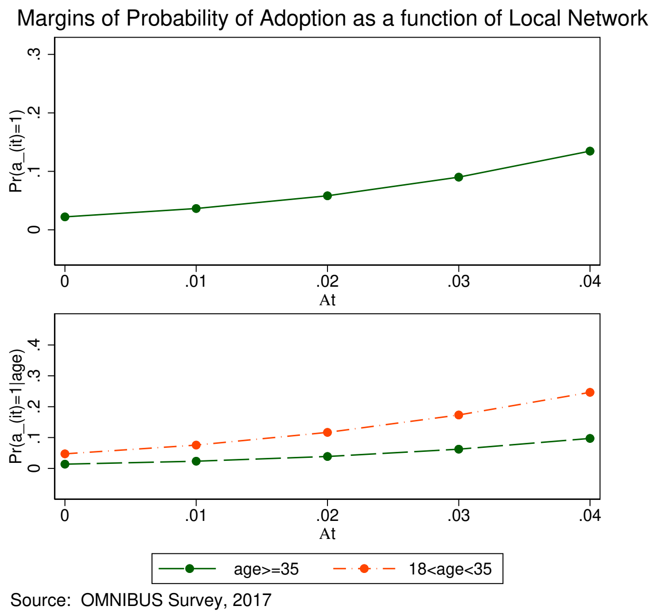

Figure 6: **The Marginal Effects of Probability of Bitcoin Adoption by Local Network**

suggest a nonlinear effect of age with higher age groups individuals making few or no adoptions, leading to a low but significant average effect of the age.

These empirical results are consistent with the theoretical model presented in §2 and with the simulations depicted in Figure 3. In particular, Figure 5 shows that the probability of adoption as a function of beliefs increases (with a steeper increase if the beliefs about expected Bitcoin survival pass the median). Moreover, Figure 5 depicts a decomposition of the margins for the probability of adoption by age categories (below and above 35 years old). Notice that younger individuals are more optimistic than older individuals. These age group differences are statically significant,[24] as seen in the top results of Table 9.

- insert Table 9 here -

Similarly, the top panel of Figure 6 shows that the probability of adoption as a function of network size is also increasing. The bottom panel considers a decomposition of the margins for the probability of adoption by age categories (below and above 35 years old). We see that younger individuals adopt more than the older individuals. These age group differences are also statically significant;[25] see the bottom results of Table 9.

[24]The joint hypothesis test for all specified contrasts rejects equality of the two age groups paths; χ^2-test is 35.15 and highly significant at 1%.

[25]The joint hypothesis test for all specified contrasts rejects equality of the two age groups paths; χ^2-test is 49.62 and is significant at 1%.

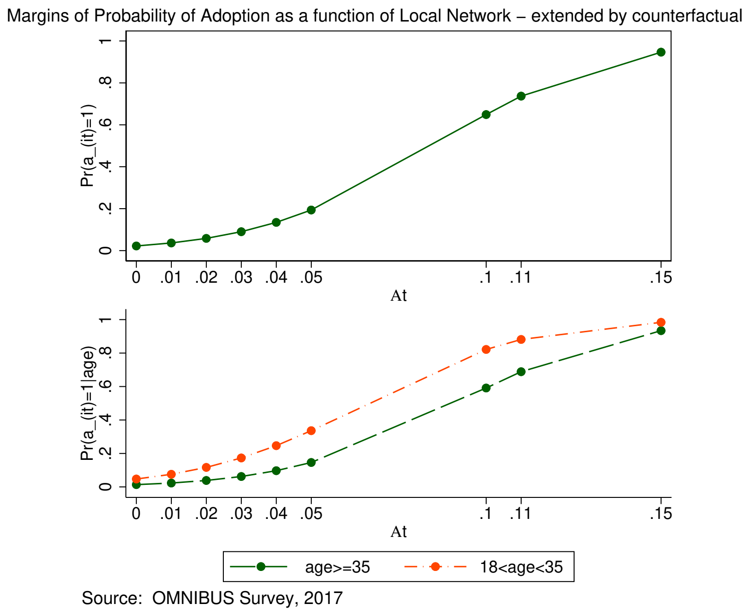

Figure 7: **The Marginal Effects of Probability of Bitcoin Adoption by Local Network**

