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ESSAYS IN FINANCIAL DEVELOPMENT, FOCUSING ON NASCENT FINANCIAL TECHNOLOGIES

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Sommaire

Introduction Générale

Thesis overview

It is increasingly clear that the area of payments – how consumers and businesses choose to pay for things – is at the forefront of financial development in many areas across the world. Nascent financial technologies are actually changing the way that economies function, and the number of payment innovations alone can be overwhelming to consider: Bitcoin, M-Pesa, Venmo, Apple pay, mobile payment apps, e-Transfer, and many, many more. Tired of messing about with quarters at the parking meter? How about letting your car pay for your parking spot? [1] This is not even to mention continuing innovations among more familiar payment methods that make them more secure and easier to use, for example contactless credit and debit cards. Even cash has undergone technical innovations, with paper banknotes being replaced in many countries by polymer notes having ever-advanced security features to deter counterfeiting.

The example of Kenya and the proliferation of M-Pesa demonstrates the truly transformative nature that payments can have on an economy. Allowing users to deposit money into a mobile phone account, to send money via SMS, and redeem mobile deposits for cash, this 'digital money' was successful in large part because it leveraged *existing* financial structures, while also providing new benefits to users. As of 2012 there were over 17 million registered M-Pesa accounts, and the model has spread to countries such as Tanzania and Afghanistan, among others.

Meanwhile, countries such as Sweden are facing the reality that certain 'old' payment technologies, such as cash, may soon by dying out. This fact has driven discussion of the potential that central banks may issue their own digital form of cash, aka Central Bank Digital Currency (CBDC). Of course, the question of whether and how this should be done is daunting. Aside from functioning as a digital way to make payments, some have argued that a CBDC can open up new opportunities for forms of monetary policy, or promote greater financial inclusion.

In discussing CBDC it is hard to ignore the looming elephant in the room – that of privately issued digital currencies, such as Bitcoin. Bitcoin provides a useful case study in the diffusion

[1] www.mobilepaymentstoday.com: "Honda unveils in-vehicle payment experience."

and impact of nascent financial payment technologies for several reasons. The original intention behind Bitcoin was, in fact, to do away with the need for central banks and their money, by functioning as a decentralized payments platform. In place of central banks issuing cash or traditional financial institutions, these third parties were to be replaced by use of cryptography to secure transactions. Of course, intentions do not always reflect reality, and the trajectory of Bitcoin has been complicated to say the least. While it certainly can be (and is) used for transactions, many have come to view it more as a 'cryptoasset' than a cryptocurrency.

This thesis contributes to two important questions about nascent financial technologies within the literature on the economics of payments: 1] What is the most effective way to collect data that can help us understand and assess the impact of new payments technologies on the economy? (Methodology) 2] What trade-offs are relevant for consumers when deciding on the adoption and use of new forms of payment technologies? (Economic modelling). Correspondingly, this thesis is organized into two parts.

In Part 1 (Chapter 1-2), we take up methodological concerns. These are crucial for studying emerging technologies because there is often little consensus or data available to guide researchers; often, collecting useful data is a large part of the endeavor. While there has been a long history of consumer (and merchant) payment surveys among central banks, Chapter 1 offers a unique opportunity to test and validate survey-based methodology for studying payment choice – specifically cash versus electronic card payments – using a novel dataset from Hungary consisting of the universe of all retail transactions. Chapter 2 reflects ongoing work to measure changes in awareness and usage of Bitcoin in Canada. We report on results from the 2018 Bitcoin Omnibus Survey conducted by the Bank of Canada, while highlighting efforts to improve the survey instrument, data and accuracy of estimates.

In Part 2 (Chapter 3 and 4) we turn to economic modelling of consumer decisions. Chapter 3 confronts the standing assumption that adoption of new digital payment technologies will necessarily lead to a decline in cash usage. Based off our finding that Bitcoin owners tend to hold relatively large amounts of cash, we use advanced econometric techniques to account for possible sources of selection/endogeneity, and thereby uncover a clearer picture of what is driving this result. Finally, Chapter 4 investigates potential mechanisms behind the future evolution of Bitcoin adoption over time. Motivated by the literature on diffusion of technology, we examine empirical evidence on the role of both beliefs and network externalities in Bitcoin adoption.

Payment survey data

This thesis relies largely on the use of micro data collected from so-called ‘payment surveys’. This type of survey, in one way or another, collects data with the ultimate goal of better understanding *how* economic transactions are carried out. Put simply: “How would you like to pay?” This can take many forms, for example: measuring how frequently a consumer makes cash versus card payments in a typical week for their usual retail shopping needs; measuring acceptance of various forms of payments by businesses; understanding how person-to-person transactions are carried out. These are just several examples from a field that has grown in scope and sophistication over the last thirty years.

One important question that has driven the proliferation of payment surveys is the following: What is the best way to accurately measure cash payments in the economy? Cash by its’ nature is an anonymous payment method which does not necessarily lend itself well to measurement via aggregate network statistics, especially relative to other payment methods such as debit or credit cards. One often cited aggregate cash statistic is *notes in circulation*, i.e. the value (or volume) of banknotes extant in the economy at a given time. Such a measurement can be produced based on the fact that the central bank controls the flow of physical currency into and out of the economy. However, it cannot speak to how cash is actually being used by consumers or businesses. This is particularly relevant in the case of cash, since we know that it can serve both as a *store of value* as well as a means of transaction.

Central banks in particular have a keen interest in the future evolution of cash since it directly impacts *seigniorage*, which serves as a source of revenue for the central bank. A long standing puzzle observed across the world is that, while notes in circulation continues to grow over time – at a pace in line with the growth in the economy – anecdotal evidence suggests that cash is being used less and less frequently for making purchases. This is largely due to the increasing number of electronic payment methods available, but also because of increased access to banking services (and thereby debit and credit cards), as well as new technological innovations that directly provide the ability to pay electronically. Further, the economy itself has increasingly shifted to an online format wherein using cash to pay is not even feasible.

A survey based approach provides several advantages for understanding this puzzle (and payment choice in general) relative to analysis of network data. For one, surveys can take into account heterogeneity of agents by collecting information on their demographic characteristics such as age, gender, income etc. Further, with properly employed sampling approaches, repeated observations allow for analysis of trends across time. Surveys are flexible, allowing economic policy makers to quickly gather data on topics of concern. Finally, when done properly, surveys can be relied on as a source of quality data, i.e., not only can we gain insight into the economic decisions of individual agents, but surveys can closely approximate the aggregation of individual decisions, producing estimates that are in line with network data. As a prime example, an exercise conducted in Bagnall et al. (2016) showed that consumption estimates based on aggregating results from a payment diary survey matched strikingly well with standardized statistics on consumption produced by national agencies.

Payment surveys have evolved over time in several different and important ways. First, it was quickly understood by economists that measuring only one specific type of payment (e.g. cash) was altogether insufficient, since it did not capture the relevant opportunity costs. This led to the concept of ascertaining an agent's 'payment portfolio'. For consumers this amounts to collecting information on the full range of payment instruments (with associated costs and benefits) available to them for making a given payment. Likewise, for businesses, the set of payment methods a business is willing and able to accept depends on many factors such as the size and type of the business, merchant fees, etc. Thus, payment surveys expanded in scope in order for economists to account for what is driving payment behavior.

Second, survey methodology became recognized as crucial for capturing accurate data that would shed light on the relevant trade-offs involved in payment choice. One prominent example of such a methodological issue arose with respect to measurements of cash use. Asked about the frequency and amount of cash transactions (even over a short period of time, say one week), respondents often had trouble accurately recalling all of the associated transactions. The reason for this is that cash transactions tend to be lower in value, and therefore do not stand out in the mind of the respondent. In response to these problems, diary methodology increasingly became a relied upon component of payment studies. With a diary methodology, respondents are asked to record transactions in real time (or at the end of each day), thereby reducing recall bias.

Third, the methodology of payment surveys has evolved to mirror the changing landscape of payments towards an electronic format. Paper-based and in-person surveys produce high quality micro data, but are extremely time and cost intensive to conduct. Further, the ability of survey companies / marketing firms to maintain a representative panel of participants, from which to draw survey respondents, depends on making surveys easy to fill out. This has also shifted methodology towards computers and smartphones. Surveys conducted in an electronic format have benefits in terms of reduced cost for data collection and processing, but can face data quality issues

Finally, payment surveys have been forced to confront the multitude of new payment innovations available on the market. This can be daunting, as new innovations which may show promise for disrupting the traditional payments space – i.e. cash, credit and debit – can appear and disappear rapidly from the market. This begs the question of why we should bother to follow them at all, and if so, which ones? The answer as to "why" is that successful payment innovations can have a significant impact not just on the payments landscape itself, but in fact on the economy as a whole (we discuss this further below).

Against this background, this thesis makes several important contributions in the context of the literature on payment surveys. In Chapter 1, we leverage a unique data set from Hungary consisting of the universe of retail payments, enabled by special legislation requiring all cash registers to link to a central administrative database. Having access to these data allows us to test and validate the effectiveness of payment surveys and provide practical guidance to survey practitioners. We do this in two ways. First we simulate different sampling approaches from merchant surveys to determine which approach yields the best estimates of card payment acceptance by businesses. Second, we conduct regressions to verify which determinants of payment choice, as established by the payment survey literature, are borne out by the full data.

Chapter 2 reflects the ongoing work by the author, in collaboration with colleagues from the Bank of Canada and market research firm Ipsos, to pioneer and continue development of a survey dedicated to a new financial payment technology – Bitcoin. The Bitcoin Omnibus Survey (BTCOS) was launched in 2016 and was among the first surveys dedicated to measuring Bitcoin awareness and usage. There have been many lessons learned from 2016 to the current analysis of the 2018 BTCOS presented in Chapter 2. These lessons contribute to an increased understanding of how best to measure and understand new payment technologies. Specifically, the 2018 BTCOS introduced questions on financial literacy as a potential key factor for understanding the adoption of Bitcoin (see Lusardi and Mitchell (2014)). Other elements introduced to increase understanding of the motivation of Bitcoin owners include stated plans to go 'cashless' in the future, as well as rankings of features relevant for making online payments. These advances in methodology are paired with a longitudinal analysis across the three existing waves of the survey (2016 to 2018) in order to analyze trends in Bitcoin awareness and ownership.

Economics of payments and nascent financial technology

Building on the first two chapters and utilizing data from the BTCOS, the thesis turns in Chapters 3 and 4 to address questions specific to the economics of payments; in particular, with respect to a new and potentially "game-changing" technology – Bitcoin. What do we mean by the economics of payment behaviour? And why should payments be considered important for the economy and financial development?

First, at an aggregate level, it is important to recognize that payment costs account for a non-negligible portion of the overall economy as measured by GDP [2] Costs exist in a variety of forms, whether it be the physical processing of cash (counting, transportation, etc.); establishing and maintaining a viable electronic payment network in the case of debit or credit cards; offering consumers enhanced security and rewards options in the case of credit cards. An im-

[2] Kosse et al. (2017) puts the costs of payments at 0.8% of GDP in Canada; similar estimates of around 1% for Europe were found in Schmiedel et al. (2013)

portant aspect for studying payment economics is to recognize the extent to which different agents in the economy bear these costs e.g. consumers versus businesses, society/government versus private entities. Kosse et al. (2017) provide an example of a systematic way of thinking about the cost of payments and how they are distributed.

The reason that the distribution of costs matters is because it provides context for assessing claims of 'increased efficiency', or 'potential benefits', either from the introduction of new payment innovations, or adjustments to existing economic policy. As an example, many have called for the so-called 'death of cash'. Rogoff (2016) argues that high-value denominations facilitate the underground economy and therefore doing away with large value banknotes would somehow frustrate criminals, and lead to increased legitimate economic activity. Van Hove (2008) makes the case that shifting to electronic forms of payment would provide substantial benefits to the overall economy via increased efficiency of payments. On the other side of this issue it can be argued that cash plays an important role with respect to financial inclusion (allowing the un-banked or under-banked to participate in the economy) as well as financial literacy (cash acts as a simple but effective budgeting tool).

Second, in terms of the overall impact that a new payment technology can have on the economy at large, no example is more striking than that of *M-Pesa*. M-Pesa, originally developed in Kenya in 2006, is a form of mobile money, i.e. it exists as a credit on a mobile phone account. Using this credit, agents can buy airtime for their phone, send credit vis SMS to other agents, and redeem the credit for currency (cash) from participating vendors. This design allowed M-pesa to bypass traditional banking structures, which were not accessible to a large proportion of the Kenyan population, and instead facilitated banking-type services via the existing mobile phone network. Suri and Jack (2016) have studied the effects of M-pesa on the Kenyan economy, concluding that access to M-pesa has lifted roughly 2% of Kenyans out of poverty and significantly increased financial inclusion.

Part of the success and widespread adoption of M-pesa in Kenya can be attributed to two related economic forces which are relevant for payment economics in general. First, payments should be naturally viewed as a *two-sided market*. For consumers to want to adopt and use new payment methods it is helpful for such methods be widely accepted by businesses; conversely, a business will only incur certain costs associated with accepting a method of payment if it ascertains that consumers will demand it. Second, these forces feed off each other in the form of *network effects*. As the network of consumers using a given payment method grows, the utility from an additional adopter is higher than when the network is small, and similarly on the merchant side.

Turning to the micro level, what factors are important for understanding the adoption and use of payment methods by an individual consumer? There are many, and we mention only a few here. To an extent, preferences about the various features of different payment methods can play a role. Cash is viewed as fast and easy to use, whereas credit cards are often viewed as being costly due to the potential to incur interest charges. Demographic also play a role. For example, older respondents may be less familiar with new payment technologies, have higher switching costs, and therefore are on average more likely to use cash and less likely to adopt payment innovations. Interestingly, for a given transaction, the size (dollar amount) of the transaction has been shown to be a key predictor in the choice of payment method used. Cash is often used for smaller transactions, debit cards for medium sized transactions, and credit cards for larger transactions. This finding was first made prominent in Klee (2008), and we confirm it in Chapter 1.

Finally, understanding the economics behind a new payment technology such as Bitcoin can be a challenging endeavor. By all available evidence, Bitcoin is still in an early stage of technology diffusion, with surveys conducted across the world pegging ownership rates anywhere from 1.5% to 5%. It may be the case that owners themselves are still experimenting with the technology, figuring out its potential costs and benefits. As mentioned above, while Bitcoin was originally designed with the intention to function as a decentralized currency, it has garnered much more attention due to its extreme swings in value, and the perception of it as being more akin to an asset, likened to a “digital gold”.

