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Bitcoin Adoption and Beliefs in Canada

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Abstract

We develop a tractable model of Bitcoin adoption with network effects and social learning, which we then connect to unique data from the Bank of Canada's Bitcoin Omnibus Survey for the years 2017 and 2018. The model determines how the probability of Bitcoin adoption depends on (1) network effects; (2) individual learning effects; and (3) social learning effects. After accounting for the endogeneity of beliefs, we find that both network effects and individual learning effects have a positive and significant direct impact on Bitcoin adoption, whereas the role of social learning is to ameliorate the marginal effect of the network size on the likelihood of adoption. In particular, in 2017 and 2018, a one percentage point increase in the network size increased the probability of adoption by 0.45 and 0.32 percentage points, respectively. Similarly, a one percentage point increase in Bitcoin beliefs increased the probability of adoption by 0.43 and 0.72 percentage points. Our results suggest that network effects, individual learning, and social learning were important drivers of Bitcoin adoption in 2017 and 2018 in Canada.

Topics: Digital currencies and fintech; Economic models; Econometric and statistical methods
JEL codes: D83, O33

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).[1] In the last few years, there has been an explosion of so-called "cryptocurrencies," with more than 740 available. Bitcoin is the leader among them, enjoying the highest market capitalization and volume, as well as significant mainstream media attention.[2]

Bitcoin is a form of 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 et al. (2021) for a recent survey. Recent evidence indicates that Bitcoin is in an early stage of diffusion: surveys conducted across the world put estimates of Bitcoin ownership in the range of 1.5% to 5% (Stix, 2021; Henry et al., 2018; Authority, 2019; Hundtofte et al., 2019). Still, there is no consensus on whether or not this new technology will survive in the future.[3] It appears that individuals are still experimenting with Bitcoin and learning its potential benefits and costs. At the same time, cryptocurrencies are prone to exhibit network effects (Gandal and Halaburda, 2016).[4] Thus, as the size of the network (or the number of adopters) increases, presumably the incentives to adopt Bitcoin increase, as does the ability to learn about the unobserved technological quality of this innovation.

In this paper, we ask how much Bitcoin adoption is explained by network effects, individual (or exogenous) learning effects, and social (or endogenous) learning effects. 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 (Athey et al., 2016; Bolt and Van Oordt, 2020); see Halaburda et al. (2021) and references therein.

[1] Indeed, Central banks across the world are taking Bitcoin and other private digital currencies seriously, as evidenced in part by research and policy initiatives geared towards central bank digital currencies (CBDC). Deputy Governor Tim Lane of the Bank of Canada stated "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 $1,000, and it spiked to around US $19,000 on December 16, 2017. (Source: www.coindesk.com) Likewise, the number of Google searches on Bitcoin has also been steadily increasing.

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

[4] According to Gandal and Halaburda (2016): "Currencies in general provide one of the cleanest examples of network effects: The more popular a currency is, the more useful it is, and the easier it attracts new users" (p. 1).

However, because of the lack of micro-data on agents' beliefs, 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 to examine how the individual probability of adoption is affected by (1) network effects, (2) individual learning effects, and (3) social learning effects.[5] Our analysis leverages 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 ownership of Bitcoin among Canadians; it has been conducted annually since then (Henry et al., 2017, 2018, 2019a). Key to this paper is BTCOS information on both Bitcoin adoption decisions and individual beliefs about Bitcoin.

To motivate our empirical exercise, we first develop a simple model of Bitcoin adoption with network effects and social learning. In our model, there is a continuum of risk-neutral agents who, at every period, choose whether to make the costly adoption of Bitcoin. Agents have heterogeneous reservation utilities and are symmetrically uncertain about Bitcoin technology *quality*, which can be either high or low. Agents form beliefs about the quality of the technology and learn from the random arrival of "news" — namely, a public signal that is correlated with the hidden technology quality.[6] To capture social learning effects, we assume that the arrival rate of news depends not only on the quality of the technology, but also on the level of adoption: the speed of learning rises as more people adopt Bitcoin.[7] Our flexible specification also allows us to distinguish between exogenous and endogenous learning effects. Finally, to capture standard network effects, we assume that agents benefit from a large network regardless of the technology quality.

The model determines how individual incentives to adopt depend on network size, agents' beliefs, and adoption costs. Network effects are captured by the *direct* marginal impact of network size on the probability of adoption, whereas individual learning effects are captured by the *direct* marginal impact of beliefs. Social learning introduces an *indirect* force that shapes the marginal effect of network size: if learning is endogenous, then the total marginal impact of network size on the probability of adoption depends on the level of agents' beliefs. We show that these effects can be encapsulated into constants (Lemma 1), which can then be estimated using an empirical binary choice model. The main empirical challenge is the potential simultaneity between 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

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

[6] In other words, we consider an experimentation model with a two-armed bandit whose arms yield adoption rewards according to a Poisson process with unknown arrival rate; see Hörner and Skrzypacz (2017) for a recent survey.

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

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 automated teller machines (ATMs)*. This exclusion restriction comes from the supply side, which arguably is correlated with past Bitcoin adoption but not with current adoption. In the second stage, we use the residual from the first stage as a control function to correct for the potential endogeneity problem.

After accounting for the endogeneity of beliefs, we find that both network effects and individual learning effects have a significant and positive direct impact on the probability of Bitcoin adoption. Specifically, results show that a one percentage point increase in the network size increases the probability of Bitcoin adoption by 0.45 and 0.32 percentage points in 2017 and 2018, respectively. Similarly, a one percentage point increase in beliefs increases the probability of Bitcoin adoption by 0.43 and 0.72 percentage points in 2017 and 2018, respectively. As for social learning, we find that it attenuates the marginal effect of network size. In other words, the coefficient on the interaction of network size and beliefs is significant and negative. This suggests that a one percentage point increase in network size triggers adoption more when beliefs are low than when they are high. That is, individuals with high beliefs about the survival of Bitcoin are less sensitive to variations in network size.

Finally, while we do not observe adoption costs directly in the data, we consider several variables that are reasonable proxies for adoption costs such as age,[8] income, and gender.[9] These channels of potential adoption costs provide evidence that is consistent with the theoretical model. For example, age has a significant negative correlation with adoption and beliefs in both 2017 and 2018, with young people associated with both more adoption and higher beliefs about the survival of Bitcoin. These findings are consistent with the understanding that early adopters of new technology tend to be young, whereas older individuals face greater barriers to adoption.

We set up the model in §2, and discuss the data in §3 and methodology in §4. We present our empirical results in §5. Finally, we offer conclusions in §6. Mathematical proofs, figures, and tables are available in the Appendices.

2 A Model of Bitcoin Adoption and Learning

The goal of this section is to develop a stylized partial equilibrium model that allows us to structure the empirical analysis. Time is discrete and infinite: $t = 1, 2, \ldots, \infty$. There is a unit-mass continuum of *potential adopters* with types $i \in [0, 1]$. These types reflect inherent observable characteristics that influence social interactions such as adoption behaviors and beliefs. Types include

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

[9] An OECD report from 2018 (OECD, 2018) documents a persistent gap between men and women in terms of the "access, use and ownership of digital technologies" in many G20 countries. See also Shin et al. (2021).

attributes such as gender, age, education level, income level, region, etc.; in other words, types define submarkets. The model need not specify the exact list of attributes; however, in our empirical section, we focus on a specific subset of characteristics, given our available data set. For instance, type i may represent potential adopters who are male, live in Ontario, are aged 18-34, have an income between \$50,000 and \$100,000, and have post-secondary education. Thus, given type i, our model will determine the evolution of beliefs and adoption over time within that submarket.[10]

Agents with the same type i may choose whether or not to adopt Bitcoin, depending on some unobserved characteristic. Thus, we assume that agents with type i have heterogeneous *reservation utilities* $u_{it} \in \mathbb{R}$, which are independently and identically distributed across types and time, according to a cumulative distribution function (CDF) F.

Next, we fix a generic type i and introduce a tractable exponential learning process.[11] First, we assume that the *quality* of Bitcoin technology is unknown and can be either *high* (h) or *low* (ℓ). Second, we assume that agents observe the stochastic arrival of a public signal, which we henceforth refer to as *news*. The arrival of news conveys information about the unknown Bitcoin quality. Specifically, in every period, there is a chance that news arrives depending on the technology quality and the level of adoption. Following Frick and Ishii (2016), we assume that if the technology is of high quality, then news arrives with instant chance $\Phi_h(A_{it}) \equiv \varphi_h + \phi_h A_{it}$, where $A_{it} \in [0, 1]$ is the *adoption rate* in period t for type i. Yet, if the quality of the technology is low, then news arrives with probability $\Phi_\ell(A_{it}) \equiv \varphi_\ell + \phi_\ell A_{it}$, where the parameters $\varphi_h, \varphi_\ell, \phi_h, \phi_\ell \geq 0$.[12]

Notice that the arrival rate of news is influenced by the endogenous adoption rate A_{it}, which aims to reflect *social learning effects* — namely, the information generated by current adopters. Intuitively, news arrives at a faster rate when more people use Bitcoin, i.e., when A_{it} is higher. Additionally, to capture *individual learning effects*, we allow agents to learn from exogenous sources as well, such as professional critics or reviewers, and thus the arrival of news is scaled by the exogenous constants φ_h and φ_ℓ. For instance, without social learning effects (i.e., $\phi_\ell = \phi_h = 0$), learning would solely be determined by exogenous factors. Conversely, if $\varphi_\ell = \varphi_h = 0$, then all learning would be social, or endogenous. The empirical question of whether and to what extent learning is social is addressed in §4–§5. Altogether, our specification reflects that non-adopters can learn from adopters, leading both parties to hold similar beliefs.[13]

[10]It has been documented that adoption is influenced by peers or "local networks" (Rogers, 2010). We capture this by assuming that individuals with the same type i are connected to each other, and so their adoption behaviors and beliefs influence one another. This assumption also facilitates the use of observable characteristics in the data to construct local networks (see §3.2).

[11]See Hörner and Skrzypacz (2017) for a recent survey of papers that use this learning technology.

[12]Technically, we consider an experimentation model with a two-armed bandit whose arms yield rewards according to a Poisson process with an unknown arrival rate; see, for example, Keller and Rady (2015). However, unlike that literature, in this paper, experimentation takes place in a *large* market, as in Bergemann and Välimäki (1997).

[13]Having a more general learning model in which beliefs are private and different across adopters and non-adopters is a natural next step. However, given the scope of our empirical exercise, such extension is not needed, as seen in §4.