Next, we perform a counterfactual analysis. Figure 6 shows that the network sizes at the time of measurement (i.e., 2017) were small. To understand what would happen to the probability of Bitcoin adoption if the network size were to increase, we perform a counterfactual in which the network size was increased until the individual probability of adoption reaches one. This happens when the network size increases 400% (i.e., by a factor of 4). As seen in Figure 7, an increase in network size shows a continuation in the increase in Bitcoin adoption until the current network size is about four times larger than the current one (reaches about 15% of the specific groups population). Both age groups reach the maximum of adoption at about the same network size. The age groups differences in network size creation can be explained by the fact that older individuals face higher costs when forming networks, as there are inherent costs of accessing technologies that facilitate participation in discussion groups, etc.

Although we are in an early stage of diffusion, network effects are important for technology adoption.[26] Indeed, Table 8 indicates that network effects are dominant for the young cohort: about 17.2% of the young respondents stated this as the main reason for owning Bitcoin, whereas this number drops to below 3% for older age groups. Another plausible reason why young individuals are inclined to adopt Bitcoin is that they may have some constraints to open a formal financial account, as these ones are associated with paperwork, regulations, and fees. Therefore, it maybe easier and cheaper for young people to just buy Bitcoin directly at an ATM. Adoption by young individuals may also be driven by other reasons such as speculation, technology-related, payments

[26] Rogers (2010) suggests that early adopters are usually young and socially active individuals.

related, and trust/privacy issues (see Table 8 for further details).

- insert Table 8 here -

Finally, our results also emphasize the role of individual characteristics. We find that the likelihood of Bitcoin adoption declines with being female and living in regions outside British Columbia. Conversely, the probability of adoption increases with education and employment: respondents with higher education (university) in 2017 were more optimistic about Bitcoin adoption.

6 Concluding Remarks

Motivated by an empirical observation that Bitcoin adopters are more optimistic about the survival of Bitcoin than non-adopters, this paper develops a tractable Bitcoin adoption model with externalities. The model predicts how individual learning effects, payoff-based network externalities, and information externalities shape adoption decisions. We then connect the theory with detailed micro-level data from the BTCOS 2016 and 2017 surveys in order to test and quantify the behavioral determinants of individual Bitcoin adoption. To address the simultaneity between adoption and beliefs, we consider a two-stage control function approach, in which the first stage estimates beliefs using an exclusion restriction — the regional growth in Bitcoin ATMs. The second stage then estimates the individual probability of Bitcoin adoption using the residual from the first stage as a control function to correct for endogeneity.

The data validate several testable predictions. First, we find that Bitcoin survival beliefs, network effects, and adoption costs significantly impacted Bitcoin adoption in 2017. Our results show that a one percentage point increase in the network size raises the probability of Bitcoin adoption by 0.96 percentage points, whereas a one percentage point increase in Bitcoin survival beliefs raises the chance of Bitcoin adoption by 0.17 percentage points. Also, we find that one year increment in age lowers the probability of adoption by 0.03 percentage points. The small age effect is driven by the substantial variation in beliefs and network sizes between young and old individuals.

Finally, our results provide no evidence that social learning had a significant effect on individual adoption in 2017. This may be explained by segmentation effects across age groups, where old individuals may not be learning from the experimentation of young adopters. As for future work, a structural estimation of the model parameters seems interesting, as this would allow us to reconstruct the adoption and belief paths and perform counterfactual analysis.