On one hand, many popular commentators as well as academics view Bitcoin as doomed to fail – it is often referred to as a bubble that will inevitably burst. Budish (2018), for example, argues that the incentives underlying the security of the Bitcoin system (mining to verify transactions) will ultimately bring about its collapse, once adoption reaches a critical mass. On the other hand, central banks are taking seriously the prospect that Bitcoin could gain traction. The extent of research into CBDC corresponds simultaneously to falling use of cash, together with a viable private alternative – Bitcoin – which has the potential to function as a digital form of cash. The parallels with cash are indeed striking, and its' pseudo-anonymous nature has led it to face many of the same accusations concerning potential use for illegal activities or the underground economy.

With this in mind, Chapter 3 confronts the parallels of cash and Bitcoin head on. The analysis is motivated by the surprising finding that Bitcoin owners actually hold more cash, on average and at the median, compared with non-owners. This finding challenges the assumption that Bitcoin is, at least at this stage, a replacement for cash. We investigate factors that are predictive of Bitcoin ownership and use this to control for possible bias in terms of estimating the effect of Bitcoin ownership on cash holdings. We further explore possible mechanisms that could potentially explain why Bitcoin owners hold more cash.

Chapter 4 concludes the thesis by examining Bitcoin adoption from the lens of technology diffusion. Here, the key factors considered are *network effects* and *beliefs*. As discussed, network effects are important for payment economics because more utility is derived from the use of Bitcoin as the network of Bitcoin users grows large – indeed, there are more possible counterparties with which to transact. Given that the level of Bitcoin adoption is still low we may suspect that network effects are not particularly strong at this point in time. By contrast, beliefs about the future of Bitcoin may play an important role because early adopters may anticipate future benefits from the technology even while adoption is currently low. In this way, beliefs about the survival of Bitcoin may be predictive of current period adoption. Appropriate econometric techniques are utilized to test these hypotheses, accounting for the fact that beliefs are likely to be endogenous with ownership.

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1 Effectiveness of Stratified Random Sampling for Payment Card Acceptance and Usage

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1.1 Introduction

Central banks around the world, as issuers of bank notes, have a keen interest in understanding the use of cash. While there has undoubtedly been a shift towards use of electronic methods of payment at the point-of-sale, cash is still widely used across many countries, see e.g. Bagnall et. al (2016). In addition, many countries observe that the demand for cash as measured by the value of bank notes in circulation has been growing in line with and in some cases faster than - the rate of growth of the economy. Of course, different countries have different experiences. On one spectrum, countries such as Sweden have recently been exploring whether to issue a central bank digital currency, due to rapidly declining cash demand. By contrast, Hungary is a particularly cash intensive country with over 80% volume of transactions being conducted in cash.

A key factor influencing use of cash at the point-of-sale is whether or not card payments – debit and credit – are accepted by the merchant. Payments are a two-sided market: consumers are more likely to adopt and use cards when acceptance is widespread; similarly, merchants are more likely to want to accept card payments when there are many consumers that desire to pay with them. See, for example, the discussion in Fung and Huynh (2017). Card acceptance also has implications not just for the use of cash but also for the amount of cash held by consumers. For example, Huynh et al. (2014) show that cash holdings increase when consumers move from an area of high card acceptance to an area with low card acceptance. Consumers must hold more cash because of the higher probability of encountering a situation where cards are not accepted, and therefore they can still make a potential transaction that would otherwise not take place.

Finally, card acceptance is intimately related to the cost of payments. A recent study by the Bank of Canada (Kosse et al. (2017)) measured that the cost of accepting various methods of payment amounted to 0.8% of GDP; a similar result of 1% of GDP was found in a study across 13 Euro area countries including Hungary (Schmiedel et al. (2013)). Accepting card payments comes with fees such as interchange, terminal fees, etc, which the merchant must trade-off with the labour costs of processing cash, the opportunity cost of missing a card payment, etc.

To measure the level of card acceptance as well as the cost for accepting various forms of payments, central banks around the world have conducted merchant or retailer surveys, see: Kosse et al. (2017); European Comission (2015); Norges Bank (2014); Stewart et. Al (2014); Jonker (2013); Schmiedel et al. (2013); Danmarks Nationalbank (2012); Segendorf and Jansson (2012); Arango and Taylor (2008).

Merchant studies, however, can be difficult and expensive endeavours. Recruiting businesses / merchants to participate is no easy task, and in practice sample sizes are often low; half of the studies shown in Figure 1 of Kosse et al. (2017) were of size $N = 200$ or below. Additional challenges of merchant surveys are: coverage of small and medium sized businesses, which may not belong to an official registry; accounting for businesses with franchises or multiple locations; high costs of conducting survey interviews to obtain quality data; and more.

In this chapter, we exploit a novel administrative dataset from Hungary, which allows us to validate the approach and results of these merchant surveys with respect to measuring payment card acceptance. This rich data set is known as the Online Cashier Registry (OCR), and captures the universe of retail transactions in Hungary via a linking of cash registers / payment terminals to the centralized tax authority.

Specifically, our analysis first focuses on estimating card acceptance using different stratification variables that are commonly used in practice for merchant surveys. This allows us to see how stratification impacts point and variance estimates of acceptance, and provides guidance on which stratification variables may be most effective in practice, given the constraint of small samples sizes. Our results suggest that having full coverage with respect to geography and the size of the store would produce the most reliable estimates. Further, we quantify the uncertainty in card acceptance estimates that may be present for particularly small sample sizes.

We also conduct logistic regression analysis on the entire OCR database and stratified subsamples, in order to assess the bias in point estimates for key determinants of card acceptance and card usage. Our models are motivated by the payment survey literature and we confirm results from the literature that store size is highly correlated with card acceptance, and transaction size with card usage.

Our work is situated within an exciting research area that is a nexus between survey statistics and data science. For example, Rojas et al. (2017) investigate how various sampling techniques can be used to explore and visualize so-called 'big data' sets. Chu et. al (2018) use the additional structure of survey weights to aide in estimating functional principal components of a large and complex price dataset used for constructing the consumer price index in the United Kingdom. In a slightly different vein, Lohr and Raghunathan (2017) review methods for combining survey data with large administrative data sets, including record linkage and imputation. They further highlight the opportunity to use administrative data sets in the survey design stage, as well as for assessing non-response bias and mitigating the need for follow-up. The interplay between survey statistics and data science will become increasing relevant against the background of declining survey response rates, as well as competition for sponsor resources from large administrative data sets (see for example the discussion by Miller (2017)).

The chapter is organized as follows. In Section 2 we describe the data set and context of the Hungarian payments system. In Section 3 we outline our methodology. Section 4 presents and discusses results and Section 5 concludes.

1.2 Data description

The Hungarian payment system can be considered cash-oriented. The level of cash in circulation is higher than the European average and the share of electronic transactions in retail payment situations is fairly low. This notwithstanding, Hungarian households have good access to electronic infrastructure - 83 per cent of households have a payment account and 80 per cent have a payment card. Despite a 15 to 20 per cent increase in electronic payments over the last few years, the vast majority of transactions are still conducted in cash.

Under Decree No. 2013/48 (XI. 15.) NGM, the Ministry for National Economy mandated the installation of online cash registers directly linked to the tax authority. The replacement of cash registers was implemented as part of a gradual process at the end of 2014; subject to certain conditions, taxpayers were permitted to use traditional cash registers until 1 January 2015.

The scope of the online cash register system has been expanded significantly since the adoption of the decree. Initially, the regulation covered the retail trade primarily, however from 1 January 2017, its provisions became applicable to a substantial part of the services sector as well (e.g. taxi services, hospitality/catering, automotive repair services).

The Online Cashier Registry (OCR) database contains data from over 200,000 cash registers, totaling 7 billion transactions. The median transaction was about 1,000 HUF ($4 USD). The OCR reveals that conventional payment surveys tend to underestimate the amount of cash payments. For example, a 2014 Hungarian survey estimated that 84% of the volume of payments were conducted using cash, whereas this figure is almost 90% in the OCR.

For our analysis, we utilize two data sets derived from the OCR covering years 2015-2016:

1. An anonymized merchant-level data set. Each transaction contains a store identifier which is used to aggregate transactions to a merchant-level. Although the store identifiers are anonymized, it is possible to link stores that belong to the same network, for example franchises. The identifier also links to a four-digit primary industry code, which in Hungary is known as TEAOR'08, and allows for classification of merchant types.

2. An anonymized data set of transaction-level aggregated data. This allows us to observe the method of payment (cash vs. card) used for any given transaction. We dismissed negative transactions and those exceeding HUF 50 million, but did not apply any filters

regarding store size.

1.2.1 Key variables

Here we describe the key variables used for in our analysis. See Table 1 for a summary.

- Card acceptance: A merchant in the OCR is defined to accept cards if a debit or credit card transaction is linked to it in the database
- County: Merchants are classified into 20 geographic counties in Hungary, as well as an additional categories for mobile/online shops.
- Industry: The OCR contains the four-digit TEAOR08 identifier of the stores primary activity. For our purposes we use the first digit of the identifier which provides a broader classification, see Table 2. For convenience of producing small random stratified subsamples we drop very small industries from our final analysis.
- Size: Merchants are classified into small, medium and large sized businesses based on their annual turnover of 2-15 million HUF, 15-150 million HUF, and 150+ million HUF, respectively.

Other variables included in the logistic regression models are explained in additional detail in the Appendix.

1.3 Methodology

Our analysis consists of two components which we describe below.

1.3.1 Estimating card acceptance

Due to the importance of card acceptance for understanding payment choice and cash usage, we first use the merchant-level aggregated version of the OCR to estimate card acceptance. We proceed in the following manner.

First we draw a random stratified sample from the merchant-level data set. From this sample, we estimate the proportion of businesses accepting card payments. Also we calculate the standard error and a 95% confidence interval. Finally, we repeat these calculations for 1000 replications. Estimates are calculated using Stata's svy command which accounts for the strata, strata level inclusion probabilities as weights, and finite population corrections.

To draw the stratified samples, we consider three target sample sizes: 0.1% 0.2% and 1% of the full data set. These sizes reflect the fact that in practice, merchant surveys often face a constraint of having small samples sizes. Stratification is performed on the three variables defined in Section 2.3 above, and we select the given proportion (0.1%,0.2%,1%) of units from each strata. Choice of the three stratification variables is motivated by those used in practice for merchant payment surveys, see e.g. Kosse et al. (2017). The purpose of stratification in general is to reduce variance estimates by finding variables which are highly correlated with card acceptance (see again Table 1). Of course, we are also limited by what is available in the OCR.

1.3.2 Models of card acceptance and usage

To estimate the logistic regression models of card acceptance and usage we take a similar approach of drawing stratified random samples. However, since we are mainly interested in understanding the bias of estimates for key explanatory variables, we fix the sample sizes: at 1% of the merchant-level data for the card acceptance model; at 0.01% of the transaction-level dataset for the card usage model. For both models we perform 10 replications and compute average point estimates. Explanatory variables are included based on what is available in the OCR combined with a review of the payments literature; see the Appendix for a more detailed explanation. Coefficient estimates are not produced using any survey weights.

1.4 Results

1.4.1 Estimates of card acceptance

Table 3 shows the results from the first component of our analysis. From the 1000 replications, we report the average estimates of card acceptance, per cent bias when compared with the true value of acceptance (0.2573804), the average standard error of the estimate and the average length of a 95% confidence interval.

Each stratification approach provides essentially unbiased estimates of card acceptance, even for the smallest sample size considered (0.1% sample; roughly N=160); the bias is below 1 per cent when compared with the true value. That being said, stratification by size leads to the most biased estimates. County and size stratification underestimates card acceptance in small sample sizes, whereas industry stratification provides an over estimate.

The main issue with small sample sizes – which has implications for practical merchant surveys – is the precision of the estimates. For small sample sizes, the average length of a confidence interval for both county and industry strata is about 13.5 percentage points; size stratification provided a relatively more precise estimate. However, increasing the sample size from 0.1% to 0.2% leads to a noticeable increase in the precision of the estimates, and there was not much additional improvement by increasing the sample size from 0.2% to 1%. For larger sample sizes, county stratification provides the least biased estimates, whereas store size estimates are most precise. This is driven by the high correlation between card acceptance and store size; see again Table 1.

There are some key lessons to draw from these results for actual merchant payment surveys. A combination of geographic and merchant size coverage would likely provide the most reliable estimates of card acceptance, reducing both bias and variance. Further, very small sample sizes could produce unreliable estimates (large confidence interval), but this can rapidly be improved with even a small increase to the sample, without having to increase cost too significantly, since the increases to precision show diminishing returns beyond $\approx N = 300$.

1.4.2 Regression models of card payments

Now we discuss results from logistic regression models of card acceptance and usage; see the Appendix for details on model selection and full results.

Acceptance

Our analysis focuses on three types of explanatory variables: county effects, industry effects and store size effects. Overall, for the 88 parameter estimates used in the model, the stratification based on the size of the store provides the best estimates. The average of the point estimates over the 10 samples falls inside of a 95% confidence interval for 52 of the parameters. Due to the high number of control variables, we proceed to discuss selected results, see Table 4.

The model based on the entire database clearly shows that the most important factor, in line with the literature results, is the size of the store, which we characterise by the annual revenue. The distribution of store sizes follow a lognormal distribution which means that in the county and industry-based stratification, there is a low probability that large stores will be included in the sample. Without the biggest retailers, where county and industry effects are small, the estimates for these variables will in general be biased. The county and industry stratification overestimate these effects.

Since the functional relation between size and acceptance is non-linear and non-monotone, the stratas of the counties and industries do not provide good fits for these higher order polynomials and most of the size related variables share of different size transactions, volume of transactions. In the case of industry effects the size based stratification underperforms an industry-based approach. The industry distribution of the database is heavily concentrated on retail services and the other categories have only a very small share. The three categories of size effects direct annual revenue, share of different size transactions and volume of transactions are in general better estimated by size stratification.

In conclusion we can state that the most efficient stratification is a random stratified sampling based on different store size categories and not on geographical or industry classification. The main causes are the importance of annual revenue over county and industry effects in card acceptance decisions, and the complex functional relation between the two. By not basing stratification on store sizes, the model tends to overestimate the other effects.