We focus on *conclusive* news,[14] as is widely used in the exponential learning literature (Hörner and Skrzypacz, 2017). This means that the arrival of news provides conclusive evidence about the quality of the technology. This is the case because the arrival of news brings along an observable adoption *reward* $r_\ell \geq 0$ when the technology quality is low and higher rewards $r_h \geq r_\ell$ when it is high. Intuitively, if the quality of the technology is found to be high, then the returns to adopting Bitcoin should increase, as the market would presumably react positively to such information. By contrast, if evidence suggests that Bitcoin technology quality is low, the market might react negatively to this information leading to lower adoption returns. In any case, conditional on observing news, agents can correctly infer the quality of the technology by observing the arrival of adoption rewards. However, in the absence of news, agents remain uncertain about the quality of the technology and their adoption decisions will non-trivially be influenced by their beliefs about Bitcoin quality, which evolve over time, as we explain next.

Having described the learning process, we now turn to characterizing how agents' beliefs evolve over time. At the initial period, agents hold a prior belief probability $\bar{\xi}_{i1} \in (0, 1)$ that the quality of Bitcoin is high.[15] 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, news arrives and agents perfectly learn whether the quality of the technology is either high or low. In the other, no news has arrived yet and agents remain uncertain about the technology quality. Let us call ξ_{it+1} the *no-news posterior* probability that Bitcoin quality is high. Then, by Bayes' rule:

$$\xi_{it+1} = \frac{\xi_{it}(1 - \Phi_h(A_{it}))}{\xi_{it}(1 - \Phi_h(A_{it})) + (1 - \xi_{it})(1 - \Phi_\ell(A_{it}))}. \tag{1}$$

The denominator in (1) is the probability of observing no news between periods t and $t + 1$, whereas the numerator reflects the probability that the technology quality is high and that no news is observed. Appendix A.2 shows that, *in the absence of news, beliefs weakly increase over time if and only if* $\Phi_\ell(A_{it}) \geq \Phi_h(A_{it})$. This means that if news is more likely to arrive when Bitcoin technology quality is low (i.e., $\Phi_\ell(A_{it}) \geq \Phi_h(A_{it})$), then observing no news is "good news," meaning that agents become more optimistic that Bitcoin's quality is high as time goes by.[16]

[14] For an exception, see Keller and Rady (2010).

[15] Beliefs may be influenced by other unmodeled factors (e.g., prices). Crucially, our data allow us to directly measure beliefs, and so it is conceivable that these beliefs already contain other relevant information (e.g., pricing information) for decision making. In §5.1, we consider the role of financial investment affecting adoption through agents' beliefs.

[16] For instance, suppose that $\varphi_h = \phi_h = 0$. Then, if news arrives that leads to conclusive evidence of a bad technology, observing no news reflects "good news" in the sense of beliefs ξ_{it} drifting upwards. Conversely, if $\varphi_\ell = \phi_\ell = 0$, then a single arrival of news provides conclusive evidence that the technology is good, and so observing no news indicates "bad news" — a signal that the technology quality is low. Frick and Ishii (2016) examine an adoption model in which agents learn from exogenous and endogenous 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

In every period, each potential adopter chooses whether or not to adopt Bitcoin. As discussed in Halaburda et al. (2021), cryptocurrencies exhibit *network effects*. Thus, we assume that, regardless of the quality of the technology, the benefit of using Bitcoin is increasing in how many other individuals use Bitcoin and given by $B(A_{it}) \geq 0$ with $B' > 0$.[17] Finally, the *adoption cost* of Bitcoin is given by $c_i \geq 0$. Altogether, given adoption costs c_i, beliefs ξ_{it}, and adoption rate A_{it}, a potential adopter with reservation utility u_{it} adopts Bitcoin in period t if and only if the *expected net adoption utility* $\mathcal{U}(A_{it}, \xi_{it}, c_i)$ is at least u_{it}, where:

$$\mathcal{U}(A_{it}, \xi_{it}, c_i) \equiv B(A_{it}) + \Phi_h(A_{it})\xi_{it}r_h + \Phi_\ell(A_{it})(1 - \xi_{it})r_\ell - c_i. \tag{2}$$

Clearly, an increase in adoption costs c_i disincentivizes adoption, i.e., $\partial\mathcal{U}(A_{it}, \xi_{it}, c_i)/\partial c_i < 0$. Likewise, an increase in the adoption rate A_{it} unambiguously raises the incentives to adopt Bitcoin:

$$\frac{\partial\mathcal{U}(A_{it}, \xi_{it}, c_i)}{\partial A_{it}} = B'(A_{it}) + \phi_h\xi_{it}r_h + \phi_\ell(1 - \xi_{it})r_\ell > 0.$$

Intuitively, as the adoption of Bitcoin rises, agents benefit not only from greater network effects, but also from the higher likelihood of observing news about the quality of Bitcoin.

The effect of beliefs on adoption is more subtle and, in principle, can go either way. Indeed,

$$\frac{\partial\mathcal{U}(A_{it}, \xi_{it}, c_i)}{\partial \xi_{it}} = \Phi_h(A_{it})r_h - \Phi_\ell(A_{it})r_\ell \gtrless 0.$$

Although $r_h \geq r_\ell$, if news arrives much faster when Bitcoin quality is low than when it is high, then an increase in beliefs ξ_{it} reduces the net chance of obtaining an adoption reward in period t.

Finally, the cross-partial derivative captures social learning effects. Indeed, social learning implies that the marginal effect of network size A_{it} on the incentives to adopt depends on the level of beliefs ξ_{it}:

$$\frac{\partial^2\mathcal{U}(A_{it}, \xi_{it}, c_i)}{\partial A_{it}\partial\xi_{it}} = \phi_h r_h - \phi_\ell r_\ell \gtrless 0.$$

In other words, an increase in beliefs ξ_{it} may raise or lower the marginal effect of network size A_{it} on the incentives to adopt. In particular, the effect of beliefs on $\partial\mathcal{U}(A_{it}, \xi_{it}, c_i)/\partial A_{it}$ depends crucially on the social learning constants ϕ_ℓ and ϕ_h. For instance, with no social learning, $\phi_\ell = \phi_h = 0$, then beliefs ξ_{it} have no impact on $\partial\mathcal{U}(A_{it}, \xi_{it}, c_i)/\partial A_{it}$. However, if $\phi_\ell r_\ell > \phi_h r_h$, then the marginal effect of A_{it} on the incentives to adopt $\mathcal{U}$ decreases as beliefs ξ_{it} rise. This would mean

the nature of learning — namely, whether it is via "good" or "bad" news — affects adoption patterns.

[17] When network effects are positive, the value of a product rises with the number of users. Evidence from Halaburda et al. (2021) suggests that Bitcoin seems to have dominated other cryptocurrencies, despite its shortcomings. Although there may be alternative higher quality cryptocurrencies, strong network effects have led Bitcoin to become a consistent leader since early 2014.

that an increase in A_{it} raises the arrival of news at a lower rate when beliefs are higher, reflecting that network effects would be stronger when agents have lower beliefs about Bitcoin (i.e., low ξ_{it}). The next result will serve as a stepping stone in our empirical exercise.

Lemma 1. *Suppose that $B(A_{it}) \equiv b_0 + b_1 A_{it}$. Then, there exist constants $(\beta_0, \beta_1, \beta_2, \beta_3) \in \mathbb{R}^4$ such that:*

$$\mathcal{U}(A_{i,t}, \xi_{i,t}, c_i) = \beta_0 + \beta_1 A_{it} + \beta_2 \xi_{it} + \beta_3 A_{it} \xi_{it} - c_i. \tag{3}$$

As previously discussed, β_3 captures social learning effects, whereas β_1 and β_2 capture the respective direct effects of network size and beliefs. Therefore, equation (3) captures three economic forces driving individual adoption: (1) network effects (β_1); (2) individual learning effects (β_2); and (3) social learning effects (β_3). Indeed, if social learning is relevant (i.e., $\beta_3 \neq 0$), a one unit increment in the network size A_t or in beliefs ξ_t has both a *direct and indirect effect* on the incentives to adopt:

$$\frac{\partial \mathcal{U}}{\partial A_{it}} = \underbrace{\beta_1}_{\text{direct effect}} + \underbrace{\beta_3 \xi_{it}}_{\text{indirect effect}} \quad \text{and} \quad \frac{\partial \mathcal{U}}{\partial \xi_{it}} = \underbrace{\beta_2}_{\text{direct effect}} + \underbrace{\beta_3 A_{it}.}_{\text{indirect effect}} \tag{4}$$

Intuitively, an increase in network size not only raises the benefits of adopting Bitcoin, but it also speeds up learning, thereby influencing adoption. The magnitude of this nonlinear indirect effect is regulated by β_3. If individuals did not learn from others or learning was purely exogenous (i.e., $\beta_3 = 0$), the indirect effects would vanish. In such a case, β_1 and β_2 would only reflect total network and individual 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.

Let us call $a_{it} \in \{0, 1\}$ the optimal individual adoption decision in period t, with the interpretation that $a_{i,t} = 1$ means adopt Bitcoin. Then, given Lemma 1, the conditional probability of Bitcoin adoption is given by the chance that the event $\{u_{it} \leq \mathcal{U}(A_{i,t}, \xi_{i,t}, c_i)\}$ occurs:

$$\mathbf{P}(a_{it} = 1 | A_{it}, \xi_{it}, c_i) = F(\beta_0 + \beta_1 A_{it} + \beta_2 \xi_{it} + \beta_3 A_{it} \xi_{it} - c_i). \tag{5}$$

To finalize 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 number of individuals who have not yet adopted, $1 - A_{it}$. Precisely, starting with an initial mass of adopters $A_{i1} = \bar{A}_{i1} \in (0, 1)$, the evolution of adoption obeys:

$$A_{it+1} = A_{it} + \mathbf{P}(a_{it} = 1 | A_{it}, \xi_{it}, c_i)(1 - A_{it}). \tag{6}$$

The model is solved by a joint adoption-belief process $(A_{it}, \xi_{it})_{t=1}^{\infty}$ obeying (1) and (6), given (3), and initial conditions $A_{i1} = \bar{A}_{i1}$ and $\xi_{i1} = \bar{\xi}_{i1}$.[18]

Proposition 1. *(i) There exists a unique solution $(A_{it}, \xi_{it})_{t=1}^{\infty}$ to the initial value problem; this solution is increasing over time. (ii) If adoption costs fall, then the adoption path A_t and beliefs ξ_t strictly increase for all time $t > 1$.*

Let us end this section with a few remarks. First, Appendix A.2 proves the existence and uniqueness of an equilibrium. To see this, notice that conditional on observing no news, only one path exists: Given initial beliefs $\bar{\xi}_{i1}$ and adoption $\bar{A}_{i1}$, there is only a single solution for belief ξ_{i2} and adoption A_{i2}, given (1) and (6), respectively. These, in turn, determine beliefs and adoption ξ_{i3} and A_{i3} by the same logic, and so on. The top panels of Figure 1 depict how the individual probability of adoption may co-move with beliefs and network size, respectively.

