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THE RELATIONSHIP BETWEEN GOVERNANCE, BANK RISKS AND FINANCIAL STABILITY

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Dedication

I dedicate this thesis to my daughter, Ilinca-Maria. You have made me stronger, better and more fulfilled than I could have ever imagined. I love you!

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Résumé

L'effondrement de l'emblématique banque d'investissement américaine Lehmann Brothers en septembre 2008 a eu un impact énorme sur les marchés financiers et l'économie mondiale en érodant la confiance des citoyens dans leurs institutions, leur système bancaire et la stabilité financière globale. En général, une crise a tendance à remettre en cause les opinions et les perceptions individuelles, mais tous les processus et expériences d'apprentissage sont ancrés dans un cadre culturel et sociétal qui joue un rôle vital, même s'il est indétectable en surface. L'objectif principal de cette thèse est de mettre en évidence les risques potentiels pour la stabilité financière sous deux angles, d'abord ceux liés à la diversité culturelle et d'autre part ceux liés à la perturbation possible du système financier en raison de l'essor des nouvelles technologies, les FinTech.

Les institutions financières ont été en proie à des fautes professionnelles majeures, à des manquements éthiques et à des problèmes de respect des règles, ce qui a entraîné une longue liste d'amendes et de pénalités importantes. La faiblesse des fondements culturels et les défaillances n'ont pas cessé avec la crise financière mais ont plutôt persisté malgré l'intervention importante du secteur public requise pour stabiliser le système financier. La culture fait référence aux normes implicites qui guident le comportement en l'absence de réglementation ou de règles de conformité et est désormais largement reconnue comme un facteur essentiel pour la stabilité financière à long terme et le maintien de la confiance du public dans le système financier. Cependant, l'effet des aspects culturels sur la stabilité financière a été négligé dans la littérature ; ainsi, le premier chapitre examine les effets culturels potentiels sur les mesures du risque systémique dans les pays développés et en développement.

Au cours de la dernière décennie, la crise et ses conséquences ont entraîné des changements importants dans le secteur financier. Premièrement, les banques deviennent plus résilientes grâce aux nouvelles réglementations et à une meilleure gestion des risques. D'autre part, le manque de confiance dans le système bancaire qui a augmenté après 2008 a conduit à l'essor d'une nouvelle technologie destinée à remodeler le crédit à la consommation. Environ deux mois après la crise de Lehman, le pseudonyme présumé de Satoshi Nakamoto a publié un article blanc intitulé « Bitcoin : un système d'argent électronique Peer-to-Peer », décrivant les

méthodes d'utilisation d'un réseau peer-to-peer pour générer ce qui a été décrit comme « un système de transactions électroniques sans s'appuyer sur la confiance » (Nakamoto, 2008). De nos jours, la devise Bitcoin, d'abord conçu comme une version électronique de l'argent liquide, libre du contrôle du gouvernement et de la banque centrale, est devenu un phénomène mondial qui pourrait avoir de graves implications pour la stabilité financière. Les trois chapitres suivants se concentrent sur les sujets liés au Bitcoin pour un pays particulier, le Canada. Bitcoin et ses dérivés (crypto-monnaies) pourraient affecter les fonctions essentielles des banques centrales liées à la production et à la distribution des billets de banque. En ce qui concerne le rôle de la Banque du Canada dans le maintien de la stabilité financière, sa Revue du Système Financier (RSF) de 2019, inclut les crypto-monnaies comme l'une des six vulnérabilités financières clés qui devraient être surveillées de près. Même si, en ce moment, le marché actuel des crypto-monnaies ne pose pas de problème de stabilité financière, la Banque du Canada continuera de surveiller cette technologie pour comprendre sa dynamique au niveau des consommateurs. En conséquence, le deuxième chapitre analyse l'impact de la possession de Bitcoin sur l'utilisation des espèces à l'aide de données d'enquête. Le troisième chapitre examine les mécanismes potentiels derrière l'évolution future de l'adoption de Bitcoin. Enfin, le quatrième chapitre met en évidence la dynamique de sensibilisation, d'adoption et d'utilisation du Bitcoin au sein de la population canadienne au cours de la période 2016-2020.

Introduction

The collapse of the iconic US investment bank Lehmann Brothers in September 2008 had an enormous impact on the financial markets and the global economy by eroding citizens' trust in their institutions, banking system, and overall financial stability. In general, a crisis tends to challenge the individual views and perceptions, but all processes and experiences of learning are embedded in a cultural and societal framework which plays a vital role, even if it is undetectable on the surface. **The main aim** of this thesis is to highlight the potential risks for financial stability from two perspectives, first related to cultural diversity and second related to the possible disruption in the financial system due to the rise of new technology, FinTech.

Financial institutions have been plagued by major professional misconduct, ethical shortcomings, and compliance problems, resulting in a long list of big fines and penalties. Poor cultural foundation and failures did not cease with the financial crisis but rather persisted despite the significant public sector intervention required to stabilize the financial system. Culture refers to the implicit norms that guide behavior in the absence of regulations or compliance rules and is now widely recognized as an essential factor for long-term financial stability and maintaining public confidence in the financial system. However, the effect of cultural aspects on financial stability literature has been neglected; thus, the **first chapter** looks at the potential cultural effects on systemic risk measures across developed and developing countries.

Over the last decade, the crisis and its consequences resulted in significant changes in the financial sector. First, banks become more resilient as a result of new regulations and better risk management. On the other hand, the lack of trust in the banking system instilled after 2008 led to the rise of the new technology intended to reshape consumer finance. About two months after the Lehman crisis, presumed pseudonymous Satoshi Nakamoto published a white paper named "Bitcoin: A Peer-to-Peer Electronic Cash System", outlining methods of using a peer-to-peer network to generate what was described as "a system for electronic transactions without relying on trust" [Nakamoto, 2008]. Nowadays, Bitcoin, first designed as an electronic version of cash, free of government and central bank control, has become a global phenomenon that could have serious implications for financial stability. The following three chapters zoom in on the topics related to Bitcoin for a particular country,

Canada. Bitcoin and its siblings could affect the core functions of the central banks related to the production and distribution of banknotes. Regarding the Bank of Canada's role in maintaining financial stability, its 2019 Financial System Review (FSR) includes cryptocurrencies as one of the six key financial vulnerabilities that should be closely monitored. Even if, at this moment, the current cryptocurrencies market does not pose financial stability concern, the Bank of Canada will continue to monitor this technology to understand its dynamics at the consumer level. Accordingly, the **second chapter** analyzes the impact of Bitcoin ownership on cash usage using survey data. The **third chapter** looks at the potential mechanisms behind the future evolution of Bitcoin adoption. Finally, the **fourth chapter** highlights the dynamics of Bitcoin awareness, adoption, and usage among the Canadian population over the 2016-2020 period.

A summary of each chapter is presented below:

The first chapter, titled “*The impact of national culture on systemic risk*”, joined with prof. Alin Andries, investigates the effects of national culture dimensions defined by Hofstede on systemic risk using a comprehensive dataset over the 2003-2016 period.

We find a strong relationship between cultural values and systemic risk measures after controlling for various country and bank-level characteristics. In general, the analysis indicates that banks from societies characterized by individualism and masculinity increase the individual contribution ($\Delta CoVaR$) to the systemic risk. On the other hand, the relationship of cultural traits and systemic risk is found to vary in a nonlinear way, especially for power distance and uncertainty avoidance. This variation may be driven by the dual information found in the national culture dimensions and the skewness effect found in the systemic risk measures. Finally, using quantile analysis, we confirm the nonlinear effects found in the data. These findings have policy implications for macroprudential policies that may help to mitigate some of the negative effects conditioning on the type of culture promoted in a specific country. For example, designing uniform regulation and supervision policies to avoid contagion risk in the banking system for countries with heterogeneous cultures may not have the expected impacts.

The second chapter, titled “*Cash in the Pocket, Cash in the Cloud: Cash Holdings of Bitcoin Owners*” joint with Christopher Henry, Kim P. Huynh and Marcel C. Voia (in preparation for submission) analyzes the effect of Bitcoin ownership on the level of cash holdings of Canadian consumers by looking at two waves of the Bitcoin Omnibus Surveys (BTCOS) in 2017 and 2018.

The year 2017 was pivotal in the evolution of cryptocurrencies. As the price of Bitcoin reached its historical peak at that time, these instruments gained increased widespread interest along with scrutiny from regulatory bodies and the financial sector. However, in 2018 the price of Bitcoin plunged dramatically, losing 84 per

cent of its value between December 2017 and December 2018. The core of the discussion on Bitcoin came down to how consumers were using it: Was it a vehicle for speculation and investment? Or a convenient way to transact for the illicit activities? Were people using Bitcoin as initially designed, i.e., a decentralized currency that is not backed by an institution? The answers to these questions are still unclear but have become increasingly relevant due to concerns about the so-called "death of cash," and the possible issuance of the Central Bank Digital Currency.

This chapter sheds light on a surprising finding that suggests that Bitcoin may play a role in supplementing existing cash rather than supplanting it. Controlling for observable factors, and most importantly, selection into Bitcoin ownership, we show that cash holdings of Bitcoin owners are substantially higher than non-owners. On average, Bitcoin owners hold between 83 (in 2018) to 95 (in 2019) percent more cash than non-owners. Focusing on the quantiles of cash holdings, we find that Bitcoin ownership has a highly nonlinear effect: the difference in cash holdings between Bitcoin owners and non-owners varies from 63 percent in 2017 to 39 percent in 2018 at the 25 quantile of cash and from 176 percent in 2017 to 203 percent in 2018 at the 95 quantile of cash.

To build on this work, we suggest several directions for future research. First, it is necessary to identify the specific features that Bitcoin owners deem relevant for determining their adoption and usage – this may help explain what is driving large cash holdings among owners. Second, it would be useful to classify Bitcoin owners into various types, e.g. investors, casual users, etc. It is not unreasonable to assume that Bitcoin owners themselves are heterogeneous, and this needs to be factored into any analysis that attempts to explain the relationship between Bitcoin ownership and cash holdings. Finally, it would be helpful to examine evidence from other countries, as Canada may be considered relatively advanced in terms of financial inclusion and the structure of its financial institutions – how would our results differ in countries where this is not the case?

The third chapter, titled *“Bitcoin Adoption and Beliefs in Canada”* with Christopher Henry, Jorge Vasquez and Marcel Voia, examines how the individual probability of Bitcoin adoption is influenced by network size, individual learning, and social learning. To test and quantify these behavioral determinants driving Bitcoin adoption, we develop a tractable Bitcoin adoption model which 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 the network size and beliefs has a significant pos-

itive impact on the probability of Bitcoin adoption. Specifically, after accounting for the endogeneity of beliefs, our results show that a one percentage point increase in the network size increases the probability of Bitcoin adoption by 0.41 and 0.45 percentage points in 2017 and 2018, respectively. Likewise, a one percentage point increase in beliefs raises the probability of Bitcoin adoption by 0.43 and 0.55 percentage points in 2017 and 2018, respectively. We also provide evidence of social learning effect, an interaction between network size and beliefs that is negative and statistically significant. Finally, in terms of adoption costs, we find that age has a significant negative impact on adoption and beliefs in 2017 and 2018 (with stronger effects in 2017), meaning that young people are more likely to adopt and be more optimistic about Bitcoin survival in the future.

Last chapter, titled ***“Bitcoin awareness, adoption and usage in Canada: 2016-2020”*** joint with Marie-Hélène Felt, Gradon Nicholls and Marcel C. Voia provides the results of the latest iteration of the Bitcoin Omnibus Survey (BTCOS 2019) and wave two of the 2020 Cash Alternative Survey (CAS) describing the dynamics of Bitcoin awareness and ownership before and during the COVID-19 Pandemic. The BTCOS has been commissioned yearly between 2016 and 2019 by the Bank of Canada to monitor trends in the adoption and usage of Bitcoin and other crypto assets. It allows us to study awareness, ownership, holdings and usage patterns over the four years prior to the COVID-19 pandemic. By contrast, the main objective of the November 2020 CAS was to understand better the demand for and use of cash during the pandemic, but questions on the adoption of digital payment methods were also included in the survey. This data enables us to assess if any significant changes in awareness and ownership of Bitcoin were observed six months in the pandemic.

Overall, the results from the 2019 BTCOS and the November 2020 CAS show that the level of awareness among Canadians remains stable compared to 2018. Specifically, 87 per cent in 2019 and 88 per cent in 2020 reported having heard of Bitcoin compared to 89 per cent in 2018. Similarly, Bitcoin ownership remains around 5 per cent from 2018 to 2020, compared to 4 per cent in 2017 and 3 per cent in 2016. Even if we do not see significant changes in the average Bitcoin ownership since 2018, we observe changes over the years in the demographic characteristics of Bitcoin owners in terms of gender, age, and income level. However, Bitcoin ownership remains concentrated within the young, educated males group. The main reasons for owning Bitcoin are investment and technology related. Bitcoin owners, while having higher Bitcoin knowledge, have lower financial literacy than non-owners.

Chapter 1

The impact of national culture on systemic risk

1

Abstract

This study investigates the effects of national culture on systemic risk. Using a comprehensive dataset for the period 2003–2016, we find a strong relationship between cultural values and systemic risk after controlling for various country and bank level characteristics. In particular, we show that between national culture traits and systemic risk measures exists a statistically significant and nonlinear relationship driven by the duality information of national culture indexes, but also driven by the skewness of the systemic risk measures. Moreover, our results show that during the crisis when are recorded higher values of systemic risk, the impact of national culture is different from normal times. In general, the analysis indicates that societies characterized by individualism, low power distance and masculinity increase the bank individual contribution ($\Delta CoVaR$) to the systemic risk.

1.1 Introduction

National culture has an essential role in the development of any society. Culture is defined as a set of norms, beliefs, expected behaviors, and shared values that guide people's lives [Hofstede, 2001, Schwartz, 1994]. Consequently, the culture of a country influences the culture of organizations where they function [Lindholm, 2000], influencing the organizational culture and the practices of national institutions with an impact on the governance of these organizations [Li and Harrison, 2008]. By guiding human behavior, cultural values reflect what a society/group

¹This Chapter is co-written with Alin M. Andries. This version of the paper received a Revised & Resubmit at Economic Systems journal.

considers acceptable or unacceptable, legitimate or illegitimate, good or bad, or ethical or unethical [Hofstede, 2001]. Therefore, culture has important implications for the decision-making attitude of managers and the formal institutions and level of economic and financial development of a country [Ashraf et al., 2016].

Understanding how national culture affects the decisions made at the corporate level it is an important task for policymakers. Consequently, a good understanding of the link between the level of risk managers is taking and their cultural identities are relevant for designing policies that improve corporate governance [Mihet, 2013, Volontè, 2015]. It becomes essential to establish the role of culture in the banking activity and its impact on systemic risk. While the idea of culture was explored in many research areas at macro and micro-levels, its impact on systemic risk was not yet explored, which is examined in this paper by filling an important gap in the literature. Also, the recent financial crises outlined the importance of understanding the systemic risk, especially at its core, which is linked with the cultural values of specific countries. Additionally, answering this question is important for policymakers to improve government policies designed to promote better business environments.

In our analysis, we refer to systemic risk using De Bandt and Hartmann [2001] definition that defines systemic risk as a systemic event that affects a great number of institutions or financial markets by distorting the financial system as a whole. Since then, both researchers and regulatory bodies developed different systemic risk measures that were further used to quantify the contribution and exposure of the banking system to systemic risk and further improve the regulatory framework. Bisias et al. [2012] provide an extensive survey of 31 measures of systemic risk. In our analysis, we are using the Conditional Value at Risk (ΔCoVaR) developed in Adrian and Brunnermeier [2016] as the main measure of systemic risk (it accounts for the contribution of the banking system to systemic risk). As an alternative (for robustness checks) we are using the Marginal Expected Shortfall (MES) proposed by Acharya et al. [2017] that accounts for the exposure of the banking system to systemic risk.

To assess the role of national culture on systemic risk, we focused on four dimensions of national culture identified by Hofstede [2001], namely, power distance, uncertainty avoidance, masculinity and individualism, which we argue are related to bank risk-taking. Using previous theoretical results, we are tested several predictable hypotheses that are linking national culture to systemic risk.

First, based on Merton [1977], we hypothesize that high contribution to systemic risk by banks is more likely in societies characterized by individualism and masculinity. This hypothesis is linked to the idea that bankers are lending more aggressively in these societies by taking excessive risks and ignoring prudent risk management. Second, we hypothesize that banks in countries with high uncertainty avoidance are

more risk-averse, which will reduce the impact on systemic risk, as their investors have higher sensitivity toward risk and lower tolerance on uncertainty, see [Kwok and Tadesse \[2006\]](#) and [Mihet \[2013\]](#).

Third, using [Mihet \[2013\]](#) results that also suggested that low power distance societies are characterized by egalitarian values, promoting independence and innovation by taking additional risks, we hypothesize that societies characterized by egalitarian values register higher systemic risks compared with hierarchical societies. To test these hypotheses, proper identification is required. In particular, one can argue that the endogenous selection role of the national culture has on systemic risk information. To address this endogenous problem, a two-stage approach is proposed. The identification requires exclusion restrictions/instruments impacting the national culture measures but not the systemic risk. Here, the following instruments are proposed: a) “diseases” as an instrument for individualism. [Berger et al. \[2021\]](#) use this instrument following [Fincher et al. \[2008\]](#), which argue that societies where the prevalence of pathogens is lower are associated with more individualistic societies; b) “gender inequality index” is used as an instrument of masculinity, being positively correlated with cultural variable; c) the “pronoun politeness” is proposed as an instrument for power distance, which, according to [Davis and Abdurazokzoda \[2016\]](#) relates to languages that use more than one second-person pronoun to create a social distance in interactions; and lastly, d) we use different religion categories (Catholic, Orthodox, Protestant) as instruments for uncertainty avoidance. [Hofstede \[2001\]](#) suggested that the Catholic and Orthodox countries tend to score higher on uncertainty avoidance, while Protestant countries tend to be more accepting of uncertainty.

The results of this paper, which are robust to endogenous results, emphasize the importance of these cultural measures on explaining systemic risk by showing 1) in countries with low power distance, the contribution of banks to systemic risk is larger than in countries with high power distance; 2) the effect of individualism on both systemic risk measures is similar, in collectivist countries the effects on systemic risk are smaller than in countries with high levels of individualism; 3) countries characterized by femininity have higher exposure to systemic risk than countries characterized by masculinity, while the reverse is true when we talk about the contribution to systemic risk. Additional to these direct effects that link these national culture measures to systemic risk, we also found that 4) power distance and uncertainty avoidance have a nonlinear effect over the support of the systemic risk measures, and 5) in the period of crises when are recorded higher values of systemic risk, the impact of national culture is differently compared with normal times. These findings have important policy implications for managing different types of crises (financial and health crises, such as COVID-19) in the sense that it is important to know how to design banking policies to avoid risks for countries with

heterogeneous cultures.

The remainder of our paper is structured as follows: §1.2 summarizes the related literature review. §1.3 and §1.4 describes the data and methodology that were employed. §1.5 reports the empirical findings, while §1.6 presents the concluding remarks.

1.2 Literature review

Previous studies have highlighted the importance of culture in economics and finance and documented that national culture through its various dimensions manifests a significant impact on the economic exchange [Guiso et al., 2009], economic growth [Gorodnichenko and Roland, 2017], norms of governance and quality of institutions [Licht et al., 2007, Klasing, 2013], financial system configuration [Kwok and Tadesse, 2006], banks [Boubakri et al., 2017, Mourouzzidou-Damtsa et al., 2019, Mourouzzidou-Damtsa and Stathopoulos, 2021] and cross-border financial contracts [Giannetti and Yafeh, 2012].

Guiso et al. [2009] studied the effects of trust on international trade and investments among the European countries, concluding that higher bilateral trust leads to more trades between the two countries. The economic growth of one country is influenced by the individualism dimension as it encourages an individual to innovate and stand out [Gorodnichenko and Roland, 2017]. Moreover, the economic outcomes are driven by individuals' possibility to pursue their preferences and their moral equality that influences one country's rule of law, corruption and democracy [Licht et al., 2007]. These results are confirmed by Klasing [2013], sustaining that the degree of individualism in one society and the degree of inequality in the distribution of power are important cultural determinants of a society's quality of institutions. Nikolaev and Salahodjaev [2017] used the prevalence of infectious diseases as an instrument for cultural traits (individualism) to show that cultural values affect economic institutions such as competitive markets, the banking system, and the structure of property rights, which are essential for economic development.

Kwok and Tadesse [2006] assess the role of national culture in the financial system configuration. Their results show that countries with national cultures strong on uncertainty avoidance tend to have bank-based systems, as investors from these countries have a higher sensitivity toward risk and lower tolerance of uncertainty. Moreover, culture manifests an impact on a borrower-lender relationship, as banks from more culturally distant countries offer smaller loans at higher costs, considering them riskier [Giannetti and Yafeh, 2012].

At the bank level, national culture influences the level of loans granted [Gaganis et al., 2019], leverage [Haq et al., 2018], bank performance [Halkos and Tzeremes, 2011], bank risk-taking (e.g. [Kanagaretnam et al., 2011, Ashraf et al., 2016]). Gaganis

nis et al. [2019] highlighted the importance of power distance and uncertainty avoidance on residential loans, as these cultural dimensions manifest a negative impact on the value of total outstanding residential loans to GDP. Moreover, banks from countries with high uncertainty-avoidance and power distance have less leverage, while banks in highly individualistic countries hold more leverage [Haq et al., 2018]. Halkos and Tzeremes [2011] proved that bank performance is positively influenced by lower masculine, uncertainty avoidance, power distance values and moderate individualistic values.

The relationship between national cultural dimensions and bank risk behavior has been studied in several papers. Using data for 39 countries, Kanagaretnam et al. [2011] shows that banks in high individualism, high power distance and low uncertainty avoidance societies report smoother earnings in the pre-financial crisis period. During the crisis period, results suggested that cultures that encouraged higher risk-taking have experienced larger losses. Kanagaretnam et al. [2014] have confirmed the positive relationships between individualism and bank risk-taking and the negative influence of uncertainty avoidance on bank risk-taking. Gunzinger and Sturm [2016] emphasize the role of political constraints that have roots in cultural values in reducing the size of a country’s fiscal stimulus package due to the Great Recession with implications for controlling the systemic risk.

These results have been confirmed by Ashraf et al. [2016] that studied the effects of national culture dimensions identified by Hofstede on bank risk-taking behavior using an international sample of banks from 75 countries. Their findings reveal that bank risk-taking is significantly higher in countries with higher individualism, lower uncertainty avoidance, and lower power distance, while for masculinity, the effects were insignificant. The effects of individualism hold for domestic bank risk-taking, but not for globally active banks as these are subject to additional regulatory requirements reducing their flexibility and exposure to national culture influences. Also, the relationship between national culture and bank risk weakens during financial crises [Mourouzigidou-Damtsa et al., 2019] (Mourouzigidou-Damtsa et al., 2019).

Furthermore, national culture manifests an impact on bank failure probability. Berger et al. [2021] findings suggest that individualism and masculinity are positively associated with bank failure. Managers in individualist countries assume more portfolio risks, while governments in masculine countries allow the banks to operate with less capital and liquidity. On the other hand, banks located in countries with high uncertainty avoidance, collectivism and power distance performed relatively better during the financial crisis [Boubakri et al., 2017]. Mourouzigidou-Damtsa et al. [2019] show that banks in countries with high trust and hierarchy scores have higher levels of deposits as opposed to banks in countries with high individualism which have lower levels of deposits.

1.3 Data

The dataset includes 339 publicly listed Global Banks from 61 countries for the 2003–2016 period. The sample represents a value of total assets of more than 70 trillion USD at the end of 2016, where the sizes of the banks vary from 19.5 million USD to 3.2 trillion USD, with a mean of 174 billion USD at the end of 2016. From the sample are excluded banks that do not have the daily market capitalization (required for systemic risk computation). The final sample accounts for 61 per cent of the total assets of the Global Banks sample (560 banks) as of the end of 2016. The source of the data is Thomson Reuters Datastream.

1.3.1 Systemic risk measures

In our analysis, we employ two of the most exploited systemic risk measures based on market and accounting data in order to calculate the contribution and exposure to systemic risk for each bank. The first one is the Conditional Value at Risk (ΔCoVaR) of [Adrian and Brunnermeier \[2016\]](#).

Similar to [Andries et al. \[2020\]](#), we compute each bank's VaR using a linear model that captures the dependence of a bank's asset returns on lagged market indices (i.e., vector MI'_{t-1}

$$R^i_{Market\ Assets,t} = \alpha^i + \beta^i \times MI'_{t-1} + \varepsilon^i \quad (1.1)$$

where α^i is the constant (unobserved characteristics of bank i), β^i is a $(k \times 1)$ vector that captures the bank's i return dependence relationship with the market indices, and ε^i is an iid error term. The return of the system can vary with each bank's return and with the lagged market indices as well:

$$R^{System}_{Market\ Assets,t} = \alpha^{System|i} + \delta^{System|i} \times R^i_{Market\ Assets,t} + MI'_{t-1} \times \beta^{System|i} + \varepsilon_t^{System|i} \quad (1.2)$$

where $\alpha^{System|i}$ is the constant, capturing the banking system characteristics conditioned on bank i , $\beta^{System|i}$ is a $(k \times 1)$ vector of coefficients that captures the system's return dependence relationship with the lagged market indices, $\delta^{System|i}$ reflects the conditional dependence of the system's return on bank's i return, and $\varepsilon_t^{System|i}$ is the iid error term. Running regression from Eq. (1) and Eq. (2) for a quantile of 5% (distressed periods) and a quantile of 50% (median or tranquil state), we obtain the value of regressors to be used in VaR and CoVaR estimations:

$$\widehat{VaR^i_{q,t}} = \widehat{\alpha^i_q} + MI'_{t-1} \times \widehat{\beta^i_q} \quad (1.3)$$

$$\widehat{CoVaR^i_{q,t}} = \widehat{\alpha^{System|i}_q} + \widehat{\delta^{System|i}_q} \times \widehat{VaR^i_{q,t}} + MI'_{t-1} \times \widehat{\beta^{System|i}_q} \quad (1.4)$$

ΔCoVaR represents the contribution of each financial institution to systemic risk, and it equals the difference between CoVaR of the whole system conditioned on the event that the financial institutions register the lowest return at a given confidence level and CoVaR of the whole system conditioned on the event that the financial institution faces the median return:

$$\Delta\text{CoVaR}_{q,t}^{\text{Sys}|i} = \text{CoVaR}_{q,t}^{\text{Sys}|R_{\text{MarketAsset}}^i = \text{VaR}_{q,t}^i} - \text{CoVaR}_{q,t}^{\text{Sys}|R_{\text{MarketAsset}}^i = \text{VaR}_{50\%}^i} \quad (1.5)$$

A greater value of ΔCoVaR is associated with an enhanced contribution to overall systemic risk and thus an increased interconnectedness. To capture slightly different aspects of the systemic risk and test the robustness of our results, we consider as an alternative measure of risk the Marginal Expected Shortfall (MES) of [Acharya et al. \[2017\]](#), which denotes the exposure of banks to systemic risk. MES is defined as the average return on an individual bank's stock on the days the market (MSCI World Financials index) experienced a loss greater than a specified threshold C indicative of market distress.

$$\text{MES}_{t-1}^i = E_{t-1} (R_t^i | R_t^{\text{system}} < C) \quad (1.6)$$

where R_t^i is the return of bank i at time t and R_t^{system} is the return of the financial system, defined as MSCI World Financials index. As in [Andries and Sprincean \[2020\]](#), we consider the threshold C equal to the conditional VaR of the system return, i.e., VaR (5%), which is common for all institutions. The higher the MES, the higher is the exposure of the bank to the systemic risk.

1.3.2 National culture measures

In order to establish the influence of cultural characteristics on banks' systemic risk, we used four cultural dimensions identified by Hofstede (2001) that are widely studied in the literature and found to drive most of the cross-country cultural differences.

Power distance dimension

Power distance is defined as the strength of social hierarchy. Higher power distance indicates a higher acceptance of unequal distribution of power and status among society members [\[Ashraf et al., 2016\]](#). These cultures are characterized by a high level of authority and conformity, hampering innovation and risk-taking [\[Boubakri et al., 2017\]](#). Therefore, we would expect banks from high power distance societies to take less risk and perform better during crises. Higher power distance is more present in low-income countries [\[Mihet, 2013\]](#). Low power distance societies are characterized by egalitarian values, promoting independence and innovation by taking additional risks [\[Mihet, 2013\]](#). The overall results suggest that societies characterized by egalitarian values register higher systemic risks compared

with hierarchical societies.

Individualism dimension

Further, we considered the individualism dimension. This dimension has been defined as the tendency of individuals to look first after themselves and their immediate families [Franke et al., 1991] and can be linked to overconfidence [Chui et al., 2010]. In high individualism cultures, the main emphasis is on individual achievements, self – orientation, goals and performance [Boubakri et al., 2017]. Moreover, managers from these societies are tempted to choose relatively high expected return, high-risk portfolios and be less likely to adopt compensating risk mitigation controls [Berger et al., 2021]. According to Chui et al. [2010], this dimension can be linked to overconfidence and overoptimism due to managers’ belief that their abilities are above average. Therefore, banks from these societies have greater risk-taking incentives to assure the wealth maximization for their customers and shareholders [Mourouzidou-Damtsa et al., 2019]. This implies that banks in individualistic societies are likely to take more risk and to perform worse during crises [Boubakri et al., 2017]. According to [Mihet, 2013], developed countries tend to be more individualistic than emerging countries. These arguments suggest that the level of systemic risk will be higher in high individualism societies as well as the incidence of bank financial trouble during the crisis period.

Masculinity dimension

According to Hofstede [2001], masculinity stands for societies where social gender roles are clearly defined. In masculine societies, men are supposed to be assertive, tough and focused on the advancement and earnings, while feminine societies are supposed to be more modest, nurturing, and concerned with the quality of life. Alternatively, in feminine societies, there is an overlap in the gender roles, with both genders being modest, tender and concerned with the standard of living [Hofstede, 2001]. As masculine societies are more oriented toward social recognition and ego, competitiveness, achievements and little compassion for the weak, all these characteristics are associated with an orientation toward acquisition and overinvestment [Berger et al., 2021], and we would expect these societies to assume more risks [Ashraf et al., 2016]. In high-income economies prevail the masculinity dimension [Mihet, 2013], also bank managers in these societies are less likely to restrict credit availability to new (e.g., Bellucci et al. [2010]) and may be more likely to manage earnings than control risk (e.g., Kanagaretnam et al. [2011]). Feminine societies are more relationship-oriented and have greater consideration of the impact of their actions on society [Ashraf et al., 2016]. Based on the above, we expect that in societies characterized by masculinity, systemic risk to be higher than that in feminine societies.

Uncertainty avoidance dimension

First, we considered the impact of the uncertainty avoidance dimension on the

systemic risk that deals with a society’s tolerance for uncertain, unknown or unstructured situations. Hofstede [2001] defines uncertainty avoidance as ‘feeling uncomfortable with uncertainty and ambiguity and therefore valuing beliefs and institutions that provide certainty and conformity. People from societies with high uncertainty avoidance favor an orderly structure in their organizations, institutions and personal relationships and prefer well-anticipated events [Mihet, 2013]. Therefore, due to the need for predictability, banks from these societies will take less risky financial actions from which they will benefit during the crisis when we expect to perform relatively better [Boubakri et al., 2017]. Emerging countries have higher uncertainty avoidance than developed ones, that is consistent with the idea that growth has an inherent risk component [Mihet, 2013].

On the other hand, low uncertainty avoidance societies accept or tolerate uncertainty in a much easier way pursuing more business ventures. Therefore, banks from these countries will take riskier financial actions in periods of economic upswing, while in periods of economic downturn, they are likely to run into problems [Mihet, 2013]. The overall results suggest that banks in countries with high uncertainty avoidance tend to lower risk, leading to lower systemic risk. Consequently, during the financial crisis, we are more likely to observe a lower incidence of bank financial trouble in countries with higher uncertainty avoidance.

1.4 Methodology

The banks in the sample are the most representative banks from the analyzed countries, embedding in their decision making the most dominant characteristics of the nation.² The cultural values used in the analysis are neither time-varying measures nor varying at the banking level. However, they also do not overlap with the country-fixed effects because they are four measures that have different characteristics and distributions. These measures of culture may also have a different impact at different points in time as some of the between measures variations play a different role at times when different decision-making take place, either in time of crises or during the regular times (we show that during the crisis time the importance of cultural characteristics is diminishing). Therefore, while these measures of culture taken individually may not reflect a given strategic position of any given bank at a given point in time, taken jointly, the between variation of these measures can reflect average decisions the banks take to affect the systemic risk.

We model the systemic risk as a function of the cultural traits. Additionally, we control for a rich set of bank-level and country-level information and to control the aggregate shocks, we add time dummies. Consequently, our benchmark model of

²These banks have clients from all layers of the society, the management decisions of these banks should take into account the characteristics of the society.

interest is defined in equation 7:

$$SR_{ijt} = \alpha + \beta C_j + \gamma B_{ijt} + \delta X_{jt} + \eta D_t + u_{ijt} \quad (1.7)$$

where SR_{ijt} is the systemic risk measure (ΔCoVaR) that varies across individual banks (i), countries (j) and time (t), C_j are culture characteristics specific to country j, B_{ijt} is a set of bank-specific variables that varies across individual banks (i), countries (j) and time (t), X_{jt} is a set of macroeconomic variables that vary with countries (j) and time (t), D_t are year dummies and u_{ijt} are unobserved errors.

Following previous studies on systemic risk [Berger et al., 2009, Laeven et al., 2016], we have used a vector of control variables: a) Bank-level - the size of banks, ROA, Capitalization, Non-performing loans, Non-interest income; b) Country-level: GDP Growth per capita, Inflation, Market Power, Loss Coverage Ratio and the Financial Freedom). All variables used in our analyses are defined in Appendix 1.10, and the summary statistics are presented in Table 1.1.

We consider in the analysis that unobserved heterogeneity is part of the error (a random-effects type model), but we cluster the errors at the country level to account for within-country correlation, in other words, we allow for country-specific heteroskedasticity in our estimation.³ We estimate the equation (7) sequentially, first by estimating the model separately with each cultural variables and lastly, by adding all the cultural variables simultaneously in the estimated model. Subsequently, several robustness checks are performed.

First, we check if the linear specification of the cultural variables holds if we add nonlinear effects for these variables. Consequently, we test the functional form specification associated with the effect of the cultural variables on the systemic risk by augmenting the benchmark model with quadratic terms of culture:

$$SR_{ijt} = \alpha + \beta C_j + \sum_{p=2}^P \beta_p C_j^p + \gamma B_{ijt} + \delta X_{jt} + \eta D_t + u_{ijt} \quad (1.8)$$

where P is the order of the polynomial.

Second, to check if the skewness of the risk measures also drives the nonlinearities, a generalized quantile model is estimated. Additionally, we use this specification to test what are the effects of culture at levels of risk associated with crises, which are specific to high quantiles of risks:

$$Q_{SR}(q)_{ijt} = \alpha^q + \beta^q C_j + \gamma^q B_{ijt} + \delta^q X_{jt} + \eta^q D_t + u_{ijt}^q \quad (1.9)$$

We should emphasize that during crises, the systemic risk measures are at their

³We do not use bank-fixed effects as they aggregate to country-fixed effects and the country-specific clustering allows for the within country variation, in other words the clustering allows for country specific bank correlations.

highest quantiles (we overlay the values of systemic risk during the crises, and they are at the highest quantiles). Therefore, the quantile analysis is useful to emphasize the contribution of different culture measures during these highest quantiles associated with crises. Simultaneously, the quantile analysis may provide insightful information at different other quantiles of risk, when the risk is at very low levels when probably there is a high optimism about the strength of the economy. Regular times could be picked up by the mean effects of the risk measures. At the same time, if the culture measures have a nonlinear effect on the risk measures, a nonlinear effect can be captured at different quantile levels.

Third, we check if the data selection associated with the model specifications specific to the risk measure is missing at random, which will be a check for endogeneity due to data selection. To do this, we propose a two-stage procedure. In the first stage, we estimate the probability of being observed (observed selection):

$$O_{ijt}^* = Pr(\varphi Z_{ij}) + \varepsilon_{ijt} \quad (1.10)$$

where

$$O_{ijt}^* = 1\{data\text{is}observed\} \quad (1.11)$$

is an indicator that is 1 if data is observed and 0 if it is not observed. Z_{ij} variables that explain the selection (here we consider a set of exclusion restrictions, which explain the possible selection due to our observable characteristics and do not affect the systemic risk measures) and $\varepsilon_{ijt} \sim N(0, \sigma^2)$. The proposed exclusion restrictions are: diseases as an instrument for individualism. [Berger et al. \[2021\]](#) suggest this instrument referencing [Fincher et al. \[2008\]](#), which argue that societies where the prevalence of pathogens is lower are associated with more individualistic societies; gender inequality index is used as an instrument of masculinity, being positively correlated with this cultural variable; the pronoun politeness is proposed as an instrument for power distance, which, according to Davis and [Davis and Abdurazokzoda \[2016\]](#) relates to languages that use more than one second-person pronoun to create a social distance in interactions; and lastly, we use different religion categories (Catholic, Orthodox, Protestant) as instruments for uncertainty avoidance. [Hofstede \[2001\]](#) suggested that Catholic and Orthodox countries tend to score higher on uncertainty avoidance, while Protestant countries tend to be more accepting of uncertainty.

In the second stage, a selection term is added to the original model to control for the potential selection issue. The new outcome equation is given by:

$$SR_{ijt}^* = SR_{ijt} + \varphi IM_{ijt} + u_{ijt} \quad (1.12)$$

where $IM_{ijt} = \frac{pdf(\varphi Z_{ij})}{1 - Pr(\varphi Z_{ij})}$ is the inverse Mills Ratio, which is obtained using the

model estimated in the first stage.

Forth, we check if banking crises impact the role of cultural traits on the SR measure by estimating the benchmark model for two periods: with no banking crises and with banking crises.