Usage

In the case of modelling payment card use at the point-of-sale, a store size stratification does not lead to good estimates. The model estimated on the full dataset clearly shows that the single most important factor is the transaction value (and its higher order orthogonal polynomials). We find there is no single best method from these three types of stratification, see Table 5. Because of the extremely small standard errors calculated from nearly 5 billion transactions, all subsample estimations are on average outside of the 95% confidence intervals. Based on the average estimations, the county stratification provides the closest estimates for the most variables. The reason for this is due to the much greater county effects in card use decisions, compared with card acceptance. However, as opposed to what we observed in the card acceptance model, there is not much difference in biases between the three types of stratification. All three models on average overestimate the county and transaction size effects, and underestimate the industry effects.

The main reason that the above stratifications provide poor results is the lognormal distribution of transaction size. By not basing the stratification on this characteristic we cannot ensure that enough high value transaction are in the subsample. This bias is present even by limiting the sample to transaction below 32 thousand HUF (100 EUR). Without this filtering, the absence of these extreme value transactions together with the non-monotonic, non-linear relationship between transaction size and card use for the entire database would probably create even less efficient estimations.

In conclusion we can state that the usual stratification of merchant surveys based geographical location, industry, or store size is not conducive for estimating card use models because they omit the most important factor in card use decision, the value of the transaction. From these three types of stratification, the county stratification provides the best estimates, but there is a systematic bias for all three types.

1.4.3 Conclusions

In this chapter of the thesis we analysed payment card acceptance and payment card use decisions in retail situations using the comprehensive Online Cashier Register database and random stratified subsamples. We compare county, industry and store size stratifications with the true population estimates, to simulate the usual stratification criteria for merchant surveys.

Our results from estimating levels of card acceptance suggest that having full coverage with respect to geography and the size of the store produces the most reliable estimates. Further, we quantify the uncertainty in card acceptance estimates that may be present for particularly small sample sizes, finding that increasing the sample size from around N = 160 to N = 300 can reduce the length of confidence intervals by half. These findings have important practical implications for merchant surveys.

Further, we estimated logistic regression models of both card acceptance and usage. In our models, we controlled for relevant factors in payment instrument adoption and use, but focused on the performance of the three types of stratifications variables to estimate the county, industry and size effects for the entire population. In our comparison we created 10 random stratified subsamples of 1 per cent of the merchant database, and 10 random stratified subsamples of 0.01 per cent of the transaction database. In the card acceptance model, the stratification based on the store sizes provided the best estimates. However, as store sizes follow a skewed distribution, with small samples there is a high probability that the subsample does not have enough big stores and therefore the effects of size will be underestimated, while the county and industry effects are overestimated.

In the card usage model, we evaluated the same subsample types and show that county stratification provides the best results. However, due to not being able to stratify on transaction size, all of the three analysed subsampling show systematic biases. In conclusion, it can be stated that in card acceptance models the store size stratification provides good estimates, however the same stratification cannot be used to accurately estimate variable effects in a card usage model.

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Tables and Figures

Table 1: Description of key variables used in the study

	N	Acceptance (%)		N	Acceptance (%)
Overall	157,071	25.7			
County			*County*		
Moblie shops	5294	16.0	Jasz-Nagykun-	4442	29.0
Bacs-Kiskun	30851	37.1	Komarom-Eszte	2518	18.0
Baranya	5519	26.4	Mozgobolt	15982	26.3
Bekes	8189	18.7	Nograd	5746	20.7
Borsod-Abauj	5543	17.5	Pest	7936	14.2
Budapest	8552	21.7	Somogy	5634	20.8
Csongrad	6517	26.2	Szabolcs-Szat	3469	22.8
Fejer	5548	28.6	Tolna	4004	21.1
Gyor-Moson-So	7656	24.4	Vas	6106	28.3
Hajdu-Bihar	7796	24.0	Veszprem	5037	25.9
Heves	4732	25.1			
Industry			*Size*		
1	7562	16.8	Small	65373	6.4
4	96152	29.5	Medium	76312	32.5
5	36483	18.4	Large	15386	74.2
6	3545	27.3			
7	3064	26.8			
8	3067	29.2			
9	7198	19.2			

Note: This table shows the distribution of key variables used in our study based on the merchant level data set derived from the OCR database. For store size, *small* businesses are defined as those with 2-15 million HUF in annual turnover; *medium* are businesses with between 15 and 150 million HUF; *large* are businesses with over 150 million HUF.

Table 2: **Industry classifications: TEAOR08**

Industry code	Description
0	Agriculture, Forestry, Fishing and Mining
1	Manufacture of textiles, wood, paper and coke
2	Manufacture of chemicals, fabricated products and electronic equipment
3	Manufacture of machinery, Electricity, Gas and Other Industries
4	Construction, Wholesale and Retail
5	Transportation and Housing
6	Information, Communication, Financial and Legal Services
7	Professional, Scientific and Other Support Activities
8	Administration, Defense, Education and Human Health
9	Arts, Entertainment and Recreation

Note: This table shows the industry code descriptions used in the TEAOR08 classification. These codes correspond to European NACE rev. 2.

Table 3: **Effect of stratification on estimates of card acceptance**

	County	Size	Industry
0.1% sample			
mean	0.25625	0.25604	0.25831
percent bias	-0.439	-0.519	0.362
se	0.034	0.031	0.035
CI length	0.134	0.122	0.136
0.2% sample			
mean	0.25732	0.25693	0.25682
percent bias	-0.025	-0.175	-0.220
se	0.015	0.014	0.015
CI length	0.060	0.054	0.061
1% sample			
mean	0.25749	0.25704	0.25721
percent bias	0.044	-0.134	-0.067
se	0.011	0.010	0.011
CI length	0.043	0.038	0.043

Note: This table shows estimates of card acceptance for different stratification variables and sample sizes. Stratification is performed on county, industry and store size variables. From 1000 replications, we report the average point estimate and its per cent bias from the true value estimated on the full merchant-level data set derived from the OCR. We also report the average standard error of the estimate, along with the average length of a 95% confidence interval.

Table 4: **Effect of stratification on key determinants of card acceptance**

		Full dataset	**County**	**Industry**	**Size**
County	Moblie shops	-0.649	-0.678	-0.671	-0.663
	Bacs-Kiskun	0.136	0.157	0.142	0.135
	Baranya	-0.035	-0.035	-0.034	-0.052
	Bekes	-0.295	-0.240	-0.292	-0.295
	Borsod-Abauj	-0.360	-0.329	-0.341	-0.366
	Budapest	-0.143	-0.097	-0.126	-0.142
	Csongrad	-0.100	-0.089	-0.074	-0.108
	Fejer	-0.082	-0.065	-0.055	-0.096
	Gyor-Moson-So	-0.225	-0.217	-0.216	-0.243
	Hajdu-Bihar	-0.103	-0.100	-0.073	-0.101
	Heves	0.040	0.099	0.046	0.022
	Jasz-Nagykun-	0.053	0.072	0.048	0.013
	Komarom-Eszte	-0.209	-0.171	-0.171	-0.176
	Mozgobolt	-0.070	-0.050	-0.054	-0.064
	Nograd	-0.198	-0.195	-0.172	-0.224
	Pest	-0.441	-0.410	-0.423	-0.457
	Somogy	-0.185	-0.164	-0.176	-0.173
	Szabolcs-Szat	-0.256	-0.246	-0.237	-0.255
	Tolna	-0.554	-0.511	-0.509	-0.570
	Vas	-0.012	0.000	0.032	-0.054
	Veszprem	0.000	0.000	0.000	0.000
Store turnover	1st order orthogonal polynomial	59.296	59.525	59.503	63.279
	2nd order orthogonal polynomial	-81.847	-80.740	-84.464	-78.947
	3rd order orthogonal polynomial	-24.489	-24.085	-24.322	-21.949

Note: This table shows selected point estimates from a logistic regression model with card acceptance as the dependant variable; results from the full model are shown in the appendix. In the first column, we show estimates from the model estimated on the full merchant-level dataset derived from the OCR. The last three columns shows the average estimates from ten 1% stratified sub-samples, where the stratification variable is indicated in the column heading.

Table 5: **Effect of stratification on key determinants of card usage**

		Full dataset	**County**	**Industry**	**Size**
Industry code	1	-0.238	-0.225	-0.253	-0.309
	2	0.262	0.245	0.182	0.214
	3	0.105	0.124	0.048	0.071
	4	0.026	0.019	-0.021	-0.051
	5	0.733	0.676	0.629	0.608
	6	0.048	0.03	-0.055	-0.057
	7	0.383	0.385	0.329	0.307
	8	0.846	0.805	0.717	0.705
	9	0.143	0.12	0.128	-0.039
Transaction value	1st order orthogonal polynomial	-184.446	-157.517	-167.243	-176.342
	2nd order orthogonal polynomial	-206.922	-189.216	-194.939	-200.644
	3rd order orthogonal polynomial	-76.017	-68.811	-71.832	-72.792

Note: This table shows selected point estimates from a logistic regression model with card usage as the dependant variable; results from the full model are shown in the appendix. In the first column we show estimates from the model estimated on the full transaction-level dataset derived from the OCR. The last three columns shows the average estimates from ten 0.01% stratified sub-samples, where the stratification variable is indicated in the column heading.

A Appendix

This appendix reviews the literature on payment card acceptance and usage, which justifies the explanatory variables included in our models. In addition we provide description of the variables not discussed in the main text and the full results for the logitstic regression models.

A.1 Review of literature

Card acceptance is primarily a theoretical field in payment studies. Most studies focus on the effect of the interchange fee on card acceptance, and the calculation of the equilibrium, competitive fee level on the oligopolistic market of card issuing. In one of the first analysis in this field, Baxter (1983) argues in favour of the interchange fees to achieve a higher level of card acceptance and use. However, his model received criticism form Rochet and Tirole (2003) and Wright (2003), who significantly updated the model, but still concluded that without surcharge the interchange fee has a neutral effect on the market.

In Rochet and Tirole (2007) they created an empirical test, called the tourist test, to calculate an equilibrium fee level. Based on this test, Keszy-Harmath et al. (2012) concluded that in the Hungarian market the fee is above desired levels, which resulted in a legislative cap in 2013. These theoretical studies however provide little guidance to analys card acceptance in cross samples, because in the abstract and simplified models the merchants usually only differ in unit acceptance costs. In line with the theoretical studies a considerable part of the empirical literature focuses also on the costs of card acceptance, e.g. Humphrey et al. (2003).

Our regression models primarily draw from the results of questionnaire-based surveys. Jonker (2011) explored card acceptance and surcharging using survey data collected among 1,008 Dutch merchants. The authors regression analysis revealed that, while the merchants revenue and the number of employees are significant explanatory variables, the cost of card payments also influences card acceptance. Arango and Taylor (2008) investigated card acceptance decisions in the Canadian market primarily focusing on merchant perceptions, whereas Polasik and Fiszeder (2014) studied the payment method acceptance decisions of online shops. The lions share of empirical studies, however, concentrates on consumers card usage rather than the supply side [Bolt (2008), Bolt et al (2010), and Borzekowski et al. (2008)].

In our research, the online cash register (OCR) database enables us to analyse turnover across a large-scale sample covering a substantial segment of the retail sector. Previous payment studies were typically rooted in questionnaire-based surveys, and the literature offers few examples of payment analyses that cover such a significant volume of data as

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In our research, the online cash register (OCR) database enables us to analyse turnover across a large-scale sample covering a substantial segment of the retail sector. Previous payment studies were typically rooted in questionnaire-based surveys, and the literature offers few examples of payment analyses that cover such a significant volume of data as ours. The focus of questionnaire-based surveys is the relationship between respondents socio-demographic characteristics and their payment choices.

At the European level, van der Cruijsen and Plooij (2015) compared the results of two Dutch questionnaire-based surveys over a decade-long horizon. Although the use of electronic payment methods is far more intense in the Netherlands, education and age proved to be similarly important explanatory variables. The authors emphasised the role of subjective perceptions speed and safety in payment choices. Although the non-linear and non-monotonic relationship observed in the cross-sectional analysis of the OCR database between payment value and card usage intensity was not observed in the Dutch survey, it is important to note that the highest category selected by the authors above EUR 60 is still below the Hungarian maximum.

Similarly, using US household panel data Cohen and Rysman (2013) identified transaction size as the most important determinant of payment choice. The study by Bagnall et. al (2016) is an important cross-country comparison harmonising questionnaire-based surveys from seven countries: Canada, the United States, Austria, Germany, the Netherlands, France and Australia. The authors main conclusions are consistent with the results of the Hungarian surveys: card usage increases with higher income and education; the most significant variable is transaction value, while subjective factors also play an important role in all countries considered. Takács (2011) used data from a 1,000-person questionnaire-based survey to examine Hungarian payment habits. The author found that payment account and card coverage was primarily driven by education and income level. Also based on a 1,000-person questionnaire survey and on payment diary data, Ilyés and Varga (2015) arrived at similar conclusions; the relationship between socio-demographic variables and card usage habits showed no difference in the two surveys.

Beside questionnaire-based surveys, over the past decade only two surveys have provided an opportunity for the analysis of a large volume of receipt-level data. The first one is a survey conducted by Klee (2008) analysing the transaction data of US households. In her survey, the author matched the receipts of 99 retail outlets with demographic information on the local environment of the stores concerned. The main finding of the study is that transaction costs and opportunity costs influence the choice of payment instruments significantly, with transaction value being the most important explanatory variable.

Wang and Wolman (2014) used transaction-level data from a large US discount chain covering the transactions of a three-year period. In their research paper, the authors presented a detailed analysis of the marginal effects of the individual variables and, with the assistance of the three-year time horizon; they were able to forecast the long-term trends of future card usage. Wang and Wolman (2014) analysed more than two billion transactions in their research. Based on the results presented, neither Klee's, nor Wolman and Wangs database shows a non-monotonic relationship between cash use and transaction value on the values examined by the authors. Empirical results show that several theoretical models have been constructed to explain the relationship between transaction value and the card usage rate. Briglevics and Schuh (2014) used US payment diary data, while Huynh et al. (2014) relied on Canadian and Austrian data to construct their respective decision models. According to transaction value, both models estimate monotonic and concave card usage patterns. While Briglevics and Schuh (2014) described payment instrument choice as a dynamic optimisation problem, Huynh et al. (2014) supplement the BaumolTobin model.