Second, Appendix A.3 shows that an increase in adoption costs lowers adoption and beliefs at all non-trivial time periods. As seen in the bottom panels of Figure 1, the individual probability of adoption (3) falls as adoption costs rise. Intuitively, when adoption costs fall, individuals are more likely to adopt at any non-trivial belief ξ_{it}, leading to more aggregate adoption A_{it}. This could lead to higher posterior beliefs if not observing news provides a stronger signal that the technology quality is high. In turn, this effect can trigger more individual adoption, and so on.

Finally, as seen in the top panels of Figure 1, the model is able to generate positive co-movements between the individual probability of adoption (5) and beliefs ξ_{it}, and also between the individual probability of adoption (5) and network size A_{it}. The next section estimates equation (5) and shows that these patterns hold in the data.

– insert Figure 1 here –

3 The Bitcoin Omnibus Survey Data

3.1 Data Overview

We use data from the Bank of Canada's BTCOS. First conducted in late 2016, the original purpose of the BTCOS was to serve as a monitoring tool, obtaining basic measurements of Bitcoin awareness and ownership among the Canadian population. As the survey has evolved over time, its scope has broadened based on a demand for more detailed information about the motivation of Bitcoin owners and their usage behavior.

[18] Notice that along the solution path, agents' adoption decisions are optimal at any instant t and determined by the state variables (A_{it}, ξ_{it}). Thus, our solution notion coincides with a Markovian equilibrium.

Respondents to the BTCOS are recruited via an online panel managed by the research firm Ipsos, and complete the survey in an online format. The core components of the survey are as follows: awareness of Bitcoin; ownership/past ownership of Bitcoin; amount of Bitcoin holdings; and reasons for ownership/non-ownership. Our analysis relies mostly on the 2017 and 2018 BTCOS results 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; and cash holdings.

In 2017, a total of 2,623 Canadians completed the BTCOS, of which 117 self-identified as Bitcoin owners. In 2018, the BTCOS was answered by 1,987 Canadians, of which 99 reported that they owned Bitcoin. In addition to content questions, respondents are also asked to provide demographic information, as seen in Table 1.

– insert Table 1 here –

Most of these questions require the respondent's 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 some data are missing. 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 across a variety of dimensions (see Henry et al. (2019b) for details).

3.2 Bitcoin Adoption, Network Size, Beliefs, and Adoption Costs

A Bitcoin adopter is identified by looking at each respondent who indicates that they are aware of Bitcoin and 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 to be non-adopters.[19]

Table 2 shows the adoption rates of Bitcoin in 2016, 2017, and 2018, 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 3.2% of those aged 35-54 and only 0.5% among those over age 55. These numbers are similar in 2018: there are 10.5% Bitcoin owners in the age category 18-34, 4.9% in the age category 35-54, and 1.7% over age 55. The results, however, provide evidence of a marginal

[19] 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 and to 89% in 2018.

shift in age towards older individuals. In terms of gender, adoption is higher among males versus females (6.6% versus 2.1% in 2017 and 6.7% versus 3.7% in 2018). Regional variation is less stark; nonetheless, adoption is observed to be higher in British Columbia and Quebec in 2017 and lowest in the Atlantic provinces, while in 2018 we see an increase in adoption in Ontario.

– insert Table 2 here –

We use some of these characteristics to construct a network size measure, A_{it}, in order to estimate the effects of network size on the individual probability of Bitcoin adoption. Given our data limitations, we consider a two-step approach. First, we use the answer "My friends own Bitcoin" from the question "Please tell us your main reason for owning Bitcoin," and then we estimate the probability of having friends owning Bitcoin on the observed demographic characteristics of the respondents in the previous year (i.e., we use 2016 and 2017 BTCOS for the 2017 and 2018 analysis, respectively). To choose the relevant demographic variables for these probabilities, we consider a standard model selection using the Lasso procedure. Second, we use the estimated betas from the previous step to impute the network size variable using a logistic function of the form $e^{\hat{\beta}_{t-1}\tilde{X}_{it}}/(1+e^{\hat{\beta}_{t-1}\tilde{X}_{it}})$, where $\tilde{X}_{it}$ denotes the relevant demographics selected by Lasso. For robustness, we report in Online Appendix D an alternative non-parametric approach to constructing the network size variable, in which we count the number of adopters for each joint cell defined by the demographic characteristics selected by the Lasso procedure and then weight these counts by the appropriate cell-specific populations. Both approaches yield similar qualitative results.

Next, as a proxy for beliefs, ξ_{it}, respondents who are aware of Bitcoin and answer the following 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_{it}, the answer to this question is divided by 100 and interpreted as a probability. The mean is 0.45 and 0.41 in 2017 and 2018, respectively. The median is 0.5 in 2017 and 0.42 in 2018.

Finally, while not observed directly, we use gender, income per year, and age to proxy for adoption costs c_i. The categories for these variables as considered in our modeling can be found in Table 1.

4 Empirical Strategy and Econometric Methodology

4.1 Empirical Specification

The theoretical model in §2 (see equation (5)) hinges on testing whether and to what extent individual Bitcoin adoption is influenced by network size A_{it}, beliefs ξ_{it}, and adoption costs c_i. This allows us to determine how Bitcoin adoption decisions are affected by (1) network effects, (2) individual learning effects, and (3) social learning effects. Because individual adoption a_{it} is a binary variable, equation (5) suggests the following empirical specification:

$$a_{it} = F(\beta_0 + \beta_1 A_{it} + \beta_2 \xi_{it} + \beta_3 A_{it}\xi_{it} + \beta_c X_i) + \epsilon_{it}, \tag{7}$$

where a_{it} is a dummy for Bitcoin adoption of individual i at the time of the evaluation, ϵ_{it} is the usual error term, and F denotes a logistic cumulative distribution function. The control variables X_i include demographic characteristics about individual i, namely age, gender, income, employment, education, number of children in the household, marital status, household grocery shopping responsibilities, and regional dummies.[20]

As discussed in §2, the interaction term $A_{it}\xi_{it}$ captures social learning effects. In particular, the parameters β_1 and β_2 capture direct network effects and exogenous learning effects, respectively, whereas the coefficient β_3 reflects social, or endogenous, learning effects. Our empirical specification tests the importance and direction of these effects for individual Bitcoin adoption for both 2017 and 2018 BTCOS data.

4.2 Identification

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

We propose to break this simultaneity using a *control function (CF)* that uses a two-stage modeling approach. This approach has several technical advantages compared to other methods, given the nonlinear nature of our empirical model (Wooldridge, 2011). First, other two-stage approaches that mirror two-stage least squares (2SLS) are not suitable for nonlinear models. Second, the CF approach allows for a simpler test of endogeneity via a Wald test.

[20] The regional dummies are introduced in the model as controls. However, to check if beliefs are different across different regions, we interact beliefs with the regional dummies. While this interaction does not affect the parameters of the benchmark model, it emphasizes the difference in beliefs in Quebec and the Atlantic provinces, where beliefs about Bitcoin survival are lower than the benchmark province (British Columbia).

In the first stage, we model the beliefs as a function of observed demographic characteristics and an additional exclusion restriction: *the growth in Bitcoin ATMs)*. For the growth in Bitcoin ATMs, we assume that current ATM density is based on past adoption decisions, requiring ATM density to be orthogonal to current adoption decisions. To capture the dynamics in ATM density, we consider not only current ATM density, but also past ATM density. Indeed, the exclusion restriction is determined by the change in ATM density between time t and $t-1$.[21] Table 3 presents the regional growth in Bitcoin ATMs over 2016-2017 and 2017-2018. We collected data on Bitcoin ATMs in Canada for 2016-2018 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 regional level, as seen in Table 3.

Notice that there is no uniform growth of Bitcoin ATMs over different cities in Canada; in some cities we see ATM closures (e.g., Surrey and Whistler in British Columbia) or no change (e.g., Maple Ridge in British Columbia; North Bay and Sault Ste. Marie in Ontario; Red Deer in Alberta; and Gatineau in Quebec). These observations suggest that, while adoption increased substantially (in fact, doubled) in Canada between 2016 and 2017 (see Henry et al. (2017)), the regional change in Bitcoin ATMs does not follow a similar path — at least from a contemporaneous perspective. From 2017 to 2018, we observe a substantial growth in Bitcoin ATMs, even though Bitcoin adoption marginally increased from 2017 to 2018.

– insert Table 3 here –

Observe that this 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 affect ATM 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,[22] presumably leading suppliers to carefully choose their location based on previously observed levels of adoption. Thus, Bitcoin ATM network size does not reflect current adoption, but rather previous levels of adoption.[23]

[21] 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.

[22] These costs involve, for example, 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/`.

[23] 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 ATMs would not capture current Bitcoin adoption, but past adoption levels.

In contrast, 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.[24]

To formally check if the growth in ATMs is a valid exclusion restriction, we compute the regional correlation between the growth in ATMs and growth in Bitcoin adoption and beliefs. The results are presented in 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 –

Altogether, we use this exclusion restriction as an identification mechanism to uncover the true effect of beliefs on individual adoption decisions.[25] Our proposed identification mechanism is based on a two-stage CF approach (Heckman and Robb, 1985), given the non-linear probabilistic nature of our model. In the first stage, Bitcoin belief ξ_{it} is projected on the exclusion restriction and a set of observed characteristics at an individual and a regional level:

$$\xi_{it} = \alpha_0 + \alpha_1 \Delta ATM_{jt} + \alpha_2 Age^2 + \alpha_c X_i + u_{it}, \tag{8}$$

where ΔATM_{jt} is the growth in Bitcoin ATMs in region j at time t, and u_{it} is an error term. Also, as seen in (8), we follow Escanciano et al. (2016) and exploit non-linearities in age — featured in our data — to improve the identification.[26]

The residual from the first stage is subsequently used in the second stage as a CF. That is, the benchmark model in equation (7) is augmented with CF_{it} as follows:

$$a_{it} = F(\beta_0 + \beta_1 A_{it} + \beta_2 \xi_{it} + \beta_3 A_{it}\xi_{it} + \beta_c X_i + \beta_r R_j + \beta_{CF} CF_{it}) + \epsilon_{it}, \tag{9}$$

where CF_{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.

[24] 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 are mostly young non-educated males with low financial literacy scores, making the use of Bitcoin ATMs appealing given their simplicity for converting cash to Bitcoin.

[25] As a robustness check, we examine possible cross-type learning from submarkets other than one's own, capturing that individuals may learn not only from their own network, but also from others. To this end, we aggregate the information on the network size of all other groups but i. We find that this aggregation does not provide enough variation to change the impact on our measures of interest, justifying our empirical approach. Finally, since our data are at the cross-sectional level, lag instruments are harder to generate and motivate in this context.