A Appendix: Technical Details of Proofs

A.1 The Probability of Adoption: Proof of Lemma 2.1

Notice that, given the optimality condition (2), we have:

$$\begin{aligned}
\mathbb{P}(a_{i,t}=1|\xi_t,A_t) &= \mathbb{P}(\{c \leq B(A_t)-\Phi(A_t)(1-\xi_t)\}\,|\xi_t,A_t) \\
&= B(A_t)-\Phi(A_t)(1-\xi_t) \\
&= b+(1-b)A_t-(\varphi+\phi A_t)(1-\xi_t) \\
&= b-\varphi+(1-b-\phi)A_t+\varphi\xi_t+\phi A_t\xi_t \\
&= \beta_0+\beta_1 A_t+\beta_2\xi_t+\beta_3 A_t\xi_t,
\end{aligned}$$

where we used that $c \sim \mathcal{U}[0,1]$ and that $B(A_t)-\Phi(A_t)(1-\xi_t) \in [0,1]$ for all $A_t, \xi_t \in [0,1]$. $\square$

A.2 Existence and Uniqueness: Proof of Proposition 1-(i)

For expositional clarity, we examine the continuous-time version of the model.

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 $dt \to 0$ and using Lemma 2.1 yields the following law of motion,

$$\dot{\xi}_t=\xi_t(1-\xi_t)(\beta_2+\beta_3 A_t).$$

ADOPTION. Consider the adoption process (5) and two periods t and $t+dt$. Then,

$$A_{t+dt}=A_t+\mathbb{P}(a_{i,t}=1|\xi_t,A_t)(1-A_t)dt.$$

Next, subtract A_t, then divide both sides by dt, and finally take $dt \to 0$. Then, by Lemma 2.1:

$$\dot{A}_t=(\beta_0+\beta_1 A_t+\beta_2\xi_t+\beta_3 A_t\xi_t)(1-A_t)$$

Define $x = (A, \xi)$ and $\mathcal{X} : \mathbb{R}^2_+ \mapsto \mathbb{R}^2_+$, where

$$\mathcal{X}(x) = [(\beta_0 + \beta_1 A + \beta_2 \xi + \beta_3 A\xi)(1-A), \xi(1-\xi)(\beta_2 + \beta_3 A)] \in \mathbb{R}^2_+.$$

EXISTENCE AND UNIQUENESS. We will show that the initial value problem (IVP) below has a unique solution.

$$\dot{x}_t = \mathcal{X}(x_t), \quad x_1 = (\bar{A}_1, \bar{\xi}_1) \in \mathbb{R}^2_+$$

Indeed, notice that $\mathcal{X}(x)$ is continuously differentiable, because its partial derivatives are clearly continuous, and so $\mathcal{X}(\cdot)$ is locally Lipschitz continuous in x. Thus, by the Picard-Lindelöf Theorem (Theorem 2.2 in Teschl (2012)), there exists a unique local solution $t \in [0, T] \mapsto x^*_t$ of the IVP, for some $T > 0$. □

A.3 The Effects of Adoption Costs: Proof of Proposition 1-(ii)

Suppose adoption costs are uniformly distributed between $[0, \bar{c}]$, $\bar{c} \geq 1$.[27] In the baseline model, $\bar{c} = 1$, for expositional clarity. We now examine the effects of an increase in adoption costs $\bar{c}$. Formally, the distribution of adoption costs increases in the first-order stochastic dominance sense. Consider $\bar{c}_\ell$ and $\bar{c}_h$ with $\bar{c}_h > \bar{c}_\ell$. Likewise, consider $x^\ell_t \equiv (A^\ell_t, \xi^\ell_t)$ and $x^h_t \equiv (A^h_t, \xi^h_t)$, solving

$$\dot{x}^\ell_t = \mathcal{X}^\ell(x^\ell_t) \quad \text{and} \quad \dot{x}^h_t = \mathcal{X}^h(x^h_t), \quad x^\ell_1 = x^h_1 = (\bar{A}_1, \bar{\xi}_1),$$

where we scale the adoption probability in Lemma 2.1 with the respective scalars $\bar{c}_\ell$ and $\bar{c}_h$:

$$\begin{aligned}
\mathcal{X}^\ell(A, \xi) &\equiv [\bar{c}_\ell^{-1}(\beta_0 + \beta_1 A + \beta_2 \xi + \beta_3 A\xi)(1-A), \xi(1-\xi)(\beta_2 + \beta_3 A)]; \\
\mathcal{X}^h(A, \xi) &\equiv [\bar{c}_h^{-1}(\beta_0 + \beta_1 A + \beta_2 \xi + \beta_3 A\xi)(1-A), \xi(1-\xi)(\beta_2 + \beta_3 A)].
\end{aligned}$$

The paths $t \mapsto x^\ell_t$ and $t \mapsto x^\ell_h$ are well-defined, following the same logic given in §A.2 and using the Picard-Lindelöf Theorem (Theorem 2.2 in Teschl (2012)).