Despite the use of receipt-level data, our database differs significantly from the two studies analysing transaction data and from the surveys built on payment diaries in several regards. The database of online cash registers provides national coverage and the vast majority of merchants are subject to the relevant regulation. Accordingly, compared to the studies mentioned above, we were able to distinguish between far more merchants both in terms of size and type. On the other hand, due to the anonymisation, we had little data on the customers of the stores. County identifiers were of limited use as there is scant variance across the counties with regard to the main demographical aspects; consequently, as opposed to Klee (2008), there is no sufficient variance to add a consumer characteristics proxy. However, as opposed to the payment diaries, there is significantly more information available on payment location; moreover, due to the statutory obligations, the reliability of the data is presumably better.

A.2 Logistic regression models of card acceptance and usage

A.2.1 Card acceptance: variables

- **Dependent variable:** In line with our research question, the primary dependent variable is card acceptance. A merchant or a store is considered to be a point of sale when payment card transactions are linked to it in the database.

- **Value categories:** Based on the payment literature, the willingness to accept payment cards strongly depends on payment value. Presumably, therefore, in the case of stores with the same annual turnover actual card usage is likely to be higher in businesses where the majority of transactions fall into the appropriate value category as opposed to the stores whose turnover, for the most part, comprises mainly very small-value or very large-value transactions.

  As regards the turnover structure, we can examine absolute and relative turnover separately in each individual category. In the case of ratios, the benchmark category is always the highest value category. Due to the nature of the relationship, given the limited number of explanatory variables, the final models include the turnovers log and its square.

- **Temporal attributes of the store:** Not only the annualised turnover of the stores, but also the turnovers monthly and weekly distribution can be established based on the dates indicated on the receipts. Accordingly, in our analysis we also studied the effect of the weekly turnover structure on card acceptance. For the most part during the two years under review, the decree on Sunday store closure was in effect in the retail sector. Family-owned stores represented the main exceptions. Consequently, Sunday opening hours can be used as a proxy for ownership. Since the correspondence is imperfect, this variable is included in conjunction with the TEÁOR variable in the models. In this way, we can separate the effects of individual sectorial exceptions from the attributes of the owner.

  Since the stores closure on Mondays and Tuesdays proved to have a significant explanatory power in our analysis, this serves as the control variable in the rest of the models. These attributes are linked to special stores e.g. museum gift shops, sample stores where the business is not considered to be an independent financial unit.

- **Network attributes** A large part of the retail sector operates in the form of a network; in other words, numerous outlets are operated by a single legal entity. According to our hypothesis, the fact that the store is part of a chain affects card acceptance decisions in two ways. In networks were each member of the network belongs to the same category it accepts or does not accept card payments card acceptance is presumably based on a network-level decision; therefore, the decision situation itself may differ from that of independent stores. By contrast, in networks where, according to the observations, card acceptance is based on the independent decision of the store, the decision situation is determined by the stores unique characteristics. Therefore, our models we included dummy variables for the three types of stores independent store, independent decision, network decision ; moreover, in the case of network stores, we also included the networks total turnover and the number of stores included in the network. According to the cross-sectional analyses, the correlation is non-linear; therefore, we also include the squared terms in the regressions.

- **Item number:** The database includes the number of products purchased under each receipt. This allowed us, on the one hand, to use the total item number of the store as another approach to the size variable and to introduce average and maximum item numbers. The average and the maximum item number presumably correlates strongly with the payment time and as such, it is used as the proxy variable of the latter.

We used average payment value as the control variable in several cases; however, this variable correlates extremely strongly with the decomposition of the turnover by value and with the proportions of the ranges.

A.2.2 Card acceptance: results

Tables 6 and 7 below shows the point estimates from the full regression model of card accceptance.

Table 6: **Full logistic regression results: card acceptance model**

	Full dataset	County stratas	Industry stratas	Size stratas
(Intercept)	-1.276	-2.216	-0.862	-1.647
Average number of items	-0.135	-0.140	-0.135	-0.138
Average value of transaction	0.000	0.000	0.000	0.000
Closed on Monday	-0.254	-0.261	-0.241	-0.238
Closed on Tuesday	0.018	0.021	0.003	0.001
Open on Sunday	-0.392	-0.380	-0.410	-0.403
Number of items	0.000	0.000	0.000	0.000
County - Moblie shops	-0.649	-0.678	-0.671	-0.663
Bacs-Kiskun	0.136	0.157	0.142	0.135
Baranya	-0.035	-0.035	-0.034	-0.052
Bekes	-0.295	-0.240	-0.292	-0.295
Borsod-Abauj	-0.360	-0.329	-0.341	-0.366
Budapest	-0.143	-0.097	-0.126	-0.142
Csongrad	-0.100	-0.089	-0.074	-0.108
Fejer	-0.082	-0.065	-0.055	-0.096
Gyor-Moson-So	-0.225	-0.217	-0.216	-0.243
Hajdu-Bihar	-0.103	-0.100	-0.073	-0.101
Heves	0.040	0.099	0.046	0.022
Jasz-Nagykun-	0.053	0.072	0.048	0.013
Komarom-Eszte	-0.209	-0.171	-0.171	-0.176
Mozgobolt	-0.070	-0.050	-0.054	-0.064
Nograd	-0.198	-0.195	-0.172	-0.224
Pest	-0.441	-0.410	-0.423	-0.457
Somogy	-0.185	-0.164	-0.176	-0.173
Szabolcs-Szat	-0.256	-0.246	-0.237	-0.255
Tolna	-0.554	-0.511	-0.509	-0.570
Vas	-0.012	0.000	0.032	-0.054
Veszprem (base)	0.000	0.000	0.000	0.000
Network store count	-0.008	-0.008	-0.008	-0.008
Network store count squared	0.000	0.000	0.000	0.000
Network sum value	-0.275	-0.226	-0.332	-0.230
Network sum value squared	0.015	0.014	0.016	0.014

Table 7: **Full logistic regression results: card acceptance model (cont'c**

SHARE_10K	0.079	0.660	0.445	0.111
SHARE_10K2	-0.186	-0.458	-0.440	-0.238
SHARE_1K	1.422	1.978	1.574	1.445
SHARE_1K2	-0.968	-1.003	-0.965	-1.056
SHARE_20K	2.608	3.255	2.569	2.612
SHARE_20K2	-2.465	-2.738	-2.222	-2.533
SHARE_5K	0.401	0.722	0.599	0.311
SHARE_5K2	0.125	0.249	0.087	0.167
Industry code = 0	-0.609	-0.595	-0.642	-0.634
Industry code = 1	-0.337	-0.299	-0.370	-0.386
Industry code = 2	-0.303	-0.343	-0.349	-0.280
Industry code = 3	-0.066	-0.068	-0.076	-0.071
Industry code = 4	0.004	0.026	-0.031	-0.038
Industry code = 5	0.128	0.151	0.094	0.101
Industry code = 6	0.231	0.215	0.226	0.189
Industry code = 7	0.260	0.265	0.239	0.220
Industry code = 8	0.427	0.441	0.430	0.410
Industry code = 9 (base)	0.000	0.000	0.000	0.000
TIME_DUMMY=S_2015_1	-0.027	-0.021	-0.058	-0.008
TIME_DUMMY=S_2015_10	-0.178	-0.137	-0.208	-0.190
TIME_DUMMY=S_2015_11	-0.173	-0.202	-0.208	-0.162
TIME_DUMMY=S_2015_12	-0.373	-0.393	-0.392	-0.367
TIME_DUMMY=S_2015_2	-0.158	-0.153	-0.194	-0.146
TIME_DUMMY=S_2015_3	-0.277	-0.285	-0.310	-0.294
TIME_DUMMY=S_2015_4	-0.248	-0.273	-0.291	-0.248
TIME_DUMMY=S_2015_5	-0.259	-0.229	-0.285	-0.258
TIME_DUMMY=S_2015_6	-0.235	-0.217	-0.294	-0.249
TIME_DUMMY=S_2015_7	-0.225	-0.242	-0.242	-0.215
TIME_DUMMY=S_2015_8	-0.208	-0.186	-0.223	-0.198
TIME_DUMMY=S_2015_9	-0.147	-0.144	-0.179	-0.136
TIME_DUMMY=S_2016_1	-0.043	-0.078	-0.097	-0.043
TIME_DUMMY=S_2016_10	0.141	0.105	0.139	0.147
TIME_DUMMY=S_2016_11	0.028	0.020	0.009	0.045
TIME_DUMMY=S_2016_12	0.000	0.000	0.000	0.000
TIME_DUMMY=S_2016_2	-0.097	-0.117	-0.110	-0.102
TIME_DUMMY=S_2016_3	-0.072	-0.052	-0.099	-0.037
TIME_DUMMY=S_2016_4	0.096	0.089	0.062	0.125
TIME_DUMMY=S_2016_5	-0.017	-0.044	-0.059	0.000
TIME_DUMMY=S_2016_6	0.021	-0.014	-0.031	0.018
TIME_DUMMY=S_2016_7	0.103	0.095	0.088	0.117
TIME_DUMMY=S_2016_8	0.029	0.000	-0.026	0.044
TIME_DUMMY=S_2016_9	0.103	0.069	0.088	0.096
Network decison store dummy (base)	0.000	0.000	0.000	0.000
Individual store dummy	0.201	0.207	0.179	0.213
Network independent store dummy	0.532	0.520	0.537	0.525
Annual revenue 1th order orthogonal polynomial	59.296	59.525	59.503	63.279
Annual revenue 2nd order orthogonal polynomial	-81.847	-80.740	-84.464	-78.947
Annual revenue 3rd order orthogonal polynomial	-24.489	-24.085	-24.322	-21.949

A.2.3 Card usage: variables

- **Dependent variable** The main outcome variable of the analysis is the binary variable of card payment. Unlike in theoretical models, in practice payers may use cash and payment cards simultaneously. In the database, the share of cards was 100 per cent in 98 per cent of the card transactions. For the rest of the transactions, the limit of card payment has been defined at a share of 10 per cent.

- **Transaction value** The database contains the receipts gross and net value and its breakdown according to the five VAT rates. Gross value is considered to be the main value of the transaction and in view of the high multicollinearity, we do not use the net value. Since transaction values roughly follow a log-normal distribution, the log of the gross value was also included. In addition, because of the decreasing card usage rate observed for high payment values, we doubled all size variables into values above and below HUF 32,000, which allows the originally monotonic functional form to have an up-sloped and a down-sloped section.

- **Item number** The number of items purchased was also indicated on the receipts, and the model includes this information as an explanatory variable. Since we do not have direct information on the exact number of items, item number became a proxy variable of purchase size. Based on the non-linear relationship observed by the cross-sectional analysis, we also included the square of the item number in the model.

- **Ease of payment** The granulated nature of the database provides the means for using such computed variables in the model that can be generated only with a low degree of reliability based on questionnaire and diary based surveys. We approximate the ease of payment by using the number of banknotes and coins handled in the ideal case as a dummy variable, up to a value of 10. These variables capture the ease of cash payment, which presumably correlates with payment time and as such, it can be considered a cost variable.

- **Store attributes** Although the model constructed for card acceptance contained numerous variables, due to space limitations, we can only include the most important ones in this part of the study. As regards store attributes, most models include the log and square of annualised turnover and the aggregate form of the activity.

- **County data** In the card acceptance model, county effects did not correlate significantly with the countys level of development, but a correlation can be observed during card usage on raw data. We estimated county codes in two steps: the main regression includes only the county dummy variables, while in the second step we focus on the correlation between the coefficients and the main socio-demographic data of individual counties.

- **Temporal data** The database contains data for a two-year period, which reflect significant monthly and weekly seasonality. Since a sufficient amount of data was available, we included yearly and monthly dummy variables and dummies pertaining to the days of the month and the days of the week.

- **Inverse Mills ratio** As card usage and card acceptance mutually affect each other, the model calculated by us reflects a significant degree of selection bias. In order to remove the bias, we also included the inverse Mills ratio computed from the probit version of the model constructed for card acceptance. The Heckman selection thus performed reduces estimation uncertainty, especially in the case of the affiliated store data.

A.2.4 Card usage: results

Table 8 below shows the point estimates from the full regression model of card usage.

Table 8: **Full logistic regression results: card usage model**

	Full dataset	County stratas	Industry stratas	Size stratas
Inverse Mills ratio	-0.624	-0.713	-0.702	-0.714
Logarith of store annual revenue	0.174	0.152	0.150	0.147
County = Bacs-Kiskun	-0.475	-0.417	-0.336	-0.408
County = Baranya	-0.140	-0.094	-0.017	-0.077
County = Bekes	-0.388	-0.327	-0.263	-0.337
County = Borsod-Abauj-	-0.193	-0.136	-0.049	-0.145
County = Budapest	0.297	0.350	0.435	0.360
County = Csongrad	-0.122	-0.088	-0.020	-0.109
County = Fejer	-0.040	0.021	0.114	0.018
County = Gyor-Moson-So	-0.185	-0.118	-0.038	-0.116
County = Hajdu-Bihar	-0.253	-0.206	-0.125	-0.216
County = Heves	-0.372	-0.315	-0.235	-0.301
County = Jasz-Nagykun-	-0.334	-0.294	-0.202	-0.281
County = Komarom-Eszte	-0.094	-0.027	0.049	-0.011
County = Mozgobolt	0.000	0.000	0.000	0.000
County = Nograd	-0.509	-0.469	-0.404	-0.460
County = Pest	-0.129	-0.071	0.007	-0.053
County = Somogy	-0.332	-0.256	-0.179	-0.247
County = Szabolcs-Szat	-0.536	-0.484	-0.395	-0.452
County = Tolna	-0.261	-0.194	-0.110	-0.187
County = Vas	-0.334	-0.249	-0.201	-0.277
County = Veszprem	-0.065	-0.032	0.041	-0.017
County = Zala	-0.270	-0.209	-0.129	-0.214
Number of bills = 1 (base)	0.000	0.000	0.000	0.000
Number of bills = 2	0.263	0.266	0.285	0.267
Number of bills = 3	0.407	0.406	0.409	0.400
Number of bills = 4	0.465	0.462	0.471	0.462
Number of bills = 5	0.504	0.512	0.518	0.505
Number of bills = 6	0.541	0.551	0.566	0.542
Number of bills = 7	0.572	0.617	0.626	0.597
Number of bills = 8	0.607	0.677	0.630	0.772
Industry code = 0 (base)	0.000	0.000	0.000	0.000
Industry code = 1	-0.238	-0.225	-0.253	-0.309
Industry code = 2	0.262	0.245	0.182	0.214
Industry code = 3	0.105	0.124	0.048	0.071
Industry code = 4	0.026	0.019	-0.021	-0.051
Industry code = 5	0.733	0.676	0.629	0.608
Industry code = 6	0.048	0.030	-0.055	-0.057
Industry code = 7	0.383	0.385	0.329	0.307
Industry code = 8	0.846	0.805	0.717	0.705
Industry code = 9	0.143	0.120	0.128	-0.039
Number of items	0.005	0.005	0.005	0.005
Transaction value 1th order orthogonal polynomial	-184.446	-157.517	-167.243	-176.342
Transaction value 2nd order orthogonal polynomial	-206.922	-189.216	-194.939	-200.644
Transaction value 3rd order orthogonal polynomial	-76.017	-68.811	-71.832	-72.792

2 2018 Bitcoin Omnibus Survey: awareness and usage

Notes: A version of this paper was published: *Bank of Canada Staff Discussion Paper*, 2019-10. (2019). A version of this paper is published as: "Benchmarking Bitcoin Adoption in Canada: Awareness, Ownership and Usage in 2018," *Ledger*, vol. 5: 74-88. (2020).