[26] Escanciano et al. (2016) show that changes in functional forms can be used as identification mechanisms. A similar result appears in Dong (2010); see Section 3.7 in Lewbel (2019) for a survey.

Also, to account for the low adoption rate at the evaluation time (about 5%), for robustness checks we estimate a penalized logistic-based likelihood (Heinze and Schemper, 2002).

5 Results

The discussion of our results follows the stages of identification for BTCOS data in 2017 and 2018, respectively. We start presenting the first stage results, estimated via ordinary least squares (OLS), which examines 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 effects, individual learning effects, social learning effects, and adoption costs.

5.1 Modeling Bitcoin Beliefs

Table 5 shows the results of the first stage analysis. The first and second columns display the results for the 2017 and 2018 data, respectively.

– insert Table 5 here –

In the third column of Table 5, we exploit additional information provided only in 2018 data and verify that our insights hold even if more data are considered. Specifically, we consider an additional exclusion restriction, which is based on respondents' expectations of future Bitcoin price and the actual price of Bitcoin at the time of the survey. This survey question showed respondents the current price of Bitcoin and asked what they expected the price to be in one month. This information allows us to measure the relative difference of the expected and realized Bitcoin price, or the *expected financial return* ER_{it} of holding Bitcoin:

$$ER_{it} = \frac{EP_{it+30} - P_{it}}{P_{it}}, \tag{10}$$

where t represents the day the respondent completed the survey; EP_{it+30} is the projected Bitcoin price in a month; and P_{it} is the spot price of Bitcoin. We assume that our measured beliefs about Bitcoin survival, ξ_{it}, embeds this financial incentive/speculation effect; namely, we assume ER_{it} affects adoption via its effect on beliefs about Bitcoin survival. That is, ER_{it} captures the financial investment incentives that influence individuals' beliefs about Bitcoin survival (see Footnote 15).[27]

[27]The expected return variable is not correlated with Bitcoin adoption ($\rho = 0.0319$) and also is not correlated with the regional growth of Bitcoin ATMs ($\rho = 0.032$).

As seen in the third column of Table 5, this new expected return variable is a significant source of identification. Specifically, beliefs about future Bitcoin prices and beliefs about Bitcoin survival positively and significantly co-move. Table 5 also shows the relevance of the regional growth of ATMs, especially in 2018. The first stage results pass the identification requirement for the second stage. The respective F-stat for the 2017 and 2018 data are 18.83 and 18.7, and 16.45 for the model with the expected return variable.

The results of the individual characteristics are very similar across the two years' specifications. In particular, from the demographic characteristics, age is significantly and negatively correlated with future beliefs about Bitcoin survival, meaning that older respondents think that Bitcoin is less likely to survive. Interestingly, those without children or who are not responsible for grocery shopping are more pessimistic about Bitcoin's survival than those with children or who actively do 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).[28] Moreover, the gender effect becomes significant in 2018, with females being less optimistic about Bitcoin survival. Following these estimations, the residuals are retained to be further used as a control function in the second stage, which defines our main equation of interest.

5.2 Bitcoin Adoption

As discussed in §4.2, modeling the probability of Bitcoin adoption requires addressing an endogeneity problem related to a key variable of interest, namely beliefs about Bitcoin survival. Thus, we use the CF as a bias correction term in the second stage. As argued in §4.2, the CF approach allows for a simple endogeneity test via a Wald test. In particular, we reject the null test of exogeneity as we obtain a p-value of 0 for the Wald test. This validates our endogeneity correction via the CF.

Table 6 presents the Logit results without the CF (columns (1) and (2) for 2017 and 2018, respectively) and with the CF (columns (3) and (4) for 2017 and 2018, respectively). Column (5) shows the results for the model with the expected return variable in 2018.[29]

– insert Table 6 here –

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

[29] To account for low adoption rates, for robustness checks we also estimate a penalized logistic-based likelihood (Heinze and Schemper, 2002). The results do not significantly differ from the results obtained with our logistic specification.

Overall, our results indicate the important role the CF has in correcting the simultaneity bias associated with the existing feedback between Bitcoin adoption and beliefs about its survival. In particular, for both years (2017 and 2018), the CF is statistically significant and corrects the effect of beliefs while marginally affecting the impact on the network and interaction term.

Beliefs. 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. Specifically, the results suggest that a one percentage point increase in Bitcoin beliefs increases the chance of Bitcoin adoption by 0.43 and 0.72 percentage points in 2017 and 2018, respectively. As discussed in §2, this coefficient captures exogenous learning effects, or the direct effect of beliefs on the probability of Bitcoin adoption. Our results indicate that high beliefs about Bitcoin survival directly imply a greater likelihood of being a Bitcoin adopter. This effect is *amplified* after we control for endogeneity — the magnitude of the marginal effect is roughly three times greater (compare columns (1) and (2) to (3) and (4), resp., in Table 6). When the CF is introduced, the strong correction of beliefs indicates that early Bitcoin adopters already have high beliefs about Bitcoin's future survival.

Network size. In terms of network effects, the relationship is positive and significant at the 10% level in 2017 and becomes significant at 1% in 2018. In particular, a one percentage point increase in size of the network raises the likelihood of Bitcoin adoption by 0.45 to 0.32 percentage points in 2017 and 2018, respectively. This captures the direct effect of network size on adoption probability (see §2). Thus, we find that a large network size directly increases the probability of adopting Bitcoin, indicating that high Bitcoin adoption among peers is associated with a high propensity to adopt.

Social learning. Table 6 shows that the coefficient of the interaction term between the size of the network and beliefs is significant and negative. As argued in §2, the direction and magnitude of this coefficient capture indirect effects driven by social learning. Specifically, our findings indicate that a marginal increase in network size raises the probability of Bitcoin adoption more when beliefs are low than when they are high. In other words, individuals with high beliefs appear to be less sensitive to the number of peers using Bitcoin.

Adoption costs. We also examine the effects of several variables that may proxy for adoption costs: age, income, and gender. Intuitively, older individuals face higher costs to learn new technologies. Similarly, low income increases the barriers to adopting Bitcoin by making technology adoption relatively more expensive. Finally, there is a documented gender gap in terms of access to and use of digital technologies that should also apply to Bitcoin. Our analysis shows that *age* is negative and statistically significant in 2017 and also in 2018, provided the expected return variable is considered.[30] *Income* is positive and statistically significant in 2018 but not in 2017. The change in results may be explained by the change in the composition of Bitcoin owners in 2018, who come from relatively higher income categories. *Gender* is the most persistent effect in terms of its statistical significance across all years and specifications of the model; being female is indeed associated with lower adoption of Bitcoin.

In terms of other individual characteristics, we find that the likelihood of Bitcoin adoption declines with living in regions outside of British Columbia. Conversely, the probability of adoption increases with employment and education.

Predictive margins. The predictive margins of our estimation results can be used to empirically examine Bitcoin adoption as a function of beliefs and network size.[31] Figure 2 shows that the probability of Bitcoin adoption positively co-moves with beliefs. Moreover, the data suggest that the speed of adoption is higher for low beliefs, and the effect of beliefs on Bitcoin adoption is stronger in 2018 compared to 2017. In Figure 3, we decompose the predicted margins of Bitcoin adoption as a function of beliefs by age categories (18-35, 35-55, >55). Notice that, in 2017 and 2018, the adoption curve is S-shaped across all age groups. Also, in 2017, adoption is most pronounced for the age group 18-35, followed by the 35-55 age group, and lastly by the 55 plus age group. In 2018, we did not find a significant difference across age groups.

– insert Figure 2 here –

– insert Figure 3 here –

Figure 4 depicts the predictive margins of Bitcoin adoption by network size, showing a positive co-movement between these variables. In 2018, however, we see an increase in network size compared to 2017, which is a factor that raises Bitcoin adoption in 2018. As seen in Table 2, Bitcoin adoption is 4.3% in 2017 and 5.2% in 2018.

– insert Figure 4 here –

Figure 5 shows the predicted margins of Bitcoin adoption as a function of network size by age categories, assuming network size increases until full adoption is reached. In other words, it shows

[30] In general, adding the expected return variable in 2018 makes the results of 2018 closer to those of 2017 in terms of beliefs and network size.

[31] Because we use cross-sectional data, we can distinguish the margins of our estimation in three categories. The ones related to beliefs can be seen as long-run effects, since they are based on the expected level of beliefs about Bitcoin survival in the next 15 years. For the network size we can distinguish between two effects: ones based on current levels of network size (short-run effects), and ones based on extended support of network size (long-run effects).

counterfactual margins. We observe stronger network effects for younger individuals (18-35), followed by middle aged (35-55) and lastly by the 55+ age group. As previously mentioned, age differences are not significant in 2018.[32] Contrast tests by age group for the margins of the probability of adoption by beliefs and network size are provided in Table 7. The results emphasize the significance of the differences observed in the predicted margins figures.

– insert Figure 5 here –

Table 8 complements our previous discussion. It shows that network effects are dominant for the younger cohort:[33] about 17.2% of the younger respondents stated this as the main reason for owning Bitcoin, whereas this number drops to below 3% for older age groups. In 2018, there is a shift of the network effects towards the older age groups (9% for older respondents versus 6% for younger respondents).[34]

– insert Table 8 here –

6 Concluding Remarks

In this paper, we examine how the individual probability of Bitcoin adoption is influenced by network effects, individual learning effects, and social learning effects. To test and quantify the behavioral determinants driving Bitcoin adoption, we develop a tractable Bitcoin adoption model that we connect with detailed and novel micro-level data from the 2017 and 2018 BTCOS. 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.

We find that an increase in network size or in beliefs has a significant and positive direct impact on the probability of adoption. Specifically, our results show that a one percentage point increase in network size increases the probability of Bitcoin adoption by 0.45 and 0.32 percentage points

[32]The age effects are not significant unless we include the expected return variable in the first stage. In this case, we see that the age effects in 2018 are significant but smaller in magnitude than in 2017.

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

[34]Another plausible reason why young individuals are inclined to adopt Bitcoin is that they may have some constraints to opening a formal financial account, as these 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 issues, payment-related issues, and trust/privacy issues (see Table 8 for further details).

in 2017 and 2018, respectively. Likewise, a one percentage point increase in beliefs raises the probability of Bitcoin adoption by 0.43 and 0.72 percentage points in 2017 and 2018, respectively. We also provide evidence of social learning effects, which manifest as a negative and significant interaction term between network size and beliefs. That is, we find that the effect of network size on the probability of adoption is greater when beliefs about the survival of Bitcoin are low. Finally, we find empirical evidence, using several reasonable proxy variables, that variations in adoption costs lead to effects on beliefs and adoption, as predicted by the model.