Next, notice that since $\bar{c}_h > \bar{c}_\ell$, we have $\dot{x}^h_t = \mathcal{X}^h(x^h_t) \leq \mathcal{X}^\ell(x^h_t)$. Therefore, it follows that

$$\dot{x}^h_t - \mathcal{X}^\ell(x^h_t) \leq \dot{x}^\ell_t - \mathcal{X}^\ell(x^\ell_t), \quad \text{and} \quad x^\ell_1 = x^h_1$$

Finally, since $\mathcal{X}^\ell(x)$ is continuously differentiable (and thus Lipschitz continuous), we have that $x^h_t \leq x^\ell_t$ by Theorem 1.3 in Teschl (2012). Moreover, since $x^h_t < x^\ell_t$ for $t > 1$, the inequality remains strict true for all later times. That is, $A^h_t < A^\ell_t$ and $\xi^h_t < \xi^\ell_t$ for $t > 1$. □

[27] The results of this section trivially extend to any continuously differentiable cumulative distribution function.

B Tables

Table 1: **Sample description, 2017 Bitcoin Omnibus Survey**

		%	N
Overall	N		2,623
Age	18-34	0.250	657
	35-54	0.409	1,074
	55+	0.340	892
	Total		2,623
Gender	Male	0.463	1,214
	Female	0.537	1,409
	Total		2,623
Region	BC	0.144	377
	Prairies	0.187	491
	Ontario	0.340	891
	Quebec	0.244	639
	Atlantic	0.086	225
	Total		2,623
Income	<50k	0.373	877
	50k-99k	0.398	935
	100k+	0.229	538
	Total		2,350
Education	High School or less	0.226	592
	College / trade school	0.346	908
	University	0.428	1,123
	Total		2,623
Employment	Retired	0.224	581
	Employed	0.596	1,546
	Unemployed / not in labour force	0.180	467
	Total		2,594
Number of kids	Kids	0.242	636
	No kids	0.758	1,987
	Total		2,623
Marital status	Married / common law	0.593	1,555
	Not married or common law	0.407	1,068
	Total		2,623
Grocery shopping	All of it	0.544	1,427
	Not all of it	0.456	1,196
	Total		2,623

This table shows the distribution (proportion) and counts of demographic variables associated to respondents from the 2017 Bitcoin Omnibus Survey. The total sample size was $N = 2,623$. The first column shows the proportion of respondents in each category, while the second column reports total counts. We use these individual-level characteristics as control variables in subsequent regressions.

Table 2: **Bitcoin adoption rates in 2016 and 2017:**

		2016	2017
Overall	%	3.2	4.3
	N	58	117
Age	18-34	9.1	11.1
	35-54	1.6	3.2
	55+	0.5	0.5
Gender	Male	4.4	6.6
	Female	2.2	2.1
Region	BC	2.8	5.2
	Prairies	2.1	4.1
	Ontario	2.5	3.9
	Quebec	5.5	5.1
	Atlantic	3.2	3.1

These tables show the adoption rates of Bitcoin among several demographic groups in 2016 and 2017. Data are from the Bitcoin Omnibus Survey and have been weighted to be reflective of the Canadian population.