1.5 Empirical results

Summary statistics

In Table 1.1 are presented descriptive statistics for the variables used in our analysis. The average contribution of systemic risk measured by ΔCoVaR was about 1.2% loss of the system's market assets for our key dependent variable. For the key independent variables, the average value of power distance (PDI) is 0.57, masculinity (MAS) is 0.51, individualism (IDV) is 0.58, and uncertainty avoidance (UAI) is 0.66. These results are closed with the means reported in Hofstede [2001], suggesting that our sample represents the overall population of countries. Looking at the bank-level characteristics, the average bank from our sample has a capitalization of 9%, a return on average assets of about 1.4%, a high share of non-interest income to total assets of about 70% and average bank non-performing exposures is about 3.7%. At the macro-level, the average loan loss provisions to NPL ratio is about 1.7%, the average economic growth per capita rate is 1.3%, and the average inflation is 3.0%. Financial freedom is about 60, meaning that central banks for the countries analyzed are not fully independent, while the Lerner indicator shows banks are operating under moderate competition conditions.

We compare the effects of different cultural traits on systemic risk via a t-test. The test results (Table 1.2) show that societies characterized by individualism, masculinity, low power distance, and low uncertainty avoidance have a higher contribution to systemic risk than societies characterized by collectivism, femininity, hierarchy and high uncertainty avoidance.

Regression results

In our paper, we test three different hypotheses to identify whether national culture influences systemic risk measured using ΔCoVaR . First, we test if the national culture measures are affecting the systemic risk measure individually and jointly. The results on the benchmark are compared with the ones obtained via other tests: first, we add nonlinearities of culture in the analysis; second, we estimate the effects of culture at different quantiles of systemic risk to check if, at higher levels of systemic risk, associated with crisis periods, national culture measures have different effects than when are recorded lower levels of systemic risk; third, we check the effects during financial crises versus non-crisis times; fourth, we check if culture is driving

by an endogenous selection in the observed data and if this potential issue alters the results.

In Table 1.3 are presented the results for the first test, whether the national culture measures are affecting the systemic risk measure individually and jointly. In column (1), we present the joint effects of the cultural variables on the systemic risk, while columns (2) to (5) are presented the individual effects on the systemic risk. The results show that individualism and masculinity have a positive effect on ΔCoVaR . Our results are in line with Berger et al. [2021] that shows that individualism and masculinity increase bank failure probability. Further, when we consider independent effects of these cultural values on the systemic risk, the results are similar both in sign and marginal effects. Results are also economically significant. Based on the specification in column (1), we find that a one standard deviation increase in the individualism dimension produces, on average, a 10.90% increase in the contribution to systemic risk. Similarly, we find that a one standard deviation increase in the masculinity dimension produces, on average, a 9.70% increase in the contribution to systemic risk. The relatively greater effect of individualism on systemic risk relative to masculinity is consistent with Berger et al. [2021]. When we look at power distance and uncertainty avoidance effects, they are not fully consistent across specifications and robustness checks.

Our results show that bank size and non-performing loans are positively associated with systemic risk [Festic et al., 2011, Laeven et al., 2016]. Regarding the country-level controls, our results reveal that the Lerner indicator is positively associated with systemic risk (i.e. greater competition increase the banking system less resilience to shocks) [Anginer et al., 2014]. The fact that power distance and uncertainty avoidance are not significant in the benchmark model may be that these variables, while not having a linear effect on systemic risk, may have a nonlinear effect on systemic risk (see the non-parametric results presented in Figure 1.2). We consider that functional form may play a role for several reasons. First, Hofstede cultural measures are embedded two types of information in each measure (masculinity vs femininity, individualism vs collectivism, low vs high power distance and low vs high uncertainty avoidance). This dual information may induce nonlinear effects of culture measures on systemic risk measures. Second, the skewness of the systemic risk measure may also be explained by the nonlinear cultural effects (see Figure 1.1).

In Table 4 we present the results when we add nonlinearities for the cultural measures that show significant nonlinearity in Figure 1.1. Again, we do this exercise for the cultural variables introduced independently (columns 1-4) and jointly in the model (column 5). The result shows that while masculinity and individualism remain positive and significant and preserving their linear effect, for power distance, the results are showing an inverted U-shaped, while for the uncertainty avoidance,

we observe a U-shaped relationship. The effects are similar to those observed in the non-parametric regression. The results for power distance emphasize the fact that in egalitarian societies, there is no barrier between management and employees [Brett et al., 1998], thus, employees are more likely to challenge managerial decisions. Also, managers need to consider the interests of all stakeholders, including lower-ranked employees, as they have the potential to affect the firm (Gibson, 2000). Furthermore, egalitarian societies consider the interest of all stakeholders and the society at large, therefore, they are more likely to be concerned about financial stability. Also, bank managers in egalitarian societies are more trusting, leading to higher risk [Das and Teng, 2004]. On the other hand, hierarchical societies characterized by a high level of authority and conformity are likely to hamper innovation and risk-taking [Boubakri et al., 2017].

Results for uncertainty avoidance show a U-shaped relationship meaning that it is common to assume that countries with low uncertainty aversion during periods of economic growth and speedy developments will benefit from the financial actions that involve risks, while the reverse is true in periods of economic downturn. Although Hofstede [2001] states that uncertainty avoidance does not equal risk avoidance. As a result, bank systems may be more prevalent if national cultures are strong on uncertainty avoidance [Kwok and Tadesse, 2006]. On the other hand, societies characterized by high uncertainty avoidance may also have a high contribution to systemic risk by avoiding competition which may be associated with greater bank risk according to the “competition-stability” view. In particular, in countries with low competition, banks charge high-interest rates on loans, which will increase moral hazard and adverse selection problems by making the bank loans riskier. These spillover effects on the riskiness of the loans are increasing the contribution to systemic risk [Boyd and De Nicolo, 2005]. The results are also preserved when we consider all four risk measures jointly in the model. The stability of these results is also seen in the marginal effects; this is an important finding as it shows that the results may not be affected by potential endogeneity issues. However, we will test if selection of available data suffers from endogeneity by discussing alternative results estimates via the Heckman model. Given these observed nonlinear effects of culture, we test the effects of national culture at higher systemic risk levels specific to crises (and at all other quantiles of risk as a comparison, see Table 1.5). We find that these cultural measures have a different impact at different percentiles of the distributions of ΔCoVaR (masculinity, individualism and uncertainty avoidance). The quantile regression results are in line with the results observed using the models that capture the nonlinear effects of the cultural values, and additionally, they show that cultural values have different effects relative to other percentiles of SR.

Further, given these observations on quantiles, we separate the effects for the

periods where there was a financial crisis from the periods that there was no financial crisis and estimate the benchmark model on these subsamples. We consider the non-crisis sample from 2003 to 2006 and 2011 to 2016, whereas the crisis sample is from 2007 to 2010. We define the recent financial crisis period following existing literature that has studied banks during the global financial crisis [Choi, 2013, Dabrowski, 2010]. The results of this analysis are presented in Table 1.6. The results show that some of the cultural variables (individualism and uncertainty avoidance) lose their significance during the financial crisis. The loss of significance for these variables is not visible at high quantiles of risk (also specific to a crisis). Consequently, the loss of significance at the conditional mean level observed in Table 1.6 may be an artifact of the sample size (only three years) involved in the analysis. Contrary to Mourouzidou-Damtsa et al. [2019] the effect of national culture is not fully eliminated in times of crises.

For robustness check, in Table 1.9, we have used an alternative measure for systemic risk. Our results show that power distance, individualism and masculinity are statistically significant for MES, with masculinity playing a negative effect and the other two a positive effect on MES.

Endogeneity

The endogeneity concern in our analysis due to reverse causality between culture and systemic risk is unlikely as culture does change very slowly and is formed over long intervals of time (centuries or millennia – see Williamson [2000], Hofstede [2001]). Other sources of endogeneity as omitted of important variables are also minimized as we used a rich set of controls at the country and bank level. A remaining endogeneity may be due to selection, in particular, the available information at the bank level may generate a working subsample that can be correlated with the cultural traits. In particular, banks from countries that have specific characteristics may not report specific information about their economic activity. We can treat this type of endogeneity via a Heckman type selection model (see Table 1.7 and 1.8).

The proposed approach is based on two steps. In the first step, we estimate the probability of being observed in the sample. This probability of being observed, as we pointed out, may be correlated with the cultural variables in our main equation. Consequently, to estimate this probability, we need a set of exclusion restrictions (instruments) correlated to the cultural variables but uncorrelated with the systemic risk variable. We chose the exclusion restrictions (instruments) set following Berger et al. [2021] choice. In particular, we use Diseases (the Murray and Schaller [2010] overall index of the historical prevalence of nine diseases) as an instrument for individualism. Berger et al. [2021] suggest this instrument referencing Fincher et al. [2008], which argue that societies where the prevalence of pathogens is lower are associated with more individualistic societies. For masculinity is suggested the

gender inequality index, which is positively correlated with this cultural variable. Further, for Power Distance is suggested the pronoun politeness, which, according to [Davis and Abdurazokzoda \[2016\]](#) relates to languages that use more than one second-person pronoun to create a social distance in interactions. Lastly, for Uncertainty Avoidance, we use different religion categories (Catholic, Orthodox, Protestant). [Hofstede \[2001\]](#) suggested that Catholic and Orthodox countries tend to score higher on uncertainty avoidance, while Protestant countries tend to be more accepting of uncertainty.

To estimate the probability of data selection, besides these instruments, we use the control variables from the second stage as follows: for the variables that have incomplete information, we use their time averages, while for the variables with complete information, we use all the information. The predicted probability from the first step is then used to generate a correction term for the selection, correction term that is called in labor literature the Inverse Mills Ratio. This correction term is then added to the main equation, and the second step is finalized by estimating the augmented equation (the equation with our variables of interest, control variables and correction term). The significance of this additional correction term will suggest that indeed there was selection associated with the observed working subsample.

The potential selection can also be checked by comparing the averages of the outcome and fully observed control variables from the original sample with the averages of the outcome and the fully observed control variables from the working sample. Table 1.7 presents the first stage estimation of the Heckman model (the probability of sample selection). We see that all the suggested exclusion restrictions (instruments) are significant for all the specifications that we considered. These results suggest that the instruments are relevant to explain the probability of selection, and they are also important for identifying the cultural variables in the main equation. Table 1.8 presents the results of the corrected linear model. As it can be seen, the adjusted model while marginally, changes the magnitude of the Masculinity and Individualism (the changes in the parameter estimates while small is due to controlling for the endogeneity due to selection) in the benchmark model, brings significance to Power Distance and Uncertainty Avoidance. The results, however, preserve the sign of all cultural variables from the benchmark model. The fact that the two variables (Power Distance and Uncertainty Avoidance) are reinforced in the selected model may be because the original sample is rebalanced, and more data points are used additionally to correcting for the endogeneity due to selection. Our results again emphasize the importance of culture in explaining systemic risk. While different model specifications were considered in the analysis, culture was always explaining about 20 per cent of the variation of the model, which means that even if culture does not have variation within the observed period, it has a high predictability power in explaining the systemic risk.

1.6 Conclusion

We find a strong relationship between cultural values and systemic risk after controlling for various country and bank level characteristics. The relationship is found to vary in a nonlinear way over the support of the systemic risk measures. This variation may be driven by the dual information found in the national culture measures but also by the skewness effect found in the systemic risk measures. Using quantile analysis, we confirm the nonlinear effects found in the data. Additionally, an interesting finding is that at risks associated with banking crises, the impacts of these cultural variables may change their course significantly. In general, the analysis indicates that societies characterized by individualism, low power distance and masculinity increase the individual contribution to the systemic risk. Another interesting fact is that societies characterized by masculinity will have a higher contribution to the risk of the financial system, but the exposure will be lower. These findings also have important policy implications in the sense that it is important to understand the road a decision-maker has to take to avoid potential banking crises conditioning on the type of culture he or she is activating; as a result designing uniform banking policies to avoid risks for countries with heterogeneous cultures may not have the expected impacts.

1.7 Appendix

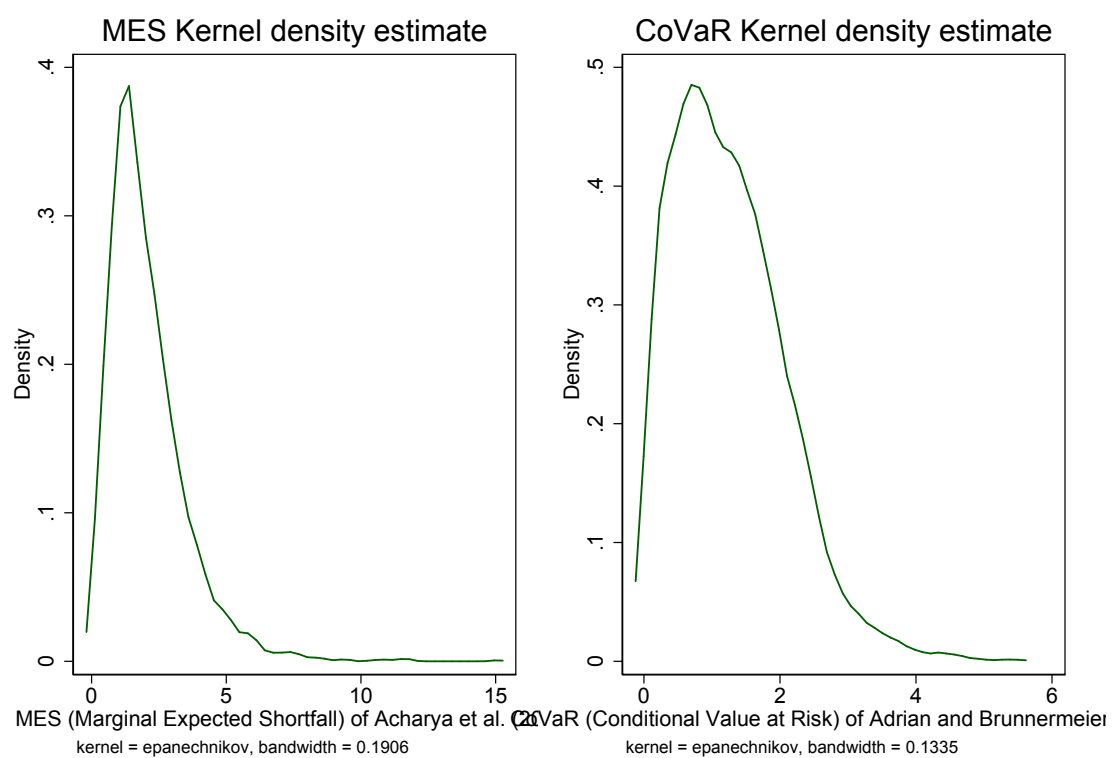


Figure 1.1: Non-parametric Densities MES and ΔCoVaR .

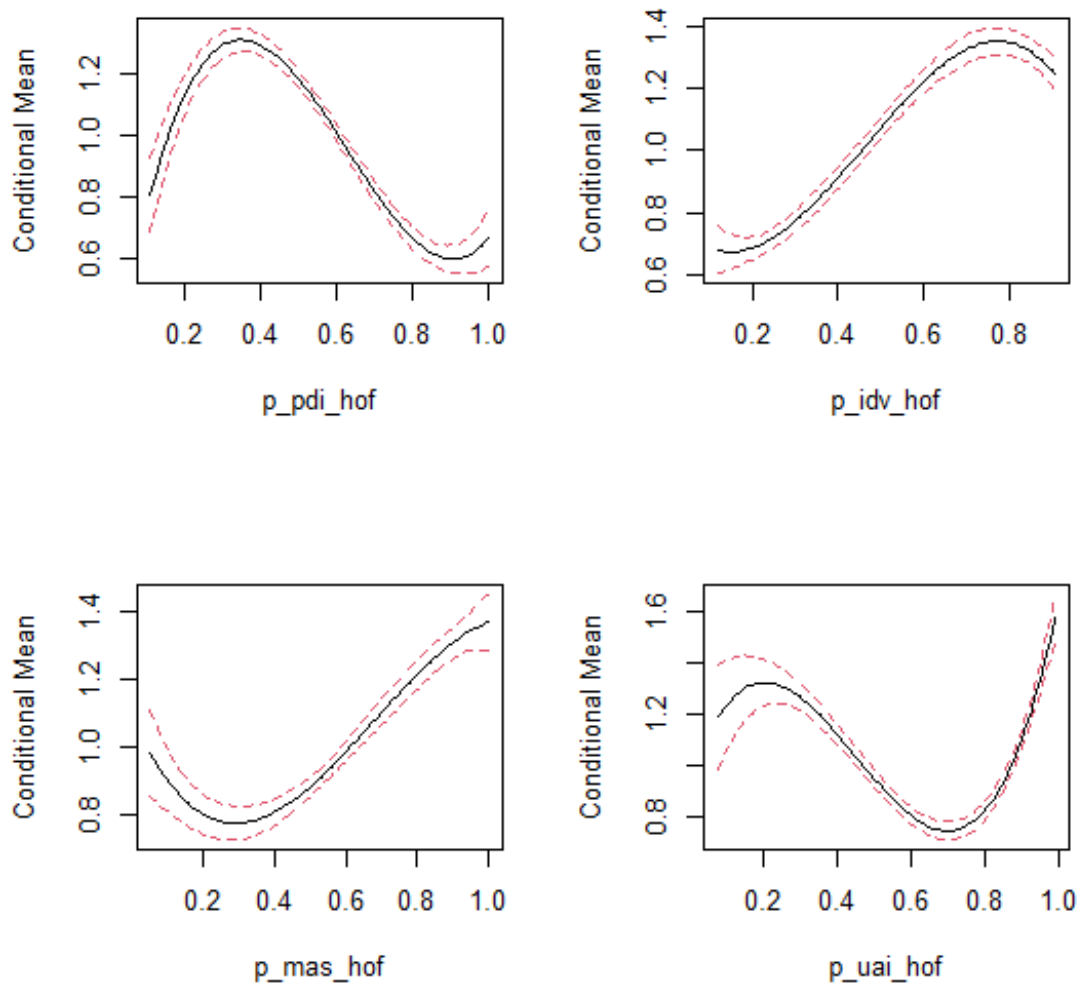


Figure 1.2: Non-parametric Densities of cultural dimensions.

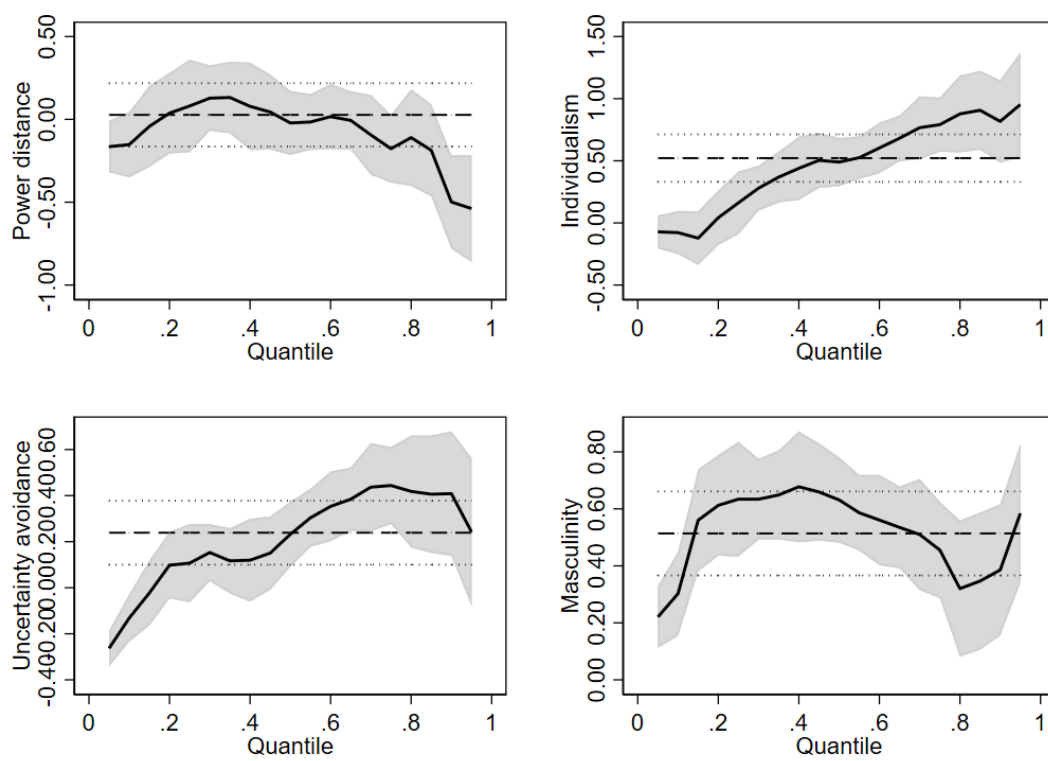


Figure 1.3: Quantile Regression Results for ΔCoVaR .

Table 1.1: Summary Statistics

VARIABLES	N	Mean	SD	Min	Max
MES	4,942	2.064	1.479	0.001	15.075
ΔCoVaR	4,942	1.231	0.814	0.012	5.484
Power distance	4,942	0.573	0.203	0.110	1.000
Individualism	4,942	0.507	0.255	0.120	0.910
Masculinity	4,942	0.581	0.205	0.050	1.000
Uncertainty avoidance	4,942	0.662	0.213	0.080	0.990
Size	4,934	17.070	1.751	10.681	21.895
ROA	4,394	0.014	0.017	-0.148	0.412
Equity/TA	4,552	0.089	0.063	0.006	1.055
Provisions/NPL	4,407	0.017	0.018	-0.010	0.284
NPL/Total loans	4,320	0.037	0.049	0.000	0.972
Non-interest income/TA	4,907	0.724	0.436	0.139	6.041
Inflation	4,588	0.031	0.041	-0.049	1.097
Financial freedom Heritage	4,835	60.356	16.924	10.000	90.000
GDP per capita growth	4,940	0.017	0.032	-0.152	0.163
Higher market power – Lerner Indicator	4,942	0.442	0.497	0.000	1.000

Table 1.2: Mean difference of ΔCoVaR across different culture characteristics

	Effect of PDI	Effect of IDV	Effect of MAS	Effect of UAI
Low	1.26	1.17	1.10	1.26
High	1.20	1.30	1.31	1.21
Diff	0.06**	-0.13***	-0.21***	0.05**
T-test	2.45	-5.57	-9.13	2.37

Note: Significance stars ***, **, and * represent 1%, 5% and 10% significance, respectively

Table 1.3: Benchmark model specification for ΔCoVaR

VARIABLES	(1) ΔCoVaR	(2) ΔCoVaR	(3) ΔCoVaR	(4) ΔCoVaR	(5) ΔCoVaR
Power distance	-0.0140 (0.318)	-0.390 (0.264)			
Individualism	0.431* (0.261)		0.442** (0.178)		
Masculinity	0.475* (0.253)			0.597** (0.253)	
Uncertainty avoidance	0.189 (0.234)				0.233 (0.285)
Size	0.130*** (0.0313)	0.132*** (0.0334)	0.129*** (0.0304)	0.135*** (0.0338)	0.138*** (0.0351)
ROA	-1.123 (1.604)	-1.365 (1.678)	-1.292 (1.704)	-1.260 (1.584)	-1.482 (1.660)
Equity/TA	-0.136 (0.455)	-0.121 (0.452)	-0.167 (0.459)	-0.129 (0.458)	-0.136 (0.460)
NPL/Total loans	1.198*** (0.355)	1.207*** (0.346)	1.195*** (0.341)	1.189*** (0.365)	1.182*** (0.354)
Non-interest income/TA	-0.894 (1.316)	-0.870 (1.339)	-0.904 (1.345)	-0.848 (1.329)	-0.903 (1.343)
Provisions/NPL	-0.0317 (0.0566)	-0.0323 (0.0555)	-0.0316 (0.0555)	-0.0334 (0.0557)	-0.0345 (0.0553)
Higher market power - Lerner Indicator	0.0990** (0.0480)	0.0972* (0.0504)	0.100** (0.0494)	0.0946* (0.0490)	0.0938* (0.0496)
Financial freedom Heritage	-0.000564 (0.00148)	-0.000591 (0.00169)	-0.000881 (0.00160)	6.08e-05 (0.00145)	3.72e-05 (0.00145)
GDP per capita growth	-0.216 (0.717)	-0.328 (0.698)	-0.301 (0.688)	-0.320 (0.709)	-0.352 (0.713)
Inflation	0.544 (0.737)	0.402 (0.718)	0.434 (0.699)	0.461 (0.749)	0.366 (0.729)
Constant		-1.193* (0.691)	-1.570** (0.609)	-1.862*** (0.668)	-1.698** (0.744)
Year FE	YES	YES	YES	YES	YES
Observations	3,368	3,368	3,368	3,368	3,368
Number of banks	339	339	339	339	339

Note: Results obtained using Robust standard errors.

Significance stars ***, **, and * represent 1%, 5% and 10% significance, respectively

Table 1.4: Nonlinear Specification

VARIABLES	(1) CoVaR	(2) CoVaR	(3) CoVaR	(4) CoVaR
Power distance	1.965*** (0.710)			
Power distance ²	-1.961*** (0.651)			
Individualism		1.568 (1.384)		
Individualism ²		-1.040 (1.197)		
Masculinity			-0.141 (0.734)	
Masculinity ²			0.610 (0.637)	
Uncertainty avoidance				-2.725** (1.222)
Uncertainty avoidance ²				2.363** (1.033)
Size	0.129*** (0.0332)	0.128*** (0.0320)	0.135*** (0.0344)	0.126*** (0.0346)
ROA	-1.574 (1.667)	-1.499 (1.689)	-1.460 (1.589)	-1.604 (1.623)
Equity/TA	-0.206 (0.475)	-0.200 (0.477)	-0.146 (0.483)	-0.190 (0.466)
NPL/Total loans	1.215*** (0.331)	1.188*** (0.344)	1.181*** (0.374)	1.194*** (0.358)
Non-interest income/TA	-1.006 (1.379)	-0.963 (1.367)	-0.837 (1.354)	-0.897 (1.357)
Provisions/NPL	-0.0315 (0.0559)	-0.0279 (0.0563)	-0.0298 (0.0559)	-0.0299 (0.0555)
Higher market power - Lerner Indicator	0.0971** (0.0493)	0.100** (0.0487)	0.0941** (0.0478)	0.0934* (0.0493)
Financial freedom Heritage	-0.000444 (0.00161)	-0.000799 (0.0015)	6.23e-05 (0.00141)	0.000166 (0.00142)
GDP per capita growth	-0.349 (0.728)	-0.310 (0.737)	-0.358 (0.744)	-0.445 (0.740)
Inflation	0.210 (0.793)	0.319 (0.770)	0.324 (0.837)	0.217 (0.798)
Constant		-1.788*** (0.634)	-1.658** (0.674)	-0.670 (0.839)
Observations	3,310	3,310	3,310	3,310
Number of banks	331	331	331	331
Year FE	YES	YES	YES	YES

Note: Results obtained using Robust standard errors.

Significance stars ***, **, and * represent 1%, 5% and 10% significance, respectively

Table 1.5: Generalized quantile model - ΔCoVaR

VARIABLES	(1) ΔCoVaR OLS	(2) ΔCoVaR Q5	(3) ΔCoVaR Q10	(4) ΔCoVaR Q25	(5) ΔCoVaR Q50	(6) ΔCoVaR Q75	(7) ΔCoVaR Q90	(8) ΔCoVaR Q95
Power distance	-0.0421 (0.234)	-0.165* (0.0902)	-0.152 (0.130)	0.0808 (0.139)	-0.0214 (0.110)	-0.177 (0.138)	-0.499*** (0.172)	-0.538*** (0.207)
Individualism	0.521** (0.212)	-0.0719 (0.0903)	-0.0778 (0.130)	0.162 (0.139)	0.490*** (0.110)	0.791*** (0.138)	0.817*** (0.173)	0.953*** (0.207)
Masculinity	0.502*** (0.181)	0.221*** (0.0697)	0.302*** (0.100)	0.634*** (0.107)	0.632*** (0.0851)	0.456*** (0.106)	0.386*** (0.133)	0.585*** (0.160)
Uncertainty avoidance	0.162 (0.185)	-0.263*** (0.0656)	-0.132 (0.0946)	0.107 (0.101)	0.232*** (0.0801)	0.444*** (0.100)	0.408*** (0.125)	0.242 (0.151)
Size	0.0897*** (0.0207)	0.0693*** (0.00791)	0.0824*** (0.0114)	0.117*** (0.0122)	0.158*** (0.00966)	0.171*** (0.0121)	0.167*** (0.0151)	0.152*** (0.0182)
ROA	-0.456 (1.403)	-0.819 (1.287)	-1.244 (1.856)	1.666 (1.981)	6.283*** (1.572)	6.394*** (1.964)	2.090 (2.460)	-0.179 (2.955)
Equity/TA	-0.469 (0.433)	-0.0572 (0.340)	-0.496 (0.490)	-1.852*** (0.523)	-1.375*** (0.415)	-0.507 (0.518)	0.525 (0.649)	1.070 (0.780)
NPL/Total loans	1.261*** (0.260)	-0.746*** (0.271)	-0.953** (0.391)	-0.645 (0.417)	-0.246 (0.331)	0.244 (0.413)	1.249** (0.518)	1.867*** (0.622)
Non-interest income/TA	-1.136 (1.383)	-0.916 (0.832)	-1.884 (1.200)	0.138 (1.281)	3.423*** (1.017)	1.481 (1.270)	1.365 (1.590)	0.565 (1.911)
Provisions/NPL	-0.00994 (0.0302)	-0.0686** (0.0299)	-0.0952** (0.0431)	-0.113** (0.0460)	-0.0972*** (0.0365)	-0.102** (0.0456)	-0.0693 (0.0571)	-0.0403 (0.0686)
Higher market power - Lerner Indicator	0.0536** (0.0237)	0.0779** (0.0319)	0.117** (0.0460)	0.252*** (0.0490)	0.266*** (0.0389)	0.208*** (0.0486)	0.155** (0.0609)	0.143* (0.0732)
Financial freedom Heritage	-0.00169 (0.00119)	-0.00185* (0.00112)	-0.000680 (0.00162)	0.00201 (0.00173)	-0.00294** (0.00137)	-0.00319* (0.00171)	-0.00305 (0.00214)	0.000665 (0.00257)
GDP per capita growth	0.251 (0.411)	0.302 (0.548)	1.261 (0.791)	2.298*** (0.844)	0.831 (0.670)	0.471 (0.837)	1.943* (1.048)	2.112* (1.259)
Inflation	0.620 (0.398)	-0.0805 (0.420)	0.383 (0.605)	-0.144 (0.646)	-1.031** (0.513)	-0.746 (0.640)	0.290 (0.802)	0.637 (0.963)
Constant	-1.118** (0.499)	-0.602*** (0.194)	-0.921*** (0.279)	-2.040*** (0.298)	-2.317*** (0.237)	-2.259*** (0.296)	-1.760*** (0.370)	-1.580*** (0.445)
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	3,368	3,368	3,368	3,368	3,368	3,368	3,368	3,368

Note: Results obtained using Robust standard errors.

Significance stars ***, **, and * represent 1%, 5% and 10% significance, respectively.

Table 1.6: Crises and Non-Crises Specification

VARIABLES	Global financial crises (2007-2010)				Non-financial crises (2003-2006; 2011-2016)			
	(1) ΔCoVaR	(2) ΔCoVaR	(3) ΔCoVaR	(4) ΔCoVaR	(5) ΔCoVaR	(6) ΔCoVaR	(7) ΔCoVaR	(8) ΔCoVaR
Power distance	0.245 (0.336)				-0.494** (0.231)			
Individualism		0.0148 (0.263)				0.468** (0.220)		
Masculinity			0.664* (0.389)				0.713*** (0.275)	
Uncertainty avoidance				0.399 (0.367)				0.303 (0.326)
Size	0.209*** (0.0455)	0.208*** (0.0431)	0.209*** (0.0465)	0.213*** (0.0479)	0.0917*** (0.0262)	0.0892*** (0.0234)	0.0950*** (0.0269)	0.0985*** (0.0286)
ROA	-1.604 (2.309)	-1.629 (2.351)	-1.220 (2.102)	-1.732 (2.310)	-1.055 (1.800)	-1.014 (1.837)	-0.886 (1.684)	-1.214 (1.781)
Equity/TA	-0.0297 (1.145)	0.0719 (1.101)	0.100 (1.147)	0.181 (1.140)	0.0852 (0.257)	0.0404 (0.254)	0.0774 (0.257)	0.0745 (0.249)
NPL/Total loans	3.374*** (1.029)	3.378*** (1.022)	3.382*** (1.054)	3.301*** (1.008)	0.806*** (0.237)	0.791*** (0.239)	0.792*** (0.255)	0.777*** (0.246)
Non-interest income/TA	0.375 (1.393)	0.375 (1.421)	0.556 (1.328)	0.398 (1.328)	-0.257 (1.226)	-0.291 (1.235)	-0.249 (1.210)	-0.348 (1.257)
Provisions/NPL	0.0760 (0.170)	0.0785 (0.168)	0.0957 (0.183)	0.0739 (0.177)	-0.00511 (0.0505)	-0.00491 (0.0506)	-0.00700 (0.0499)	-0.00757 (0.0502)
Higher market power - Lerner Indicator	0.0434 (0.0899)	0.0691 (0.0993)	0.106 (0.0926)	0.0652 (0.0918)	0.0615* (0.0366)	0.0655* (0.0365)	0.0539 (0.0334)	0.0550 (0.0342)
Financial freedom Heritage	0.0140*** (0.00416)	0.0126*** (0.00402)	0.0142*** (0.00420)	0.0140*** (0.00388)	-0.00269* (0.00158)	-0.00287* (0.00151)	-0.00207 (0.00140)	-0.00205 (0.00140)
GDP per capita growth	-0.300 (0.788)	-0.214 (0.735)	-0.0761 (0.827)	-0.0884 (0.818)	0.128 (0.548)	0.146 (0.566)	0.167 (0.540)	0.0900 (0.551)
Inflation	-1.106 (1.354)	-1.088 (1.357)	-0.754 (1.196)	-0.971 (1.286)	0.940 (0.573)	0.958* (0.574)	1.003* (0.579)	0.885 (0.569)
Constant	-3.282*** (0.936)	-3.074*** (0.861)	-3.621*** (0.994)	-3.498*** (0.983)	0.272 (0.768)	-0.181 (0.741)	-0.518 (0.614)	-0.278 (0.665)
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	1,043	1,043	1,043	1,043	2,325	2,325	2,325	2,325
Number of banks	297	297	297	297	339	339	339	339

Note: Results obtained using Robust standard errors.

Significance stars ***, **, and * represent 1%, 5% and 10% significance, respectively

Table 1.7: First Stage Estimation: Probability of being observed (sample selection issues)

VARIABLES	(1)	(2)	(3)	(4)	(5)
Size	0.0644*** (0.0159)	0.0629*** (0.0159)	0.0659*** (0.0159)	0.0624*** (0.0158)	0.0630*** (0.0158)
Equity/TA	0.141 (0.602)	0.101 (0.600)	0.162 (0.597)	0.0628 (0.605)	0.160 (0.600)
Higher market power - Lerner Indicator	0.994*** (0.123)	0.849*** (0.123)	0.933*** (0.122)	0.935*** (0.123)	0.852*** (0.122)
Financial freedom Heritage	0.0179*** (0.00232)	0.0180*** (0.00232)	0.0182*** (0.00230)	0.0177*** (0.00235)	0.0180*** (0.00232)
NPL/Total loans	1.039* (0.602)	1.128* (0.598)	1.175** (0.598)	0.982 (0.605)	1.115* (0.598)
ROA	-0.834 (2.442)	-0.272 (2.442)	0.0320 (2.425)	-1.092 (2.459)	-0.265 (2.441)
Pronoun_politeness	0.948*** (0.0958)	0.935*** (0.0960)	0.978*** (0.0950)	0.946*** (0.0962)	0.921*** (0.0956)
Disease	0.181*** (0.0541)	0.169*** (0.0544)	0.176*** (0.0534)	0.174*** (0.0555)	0.168*** (0.0544)
Protestant	-0.340** (0.152)	-0.439*** (0.154)	-0.412*** (0.152)	-0.334** (0.154)	-0.417*** (0.153)
Catholic	-0.243** (0.110)	-0.260** (0.110)	-0.235** (0.109)	-0.216* (0.112)	-0.308*** (0.111)
Ortodox	1.216*** (0.357)	1.189*** (0.355)	1.197*** (0.355)	1.269*** (0.355)	1.107*** (0.359)
Judaism	-1.791*** (0.215)	-1.834*** (0.216)	-1.794*** (0.212)	-1.762*** (0.216)	-1.825*** (0.215)
Islam	-0.488*** (0.108)	-0.525*** (0.109)	-0.514*** (0.107)	-0.459*** (0.110)	-0.554*** (0.109)
Constant	-2.093*** (0.349)	-1.967*** (0.348)	-2.112*** (0.348)	-2.013*** (0.349)	-1.959*** (0.348)
Observations	4,399	4,399	4,399	4,399	4,399

Note: Results obtained using Robust standard errors.

Significance stars ***, **, and * represent 1%, 5% and 10% significance, respectively

Table 1.8: Linear Specification controlling for sample selection issues (Heckman model)

VARIABLES	(1) ΔCoVaR	(2) ΔCoVaR	(3) ΔCoVaR	(4) ΔCoVaR	(5) ΔCoVaR
Power distance	0.118 (0.101)	-0.284*** (0.0891)			
Individualism	0.625*** (0.104)		0.678*** (0.0883)		
Masculinity	0.401*** (0.0799)			0.593*** (0.0738)	
Uncertainty avoidance	0.239*** (0.0731)				0.307*** (0.0702)
Size	0.140*** (0.00925)	0.145*** (0.00912)	0.132*** (0.00920)	0.149*** (0.00899)	0.148*** (0.00916)
ROA	3.161** (1.448)	0.153 (1.426)	1.910 (1.439)	2.266 (1.439)	-0.244 (1.423)
Equity/TA	-0.461 (0.411)	0.00867 (0.406)	-0.519 (0.395)	-0.333 (0.392)	-0.0399 (0.399)
NPL/Total loans	-0.329 (0.309)	-0.296 (0.312)	-0.188 (0.310)	-0.368 (0.305)	-0.570* (0.310)
Non-interest income/TA	1.702* (0.956)	2.832*** (0.960)	2.279** (0.955)	2.540*** (0.953)	2.543*** (0.963)
Provisions/NPL	-0.129*** (0.0338)	-0.123*** (0.0336)	-0.0948*** (0.0336)	-0.147*** (0.0334)	-0.150*** (0.0339)
Higher market power - Lerner Indicator	0.264*** (0.0369)	0.222*** (0.0354)	0.299*** (0.0369)	0.202*** (0.0346)	0.178*** (0.0353)
Financial freedom Heritage	-0.000329 (0.00126)	-0.000771 (0.00104)	-0.00436*** (0.00113)	0.00328*** (0.000954)	0.00246** (0.000991)
GDP per capita growth	1.001* (0.605)	-0.542 (0.575)	0.190 (0.578)	-0.294 (0.564)	-0.0825 (0.594)
Inflation	-0.180 (0.478)	-1.631*** (0.460)	-1.176** (0.462)	-0.634 (0.475)	-1.285*** (0.469)
IMR	-0.505*** (0.148)	-0.520*** (0.145)	-0.558*** (0.132)	-0.345*** (0.131)	-0.614*** (0.133)
Constant	-1.905*** (0.224)	-0.900*** (0.192)	-1.064*** (0.185)	-1.767*** (0.203)	-1.454*** (0.206)
Year FE	YES	YES	YES	YES	YES
Observations	4,399	4,399	4,399	4,399	4,399

Note: Results obtained using Robust standard errors.