A Appendix: Technical Details of Proofs

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

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

$$\begin{aligned}
\mathbb{P}(a_{i,t}=1|\xi_t, A_t) &= \mathbb{P}(\{u_{it} \le \mathcal{U}(A_{it}, \xi_{it}, c_i)\}\,|\xi_{it}, A_{it}) \\
&= F(\mathcal{U}(A_{it}, \xi_{it}, c_i)) \\
&= F(b_0 + b_1 A_{i,t} + \Phi_h(A_{i,t})\xi_{i,t} r_h + \Phi_\ell(A_{i,t})(1-\xi_{i,t}) r_\ell - c_i) \\
&= F((b_0 + \varphi_\ell r_\ell) + (b_1 + \phi_\ell r_\ell) A_{it} + (\varphi_h r_h - \varphi_\ell r_\ell)\xi_{it} + (\phi_h r_h - \phi_\ell r_\ell) A_{it}\xi_{it} - c_i) \\
&= F(\beta_0 + \beta_1 A_t + \beta_2 \xi_t + \beta_3 A_t \xi_t - c_i),
\end{aligned}$$

where $\beta_0 = b_0 + \varphi_\ell r_\ell$, $\beta_1 = b_1 + \phi_\ell r_\ell$, $\beta_2 = \varphi_h r_h - \varphi_\ell r_\ell$, and $\beta_3 = \phi_h r_h - \phi_\ell r_\ell$. □

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

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

BELIEFS. Consider two periods, namely, t and $t+dt$. Then, applying Bayes' rule (1), given A_{it}, yields a posterior belief:

$$\xi_{it+dt} = \frac{\xi_{it}(1-\Phi_h(A_{it})dt)}{\xi_{it}(1-\Phi_h(A_{it})dt) + (1-\xi_{it})(1-\Phi_\ell(A_{it})dt)}.$$

Subtracting ξ_{it} and dividing both sides by dt we obtain, after some algebra, the following expression:

$$\frac{\xi_{it+dt}-\xi_{it}}{dt} = \frac{\xi_{it}(1-\xi_t)(\Phi_\ell(A_{it}) - \Phi_h(A_{it}))}{1-\Phi_\ell(A_{it})dt + \xi_{it}(\Phi_\ell(A_{it}) - \Phi_h(A_{it}))dt}.$$

Taking $dt \to 0$ yields the following law of motion:

$$\dot{\xi}_{it} = \xi_{it}(1-\xi_{it})(\Phi_\ell(A_{it}) - \Phi_h(A_{it})).$$

Notice that beliefs increase over time, i.e., $\dot{\xi}_{it} \geq 0$, if and only if $\Phi_\ell(A_{it}) \geq \Phi_h(A_{it})$.

ADOPTION. Consider the adoption process (6) and two periods t and $t + dt$. Then,

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

Next, subtract A_{it}, then divide both sides by dt, and finally take $dt \to 0$. Then, given equation (2):

$$\dot{A}_{it} = F(\mathcal{U}(A_{i,t}, \xi_{i,t}, c_i))(1 - A_{it}).$$

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

$$\mathcal{X}(x) = [F(\mathcal{U}(A, \xi, c))(1 - A), \xi(1 - \xi)(\Phi_\ell(A) - \Phi_h(A))] \in \mathbf{R}^2_+.$$

EXISTENCE AND UNIQUENESS. We show that, given $c = c_i$, the the initial value problem (IVP) below has a unique solution.

$$\dot{x}_{it} = \mathcal{X}(x_{it}), \quad x_{i1} = (\bar{A}_{i1}, \bar{\xi}_{i1}) \in \mathbf{R}^2_+$$

To this end, 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 $t \in [0, T] \mapsto x^*_{it}$ of the IVP, for some $T > 0$. □

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

We now examine the effects of an increase in adoption costs c_i. Consider c^ℓ_i and c^h_i with $c^h_i > c^\ell_i$. Likewise, consider $x^\ell_{it} \equiv (A^\ell_{it}, \xi^\ell_{it})$ and $x^h_{it} \equiv (A^h_{it}, \xi^h_{it})$, solving

$$\dot{x}^\ell_{it} = \mathcal{X}^\ell(x^\ell_{it}) \quad \text{and} \quad \dot{x}^h_{it} = \mathcal{X}^h(x^h_{it}), \quad x^\ell_{i1} = x^h_{i1} = (\bar{A}_{i1}, \bar{\xi}_{i1}),$$

where $\mathcal{X}^\ell(\cdot)$ and $\mathcal{X}^h(\cdot)$ are given by:

$$\begin{aligned}
\mathcal{X}^\ell(A, \xi) &\equiv [F(\mathcal{U}(A, \xi, c^\ell_i))(1 - A), \xi(1 - \xi)(\Phi_\ell(A) - \Phi_h(A))]; \\
\mathcal{X}^h(A, \xi) &\equiv [F(\mathcal{U}(A, \xi, c^h_i))(1 - A), \xi(1 - \xi)(\Phi_\ell(A) - \Phi_h(A))].
\end{aligned}$$

The paths $t \mapsto x^\ell_{it}$ and $t \mapsto x^h_{it}$ 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 $c_i^h > c_i^\ell$, we have $\dot{x}_{it}^h = \mathcal{X}^h(x_{it}^h) \leq \mathcal{X}^\ell(x_{it}^h)$. Therefore, it follows that

$$\dot{x}_{it}^h - \mathcal{X}^\ell(x_{it}^h) \leq \dot{x}_{it}^\ell - \mathcal{X}^\ell(x_{it}^\ell), \quad \text{and} \quad x_{i1}^\ell = x_{i1}^h.$$

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

B Appendix: Tables

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

Variable	2017 Counts	2017 Proportion	2018 Counts	2018 Proportion
Overall	2,623	1	1,987	1
Age: 18-34	657	0.250	449	0.226
Age: 35-54	1,074	0.409	722	0.363
Age: 55+	892	0.340	816	0.411
Male	1,214	0.463	834	0.420
Female	1,409	0.537	1,153	0.580
British Columbia	377	0.144	271	0.136
Prairies	491	0.187	298	0.150
Ontario	891	0.340	805	0.405
Quebec	639	0.244	482	0.243
Atlantic	225	0.086	131	0.066
Income: $<$\$50K	877	0.334	671	0.338
Income: \$50K-\$99K	935	0.356	704	0.354
Income: \$100K+	538	0.205	379	0.191
High school or less	592	0.226	457	0.230
College / CEGEP / Trade	908	0.346	719	0.362
University	1,123	0.428	811	0.408
Not employed	1,060	0.404	813	0.409
Employed	1,563	0.596	1,174	0.591
No children	1,987	0.758	1,597	0.804
Children	636	0.242	390	0.196
Not married	1,068	0.407	841	0.423
Married/common-law	1,555	0.593	1,146	0.577
Grocery shopping: Not all of it	1,196	0.456	916	0.461
Grocery shopping: All of it	1,427	0.544	1,071	0.539

Table presents the distribution (proportion) and counts of demographic variables associated with respondents from the 2017 and 2018 Bitcoin Omnibus Survey. The total sample size was $N = 2,623$ in 2017 and $N = 1,987$ in 2018. Columns (1) and (3) report the total counts of respondents in each category for 2017 and 2018, while columns (2) and (4) report the proportion. We use these individual-level characteristics as control variables in subsequent regressions.

Table 2: **Bitcoin adoption rates in 2016, 2017, and 2018:**

Adoption rates	2016	2017	2018
Overall	**3.2**	**4.3**	**5.2**
Gender			
Male	4.4	6.6	6.7
Female	2.2	2.1	3.7
Age			
18-34	9.1	11.1	10.5
35-54	1.6	3.2	4.9
55+	0.5	0.5	1.7
Education			
High School	3.8	3.7	2.3
College	1.5	3.1	5.7
University	4.3	6.7	9.1
Income			
<$30K	3.1	4.3	2.8
$30K-$69K	3.9	5.6	4.8
$70K+	3.7	4.3	7
Region			
British Columbia	2.8	5.2	6.3
Prairies	2.1	4.1	6
Ontario	2.5	3.9	5.2
Quebec	5.5	5.1	4.6
Atlantic	3.2	3.1	2.8

This table reports the adoption rates of Bitcoin among several demographic groups in 2016, 2017, and 2018. Data are from the Bitcoin Omnibus Survey and have been weighted to reflect the Canadian population.

Table 3: **Growth in Bitcoin ATMs across Canadian: Cities, Provinces, and Regions; 2016-2017 and 2017-2018**

City	Province	Region	2016	2017	2018	2017-2016	2018-2017
Fredericton			0	0	1	0	1
Moncton	New Brunswick		0	0	1	0	1
Saint John			0	0	2	0	2
St. John's	Newfoundland and Labrador		0	1	5	1	4
Antigonish		Atlantic Provinces	0	0	1	0	1
Dartmouth	Nova Scotia		0	0	5	0	5
Halifax			0	3	7	3	4
Truro			0	0	1	0	1
Charlottetown	Prince Edward Island		0	0	1	0	1
Summerside			0	0	1	0	1
Total			0	4	25	4	21
Coquitlam			0	0	1	0	1
Delta			0	1	0	1	-1
Kamloops			0	0	2	0	2
Kelowna			0	4	8	4	4
Lumpy					1		
Maple Ridge			1	1	0	0	-1
Nanaimo	British Colombia	British Colombia	0	1	5	1	4
Prince George			0	0	1	0	1
Richmond			0	0	1	0	1
Surrey			1	0	4	-1	4
Vancouver			18	49	70	31	21
Victoria			1	4	6	3	2
Whistler			2	1	1	-1	0
Total			23	61	100	38	38
Brantford			0		1	0	1
Fenelon Falls			0		1	0	1
Hamilton			0		1	0	1
Kitchener			0		1	0	1
London			0	4	10	4	6
Mississauga			0		1	0	1
Niagara Falls			0		1	0	1
North Bay			1	1	2	0	1
Orillia	Ontario	Ontario	0		1	0	1
Ottawa			4	15	37	11	22
Peterborough			0	0	3	0	0
Sault Ste. Marie			1	1	1	0	0
Smiths Falls			0		1	0	1
Sudbury			0	1	3	1	2
Thunder Bay			0		2	0	2
Toronto			45	127	199	82	72
Windsor			0		2	0	2
Total			51	149	267	98	115
Calgary			14	29	47	15	18
Edmond			7	10	21	3	11
Grand Prairie	Alberta		0	3	4	3	1
Red Deer			1	1	0	0	-1
St Albert		Prairies	0	0	1	0	1
Regina	Saskatchewan		1	3	4	2	1
Saskatoon			1	2	2	1	0
Brandon	Manitoba		0	0	1	0	1
Winnipeg			2	5	19	3	14
Total			26	53	99	27	46
Gatineau			1	1	0	0	-1
Montreal	Quebec	Quebec	33	51	83	18	32
Quebec City			1	2	4	1	2
Total			35	54	87	19	33
Total General			135	321	578	186	253

Data are taken from coinatmradar.com.
Counts of Bitcoin ATMs are reported at the city/province/region levels.