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2.1 Introduction

The Bank of Canada continues to use the Bitcoin Omnibus Survey (BTCOS) to monitor trends in Canadians' awareness, ownership and use of Bitcoin and other cryptoassets. The most recent iteration was conducted in late 2018, following an 85 percent decline in the price of Bitcoin throughout the year (see Figure 1). In 2017, almost half of Bitcoin adopters reported investing as their primary reason for owning it, meaning that the dramatic decline in price could have implications for whether Canadians continue to own Bitcoin and, if so, how they use it.

The Bank of Canada's main interest in monitoring Bitcoin adoption is to understand how its usage by Canadians could affect the financial system. Consequently, the BTCOS will aid the Bank of Canada in understanding Bitcoin's potential impact on its core functions. First, our findings on Canadians' cash holdings and plans to go cashless may have implications for the production and distribution of Canadian currency. Regarding the Bank of Canada's role in maintaining financial stability, its 2019 Financial System Review (FSR) upgraded cryptoassets to one of the six key financial vulnerabilities it closely monitors. The FSR states that while cryptoassets do not currently pose a financial stability concern, the Bank of Canada will continue to monitor this rapidly evolving technology. [3] The BTCOS contributes to these efforts by characterizing the adoption of cryptoassets by Canadians, which may inform the Bank of Canada about the likelihood of risks materializing.

[3] Similarly, the Bank of International Settlements released a statement in March 2019 acknowledging that cryptoassets may pose future financial stability risks faced by banks.

In 2018, Canadians continued to increase their awareness, as 89 percent reported having heard of Bitcoin. Similarly, Bitcoin ownership increased, although it remained concentrated within a few sub-demographics, such as populations that are aged 18 to 34, university educated and male. We estimate that 5 percent of Canadians owned Bitcoin in 2018, which represents an increase from 2017 (4 percent) and 2016 (3 percent). The primary reason for owning Bitcoin remained speculation in 2018, though reasons such as an interest in the technology and privacy concerns became more common compared with the previous year. While ownership has grown, we also observed an increase in the number of Canadians who reported having stopped owning Bitcoin; and those who remained owning Bitcoin tended to hold smaller amounts than in previous years.

This paper is structured as follows: Section 2 describes the survey design and methodology of the 2018 BTCOS; Section 3 discusses Canadians' financial literacy and their awareness and knowledge of Bitcoin; Section 4 provides a profile of Bitcoin users in 2018; and finally, Section 5 summarizes the overarching takeaways of the 2018 BTCOS and presents a road map going forward.

2.2 The 2018 Bitcoin Omnibus Survey

This section summarizes improvements made to the survey design and weighting methodology of the 2018 BTCOS. This iteration evolved considerably from those conducted in 2016 and 2017. First, we updated how respondents report their Bitcoin holdings and how Bitcoin knowledge is assessed. We also added new questions measuring financial literacy, preferences for payment attributes when making online transactions, and plans to stop using cash. Finally, we updated the survey weighting procedure used in previous iterations.

2.2.1 Updated survey design

In the 2018 survey we asked respondents to report their Bitcoin holdings as a continuous variable, rounded to the nearest Canadian dollar. In contrast, previous iterations asked respondents to report their holdings in categorical ranges, which were denominated in Bitcoin. This change allows us to gain more information about the distribution of Canadians' Bitcoin holdings. When comparing our estimates across time, we group the 2018 Bitcoin holdings data into the same categories used in previous years.

We simplified the knowledge module in 2018 by reducing the number of questions asked to three. The questions, which could be answered with true, false, or don't know, tested knowledge about the total supply of Bitcoin, whether Bitcoin is backed by a government, and its public ledger (Table 1). Other questions asked in previous years were removed, as they had relatively fewer attempts and correct answers in the 2017 BTCOS.

Inspired by results from the Bank of Canada's 2017 Methods-of-Payment (MOP) survey (Henry, Huynh and Welte 2018), we added a module on financial literacy. It has been demonstrated that financial literacy has an important relationship with cash holdings, see Fujiki (2020). Broadly speaking, financial literacy is a foundational understanding of economic and financial concepts central to economic decision making, such as investing and saving for retirement. The 2018 survey measured financial literacy using the "Big Three" questions of Lusardi and Mitchell (2011). These multiple choice questions, summarized in Table 2, test respondents' understanding of compound interest, inflation and the diversification of risk.

Also new to the 2018 BTCOS was a question asking respondents to rank their preferences over four features of online transactions and a question on whether respondents plan to stop using cash. The inclusion of these questions was motivated by the increasing degree of digitalization in commerce and the corresponding decline in cash use at the point of sale. These questions aim to answer whether respondents plan to go fully digital in the future, and if so, which features they value in an electronic payment method.

We report a full schematic of the 2018 survey instrument in Appendix A.1. Findings from the previous iterations of the Bitcoin Omnibus Survey are reported in Henry, Huynh and Nicholls (2018, 2019). Final sample sizes were 1,997 in 2016; 2,623 in 2017; and 1,987 in 2018. Similarly, we captured 58, 117 and 99 Bitcoin owners in each year, respectively. Note that all estimates for overall Canadians, such as the results found in Table 3 and Table 8, include the subset of Canadians who adopted Bitcoin.

2.2.2 Survey methodology

We improved the survey weighting procedure in 2018 to broadly follow the methods used in Chen, Felt and Henry (2018). Using a procedure known as raking, initially outlined in Deville, Sarndal and Sautory (1993), we adjusted for differences between the demographic composition of our samples and the Canadian population. Specifically, the procedure yields survey weights so that each sample of the BTCOS matches the 2016 Canadian Census, with respect to the following demographics: age, gender, region, education, marital status, employment and income. Some respondents chose not to report their employment and income status, so we utilized multiple imputation techniques to handle these missing values.

The previous version of the BTCOS weighting methodology only accounted for age, gender and region. As a result, our previous estimates may have been biased, since Bitcoin ownership is correlated with other demographic variables. For example, ownership of Bitcoin grew disproportionately among university-educated respondents between 2016 and 2018. Since BTCOS respondents tend to be more educated than the overall population, we may expect estimates of total Bitcoin ownership to be too large based solely on our sample. Consequently, we have updated our methodology and revised our estimates for all iterations of the BTCOS using the newly developed weighting methodology, which we refer to as MICAL (multiple imputation in calibration).

It is important to note that BTCOS respondents are sampled from an opt-in panel. Consequently, BTCOS participants must first choose to join the panel in order to be sampled. This means that the probability of someone in the population being sampled is unknown, which implies the BTCOS is a non-probability sample. With this in mind, we follow the guidelines laid out by the AAPOR Task Force on non-probability sampling (Baker et al. 2013). In particular, the guidelines emphasize that caution be used when reporting margins of error, as they cannot be computed reliably using data from non-probability surveys. As such, Appendix A.2 provides an in-depth discussion of the assumptions and methods used to produce our estimates.

After the initial data collection stage, we conducted a systematic data-cleaning exercise by flagging potentially dubious respondents. First, we used the following survey questions to flag dubious responses: respondents' estimates of current Bitcoin prices, their expectations of Bitcoin's price one month ahead, their estimated likelihood that Bitcoin will survive in 15 years, their estimate of the percentage of Canadians that will adopt Bitcoin in 15 years and their share of spending using cryptoassets. For example, the first two responses indicated how informed respondents were about the Bitcoin market. Considering that the price of Bitcoin fell substantially in November 2018, we argue that Bitcoin owners would likely have been aware of the current price level when sampled in December. After flagging the potentially dubious respondents, we performed a manual check for overall data quality. Some indicators of poor quality included streamlining (entering the same number or seemingly random numbers every time), many missing or unrealistic values, and claimed ownership of all cryptoassets listed in the survey. After the manual check, 17 dubious Bitcoin owners were dropped from the final sample.

2.3 Knowledge, financial literacy and awareness

This section analyzes the state of knowledge about certain aspects of Bitcoin and financial literacy, and explores the differences between Bitcoin owners and the Canadian population. Further, we examine how awareness of Bitcoin has evolved since previous iterations of the BTCOS.

2.3.1 Bitcoin knowledge and financial literacy in 2018

We report the Bitcoin knowledge module and the "Big Three" financial literacy questions from Lusardi and Mitchell (2011) in Table 1 and Table 2, respectively. For each set of questions, we computed an overall measure by summing the number of correct answers and subtracting incorrect answers, while questions answered "don't know" did not contribute to the measure. Our measure, denoted score, can take any integer from -3 to 3, with 3 indicating all questions were answered correctly and -3 indicating all were answered incorrectly. Knowledge and literacy were categorized as low ($score \leq 0$), medium ($score = 1$ or $score = 2$) or high ($score = 3$).

Notably, we found no change in Bitcoin knowledge from 2017 to 2018, in contrast to the sizable increase previously observed between 2016 and 2017. In 2018, almost two-thirds of Canadians had low Bitcoin knowledge and only 6 percent answered all three questions correctly (Table 3). As expected, knowledge scores were higher among Bitcoin adopters. In particular, non-adopters were much more likely to answer "don't know" to a knowledge question (almost 50 percent) compared with Bitcoin adopters (less than 15 percent). However, Bitcoin knowledge was not universal even among those who owned the digital currency, with about one-fifth of adopters having low knowledge.

Consistent with the 2017 MOP Survey (Henry, Huynh and Welte 2018), we found that 27 percent of Canadians had low financial literacy and 36 percent had a medium level of financial literacy (Table 3). Moreover, 37 percent answered all three questions correctly, indicating high financial literacy. While the share of Canadians with high financial literacy may seem low, Canada has historically scored better than many other developed countries (Lusardi and Mitchell 2014).

2.3.2 Canadians' awareness of Bitcoin

Awareness of Bitcoin continued to increase in 2018, with 89 percent of Canadians stating they had heard of Bitcoin, compared with 83 percent in 2017 and 62 percent in 2016. Most demographic patterns observed in previous years persisted in 2018 (Table 4). In particular, Canadians who were male, young, university educated or had high household income were more likely to be aware of Bitcoin. However, gaps in awareness decreased as those groups who were less aware of Bitcoin in previous years became more aware in 2018. For example, awareness among males grew marginally from 90 to 93 percent, while awareness among females increased from 77 percent to 85 percent. Other examples of demographic groups catching up include those who have a high school education (76 to 84 percent) and those with household incomes below $30,000 (74 to 87 percent). Finally, as expected we found that higher financial literacy was associated with higher awareness.

2.4 A profile of Bitcoin adopters in 2018

In this section, we analyze the demographic composition of Bitcoin ownership in Canada. We also discuss cross-validation of our estimates using other surveys on Bitcoin adoption and we utilize regression analysis to drill down further on Bitcoin ownership. Moreover, we delineate the main reasons respondents gave for owning Bitcoin and we study how preferences over features of online transactions differed between Bitcoin adopters and overall Canadians. Further, we analyze the group of past owners and the changes in Bitcoin holdings amongst adopters. Lastly, we study the interplay between cash holdings and Bitcoin adoption, as well as Canadians' plans to go cashless.

2.4.1 Ownership of Bitcoin in 2018

Bitcoin ownership continued to increase in 2018; we estimate that 5 percent of Canadians owned Bitcoin in 2018, an increase from 4 percent in 2017 and 3 percent in 2016 (Table 5). However, Bitcoin ownership did not increase for all demographic groups. For instance, male ownership remained constant at around 6.7 percent, while female ownership increased from 2.1 to 3.7 percent. Similarly, ownership for those aged 18 to 34 remained relatively unchanged in 2018, while ownership tripled among those aged 55 and older from 0.5 to 1.7 percent.

In contrast, the disparity in ownership by education widened. Ownership among the high-school-educated demographic fell from 3.7 to 2.3 percent, while university-educated Canadians increased their ownership from 6.7 to 9.1 percent. Additionally, ownership fell from 4.3 to 2.8 percent among those with household incomes below $30,000 and rose from 4.3 to 7.0 percent among those with incomes above $70,000, creating an ownership gap that did not exist in previous years. Geographically, ownership in the Prairies and British Columbia continued to rise, while Quebec and the Atlantic region experienced a decline in ownership during 2018.

Bitcoin owners were more likely to have low financial literacy (38 percent), compared with the overall population (27 percent) (Table 3). In particular, we estimate that 4.1 percent of Canadians with high financial literacy owned Bitcoin, compared with 7.3 percent of those with low literacy. This yields an interesting result, as those with high financial literacy are more likely to have heard of Bitcoin but less likely to adopt it. Technology adoption among those with lower literacy has also been observed by Lusardi, Scheresberg and Avery (2018), who found higher financial literacy was negatively associated with using mobile payments.

The 2018 BTCOS also asked respondents to report if they owned alternative cryptoassets, which are often referred to as altcoins. We estimate that over half of Bitcoin adopters, or 3.2 percent of all Canadians, owned at least one altcoin. A further 1.6 percent reported owning altcoins but not Bitcoin. The most commonly owned altcoins were Bitcoin Cash (3 percent) and Ethereum (2 percent).