Table 3: **Growth in Bitcoin ATMs across Canadian: Cities, Provinces and Regions; 2016-2017**

BtC ATM City	Province	Region	Year 2016	Year 2017	ATM Growth 2017-2016
Halifax	Nova Scotia	Atlantic Provinces	0	3	3
Total		Atlantic Provinces	0	3	3
Delta	British Colombia	British Colombia	0	1	1
Kelowna	British Colombia	British Colombia	0	4	4
Maple Ridge	British Colombia	British Colombia	1	1	0
Nanaimo	British Colombia	British Colombia	0	1	1
Surrey	British Colombia	British Colombia	1	0	-1
Vancouver CA	British Colombia	British Colombia	18	49	31
Victoria	British Colombia	British Colombia	1	4	3
Whistler	British Colombia	British Colombia	2	1	-1
Total		British Colombia	23	61	38
London	Ontario	Ontario	0	4	4
North Bay	Ontario	Ontario	1	1	0
Ottawa	Ontario	Ontario	4	15	11
Sault Ste, Marie	Ontario	Ontario	1	1	0
Sudbury	Ontario	Ontario	0	1	1
Toronto	Ontario	Ontario	45	127	82
Total		Ontario	51	149	98
Calgary	Alberta	Prairies	14	29	15
Edmond	Alberta	Prairies	7	10	3
Grand Prairie, AB	Alberta	Prairies	0	3	3
Red Deer	Alberta	Prairies	1	1	0
Subtotal	Alberta	Prairies	22	43	21
Regina	Saskatchewan	Prairies	0	3	3
Saskatoon	Saskatchewan	Prairies	1	2	1
Subtotal	Saskatchewan	Prairies	1	5	4
Winnipeg	Manitoba	Prairies	2	5	3
Subtotal	Manitoba	Prairies	2	5	3
Total		Prairies	25	53	28
Gatineau	Quebec	Quebec	1	1	0
Montreal	Quebec	Quebec	33	51	18
Quebec City	Quebec	Quebec	1	2	1
Total		Quebec	35	54	19

The data is taken from coinatmradar.com.
Counts of Bitcoin ATMs are reported by the city/province/region.

Table 4: **Correlation of Bitcoin ATMs with Bitcoin Adoption and Bitcoin Survival**

Correlation	Bitcoin ATM Growth (2016-2017)
Bitcoin Ownership Growth (2016-2017)	-0.0507
Expected Survival	0.4113

The correlations are computed using the data from the 2016 and 2017 Bitcoin Omnibus Surveys (BTCOS) and the Coin ATM Radar. The computed correlations are based on the regional variation in Bitcoin ATM growth, Bitcoin Adoption growth and Expected Bitcoin Survival.
The Growth in Bitcoin Adoption between 2016 and 2017 was computed by weighting the sample size in 2016 to match the sample size in 2017.

Table 5: **First Stage: Estimation of Expected Survival**

VARIABLES	(1)	(2)	(3)
Age	-0.00220***		-0.00534***
	(0.000331)		(0.00186)
Female	0.00335		0.00362
	(0.00974)		(0.00977)
Income: 50k-99k	0.00606		0.00708
	(0.0115)		(0.0114)
Income: 100k+	-0.00993		-0.00768
	(0.0141)		(0.0142)
Employment: employed	0.0114		0.0168
	(0.0107)		(0.0112)
College/CEGEP/Trade school	-0.0223*		-0.0206
	(0.0130)		(0.0130)
University	-0.0269**		-0.0276**
	(0.0127)		(0.0127)
No kids	-0.0528***		-0.0563***
	(0.0124)		(0.0126)
Not married or CL	-0.00644		-0.00549
	(0.0118)		(0.0119)
HH grocery shop: Not at all	-0.0274**		-0.0277**
	(0.0110)		(0.0111)
ΔATM_AT		0.0153**	0.0157**
		(0.00680)	(0.00682)
ΔATM_PR		5.35e-05	2.75e-05
		(0.000595)	(0.000596)
ΔATM_QC		0.00169**	0.00164*
		(0.000847)	(0.000843)
ΔATM_ON		0.000304**	0.000319**
		(0.000154)	(0.000154)
Age^2		-2.64e-05***	3.36e-05*
		(3.06e-06)	(1.95e-05)
Constant	0.618***	0.492***	0.660***
	(0.0255)	(0.0157)	(0.0461)
Observations	2,623	2,623	2,623
F-stat	11.67***	17.28***	8.55***