Table 4: **Correlation of Bitcoin ATMs Growth with Bitcoin Adoption**

ρ	Btc ATM Growth (2016-2017)	Btc ATM Growth (2017-2018)
Bitcoin Ownership	0.0029	0.0052

The correlations are computed using data from the 2016, 2017, and 2018 Bitcoin Omnibus Surveys (BTCOS) and Coin ATM Radar. The computed correlations are based on the regional variation in Bitcoin ATM growth.

Table 5: **First Stage: Estimation of Bitcoin Beliefs**

VARIABLES	2017	2018	2018 (with E(return))
Age	-0.584***	-0.645***	-0.646***
	(0.181)	(0.218)	(0.227)
Gender: Female	0.259	-2.511**	-2.120*
	(0.965)	(1.148)	(1.195)
Income: 50K-99K	-0.0432	0.563	0.403
	(1.121)	(1.272)	(1.333)
Income: 100K+	-1.125	2.308	2.276
	(1.412)	(1.641)	(1.718)
Employment	2.300**	0.00143	-0.152
	(1.107)	(1.265)	(1.327)
Education: College/CEGEP/Trade school	-2.049	-1.812	-2.012
	(1.281)	(1.431)	(1.552)
Education: University	-2.078	-2.031	-1.660
	(1.266)	(1.459)	(1.554)
Number of children: No children	-4.140***	-3.153**	-4.017**
	(1.239)	(1.533)	(1.638)
Marital status: Not married/CL	-1.576	-0.839	-0.587
	(1.180)	(1.386)	(1.477)
Responsible for HH grocery shopping	2.680**	2.860**	2.523*
	(1.086)	(1.231)	(1.309)
ΔATM_AT	-1.256	0.0552	0.712
	(1.785)	(2.362)	(2.533)
ΔATM_PR	-3.615*	-5.675**	-6.056**
	(1.854)	(2.570)	(2.712)
ΔATM_QC	-4.703**	-4.990**	-5.056*
	(1.960)	(2.512)	(2.671)
ΔATM_ON	-0.656	-3.773*	-4.408*
	(1.715)	(2.253)	(2.388)
Age squared	0.00374**	0.00363	0.00373
	(0.00188)	(0.00228)	(0.00237)
Expected Return (ER_{it})			1.901***
			(0.728)
Constant	67.73***	69.70***	70.58***
	(4.466)	(5.574)	(5.879)
Observations	2,623	1,987	1,787
R-squared	0.045	0.054	0.065
F-stat (instruments)	18.83	18.70	16.45

ΔATM is the regional growth in Bitcoin ATMs (from 2016 to 2017 and from 2017 to 2018) at the regional level, whereas Expected Return = (respondent beliefs about Bitcoin price in a month-Bitcoin market price at the time of the interview)/(Bitcoin market price at the time of the interview).
Column (1) is the first stage model for 2017.
Column (2) is the first stage model for 2018.
Column (3) is the first stage model for 2018 with Expected Return on Bitcoin.
Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

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

VARIABLES	2017	2018	2017	2018	2018 (CF with E(return))
Beliefs (ξ_{it})	0.169***	0.204***	0.432***	0.722***	0.551***
	(0.017)	(0.013)	(0.086)	(0.093)	(0.08)
Network size (A_{it})	0.588***	0.393***	0.452*	0.319***	0.411***
	(0.210)	(0.029)	(0.273)	(0.039)	(0.054)
Interaction ($\xi_{it} \times A_{it}$)	-0.518***	-0.493***	-0.481**	-0.563***	-0.619***
	(0.167)	(0.157)	(0.194)	(0.145)	(0.151)
CF ($\widehat{u_{it}}$)			-0.003**	-0.005***	-0.003***
			(0.001)	(0.0009)	(0.0008)
Age: 35-55	-0.0376***	-0.0416***	-0.026***	-0.013	-0.023*
	(0.005)	(0.014)	(0.001)	(0.009)	(0.014)
Age: $>$ 55	-0.058***	-0.064***	-0.042***	-0.008	-0.035***
	(0.004)	(0.012)	(0.003)	(0.011)	(0.012)
Gender: Female	-0.0286**	-0.0278**	-0.0353**	-0.0209*	-0.0270*
	(0.0134)	(0.0119)	(0.0173)	(0.0114)	(0.0140)
Income: 50K-99K	-0.00529	0.0411***	-0.00603	0.0387***	0.0440***
	(0.00606)	(0.0116)	(0.00553)	(0.0106)	(0.0140)
Income: 100K+	-0.0112**	0.0397***	-0.00895	0.0279**	0.0333**
	(0.00519)	(0.0146)	(0.00565)	(0.0137)	(0.0151)
Employment	0.0278***	0.00610	0.0209***	0.00804	0.00848
	(0.00710)	(0.0148)	(0.00427)	(0.0141)	(0.0168)
Education: College/CEGEP/Trade school	0.00157	0.0357***	0.00762	0.0473***	0.0481***
	(0.0165)	(0.00459)	(0.0133)	(0.00775)	(0.01000)
Education: University	0.0158*	0.0379***	0.0213***	0.0535***	0.0474***
	(0.00861)	(0.00256)	(0.00669)	(0.00932)	(0.0117)
Marital status: Not married/CL	-0.00861**	-0.0109	-0.00269	-0.00802	-0.0118
	(0.00356)	(0.00788)	(0.00614)	(0.00942)	(0.0105)
Region: Prairies	-0.0265***	-0.00609	-0.0285***	-0.00656	-0.00571
	(0.00546)	(0.0184)	(0.00638)	(0.0181)	(0.0225)
Region: Ontario	-0.0171***	-0.0122	-0.0283***	-0.0222*	-0.0159
	(0.00548)	(0.0131)	(0.00990)	(0.0121)	(0.0130)
Region: Quebec	-0.0146***	-0.0238***	-0.0240***	-0.0535***	-0.0424***
	(0.00353)	(0.00551)	(0.00314)	(0.00251)	(0.00187)
Region: Atlantic	-0.0302***	-0.0288	-0.0428***	-0.0578	-0.0473
	(0.00543)	(0.0311)	(0.00322)	(0.0352)	(0.0400)
Observations	2,623	1,987	2,623	1,987	1,787

ξ_{it} is Bitcoin survival beliefs variable and A_{it} is the local network variable.
$\widehat{u_{it}}$ 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), year 2017.
Column (2) is the benchmark second stage model for Bitcoin adoption (without the CF), year 2018.
Column (3) is the model in (1) augmented with the CF ($\hat{u_{it}}$) estimated in 2017 first stage.
Column (4) is the model in (1) augmented with the CF($\hat{u_{it}}$) estimated in 2018 first stage.
Column (5) is as column (4) but the CF has incorporated the beliefs about Bitcoin expected return in one month.
Robust standard errors in parentheses *** p$<$0.01, ** p$<$0.05, * p$<$0.1

Table 7: **Margins of probability of adoption by ξ_{it} and A_{it}** - Contrast by age group

2017				2018			
ξ_{it}	df	χ^2	$P > \chi^2$	ξ_{it}	df	χ^2	$P > \chi^2$
0.01	1	12.05***	0.0005	0.01	1	58.41***	0
0.1	1	187.14 ***	0	0.1	1	150.73***	0
0.25	1	60.18***	0	0.25	1	31.21***	0
0.5	1	130.2***	0	0.5	1	36.78***	0
0.75	1	7.94***	0.0048	0.75	1	5.01**	0.0253
0.9	1	3.78*	0.052	0.9	1	4.19**	0.0406
0.99	1	2.65	0.1035	0.99	1	3.44*	0.0636
Joint	2	169.14***	0	Joint	2	74.12***	0
A_{it}	df	χ^2	$P > \chi^2$	A_{it}	df	χ^2	$P > \chi^2$
0.01	1	6.09 **	0.0136	0.01	1	109.46***	0
0.02	1	13.65***	0.0002	0.1	1	819.23***	0
0.05	1	46.25***	0	0.15	1	3234.71***	0
0.1	1	85.77 ***	0	0.2	1	3173.37***	0
0.15	1	14.23***	0.0002	0.25	1	1428.7***	0
0.18	1	10.59***	0.0011	0.3	1	620.08***	0
				0.35	1	250.36***	0
Joint	2	3563.99***	0	Joint	2	252.94***	0

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

Table 8: **Reasons for owning Bitcoin**

	Counts			Percentage		
Age / Reasons for owning Bitcoin	18-34	35-54	55+	18-34	35-54	55+
2017						
Payments	6	5	0	8.1	13.5	0.0
Investment	37	18	6	50.0	48.6	100.0
Lack of Trust	4	3	0	5.4	8.1	0.0
Technology	12	9	0	16.2	24.3	0.0
Friends own BTC	13	1	0	17.6	2.7	0.0
Other	2	1	0	2.7	2.7	0.0
Total	74	37	6	100.0	100.0	100.0
2018						
Payments	6	6	1	12.2	17.6	7.7
Investment	15	10	8	30.6	29.4	61.5
Lack of Trust	6	8	2	12.2	23.5	15.4
Technology	19	7	2	38.8	20.6	15.4
Friends own BTC	3	3	0	6.1	8.8	0.0
Other	2	1	0	4.1	2.9	0.0
Total	49	34	13	100.0	100.0	100.0

The table presents the categorized choices of Bitcoin owners when asked about their main reason for owning Bitcoin. For example, the payment-related reasons include: “I use it to buy goods and services on the internet in Canada/elsewhere,” “I use it to buy goods and services in physical stores in Canada/elsewhere,” and “I use it to make remittances or other international payments.” The investment-related reason includes: “It is an investment.” The trust/privacy related reasons include: “It allows me to make payments anonymously,” “I do not trust the government or the Canadian dollar,” and “I do not trust banks.” Technology-related reasons include: “I am interested in new technologies” and “It is a cost-saving technology.” Finally, the friend-related reason is: “My friends own Bitcoin.”