To cross-validate our estimates, we compare results with the Ontario Securities Commission (OSC), which surveyed over 2,500 Ontarians in March 2018 regarding their views on cryptoassets (Ontario Securities Commission 2018). This acts as a good source of external validation, as the OSC used a different survey provider and sampling methodology but included several of the same survey questions. The OSC estimates that 5 percent, or approximately 500,000 Ontario residents, owned Bitcoin and an additional 4 percent owned Bitcoin in the past. The BTCOS estimates the same for ownership (5 percent) and slightly lower for past ownership (3 percent). Similarly, the Canadian Consumer Payments Survey, conducted by Technology Strategies International, estimates that 3.9 percent of Canadians owned Bitcoin in 2019 (Technology Strategies International 2019).

Surveys from other countries on the adoption of Bitcoin provide another source of crossvalidation. Stix (2019) estimates 1.5 percent of Austrians owned Bitcoin in 2018. The United Kingdom's Financial Conduct Authority conducted a survey in 2018 and concluded Bitcoin ownership was 3 percent (Financial Conduct Authority 2019). Closer to home, in 2018 the Federal Reserve Bank of New York added several questions on cryptoassets to their Survey of Consumer Expectations and found that 85 percent of respondents had heard of cryptoassets, while 5 percent reported they currently or previously owned them (Hundtofte et al. 2019). Together, these other surveys provide evidence that the magnitude of our ownership estimates are reasonable.

2.4.2 Regression analysis of awareness and ownership

We complement our analysis of Canadians' awareness and ownership of Bitcoin by employing a logistic regression framework, which allows us to control for all demographics simultaneously. Being aware of Bitcoin and deciding to own Bitcoin are both binary events, making logistic regression a natural choice. In particular, we model choices as a sequential logit, where one first becomes aware of Bitcoin, then chooses whether to own it. In this way we can decompose demographic effects on ownership into these two stages. Table 6 reports our estimates of the awareness stage (column 1), ownership stage conditional on awareness (column 2) and overall ownership taking into account both stages (column 3). All estimates reported represent the marginal effect of each demographic variable on the outcome variable of interest, holding all other demographic variables constant.

In all three regression models, we include dummy variables for the following demographic variables: age, gender, region, education, marital status, employment and income. We also include dummy variables for responses to each financial literacy question. We have specified the model so that marginal effects are measured relative to the following reference groups: male, aged 18 to 24, from British Columbia, high school educated, married, employed full-time, earning income less than $25,000, and who have correctly answered each financial literacy question.

We find that the likelihood of Bitcoin awareness declines with age, being female and living in regions outside British Columbia. Conversely, we estimate Canadians are more likely to be aware of Bitcoin as their education and income increases, as well as if they answer any financial literacy question correctly. These findings are largely consistent with our unconditional, tabular analysis discussed in Section 3.2.

The second column displays our estimates of the probability of Canadians owning Bitcoin, conditional on being aware of it. Our results are consistent with our findings in the first column and our discussion in Section 4.1. In particular, we estimate that the probability of ownership, conditional on awareness, decreases with age and for Canadians living outside British Columbia. Conversely, we estimate that the likelihood of ownership increases with income and education, as well as with being unemployed. As we previously noted, we find that Bitcoin awareness increases with financial literacy but the likelihood of ownership decreases as financial literacy increases. This finding is also present in the logit framework, as all coefficients on the incorrect component of each financial literacy question became positive in the second column.

Finally, the third column of Table 6 reports our findings from the full sequential logit model. These estimates support our previous findings: that ownership decreases with age and location but increases with education and income. In particular, we estimate the likelihood of Canadians owning Bitcoin, conditional on holding all other demographics constant, is 8 percentage points lower if they are aged 55 or older than if they are between 18 and 24 years old. Similarly, we estimate Canadians are 3 percentage points more likely to own Bitcoin if they are university-educated as opposed to only graduating from high school, holding all other demographic variables constant. The most interesting finding is the net positive correlation between low financial literacy and Bitcoin ownership. For example, we estimate that failing to understand the diversification of risk is associated with an increase in the likelihood of Bitcoin ownership by 6 percentage points.

2.4.3 Why do Canadians own Bitcoin?

We study Canadians' usage of Bitcoin to pay for goods and services (Figure 2a) or to send peer-to-peer payments (Figure 2b). An overarching trend emerged in 2018 for both types of transactions: Bitcoin adopters are trending toward using Bitcoin more frequently for transactions. The observation is consistent with the increasing trend in aggregate Bitcoin transactions throughout 2018, reported in Figure 1.

Table 7 summarizes the share of adopters who reported each category as their primary reason for owning Bitcoin. In 2018, speculation decreased from 56 to 40 percent but remained the most selected option. Moreover, privacy-related reasons tripled to 19 percent and payments remained stable around 20 percent. Further, interest in the technology increased from 16 to 22 percent, approaching the level observed in 2016, prior to the large run-up in prices.

Henry, Huynh and Welte (2018) found that Canadians aged 18 or older made 82 percent of transactions with credit and debit cards in 2017. Similarly, Statistics Canada's Digital Economy Survey (DES) found that for 76 percent of their personal spending, Canadians used digital payment methods. Moreover, the DES found that almost 80 percent of Canadians purchased or used free versions of digital products, such as music, e-books, mobile applications and computer software (Statistics Canada 2018).

Given the upward trend of digitalization in commerce, we added a question in the 2018 BTCOS asking respondents to rank their preferences over four features of online transactions: privacy, security, ease of use and acceptance. Table 8 reports the share of Bitcoin owners and overall Canadians who ranked each feature from most to least important. Two clear trends emerge: typical Canadians value the security of online transactions much more than Bitcoin adopters, and Bitcoin adopters tend to have more varied preferences than typical Canadians. While Bitcoin adopters tend to prefer privacy almost twice as much as typical Canadians, a similar finding is present for the acceptance and ease-of-use features.

Further research is required to reconcile these results, as cryptoassets tend to be viewed as a form of privacy-enhancing technology. Moreover, cryptoassets have much lower acceptance rates by merchants and are significantly less easy to use than traditional payment methods, such as cash or contactless credit cards. As a result, one would expect Bitcoin adopters to rank privacy higher than all other features and place less emphasis on ease of use and acceptance. This finding is related to the privacy paradox, found by Athey, Catalini and Tucker (2017), which states that despite people saying they care about privacy, they are willing to relinquish private data for a relatively small incentive. The 2018 BTCOS results are related because Bitcoin adopters did not report valuing privacy significantly more than other features of online transactions, despite Bitcoin's pseudo-anonymous design.

2.4.4 Trends in past ownership of Bitcoin

We classify past owners as the group of Canadians who once adopted Bitcoin but have decided to stop owning it as of the time they are surveyed. As Figure 3 shows, around 2 percent of Canadians were past owners in 2016, and this share decreased to 1 percent in 2017 as Bitcoin's price rose. However, in 2018, after a dramatic drop in the price of Bitcoin, the share of past owners grew once again to 3 percent. Taken on face value, the fact that current and past ownership grew in 2018 suggests an influx of new Bitcoin owners who then quickly sold their Bitcoin in between the 2017 and 2018 surveys, and suggests that a total of 8 percent of Canadians have ever owned Bitcoin.

In 2018, almost 50 percent of past users reported one of three main reasons for not owning Bitcoin. Consistent with results from Section 3.1, the most common reason provided was that they do not understand enough about the technology. Other reasons included that they do not trust privately issued currencies, and that they do not believe the Bitcoin system will survive in the future.

Since the 2017 BTCOS was conducted, Canada has experienced two major incidents with cryptoasset exchanges: Edmonton-based Maple Change lost $6 million of users' funds in October 2018, and QuadrigaCX lost access to customers' funds in January 2019, resulting in losses over $260 million (Ernst and Young 2019). Furthermore, the Canadian Securities Association and the Investment Industry Regulatory Organization of Canada recently proposed a regulatory framework for cryptoasset exchanges and platforms. In light of these events, we will consider asking respondents if these events had an impact on their Bitcoin adoption in the next iteration of the survey.

2.4.5 Bitcoin holdings

We estimate the median amount of Bitcoin holdings in 2018 to be $600. The holdings question was asked differently in previous years, so for comparisons over time we group 2018 numbers into ranges, shown in Figure 4. We found a decrease in the share of Canadians who reported holding 1 to 10 Bitcoin and 10 or more Bitcoin, offset by a sizable increase in the share of Canadians who reported owning less than 1 Bitcoin. Together, these observations suggest that Canadian's median holdings, denominated in Bitcoin, decreased in 2018.

2.4.6 Cash holdings and plans to go cashless

Based on the results of the 2017 and 2018 BTCOS, as well as Henry, Huynh and Welte (2018), three different Canadian survey instruments yield the same conclusion: Bitcoin adopters hold more cash than typical Canadians (Table 9). The 2018 BTCOS estimates Canadians' median cash on hand to be \$40, while the subset of Bitcoin adopters have median cash holdings of \$200. Interestingly, the share of the population that reported currently holding no cash was stable at around 8 percent across all survey instruments and for both Bitcoin adopters and typical Canadians.

Motivated by Engert, Fung and Hendry (2018), who discuss the potential implications of a cashless society in Canada, the 2018 BTCOS included a question on whether respondents have stopped using cash or plan to stop in the future (Table 9). We found that Bitcoin owners were more likely to report having stopped using cash (18 percent) and having plans to go cashless within the next five years (17 percent). In comparison, the overall Canadian average was 7 percent and 5 percent, respectively.

Given this finding, an interesting puzzle emerges: Bitcoin adopters hold more cash than typical Canadians but are more likely to go cashless. This puzzle may be driven by a key distinction between interpretations of going cashless. That is, some Canadians may interpret being cashless as ceasing to use cash for transactions. Others may have a stronger interpretation: that, along with ceasing to use cash for transactions, being cashless implies one no longer holds cash for precautionary savings or as a store of value. The Bank of Canada plans to conduct further research on the transactional and non-transactional roles of cash in Canada.

2.5 Conclusion

Findings from the BTCOS suggest that between 2016 and 2018 the share of Canadians who were aware of Bitcoin increased from 62 percent to 89 percent and of those who owned Bitcoin increased from 3 percent to 5 percent. However, consistent with dramatic drops in Bitcoin prices in 2018, we also observed an increase in the number of past owners of Bitcoin, and those who continued to own Bitcoin did so in slightly smaller quantities. As in 2017, the main reason for owning Bitcoin remained as speculation, though this reason was less common in 2018. In contrast, Bitcoin owners reported using it more often for buying goods and services or making person-to-person transfers in 2018.

While overall ownership increased, this was not uniform across demographics. For example, while there was little change in ownership among men or those aged 18 to 34, ownership increased more among women and those aged 35 or older. Further, those with high education or household income have become much more likely to own Bitcoin than their counterparts with low education or income. Inspired by the work of Lusardi and Mitchell (2011), we included the "Big Three" financial literacy questions on the 2018 BTCOS. We found that, despite the fact that higher-literacy individuals were more likely to have heard of Bitcoin, they were less likely to own it.

New to the survey were questions related to cash and online payment preferences. We found that, while Bitcoin owners held more cash in their pockets at the median, they were more likely to say they had already stopped using cash. This presents something of a puzzle, which may be explained by how respondents interpret the phrase "stop using cash". For example, someone could claim to have stopped using cash at the point of sale, while still holding cash for precautionary purposes. Future surveys by the Bank of Canada will delve deeper into how respondents plan to use their cash for transactional or non-transactional purposes. We also asked respondents which features of online transactions they viewed as most important. Overall, Canadians rated security the most important feature, while privacy, acceptance and ease of use were much less common. The subset of Bitcoin adopters had much more varied preferences, with about an equal share of Canadians rating each attribute the most important.

Going forward, the Bank of Canada will continue to monitor the awareness and ownership of Bitcoin in Canada using the BTCOS. To address this goal, we will continue to improve the design of the BTCOS. Regarding our sampling methodology, for the next iteration of the BTCOS we are considering implementing a choice-based sampling procedure, as discussed in Cosslett (1981). This methodology involves over-sampling Bitcoin adopters, relative to typical

Canadians, and then taking into account the increased sampling probability in our weighting methodology. This approach will allow us to obtain more observations of Bitcoin adopters, to produce more granular analysis and to improve statistical precision while maintaining comparability across previous iterations of the BTCOS.

In addition, we may include several new survey questions in the next BTCOS to improve our understanding of Canadians' awareness and ownership. For example, we may ask Bitcoin adopters if they initially obtained their Bitcoin through a cryptoasset exchange, an automatic teller machine, mining, a peer-to-peer transaction or another source. Also, we may ask Canadians about their awareness of the proposed regulatory framework surrounding cryptoasset in Canada and whether the recent experiences involving cryptoasset exchanges have discouraged them from adopting Bitcoin. Such questions may provide evidence of a negative demand shock arising from the recent incidents involving cryptoasset exchanges in Canada. Finally, we may add questions concerning expected lotteries to elicit Canadians' preferences regarding risk. Our hypothesis is that Bitcoin adopters have a low degree of risk aversion relative to typical Canadians, as the price of Bitcoin has historically been very volatile.

Regarding the Bank of Canada's broader mandate, we will continue to monitor the interplay between Canadians' adoption of Bitcoin and their current and planned cash usage. Given its role as the sole issuer of currency in Canada, the Bank of Canada is also interested in understanding Canadians' adoption and usage of privately issued digital currency. One such form, known as stablecoins, is a form of digital money that is designed to maintain a fixed peg with an underlying currency or asset. Correspondingly, we may also study Canadians' views of the emergence this new type of privately issued digital currency and to what extent they would adopt this technology for payments.