Significance stars ***, **, and * represent 1%, 5% and 10% significance, respectively

Table 1.9: Benchmark model specification for MES

VARIABLES	(1) MES	(2) MES	(3) MES	(4) MES	(5) MES
Power distance	0.585 (0.618)	-0.914* (0.542)			
Individualism	2.393*** (0.584)		1.705*** (0.523)		
Masculinity	-1.772*** (0.523)			-1.261** (0.620)	
Uncertainty avoidance	0.711 (0.436)				-0.344 (0.879)
Size	0.381*** (0.0510)	0.400*** (0.0665)	0.377*** (0.0543)	0.412*** (0.0667)	0.405*** (0.0677)
ROA	-4.369 (7.072)	-4.613 (7.290)	-3.002 (7.203)	-6.524 (7.276)	-5.175 (7.239)
Equity/TA	1.503 (1.010)	2.050* (1.063)	1.703 (1.050)	1.754* (1.024)	1.772* (1.045)
NPL/Total loans	3.291*** (1.041)	3.289*** (1.183)	3.353*** (1.143)	3.111*** (1.126)	3.154*** (1.212)
Non-interest income/TA	1.168 (2.004)	1.490 (2.225)	1.325 (2.228)	1.521 (2.176)	1.601 (2.316)
Provisions/NPL	0.0239 (0.117)	0.0139 (0.118)	0.0273 (0.121)	0.00564 (0.112)	0.0101 (0.120)
Higher market power - Lerner Indicator	0.184 (0.177)	0.140 (0.166)	0.179 (0.167)	0.125 (0.180)	0.128 (0.180)
Financial freedom Heritage	-0.00228 (0.00334)	0.00342 (0.00358)	-0.000715 (0.00335)	0.00473 (0.00315)	0.00525 (0.00342)
GDP per capita growth	-0.577 (2.233)	-1.218 (2.343)	-0.612 (2.332)	-1.940 (2.281)	-1.714 (2.170)
Inflation	1.028 (2.137)	0.945 (2.749)	1.615 (2.695)	-0.0596 (2.256)	0.546 (2.522)
Constant		-5.217*** (1.528)			
Year FE	YES	YES	YES	YES	YES
Observations	3,394	3,394	3,394	3,394	3,394
Number of banks	345	345	345	345	345

Note: Results obtained using Robust standard errors.

Significance stars ***, **, and * represent 1%, 5% and 10% significance, respectively

Table 1.10: Definition of variables

Variable	Definition	Source
Size	Defined as the natural logarithm of total assets. Bank size (SIZE) is introduced to account for existing economies or diseconomies of scale in the market.	WorldScope
ROA	Defined as the ratio of EBITDA to total assets.	WorldScope
Equity/TA	which is defined as profit before tax as a percentage of average assets of a bank. A proxy for performance	WorldScope
NPL/Total loans	Defined as the ratio of equity to total assets. Bank equity to total assets ratio. A proxy for solvability.	WorldScope
Non-interest income/TA	Defined as the ratio of non-performing loans to total loans. An indicator of bank non-performing exposures	WorldScope
Provisions/NPL	Defined as the ratio of non-interest income to total assets. An indicator of bank income to total assets ratio would be attributed to the high diversification.	World Bank
Lerner Indicator	Defined as a ratio of loan loss provision to NPL, aggregated at country level. An indicator of how protected a bank is against future losses.	World Bank
Financial Freedom	Defined as the ratio of total bank revenue over assets (using total assets as a proxy for bank production). It is a measure of market power.	Heritage Foundation
GDP/Capita Growth	Financial freedom is a measure of banking efficiency as well as a measure of independence from government control and interference in the financial sector.	World Bank
Inflation (annual %)	Annual GDP per capita Growth	World Bank
	Annual inflation Rate	World Bank

Chapter 2

Cash in the pocket, cash in the cloud: cash holdings of Bitcoin owners

1

Abstract

We estimate the effect of Bitcoin ownership on the level of cash holdings of Canadian consumers. Bitcoin ownership positively correlates with cash holdings even after accounting for selection into ownership via a control function approach. On average, Bitcoin owners hold between 83 (in 2018) to 95 (in 2019) percent more cash than non-owners. Focusing on the quantiles of cash holdings, we find that Bitcoin ownership has a highly nonlinear effect: the difference in cash holdings between Bitcoin owners and non-owners varies from 63 percent in 2017 to 39 percent in 2018 at the 25 quantile of cash and from 176 percent in 2017 to 203 percent in 2018 at the 95 quantile of cash. Our results provide evidence against the narrative that certain new technologies, such as Bitcoin will necessarily lead to a decline in cash usage.

¹This Chapter is co-written with Christopher Henry, Kim P. Huynh, and Marcel C. Voia and is submitted to the Bank of Canada's Working Papers series. As a special note, an earlier version of this joint work was also part of Christopher Henry's thesis (defended in December 2020). As additional improvements, this Chapter includes additional identification corrections (the use of fractional polynomial of age to capture nonlinear differences of age in the probability of Bitcoin adoption) and adds another year of analysis. The extra year of data provides more insightful information on understanding the dynamics of cash demand, as the two years represent total different aspects of the Bitcoin market: 2017, a year of a high pick in Bitcoin prices where the typical Bitcoin adopter was a young male with lower education levels with a focus on speculative based investment; and 2018, a year with the lowest level of price post-2017 pick in price, where the typical Bitcoin owner is more mature, better educated and with higher income. In addition, the proportion of females also increased significantly. These changes in the distribution of the demographic characteristics make the analysis of the cash demand in this context more comprehensive.

2.1 Introduction

There has been a documented decline in the use of cash by consumers for undertaking point-of-sale (POS) transactions over the last decade in Canada. The Bank of Canada’s 2017 Methods-of-Payment (MOP) survey reports that the share of cash used for retail transactions declined from 54 per cent in 2009 to 33 per cent in 2017, see [Henry et al. \[2018a\]](#). However, cash remains popular among certain demographic groups (older, less-educated, and lower-income) and certain types of transactions (small-value transactions). For some demographic groups, it is commonly used as a convenient store-of-value. Similarly, most advanced economies have witnessed a similar pattern of cash usage at the POS. [\[Bagnall et al., 2016\]](#) undertakes an international comparison and shows that cash is resilient across seven countries.²

The country that has been touted as being closest to a cashless society is Sweden due primarily to a lack of consumer demand for cash, see: Sveriges Riksbank [\[rik, 2017, 2018a,b\]](#). [Engert et al. \[2019\]](#) undertake a cross-country comparison of Canada and Sweden to understand the potential drivers of the difference between the two countries. They find that both countries have similar payment infrastructures, so the difference in cash usage is due to bank notes’ legal tender status and banking regulations to secure deposits in Sweden. In addition, they argue that cash demand has two components: transactional and non-transactional. In Canada and many other countries, banknotes in circulation continue to grow at pace with GDP while at the same time, cash used for payments is declining. The stable or increasing demand for cash is thought of as a store-of-value motive. The prospect of a cashless society is driving a flurry of research and policy analysis into Central Bank Digital Currency (CBDC) – a digital form of central bank money. [Lane \[2020\]](#) discusses two potential reasons for issuing CBDC: one, if cash demand falls to negligible amount and two if a private digital currency threatens to takeover payments in Canada. The two conditions may be inter-related as some pundits argue that privately-issued digital currencies, such as Bitcoin, may supplant cash. First, is the role of consumer preferences in driving the demand for cash and alternatives, see [Loix et al. \[2005\]](#). Questions like: What characteristics of cash do consumers value, and would these translate to cash in a digital form? Why consumers want a digital form of cash? are becoming relevant. Characteristics that consumers deem important for in-person transactions – such as speed, ease of use, etc. – may not be as relevant in an online setting. [Huynh et al. \[2020\]](#) estimate the demand for payment services and find that a CBDC that reflects the best of both cash and debit cards would not have wide adoption and usage despite widespread merchant acceptance. Second, it is important to understand the extent to which existing private digital currencies function for consumers as a method of payment versus store-of-value/investment (or some

²The seven countries are: Australia, Austria, Canada, France, Germany, Netherlands, and the United States of America.

combination; see [Glaser et al. \[2014\]](#)). Bitcoin was originally developed more than a decade ago with the purpose of functioning as a decentralized digital currency [[Nakamoto, 2008](#)]; i.e., that it would provide individuals/economic agents with the ability to make peer-to-peer payments without the need for a trusted third-party [[Böhme et al., 2015a](#)]. However, the stunning increase in the price of Bitcoin, which rose from US\$1,000 (late of 2016) to a peak of almost US\$20,000 (late 2017) has led many to reassess whether Bitcoin should be considered as something more akin to a 'cryptoasset' than a cryptocurrency. To better understand consumer adoption and use of Bitcoin, the Bank of Canada commissioned the Bitcoin Omnibus Survey (BTCOS) in 2016 [[Henry et al., 2018b](#)]; the survey has been running annually in subsequent years [[Henry et al., 2019a,b](#)]³. In the current paper, we use data from the 2017 and 2018 BTCOS. The 2017 BTCOS included a new question designed to measure Canadians' consumer cash holdings (i.e., cash held in the person's wallet, purse, or pockets). This question was repeated in 2018. A striking finding was that Bitcoin owners tend to hold noticeably more cash, both on average and at the median, compared with non-owners. This finding alone challenges the assumption that digital currencies will necessarily displace cash in an increasingly digital world, and it also corroborates a similar finding by [Fujiki and Tanaka \[2014\]](#). However, it also raises questions about how to properly interpret this fact, specifically whether there may be factors driving both cash holdings and Bitcoin ownership. This simultaneity may potentially drive selection into holding Bitcoin for the following possible reasons: Bitcoin owners may prefer anonymous liquidity, and hence cash may be a hedge (or vice versa); some Bitcoin owners may not trust institutions (e.g. government or banks), leading to large cash holdings outside of traditional financial institutions. These sources of selection induce endogeneity that is likely to bias estimates of the effect of Bitcoin ownership on cash holdings.

Therefore, considering this potential source of endogeneity, this paper aims to estimate the effect of Bitcoin ownership on the level of consumer cash holdings. In doing so, we also examine whether there are additional distributional effects that affect the relationship between the cash holdings and Bitcoin ownership and finally explore how consumer preferences may account for this relationship. Anticipating the sources of selection, both the 2017 and 2018 BTCOS were designed with a question that can be used as an exclusion restriction or an instrumental variable: "What percentage of Canadians do you think will be using Bitcoin 15 years from now?". This variable works well as an exclusion restriction because owners are more optimistic about the prevalence of future Bitcoin use; however, there is no obvious direct relationship with the current level of cash holdings. Further, to improve identification we exploit differences in non-linearity of age that are present

³The BTCOS was among the first in terms of consumer-focused surveys dedicated to Bitcoin, which was similar to research by [Polasik et al. \[2015\]](#) and [Schuh and Shy \[2016\]](#)

in the model for Bitcoin ownership but not present in the model for cash. Using these non-linearities of age as identification mechanisms two stage models were also suggested by [Dong \[2010a\]](#) and [Escanciano et al. \[2016a\]](#). Based on the results that are controlling for selection, we found that the difference in cash holdings between Bitcoin holders and non-holders varies from 38.7 % (in 2018) to 63.4 % (in 2017) at the 25 quantile of cash and from 176 % (in 2017) to 203% (in 2018) at the 95 quantile of cash, with a mean effect that varies between 82.5% (in 2018) to 95 % (in 2017). These results complement the findings of [Fujiki \[2021\]](#) related to cash hording behavior of crypto assets owners conditional on their experience with investing in conventional risky financial assets. These results suggest that adoption of cryptocurrencies, such as Bitcoin, may not lead to a decrease in the demand for cash.

The chapter is organized as follows: Section [2.2](#) describes the 2017 and 2018 BTCOS, Section [2.3](#) discusses the identification strategy while Section [2.4](#) presents our findings. Section [2.5](#) concludes.

2.2 2017 and 2018 Bitcoin Omnibus Surveys

We base our analysis on the 2017 and 2018 BTCOS conducted by the Currency department at Bank of Canada. The 2017 survey was an extension to the pilot survey (run in two waves) initiated by the same department in 2016, which was designed mostly to measure public awareness of Bitcoin, ownership and reasons for ownership and Bitcoin holdings in Canada. As the price of Bitcoin grew exponentially over 2017, the Bank of Canada decided to conduct a third wave of the BTCOS in 2017 (from December 12 to 15) at the peak price for Bitcoin. This wave, extended the 2016 survey by adding questions that were used to identify the reasons for holding Bitcoin. The 2018 survey was conducted in November when the price of Bitcoin was close to a minimum after the 2017 exponential increase. The two important questions of the 2017 and 2018 surveys referred to Bitcoin awareness (reasons for choosing to own or not to own Bitcoin) and ownership (the amount of Bitcoin held by owners) but also questions about the methods of payment preferred for online purchases, and an assessment of the knowledge of the properties of Bitcoin. Also, the survey collects standard demographic information about each respondent. Between 2016 and 2017 there was a shift in reasons for holding Bitcoin; in 2016 the reasons for holding Bitcoin were for transactional purposes and the new technology associated with it, in 2017 the weight shifted towards investment interests (see [Henry et al. \[2018b, 2019a\]](#)), while in 2018 some of the investment weight from 2017 move towards anonymity. In 2017, the awareness of Bitcoin reached 85 per cent while ownership was only at 4.3 percent. In the same time in 2018 the awareness increased to 89 percent while Bitcoin ownership increased to 5.2 percent. However, compared

to 2016 when ownership was at 3.2 percent, the jump in ownership by 2017 was almost 35 percent and from 2017 to 2018 the jump was of 21 percent. The jump in ownership from 2016 to 2017 was driven by new entrants in the Bitcoin market that got awareness in the past year and got a higher test score on the Bitcoin knowledge, while the subsequent jump was driven by the increase in the awareness for women (from 77 percent in 2017 to 85 percent in 2018) which led to an increase in the Bitcoin ownership for females from (2.1 percent in 2017 to 3.74 percent in 2018). This information about new owners and past owners suggests that selection into Bitcoin ownership is an important mechanism that one needs to consider when the relationship of Bitcoin ownership is linked to cash holdings.

The chosen samples for the 2017 and 2018 BTCOS were post-stratified by region, age and gender to match the population totals observed in the 2016 Canadian census, comprising 2623 individuals' answers in 2017 and 1987 individuals in 2018. We benchmark our observations from the three BTCOS surveys with another survey on methods of payments (MOP) that was also conducted by Bank of Canada in 2017 (as a follow up to one in 2013). While this survey focused on methods of payments, it has an important question that relates to the outcome of interest in this analysis (the cash on hand)⁴, but also one about no cash. Additionally, these questions are also addressed to Bitcoin adopters (both current and past owners) and to those that used digital currency at least once in the past year.

Descriptive statistics

What we can see from both surveys (BTCOS and MOP, see Table 2.1) is that there is a big difference between Bitcoin adopters and non-adopters in terms of cash holdings (the adopters of Bitcoin on average hold at least three times more cash). Also, an interesting finding from all these surveys is that while the no cash users increased by 50 % from 2013 (from 6% to 9%) the average cash on hands also increased from 84 dollars in 2013 to 104 in 2017 and to 170.5 in 2018, increase probably driven by the increase in holdings of higher notes.

- insert Table 2.1 here -

Table 2.2 provides a demographic breakdown of Bitcoin owners versus non-owners. Bitcoin owners are dominated by young, employed, or males. In particular, looking at the within-group numbers we see that for owners, the age group 18 to 34 represents 71 percent of the owners in 2017 and 55 percent in 2018, while for the age group 35 to 54, 25 percent are owners in 2017 and 32 percent in 2018, the remaining Bitcoin owners (5 percent in 2017 and 13 percent in 2018) are above 55 years old. Also, we see that 75 percent of the owners are males in 2017 versus 63

⁴Thinking now about regular Canadian currency, how much cash do you currently have in your purse, wallet, or pockets?

percent in 2018, and 86 percent of the owners are employed in 2017 versus 83 percent in 2018. There is little difference between Bitcoin holders and non-holders in terms of income in 2017 but in 2018 we see a difference at high incomes. If we look at the cash side, we see that the Bitcoin owners hold about four times more cash than non-owners (for the young and mid-age categories) and about 40 percent more cash for the highest age category.

- insert Table 2.2 here -

Also, we observe that male owners hold more cash than their female counterparts (25 percent more). What is also interesting to point out from Table 2.2 results is that the unemployed Bitcoin owners hold 30 per cent more cash than their employed counterparts. These observations also suggest that demographic characteristics are important to our analysis as there are important differences between the demographics associated with Bitcoin owners and non-owners.

Finally, if we look at the distribution of cash by Bitcoin owners and non-owners (here we look at the log of cash, see Figure 2.1 below) we see that Bitcoin owners hold more cash across almost all the support of cash (except at lower levels of cash, below 15th quantile, where the holding of cash is similar across the two groups)⁵. The figure also emphasizes that Bitcoin owners hold high levels of cash, the distribution of cash holding for Bitcoin owners is heavy-tailed to the right. We also see that the distribution of non-holders of Bitcoin after the log transformation is heterogeneous (with multiple modes). These two observations suggest that an estimation that is based on mean average responses of cash holdings by Bitcoin holders will be affected by this observed skewness and heterogeneity. Consequently, while we look at the mean responses of cash holdings as a benchmark model, we analyze also the quantiles of cash.

- insert Figure 2.1 here -

Preferences and Quantities of Bitcoin

This subsection quantifies the effects of different preferences associated with Bitcoin ownership on the amount of Bitcoins the owners chose to have. Understanding the role of these preferences is also of relevance as increased amounts of Bitcoin owned may signal shifts in investments towards these speculative assets with implications to the role the Bitcoin may have when it is compared to cash (substitute versus complement). We construct four categories of preferences using the questions from 2017 BTCOS:⁶

⁵The observation is valid for both years: 2017 and 2018.

⁶For further details on these measures, see Henry et al. [2019a], questions that were repeated in 2018 BTCOS survey.

-
1. The non-trust related (or anonymity) index takes one if Bitcoin users mention that they do not trust either the banks, the government, or the Canadian dollar and Bitcoin allows making anonymous payments.
 2. Technology related index would take value one if respondents chose one of the following: they are interested in new technology, Bitcoin uses secured blockchain technology to prevent loss and fraud, and is a cost-saving technology.
 3. Canadians usage of Bitcoin to pay for goods and services, either online or in physical stores, or to sent peer-to-peer payments reflect their preferences related to transactions.
 4. To measure the effect of investment preferences on the amount of Bitcoin, we created a dummy variable that takes the value of one if respondents chose to own it as an investment and zero otherwise.

We tabulate these preferences on the amounts of Bitcoins owned by the subsample of Bitcoin owners using an ordered logit model. We account for the demographic characteristics, considering the preferences one by one and jointly. The results are presented in Table 2.3.

- insert Table 2.3 here -

The first column is showing the results with individual preferences for 2017, while the second column are the results for the 2018. The results suggests that at the time of the 2017 BTCOS survey, the dominant characteristic of Bitcoin ownership (quantitatively) was the investment motive, while for 2018 none of the preferences related measures were significant.

These results suggest that while there are different reasons for holding Bitcoins, at the time of the 2017 survey the Bitcoin owners preferred to hold Bitcoin for investment reasons, while for 2018 no reason was found dominant. Consequently, as it was pointed out in the introduction, in the current stage of the Bitcoin market, we cannot answer if Bitcoin is a complement or a substitute to cash (the Bitcoin owners are not holding Bitcoin for payments reason), even if we observe that Bitcoin owners are owning more cash than non-owners.

2.3 Identification Strategy

Identifying the relationship that links the cash holdings to Bitcoin adopters builds on the information available in the 2017 BTCOS, characteristics of the data, and the interactions present in the data. Given that the survey is based on a random assignment, we can use a Bitcoin ownership question to separate the Bitcoin owners from

the non-owners and, as a benchmark we estimate a simple linear model where the variable of interest (or the treatment variable) is Bitcoin ownership. However, we do not assume that the adoption of Bitcoin is exogenous. We base our assumption that the two subpopulations (owners and non-owners) are different in distributions. Table 2.4 demonstrates the differences in means for different demographic characteristics: age, gender, employment, education, number of kids and marital status.

- insert Table 2.4 here -

These differences suggest that the unconditional mean effects on cash usage should not be identical with the conditional mean effects of cash usage. In particular, for 2017, the Bitcoin adopters are younger (almost 14 years mean age difference), almost 75 per cent males, and 45 % more likely to be employed than the non-owners counterparts. In 2018 while there are still observed differences between Bitcoin adopters and non-adopters, these differences are reduced (9 year mean difference in age, 56 percent males and 38 % more likely to be employed). These differences in the distribution of observables suggest that owning Bitcoin is selective and, therefore, we should account for the selection in our identification strategy. The difference in findings between 2017 and 2018 may suggest that the selection effect may be stronger in 2017 than 2018.

We already saw from summary statistics that Bitcoin users hold more cash comparing with non-Bitcoin users. This raises the possibility of some simultaneity that links cash holding and Bitcoin ownership, simultaneity that can drive selection into holding Bitcoin as it can be used as a hedge for anonymous liquidity, or alternatively, the Bitcoin holders may not like institutions and avoid reporting their Bitcoin holdings. To solve these selection issues, we propose to use identification methods that are accounting for the endogenous selection via a control function approach. The control function approach is further used to quantify the effect of Bitcoin ownership on quantiles of cash.

We test two hypotheses of interest that link Bitcoin ownership to cash holdings. We conduct these hypotheses for mean cash holdings using a linear model and the distribution of cash holdings via a quantile model.

2.3.1 Expected cash holdings

The first question of interest refers to the average cash holdings and tests the hypothesis:

$$H_{01} : E(Cash|Btc, X, P) > E(Cash|No - Btc, X, P),$$

where X includes individual characteristics as gender, age, education, marital status, number of kids, employment status, household grocery shopping and income, while

P are province fixed effects. In other words, this hypothesis tests if the average holdings of cash are higher for Bitcoin owners than for non-owners.

As outline at the beginning of the section, this hypothesis is tested via different approaches. As a benchmark, we estimate a simple linear model of the form:

$$cash_{i,t} = \alpha + \beta Btc_{i,t} + \gamma X_{i,t} + \delta P_j + u_{i,t},$$

where $cash_{i,t}$ is the log of cash holdings of individual i from time $t = \{2017, 2018\}$ ⁷, $Btc_{i,t}$ is equal to 1 if the respondent i from period t is a Bitcoin owner and zero otherwise, $X_{i,t}$ is a set of respondent characteristics for individual i from period t , P_j are regional fixed-effects, while $u_{i,t}$ is the cross-section specific error term.

The parameter of interest is β or the effect of Bitcoin ownership on cash holdings. If the Btc is randomly-assigned, then the β parameter can be treated as a causal parameter. However, we know that there is selection into the ownership of Bitcoin. This selection will generate bias. Heckman and Robb Jr [1985] provide a method to model the selection by using a two-stage estimation procedure. In the first stage, the endogenous variable (Btc) is projected on an exclusion restriction and a set of observed characteristics at individual and regional dummies via a binary choice model:

$$Btc_{i,t} = Pr(Z_{i,t}, X_{i,t}, P_j) + \epsilon_{i,t},$$

where $Z_{i,t}$ is the exclusion restriction of individual i from period t and $\epsilon_{i,t}$ is the error term that has an i.i.d. logistic distribution. The exclusion restriction is based on the survey question on a respondent's expectation of the adoption rate of Bitcoin in 15 years (EAR15)⁸. The EAR15 is positively correlated with Bitcoin ownership as the owners have a positive outlook on the adoption of Bitcoin⁹. EAR15 is not correlated with cash holdings as the survey question asks respondents to count the amount of cash on their wallet, purse, or person during the survey. They cannot re-optimize their cash holdings. Therefore, EAR15 should not be correlated with cash holdings¹⁰.

Additionally, Figure 2.2 illustrates the cumulative distribution function (CDF) plot of Bitcoin expected adoption rate for the Bitcoin owners versus non-owners. The CDF of the two distributions do not intersect (The adoption rate of Bitcoin owners First Order Stochastic Dominate (FOSD) the adoption rate of non-owners¹¹).¹²

⁷As there are two cross-sections, at each period t there is a unique individual i that is not the same across the two cross-sections

⁸What percentage of Canadians do you predict will be using Bitcoin in the next 15 years?

⁹The correlation coefficient between the EAR15 variable and Bitcoin ownership is 0.24.

¹⁰The correlation coefficient between the EAR15 variable and cash holdings is 0.06.

¹¹FOSD test based on Kolmogorov-Smirnov has a p-value =1

¹²The median of the distribution shows that non-owners believe that expected adoption rate will be around 30 per cent, while owners believe that the expected adoption rate will be around 60 per cent.

The EAR15 restriction also satisfies the conditional independence assumption as in [Abadie et al. \[2002\]](#). Consequently, *EAR15* acts as an exclusion restriction to delineate between the bitcoin owners and non-owners

- insert Figure 2.2 here -

Further, to improve identification we exploit differences in non-linearity of age that may be present in the model for Bitcoin ownership but not present in the model for cash. This source of additional nonlinearity can be exploited in identification as it was suggested by [Dong \[2010a\]](#) and [Escanciano et al. \[2016a\]](#). Figure 2.3 provides the predictive margins of Bitcoin ownership and Cash as a function of Age. The graph clearly shows that age has a nonlinear effect on ownership while it has a linear effect on cash holdings.

- insert Figure 2.3 here -

This additional source of non-linearity can be exploited in the first stage model by introducing fractional polynomial (FP) terms of age. The use of FP as a source of fuller nonlinear representation of the relationship between the predictor (age) and a binary choice outcome was previously studied by [Williams \[2011\]](#). His study suggested that FP can fully capture the nonlinear relationship between the predictor (age) and the discrete outcome that was studied, suggesting that FP is a better alternative to other methods designed to capture nonlinearity in the discrete choice settings. Consequently, we augment our first stage model with FP terms as follows:

$$Btc_{i,t} = Pr(Z_{i,t}, X_{i,t}, Age_{i,t}^{p_k}, P_j) + \epsilon_i,$$

where $Age_{i,t}^{p_k}$ represent the fractional polynomial (FP) terms of age for individual i in period t . In our specification the selected FP is of order two and is provided by [Royston and Altman \[1994\]](#) algorithm, which provides the best fit between the predictor (here age) and the outcome (here the Bitcoin ownership).

The residuals from this stage are further used as a correction term in the second stage that defines the main equation of interest. As the endogenous variable is binary, we have to construct appropriate residuals that are not correlated with the error in the main equation and have statistical properties similar to those used in the least squared approaches. As we chose the logit link function to estimate the probability of Bitcoin ownership, we chose as a CF the deviance residuals ($\widehat{\epsilon}_{i,t}$) as their distribution is closer to the distribution of residuals from the OLS regression models:

$$\widehat{\epsilon}_{i,t} = sign_{i,t} \sqrt{-2(Btc_{i,t} \log(Pr(Z_{i,t}, \widehat{X}_{i,t}, \widehat{Age}_{i,t}^{p_k}, P_j)) + (1 - Btc_{i,t}) \log(1 - Pr(Z_{i,t}, \widehat{X}_{i,t}, \widehat{Age}_{i,t}^{p_k}, P_j))),}$$

where $sign_{i,t}$ is positive if $Btc_{i,t}$ takes the value of one and is negative if $Btc_{i,t}$ takes the value of zero.

The testable hypothesis for this control function is:

$$H'_{01} : E(Cash|Btc, EAR15, X, P) > E(Cash|No - Btc, EAR15, X, P),$$

where *EAR15* is the exclusion restriction. This hypothesis is tested using the second stage, where the CF is introduced as a correction term in the main equation of interest, to estimate the following model:

$$cash_{i,t} = \alpha + \beta Btc_{i,t} + \gamma X_{i,t} + \delta P_j + \phi \widehat{\epsilon}_{i,t} + u_{i,t}.$$

2.3.2 Quantiles of cash holdings

Figure 2.1 shows that the distribution of cash holdings has a heavy right tail for the Bitcoin holders and is multimodal for the non-holders. The average response of the cash holder is affected by these characteristics of the data and therefore, a subsequent hypothesis of interest tests if Bitcoin owners hold more cash than non-owners for all quantiles of cash:

$$H_{02} : Q_{\tau}(Cash|Btc, X, P) > Q_{\tau}(Cash|No - Btc, X, P),$$

where X and P are defined above. This hypothesis can be tested using the following reduced form specification:

$$Q_{Cash}(\tau)_{i,t} = \alpha^{\tau} + \beta^{\tau} Btc_{i,t} + \gamma^{\tau} X_{i,t} + \delta^{\tau} P_j + u_{i,t}^{\tau}.$$

This model can be viewed as a conditional quantile treatment effects type model. The underlying assumption required for the identification of the quantile treatment effects is that the errors are orthogonal to the treatment (*Btc* indicator) and the selection on observables is exogenous. As we previously argued, the selection is not exogenous and, to account for it we use a CF-quantile approach:

$$H'_{02} : Q_{\tau}(Cash|Btc, EAR15, X) > Q_{\tau}(Cash|No - Btc, EAR15, X),$$

where, the Bitcoin holders are entering in the quantile equation also via a CF as suggested in the linear specification above. This hypothesis is estimated via the following equation:

$$Q_{Cash}(\tau)_{i,t} = \alpha^{\tau} + \beta^{\tau} Btc_{i,t} + \gamma^{\tau} X_{i,t} + \delta^{\tau} P_j + \phi^{\tau} \widehat{\epsilon}_{i,t} + u_{i,t}^{\tau}.$$

where $\widehat{\epsilon}_i$ is the deviance residual from the $Pr(Z_i, X_i, P_j)$ estimation.

2.4 Empirical Results

To test our hypotheses, we use a two stage approach. For first hypothesis of interest, we estimate the log-linear model of cash holdings on Bitcoin ownership (variable of interest), demographic characteristics and regional fixed-effects. However, to control the endogenous selection, we need to augment this model with a correction term that requires estimating the probability of Bitcoin ownership. Consequently, we start presenting the results with the extensive margin analysis that quantifies the effects of the demographics and province fixed effects on the probability of holding Bitcoin (propensity score).

Further, we augment the propensity score with the exclusion restriction (*EAR15*) to estimate the probability of holding Bitcoin that is the first stage in the CF approach. A concern associated with this estimations is that Bitcoin ownership to be perceived as a rare event (5 percent of the Canadian are holding Bitcoins). To address this potential issue, the two probability models are adjusted to account for this possibility via a penalized likelihood approach initially introduced by Firth (1993) for generalized linear models and extended for logistic regression models by [Heinze and Schemper \[2002a\]](#)¹³.

Second, we present the results of the first hypothesis of interest without and with the correction for selection. Third, we present the results of the second hypothesis of interest without and with the correction for selection.

2.4.1 Probability of owning Bitcoin

The results are presented in Table 2.5. The first four columns are the results for the year 2017, while the last four for the year 2018. The first column refers to the results of the probability of Bitcoin ownership (propensity score) when accounting for demographic characteristics and province fixed effects, the second column augments the model with the *EAR15* variable, the third column adds the quadratic of age as another source of identification, while the forth column adds FP of age (see the Identification Section). The fifth to eight columns are the equivalent models for year 2018. We refer to the first stage also as the extensive margin analysis. The results for 2017 emphasize the role of gender, age, employment status, number of kids on Bitcoin ownership, while only two provinces (Prairies and Atlantic) have a significantly different impact when compared to the benchmark, British Columbia province (both regions have the lowest Bitcoin ownership, half of BC: 2% versus 4%, see [Henry et al. \[2019b\]](#)). In particular, the age, being female, having kids and being from Prairies or Atlantic provinces have a significant negative impact on the

¹³The correction for rare events does not provide any additional information, being similar with the classical logistic model, therefore we report only the logistic results, while the penalized likelihood results are available on online appendix.

Bitcoin ownership, while being employed has a positive effect on Bitcoin ownership.

- insert Table 2.5 here -

When we augmented the model with the *EAR15* variable, we observe the predictability power of this exclusion restriction as it increases the predictability of Bitcoin ownership in a significant way (54 percent higher Adjusted R^2 in 2017 due to *EAR 15* and 52 percent higher Adjusted R^2 in 2018 due to *EAR 15*).¹⁴ Additionally, the model with *EAR15* emphasize the role of provinces in the estimation of Bitcoin ownership as all provinces have a lower ownership than British Columbia.

Given that only 5 per cent of the sample represents the owners of Bitcoin (117 observations in 2017 and 99 in 2018), we check if each cell associated to the variables used in the analyses has sufficient observations to do a proper analysis. VanVoorhis et al. [2007] pointed out that for a chi-square test, 5 observations per cell are minimal, while a 7 observations per cell are minimum for a mean comparison. We have for almost all the cells much more than the required minimum. One cell with problems was the retired cell, therefore, we combine retired with unemployed and not in labour force to obtain a relevant comparison cell with employed.¹⁵

Additionally to the *EAR15* variable, to improve identification in the second stage we use additional regressors in first stage that capture the nonlinearity of age in relationship with Bitcoin ownership. Consequently in column 3 (for 2017) and column 7 (for 2018) we add the age squared as an additional variable. We see that this addition does not provide any improvement for the 2017, while only a marginal one for 2018. When FP of order two are added to the model with *EAR15* (column 4 for 2017 and column 8 for 2018), we see the increase in the predictability of the Bitcoin Ownership for both years.

Consequently, we retain this last specification as the one needed to generate the control function needed for the second stage regression model.

Further, if we look at the 2018 results (columns 5 to 8) we see the impact of the change in the demographics of Bitcoin holders as income and education become relevant for the Bitcoin ownership¹⁶.

Finally, we check the predictability power of the two model specifications. The results are presented in Table 2.6. The model with *EAR15* dominates the model

¹⁴The model that augments with *EAR15*, has a smaller sample size (about 15% smaller) because some of the respondents did not answer to this question in both years. We check if the reduced sample suffers from additional selection issues, by checking if the average observables are significantly different in the two samples. We model the missing data with missing-at-random imputation model. We find that this item non-response does not have a significant effect on the outcomes. The result of this imputation is a new *EAR15* variable that corrects for the missing data, which is further used in the analysis.

¹⁵We provide empirical estimates to demonstrate that these minimum cells do not affect the estimation results.

¹⁶In 2018 we observed a shift in the demographics of the Bitcoin owners from very young uneducated males towards more educated males with higher income.

without it by showing that there are no remaining unobservables that can improve the predictability and Bitcoin ownership (the prediction is significant while its prediction square is not) and in terms of discrimination between owners and non owners (the area under receiver operating characteristic (ROC) curve is 0.86 versus 0.81 without EAR15), see [Metz \[1978\]](#).

- insert Table [2.6](#) here -

For both years, when the model with EAR15 is augmented with nonlinear FP terms of age, there is a marginal increase in the predictability of the Bitcoin ownership, while there is no increase if only age squared is added. An analysis done only using *EAR15* as a predictor shows the importance of this variable in the prediction of the probability of having Bitcoins, see Table [2.7](#). Actually, the variable itself gives an area under the ROC of 0.78 for year 2017 and 0.77 for the year 2018, which underlines the importance of this variable to discriminate between Bitcoin owners and non-owners.

- insert Table [2.7](#) here -

Next, we focus on the intensive margin of our analysis, which is designed to answer our question of interest that models the role of Bitcoin adopters on the usage of cash.

2.4.2 Cash Holdings: Mean Effects of Cash Holdings

To test the first hypothesis of interest, we estimate the benchmark linear specification that treats the adoption of Bitcoin as exogenous, then we extend the linear analysis assuming that adoption is selective using the Control Function (CF) approach.¹⁷ The results of these analyses are presented in Table [2.8](#).

- insert Table [2.8](#) here -

Column 1 of Table [2.8](#) presents the results of the benchmark model for the year 2017. Here we see that the parameter estimate of Bitcoin ownership is statistically significant and equal to 1.36, and can be interpreted that in average, Bitcoin owners hold a 136 per cent higher amount of cash than non-owners when we control for age, gender, income, education, marital status, number of kids and province of origin.

The next column of Table [2.8](#) presents the conditional mean of cash holdings model that accounts for the selection via the CF approach. The results show that the proposed correction estimates an average difference of log-cash holdings between

¹⁷The advantage of the CF approach is that allows for a simple endogeneity test via a Wald test. In particular, we reject a Null test of exogeneity of Bitcoin ownership as we obtain a p-value for the Wald test of 0.

the Bitcoin owners and non-owners of 0.948, which imply that the average difference in cash holdings between the Bitcoin owners and non-owners is about 95 per cent higher (after controlling for selection). The demographic characteristics that are relevant for cash holdings are: age (positive effect), gender-female (negative effect) and medium and higher income categories show positive effects over the benchmark category (0 to CAN\$50,000). The Prairies, Ontario and Quebec are also showing positive effects over the benchmark region (British Columbia).

Finally, to test the second hypothesis of interest, we consider that the mean log cash estimates are affected by the observed distributions of log cash, which is heavy right tail for the Bitcoin adopters and is multimodal for the non-adopters, therefore we focus our attention to the quantiles of cash holdings.

The third column of Table 2.8 presents the conditional median of cash holdings model that accounts for the selection via the CF approach for year 2017. The conditional median results are similar with the ones of conditional mean, with some differences: the median effect is smaller than the mean effect in magnitude (0.907 vs 0.948) and Ontario is no longer significant.

The last three columns for are the symmetric results for the year 2018. In general the results are consistent across the two years, however the mean effects of cash holdings are lower in 2018 than 2017 (1.18 in 2018 vs 1.36 in 2017 for the model without correction for selection and 0.825 in 2018 vs 0.948 in 2017 for the model with selection). In the same time the median effect in 2018 is above the mean effect in 2018, suggesting a shift in the distribution of cash holdings as probably more people are using less cash in 2017 than in 2018, while the center of the distribution is moving towards higher values suggesting that Canadians may increased the holdings of cash for store value purposes (see Huynh et al. [2020] for the trends of high value (\$50 and \$100) bank notes in circulation which have a positive trend).