C Appendix: Figures

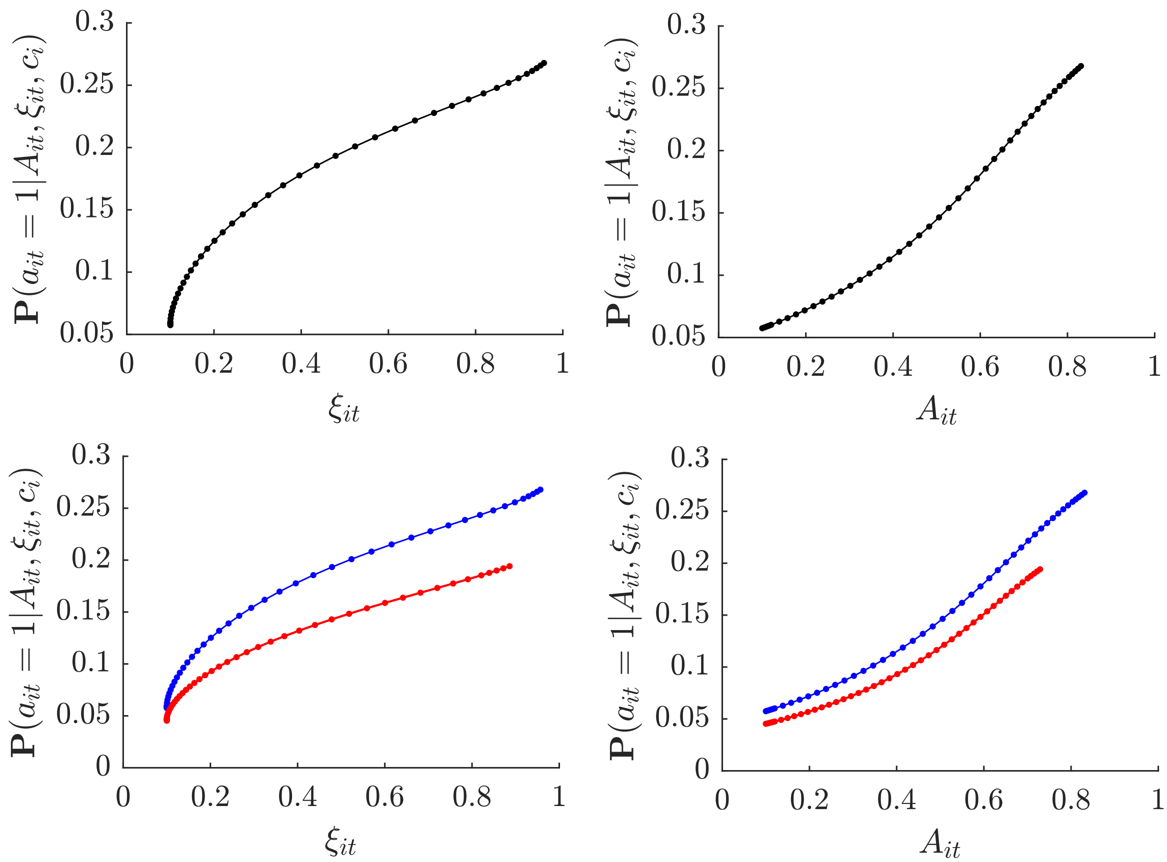

Figure 1: **Adoption and Beliefs.** All panels assume $\phi_\ell = 1, \varphi_\ell = 0.5, \phi_h = 0.1, \varphi_h = 0.6, r_h = 1, r_l = 0.5, \bar{A}_{i1} = \bar{\xi}_{i1} = 0.1$, and $B(A_{it}) = 0.5A_{it}$. The panels also assume that reservation utilities, u_{it}, are logistically distributed with mean 1.5 and scale parameter 0.4. The top panels consider adoption costs $c_i = 0$, whereas the bottom panels show an increase in adoption costs from $c_i = 0$ to $c_i = 0.1$, represented by the respective blue and red dotted curves.

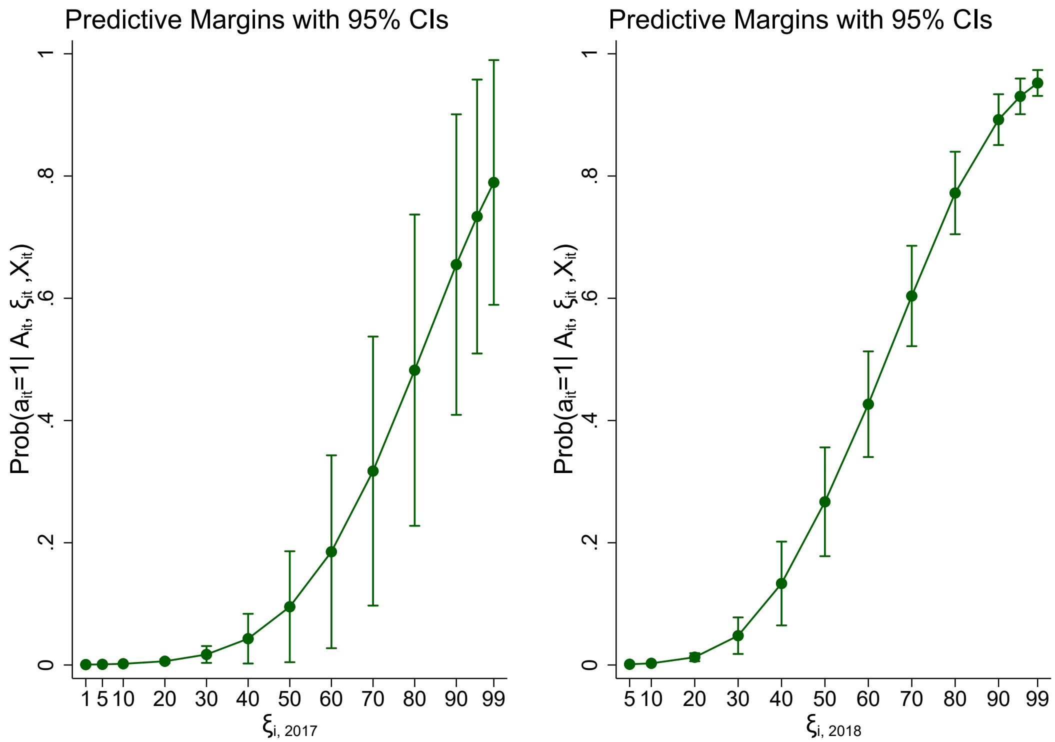

Figure 2: **The Marginal Effects of Probability of Bitcoin Adoption as a Function of Beliefs.** The panels plot the predicted margins of the second stage equation (9), representing the marginal change in the probability of Bitcoin adoption as a function of beliefs (ξ_{it}) for 2017 (left) and 2018 (right).

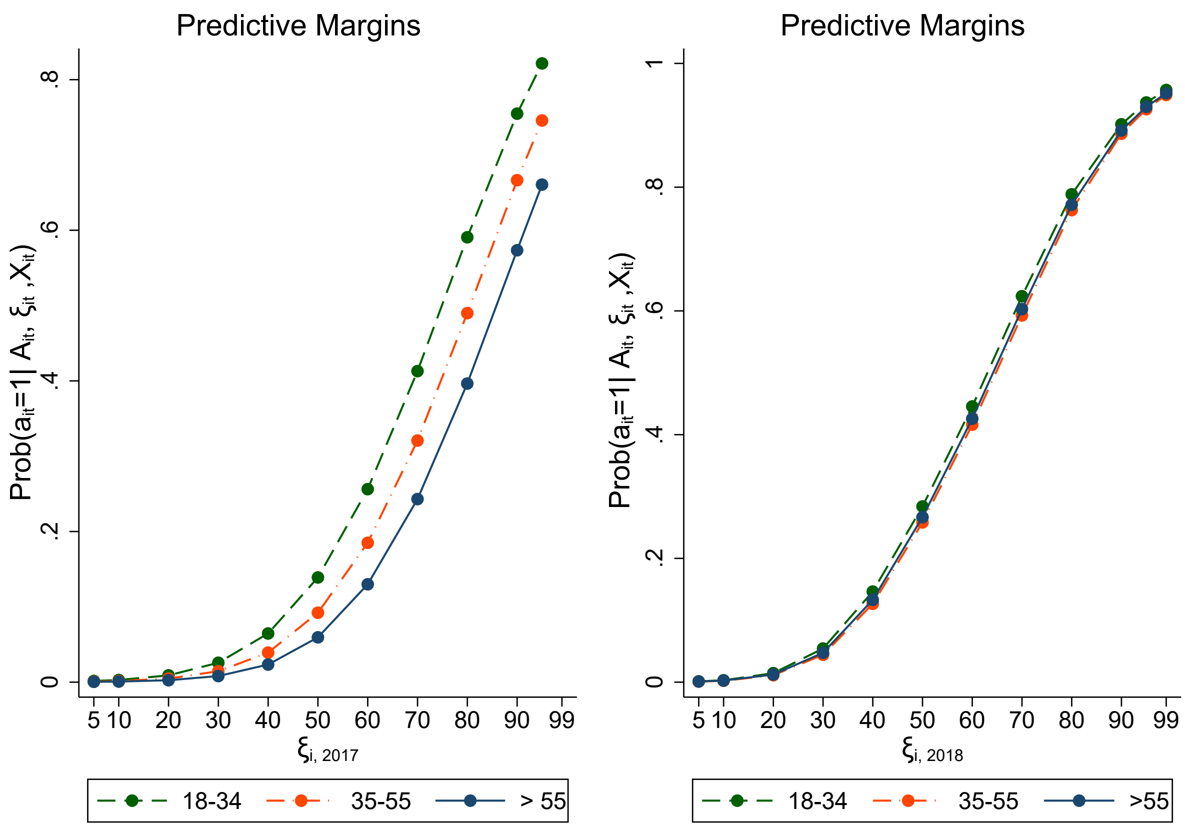

Figure 3: **The Marginal Effects of Probability of Bitcoin Adoption as a Function of Beliefs, by Age.** The panels plot the predictive margins of the second stage equation (9), representing the marginal change in the probability of Bitcoin adoption as a function of beliefs (ξ_{it}) for 2017 (left) and 2018 (right), decomposed by age categories (18-35, 35-55, and 55+).