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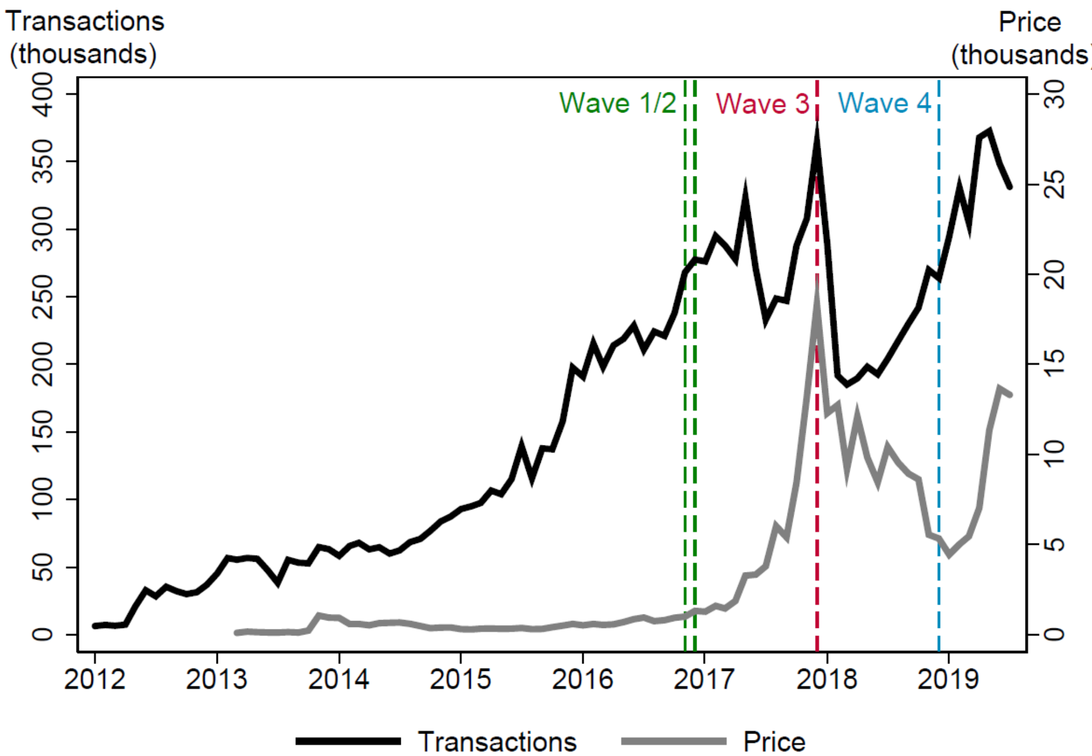
Tables and Figures

Figure 1: Price and number of Bitcoin transactions, 2012-19 (monthly average)

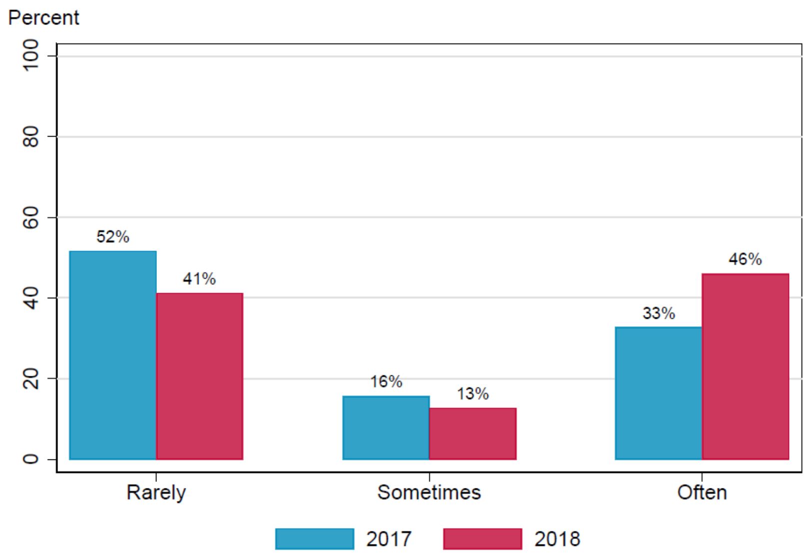


Note: This graph shows the price of Bitcoin in Canadian dollars and the number of daily transactions made with Bitcoin, averaged over each month from January 2012 to January 2019. The data series for price starts at March 12, 2013. The green vertical lines show when the first two waves of the BTCOS were in the field, the red vertical line shows the third wave and the blue line indicates the most recent iteration, the 2018 BTCOS. The last monthly observation is July 2019.

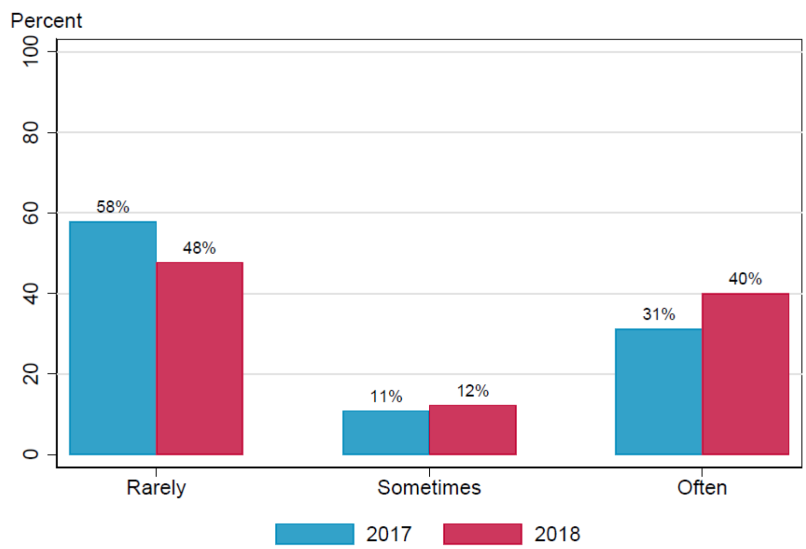
Sources: Daily Transactions (*Charts.Bitcoin.com/BTC*); Bitcoin Prices (BTC/CAD) (*Yahoo! Finance*).

Figure 2: Use of Bitcoin, 2017-18

(a) **Buying goods and services**

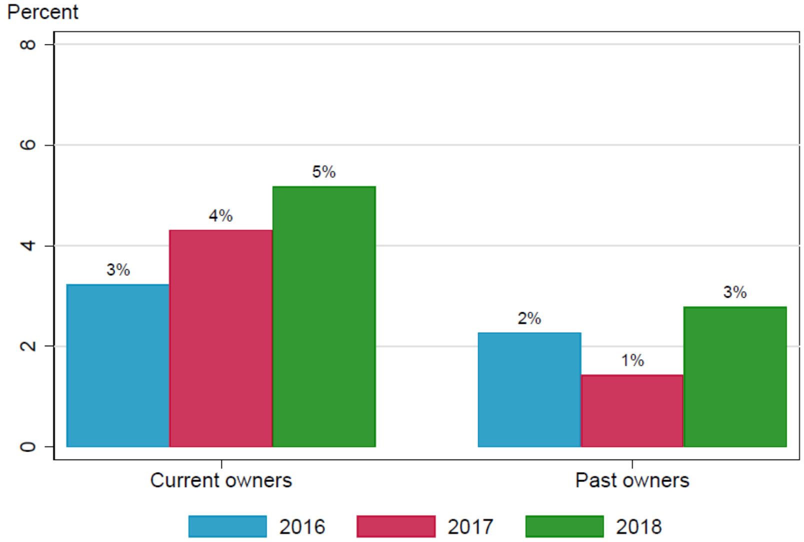


(b) **Making person-to-person transfers**



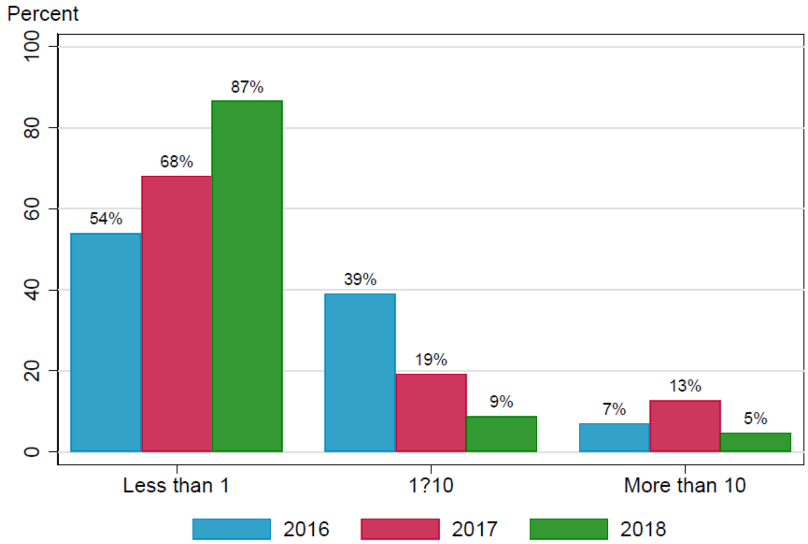
Note: The "Rarely" category consists of Canadians who used Bitcoin at most once a year for transactions. The "Sometimes" category constitutes those who used Bitcoin between a few times a year to once a month, and "Often" constitutes those who used Bitcoin at least a few times a month for transactions. The sample consists of 99 Canadians aged 18 or older who reported they owned Bitcoin in 2018; and similarly, 117 in 2017. All estimates were calculated using MICAL (multiple imputation in calibration) survey weights.

Figure 3: Current and past ownership of Bitcoin, 2016-18



Note: The sample includes 99 Canadians aged 18 or older who reported they owned Bitcoin in 2018; similarly, 117 in 2017, and 58 in 2016. Additionally, the sample includes 45 past owners in 2018, as well as 37 in 2017, and 41 in 2016. All estimates were calculated using MICAL (multiple imputation in calibration) survey weights.

Figure 4: Bitcoin holdings, 2016-18



Note: In 2018, we asked respondents 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 99 Canadians aged 18 or older who reported they owned Bitcoin in 2018; similarly, 117 in 2017, and 58 in 2016. All estimates were calculated using MICAL (multiple imputation in calibration) survey weights.

Table 1: **Bitcoin knowledge questions**

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

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

Table 2: **Financial literacy questions**

Concept	Question	Response options
Interest	*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** Exactly \$102 Less than \$102 Do not know
Inflation	*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
Risk	*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: This table reports the "Big Three" financial literacy questions, developed by Lusardi and Mitchell (2011). The "Big Three" questions have been used in many research papers to study financial literacy, including Henry, Huynh and Welte (2018), which yields comparability across survey instruments, countries and time. The correct answers are highlighted in bold.

Table 3: **Financial literacy and Bitcoin knowledge scores**

	Financial literacy		Bitcoin knowledge			
	2018		2017		2018	
	Overall	Adopters	Overall	Adopters	Overall	Adopters
Low	27	38	55	24	61	19
Medium	36	33	38	49	33	52
High	37	29	6	27	6	29

Note: This table reports the share of Canadians, in percent, in each category of financial literacy or Bitcoin knowledge. The sample consists of 99 adopters in 2018 and 117 in 2017. All estimates were calculated using MICAL (multiple imputation in calibration) survey weights.

Table 4: **Awareness of Bitcoin in Canada, 2016–18**

	2016	2017	2018
Overall	62	83	89
Gender			
Male	71	90	93
Female	54	77	85
Age			
18–34	69	87	91
35–54	58	82	88
55+	62	82	88
Education			
High school	55	76	84
College	59	85	90
University	78	92	95
Income ($)			
<30,000	49	74	87
30,000–69,999	61	82	88
70,000+	69	87	91
Region			
British Columbia	74	93	94
Prairies	66	84	89
Ontario	64	85	92
Quebec	49	75	84
Atlantic	65	80	83
Financial literacy			
Low	.	.	80
Medium	.	.	90
High	.	.	94

Note: This table reports the percentage of Canadians who were aware of Bitcoin in 2016, 2017 and 2018. The sample consists of 99 adopters in 2018, 117 in 2017 and 58 in 2016. All estimates were calculated using MICAL (multiple imputation in calibration) survey weights.

Table 5: **Ownership of Bitcoin in Canada, 2016–18**

	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 ($)			
<30,000	3.1	4.3	2.8
30,000–69,999	3.9	5.6	4.8
70,000+	3.7	4.3	7.0
Region			
British Columbia	2.8	5.2	6.3
Prairies	2.1	4.1	6.0
Ontario	2.5	3.9	5.2
Quebec	5.5	5.1	4.6
Atlantic	3.2	3.1	2.8
Financial literacy			
Low	.	.	7.3
Medium	.	.	4.7
High	.	.	4.1

Note: This table reports the percentage of Canadians who owned Bitcoin (answered"Yes" to "Do you currently have or own Bitcoin?") in 2016, 2017 and 2018. The sample consists of 99 adopters in 2018, 117 in 2017 and 58 in 2016. All estimates were calculated using MICAL (multiple imputation in calibration) survey weights.

Table 6: **Regression analysis of Bitcoin ownership**

	Pr(Aware)	**Pr(Own|Aware)**	**Pr(Own)**
Age			
25–34	-2.0	2.3	1.9
35–44	-3.9	-3.8	-3.7
45–54	-5.0 **	-7.3 **	-6.9 **
55–64	-5.0 **	-8.7 ***	-8.2 ***
65+	-4.2	-8.1 **	-7.6 **
Gender			
Female	-5.2 ***	-4.3 ***	-4.2 ***
Region			
Prairies	-2.9	0.1	-0.0
Ontario	-1.1	-0.7	-0.7
Quebec	-8.2 ***	-0.7	-1.1
Atlantic	-5.6 *	-1.2	-1.4
Education			
College	4.2 **	2.5 *	2.3 **
University	7.1 ***	3.4 **	3.3 ***
Martial status			
Single	4.3 ***	-1.7	-1.4
Employment			
Unemployed	-0.9	2.3	2.0
Not in labour force	0.6	-1.7	-1.6
Income ($)			
25,000–44,999	-1.3	1.6	1.4
45,000–64,999	1.2	3.4 **	3.1 **
65,000–84,999	1.1	4.4 **	4.0 **
85,000+	1.5	3.8 **	3.5 **
FL1 – Interest			
Incorrect	-1.5	3.6 *	3.2 *
Don't know	-8.4 ***	1.5	1.0
FL2 – Inflation			
Incorrect	-5.0 ***	1.5	1.1
Don't know	-0.4	-1.5	-1.4
FL3 – Risk			
Incorrect	-4.5	6.7 ***	5.7 **
Don't know	-5.8 ***	-0.0	-0.2

Note: This table displays marginal effects from a sequential logit of Bitcoin awareness and ownership. Column **Pr(Aware)** shows the effect of each variable on the probability of having heard of Bitcoin. Column **Pr(Own|Aware)** shows the effect of each variable on the probability of owning Bitcoin conditional on having heard of it. The final column shows the overall net effect on the probability of ownership given that Pr(Own) = Pr(Own|Aware)*Pr(Aware). FL1, FL2, and FL3 refer to the three financial literacy questions listed in **Table 2**. *** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$. Missing values for employment and income are multiply imputed using the model described in **Section A.2.6**.