ΔATM is the exclusion restriction measured by the growth in Bitcoin ATMs (from 2016 to 2017) at the regional level, Age^2 is the second exclusion restriction.
Column (1) is the first stage model without exclusion restrictions only.
Column (2) is the model with only exclusion restrictions ΔATM and Age^2.
Column (3) is the full first-stage model.
Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 6: **Second Stage: Estimation of Adoption Rate**

VARIABLES	(1)	(2)	(3)	(4)	(5)
ξ_{it}	4.398***	12.56***	12.47***	12.52***	12.66***
	(0.856)	(4.052)	(4.277)	(3.783)	(4.012)
A_{it}	55.89*	56.61*	70.65**	59.69*	64.49*
	(33.55)	(33.29)	(37.04)	(35.54)	(35.85)
$\xi_{it} \times A_{it}$	-28.75	-27.80	-48.26	-31.34	-37.27
	(37.68)	(37.35)	(40.93)	(44.12)	(45.93)
Age	-0.0443***	-0.0226*	-0.0221*	-0.0233	-0.0229
	(0.0117)	(0.0148)	(0.0128)	(0.0150)	(0.0150)
Female	-1.176***	-1.207***	-1.216***	-1.174***	-1.186***
	(0.224)	(0.223)	(0.237)	(0.225)	(0.226)
Income: 50k-99k	-0.205	-0.303	-0.303	-0.296	-0.112
	(0.263)	(0.263)	(0.277)	(0.252)	(0.295)
Income: 100k+	-0.369	-0.343	-0.352	-0.318	-0.323
	(0.306)	(0.307)	(0.309)	(0.315)	(0.317)
Atlantic	-0.966**	-1.363***	-1.362**	-1.318***	-1.334***
	(0.464)	(0.491)	(0.449)	(0.501)	(0.502)
Prairies	-0.684*	-0.668*	-0.385	-0.652*	-0.657*
	(0.362)	(0.360)	(0.348)	(0.352)	(0.351)
Ontario	-0.525*	-0.791**	-0.794**	-0.796**	-0.806**
	(0.288)	(0.316)	(0.366)	(0.329)	(0.329)
Quebec	-1.076**	-1.358***	-1.374***	-1.356***	-1.384***
	(0.494)	(0.506)	(0.449)	(0.490)	(0.491)
Employment: employed	0.874***	0.732**	0.750**	0.698**	0.688**
	(0.309)	(0.319)	(0.318)	(0.364)	(0.293)
College/CEGEP/Trade school	-0.0919	0.107	0.080	0.0993	0.106
	(0.321)	(0.329)	(0.327)	(0.311)	(0.330)
University	0.374	0.597**	0.582**	0.582**	0.585*
	(0.295)	(0.303)	(0.293)	(0.289)	(0.318)
Not married or CL	-0.193	-0.053	-0.0532	-0.0466	-0.0395
	(0.224)	(0.231)	(0.234)	(0.237)	(0.237)
$\hat{u_{it}}$		-8.058**	-7.521**	-8.289**	-7.953**
		(4.034)	(3.944)	(3.385)	(3.988)
$\hat{u_{it}} \times$ Prairies			-1.868		-1.060
			(1.342)		(0.943)
Constant	-3.737***	-8.382***	-8.436***	-8.215***	-8.380***
	(0.988)	(2.368)	(2.218)	(2.368)	(2.382)
Observations	2,623	2,623	2,623	2,623	2,623

ξ_{it} is Bitcoin survival beliefs variable and A_{it} is the local network variable.
$\hat{u_{it}}$ is the control function, CF, (the residual from the first stage regression).
Column (1) is the benchmark second stage model for Bitcoin adoption (without the CF).
Column (2) is the model in column (1) augmented with the CF.
Column (3) is the model in (2) augmented with $\hat{u_{it}} \times$ Prairies selected by Lasso.
Columns (4) and (5) parallel (2) and (3) but estimated with a penalized logistic based likelihood.
Bootstrapped standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 7: **Second Stage: Marginal Effects on The Probability of Adoption**