The median results suggests potential changes at the tail of the distribution of cash holdings. To test these changes across different quantiles we conduct a conditional quantile analysis on cash holdings.

2.4.3 Quantile Effects of Cash Holdings

First, we assume that the estimated quantiles are not affected by the selection into Bitcoin ownership, and second, we consider that selection into Bitcoin is present, which is corrected also with the CF, similarly as in the linear model.

The results of the conditional quantile model without selection (benchmark) for 2017 and 2018 are presented in Table 2.9 and Table 2.10:

- insert Table 2.9 here -

and

- insert Table 2.10 here -

Given the observed distribution of log cash for Bitcoin owners and non-owners we expect that median estimate to be below the estimated mean effect (at least in 2017), the lower quantile effects to be insignificant, while the higher quantile effects to be strongly in favour of Bitcoin owners. Indeed, for the year 2017 the estimated median effect (estimated at 0.907) of Bitcoin owner on log cash is below the conditional mean effect estimated at 0.948. The pattern across quantiles in the benchmark quantile model is not monotonically increasing as it was expected, with higher estimated values at lower quantiles than expected.

For the 2018 we observe four differences: first, at lower quantiles the estimated cash holdings are not significant between Bitcoin owners and non-owners; second, the median is above 2017 with about 30 percent; third, the high quantiles of cash are lower than in 2017 as we see a bigger bending down at the highest quantiles¹⁸ and four, there is a change in significance for gender and age at high quantiles of cash (gender remains significant while age becomes insignificant). These changes can be explained by the observed changes in demographics for Bitcoin owners in 2018.

As in the linear model, where the endogeneity test suggested that Bitcoin ownership variable is endogenous, we expect to be endogenous also in the quantile model. Therefore, to get a correct conditional quantile effect, we estimate a model that accounts for the selection at the quantile level with the same CF as the one use for the linear specification. The results of this estimation are presented in Table 2.11 and Table 2.12.

- insert Table 2.11 here -

and

- insert Table 2.12 here -

As in the linear case with correction for selection, the results emphasize that indeed the estimated conditional median effect is smaller (estimated at 0.907 for 2017 and 1.052 for 2018) than the one obtained using the benchmark quantile estimates and the unconditional median. Once we control for selection the conditional quantiles are showing the expected patterns: not significant effects at lower quantiles and increased difference in cash holdings between Bitcoin owners and non-owners over the quantiles up the 90 percentile, with a correction down at the 95 percentile.

The demographic characteristics that were relevant for the linear model are also relevant for the quantile model, however there are differences between the 2017 and 2018 quantile results: for 2017 age has a positive effect, with a marginal effect that

¹⁸The difference in cash holdings between the lower and higher quantiles is however larger in 2018 versus 2017.

varies across quantiles, gender-female has a negative effect, with marginal effects that are higher at lower quantiles and lower at high quantiles of cash for 2017, at 95 percentile gender cash holdings differences become insignificant, and higher-income categories that show positive effects over the benchmark category (0 to CAN\$50,000), an effect that is maintained across all quantiles in 2017. For 2018, the age while positive and significant at quantiles of cash below 90, becomes insignificant at high quantiles of cash, the female dummy remains significant across all quantiles of cash and increase in relevance at high quantiles, while the income effects became insignificant at high quantiles of cash. The observed changes of the impact of the demographic characteristics on the cash holdings between the 2017 and 2018 surveys are driven by the observed distributional changes in the demographics of Bitcoin owners that are more gender balanced, higher in age, more educated and with higher income in 2018 when compared to 2017.

A graphical representation of the differences between the benchmark quantiles estimates and the corrected for selection quantile estimates are presented in Figure 2.4. The results show how selection affects the quantile estimates, especially the lowest and the highest ones.

2.5 Conclusion

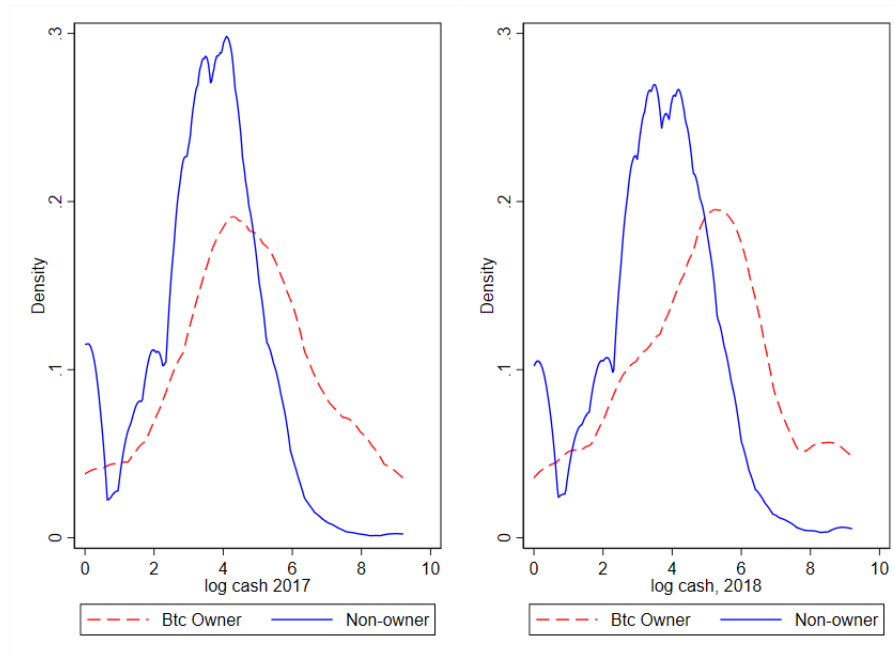
The year 2017 was pivotal in the evolution of cryptocurrencies. As the price of Bitcoin sky-rocketed, these instruments garnered increased popular interest along with scrutiny from regulatory bodies and the financial sector. In the same time 2018 was another pivotal year for the Bitcoin as the price of Bitcoin plunged to the lost level post the 2017 increase. The core of the discussion on Bitcoin came down to the question of how consumers were actually using it: Was it a vehicle for speculation and investment? Or, a convenient way for criminals to transact? Were people using Bitcoin as it was originally designed, i.e., a decentralized currency that opened up new avenues for making transactions that would otherwise not take place? The answers to these questions are still largely unclear even now, but have become increasingly relevant against the background of proposals for Central Bank Digital Currency and the so-called death of cash.

Using data from the Bank of Canada's 2017 and 2018 Bitcoin Omnibus Survey, this paper sheds light on a surprising finding which suggests that digital currencies may in fact play a role in supplementing existing payment methods and financial systems, rather than supplanting them. Controlling for observable factors, and most importantly selection into Bitcoin ownership (driven by gender difference in expectations of future Bitcoin ownership), we show that cash holdings of Bitcoin owners are substantially higher than non-owners. Further, this difference is most drastic among consumers that hold large amounts of cash.

To build on this work, we suggest several directions for future research. First, it is necessary to identify the specific features that Bitcoin owners deem relevant for determining their adoption and usage – this may help explain what is driving large cash holdings among owners. Second, it would be useful to classify Bitcoin owners into various types, e.g. investors, casual users, etc. It is not unreasonable to assume that Bitcoin owners themselves are heterogeneous, and this needs to be factored into any analysis that attempts to explain the relationship between Bitcoin ownership and cash holdings. Finally, it would be useful to examine evidence from other countries. Canada may be considered relatively advanced in terms of financial inclusion and the structure of its financial institutions – how would our results differ in countries where this is not the case?

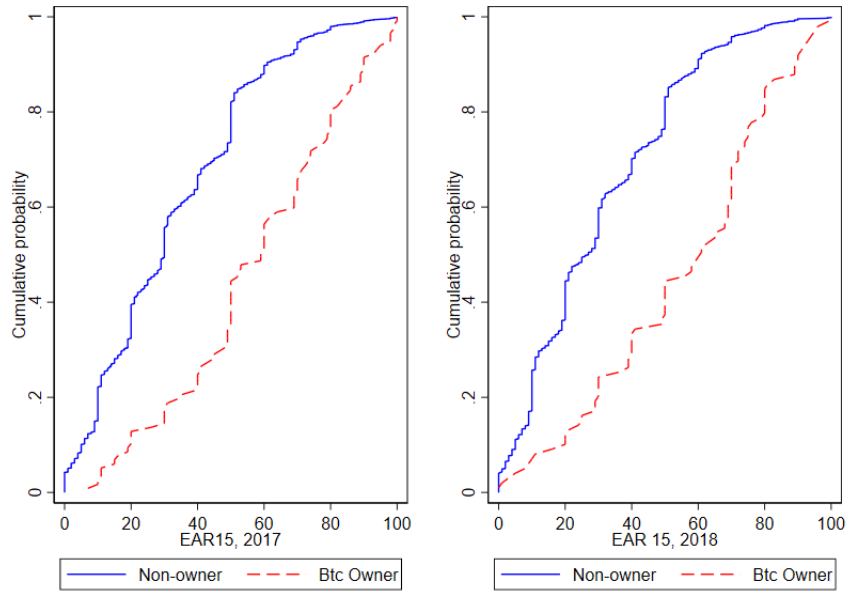
2.6 Appendix: Figures

Figure 2.1: Kernel density, log of cash holdings by BTC ownership



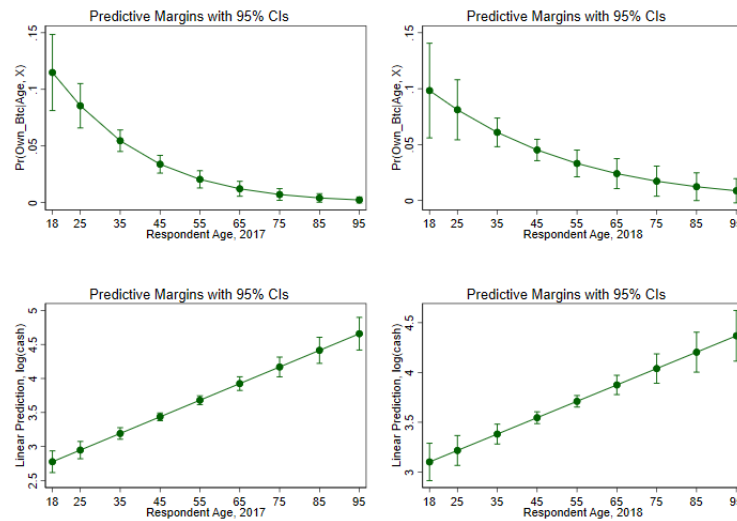
Note: Data are from the 2017 and 2018 BTCOS. The red density is for Bitcoin owners and the blue density is for non-owners.

Figure 2.2: BTC Expected Adoption Rate as an instrument



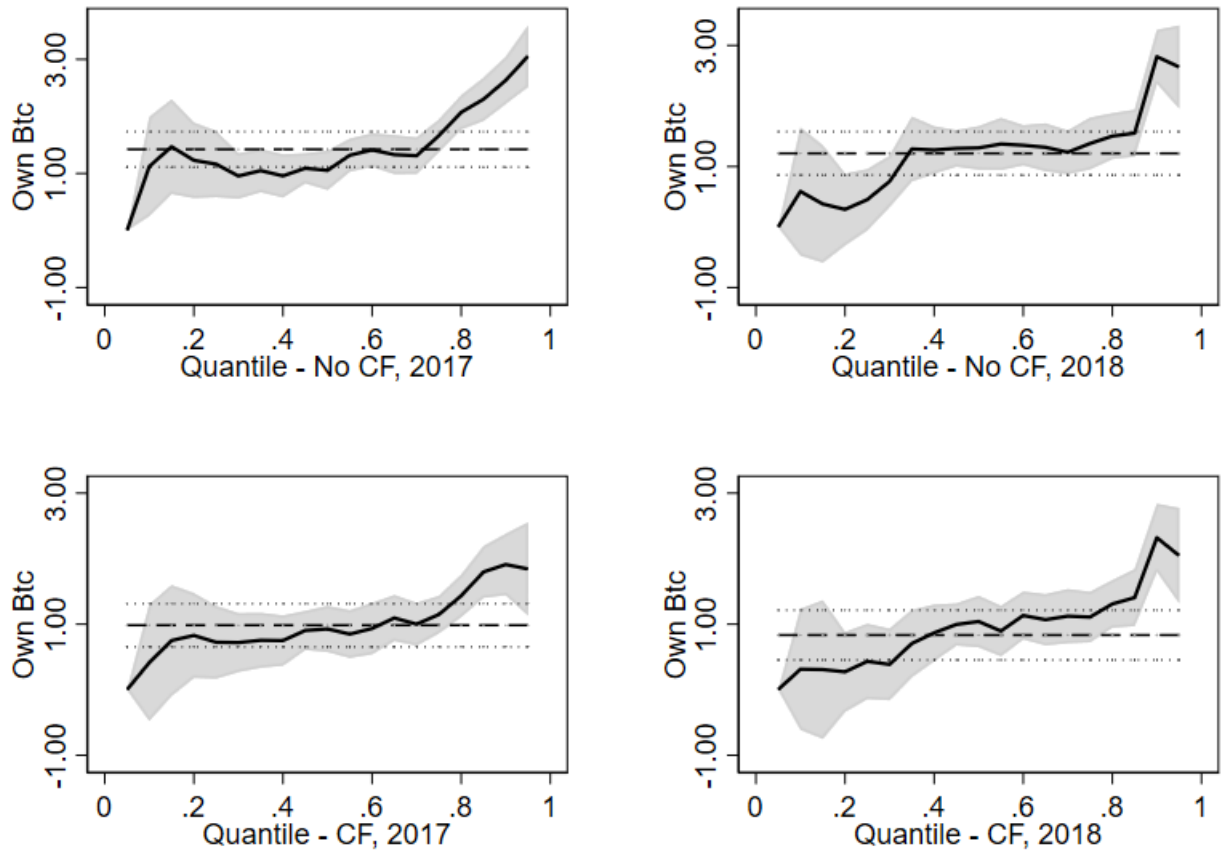
Note: Data are from the 2017 and 2018 BTCOS. The the red CDF is for Bitcoin owners and the blue CDF is for non-owners.

Figure 2.3: Predictive Margins of Bitcoin ownership and Cash as a function of Age



Note: Data are from the 2017 and 2018 BTCOS.

Figure 2.4: Quantile and Control-Function Quantile Results



Note: Top graphs present the quantile results without correction for selection (left 2017 and right 2018), while the bottom graphs present the quantile results for the model with correction for selection (left 2017 and right 2018).

Table 2.1: **Cash and Ownership of Bitcoin in Canada**

	Cash on hand		No cash	
	mean	median	percentage	N
Bitcoin Adopters				
2018 BTCOS	518	120	6%	144
2017 BTCOS	434	100	5%	154
2017 MOP	320	65	8%	93
Non Adopters				
2018 BTCOS	170.5	40	8%	1843
2017 BTCOS	104	40	8%	2469
2017 MOP	108	40	9%	3127
2013 MOP	84	40	6%	3663

Note: Data are from the Bitcoin Omnibus Survey and Methods-of-Payment Survey. BTC adopters are: both current and past owners (BTCOS); and, those who have used digital currency at least once in the past year (MOP). ‘No cash’ is the percentage of respondents not having any cash on their person.

2.7 Appendix: Tables

Table 2.2: **Demographics of Bitcoin owners in Canada and their holdings of cash**

Demographic	2017		2018	
	non-owners	owners	non-owners	owners
Male	0.47	0.75	0.48	0.63
Female	0.53	0.25	0.52	0.37
18-34	0.25	0.71	0.26	0.55
35-54	0.34	0.25	0.34	0.32
55+	0.40	0.04	0.40	0.13
High School	0.43	0.36	0.44	0.19
College	0.31	0.22	0.30	0.33
University	0.27	0.42	0.26	0.48
<30K	0.30	0.34	0.31	0.16
30k-69K	0.44	0.38	0.41	0.46
70K+	0.27	0.27	0.28	0.38
Employed	0.60	0.86	0.60	0.83
Not employed	0.40	0.14	0.40	0.17
British Columbia	0.13	0.16	0.13	0.17
Prairies	0.18	0.17	0.18	0.21
Ontario	0.39	0.34	0.38	0.38
Quebec	0.23	0.28	0.24	0.21
Atlantic	0.07	0.05	0.07	0.04
Btc literacy: Low	0.57	0.24	0.63	0.19
Btc literacy: Medium	0.38	0.49	0.32	0.52
Btc literacy: High	0.05	0.27	0.05	0.29
FL literacy: Low			0.26	0.38
FL literacy: Medium			0.36	0.33
FL literacy: High			0.37	0.29
N	2506	117	1987	99

Note: Data are from the Bitcoin Omnibus Survey 2017. BTC_no are non owners of Bitcoin and BTC_yes are Bitcoin owners.

Table 2.3: **Order Logit Model for Quantities of Bitcoin as a function of Preferences**

VARIABLES	2017	2018
Investment	-1.591** (0.669)	0.265 (0.552)
Lack of Trust	-0.999 (0.957)	-0.336 (0.677)
Technology	-0.901 (0.772)	0.144 (0.676)
Respondent Age	0.0595** (0.0235)	-0.00683 (0.0130)
Gender: Female	-0.683 (0.647)	-0.0954 (0.523)
Income: 50k-99k	0.424 (0.539)	1.303** (0.568)
Income: 100k+	0.924 (0.650)	1.203* (0.646)
Region: Prairies	-0.595 (0.640)	-0.868 (0.832)
Region: Ontario	0.000376 (0.584)	-1.278* (0.699)
Region: Quebec	0.124 (0.619)	-1.663** (0.661)
Region: Atlantic	-1.866* (1.009)	-0.638 (1.207)
Employment	0.610 (0.699)	0.680 (0.715)
College/CEGEP/Trade school	0.341 (0.684)	1.142 (1.123)
University	0.449 (0.683)	0.850 (1.102)
No kids	0.0546 (0.560)	-0.461 (0.523)
Marital status: Not married/CL	0.504 (0.522)	-0.599 (0.460)
Marital status: Not all of it	-0.0756 (0.611)	-0.417 (0.523)
Observations	117	99

Note: The first column presents the results with the effect of the preferences in 2017 and the second column is the same model but for 2018. The benchmark preference is Payments.
Significance stars ***, **, and * represent 1%, 5% and 10% significance, respectively.

Table 2.4: Mean Differences in observables between Bitcoin owners and non-owners

Variables	own, 2017	no-own, 2017	own, 2018	no-own, 2018
Age	34.78*** (1.036)	48.18*** (0.310)	38.16*** (1.430)	49.27*** (0.351)
Gender: Female	0.274*** (0.0414)	0.549*** (0.00994)	0.434*** (0.0501)	0.588*** (0.0113)
Income: 50k-99k	0.385*** (0.0452)	0.355*** (0.00956)	0.495*** (0.0505)	0.347*** (0.0110)
Income: 100k+	0.205*** (0.0375)	0.205*** (0.00807)	0.313*** (0.0468)	0.184*** (0.00893)
Region: Prairies	0.154*** (0.0335)	0.189*** (0.00782)	0.172*** (0.0381)	0.149*** (0.00819)
Region: Ontario	0.333*** (0.0438)	0.340*** (0.00946)	0.424*** (0.0499)	0.404*** (0.0113)
Region: Quebec	0.248*** (0.0401)	0.243*** (0.00857)	0.192*** (0.0398)	0.245*** (0.00990)
Region: Atlantic	0.0598*** (0.0220)	0.0870*** (0.00563)	0.0505** (0.0221)	0.0667*** (0.00575)
Employed	0.846*** (0.0335)	0.584*** (0.00985)	0.808*** (0.0398)	0.579*** (0.0114)
Education: College/CEGEP/Trade school	0.274*** (0.0414)	0.350*** (0.00953)	0.333*** (0.0476)	0.363*** (0.0111)
Education: University	0.556*** (0.0461)	0.422*** (0.00987)	0.586*** (0.0498)	0.399*** (0.0113)
Number of kids: No kids	0.598*** (0.0455)	0.765*** (0.00847)	0.556*** (0.0502)	0.817*** (0.00891)
Marital status: Not married/CL	0.453*** (0.0462)	0.405*** (0.00981)	0.374*** (0.0489)	0.426*** (0.0114)
Grocery shopping: Not all of it	0.350*** (0.0443)	0.461*** (0.00996)	0.374*** (0.0489)	0.466*** (0.0115)
Observations	117	2,506	99	1,888

Note: The last column is the difference in means between the Bitcoin owners and non-owners. The stars are associated with a t-test for difference in means. Significance stars ***, **, and * represent 1%, 5% and 10% significance, respectively.

Table 2.5: Probability of Bitcoin ownership - with sample correction

Variables	(1,2017)	(2, 2017)	(3, 2017)	(4, 2017)	(5, 2018)	(6, 2018)	(7 2018)	(8, 2018)
Respondent Age	-0.0680*** (0.00926)	-0.0563*** (0.00944)	-0.0646 (0.0561)	0.0423 (0.0425)	-0.0558*** (0.0108)	-0.0363*** (0.0116)	-0.139*** (0.0388)	3.595*** (1.060)
Age^2			0.000103 (0.000691)				0.00117*** (0.000423)	
Age^{P1}				-25.55*** (8.509)				95.98*** (33.03)
Age^{P2}				72.75*** (25.54)				-71.76*** (22.32)
Gender: Female	-1.300*** (0.210)	-1.357*** (0.222)	-1.357*** (0.222)	-1.354*** (0.226)	-0.928*** (0.223)	-0.802*** (0.238)	-0.787*** (0.243)	-0.797*** (0.245)
Income: 50k-99k	-0.138 (0.253)	-0.110 (0.265)	-0.109 (0.264)	-0.110 (0.266)	0.956*** (0.304)	1.018*** (0.311)	1.053*** (0.303)	1.052*** (0.313)
Income: 100k+	-0.377 (0.294)	-0.353 (0.311)	-0.350 (0.309)	-0.278 (0.316)	0.976*** (0.365)	0.908** (0.374)	1.000*** (0.366)	1.031*** (0.375)
Prairies	-0.678** (0.339)	-0.818** (0.361)	-0.815** (0.360)	-0.859** (0.359)	-0.0698 (0.370)	-0.0359 (0.382)	-0.00114 (0.385)	0.00335 (0.395)
Ontario	-0.353 (0.278)	-0.558* (0.298)	-0.557* (0.299)	-0.563* (0.299)	-0.210 (0.320)	-0.292 (0.335)	-0.265 (0.336)	-0.203 (0.346)
Quebec	-0.279 (0.293)	-0.610** (0.311)	-0.608* (0.311)	-0.634** (0.312)	-0.395 (0.363)	-0.459 (0.384)	-0.355 (0.388)	-0.325 (0.399)
Atlantic	-0.759* (0.447)	-0.931** (0.458)	-0.928** (0.457)	-0.915** (0.465)	-0.387 (0.570)	-0.501 (0.609)	-0.419 (0.614)	-0.381 (0.613)
Employment	0.783*** (0.303)	0.623** (0.307)	0.635** (0.320)	0.566* (0.323)	0.121 (0.279)	0.173 (0.286)	0.353 (0.300)	0.156 (0.327)
College/CEGEP/Trade school	-0.0980 (0.317)	0.0834 (0.321)	0.0878 (0.326)	0.0332 (0.323)	0.864** (0.412)	0.911** (0.423)	1.015** (0.423)	0.798** (0.405)
University	0.264 (0.288)	0.494 (0.302)	0.498 (0.306)	0.360 (0.309)	0.986** (0.396)	0.971** (0.414)	1.054** (0.416)	0.817** (0.399)
Number of kids: No kids	-0.468** (0.228)	-0.296 (0.234)	-0.303 (0.238)	-0.407 (0.249)	-0.713*** (0.249)	-0.608** (0.271)	-0.700** (0.272)	-0.583** (0.284)
Marital status: Not married/CL	-0.299 (0.249)	-0.196 (0.257)	-0.200 (0.261)	-0.0553 (0.269)	-0.201 (0.289)	0.00200 (0.291)	-0.0259 (0.294)	0.0678 (0.296)
Grocery Shopping: Not all of it	-0.657*** (0.221)	-0.275 (0.229)	-0.280 (0.235)	-0.212 (0.237)	-0.529** (0.235)	-0.242 (0.241)	-0.301 (0.245)	-0.163 (0.257)
EAR15		0.0405*** (0.00433)	0.0405*** (0.00434)	0.0406*** (0.00433)		0.0378*** (0.00538)	0.0373*** (0.00538)	0.0371*** (0.00544)
Constant	0.756 (0.558)	-1.671** (0.658)	-1.526 (1.161)	-10.36*** (3.522)	-0.593 (0.697)	-3.348*** (0.943)	-1.534 (1.186)	-141.7*** (46.19)
Observations	2,623	2,623	2,623	2,623	1,987	1,987	1,987	1,987
LR χ^2	110.4	171.3	172.9	191.9	92.43	167.5	182.4	184.2
Adj. R^2	0.175	0.270	0.270	0.277	0.162	0.246	0.254	0.263

Note:

The first column is the benchmark probability model of Bitcoin ownership for year 2017, the second column is the benchmark augmented with EAR15, third column adds the Age^2 , the forth column is the benchmark with EAR15 and augmented with two fractional polynomial terms; columns five, six, seven and eight are the symmetrical models for year 2018.

Significance stars ***, **, and * represent 1%, 5% and 10% significance, respectively.

Table 2.6: **Logit Specification Tests**

Logit Model	Btc Own	Coef.	Std. Err.	z	p-value
col 1 (2017)	Prediction	1.56	0.299	5.22	0.00
	Prediction squared	0.098	0.048	2.03	0.042
	Constant	0.657	0.409	1.60	0.109
	LROC	0.81			
col 1 (2017 with EAR15)	Prediction	1.19	0.19	6.14	0.00
	Prediction squared	0.39	0.035	1.11	0.266
	Constant	0.154	0.24	0.64	0.523
	LROC	0.866			
col 2 (2017 with Age^2)	Prediction	1.18	0.19	6.10	0.00
	Prediction squared	0.038	0.036	1.07	0.286
	Constant	0.147	0.24	0.61	0.54
	LROC	0.866			
col 3 (2017 with polynomial of Age)	Prediction	1.14	0.19	5.91	0.00
	Prediction squared	0.029	0.036	0.81	0.42
	Constant	0.106	0.23	0.45	0.65
	LROC	0.869			
col 5 (2018)	Prediction	1.65	0.321	5.15	0.00
	Prediction squared	0.12	0.054	2.21	0.027
	Constant	0.72	0.425	1.69	0.091
	LROC	0.79			
col 6 (2018 with EAR15)	Prediction	1.098	0.22	4.83	0.00
	Prediction squared	0.021	0.045	0.47	0.638
	Constant	0.72	0.264	0.28	0.782
	LROC	0.85			
col 7 (2018 with Age^2)	Prediction	1.05	0.22	4.80	0.00
	Prediction squared	0.04	0.037	1.10	0.271
	Constant	0.12	0.045	0.28	0.77
	LROC	0.854			
col 8 (2018 with polynomial of Age)	Prediction	1.046	0.21	4.94	0.00
	Prediction squared	0.01	0.043	0.23	0.814
	Constant	0.03	0.24	0.12	0.9
	LROC	0.86			

Note: Two specification tests were provided: 1) a linktest that regresses the Bitcoin ownership on its prediction and squared prediction. A significant square prediction may emphasize missing information in the Bitcoin ownership model; 2) a test that quantifies the power of discrimination between Bitcoin owners and non-owners, the LROC is the value of the area under receiver operating characteristic ROC curve. A value close to 1 suggesting a high power of discrimination. Significance stars ***, **, and * represent 1%, 5% and 10% significance, respectively.

Table 2.7: **Logit EAR15 Estimation and Specification Tests**

Logit Model with EAR15 only	2017	2018
VARIABLES	Estimates 2017	Estimates 2018
EAR15	0.0468*** (0.0042)	0.0456*** (0.0045)
Constant	-5.14*** (0.253)	-4.878 (0.263)
Linktest	2017	2018
Prediction	1.375***	1.519***
Prediction squared	0.07	0.106
LROC	0.78	0.77
Observations	2,623	1987

Note: Similar specification tests as in Table 5. Significance stars ***, **, and * represent 1%, 5% and 10% significance, respectively.

Table 2.8: Cash Holdings modeled by: OLS; OLS with CF; Q50 with CF

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Own Bitcoin	1.362*** (0.171)	0.948*** (0.203)	0.907*** (0.220)	1.179*** (0.171)	0.825*** (0.243)	1.052*** (0.317)
Respondent Age	0.0185*** (0.00196)	0.0244*** (0.00218)	0.0210*** (0.00253)	0.0114*** (0.00294)	0.0165*** (0.00321)	0.0192*** (0.00356)
Gender: Female	-0.271*** (0.0657)	-0.127** (0.0574)	-0.195*** (0.0727)	-0.393*** (0.0717)	-0.290*** (0.0851)	-0.351*** (0.0835)
Income: 50k-99k	0.244*** (0.0664)	0.258*** (0.0588)	0.263*** (0.0803)	0.251*** (0.0778)	0.167** (0.0816)	0.270*** (0.0858)
Income: 100k+	0.511*** (0.0903)	0.552*** (0.0660)	0.567*** (0.0934)	0.455*** (0.111)	0.371*** (0.113)	0.420*** (0.123)
Prairies	0.125 (0.101)	0.216** (0.106)	0.216* (0.124)	0.0498 (0.130)	0.0750 (0.161)	0.110 (0.169)
Ontario	0.0940 (0.0894)	0.156* (0.0945)	0.151 (0.104)	0.0134 (0.101)	0.0485 (0.101)	0.0994 (0.116)
Quebec	0.142 (0.101)	0.200* (0.104)	0.187 (0.120)	-0.0301 (0.109)	0.0328 (0.0979)	0.0565 (0.108)
Atlantic	0.0434 (0.133)	0.147 (0.130)	0.107 (0.139)	-0.117 (0.171)	-0.0635 (0.160)	-0.123 (0.162)
Employment	0.0419 (0.0766)	-0.000747 (0.0627)	-0.0690 (0.0662)	-0.000752 (0.0638)	0.00125 (0.0704)	-0.0340 (0.0794)
College/CEGEP/Trade school	-0.0337 (0.0654)	-0.0154 (0.0756)	0.0592 (0.0809)	-0.0374 (0.0991)	-0.0736 (0.0855)	0.0412 (0.106)
University	0.0843 (0.0619)	0.0515 (0.0907)	0.111 (0.0821)	0.231** (0.0905)	0.163** (0.0782)	0.301*** (0.103)
Number of kids: No kids	-0.0445 (0.0644)	-0.000459 (0.0665)	0.00768 (0.0944)	-0.118 (0.107)	-0.00573 (0.114)	0.0138 (0.120)
Marital status: Not married/CL	0.00622 (0.0790)	0.0435 (0.0687)	0.0831 (0.0748)	0.0958 (0.0687)	0.134 (0.101)	0.142 (0.104)
Grocery Shopping: Not all of it	-0.174** (0.0705)	-0.0963 (0.0690)	-0.112 (0.0747)	-0.168** (0.0790)	-0.0907 (0.0807)	-0.250*** (0.0953)
$\hat{\epsilon}_i$		3.067*** (0.559)	1.914*** (0.635)		2.716*** (0.645)	1.550* (0.799)
Constant	2.481*** (0.165)	1.877*** (0.174)	2.212*** (0.223)	3.098*** (0.187)	2.581*** (0.254)	2.516*** (0.303)
Observations	2,623	2,623	2,623	1,987	1,987	1,987
R-squared	0.089	0.108		0.080	0.093	

Note:

Column 1 is for benchmark OLS model for year 2017; Column 2 is OLS with CF correction for year 2017; Column 3 is the Median model with CF correction for year 2017. Columns 4, 5, 6 are symmetrical models for year 2018.

Baseline categories are Male, <50k income, from BC, unemployed, conducts all HH grocery shopping.

$\hat{\epsilon}_i$ is the CF.

Significance stars ***, **, and * represent 1%, 5% and 10% significance, respectively.

Standard errors are obtained via bootstrap.

Table 2.9: **Quantiles of Cash Holdings, 2017**

VARIABLES	(1) Q10.2017	(2) Q25.2017	(3) Q50.2017	(4) Q75.2017	(5) Q90.2017	(6) Q95.2017
Own Bitcoin	0.874* (0.451)	1.063*** (0.234)	1.038*** (0.255)	1.654*** (0.441)	2.629*** (0.383)	3.051*** (0.420)
Respondent Age	0.0261*** (0.00533)	0.0304*** (0.00334)	0.0169*** (0.00225)	0.0156*** (0.00232)	0.0170*** (0.00308)	0.0134*** (0.00451)
Gender: Female	0.0400 (0.123)	-0.282*** (0.105)	-0.293*** (0.0619)	-0.301*** (0.0648)	-0.455*** (0.0941)	-0.350*** (0.119)
Income: 50k-99k	0.0981 (0.157)	0.312*** (0.102)	0.287*** (0.0713)	0.210*** (0.0693)	0.366*** (0.102)	0.347*** (0.128)
Income: 100k+	0.559*** (0.186)	0.574*** (0.137)	0.572*** (0.0983)	0.403*** (0.0978)	0.588*** (0.114)	0.493*** (0.191)
Region: Prairies	0.248 (0.214)	0.123 (0.199)	0.155 (0.112)	0.0489 (0.116)	0.227 (0.145)	0.237 (0.170)
Region: Ontario	0.169 (0.222)	0.145 (0.153)	0.152* (0.0899)	-0.0389 (0.0930)	-0.0536 (0.142)	-0.100 (0.135)
Region: Quebec	0.286 (0.250)	0.154 (0.150)	0.146 (0.102)	0.0312 (0.106)	-0.0297 (0.162)	-0.110 (0.165)
Region: Atlantic	-0.0714 (0.261)	0.142 (0.255)	0.0835 (0.122)	-0.122 (0.163)	0.324 (0.213)	0.294 (0.290)
Employment	0.115 (0.133)	-0.0178 (0.119)	-0.0607 (0.0737)	0.0684 (0.0742)	0.130 (0.0996)	0.214* (0.126)
Education: College/CEGEP/Trade school	-0.0868 (0.139)	-0.0376 (0.122)	0.0413 (0.0913)	-0.0494 (0.0852)	-0.211 (0.148)	-0.0306 (0.144)
Education: University	0.0662 (0.136)	0.0913 (0.141)	0.132 (0.0860)	0.0684 (0.0757)	-0.116 (0.119)	0.0331 (0.130)
Number of kids: No kids	0.133 (0.151)	-0.144 (0.127)	-0.0343 (0.0817)	-0.0314 (0.0693)	-0.172 (0.123)	-0.153 (0.168)
Marital status: Not married/CL	-0.116 (0.151)	0.0786 (0.110)	0.0590 (0.0888)	0.0327 (0.0864)	0.132 (0.101)	0.0808 (0.143)
Grocery Shopping: Not all of it	-0.155 (0.147)	-0.174 (0.110)	-0.156** (0.0738)	-0.122 (0.0760)	-0.0564 (0.102)	-0.0864 (0.110)
Constant	-0.340 (0.377)	1.062*** (0.294)	2.598*** (0.186)	3.662*** (0.188)	4.414*** (0.294)	4.857*** (0.327)
Observations	2,623	2,623	2,623	2,623	2,623	2,623

Note: Baseline categories are Male, <50k income, from BC, unemployed, conducts all household grocery shopping.

Significance stars ***, **, and * represent 1%, 5% and 10% significance, respectively.

Standard errors are obtained via bootstrap.

Table 2.10: Quantiles of Cash Holdings, 2018

VARIABLES	(1) Q10_2018	(2) Q25_2018	(3) Q50_2018	(4) Q75_2018	(5) Q90_2018	(6) Q95_2018
Own Btcoin	0.422 (0.450)	0.459 (0.423)	1.314*** (0.210)	1.367*** (0.316)	2.811*** (0.745)	2.642*** (0.418)
Respondent Age	0.0235*** (0.00735)	0.0226*** (0.00430)	0.0155*** (0.00295)	0.00818** (0.00384)	-4.05e-05 (0.00389)	-0.00472 (0.00694)
Gender: Female	0.0717 (0.186)	-0.351*** (0.105)	-0.372*** (0.0802)	-0.474*** (0.0995)	-0.535*** (0.121)	-0.608*** (0.186)
Income: 50k-99k	0.284 (0.193)	0.424*** (0.120)	0.331*** (0.0856)	0.216** (0.0897)	0.143 (0.120)	-0.00868 (0.182)
Income: 100k+	0.415 (0.256)	0.570*** (0.129)	0.466*** (0.103)	0.488*** (0.141)	0.368*** (0.132)	0.212 (0.270)
Region: Prairies	-0.483 (0.322)	-0.270 (0.173)	0.0602 (0.175)	0.339** (0.170)	0.331 (0.205)	0.315 (0.258)
Region: Ontario	-0.127 (0.305)	-0.0494 (0.131)	0.0838 (0.109)	0.101 (0.125)	0.0488 (0.155)	-0.102 (0.234)
Region: Quebec	-0.0809 (0.336)	-0.153 (0.171)	0.0509 (0.117)	0.0724 (0.137)	-0.168 (0.181)	-0.200 (0.276)
Region: Atlantic	-0.379 (0.315)	-0.600* (0.342)	-0.144 (0.160)	-0.0580 (0.239)	0.0271 (0.364)	0.183 (0.505)
Employment	0.0199 (0.174)	0.0215 (0.0998)	-0.0602 (0.0749)	-0.0936 (0.0959)	0.0383 (0.135)	0.0758 (0.172)
Education: College/CEGEP/Trade school	-0.0108 (0.200)	-0.0753 (0.175)	0.0569 (0.102)	0.0529 (0.118)	0.114 (0.166)	-0.0426 (0.226)
Education: University	0.442* (0.233)	0.215 (0.166)	0.320*** (0.0992)	0.268** (0.124)	0.202 (0.148)	-0.0473 (0.201)
Number of kids: No kids	-0.0634 (0.213)	-0.174 (0.150)	-0.0401 (0.0990)	-0.0774 (0.139)	0.0895 (0.176)	-0.147 (0.306)
Marital status: Not married/CL	0.219 (0.172)	0.296* (0.162)	0.110 (0.102)	0.0265 (0.133)	-0.107 (0.128)	-0.0778 (0.195)
Grocery Shopping: Not all of it	0.183 (0.157)	-0.132 (0.120)	-0.321*** (0.0915)	-0.230** (0.107)	-0.123 (0.134)	-0.113 (0.176)
Constant	-0.144 (0.612)	1.623*** (0.319)	2.846*** (0.261)	4.203*** (0.286)	5.339*** (0.302)	6.615*** (0.559)
Observations	1,987	1,987	1,987	1,987	1,987	1,987

Note: Baseline categories are Male, <50k income, from BC, unemployed, conducts all household grocery shopping.