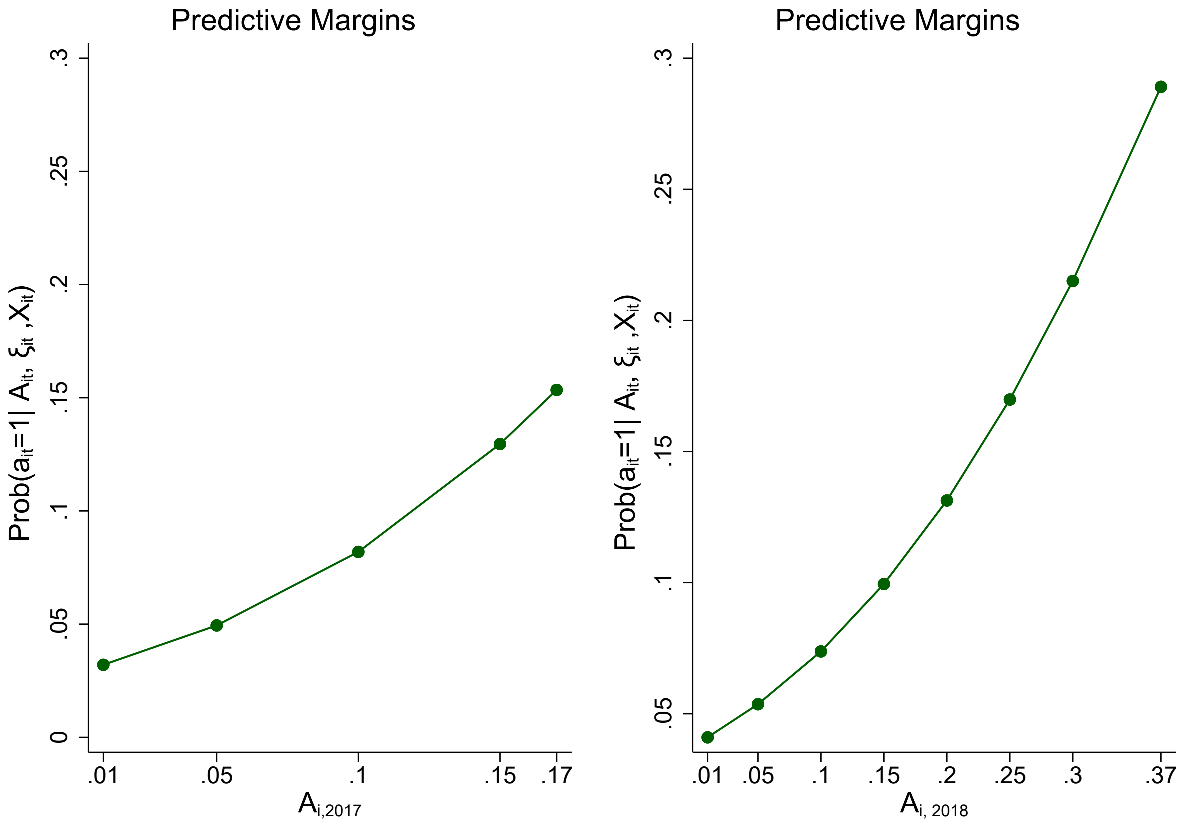

Figure 4: **The Marginal Effects of Probability of Bitcoin Adoption as a Function of Network Size.** The panels plot the predicted margins of the second stage equation (9), representing the marginal change in the probability of Bitcoin adoption as a function of the local network (A_{it}) for 2017 (left) and 2018 (right).

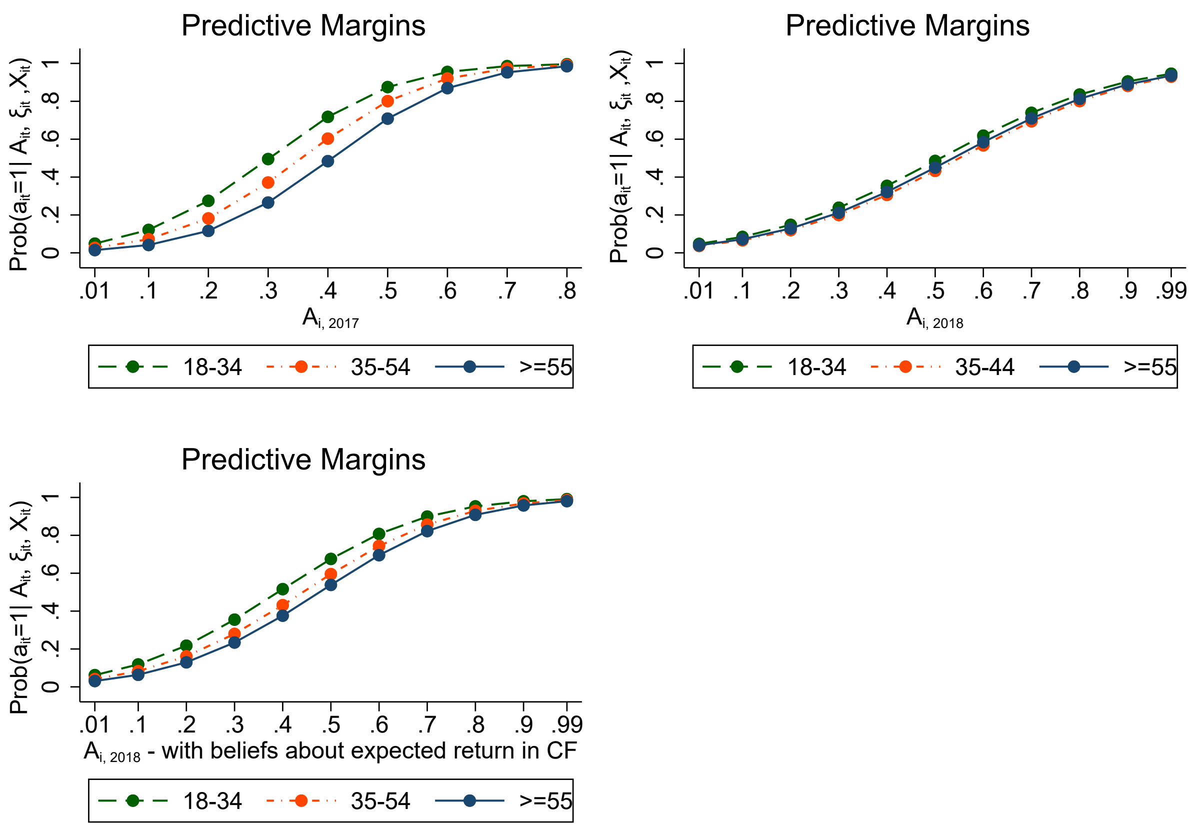

Figure 5: **The Marginal Effects of Probability of Bitcoin Adoption as a Function of Network Size, by Age.** The top panels represent the counterfactual predicted margins of the second stage equation (9), representing the marginal change in the probability of adoption as a function of the local network(A_{it}) in 2017 (left) and 2018 (right) decomposed by three age groups (18-34, 34-54, and 55+). The bottom panel represents the marginal change in the probability of adoption as a function of the local network(A_{it}) in 2018 decomposed by three age groups (18-34, 34-54, and 55+) when the model in the first stage (8) is augmented with beliefs about expected Bitcoin returns in one month.

D Appendix: Non-parametric Network Size

In this section, we describe the computation of the network size variable (A_{it}) using a non-parametric approach. Of course, to avoid contemporaneous collinearity between individual Bitcoin adoption and A_{it}, we use as a proxy the adoption rate in the previous year. To this end,

- We identify the relevant cells for doing the imputation by estimating the probability of having friends owning Bitcoin conditional on the available demographic characteristics in the previous year. We retain the variables that explain this probability. For the 2017 BTCOS, we find that age, gender, and province are relevant, while for the 2018 BTCOS, age, gender, education, marital status, and employment are relevant.

- For each of the evaluation years (resp. 2017 and 2018), we count at the joint cell-based level the number of Bitcoin adopters on the previous year.
- Next, we divide these counts with the equivalent sub-populations and retain these weights as a cell-specific adoption rate in the prior year.
- We use these generated weights as proxies for the network size variable A_{it}.

Table 9 reports the summary statistics for the two approaches (parametric and non-parametric) for 2017 and 2018. For both parametric and non-parametric approaches, the support of the network size variable increased in 2018 relative to 2017. Table 10 reports the equivalent results to those reported in Table 6, but using the non-parametric network size variable. While the two approaches provide similar qualitative results, there are marginal differences in the estimated parameters.

Table 9: **Network size: parametric vs non-parametric approach**

Parametric	Obs	Mean	Std. Dev.	Min	Max
2017	2,623	0.0182	0.0303	0.00007	0.177
2018	1,987	0.0168	0.0378	1.89E-06	0.375
Nonparametric					
2017	2,623	0.0282	0.033	0.005	0.14
2018	1,987	0.0424	0.0413	0.012	0.198

Reported summary statistics for Local Network variable using parametric and non-parametric approaches in 2017 and 2018.

Table 10: **Second stage: Estimation of adoption rate using non-parametric local network**

VARIABLES	2017	2017(CF)	2018	2018 (CF)
Beliefs (ξ_{it})	0.151***	0.548***	0.188***	0.561***
	(0.0250)	(0.0719)	(0.0209)	(0.114)
Network (A_{it}) k	0.402**	0.378**	0.210	0.273*
	(0.163)	(0.167)	(0.143)	(0.147)
Social Interaction ($\xi_{it} \times A_{it}$)	-0.150	-0.121	-0.132	-0.242
	(0.255)	(0.261)	(0.193)	(0.196)
CF ($\widehat{u_{it}}$)		-0.004***		-0.0035***
		(0.0009)		(0.0012)
Age	-0.00141***	-0.000279	-0.00149***	-0.000451
	(0.0002)	(0.0005)	(0.0004)	(0.0008)
Gender: Female	-0.0421***	-0.0430***	-0.0305***	-0.0263***
	(0.0138)	(0.0129)	(0.008)	(0.0066)
Income: 50k-99k	-0.00609	-0.00720	0.0393***	0.0415***
	(0.0059)	(0.0053)	(0.0116)	(0.0144)
Income: 100k+	-0.012**	-0.008	0.035**	0.028*
	(0.005)	(0.005)	(0.015)	(0.016)
Employment	0.0276***	0.0181***	0.0106	0.0115
	(0.0074)	(0.0046)	(0.0135)	(0.0153)
Education: College/CEGEP/Trade school	-0.0007	0.0083	0.036***	0.048***
	(0.0168)	(0.0129)	(0.0068)	(0.0116)
Education: University	0.0147*	0.023***	0.043***	0.050***
	(0.008)	(0.006)	(0.006)	(0.013)
Marital status: Not married/CL	-0.0075*	0.0013	-0.0133*	-0.0114
	(0.004)	(0.0058)	(0.0074)	(0.0114)
Region: Prairies	-0.0179***	-0.0216***	0.0033	0.0033
	(0.0032)	(0.0034)	(0.0141)	(0.0175)
Region: Ontario	-0.0140***	-0.0308***	-0.0072	-0.0113
	(0.00281)	(0.0071)	(0.0178)	(0.0167)
Region: Quebec	-0.0263***	-0.0407***	-0.0208**	-0.0410***
	(0.0099)	(0.0117)	(0.0105)	(0.0049)
Region: Atlantic	-0.0258**	-0.0448***	-0.0224	-0.0442
	(0.0104)	(0.0082)	(0.0227)	(0.038)
Observations	2,623	2,623	1,987	1,987

ξ_{it} is Bitcoin survival beliefs variable and A_{it} is the local network variable.
$\widehat{u_{it}}$ 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), year 2017.
Column (2) is the model in (1) augmented with the CF ($\hat{u_{it}}$) estimated in 2017 first stage.
Column (3) is the benchmark second stage model for Bitcoin adoption (without the CF), year 2018.
Column (4) is the model in (2) augmented with the CF($\hat{u_{it}}$) estimated in 2018 first stage.
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

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