VARIABLES	(1)	(2)	(3)
ξ_{it}	0.061***	0.172***	0.169***
	(0.013)	(0.058)	(0.057)
A_{it}	0.780*	0.787*	0.958**
	(0.451)	(0.456)	(0.468)
$\xi_{it} \times A_{it}$	-0.393	-0.399	-0.655
	(0.518)	(0.511)	(0.527)
Age	-0.0006***	-0.0003*	-0.0003*
	(0.0002)	(0.0002)	(0.0002)
Female	-0.018***	-0.018***	-0.018***
	(0.005)	(0.004)	(0.004)
Income: 50k-99k	-0.003	-0.004	-0.004
	(0.003)	(0.003)	(0.004)
Income: 100k+	-0.0036	-0.004	-0.004
	(0.004)	(0.004)	(0.005)
Prairies	-0.007**	-0.007**	-0.009**
	(0.003)	(0.003)	(0.004)
Ontario	-0.007**	-0.009***	-0.0097**
	(0.004)	(0.005)	(0.0045)
Quebec	-0.012***	-0.014**	-0.014***
	(0.004)	(0.005)	(0.0045)
Atlantic	-0.009***	-0.012***	-0.011***
	(0.004)	(0.003)	(0.0036)
Employment: employed	0.01***	0.009	0.009***
	(0.004)	(0.005)	(0.0036)
College/CEGEP/Trade school	-0.001	0.005	0.001
	(0.004)	(0.004)	(0.005)
University	0.005	0.014**	0.008*
	(0.004)	(0.006)	(0.005)
Not married or CL	-0.002	-0.0006	-0.0007
	(0.003)	(0.003)	(0.003)
$\hat{u_{it}}$		-0.112**	-0.106*
		(0.056)	(0.063)
$\hat{u_{it}}\times$ Prairies			-0.025
			(0.018)
Observations	2,623	2,623	2,623

ξ_{it} is Bitcoin survival beliefs and A_{it} is the local network.
$\hat{u_{it}}$ is the control function (CF), the residual from the first stage regression.
Column (1) shows the marginal effects (ME) of the benchmark second stage model for Bitcoin adoption (without the CF) .
Column (2) shows the ME of the model in (1) augmented with the CF.
Column (3) shows the ME of the model in (2) augmented with the CF interaction selected by Lasso.
*** p<0.01, ** p<0.05, * p<0.1

Table 8: **Reasons for owning Bitcoin**

	Counts			Percentage		
Age /Reasons for owning Bitcoin	18-34	35-54	55+	18-34	35-54	55+
Payment related	6	5	0	8.11	13.51	0
Store-of-value (investment)	37	18	6	50	48.648	100
Trust/privacy related	4	3	0	5.405	8.11	0
Technology related	12	9	0	16.22	24.32	0
My friends own Bitcoin	13	1	0	17.56	2.70	0
Other	2	1	0	2.70	2.70	0
Total	74	37	6	100	100	100

Table 9: **Margins of Probability of Adoption by ξ_{it} and** A_{it} - Contrast by age group

ξ_{it}	df	χ^2	$P > \chi^2$
0.1	1	8.32***	0.0039
0.25	1	6.66***	0.0099
0.5	1	21.62***	0.000
0.75	1	4.09*	0.0431
0.9	1	1.58	0.2092
Joint	5	35.15***	0.000
A_{it}	df	χ^2	$P > \chi^2$
0.01	1	7.68***	0.0056
0.02	1	29.07***	0.000
0.03	1	36.36***	0.000
0.04	1	21.03***	0.000
0.05	1	18.24***	0.000
Joint	5	49.62***	0.000

ξ_{it} is Bitcoin survival beliefs and A_{it} is the local network.
Joint χ^2 - joint hypothesis test for all specified contrasts - chi square test.
*** p<0.01, ** p<0.05, * p<0.1

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