Significance stars ***, **, and * represent 1%, 5% and 10% significance, respectively. Standard errors are obtained via bootstrap.

Table 2.11: **Quantiles of Cash Holdings corrected for Selection via a Control Function - with sample correction**

VARIABLES	(1) Q10CF_2017	(2) Q25CF_2017	(3) Q50CF_2017	(4) Q75CF_2017	(5) Q90CF_2017	(6) Q95CF_2017
Own Bitcoin	0.257 (0.437)	0.634*** (0.220)	0.907*** (0.179)	1.150*** (0.360)	1.960*** (0.480)	1.759*** (0.602)
RespondentAge	0.0351*** (0.00500)	0.0355*** (0.00363)	0.0210*** (0.00234)	0.0196*** (0.00234)	0.0202*** (0.00351)	0.0168*** (0.00433)
Gender: Female	0.234 (0.147)	-0.189* (0.0978)	-0.195*** (0.0711)	-0.187*** (0.0712)	-0.266*** (0.103)	-0.208 (0.136)
Income: 50k-99k	0.234 (0.145)	0.312*** (0.120)	0.263*** (0.0865)	0.226*** (0.0786)	0.347*** (0.100)	0.324** (0.135)
Income: 100k+	0.665*** (0.199)	0.602*** (0.111)	0.567*** (0.101)	0.444*** (0.105)	0.538*** (0.130)	0.533*** (0.191)
Region: Prairies	0.358* (0.209)	0.146 (0.171)	0.216* (0.128)	0.0708 (0.126)	0.206 (0.154)	0.275 (0.178)
Region: Ontario	0.134 (0.220)	0.168 (0.126)	0.151 (0.0990)	0.0184 (0.102)	0.0192 (0.133)	-0.0168 (0.168)
Region: Quebec	0.316 (0.241)	0.165 (0.147)	0.187 (0.119)	0.0674 (0.105)	0.0179 (0.157)	0.0359 (0.164)
Region: Atlantic	-0.0177 (0.226)	0.218 (0.240)	0.107 (0.145)	-0.0250 (0.209)	0.309 (0.213)	0.508* (0.300)
Employment	0.0272 (0.146)	-0.0441 (0.106)	-0.0690 (0.0690)	0.0681 (0.0667)	-0.0143 (0.104)	0.145 (0.128)
Education: College/CEGEP/Trade school	-0.0120 (0.177)	0.00606 (0.121)	0.0592 (0.0946)	-0.0301 (0.0879)	-0.154 (0.144)	-0.0315 (0.173)
Education: University	0.0579 (0.154)	0.0974 (0.140)	0.111 (0.0968)	0.0540 (0.0963)	-0.122 (0.137)	-0.0815 (0.155)
Number of kids: No kids	0.160 (0.145)	-0.142 (0.141)	0.00768 (0.0815)	0.0237 (0.0747)	-0.0954 (0.121)	-0.115 (0.172)
Marital status: Not married/CL	-0.0730 (0.154)	0.0505 (0.106)	0.0831 (0.0689)	0.0525 (0.0711)	0.133 (0.111)	0.229 (0.142)
Grocery Shopping: Not all of it	-0.178 (0.165)	-0.127 (0.103)	-0.112 (0.0810)	-0.0479 (0.0702)	-0.0142 (0.104)	0.0361 (0.129)
$\hat{\epsilon}_i$	4.068*** (0.876)	3.216*** (0.629)	1.914*** (0.545)	2.539*** (0.602)	3.002*** (1.148)	3.753** (1.637)
Constant	-1.078*** (0.412)	0.631** (0.284)	2.212*** (0.230)	3.178*** (0.218)	4.020*** (0.343)	4.379*** (0.413)
Observations	2,623	2,623	2,623	2,623	2,623	2,623

Note: Baseline categories are Male, <50k income, from BC, unemployed, conducts all HH grocery shopping.

$\hat{\epsilon}_i$ is the CF.

Significance stars ***, **, and * represent 1%, 5% and 10% significance, respectively.

Standard errors are obtained via bootstrap.

Table 2.12: **Quantiles of Cash Holdings corrected for Selection via a Control Function - with sample correction, 2018**

VARIABLES	(1) Q10CF_2018	(2) Q25CF_2018	(3) Q50CF_2018	(4) Q75CF_2018	(5) Q90CF_2018	(6) Q95CF_2018
Own Bitcoin	0.0916 (0.428)	0.387 (0.397)	1.052*** (0.253)	1.094*** (0.249)	2.485*** (0.780)	2.029*** (0.725)
Respondent Age	0.0261*** (0.00616)	0.0258*** (0.00408)	0.0192*** (0.00330)	0.0113*** (0.00386)	0.00307 (0.00476)	-0.000224 (0.00631)
Gender: Female	0.0407 (0.166)	-0.199* (0.119)	-0.351*** (0.0795)	-0.381*** (0.0964)	-0.468*** (0.127)	-0.668*** (0.163)
Income: 50k-99k	0.174 (0.193)	0.385*** (0.122)	0.270*** (0.0933)	0.185* (0.100)	0.124 (0.122)	-0.113 (0.170)
Income: 100k+	0.356 (0.231)	0.516*** (0.167)	0.420*** (0.144)	0.416*** (0.132)	0.361** (0.163)	0.0454 (0.226)
Region: Prairies	-0.202 (0.319)	-0.294 (0.180)	0.110 (0.171)	0.441*** (0.160)	0.420** (0.199)	0.350 (0.254)
Region: Ontario	0.126 (0.335)	-0.0504 (0.146)	0.0994 (0.107)	0.125 (0.122)	0.147 (0.181)	0.115 (0.191)
Region: Quebec	0.123 (0.358)	-0.126 (0.188)	0.0565 (0.122)	0.145 (0.132)	-0.0890 (0.198)	0.107 (0.252)
Region: Atlantic	-0.0870 (0.358)	-0.593** (0.265)	-0.123 (0.164)	-0.0749 (0.191)	0.131 (0.347)	0.378 (0.421)
Employment	0.0281 (0.155)	0.0174 (0.123)	-0.0340 (0.0748)	-0.104 (0.0875)	-0.0185 (0.134)	0.179 (0.195)
Education: College/CEGEP/Trade school	-0.0989 (0.196)	-0.0584 (0.157)	0.0412 (0.104)	0.0164 (0.112)	0.0316 (0.198)	-0.205 (0.213)
Education: University	0.276 (0.233)	0.179 (0.132)	0.301*** (0.105)	0.254** (0.125)	0.0735 (0.194)	-0.189 (0.205)
Number of kids: No kids	0.0805 (0.198)	-0.137 (0.143)	0.0138 (0.114)	0.0478 (0.117)	0.150 (0.177)	0.315 (0.263)
Marital status: Not married/CL	0.207 (0.183)	0.347** (0.143)	0.142 (0.101)	0.0293 (0.120)	-0.0738 (0.112)	-0.0281 (0.189)
Grocery Shopping: Not all of it	0.258 (0.161)	-0.0813 (0.129)	-0.250** (0.0974)	-0.151 (0.123)	-0.0901 (0.129)	-0.0436 (0.181)
$\hat{\epsilon}_i$	3.546*** (0.799)	2.021** (0.851)	1.550* (0.795)	2.011*** (0.654)	1.873 (1.707)	4.009 (2.805)
Constant	-0.646 (0.538)	1.236*** (0.352)	2.516*** (0.271)	3.793*** (0.319)	5.044*** (0.337)	5.774*** (0.538)
Observations	1,987	1,987	1,987	1,987	1,987	1,987

Note: Baseline categories are Male, <50k income, from BC, unemployed, conducts all HH grocery shopping.

$\hat{\epsilon}_i$ is the CF.

Significance stars ***, **, and * represent 1%, 5% and 10% significance, respectively.

Standard errors are obtained via bootstrap.

Chapter 3

Bitcoin adoption and beliefs

1

Abstract

We develop a tractable model of Bitcoin adoption with network effects and social learning, which we then connect it 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) own learning effects; and (3) social learning effects.

After accounting for the endogeneity of beliefs, we find that both network effects and own 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 adoption chance. 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 and social learning were important drivers of Bitcoin adoption in 2017 and 2018 in Canada.

¹This Chapter is co-written with Christopher Henry, Jorge Vasquez, and Marcel C. Voia. This version of the paper has been accepted at Canadian Journal of Economics and Bank of Canada's Working Papers series. A old version of this joint work was part of Christopher Henry's thesis. In addition to the old version, this chapter provides a theoretical justification of the empirical analysis. In particular, it develops a tractable stylized partial equilibrium model that allows capturing the Bitcoin adoption as a function network size, own learning and social learning. Second, this chapter adds another year of analysis, respectively 2018; this addition brings new insights about Bitcoin's adopters, which are different in 2018 than 2017. These changes in Bitcoin adopters are providing more useful information about the paths of future Bitcoin adoption. Third, we have used a different identification strategy: a different exclusion restriction to account for endogeneity, additional nonlinearities of age and a new variable that capture beliefs about expected return of Bitcoin (2018) in first stage of analysis.

3.1 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).² 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.³

Bitcoin is a decentralized electronic fiat money with floating value that allows agents to make peer-to-peer payments and transactions without needing a trusted third party [Nakamoto, 2008, Böhme et al., 2015b]. 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, 2019, Henry et al., 2018c, Authority, 2019, Hundtofte et al., 2019]. Still, there is no consensus on whether this new technology will survive or not in the future.⁴ 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].⁵ Thus, as the size of the network (or the number of adopters) rises, presumably the incentives to adopt Bitcoin increase as well as the ability to learn the unobserved technological quality of this innovation.

In this paper, we ask how much Bitcoin adoption is explained by network effects, social (or, endogenous) learning effects, and individual (or, exogenous) 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 deter-

²Indeed, 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 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/>.

³In 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.

⁴Budish [2018] argues that if Bitcoin were to achieve a broad level of acceptance as a digital currency, this would only result in certain economic incentives becoming strong enough that would effectively cause the system to collapse.

⁵According 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).

minants 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. 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.⁶ 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 ownership of Bitcoin among Canadians; it has been conducted annually since then [Henry et al., 2017, 2018c, 2019c]. Key to this paper is the 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 that at every period chooses whether to costly adopt Bitcoin. Agents have heterogeneous reservation utilities, and are symmetrically uncertain about the 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.⁷ 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.⁸ Our 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 the individual incentives to adopt depends on the network size, agents’ beliefs, and adoption costs. Network effects are captured by the *direct* marginal impact of the network size on the adoption chance, whereas individual learning effects by the *direct* marginal impact of beliefs. Social learning introduces an *indirect* force that shapes the marginal effect of the network size: if learning is endogenous, then the total marginal impact of the 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

⁶See, for example, Goolsbee and Klenow [2002], Moretti [2011], Fafchamps et al. [2020] for other studies of adoption with network and/or information externalities in other economic contexts.

⁷In 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 [2016] for a recent survey.

⁸The speed of learning is endogenous, as in the experimentation literature in small markets Bolton and Harris [1999], Keller et al. [2005] and in large ones Bergemann and Välimäki [1997], Frick and Ishii [2016].

using a binary choice model. 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*. This exclusion restriction comes from the supply side, which arguably is correlated with past Bitcoin adoption but not with current one. 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 own 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 the network size. In other words, the coefficient on the interaction of the network size and beliefs is significant and negative. This suggests that a one percentage point increase in the network size triggers adoption more when beliefs are low than when these ones are high. That is, individuals with high beliefs about the survival of Bitcoin are less sensitive to variations in the network size.

Finally, we find that age — a proxy for adoption costs — has a significant negative impact on adoption and beliefs in both 2017 and 2018, with young people being associated with both more adoption and higher beliefs about the survival of Bitcoin. Specifically, our results indicate that age effects are different across different categories of age⁹. Additionally, considering another potential proxy for adoption costs — namely, income — we see that in 2018 income becomes an important driver for adoption, with people with higher income being more likely to adopt Bitcoin. These two channels of potential adoption costs provide evidence that is consistent with the theoretical model; the older the individuals, the more likely they are to face greater adoption costs.¹⁰ and, given the increase in the price of Bitcoin observed at the end of 2017, individual with lower incomes can face a potential barrier to Bitcoin adoption starting 2018.

We set up the model in §3.2, and discuss the data in §3.3 and methodology

⁹Relative to the benchmark age category 18-34, the age categories 35-55 and 55 and older have a negative effect with a more substantial negative effect for the age category 55 +.

¹⁰Early adopters are typically young living in urban areas, are educated, and socially active [Rogers, 2010].

in §3.5. We present our empirical results in §3.6. Finally, we conclude in §3.7. Mathematical proofs, figures, and tables are available in the Appendix.

3.2 A Model Bitcoin Adoption and Learning

The goal of this section is to develop a stylized partial equilibrium model that allows us to motivate the empirical analysis. Time is discrete and infinite $t = 1, 2, \dots, \infty$. 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 attributes such as gender, age, education level, income level, region, etc; in other words, types define submarkets. The model need not specify the exact the 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, living in Ontario, with age category 18-34, income between 50-100K, and with college education.

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 the 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 arrive 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 arrive 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, 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

¹¹See Hörner and Skrzypacz [2016] for a recent survey of papers that use this learning technology.

¹²Technically, 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, e.g., Keller and Rady [2015]. However, unlike that literature, in this paper, experimentation takes place in a *large* market, as in Bergemann and Välimäki [1997].

or reviewers, and thus the arrival of news is scaled by the exogeneous 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 §3.5–§3.6.

As widely used in the exponential learning literature [Hörner and Skrzypacz, 2016], we focus on *conclusive* news.¹³ 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, because Bitcoin is not backed by a central authority, some of the rewards of adopting Bitcoin can be seen as random from an ex-ante perspective. Consequently, 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 the Bitcoin quality, as we explain next.

Having described the learning process, we now turn to characterize 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. 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 have 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:

$$\xi_{it+1} = \frac{\xi_{it}(1 - \Phi_g(A_{it}))}{\xi_{it}(1 - \Phi_g(A_{it})) + (1 - \xi_{it})(1 - \Phi_b(A_{it}))}. \quad (3.1)$$

The denominator in (3.1) is the chance 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 3.8.2 shows that, *in absence of news, beliefs weakly increase over time if and only if $\Phi_b(A_{it}) \geq \Phi_g(A_{it})$* . Intuitively, given no news, agents become more optimistic that Bitcoin’s quality is high when news are relatively more likely to arrive when the Bitcoin quality is low.¹⁴

¹³For an exception, see Keller and Rady [2010].

¹⁴For instance, suppose that $\varphi_g = \phi_g = 0$. Then, if news arrives then that leads to conclusive evidence of a bad technology; thus, observing no news reflects “good news” in the sense of beliefs ξ_{it} drifting upwards. Conversely, if $\varphi_b = \phi_b = 0$, 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 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

In every period, each potential adopter chooses whether 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 $B' > 0$.¹⁵ 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:

$$\mathcal{U}(A_{it}, \xi_{it}, c_i) \equiv B(A_{it}) + \Phi_h(A_{it})\xi_{it}r_h + \Phi_\ell(A_{it})(1 - \xi_{it})r_\ell - c_i. \quad (3.2)$$

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

on understanding how the nature of learning — namely, whether it is via “good” or “bad” news — affects adoption patterns.

¹⁵When 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.

$\partial \mathcal{U}(A_{it}, \xi_{it}, c_i) / \partial A_{it}$ 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} rises. This would mean 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 us 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:*

$$\mathcal{U}(A_{i,t}, \xi_{i,t}, c_i) = \beta_0 + \beta_1 A_{it} + \beta_2 \xi_{it} + \beta_3 A_{it} \xi_{it} - c_i. \quad (3.3)$$

As previously discussed, β_3 captures social learning effects, whereas β_1 and β_2 captures the respective direct effects of network size and beliefs. Therefore, equation (3.3) captures three economic forces driving individual adoption: 1) network effects (β_1); 2) own 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 have both a *direct and indirect effect* on the incentives to adopt:

$$\frac{\partial \mathcal{U}}{\partial A_{it}} = \underbrace{\beta_1}_{\text{direct effect}} + \underbrace{\beta_3 \xi_{it}}_{\text{indirect effect}} \quad \text{and} \quad \frac{\partial \mathcal{U}}{\partial \xi_{it}} = \underbrace{\beta_2}_{\text{direct effect}} + \underbrace{\beta_3 A_{it}}_{\text{indirect effect}}. \quad (3.4)$$

Intuitively, an increase in the network size not only raises the benefits of adopting Bitcoin, but also it 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 case, β_1 and β_2 would only reflect total 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.

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:

$$\mathbf{P}(a_{it} = 1 | A_{it}, \xi_{it}, c_i) = F(\beta_0 + \beta_1 A_{it} + \beta_2 \xi_{it} + \beta_3 A_{it} \xi_{it} - c_i). \quad (3.5)$$

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 $1 - A_{it}$. Precisely, starting with an initial mass of adopters $A_{i1} = \bar{A}_{i1} \in (0, 1)$, the evolution of adoption obeys:

$$A_{it+1} = A_{it} + \mathbf{P}(a_{it} = 1 | A_{it}, \xi_{it}, c_i)(1 - A_{it}). \quad (3.6)$$

The model is solved by a joint adoption-belief process $(A_{it}, \xi_{it})_{t=1}^{\infty}$ obeying (3.1) and (3.6), given (3.3), and initial conditions $A_{i1} = \bar{A}_{i1}$ and $\xi_{i1} = \bar{\xi}_{i1}$.¹⁶

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 close this section with some few remarks. First, Appendix 3.8.2 proves the existence and uniqueness. 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 (3.1) and (3.6), respectively. These, in turn, deterministically determine beliefs and adoption ξ_{i3} and A_{i3} , by the same logic, and so on. The top panels of Figure 3.1 depict how the individual probability of adoption may co-move with beliefs and network size, respectively.

Second, Appendix 3.8.3 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 3.1, the individual probability of adoption (3.3) falls as adoption cost rises. 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 a 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 3.1, the model is able to generate positive co-movements between the individual probability of adoption (3.5) and beliefs ξ_{it} , and also between the individual probability of adoption (3.5) and the network size A_{it} . The next section estimates equation (3.5) and shows that these patterns hold in the data.

3.3 The Bitcoin Omnibus Survey Data

3.4 Data Overview

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

¹⁶Notice 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.

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 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. 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. Our analysis relies mostly on the 2017 and 2018 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, a total of 2,623 Canadians completed the BTCOS, of which 117 self-identified as Bitcoin owners. In 2018, the BTCOS sample was answered by 1,987 Canadians, of which 99 reported to own Bitcoin. In addition to content questions, respondents are also asked to provide demographic information, as seen in Table 3.1.

– insert Table 3.1 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 are 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 a variety of dimensions (see Henry et al. [2019d] for details).

3.4.1 Bitcoin Adoption, Network Size, 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 to be non-adopters.¹⁷

Table 3.2 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%

¹⁷The first question of the BTCOS asks simply “Have you heard of Bitcoin?” In 2016, 62% of Canadians indicated they were aware of Bitcoin; this increased to 83% in 2017 and to 89% in 2018.

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. 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 55. The results, however, provide evidence of a marginal 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 3.2 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 chose the relevant demographic variables for these probabilities, we consider a standard model selection using Lasso approach. 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 3.11 an alternative non-parametric approach to construct the network size variable, in which we count the number of adopters for each joint cell defined by the demographic characteristics selected by Lasso procedure, and then weight these counts by the appropriate cell specific populations. Both approaches yield similar qualitative results.

Next, we proxy for beliefs ξ_{it} . 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_{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 0.5 in 2017 and 0.42 in 2018.

Finally, we use age and income to proxy for adoption costs c_i .

3.5 Empirical Strategy and Econometric Methodology

Empirical Specification

The theoretical model in §3.2 (see equation (3.5)) translates on testing whether and to what extent individual Bitcoin adoption is influenced by the network size A_{it} , beliefs ξ_{it} , and adoption costs c_i . This will allow us to determine how Bitcoin adoption decisions are affected by (1) network effects; (2) own learning effects; and (3) social learning effects. Because individual adoption a_{it} is a binary variable, equation (3.5) suggests the following empirical specification:

$$a_{it} = F(\beta_0 + \beta_1 A_{it} + \beta_2 \xi_{it} + \beta_3 A_{it} \xi_{it} + \beta_c X_i) + \epsilon_{it}, \quad (3.7)$$

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, region, employment, education, number of kids in household, marital status, and household grocery shopping responsibilities.

As discussed in §3.2, 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 will test the importance and direction of these effects for individual Bitcoin adoption for both 2017 and 2018 BTCOS data.

3.5.1 Identification

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

We propose to break this simultaneity using a control function which 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 2SLS are not suitable for nonlinear models. Second, 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 and an additional exclusion restriction: *the growth in Bitcoin ATMs*.¹⁸

¹⁸Bitcoin ATMs are easy to use and have similar functions compared to a regular ATM, namely,

Table 3.3 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 the regional level, as seen in Table 3.3.

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. From 2017 to 2018, we observe a substantial growth in Bitcoin ATMs, even though Bitcoin adoption marginally increased from 2017 to 2018.

– insert Table 3.3 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’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

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.

¹⁹These 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/>.

²⁰This 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.

²¹Of course, other exclusion restrictions could have been considered such as the use of digital

To formally check if the growth in ATMs is valid exclusion restriction, we compute the regional correlation between the growth in ATMs, growth in Bitcoin adoption and beliefs. The results are presented in Table 3.4. 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 3.4 here –

Altogether, we use this exclusion restriction as an identification mechanism to uncover the true effect of beliefs on individual adoption decisions. Our proposed identification mechanism is based on a two-stage control function (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 regional level:

$$\xi_{it} = \alpha_0 + \alpha_1 \Delta ATM_{jt} + \alpha_2 Age^2 + \alpha_c X_i + u_{it}, \quad (3.8)$$

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 (3.8), we follow Escanciano et al. [2016b] and exploit non-linearities in age — featured in our data — to improve the identification.²²

The residual from the first stage is subsequently used in the second stage as a CF. That is, the benchmark model in equation (3.7) is augmented with the CF_{it} as follows:

$$a_{it} = F(\beta_0 + \beta_1 A_{it} + \beta_2 \xi_{it} + \beta_3 A_{it} \xi_{it} + \beta_c X_i + \beta_r R_j + \beta_{CF} CF_{it}) + \epsilon_{it}, \quad (3.9)$$

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

3.6 Results

The discussion of our results follows the stages of the identification for BTCOS data in 2017 and 2018, respectively. We start presenting the first stage results, estimated via OLS, which examines the agents’ beliefs about Bitcoin survival. We

wallets. Importantly, according to Henry et al. [2018c], 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.

²²Escanciano et al. [2016b] argues that changes in functional forms can be used as identification mechanisms. See Dong [2010b] for a previous application of this technique.

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, own learning effects, social learning effects, and adoption cost.

3.6.1 Modeling Bitcoin Beliefs

Table 3.5 shows the results of the first stage analysis. The first and second columns displays the results for the 2017 and 2018 data, respectively.

– insert Table 3.5 here –

In the third column of Table 3.5, we consider an additional regressor for the 2018 data, which is based on the respondents’ expectations of future Bitcoin price and the actual price of Bitcoin at the time of the survey. This information is available for the 2018 data only and allows us to measure the relative difference of the expected and realized Bitcoin price, or the *expected financial return* of holding Bitcoin. This extra exclusion restriction captures the financial investment incentives that may influence beliefs about Bitcoin survival. As seen in the third column of Table 3.5, this new expected return variable is a significant source of identification. Specifically, the beliefs about the future Bitcoin price and the beliefs about Bitcoin survival positively co-move.

Table 3.5 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 significant and negatively correlated with future beliefs about Bitcoin survival, meaning that older respondents think that Bitcoin is less likely to survive. 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 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

²³Balutel 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.

used as a control function in the second stage, which defines our main equation of interest.

3.6.2 Bitcoin Adoption

As discussed in §3.5.1, 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 CF as a bias correction term in the second stage. As argued in §3.5.1, 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 CF.

Table 3.6 presents the Logit results without CF (columns (1) and (2) for 2017 and 2018, respectively) and with CF (columns (3) and (4) for 2017 and 2018, respectively). Column (5) shows the results for the model with the expected return variable in 2018.²⁴

– insert Table 3.6 here –

Overall, our results indicate the important role the CF has in correcting the simultaneity bias associated with the existing feedback between the 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 1 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 §3.2, this coefficient captures exogenous learning effects, or the direct effect of beliefs on the Bitcoin adoption chance. 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.). When CF is introduced, the strong correction of beliefs indicates that early Bitcoin adopters have already high beliefs about Bitcoin’s future survival.

Network size. As 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 Bitcoin adoption chance

²⁴To account for low adoption rates, we also estimate for robustness checks a penalized logistic based likelihood [Heinze and Schemper, 2002b]. The results do not significantly differ from the results obtained with our logistic specification.

by 0.45 to 0.32 percentage points in 2017 and 2018, respectively. This captures the direct effect of the network size on the adoption probability (see §3.2). Thus, we find that a large network size directly increases the probability to adopt Bitcoin, indicating that a high Bitcoin adoption among peers is associated with a high propensity to adopt.

Social learning. Table 3.6 shows that the coefficient of the interaction term between the size of the network and beliefs is significant and negative. As argued in §3.2, the direction and magnitude of this coefficient capture indirect effects driven by social learning. Specifically, our findings indicate that a marginal increase in the 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 two variables that may proxy for adoption costs, age and income. Intuitively, older individuals face higher costs to learn new technologies, while low income raises the barriers to adopting Bitcoin, making technology adoption relatively more expensive. Our analysis shows that *age* is negative and statistically significant in 2017 and in 2018, provided the expected return variable is considered.²⁵ *Income* is positive and statistically significant in 2018 but not in 2017. The change in the results may be explained by the change in the composition of Bitcoin owners in 2018, which come from relatively higher income categories.

In terms of other 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 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. Figure 3.2 shows that the probability of Bitcoin adoption positively co-move with beliefs. Moreover, the data suggests that the speed of adoption is higher for low beliefs. The effect of beliefs on Bitcoin adoption is stronger in 2018 compared to 2017. We also decomposed the predicted margins of Bitcoin adoption as a function of Bitcoin beliefs about Bitcoin survival by age categories (18-35, 35-55, >55), as seen in Figure 3.3. We see that for both 2017 and 2018 the adoption curve is *S*-shaped across all age groups. Also, in 2017, for the age group 18-35 the adoption is the fastest followed by the 35-55 age group and lastly by the 55 plus age group. In 2018, we do not find a significant difference across the age groups.

– insert Figure 3.2 here –

²⁵In general, adding the expected return variable in 2018 make the results of 2018 to be closer to those of 2017 in terms of beliefs and network size.

– insert Figure 3.3 here –

Figure 3.4 depicts the predictive margins of Bitcoin adoption by the network size, showing a positive co-movement between these variables. In 2018, we see an increase of the support of local network compared to 2017 (Indeed our network variable show an increase in its support of about 35 percent if we consider the nonparametric specification and more than 100 percent if we consider the parametric (smooth) specification). This increase in local network size may explain the increase of the Bitcoin adoption in 2018 (see Table 2, showing that Bitcoin adoption is at 5.2% in 2018 compared to 4.3% in 2017).

In 2018, we see an increase of the support of local network compared to 2017 (Indeed our network variable show an increase in its support of about 35 percent if we consider the nonparametric specification and more than 100 percent if we consider the parametric (smooth) specification). This increase in local network size may explain the increase of the Bitcoin adoption in 2018 (see Table 2, showing that Bitcoin adoption is at 5.2% in 2018 compared to 4.3% in 2017).

– insert Figure 3.4 here –

Figure 3.5 shows the predicted margins of Bitcoin adoption as a function of local network by age categories, when the local network is extended to reach the entire population. In other words, it shows the counterfactual margins. Figure 3.5 shows stronger age effects for younger individuals 18-35, followed by the 35-55 age group and lastly by the 55 plus age group. As previously mentioned, age differences are not significant in 2018.²⁶ Contrast tests by age groups for the margins of probability of adoption by beliefs and local network are provided in Table 3.8. The results emphasize the significance of the differences observed in the predicted margins figures.

– insert Figure 3.5 here –

Finally, Table 3.7 indicates that network effects are dominant for the young cohort:²⁷ 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. In 2018, there is a shift of the network effects towards the older age groups (9% for older respondents versus 6% for young respondents).²⁸

– insert Table 3.7 here –

²⁶The age effects are not significant unless we include the expected return variable in the first stage. In such case, we see that the effect of the age effects in 2018 are significant but smaller in magnitude than in 2017.

²⁷Rogers [2010] suggests that early adopters are usually young and socially active individuals.

²⁸Another plausible reason why young individuals are inclined to adopt Bitcoin is that they

3.7 Conclusion

In this paper, we examine how the individual probability of Bitcoin adoption is influenced by network effects, own learning effects, and social learning effects. To test and quantify these behavioral determinants driving Bitcoin adoption, we develop a tractable Bitcoin adoption model which 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 the network size or in beliefs have a significant and a positive direct impact on the probability of adoption. Specifically, our 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. 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 negative and significant interaction term between the network size and beliefs. That is, we find that the effect of the network size on the probability of adoption is greater when beliefs about the survival of Bitcoin are low. Finally, in terms of adoption costs, we find that age has a significant negative impact on adoption and beliefs in both 2017 and 2018 (with stronger effects in 2017), with young people being associated with both more adoption and more optimistic beliefs about Bitcoin survival.

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 related, and trust/privacy issues (see Table 3.7 for further details).

3.8 Appendix: Technical Details of Proofs

3.8.1 The Probability of Adoption: Proof of Lemma 1

Notice that, given the optimality condition (3.2), we have:

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

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 $\beta_3 = \phi_h r_h - \phi_\ell r_\ell$. $\square$

3.8.2 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 (3.1), 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:

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

Taking $dt \rightarrow 0$ 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 (3.6) and two periods t and $t + dt$. Then,

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

Next, subtract A_{it} , then divide both sides by dt , and finally take $dt \rightarrow 0$. Then, given equation (3.2):

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

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

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

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

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

To this end, notice that $\chi(x)$ is continuously differentiable, because its partial derivatives are clearly continuous, and so $\chi(\cdot)$ 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 $T > 0$. $\square$

3.8.3 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_i^ℓ and c_i^h with $c_i^h > c_i^\ell$. Likewise, consider $x_{it}^\ell \equiv (A_{it}^\ell, \xi_{it}^\ell)$ and $x_{it}^h \equiv (A_{it}^h, \xi_{it}^h)$, solving

$$\dot{x}_{it}^\ell = \chi^\ell(x_{it}^\ell) \quad \text{and} \quad \dot{x}_{it}^h = \chi^h(x_{it}^h), \quad x_{i1}^\ell = x_{i1}^h = (\bar{A}_{i1}, \bar{\xi}_{i1}),$$

where $\chi^\ell(\cdot)$ and $\chi^h(\cdot)$ are given by:

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

The paths $t \mapsto x_{it}^\ell$ and $t \mapsto x_{it}^h$ are well-defined, following the same logic given in §3.8.2 and using the Picard-Lindelöf Theorem (Theorem 2.2 in [Teschl \[2012\]](#)).

Next, notice that since $c_i^h > c_i^\ell$, we have $\dot{x}_{it}^h = \chi^h(x_{it}^h) \leq \chi^\ell(x_{it}^h)$. Therefore, it follows that

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

Finally, since $\chi^\ell(x)$ 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 strict true for all later times. That is, $A_{it}^h < A_{it}^\ell$ and $\xi_{it}^h < \xi_{it}^\ell$ for $t > 1$. $\square$

3.9 Tables

Table 3.1: Sample description, 2017 Bitcoin Omnibus Survey

Variable	2017		2018	
	Counts	Proportion	Counts	Proportion
Overall	2623	2623	1987	1987
Age: 18 to 34	657	0.250	449	0.226
Age: 35 to 54	1073	0.409	722	0.363
Age: 55 +	891	0.340	816	0.411
Male	1213	0.463	833	0.420
Female	1409	0.537	1153	0.580
B.C.	377	0.144	270	0.136
Prairies	490	0.187	297	0.150
Ontario	891	0.340	805	0.405
Quebec	639	0.244	481	0.243
Atlantic	224	0.086	130	0.066
Income: <50k	877	0.334	670	0.338
Income: 50k-99k	935	0.356	704	0.354
Income: 100k +	538	0.205	378	0.191
High School or less	1715	0.654	1268	0.638
College / CEGEP / Trade	907	0.346	718	0.362
University	1122	0.428	811	0.408
Not emplo..	1048	0.404	801	0.409
Employed	1545	0.596	1157	0.591
Kids	1986	0.758	1596	0.804
No Kids	636	0.242	390	0.196
Not marri..	1068	0.407	840	0.423
Married/c..	1554	0.593	1146	0.577
Grocery shopping: Not all of it	1196	0.456	916	0.461
Grocery shopping: All of it	1426	0.544	1070	0.539

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 3.2: **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

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 3.3: 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	New Brunswick	Atlantic Provinces	0	0	1	0	1
Moncton			0	0	1	0	1
Saint John			0	0	2	0	2
St. John's	Newfoundland and Labrador	Atlantic Provinces	0	1	5	1	4
Antigonish			0	0	1	0	1
Dartmouth	Nova Scotia	Atlantic Provinces	0	0	5	0	5
Halifax			0	3	7	3	4
Truro			0	0	1	0	1
Charlottetown	Prince Edward Island	Atlantic Provinces	0	0	1	0	1
Summerside			0	0	1	0	1
Total			0	4	25	4	21
Coquitlam	British Columbia	British Columbia	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	British Columbia	British Columbia	1	1	0	0	-1
Nanaimo			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 CA	British Columbia	British Columbia	18	49	70	31	21
Victoria			1	4	6	3	2
Whistler			2	1	1	-1	0
Total			23	61	100	38	38
Brantford	Ontario	Ontario	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			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	Ontario	Ontario	45	127	199	82	72
Windsor			0		2	0	2
Total			51	149	267	98	115
Calgary	Alberta	Prairies	14	29	47	15	18
Edmond			7	10	21	3	11
Grand Prairie, AB			0	3	4	3	1
Red Deer			1	1	0	0	-1
St Albert			0	0	1	0	1
Regina	Saskatchewan	Prairies	1	3	4	2	1
Saskatoon			1	2	2	1	0
Brandon			0	0	1	0	1
Winnipeg	Manitoba	Prairies	2	5	19	3	14
Total			26	53	99	27	46
Gatineau	Quebec	Quebec	1	1	0	0	-1
Montreal			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

The data is taken from coinatmradar.com.

Counts of Bitcoin ATMs are reported by the city/province/region.

Table 3.4: **Correlation of Bitcoin ATMs Growth with Bitcoin Adoption**

ρ	Btc ATM Growth (2016-2017)	Btc ATM Growth (2017-2018)
Bitcoin Ownership	-0.0016	0.005

The correlations are computed using the 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 3.5: **First Stage: Estimation of Bitcoin Beliefs**

VARIABLES	2017	2018	2018 (with E(Price))
Age	-0.584*** (0.181)	-0.645*** (0.218)	-0.646*** (0.227)
Gender: Female	0.259 (0.965)	-2.511** (1.148)	-2.120* (1.195)
Income: 50k-99k	-0.0432 (1.121)	0.563 (1.272)	0.403 (1.333)
Income: 100k+	-1.125 (1.412)	2.308 (1.641)	2.276 (1.718)
Employment	2.300** (1.107)	0.00143 (1.265)	-0.152 (1.327)
Education: College/CEGEP/Trade school	-2.049 (1.281)	-1.812 (1.431)	-2.012 (1.552)
Education: University	-2.078 (1.266)	-2.031 (1.459)	-1.660 (1.554)
Number of kids: No kids	-4.140*** (1.239)	-3.153** (1.533)	-4.017** (1.638)
Marital status: Not married/CL	-1.576 (1.180)	-0.839 (1.386)	-0.587 (1.477)
Responsible for HH grocery shopping	2.680** (1.086)	2.860** (1.231)	2.523* (1.309)
ΔATM_AT	-1.256 (1.785)	0.0552 (2.362)	0.712 (2.533)
ΔATM_PR	-3.615* (1.854)	-5.675** (2.570)	-6.056** (2.712)
ΔATM_QC	-4.703** (1.960)	-4.990** (2.512)	-5.056* (2.671)
ΔATM_ON	-0.656 (1.715)	-3.773* (2.253)	-4.408* (2.388)
Age squared	0.00374** (0.00188)	0.00363 (0.00228)	0.00373 (0.00237)
Expected Return			1.901*** (0.728)
Constant	67.73*** (4.466)	69.70*** (5.574)	70.58*** (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 exclusion restriction measured by the growth in Bitcoin ATMs (from 2016 to 2017 and from 2017 to 2018) at the regional level, Age^2 is the second exclusion restriction, Expected Return = (Expected Bitcoin Price in a month - Current Bitcoin Price)/(Current Bitcoin Price).

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 3.6: Second Stage: Estimation of Individual Adoption

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

Column (4) is the model in (1) augmented with CF ($\widehat{u}_{it}$) estimated in 2018 first stage.

Column (5) is as column (4) but the CF has incorporated the Expected belief about the future price of Bitcoin.

Bootstrapped standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 3.7: Reasons for owning Bitcoin

Age /Reasons for owning Bitcoin	Counts			Percentage		
	18-34	35-54	55+	18-34	35-54	55+
18-34	18-34	35-54	55+	18-34	35-54	55+
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	18-34	35-54	55+	18-34	35-54	55+
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

Table 3.8: **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
Joint	2	3563.99***	0	0.35	1	250.36***	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

3.10 Figures

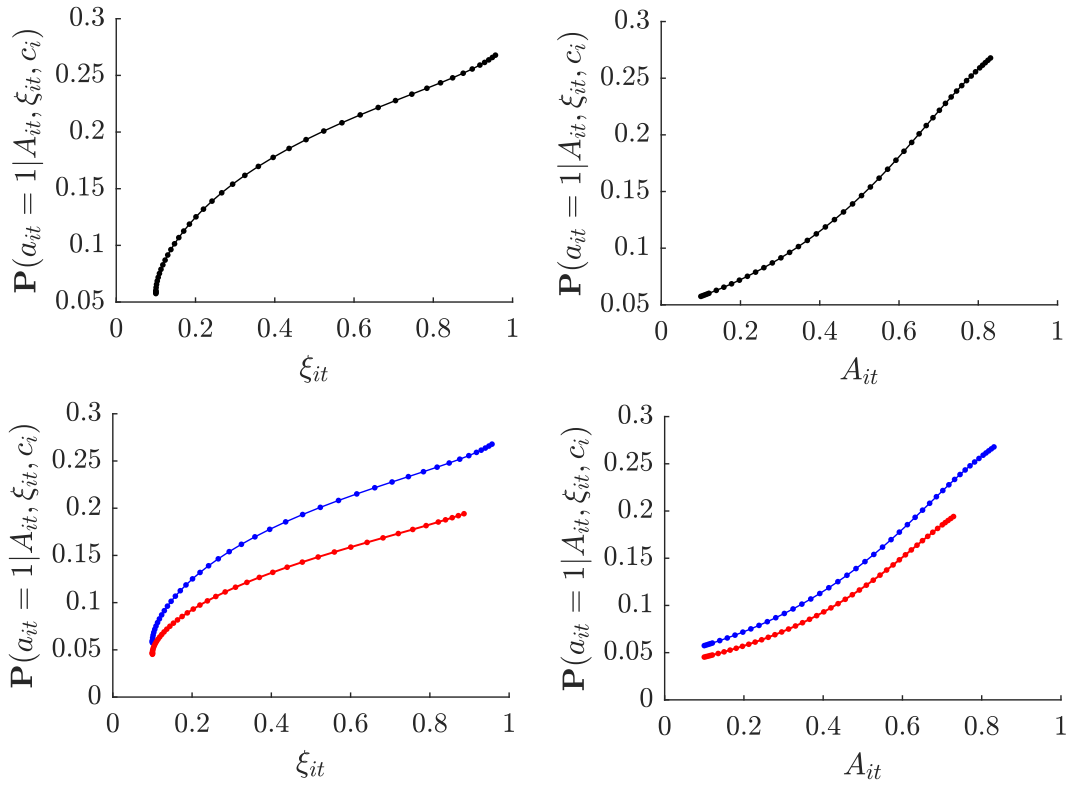


Figure 3.1: **Adoption and Beliefs.** All panels assume $\phi_\ell = 1, \varphi_\ell = 0.5, \phi_h = 0.1, \varphi_h = 0.6, r_h = 1, r_l = 0.5, \bar{A}_{i1} = \bar{\xi}_{i1} = 0.1$, and $B(A_{it}) = 0.5A_{it}$. The panels also assume that reservation utilities u_{it} are logistically distributed with mean 1.5 and scale parameter 0.4. Top panels consider adoption costs $c_i = 0$, whereas the bottom panels shows an increase in adoption costs from $c_i = 0$ to $c_i = 0.1$, represented by the respective blue and red dotted curves.

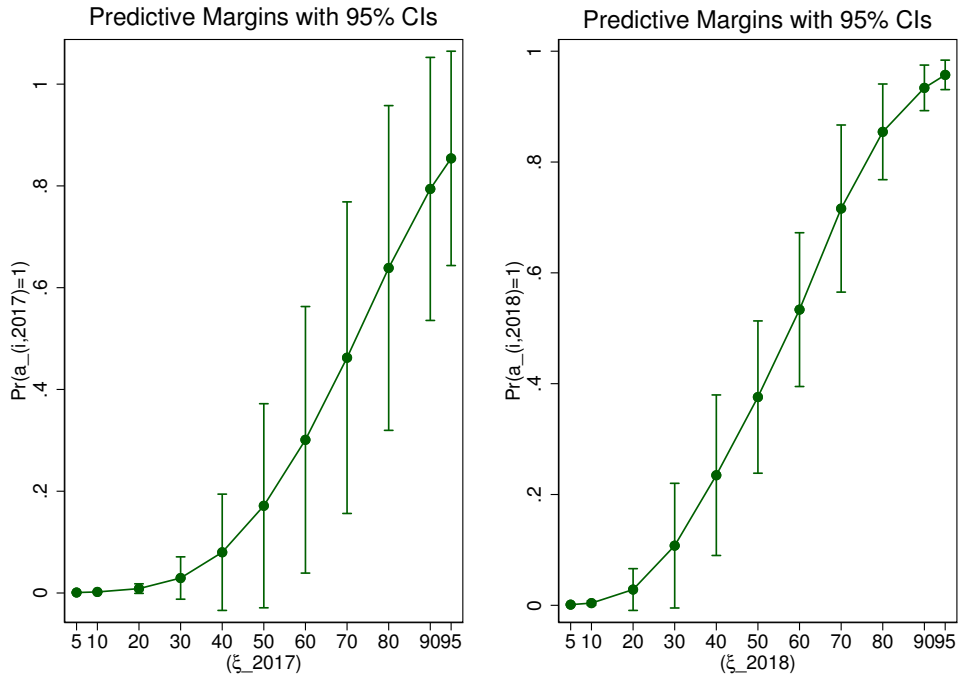


Figure 3.2: The Marginal Effects of Probability of Bitcoin Adoption function of Beliefs
The panels plot the predicted margins of the second stage equation, representing the marginal change in the probability of Bitcoin adoption as a function of beliefs (ξ_{it}) for 2017 (left) and 2018 (right)

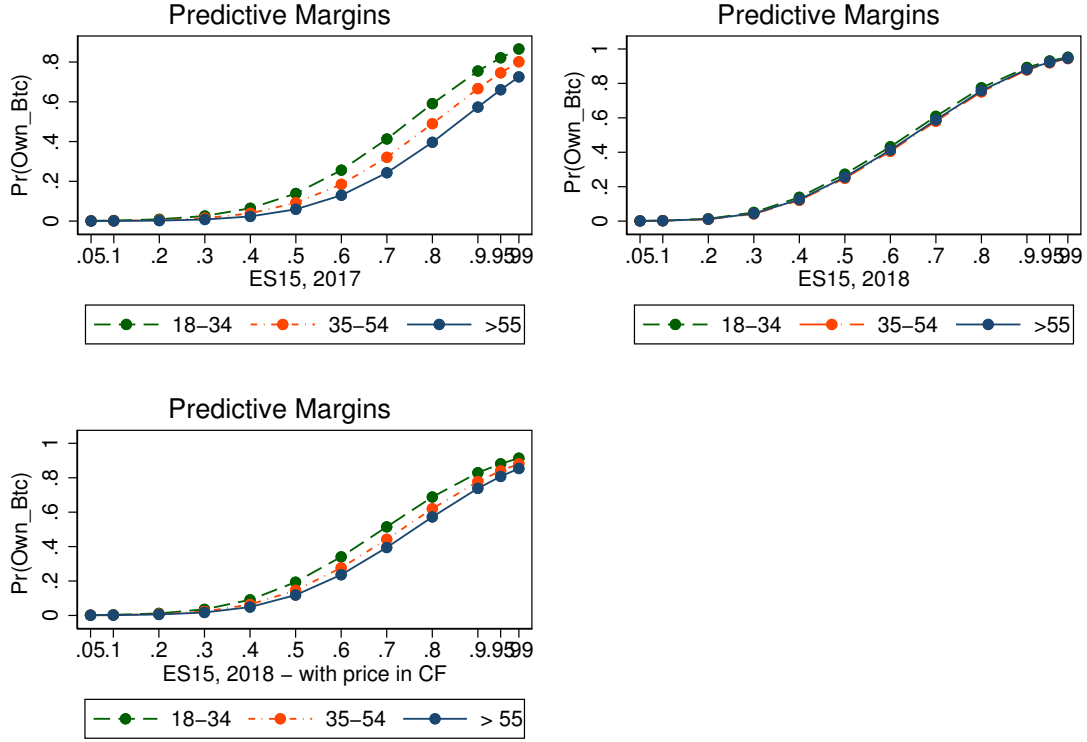


Figure 3.3: **The Marginal Effects of Probability of Bitcoin Adoption function of Beliefs, by Age** The panels plot the predictive margins of the second stage equation, representing the marginal change in the probability of Bitcoin adoption as a function of beliefs (ξ_{it}) for 2017 (left) and 2018 (right), decomposed by age categories (18-35, 35-55 and above 55)

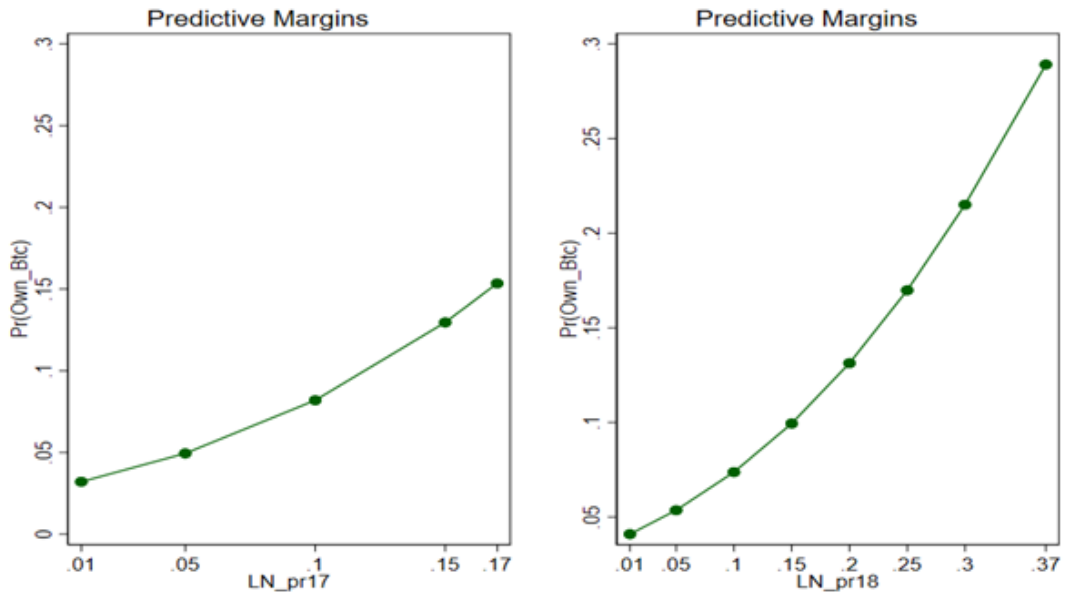


Figure 3.4: **The Marginal Effects of Probability of Bitcoin Adoption function of Local Network** The panels plot the predicted margins of the second stage equation, representing the marginal change in the probability of Bitcoin adoption as a function of the local network (A_{it}) for 2017 (left) and 2018 (right)

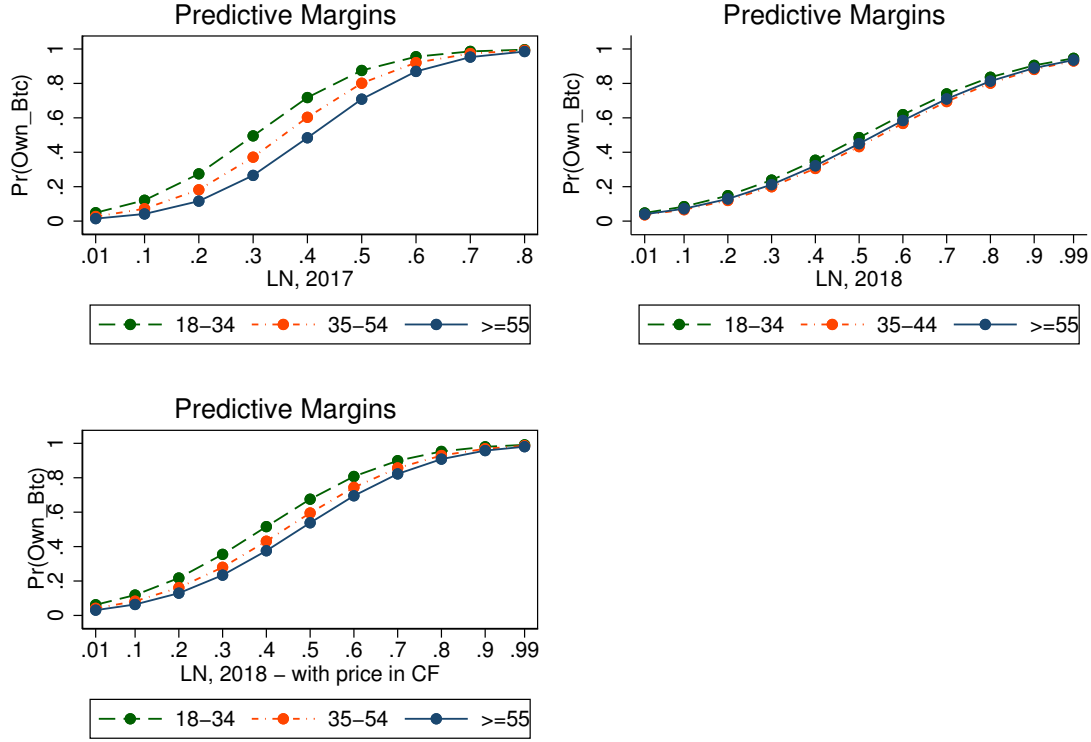


Figure 3.5: **The Marginal Effects of Probability of Bitcoin Adoption function of Network size (counterfactual), by Age** The top panels represent the counterfactual predicted margins of the second stage equation , representing the marginal change in the probability of adoption as a function of the local network(A_{it}) in 2017 (left) and 2018 (right) decomposed by three age groups (18-34, 34-54 and above 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 above 55) when the model in the first stage is augmented with the beliefs about Bitcoin expected return in one month.

3.11 Online Appendix

Table 3.9: **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

Table 3.10: **Second Stage: Estimation of Adoption Rate using Non-parametric Local Network**

VARIABLES	2017	2017 (CF)	2018	2018 (CF)
Beliefs (ξ_{it})	0.15*** (0.022)	0.11*** (0.025)	0.23*** (0.047)	0.20*** (0.045)
Network (A_{it})	0.39** (0.16)	0.31** (0.14)	0.35 (0.23)	0.40* (0.23)
Social Interaction ($\xi_{it} \times A_{it}$)	-0.0064 (0.0053)	-0.0088* (0.0048)	-0.023 (0.018)	-0.032* (0.017)
Age	-0.0014*** (0.00049)	-0.00078** (0.00036)	-0.0014** (0.00062)	-0.00062 (0.00063)
Gender: Female	-0.042*** (0.0086)	-0.021** (0.0098)	-0.031*** (0.0096)	-0.015 (0.010)
Income: 50k-99k	-0.0061 (0.0080)	-0.0038 (0.0082)	0.040*** (0.012)	0.028** (0.012)
Income: 100k+	-0.012 (0.012)	-0.0052 (0.011)	0.035** (0.014)	0.023 (0.014)
Employment	0.027*** (0.0093)	0.016** (0.0077)	0.011 (0.012)	0.0063 (0.011)
Education: College/CEGEP/Trade school	-0.00066 (0.013)	0.0011 (0.013)	0.036** (0.017)	0.026 (0.016)
Education: University	0.015 (0.011)	0.0075 (0.012)	0.043*** (0.017)	0.026 (0.016)
Marital status: Not married/CL	-0.0075 (0.0090)	-0.0038 (0.0085)	-0.014 (0.0099)	-0.0055 (0.0097)
Region: Prairies	-0.017*** (0.0048)	-0.0058 (0.0046)	-0.00060 (0.017)	0.0039 (0.017)
Region: Ontario	-0.013*** (0.0036)	-0.0063 (0.0050)	-0.0088 (0.015)	-0.0027 (0.015)
Region: Quebec	-0.022*** (0.0055)	-0.012** (0.0050)	-0.025 (0.016)	-0.014 (0.016)
Region: Atlantic	-0.023* (0.013)	-0.0099 (0.012)	-0.033 (0.026)	-0.026 (0.026)
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 benchmark second stage model for Bitcoin adoption (without the CF), year 2018.

Column (3) is the model in (1) augmented with CF ($\widehat{u}_{it}$) estimated in 2017 first stage.

Column (4) is the model in (1) augmented with CF ($\widehat{u}_{it}$) estimated in 2018 first stage.

Bootstrapped standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Chapter 4

Bitcoin awareness, ownership and usage in Canada: 2016-2020

1

Abstract

Starting from 2016, the Bank of Canada conducted annual surveys to monitor awareness, adoption and usage of Bitcoin and other crypto-assets (Henry, 2018, 2019a, 2019b). This report provides results of the latest iteration (2019) of the Bitcoin Omnibus Survey (BTCOS) and of the November 2020 Cash Alternative Survey (CAS). We find that between 2018 and 2020, the level of Bitcoin awareness and ownership among Canadians remained stable; around 90 per cent of the population were aware of Bitcoin, while only 5 per cent owned it. The main reasons for owning Bitcoin are investment and technology-related. Logically, we also see a drop in the share of past owners and those who reported regularly using Bitcoin for transactions. Finally, we discuss how Bitcoin holders differ from average Canadians with respect to their Bitcoin knowledge.

4.1 Introduction

This report provides new results relative to Bitcoin awareness and ownership measured in November 2019 and November 2020. They are derived from two Bank of Canada surveys, the 2019 Bitcoin Omnibus Survey (BTCOS) and the November 2020 Cash Alternative Survey (CAS). The Bank of Canada's fundamental interest in monitoring the adoption of Bitcoin is to understand how the financial system could be affected by its usage by Canadians. In an era of rapid developments in financial technology (FinTech), not to mention constraints imposed by a global pandemic, the safer central bank issued cash may be less convenient, and it is hard not to wonder

¹This Chapter is co-written with Marie-Hélène Felt, Gradon Nicholls and Marcel C. Voia and it was submitted to the Bank of Canada's Working Paper series.

whether cash is – or should be – disappearing.² Increased awareness of Bitcoin has raised many questions for central banks, institutions that, in many countries, are coming to terms with the so-called ‘death of cash’, the decline in the use of physical currency for making payments. In this vein, the possibility of a cashless society is thus driving a flurry of research and policy analysis into the so-called Central Bank Digital Currency (CBDC) – a digital form of central bank money. It is essential for the Bank of Canada to understand how existing decentralized digital currencies function for the consumer as a payment method versus store-of-value. Given the Bank of Canada’s role in maintaining financial stability, in its 2019 Financial System Review (FSR), the evolution of the crypto-assets market was considered one of the six financial vulnerabilities that need to be monitored closely. Currently, Bitcoin is in early stage of adoption and the size of this market is not big enough to pose risks to the financial system. Still, things may change quickly, and monitoring and analyzing the implications of these crypto-assets developments are crucial.

For this analysis, we use data from two surveys. The BTCOS has been commissioned yearly between 2016 and 2019 by the Bank of Canada to monitor trends in the adoption and usage of Bitcoin and other crypto-assets. It allows us to study awareness, ownership, holdings and usage patterns over the four years prior to the COVID-19 pandemic. By contrast, the main objective of the November 2020 CAS was to understand better the demand for and use of cash during the pandemic, but questions on the adoption of digital payment methods were also included in the survey. This data enables us to assess if any significant changes in awareness and ownership of Bitcoin were observed six months in the pandemic.

Overall, the results from the 2019 BTCOS and the November 2020 CAS show that the level of awareness among Canadians remains stable compared to 2018. Specifically, 87 per cent in 2019 and 88 per cent in 2020 reported having heard of Bitcoin compared to 89 per cent in 2018. Similarly, Bitcoin ownership remains around 5 per cent from 2018 to 2020, compared to 4 per cent in 2017 and 3 per cent in 2016 4.1. Even if we do not see a significant changes in the average Bitcoin ownership since 2018, we observe changes over the years in the demographic characteristics of Bitcoin owners in terms of gender, age, and income level. However, Bitcoin ownership remains concentrated within the young, educated males group.

– insert Figure 4.1 here –

The main reasons for owning Bitcoin in 2019 remain investment-related (39 per cent). However, technology-related reasons (31 per cent) become more prevalent compared to 2018. In addition, the share of Canadians who reported using Bitcoin

²In Canada, there has been a documented decline of 40 per cent in the use of cash by consumers for making payments over the last decade [Henry et al., 2018a], but it remains popular among certain demographic groups and for a specific type of transactions, and as a store-of-value.

for transactions and transfers a few times a month or more decreased in 2019 compared to 2018. Bitcoin holders differ from average Canadians with respect to their Bitcoin knowledge, yet 30 per cent of owners had a low knowledge score. Lack of understanding of this type of technology is also reflected in the reasons cited by past owners for not currently holding Bitcoin. In 2019 the number of Canadians who reported having stopped owning Bitcoin reduced, but those who continued to own Bitcoin tended to hold smaller amounts compared to 2018. In addition, past and current owners have reported incidents while holding Bitcoin; the most common is related to losses due to price crashes, followed by access lost to their wallet and exchange scam.

This paper is structured as follows: Section §4.2 describes the survey design and methodology of the 2019 BTCOS and November 2020 CAS; Section §4.3 discusses Canadians' awareness and ownership of Bitcoin; Section §4.3.2 takes a deeper dive into the characteristics and behavior of Bitcoin owners, and Section §4.5 briefly summarizes our findings.

4.2 Data

Early iterations of the BTCOS survey (Henry et al. 2018, 2019a and 2019b) provided valuable information about trends in Bitcoin awareness, ownership and usage, but also lessons learned for improving future surveys. The reason for doing these subsequential iterations is to deeper understand how ownership and reasons for owning Bitcoin may change over time, taking in consideration possible factors that may have an impact on Bitcoin adoption like price volatility (Chart 4.2), type of investors, Covid-19, developments in financial technology (FinTech), cryptocurrency acceptance by merchants and possible risks related to cryptocurrency incidents. The last iteration of BTCOS was done in December 2019, while in November 2020 Bank of Canada conducted a CAS that, even though it focused on the demand and usage of cash during the pandemic also contained two questions on the awareness and ownership of digital payment methods. These surveys enable us to update observations made from previous surveys [Henry et al., 2018b, 2019a,b] and assess if any significant changes were observed a few months in the COVID-19 pandemic. This section provides information on the survey designs and weighting procedures for the 2019 BTCOS and November 2020 CAS.

– insert Figure 4.2 here –

4.2.1 Design survey

The survey design of the 2019 BTCOS was very similar to that of 2018 (see [Henry et al. \[2019b\]](#) for details). The following small changes were made to the questionnaire.

A new question was added to assess awareness about stable coins among Canadians, following Facebook’s first announcement regarding their digital currency project, Libra, in June 2019. Also new to the 2019 BTCOS were questions asking respondents how they obtained Bitcoin and about potential incidents faced while holding it. The inclusion of the latter question was motivated by incidents that happened in Canada with crypto assets exchange: in October 2018, Edmonton-based Maple Change lost \$6 million of users’ funds [[ern, 2019](#)], and in January 2019, QuadrigaCX lost access to clients’ funds after the sudden death of its founder, resulting in losses of approximately \$260 million. The risks investors face in this weakly regulated industry are linked with the incidents reported by some holders, which might signal trust-related problems in this sort of technology and might lower the adoption speed of these crypto assets.

Questions about altcoin ownership were again asked in 2019, and the list of altcoins was lengthened by including BNB, Tether, USDC, and DAI. In addition, an option about owning Libra was added as a mean of identifying false answers.

In order to keep it short, questions on preferences over features of online transactions, how much cash did respondents spend on crypto assets, and the percentage of total personal spending made with crypto assets within a year were left out of the 2019 BTCOS.

Data on Bitcoin awareness and ownership in 2020 is from the November 2020 CAS. Given that this survey is focused on demand and usage of cash during the Covid-19 pandemic, only limited information about Bitcoin and crypto assets in general was collected in this survey.

To compare the key findings related to Bitcoin across years, we also report in this paper the results from previous iterations of the BTCOS and already published [[Henry et al., 2018b, 2019a,b](#)]. Final sample sizes were 1,997 in 2016; 2,623 in 2017; 1,987 in 2018 and 1,987 in 2019. These samples include 58, 117, 99, and 89 Bitcoin owners each year. The November 2020 CAS has a total number of respondents of 3893, with 181 Bitcoin owners.

4.2.2 Survey methodology

The BTCOS and November 2020 CAS rely on two sample sources: I-Say, which is an opt-in non-probability panel, and Ampario, which is a river sample collected through web pages, banners, ads, etc. Due to unforeseen technical issues, the 2019 BTCOS resulted in a roughly 2:1 ratio of Ampario to I-Say respondents, a reversal

from previous iterations of the BTCOS where this ratio was roughly 1:2. The 2020 CAS sample also has a raw Ampario to I-Say ratio around 1:2.

In Appendix A, we investigate the implication of changes in the composition in terms of sample sources on survey estimates and explain how we select the appropriate mix of the two frames (I-say and Ampario) in the final samples. We keep the current composition (37 per cent I-Say and 63 per cent Ampario) for the 2019 BTCOS sample and settle on a similar mix (30 per cent I-say and 70 per cent Ampario) for the 2020 CAS. The weighting procedure for both the 2019 BTCOS and November 2020 CAS samples follows the methodology used in the 2018 BTCOS [Henry et al., 2019b]. We use a raking procedure, outlined in Deville et al. [1993], to adjust the final sample for differences between the demographic composition of our sample and the Canadian population. Specifically, the procedure yields survey weights that match the sample to the 2016 Canadian Census with respect to the following demographics: age, gender, region, education, marital status, employment, and household income.

4.3 Bitcoin awareness and ownership

This section presents the trends in Bitcoin awareness and ownership from 2016 to 2020. In addition, using conditional analysis, we identify what demographic characteristics explain Bitcoin awareness and ownership.

4.3.1 Canadians' awareness of Bitcoin

The level of Bitcoin awareness among the Canadian population was measured using the survey question “Have you heard about Bitcoin?”. Awareness increased since 2016 when we saw a level of 62 per cent of Canadians mention that they heard about Bitcoin, followed by a jump to 83 per cent in 2017 and 89 per cent in 2018 (4.1). In 2019 and 2020, the levels of awareness remained virtually unchanged, at 87 per cent in 2019 and 88 per cent in 2020.

Overall, the demographics patterns are persistent across years. Specifically, the highest levels of awareness (above 90 percent) are observed among Canadians who are male, have a university degree, are financially literate and have relatively high household income (\$ 70,000 and above). As well, from a geographic perspective, British Colombia, Prairies and Ontario registered a higher level of awareness than Quebec and Atlantic.

In terms of changes over time, starting from 2016 to 2018, the level of awareness increased across all demographics groups. However, after 2018, awareness among females slightly decreased from 85 per cent in 2018 to 81 per cent in 2019 and 83 per cent in 2020. In contrast, from 2018 to 2020, awareness among males remains con-

stant. Other examples of demographics groups that registered a decline in awareness for 2019 and 2020 include those with low household income (from 87 to 77 per cent in 2019 and 79 per cent in 2020) and those that are low financial literate (from 80 to 78 per cent in 2019 and 76 per cent in 2020). In 2019, a new question to measure the level of awareness about stable coins was added, with the question “Have you heard about stable coins?”. Surprisingly among those who say they have heard about Bitcoin in 2019, only 5 per cent also heard about stable coins.

– insert Table 4.1 here –

We further analyse Bitcoin awareness using a logistic regression framework conditional on demographic characteristics and financial literacy. Marginal effects are plotted on 4.3 (detailed results are available in 4.2.³ It suggests that the likelihood of Bitcoin awareness decreased with age, being female and living outside of British Columbia. Conversely, we estimate Canadians are more likely to be aware of Bitcoin as their levels of education and income increase, are unemployed and are not single. The results from column 1 show that financial literacy scores about inflation, risk and diversification have a significant positive impact on awareness. These findings are consistent with our unconditional analysis of Bitcoin awareness.

– insert Figure 4.3 here –

– insert Table 4.2 here –

4.3.2 Bitcoin ownership

Table 4.3 presents Bitcoin ownership in Canada in 2019 and 2020, relative to the previous surveyed years, overall and across demographic groups. The average Bitcoin ownership in the Canadian population increased from 3 per cent in 2016 to around 5 per cent since 2018. It remained stable between 2018 and November 2020, despite the Covid-19 pandemic. Differences in Bitcoin ownership across demographic domains are telling a compelling story. Overall, across years we observe that most demographics follow the same patterns. In particular, Canadians who are young, males, with a university degree, have high household income and are relatively low

³Marginal effects are measured relative to the following benchmark group: male, aged 18 to 24, from British Columbia, high school educated, being single, employed, with household income less than \$25,000, and who have correctly answered each financial literacy question. The first column for the reported tables presents our estimates of the outcome variable of interest for the overall period (2016-2020), while subsequent columns show the results for each year.

financially literate are more likely to hold Bitcoin. The gender gap in Bitcoin ownership is still high. Between 2016 and 2020, ownership among females remained under 4 per cent (and mostly around 2 per cent) while ownership among males nearly doubled (from 4.4 per cent in 2016 to 8.3 per cent in 2020). Another pattern that stands out is with regards to financial literacy. Individuals who score lower to the three financial literacy questions show higher ownership rates (above 7 per cent for low-literate than 4 to 5 per cent for high-literate). These results reveal interesting facts, specifically Canadians with a high level of financial literacy are more likely to be aware of Bitcoin but less likely to adopt it. [de Bassa Scheresberg et al. \[2020\]](#) also found that higher financial literacy was negatively correlated with mobile payment usage.

At the same time, while there was an increase in the share of mid-age owners (from 4.9 per cent in 2018 to 6.7 per cent in 2019), there was also a sharp decrease in the share of Bitcoin owners aged 18 to 34 (from 10.5 to 7.8 per cent in 2019). Interestingly, during 2020, we see similar age profiles to 2017. The exception was the 45-to-54 age group, where ownership dropped by more than half from 1.7 to 0.7 per cent.

For the education categories, ownership among high-school educated increased from 2.3 per cent in 2018 to 3.3 per cent in 2019, while for the college- and university-educated Canadians, the ownership declined (from 5.7 per cent in 2018 to 4.3 per cent in 2019 for college graduates and from 9.1 per cent to 8.7 per cent for university graduates). In 2020, the share of university-educated owners reduced even more from 8.7 per cent in 2019 to 7.4 per cent. Even though the university-educated Canadians had the largest share of Bitcoin within the group, the dynamics from year to year is changing in favour of less-educated people.

The ownership gap in terms of income flattened in 2019 and 2020 compared to 2018. In 2018 the share of Canadians with low household income (below \$30,000) was at 2.8 per cent compared to 7 per cent for those with high income (above \$70,000). In 2019 and 2020, respectively, we see an increase in the proportion of Bitcoin owners with low income (from 2.8 per cent in 2018 to 3.7 per cent in 2019 and to 4.3 per cent in 2020) and a decrease for those with high income (from 7 per cent in 2018 to 6.6 per cent in 2019 and 5.4 per cent in 2020).

Geographically, the lowest level of ownership across years was observed in Atlantic province. In 2019, British Columbia and Prairies experienced a decline in ownership, while in Ontario and Atlantic, ownership continued to rise. In contrast, in 2020, the bitcoin ownership in Prairies almost doubled (from 3.9 per cent in 2019 to 7.6 per cent in 2020). In Quebec, the ownership decreased steadily from year to year.

– insert Table [4.3](#) here –

Chart 4.4 presents marginal effects of a conditional analysis using a logistic regression of Canadian’s Bitcoin ownership on demographic characteristics and financial literacy. Detailed results are available in Table 4.4. The probability of Bitcoin ownership decreases with being female, being older and not being employed (except for 2020 when the unemployment rate increases due to Covid-19). In contrast, the likelihood of being Bitcoin owners increase with education. Income effects are not statistically significant. As mentioned in the descriptive statistics, Bitcoin ownership is higher among those with low financial literacy (also see Fujiki [2021, 2020]). The same results are found in the logistic framework, as coefficient estimates for incorrect answers about inflation and risk diversification are positive. Overall, the results are consistent with unconditional analysis on Bitcoin ownership.

– insert Table 4.4 here –

– insert Figure 4.4 here –

4.4 The profile of Bitcoin adopters

In this section we look more deeply at Bitcoin owners. We first report the knowledge about Bitcoin of owners compared to that of the overall Canadian population. We provide Bitcoin holdings estimates. Moreover, we outline the main reasons for owning Bitcoin and how often it is used to pay for goods or services and to make P2P transaction. Next, we look at the changes in the past Bitcoin owners share and holdings of Bitcoins. Lastly, we look at the ways in which Bitcoin was obtained and the incidents faced by Bitcoin adopters when using it.

4.4.1 Bitcoin knowledge

This section analyses the state of knowledge about Bitcoin properties, exploring the differences between Bitcoin owners and the overall Canadian population.

The Bitcoin knowledge questions [Henry et al., 2019b] are reported in Appendix B . The knowledge score is computed by summing the correct answers and subtracting the incorrect answers, while “don’t know” answers do not contribute to the measure. The reason for deducting the incorrect answers is to penalize survey respondents for guessing [Henry et al., 2019a]. As a result, knowledge scores take values from -3 to 3. Based on these indices, three knowledge levels were defined as follow: low (score=0), medium (score = 1 or score =2) and high (score = 3).

The average Bitcoin knowledge of the Canadian population did not change substantially between 2018 and 2019. The share of individuals with low Bitcoin knowledge is about 60 per cent, and only 6 per cent answered all three Bitcoin questions correctly (Table 4.5). As expected, Bitcoin owners are more likely to give a correct answer compared to non-owners. However, in 2018 and 2019, respectively, only around 30 per cent of Bitcoin owners had high knowledge. The lack of knowledge hasn't stopped people from buying Bitcoin, as 19 per cent in 2018 and 28 per cent in 2019 of Bitcoin owners are ranked as low literate about crypto assets.

– insert Table 4.5 here –

4.4.2 Bitcoin holdings

In 2018 and 2019, Bitcoin users were asked to provide the value in Canadian dollars of Bitcoins they currently hold. Compared to 2018, the median of Bitcoin holdings value decreased sharply, from around 500 in 2018 to 250 in 2019. To compare the holdings of Bitcoin across years we grouped 2018 and 2019 numbers in ranges presented in Figure 4.5. Over the period, we see a decreasing proportion of Canadians that reported holding 1 to 10 Bitcoin (from 40 per cent in 2016 to 4 per cent in 2019) and 10 or more Bitcoin (from 11 per cent in 2016 to 4 per cent in 2019). Therefore, the share of holders with less than one Bitcoin has increased from 49 per cent in 2016, 66 per cent in 2017, 85 per cent in 2018 and 91 per cent in 2019. Even if the price for Bitcoin in 2019 was double compared to 2018 at the time of the interview (9100 CAD in 2019 vs 4500 CAD in 2018), this increase is not reflected in the value of Bitcoin holdings among Canadian owners, meaning that they prefer to invest in small increments.

– insert Figure 4.5 here –

Alternative to Bitcoins, Canadians also invested in Altcoins. Table 4.6 shows the dynamics of investment in Altcoins by Canadians. Besides Ethereum, which seems to oscillate in preferences, Bitcoin Cash shows a steady slow increase (from 2.6 per cent in 2017 to 3.1 per cent in 2019). About half of the Altcoin owners are also Bitcoin owners.

– insert Table 4.6 here –

4.4.3 Why do Canadians choose to own or not to own Bitcoin

Why do individuals hold Bitcoin is an essential topic to consider while researching Bitcoin and other digital currencies. Investigating this aspect has implications for central banks given its core function for production and distribution of banknotes, but also taking into consideration the potential costs and benefits for issuing its own central bank digital currency (CBDC), (see, for example, Engert and Fung (2017)).

In the 2017-2019 BTCOS surveys, Bitcoin owners were asked how often they use their Bitcoin holdings for two reasons: to pay for goods and services (Figure 4.6) and to send money to other people (Figure 4.7). In 2019, the trend for both types of transactions was similar, the share of Bitcoin adopters that tend to use Bitcoin at least a few times a month decreased. Concurrently, the proportion of Bitcoin owners that pay for services or goods and sent money at least once per year, but not on a regular basis, increased. Thus, the share of Bitcoin holders that are paying with Bitcoin “rarely” increased from 41 per cent in 2018 to 51 per cent in 2019; it increased from 13 per cent in 2018 to 22 per cent in 2019 for the “sometimes” category, while it abruptly decreased for the “often” category, from 46 per cent in 2018 to 28 per cent in 2019. The per-to-peer Bitcoin transactions that are made “rarely” increased from 48 per cent in 2018 to 54 per cent in 2019, it increases from 12 per cent to 19 per cent for the “sometimes” category, while the “often” category was decreasing from 40 per cent in 2018 to 27 per cent in 2019.

– insert Figure 4.6 here –

– insert Figure 4.7 here –

Bitcoin owners were also asked to indicate their primary reason for holding Bitcoin (Table 4.7), whereas non-owners aware of Bitcoin were asked to provide their main reason for not having it (Table 4.8). Given that owners are not using their Bitcoin holdings for regular payments or remittances, we are interested in identifying the drivers for owning Bitcoin. Thereby, we will be able to separate better the purposes of using Bitcoin as an investment vehicle or as a mean of payment.

Table 4.7 shows the distribution of adopters across four different primary reasons for owning Bitcoin: technology-, investment-, anonymity- and payment-related reasons. In 2018 and 2019, the most selected option was investment at about 40 per cent. Technology-related reasons sharply increased from 22 per cent in 2018 to 31 per cent in 2019. Concurrently, both payments related and trust-related reasons (not trusting banks/government/Canadian dollar) decreased slightly (from 19 per cent in 2018 to 15 per cent in 2019).

– insert Table 4.7 here –

Canadians that are aware of Bitcoin mainly stated that the main reason for not owning it is related to a lack of knowledge and understanding of Bitcoin (29 per cent), the fact that their current methods of payments needs are met (22 per cent), or a lack of trust for digital currencies given that they are not backed by the government (15 per cent). Other reasons related to price volatility, acceptance, the future survival of the Bitcoin system, cyber theft and regulation of crypto-assets represent less than 10 per cent each. The same pattern is observed across all available years.

– insert Table 4.8 here –

4.4.4 Trends in past ownership of Bitcoin

Past owners are defined as Canadians who have previously adopted Bitcoin but had decided to stop owning it when they were surveyed. As presented in Figure 4.8, after a decline in past ownership from 2 per cent in 2016 to 1 per cent in 2017 (due to the spike in the price of Bitcoin), in 2018, due to the dramatic drop in the price of Bitcoin, the share of past owners grew once again to 3 per cent. The fact that in 2018 the share of both current and past Bitcoin owners increased presume that within the 2017-2018 period, there was an influx of new entry Bitcoin owners that decide to sell their holdings quickly, meaning that the bitcoin ownership was even higher during that period. In 2019, when the price started to increase again, the outflow of owners that sell their holdings reduced to 2 per cent. Our evidence also suggests that the main reasons stated by past Bitcoin owners are related to price volatility, lack of understanding and knowledge about Bitcoin, concerns about cyber attacks and because it is not easy to use.

– insert Figures 4.8 here –

4.4.5 Bitcoin access and incidents

This section introduces the main channels through which Canadians obtain Bitcoins. Additionally, given the unexpected events in Canada related to crypto assets exchange, Bitcoin holders were asked if they faced Bitcoin incidents and, if yes, what type of incidents. Analyzing the way Canadians got access to Bitcoin in 2019 (Figure 4.9), we see about 40 per cent were doing mining, 34 per cent were using exchange websites, 12 per cent received it from a friend or a family member, 10 per cent used Bitcoin ATMs and only 3.4 per cent used Exchange mobile app.

– insert Figures 4.9 here –

On the other hand, Bitcoin holders also reported that they faced different incidents while holding Bitcoin, see Figure 4.10. In particular, 78 past and 43 current Bitcoin holders out of 171 enquired in 2019 reported incidents. The highest proportion of respondents (27 per cent) lose substantial value due to Bitcoin price crash, 19 per cent stated that they lost access to their personal wallets and 16 per cent mention that cryptocurrency exchange stole their funds. Data breaching, ICO scamming, having problems when purchasing crypto assets were also selected.

This evidence on Bitcoin incidences may explain the increase in exits and the lack of increase in adoption past 2018, including in 2020 (during COVID-19 Pandemic) when the price of Bitcoin was increasing exponentially, most likely driven by the entry on the market of different financial institutions including commercial companies (as TESLA).

– insert Figures 4.10 here –

4.5 Conclusion

This report looks at Bitcoin awareness and ownership dynamics prior to COVID-19 and during this period using the BTCOS 2019 survey and November CAS 2020 data. Additionally, the analysis considers the information provided in the previous iterations of BTCOS surveys (see Henry et al. (2018, 2019a, 2019b) for discussions of past iterations of BTCOS).

Findings reveal that the level of awareness and ownership in 2019 and 2020 remain stable compared to 2018, at around 88 per cent for awareness and 5 per cent for ownership. Prior to 2019, there was a steady increase in Bitcoin awareness and ownership. Between 2016 and 2018, the share of Canadians who were aware of Bitcoin increased from 62 per cent to 89 per cent, and those who owned Bitcoin increased from 3.2 per cent to 5.2 per cent. Even though the overall Bitcoin ownership in 2019 and 2020 compared to 2018 remains stable, changes in gender, age, and income level categories were identified. Still, Bitcoin owners are characterized as being males, young with higher education.

Next, we will highlight the additional results derived from BTCOS 2019 only, given the data limitation about Bitcoin in November 2020 CAS. In 2019, we observed a decrease in the number of past Bitcoin owners, but those who continued to have Bitcoin holds smaller amounts of it; respectively, 92 per cent of Bitcoin owners hold less than one Bitcoin.

As in previous years, the main reason for owning Bitcoin in 2019 remains investment-related (39 per cent); however, technology-related reasons (31 per cent) become more

prevalent year by year. The most cited reasons among Canadians aware of Bitcoin for not owning it were lack of knowledge, lack of trust in private digital currency, and the fact that the used payment method satisfies all their needs. Additionally, we see a decrease of Bitcoin owners who stated they use Bitcoin a few times a month to buy goods and services or make P2P transfers.

Also, we measure how knowledgeable are both Bitcoin adopters and non-adopters in terms of Bitcoin main characteristics. As expected, Bitcoin owners are more likely to give a correct answer compared to non-adopters. However, in 2018 and 2019, respectively, only one-third of Bitcoin owners had high knowledge.

In 2019 BTCOS two new questions were added: how Bitcoin was obtained and the incidents that happened to Bitcoin owners while holding it. The most common way to obtain Bitcoin was through mining it and using exchange cryptocurrency sites. Incidents faced by Bitcoin adopters are mainly related to cryptocurrency exchange scams and price crashes.

4.6 Appendix

4.6.1 Tables

Table 4.1: **Awareness of Bitcoin in Canada, 2016-2020**

		2016	2017	2018	2019	2020
	Overall	62	83	89	87	88
Gender	Male	72	90	93	93	92
	Female	54	77	85	81	83
Age	18-34	69	87	91	88	86
	35-34	58	82	88	84	86
	55+	62	82	88	88	91
Education	High school or less	55	76	84	82	82
	College / CEGEP / Trade	59	85	90	88	90
	University	78	93	95	92	94
Income	<30k	49	74	87	77	79
	30k-69k	61	82	88	84	86
	70k+	69	87	91	91	91
Region	B.C.	74	93	94	89	91
	Prairies	66	84	89	88	93
	Ontario	64	85	92	90	91
	Quebec	49	75	84	78	75
	Atlantic	65	80	83	88	88
Financial Literacy	Low			80	78	76
	Medium			90	86	88
	High			94	94	95

Note: The table reports the percentage of Canadians who are aware of Bitcoin over 2016- 2020. The sample size is: 1,997 in 2016; 2,623 in 2017; 1,987 in 2018; 1,987 in 2019 and 3893 in 2020. The sample consists of 181 Bitcoin owners in 2020, 89 in 2019, 99 in 2018, 117 in 2017 and 58 in 2016. Financial literacy scores were calculated based on the responses of the three financial literacy questions according to [Lusardi and Mitchell \[2014\]](#) . Financial literacy scores were computed by summing the correct answers and subtracting the incorrect answers, while “don’t know” answers do not contribute to the measure. As a result, knowledge scores take values from -3 to 3. Based on these indices, three knowledge levels were defined as follow: low (score=0), medium (score = 1 or score =2) and high (score = 3). All estimates were calculated using survey weights.

Table 4.2: **Marginal Effects of Probability of Bitcoin awareness FL: All; 2018-2020**

VARIABLES	All	2018	2019	2020
Gender: Female	-0.058*** (0.012)	-0.046** (0.021)	-0.084*** (0.023)	-0.074** (0.038)
Age: 25 to 34	-0.0016 (0.018)	0.019 (0.034)	0.0093 (0.037)	-0.028 (0.052)
Age: 35 to 44	-0.045** (0.019)	0.0060 (0.035)	-0.091** (0.042)	-0.0065 (0.049)
Age: 45 to 54	-0.042** (0.020)	-0.045 (0.042)	-0.047 (0.041)	0.020 (0.049)
Age: 55 to 64	-0.031* (0.018)	-0.034 (0.041)	-0.024 (0.038)	-0.0045 (0.067)
Age: 65+	-0.026 (0.020)	-0.031 (0.050)	-0.036 (0.038)	0.046 (0.045)
Prairies	-0.0054 (0.019)	-0.021 (0.037)	0.012 (0.037)	0.017 (0.080)
Ontario	-0.0064 (0.018)	-0.013 (0.027)	-0.00094 (0.036)	-0.029 (0.082)
Quebec	-0.088*** (0.019)	-0.076** (0.031)	-0.088** (0.040)	-0.10 (0.083)
Atlantic	-0.029 (0.022)	-0.056 (0.039)	0.010 (0.046)	-0.025 (0.085)
College / CEGEP / Trade	0.047*** (0.012)	0.042* (0.023)	0.035 (0.027)	0.094** (0.040)
University	0.060*** (0.014)	0.053* (0.027)	0.045 (0.029)	0.091** (0.046)
Marital status: Not Single	0.044*** (0.011)	0.054** (0.023)	0.045** (0.023)	0.038 (0.036)
Unemployed	0.018 (0.018)	0.027 (0.039)	-0.059 (0.066)	0.12*** (0.034)
Not in labour force	0.0076 (0.014)	0.0040 (0.029)	0.0012 (0.030)	0.068** (0.032)
Income: 25k-45k	0.024 (0.017)	-0.026 (0.034)	0.054 (0.041)	0.11** (0.052)
Income: 45k-65k	0.037** (0.019)	0.021 (0.034)	0.033 (0.043)	0.13** (0.063)
Income: 65k-85k	0.059*** (0.021)	0.0027 (0.042)	0.096** (0.046)	0.17*** (0.058)
Income: 85K-250k	0.057*** (0.019)	0.020 (0.038)	0.10** (0.044)	0.12** (0.059)
FL interest: Incorrect	-0.030* (0.016)	-0.024 (0.029)	-0.036 (0.031)	-0.041 (0.053)
FL interest: I don't know	-0.049** (0.020)	-0.073* (0.038)	-0.021 (0.036)	-0.097 (0.10)
FL inflation: Incorrect	-0.073*** (0.015)	-0.062** (0.028)	-0.079*** (0.028)	-0.078 (0.050)
FL inflation: I don't know	-0.045** (0.018)	-0.016 (0.028)	-0.071** (0.035)	0.00095 (0.051)
FL risk: Incorrect	-0.056*** (0.021)	-0.030 (0.031)	-0.049 (0.043)	0.00014 (0.047)
FL risk: I don't know	-0.048*** (0.012)	-0.066*** (0.023)	-0.044* (0.024)	-0.033 (0.033)
Observations	9,058	1,743	1,800	1,748

Note: This table presents marginal effects of the probability of Bitcoin awareness, estimated via a logistic regression. Column 1 shows the effect of each variable on the probability of having heard of Bitcoin over the period 2018-2020, while Column 2 to 4 present the results by year, starting from 2018 to 2020. FL variables refer to the three financial literacy question listed in Appendix B. Weighed Bootstrap Standard Errors in brackets: *** p<0.01, ** p<0.05, * p<0.1.

Table 4.3: **Ownership of Bitcoin in Canada, 2016-2020**

		2016	2017	2018	2019	2020
	Overall	3.23	4.31	5.18	5.08	5.14
Gender	Male	4.36	6.64	6.70	8.14	8.31
	Female	2.17	2.11	3.74	2.19	2.06
Age	18-34	9.12	11.13	10.48	7.78	11.00
	35-34	1.60	3.19	4.88	6.73	5.57
	55+	0.51	0.48	1.69	1.72	0.61
Education	High school or less	3.77	3.68	2.28	3.27	3.71
	College / CEGEP / Trade	1.51	3.10	5.70	4.34	5.09
	University	4.33	6.66	9.11	8.74	7.43
Income	<30k	3.05	4.26	2.82	3.65	4.30
	30k-69k	3.88	5.59	4.77	3.79	4.90
	70k+	3.69	4.27	6.99	6.63	5.42
Region	B.C.	2.76	5.20	6.34	5.32	5.10
	Prairies	2.14	4.06	6.03	3.86	7.64
	Ontario	2.53	3.87	5.18	6.21	5.04
	Quebec	5.48	5.07	4.56	4.41	3.94
	Atlantic	3.22	3.08	2.80	3.80	3.30
Financial Literacy	Low			7.27	7.49	8.43
	Medium			4.71	2.88	5.29
	High			4.11	5.05	5.28

Note: This table reports the percentage of Canadians who owned Bitcoin (answered Yes to "Do you currently have or own Bitcoin?") The sample size is: 1,997 in 2016; 2,623 in 2017; 1,987 in 2018; 1,987 in 2019 and 3893 in 2020. The sample consists of 181 Bitcoin owners in 2020, 89 in 2019, 99 in 2018, 117 in 2017 and 58 in 2016. Financial literacy scores were calculated based on the responses of the three financial literacy questions according to [Lusardi and Mitchell \[2014\]](#). Financial literacy scores were computed by summing the correct answers and subtracting the incorrect answers, while "don't know" answers do not contribute to the measure. As a result, knowledge scores take values from -3 to 3. Based on these indices, three knowledge levels were defined as follow: low (score=0), medium (score = 1 or score =2) and high (score = 3). All estimates were calculated using survey weights.

Table 4.4: **Marginal Effects of Probability of Bitcoin ownership (FL): 2018-2020**

VARIABLES	All	2018	2019	2020
Gender: Female	-0.046*** (0.0081)	-0.040*** (0.015)	-0.066*** (0.019)	-0.083*** (0.025)
Age: 25 to 34	0.012 (0.019)	-0.0071 (0.050)	0.062* (0.033)	0.039 (0.035)
Age: 35 to 44	-0.025 (0.016)	-0.062 (0.053)	0.010 (0.026)	-0.012 (0.034)
Age: 45 to 54	-0.033* (0.017)	-0.098* (0.051)	0.045 (0.033)	-0.033 (0.039)
Age: 55 to 64	-0.065*** (0.014)	-0.11** (0.051)	-0.014 (0.022)	-0.065** (0.027)
Age: 65+	-0.073*** (0.014)	-0.11** (0.051)	-0.023 (0.024)	-0.067** (0.027)
Prairies	0.0094 (0.013)	0.00098 (0.023)	-0.013 (0.033)	0.030 (0.039)
Ontario	0.0042 (0.010)	-0.0067 (0.019)	-0.012 (0.031)	-0.0042 (0.028)
Quebec	-0.0054 (0.012)	-0.0067 (0.024)	-0.023 (0.034)	-0.020 (0.028)
Atlantic	-0.00028 (0.014)	-0.034 (0.026)	-0.026 (0.038)	-0.020 (0.033)
College / CEGEP / Trade	0.017* (0.0085)	0.032** (0.016)	0.012 (0.020)	0.036 (0.027)
University	0.040*** (0.0092)	0.056*** (0.017)	0.049** (0.022)	0.042* (0.022)
Marital status: Not Single	-0.0042 (0.0083)	-0.016 (0.013)	-0.011 (0.015)	0.0028 (0.023)
Unemployed	-0.018* (0.011)	0.024 (0.044)	-0.047*** (0.012)	-0.061*** (0.014)
Not in labour force	-0.016* (0.0086)	-0.017 (0.017)	-0.0059 (0.017)	-0.022 (0.021)
Income: 25k-45k	-0.0053 (0.015)	0.0037 (0.032)	-0.016 (0.036)	0.034 (0.040)
Income: 45k-65k	0.0028 (0.013)	0.010 (0.031)	-0.014 (0.035)	0.030 (0.037)
Income: 65k-85k	0.0091 (0.016)	0.030 (0.032)	-0.0097 (0.039)	0.063 (0.042)
Income: 85K-250k	-0.0089 (0.014)	0.015 (0.030)	-0.020 (0.033)	-0.0039 (0.030)
FL interest: Incorrect	0.019 (0.012)	0.038 (0.026)	0.012 (0.022)	0.0074 (0.033)
FL interest: I don't know	0.0073 (0.016)	-0.0032 (0.024)	0.016 (0.034)	-0.033 (0.021)
FL inflation: Incorrect	0.025** (0.0096)	-0.0026 (0.015)	0.043* (0.025)	0.0076 (0.022)
FL inflation: I don't know	-0.0057 (0.011)	-0.026 (0.025)	0.020 (0.028)	-0.032 (0.025)
FL risk: Incorrect	0.061*** (0.017)	0.073*** (0.028)	0.043 (0.047)	0.040 (0.030)
FL risk: I don't know	-0.012* (0.0071)	0.0028 (0.017)	-0.019 (0.014)	0.0042 (0.036)
Observations	9,058	1,743	1,800	1,748

Note: This table presents marginal effects of the probability of Bitcoin ownership, estimated via a logistic regression. Column 1 shows the effect of each variable on the probability of having heard of Bitcoin over the period 2018-2020, while Column 2 to 4 present the results by year, starting from 2018 to 2020. FL variables refer to the three financial literacy questions listed in Appendix B. Weighed Bootstrap Standard Errors in brackets: *** p<0.01, ** p<0.05, * p<0.1..

Table 4.5: **Bitcoin knowledge**

	2017		2018		2019	
	Overall	Adopters	Overall	Adopters	Overall	Adopters
low	55	24	61	19	60	28
medium	38	49	33	52	34	41
high	6	27	6	29	6	31

Note: The table reports the share of Canadians, in per cent, in each category of Bitcoin knowledge. Financial literacy scores were calculated based on the responses of the three financial literacy questions according to Lusardi and Mitchell [2014]. Financial literacy scores were computed by summing the correct answers and subtracting the incorrect answers, while “don’t know” answers do not contribute to the measure. As a result, knowledge scores take values from -3 to 3. Based on these indices, three knowledge levels were defined as follow: low (score=0), medium (score = 1 or score =2) and high (score = 3).

Table 4.6: **Altcoins ownership by year**

	2017	2018	2019
Etherium	3.3	1.9	3.1
BTC Cash	2.6	2.9	3.1
Litecoin	3.1	1.9	1.8
XPR	3.9	1.0	0.9
ETHclas	4.1	0.6	
Dash	3.9	0.7	
Other	4.1	0.7	0.8
BNB			1.3
Tether			0.5
USDC			0.3
DAI			0.1

Note: This table reports the percentage of Canadians who owned Altcoins in 2017, 2018 and 2019. All estimates were calculated using survey weights.

Table 4.7: **Main reason for ownership, 2016-2019**

	2016	2017	2018	2019
Payments	0.45	0.23	0.19	0.15
Investments	0.06	0.56	0.40	0.39
Luck of trust/Anonymity	0.16	0.05	0.19	0.15
Technology	0.33	0.16	0.22	0.31

Note: The table reports the percentage of Canadians who chose each category as their primary reason for owning Bitcoin in 2016, 2017 and 2018. The sample consists of 181 Canadians age 18 or older who reported owning Bitcoin in 2020 wave 2, 89 owners in 2019, 99 in 2018, 117 in 2017, 58 in 2016. All estimates were calculated using survey weights.

Table 4.8: **Main reason for not owning Bitcoin, 2016-2019**

	2016	2017	2018	2019
I do not understand/know enough about technology	16.9	25.6	30.7	28.7
It is not widely accepted as a MOP	4.6	4.5	4.9	4.8
My current payment methods meet all my needs	19.8	18.0	21.3	22.4
The value of Bitcoin varies too much	2.0	4.2	6.7	5.9
It is not easy to acquire/use	3.5	4.3	4.3	4.0
I do not trust a private currency that is not backed by the government	7.5	8.1	11.4	14.9
I am concerned about cyber theft	2.9	3.3	4.8	3.9
I am concerned about lack of oversight from regulatory bodies	2.4	3.0	3.0	4.6
I use alternative digital currencies insted	0.2	0.2	0.2	0.4
I do not believe the Bitcoin system will survive in the future	1.2	6.0	9.8	7.5
Other	0.0	3.2	2.8	2.7

Note: This table provides the percentage of a given answer among Canadians that do not hold any Bitcoin to the following question Please name the main reason for not owning any Bitcoin.

Table 4.9: **Bitcoin knowledge questions**

Question	Response options
The total supply of Bitcoin is fixed.	True/ False
Bitcoin is backed by a government.	True/ False
Bitcoin transactions are recorded on a distributed ledger that is publicly accessible.	True/ False

Note: The table reports the three Bitcoin knowledge questions, which were also asked in the 2017 and 2018 BTCOS. The correct answers are highlighted in bold.

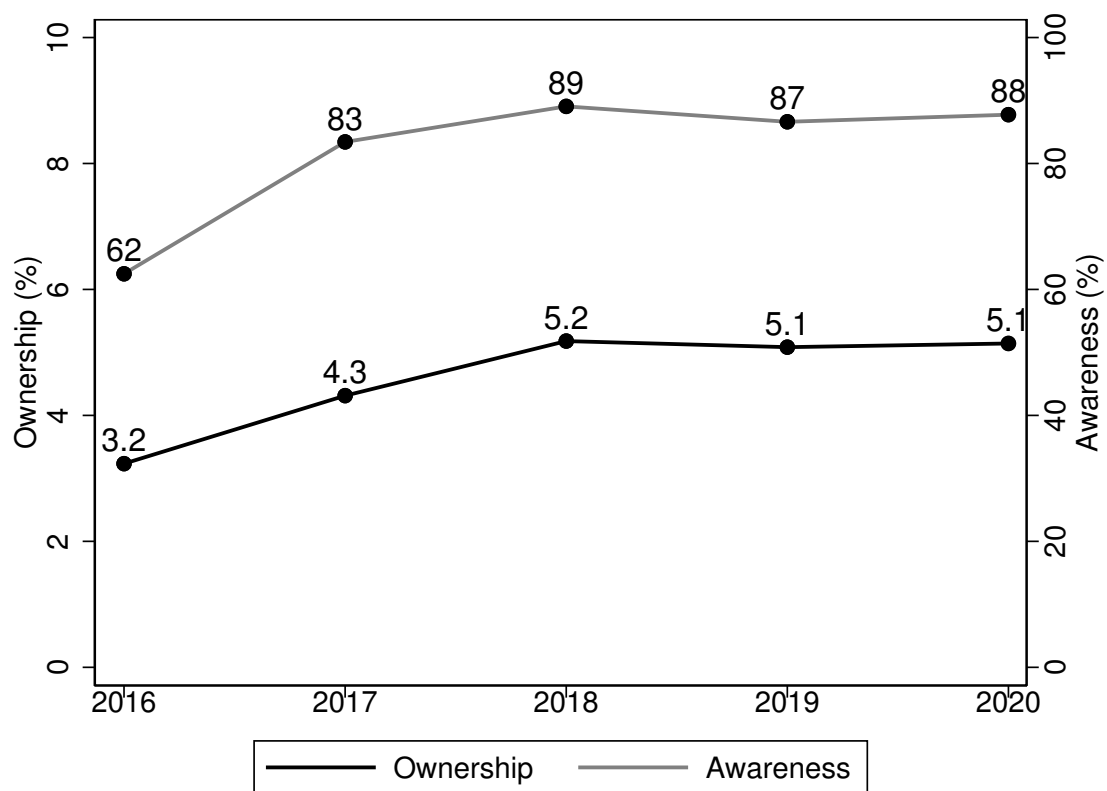
Table 4.10: **Financial Literacy questions**

Question	Response options	
Suppose you had \$100 in a savings account and the interest rate was 2% per year. After 5 years, how much do you think you would have left in the account if you left the money to grow?	More than 102/ <i>Exactly</i> 102/ Less than \$102/ Do not know	
Imagine the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, how much would you be able to buy with this money in this account?	More than today/ Exactly the same/ Less than today/ Do not know	
Please tell me whether or not this statement is true or false: Buying a single company's stock usually provides a safer return than a mutual fund of stocks.	True/ False/ Do not know	

Note: The table reports the three Bitcoin knowledge questions, which were also asked in the 2017 and 2018 BTCOS. The correct answers are highlighted in bold.

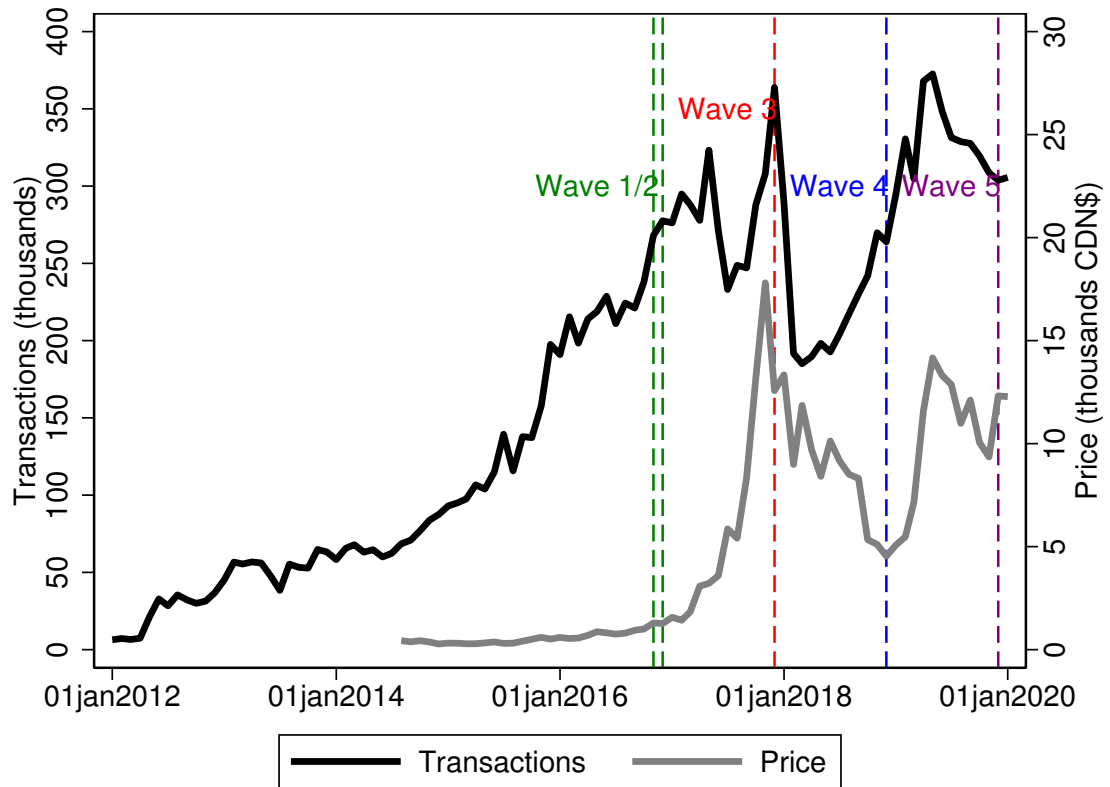
4.6.2 Figures

Figure 4.1: Bitcoin Awareness and Ownership 2016-2020



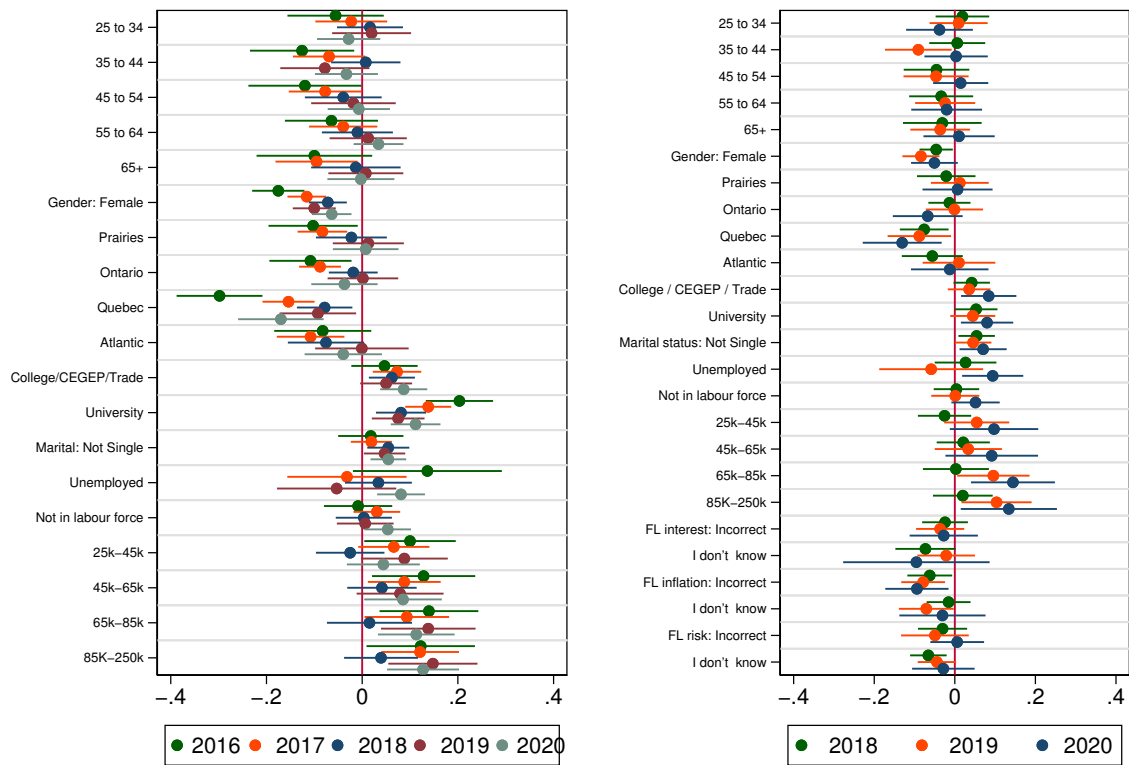
Note: The graph presents the trends of Bitcoin awareness and ownership over 2016-2020.

Figure 4.2: Price and number of Bitcoin transactions, 2016-2020



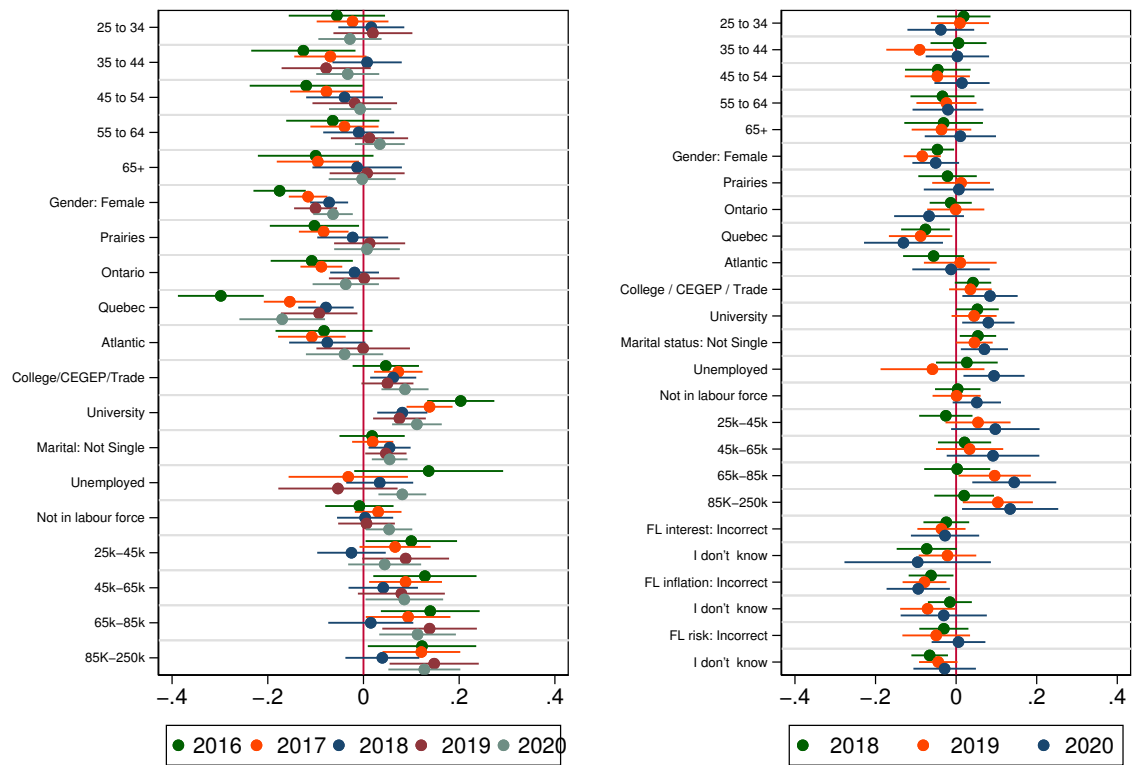
Note: The graph shows the Bitcoin price expressed in Canadian dollars and the number of daily transactions made with Bitcoin, averaged over each month from July 2014 to December 2020. The data series for price starts on March 12, 2012. Green vertical lines indicate when the first two waves of the BTCOS were conducted in 2016, the red vertical line indicates the third wave in 2017, the blue vertical line indicates the fourth wave in 2018, and the purple line indicates the fifth BTCOS iteration in 2019. In November 2020 an alternative survey (Cash Alternative Survey) containing question about digital currencies were conducted, and the orange vertical line represents it. The last monthly observation is December 2020. Sources: Daily Transactions (Charts.Bitcoin.com/BTC); Bitcoin Prices (BTC/CAD) (Yahoo! Finance).

Figure 4.3: Marginal Effects of Bitcoin Awareness



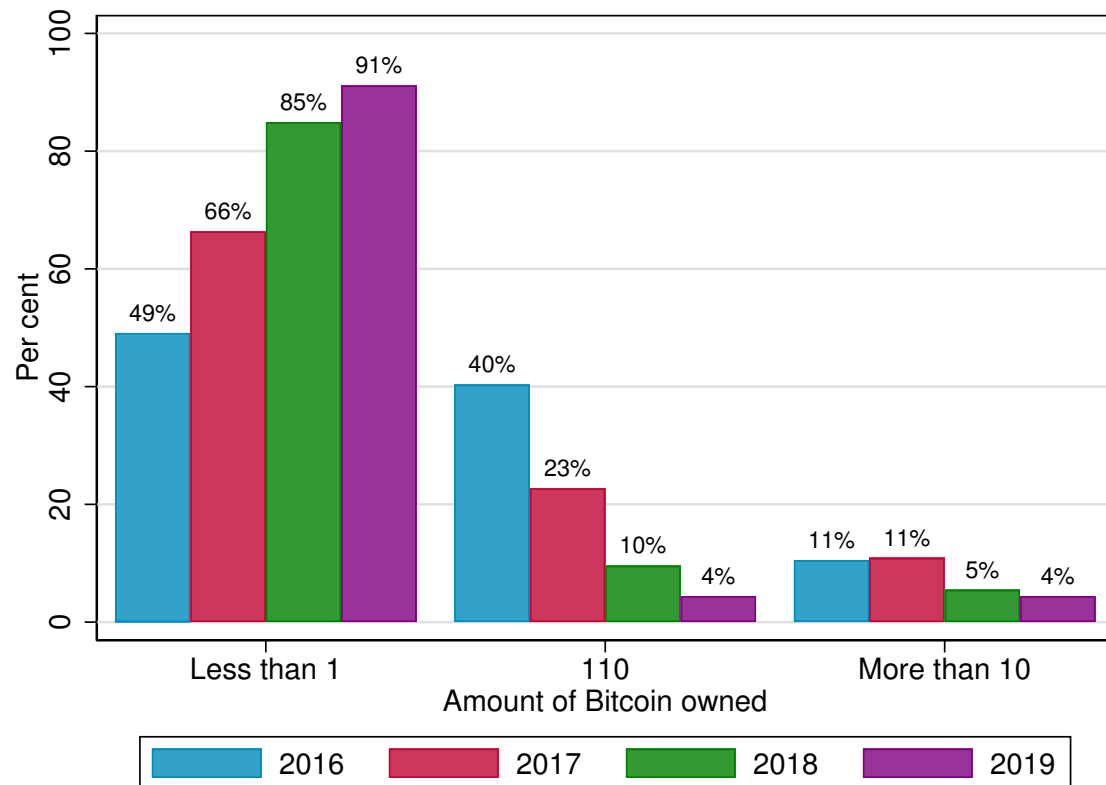
Note: The graph shows the marginal effects of Bitcoin awareness and their confidence intervals by survey years.

Figure 4.4: Marginal Effects of Bitcoin Ownership



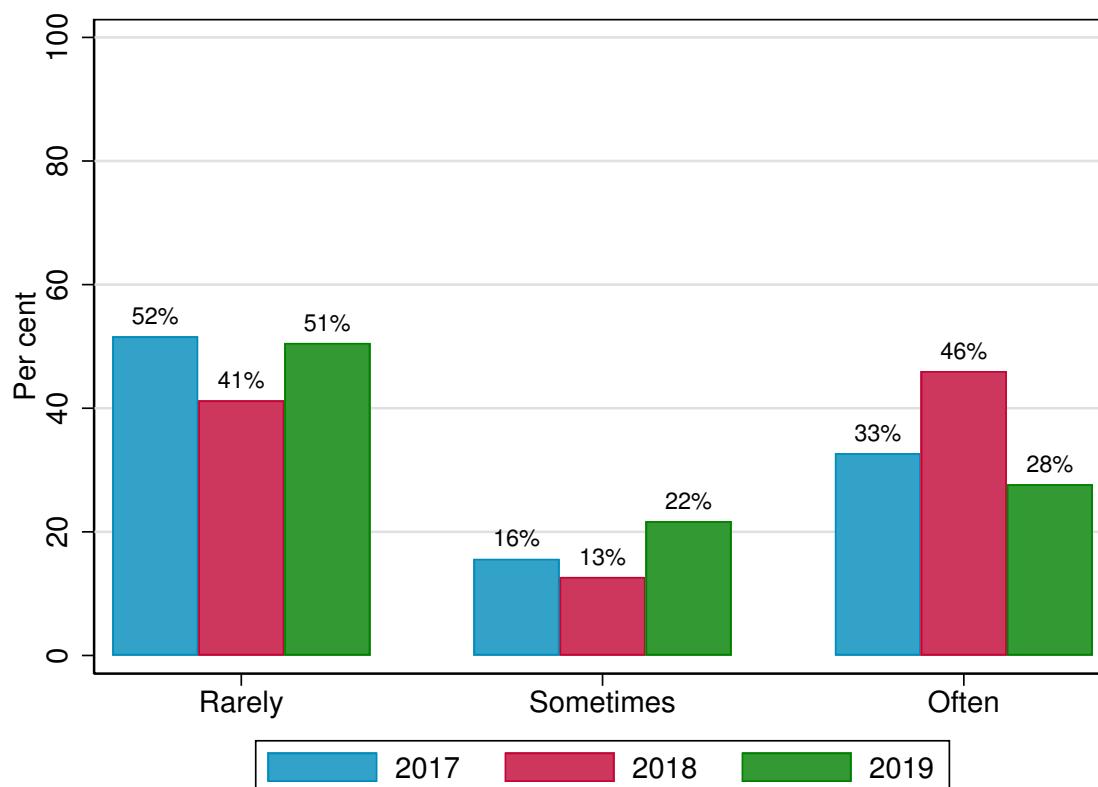
Note: The graph shows the marginal effects of Bitcoin ownership and their confidence intervals by survey years.

Figure 4.5: Bitcoin holdings, 2016-2019



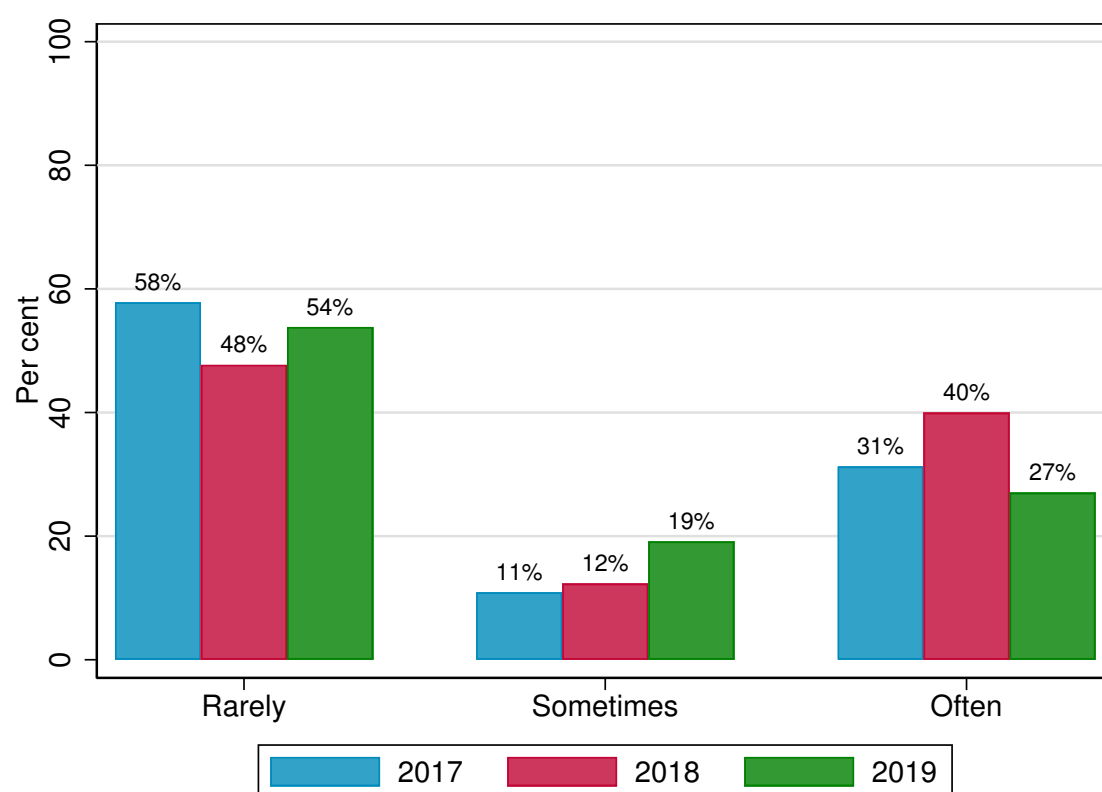
Note: In 2018 and 2019, respondents were asked to report their holdings as a continuous range, denominated in Canadian dollars. For comparability across years, in 2018, we used the prevailing price when the survey was conducted to denominate respondents' holdings in Bitcoin. The sample consists of 89 Canadians aged 18 or older who reported they owned Bitcoin in 2019, 99 in 2018, 117 in 2017, and 58 in 2016. All estimates were calculated using survey weights.

Figure 4.6: Use of Bitcoin for buying goods and services, 2017-2019



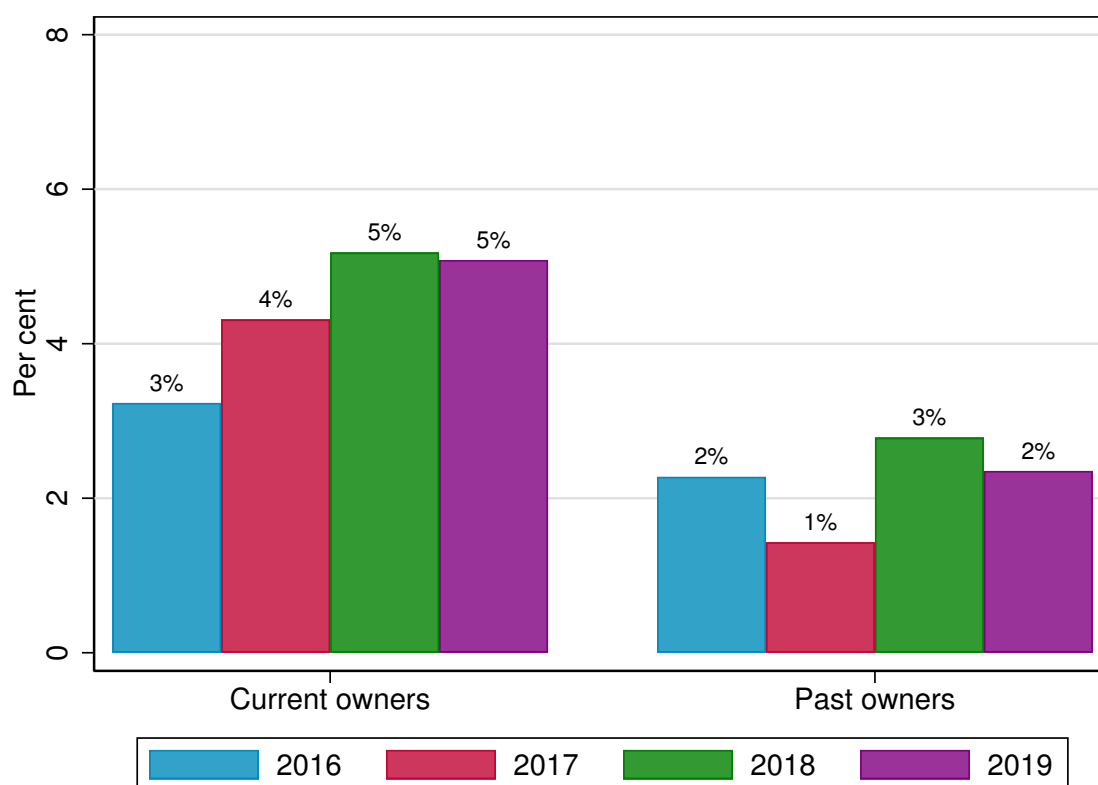
Note: The “Rarely” category includes Canadians who used Bitcoin for transactions at most once a year. The “Sometimes” category consists of Canadians who used Bitcoin between a few times a year to once a month, while those who used Bitcoin at least a few times a month for transactions are classified as “Often”. The sample consists of 89 owners in 2019, 99 in 2018 and 117 in 2017. All estimates were calculated using survey weights.

Figure 4.7: Use of Bitcoin for making person-to-person transfers, 2017-2019



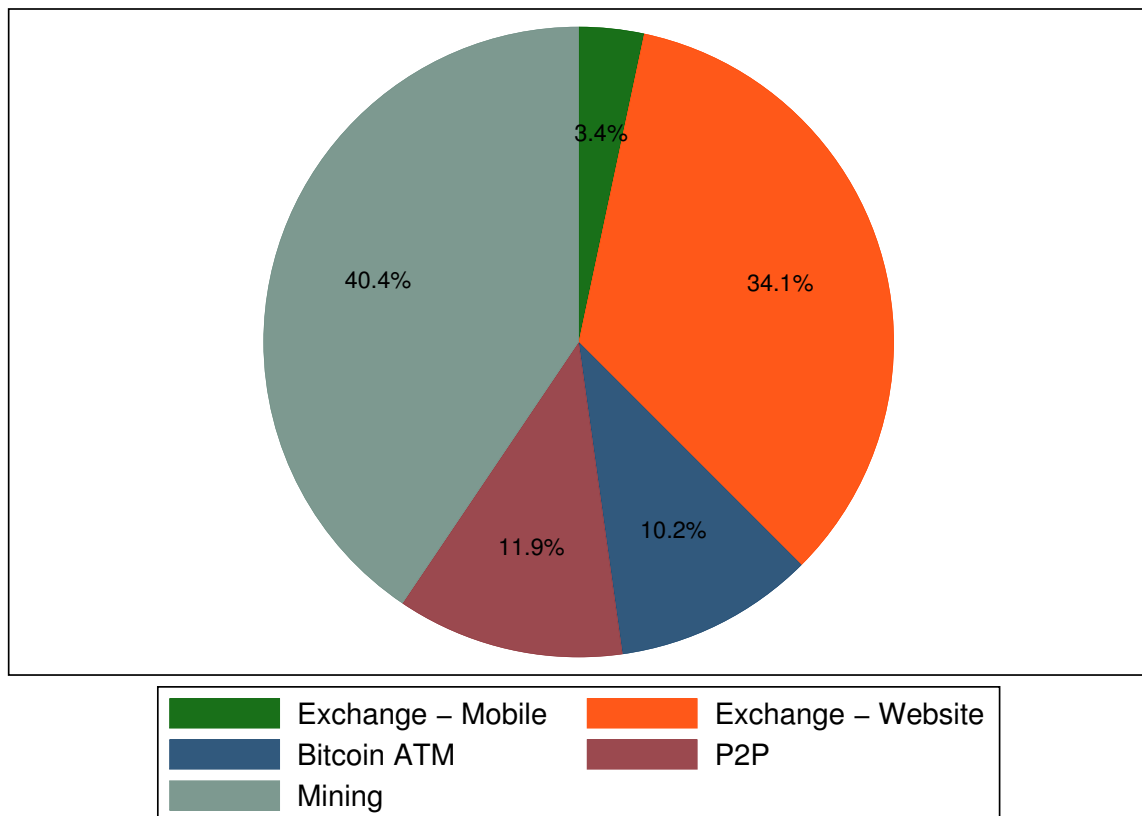
Note: The “Rarely” category includes Canadians who used Bitcoin for transactions at most once a year. The “Sometimes” category consists of Canadians who used Bitcoin between a few times a year to once a month, while those who used Bitcoin at least a few times a month for transactions are classified as “Often”. The sample consists of 89 owners in 2019, 99 in 2018 and 117 in 2017. All estimates were calculated using survey weights.

Figure 4.8: Current and past ownership of Bitcoin, 2016-2019



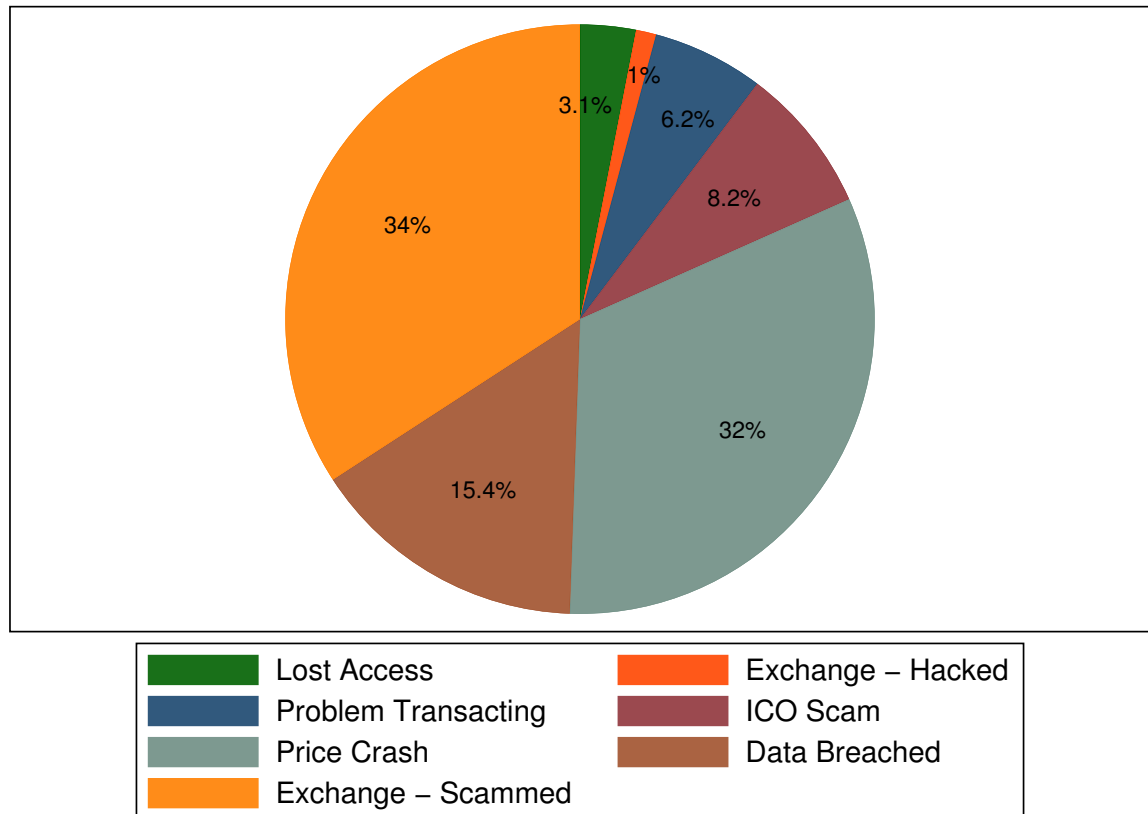
Note: The sample consists of 89 Canadians age 18 or older who reported owning Bitcoin in 2019, 99 in 2018, 117 in 2017 and 58 in 2016. Additionally, the sample includes 50 past owners in 2019, as well as 45 in 2018, 37 in 2017, and 41 in 2016. All estimates were calculated using survey weights.

Figure 4.9: **Bitcoin access, 2019**



Note: The sample consists of 89 Canadians aged 18 or older who reported they owned Bitcoin in 2019. All estimates were calculated using survey weights

Figure 4.10: Bitcoin incidents, 2019



Note: In 2019, 78 past- and 43 current Bitcoin owners out of 171 adopters reported incidents. The incidents are the following: Lost access to my personal cryptocurrency wallet; The cryptocurrency exchange holding my funds was hacked; Experienced problems with a purchase made using cryptocurrencies; I participated in an Initial Coin Offering and it turned out to be a scam; A price crash caused my cryptocurrency to lose substantial value; My personal data held by cryptocurrency exchanges was compromised; and the cryptocurrency exchange stole my funds. All estimates were calculated using survey weights.

4.6.3 Sample source mix: analysis and selection

This section discusses the choice of the sample source composition for the 2019 BTCOS and 2020 CAS samples. The BTCOS and November 2020 CAS rely on two sample sources: I-Say, which is an opt-in non-probability panel, and Ampario, which is a river sample collected through web pages, banners, ads, etc. The 2019 BTCOS sample composition (unweighted) is 37 per cent and 63 per cent Ampario, while that for the November 2020 CAS is 68 per-cent I-say and 32 per cent Ampario.

To determine if the 2019 BTCOS and the 2020 CAS samples require adjustments in terms of the two sample sources we do the following:

1. First, we check if the counts in specific cells are small. Small number of observations in specific cells may signal a poor representation of the data for that specific cell. In Table A.1, we observe that for the 2019 BTCOS there are small counts (27) in the age category 18 to 25 for I-say. This small count may induce bias when one wants to capture the cell specific population for the statistic of interest. Similarly, a small count for the same age category is observed in 2020 CASw2.
2. Second, we look at the imbalances in the demographic characteristics (at the cell level) across sample sources Table 4.11. We observe that the number of observations from I-say is, proportionally much lower than the one from Ampario for 2019 BTCOS. At the same time, in the 2019 BTCOS, the gender ratio of the overall population is better represented by the Ampario share rather than the I-say (45 per cent males in Ampario versus 40 per cent males in I-say). In 2020 CAS w2, we see imbalances related to the employment share in the I-say (40 percent not in the labor force.)
3. Given the small proportion of Bitcoin owners in the samples (about 5 per-cent), and the observed cell sample imbalances between the two frames that may affect the measured Bitcoin ownership, , a sensitivity analysis of Bitcoin ownership measure with respect to changes in the Ampario/I-say mix was conducted for both BTCOS and CAS surveys.

The graphical representation in Figure 4.11 shows that a change in the Ampario share in the total sample changes the measured Bitcoin ownership linearly for all four surveys that use Ampario as a sample selection source.⁴ Additionally, we see a parallel trend between the surveys preserved for both BTCOS and CAS surveys. These linear trends with similar slopes of Bitcoin ownership function of the Ampario share in the final sample suggest that independent of the survey type and year of the survey, the Ampario composition

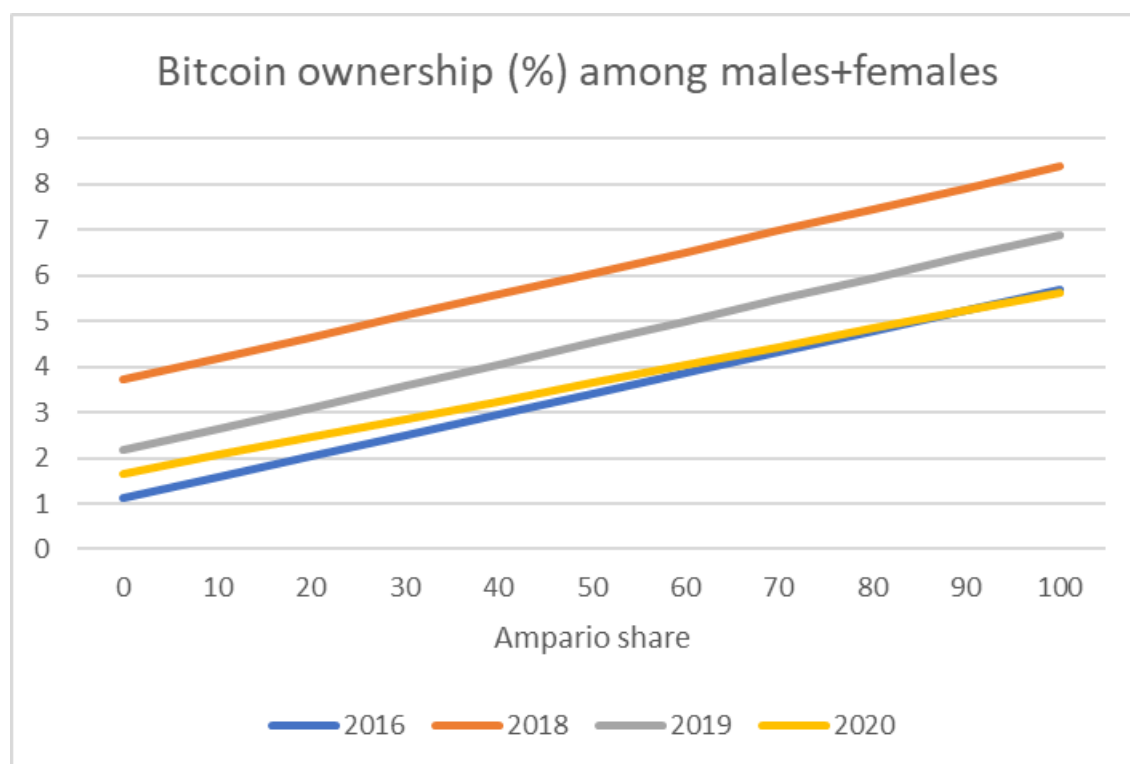
⁴Only a handful of respondents were not sampled from the I-say panel in 2017.

Table 4.11: **Counts of Demographic Characteristics by frame for 2019 BT-COS and 2020 CAS w2**

Gender	2019 BTCOS		2020 CAS W2	
	I-say	Ampario	I-say	Ampario
Male	295	568	1,133	770
Female	434	690	1,495	484
Age <25	27	115	80	466
25-35	89	148	327	230
35-45	123	186	461	179
45-55	150	206	530	152
55-65	107	291	575	109
65+	233	312	664	120
British Columbia	73	99	392	170
Prairies	133	296	534	236
Ontario	318	578	964	549
Quebec	161	164	550	210
Atlantic	44	121	197	91
High School	136	309	469	355
College	276	434	944	389
University	317	515	1,224	512
Not single	435	677	1,639	576
Single	294	581	998	680
Employment	367	663	1,389	767
Unemployment	19	55	183	94
NLF	338	527	1,053	372
Income <25K	73	198	281	241
25-45	128	259	439	223
45-65	139	207	428	210
65-85	84	148	332	178
85+	224	350	847	332

Note:

Figure 4.11: Bitcoin Ownership by share of Amaprio in Total Sample for years 2016-2020



Note: This graph shows the change in Bitcoin ownership with a change in the Amaprio share (from 0 per cent to 100 per cent) by survey year.

in the final sample impacts in the same way all the surveys; therefore, one can learn from the choice of the frame composition from past surveys.

4. Further, to understand what drives this change in Bitcoin ownership when we change the contributions of the two sources to the final samples, we look at the impact of the demographic characteristics on explaining the difference in the measured Bitcoin share in the total sample when different weights of the two frames are chosen. This analysis shows the significance of the gender (due to the male/female imbalance) in explaining this difference in Bitcoin ownership (these results are valid for both 2019 BTCOS and 2020 CAS).⁵ A graphical representation of the Bitcoin ownership by gender and sample composition (Figure 4.12) shows a high variation in the Bitcoin ownership rate among I-say male across surveys, while Bitcoin ownership among female respondents was very stable across years. In contrast with this finding, in the Ampario frame, the male contribution to Bitcoin ownership is stable across surveyed years, while the female contribution shows more variation than in the I-say frame. These results suggest that the role of the frames in the total sample matters for all surveyed years when the Bitcoin ownership is counted in the total sample.

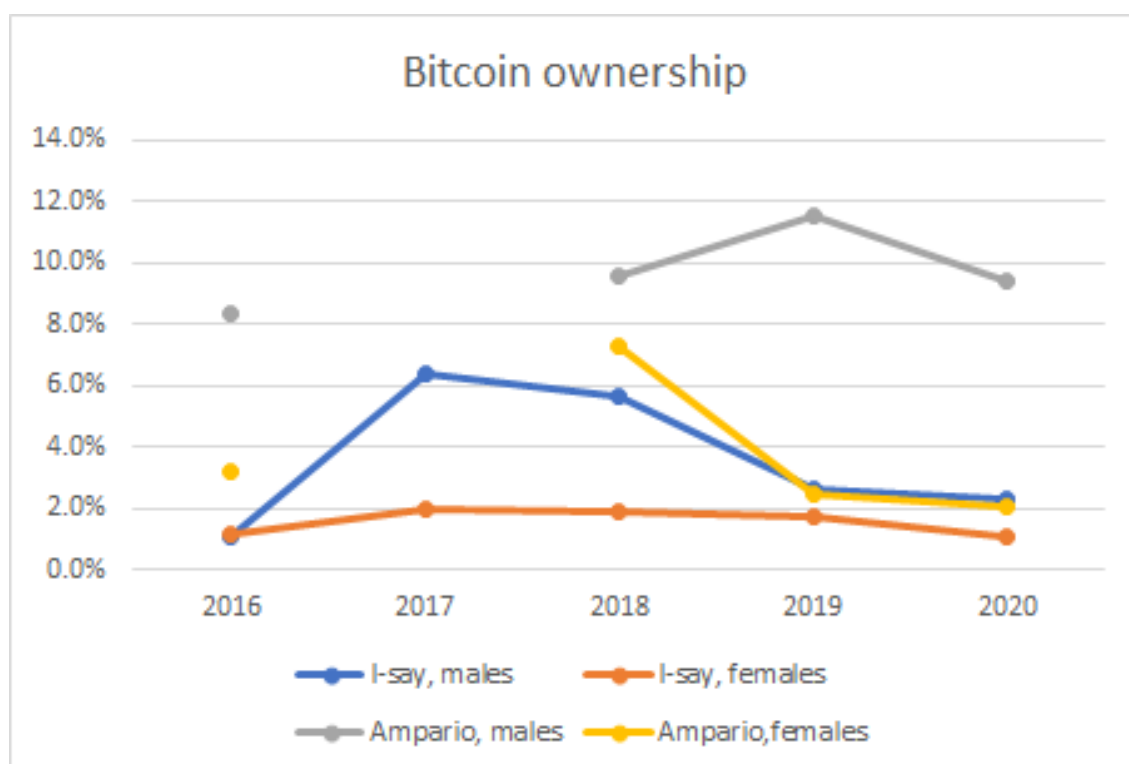
We further look at ownership among males when varying the Ampario/I-say ratio (Figure 4.13).

We see that in 2019 the Bitcoin ownership of male respondents is the same as in 2018 for the original frame composition. At the same time, for the November 2020 CAS, a similar Bitcoin ownership among males is observed at a higher Ampario share (greater than 70 per cent).

5. We use the analyzed information to decide the appropriate frame composition for 2019 BTCOS and November 2020 CAS as follows.
 - a) We check the gender composition when we change Ampario/I-say frames. In Table 4.12 we see that a decrease in the Ampario share of the 2019 BTCOS from the original share (63 per cent) to the level observed in the 2018 BTCOS (36 per cent) reduces the gender imbalance in I-say frame, while increasing the imbalance in the Ampario frame. In fact, the current mix provided the closest gender balance in Ampario, while reducing the gender imbalance in I-say. When the Ampario share is further increased relative to the original mix (to 75 per cent), we see that again the I-say gender imbalance increases while the gender balance is maintained in Ampario. Other options of Ampario to I-say ratios were considered in both directions relative to the original ratio. The

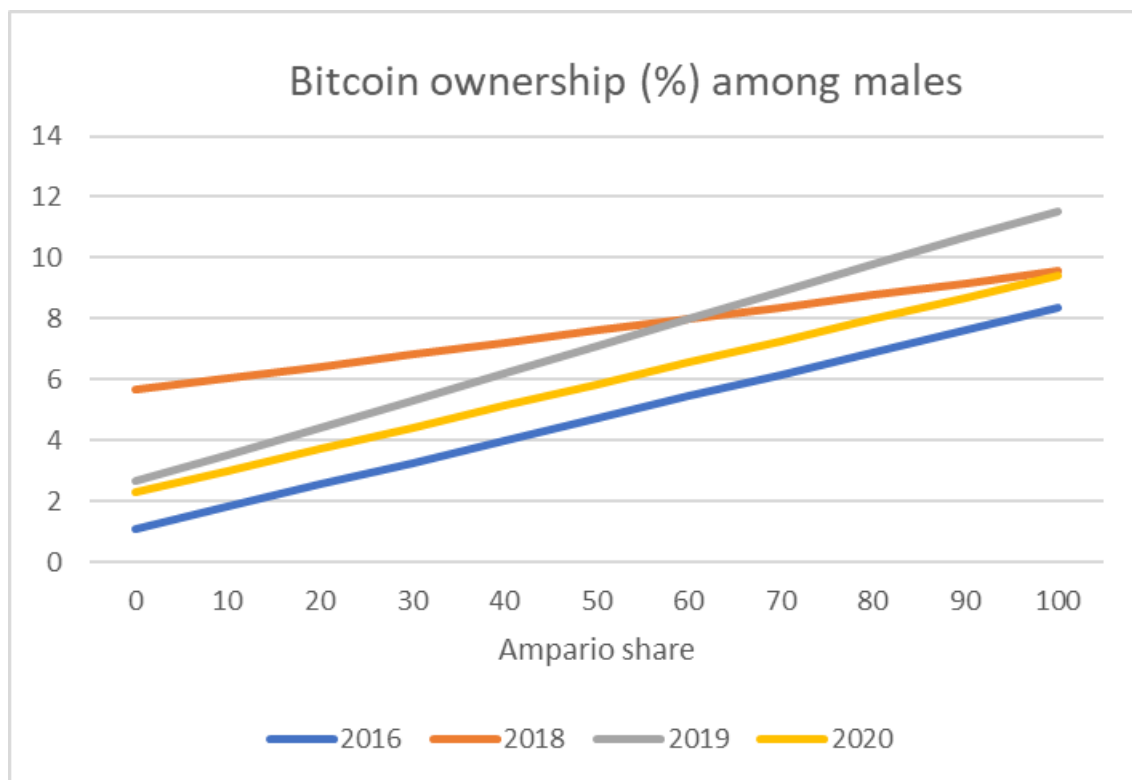
⁵Results are not reported as only gender female dummy is significant. For 2019 BTCOS the gender female dummy is negative (-411) and statistically significant with a p-value = 0, while for 2020 CAS w2 the gender dummy is positive (21.34) and statistically significant, with p-value = 0.

Figure 4.12: Bitcoin Ownership in Total Sample by gender and frame for years 2016-2020



Note: This graph shows the change in gender-specific Bitcoin ownership by frame and survey year. In 2017 there is no Ampario frame.

Figure 4.13: **Bitcoin Ownership** by share of Amaprio in Total Sample for years 2016-2020



Note: This graph shows the change of Bitcoin ownership (for males) with a change in the Amaprio share (from 0 percent to 100 percent) by survey year.

Table 4.12: **Gender Composition by frame share**

Demographics	Unweighted		amp = 63% (actual) wgt_mical7		amp = 36% wgt_mical7_amp36		amp = 75% wgt_mical7_amp75	
	I-say	Ampario	I-say	Ampario	I-say	Ampario	I-say	Ampario
Male	0.40	0.45	0.44	0.51	0.46	0.53	0.43	0.51
Female	0.60	0.55	0.56	0.49	0.54	0.47	0.57	0.49

Note: This table reports the proportion of Canadians by gender and sample source in the unweighted sample and weighted sample using 63, 36 and 75 per cent of Amparia share.

analysis confirms that as the Ampario share decreases relative to the original ratio, more gender imbalance is generated in the Ampario frame, while the reverse is happening if we further increase the Ampario share: a higher gender imbalance is observed in the I-say frame.

b) We also consider calibrating the mix of Ampario/I-say shares in 2019 BTCOS by matching the 2019 BTCOS sample with the 2018 BTCOS sample. In particular, with this exercise we practically test if adjustments in the 2019 frame composition is need it. Practically, we assume that 2018 BTCOS cell specific frame composition is the benchmark and was appropriately tested, while the 2019 BTCOS cell specific composition should not be different than the one from 2018. Specifically, we are looking at deviations of Bitcoin ownerships when we match the two samples while we control for demographics and sample composition. This test should provide information about the required composition of the two frames for 2019 BTCOS as a measured deviation in Bitcoin ownership in the matched samples should be the same when comparing the Bitcoin ownership across the two survey years and the appropriate frame composition chosen for 2019 BTCOS. Practically we assume that population demographics are not changing in significant way from 2018 to 2019.

To do this exercise, we compute the Average Treatment Effects (ATE) of the proportion of Bitcoin owners on the matched 2019 with 201 BTCOS samples (Table 4.13).

The results suggest that the proportion of Bitcoin owners in 2019 should not be significantly different than the one measured in 2018. When we control for frame composition, the ATE results suggest that in 2019 should be a negative 1.5 percentage point difference in Bitcoin ownership when compared to 2018. This difference is close to the observed difference in the two observed proportions: 5.2 per cent for BTCOS 2018 and 5.1 per cent for the original composition of the BTCOS 2019 (which gives a difference of 1.9 percentage points).

Given these findings, we consider that there is no need to alter the frame

Table 4.13: **Average Treatment Effect of Bitcoin Ownership between BT-COS 2018 and 2019**

Treatment Effect	1	2
ATE	-0.00213	-0.0149*
SE	(0.0073)	(0.0078)
Observations	3,564	3,564

Note: Column 1 computes the ATE (2019 – 2018) of Bitcoin ownership based on matched sample using data from 2019 BTCOS and 2018 BTCOS), while controlling for demographic characteristics. Column 2 computes the ATE (2019-2018) of Bitcoin ownership on the same data, while controlling for demographic characteristics and sample source.

Table 4.14: **Average Treatment Effect of Bitcoin Ownership between 2020 CAS wave 1 and 2020 CAS wave 2**

Treatment Effect	1	2
ATE	0.000981	-0.0105*
SE	(0.0048)	(0.0056)
Observations	7,296	7,296

Note: Column 1 computes the ATE (Nov. 2020 – April 2020) of Bitcoin ownership proportion using data from November CAS 2020 and April CAS2020), while controlling for demographic characteristics. Column 2 computes the ATE (Nov. 2020 – April 2020) of Bitcoin ownership on the same data, while controlling for demographic characteristics and sample source.

composition for the BTCOS 2019.

For the November 2020 CAS frame choice we use a similar analysis as for the 2019 BTCOS. In particular we first test if we need to alter the frame choice for November 2020 CAS by estimating the difference in Bitcoin proportion when we matched the November 2020 CAS with April 2020 CAS (we assume that there are no significant changes in population demographics across the two time periods). Moreover, the April 2020 CAS results were published by Chen et al., 2021, making this CAS survey as a good benchmark candidate for the analysis (distance in time short and results with April 2020 CAS published).

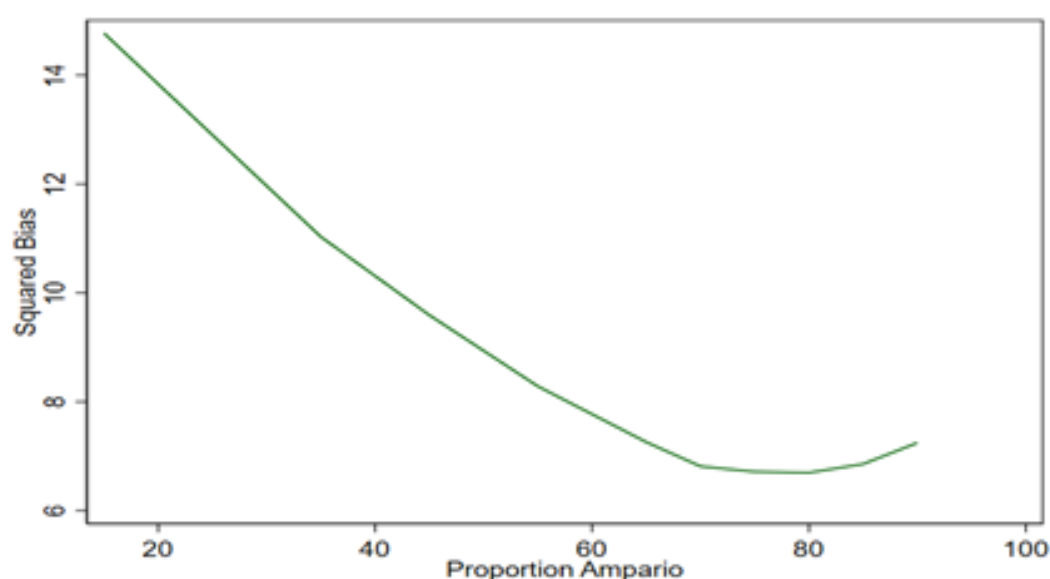
The ATE results for the analysis are provided in Table 4.14.

As in the BTCOS matching analysis, the CAS matching analysis suggests no significant difference in Bitcoin ownership between the April 2020 CAS and the November CAS. When controlling for sample source, we estimate a marginal negative effect of one percentage point between the two CAS surveys. As we should not get any statistically significant difference in Bitcoin ownership between the April CAS 2020 and November CAS 2020, we need to adjust the Ampario share in the November CAS survey to ensure no marginal significance difference between April 2020 and November 2020 CAS surveys.

As a suggested approach for the choice of Ampario/I-say shares in November 2020 CAS we calibrate the mix of the two frames by aligning the November 2020 CAS financial literacy scores to the values measured in the 2019 CAS, which are reported in [Huynh et al. \[2020\]](#).

Figure 4.14 presents the squared bias of this calibration with respect to the Ampario share. This analysis emphasizes that changing the proportion of the two frames in the final sample will minimize the bias in the neighborhood of an Ampario share of 70 per cent (practically between 70 and 80 per cent).

Figure 4.14: **Squared Bias Financial Literacy scores in 2020 CAS w2 when benchmarked to 2019 CAS by Ampario share**



Note: The figure shows the November 2020 CAS Squared Bias (as a sum of individual FL score biases) when benchmarked to 2019 CAS by Ampario share.

When a frame composition with 70 percent Ampario and 30 percent I-Say is chosen, we obtain a 5.1 percent of Bitcoin owners, identical to the one obtained in the 2019 BTCOS survey. This composition of the two frames suggest that this mix of frames satisfy the test results with matching, which show that the proportion of Bitcoin owners to be not significantly different from the previous year survey proportion of Bitcoin holders. Consequently, for the final November 2020 CAS sample we chose a mix of 70 per cent Ampario and 30 per cent I-say. This composition is close to the one found in the 2019 BTCOS. This result can be associated to the fact that the gender composition of Bitcoin owners is similar in the two samples.

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La relation entre gouvernance, risques bancaires et stabilité financière

Résumé :

L'effondrement de l'emblématique banque d'investissement américaine Lehmann Brothers en septembre 2008 a eu un impact énorme sur les marchés financiers et l'économie mondiale en érodant la confiance des citoyens dans leurs institutions, leur système bancaire et la stabilité financière globale. L'objectif principal de cette thèse est de mettre en évidence les risques potentiels pour la stabilité financière sous deux angles, d'abord liés à la diversité culturelle et ensuite liés à la perturbation possible du système financier due à l'essor des nouvelles technologies, les FinTech. L'effet des aspects culturels sur la stabilité financière la littérature a été négligée; ainsi, le premier chapitre examine les effets culturels potentiels sur les mesures du risque systémique dans les pays développés et en développement. D'autre part, le manque de confiance dans le système bancaire inculqué après 2008 a conduit à l'essor de la nouvelle technologie destinée à remodeler le crédit à la consommation. Le Bitcoin, d'abord conçu comme une version électronique de l'argent liquide, sans contrôle du gouvernement et de la banque centrale, est devenu un phénomène mondial qui pourrait avoir de graves implications pour la stabilité financière. Les trois chapitres suivants se concentrent sur les sujets liés au Bitcoin pour un pays particulier, le Canada. Bitcoin et ses frères et sœurs pourraient affecter les fonctions centrales des banques centrales liées à la production et à la distribution de billets de banque. En conséquence, le deuxième chapitre analyse l'impact de la propriété de Bitcoin sur l'utilisation de l'argent à l'aide de données d'enquête. Le troisième chapitre examine les mécanismes potentiels derrière l'évolution future de l'adoption du Bitcoin. Enfin, le quatrième chapitre met en évidence la dynamique de la sensibilisation, de l'adoption et de l'utilisation du Bitcoin au sein de la population canadienne au cours de la période 2016-2020.

Mots clés : Risque systémique, stabilité financière, culture nationale, adoption du Bitcoin, Crypto-monnaie, billets de banque

The relationship between governance, bank risks and financial stability

Abstract :

The collapse of the iconic US investment bank Lehmann Brothers in September 2008 had an enormous impact on the financial markets and the global economy by eroding citizens' trust in their institutions, banking system, and overall financial stability. The main aim of this thesis is to highlight the potential risks for financial stability from two perspectives, first related to cultural diversity and second related to the possible disruption in the financial system due to the rise of new technology, FinTech. The effect of cultural aspects on financial stability literature has been neglected; thus, the first chapter looks at the potential cultural effects on systemic risk measures across developed and developing countries. On the other hand, the lack of trust in the banking system instilled after 2008 led to the rise of the new technology intended to reshape consumer finance. Bitcoin, first designed as an electronic version of cash, free of government and central bank control, has become a global phenomenon that could have serious implications for financial stability. The following three chapters zoom in on the topics related to Bitcoin for a particular country, Canada. Bitcoin and its siblings could affect the core functions of the central banks related to the production and distribution of banknotes. Accordingly, the second chapter analyzes the impact of Bitcoin ownership on cash usage using survey data. The third chapter looks at the potential mechanisms behind the future evolution of Bitcoin adoption. Finally, the fourth chapter highlights the dynamics of Bitcoin awareness, adoption, and usage among the Canadian population over the 2016-2020 period.

Keywords: Systemic risk, financial stability, national culture, Bitcoin adoption, Cryptocurrency, Bank notes



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