Table 7: **Main reason for ownership, 2016–18**

	2016	2017	2018
Payment related	45	23	19
Store of value (investment)	6	56	40
Trust/privacy related	16	5	19
Technology related	33	16	22

Note: This table reports the percentage of Canadians who chose each category as their primary reason for owning Bitcoin in 2016, 2017 and 2018. Each column sums vertically but may sum to less than 100 percent, as we have omitted some options when consolidating the four categories. The sample consists of 99 adopters in 2018, 117 in 2017 and 58 in 2016. All estimates were calculated using MICAL (multiple imputation in calibration) survey weights.

Table 8: **Preferences for online transactions, Canadians vs. adopters**

	Overall Canadians				**Bitcoin adopters**			
	Privacy	Security	Acceptance	Ease	Privacy	Security	Acceptance	Ease
Most	14	61	11	15	26	28	20	26
More	39	19	20	22	26	28	20	26
Less	22	12	29	37	22	26	29	23
Least	25	8	40	26	26	18	31	25

Note: This table shows the percentage of Canadians who ranked each feature of online transactions, from most to least important. The estimates in each column sum vertically to 100 percent. The sample consists of 99 adopters in 2018, 117 in 2017 and 58 in 2016. All estimates were calculated using MICAL (multiple imputation in calibration) survey weights.

Table 9: **Cash management and Bitcoin adoption, 2017–18**

	Median ($)	No cash on hand (%)	Already cashless (%)	Plans to go cashless within 5 years (%)
Overall				
2017 MOP	40	9	.	.
2017 BTCOS	40	8	.	.
2018 BTCOS	40	8	7	5
Adopters				
2017 MOP (4.0%)	65	8	.	.
2017 BTCOS (4.3%)	100	4	.	.
2018 BTCOS (5.2%)	200	8	18	17

Note: We report results from three surveys conducted by the Bank of Canada: the 2017 BTCOS, the 2018 BTCOS and the 2017 Methods-of-Payment (MOP) Survey. The sample consists of 99 adopters in 2018 and 117 in 2017. All BTCOS estimates were calculated using MICAL (multiple imputation in calibration) survey weights and the 2017 MOP estimates used survey weights as well.

A Appendix

A.1 2018 BTCOS survey instrument

```
1a. Have you heard of Bitcoin?
Yes No
[IF YES TO Q1, ASK Q1b, ELSE SKIP TO Q5]

1b. Please indicate whether the following statements about Bitcoin are
true or false. If you are unsure, please select ‘‘Don’t know’’.

[COLUMNS]
True
False
Don’t know

[ROWS: RANDOMIZE]
The total supply of Bitcoin is fixed. [True]
Bitcoin is backed by a government. [False]
All Bitcoin transactions are recorded on a distributed ledger that
is publicly accessible. [True]

2. Do you currently have or own any Bitcoin?
Yes No

[IF YES TO Q2, ASK Q3a and Q3b, ELSE SKIP TO Q4a]
3a. Please tell us your main reason for owning Bitcoin.
(Select one)
[RANDOMIZE LIST]
I am interested in new technologies
It is an investment
I use it to buy goods and services on the internet in Canada/elsewhere
I use it to buy goods and services in physical stores in Canada/elsewhere
It allows me to make payments anonymously
I use it to make remittances or other international payments
It uses secure blockchain technology to prevent loss and fraud
I do not trust banks
I do not trust the government or the Canadian dollar
```

A Appendix

A.1 2018 BTCOS survey instrument

1a. Have you heard of Bitcoin?

Yes No

[IF YES TO Q1, ASK Q1b, ELSE SKIP TO Q5]

1b. Please indicate whether the following statements about Bitcoin are true or false. If you are unsure, please select ‘‘Don’t know’’.

[COLUMNS]

True

False

Don’t know

[ROWS: RANDOMIZE]

The total supply of Bitcoin is fixed. [True]

Bitcoin is backed by a government. [False]

All Bitcoin transactions are recorded on a distributed ledger that is publicly accessible. [True]

2. Do you currently have or own any Bitcoin?

Yes No

[IF YES TO Q2, ASK Q3a and Q3b, ELSE SKIP TO Q4a]

3a. Please tell us your main reason for owning Bitcoin.

(Select one)

[RANDOMIZE LIST]

I am interested in new technologies

It is an investment

I use it to buy goods and services on the internet in Canada/elsewhere

I use it to buy goods and services in physical stores in Canada/elsewhere

It allows me to make payments anonymously

I use it to make remittances or other international payments

It uses secure blockchain technology to prevent loss and fraud

I do not trust banks

I do not trust the government or the Canadian dollar

My friends own Bitcoin
It is a cost saving technology
[ANCHOR] Other (specify)

3b. What is the value, in Canadian dollars, of the Bitcoin you currently own?
(Please round off to the nearest dollar)
[INSERT NUMERIC BOX]
$ _____ CAD
Unsure/would rather not say

[IF NO TO Q2, ASK Q4a and Q4b, ELSE SKIP TO Q5]
4a. Have you owned or used Bitcoin in the past, but subsequently stopped using it?
Yes No

4b. Please tell us your main reason for not owning any Bitcoin.
[RANDOMIZE LIST]
I do not understand/know enough about the technology
It is not widely accepted as a method of payment
My current payment methods meet all my needs
The value of Bitcoin varies too much
It is not easy to acquire/use
I do not trust a private currency that is not backed by the central government
I am concerned about cyber theft
I am concerned about lack of oversight from regulatory bodies
I use alternative digital currencies instead (e.g. Dogecoin, Litecoin, Ripple,etc)
I do not believe the Bitcoin system will survive in the future
[ANCHOR] Other (specify)

[ASK ALL]
5. Please rank the following features from 1-4 in terms of how important they are for making payments online via the internet ("1" = most important, "2" = 2nd most important, etc.).
[RANDOMIZE] [DROP DOWN BOX BESIDE EACH ITEM. EACH NUMBER CAN ONLY BE USED ONCE]
Privacy/anonymity
Security

Widely accepted
Ease of use

[IF NO TO Q1, SKIP TO Q12 ELSE CONTINUE]
6a. How likely do you think it is that the Bitcoin system will fail or survive in the next 15 years?
Please use the sliding scale where 0 means that the system will certainly fail and 100 means the system will certainly survive.
[INSERT SLIDING SCALE WITH WORD ANCHORS]
[DO NOT PUT THE NUMBER 0 OR 100 WITHIN THE WORD ANCHOR BOX]

6b. What percentage of Canadians do you predict will be using Bitcoin 15 years from now?
Please use the sliding scale where 0 means no Canadians will be using Bitcoin and 100 means all Canadians will be using Bitcoin.
[INSERT SLIDING SCALE WITH WORD ANCHORS]
[DO NOT PUT THE NUMBER 0 OR 100 WITHIN THE WORD ANCHOR BOX]

7a. What is the current price of Bitcoin?
Please provide your best estimate in Canadian dollars.
Please round to the nearest dollar.
[INSERT NUMERIC BOX]
1 BTC = $ _____ CAD

7b. The current price of one Bitcoin is around $4,649 [INSERT RELEVANT PRICE EACH MORNING WHILE THE SURVEY IS IN THE FIELD] Canadian, as of this morning. What do you expect the price of Bitcoin to be in one month?
Please provide your best estimate in Canadian dollars.
Please round to the nearest dollar.
[INSERT NUMERIC BOX]
1 BTC = $_____ CAD

8. Do you hold any of the following other digital currencies?
(Please check all that apply) [RANDOMIZE LIST]
Ethereum
Bitcoin Cash
Ethereum Classic

Litecoin
Dash
Ripple
[ANCHOR] Other (please specify) [PROVIDE TEXT BOX FOR RESPONSE] [DO NOT CODE]
[ANCHOR] No, do not hold any other digital currencies

9. Approximately how often do you use Bitcoin to pay for goods and services?
(Please select the most appropriate response)
Once a week or more
A few times a month
Once a month
A few times a year
Once a year
I have used Bitcoin to pay for goods and services once or twice,
    but not on a regular basis
I have never used Bitcoin to pay for a good/service

10. Approximately how often do you use Bitcoin to send money to other people?
(Please select the most appropriate response)
Once a week or more
A few times a month
Once a month
A few times a year
Once a year
I have used Bitcoin to send money to other people once or twice,
    but not on a regular basis
I have never used Bitcoin to send money to other people

[ASK Q11a IF YES TO Q2 OR IF NO TO Q8, ELSE SKIP TO Q12]
11a. In the past 12 months, what percentage of your total personal spending
was made with cryptocurrencies?
[INSERT NUMERIC BOX]%

[ASK Q11B IF Q11a DOES NOT EQUAL ZERO, ELSE SKIP TO Q12]
11b. In the past 12 months, how much cash value did you spend in
cryptocurrencies?
$[INSERT NUMERIC BOX]

[ASK ALL]
12. Thinking now about regular Canadian currency, how much cash do you currently have in your purse, wallet, or pockets? (Please include dollars and cents)
$_____________.___

13. 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
Exactly the same
Less than $102
Don't know

14. 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
Don't know

15. 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
Don't know

16a. How would describe your current credit rating? If you don't have a sense of what your credit rating would be, please select "Not Sure".
Very poor (500 or less)
Poor (500-550)
Fair (551-640)
Good (641-720)
Excellent (721 or more)

Not sure

[IF NOT SURE TO Q16a, SKIP TO Q17 ELSE CONTINUE]
16b. If you know your exact credit score, please write it in:
[PROVIDE NUMERIC INPUT BOX]PRANGE 0-999]
Not sure

17. Do you currently have any plans to stop using cash in the future?
No, I do not have any plans to stop using cash
Yes, I have already stopped using cash
Yes, in the next 12 months
Yes, 2 to 5 years from now
Yes, more than 10 years from now
I'm not sure

[IF YES TO Q2 AND RESPONDENT IS FROM AMPARIO SAMPLE, ASK Q18, ELSE SKIP TO NEXT SECTION]
18. We may have other studies coming up in the near future about Bitcoin usage. Those who participate will receive a monetary incentive as a token of our appreciation. May we contact you with an invitation to future surveys?
Yes
No

[IF YES TO Q18 AND RESPONDENT IS FROM AMPARIO SAMPLE, ASK Q19, ELSE SKIP TO NEXT SECTION]
19. Please type in your name and the email address you would like us to use to contact you.

[INSERT TEXT BOX FOR NAME AND EMAIL ADDRESS]

3 Cash in the pocket, cash in the cloud: cash holdings of Bitcoin users

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3.1 Introduction

What would a cashless society look like? In an era of rapid developments in financial technology (FinTech), not to mention constraints imposed by a global pandemic, it is hard not to wonder whether cash is – or should be – disappearing. Central banks have a keen interest in the use of cash for a variety of reasons, most notably as a mechanism for revenue (seigniorage), but also in relation to issues such as financial literacy, payment systems efficiency, financial inclusion, etc. In Canada, there has been a documented decline in the use of cash by consumers for making payments over the last decade. The Bank of Canada's 2017 Methods-of-Payment survey reports that the share of cash used for retail transactions declined from 54% in 2009 to just 33% in 2017 (Henry et al. (2018b)). Even so, cash remains popular among certain demographic groups and for certain types of transactions, and is still commonly used as a convenient store-of-value. Bagnall et al. (2016) document an international comparison of cash usage, showing that cash is surprisingly resilient across the world.

That said, certain countries such as Sweden are facing the imminent reality that cash may not be around for much longer, due primarily to a lack of consumer demand for the product (see: Sveriges Riksbank (2017, 2018a, 2018b); or, Engert et al. (2019)). The prospect of a cashless society is driving a flurry of research and policy analysis into so-called Central Bank Digital Currency (CBDC) – a digital form of central bank money. Should central banks issue CBDC in response to the decline of cash? The question is complicated by the fact that privately-issued digital currencies, such as Bitcoin, are already widely available on the market (Kovanen (2019)). However, while Bitcoin certainly enjoys a high degree of interest in the popular culture, it and similar digital currencies have yet to reach widespread adoption. Along with a lack of consumer demand, certain voices have long argued vigorously for an *active* program to end cash (the so-called ‘War on Cash’). In their view, cash is seen as promoting illicit activities (Rogoff (2016)) or reducing the efficiency of the payment system overall (Van Hove (2008)), and therefore should be eliminated.

Two key considerations are relevant to inform the likelihood of transitioning to a cashless society and the potential implications of a CBDC. First, 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 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, 2009); 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 (Bohme et al., 2015). However, the stunning increase in the price of Bitcoin – from late 2016 to 2017 the price of a Bitcoin rose from $1,000USD to a peak of almost $20,000USD – has led many to reassess whether Bitcoin should instead be considered as something more akin to a ’cryptoasset’ than a cryptocurrency. Others, including Nobel Prize-winning economist Joseph Stiglitz, have gone further in suggesting that Bitcoin is nothing more than a speculative bubble that will ultimately burst. It should be noted that the payment versus store-of-value question is not unfamiliar to those who study cash. There has been a longstanding puzzle as to why, in many countries across the world, banknotes in circulation continue to grow at pace with GDP – while at the same time cash use for payments is declining (c.f. Hsiao et al. (2005).)

The second consideration is the role of consumer preferences in driving the demand for cash and alternatives; the introduction to Van Hove (2005) provides a nice discussion in this vein. What characteristics of cash do consumers value, and would these translate to cash in a digital form? Put more succinctly, do consumers actually want a digital form of cash? 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. In Canada, the national debit card network (Interac) has provided an increasingly popular online ‘e-Transfer’ service, facilitating easy person-to-person or person-to-business transactions via email/text message. This service already meets the digital transaction needs for many Canadians, as evidenced by an adoption rate of well over half – 57% of Canadians reported using e-Transfer at least once in the past year in 2017 (Henry et al. (2018b)). Furthermore, consumers are heterogeneous in their preferences. The OECD has documented a persistent digital gender divide across the world due to various factors (OECD (2018)). Bannier et al. (2019) confirm a gap in Bitcoin literacy specifically, in the US, and find the gap exists even after controlling for level of experience with digital technology. For whatever reason, it seems that women do not participate as actively as men when it comes to adoption of digital technologies, which begs the question: What good is a digital form of cash if only half the population is willing to adopt?

To better understand consumer adoption and use of Bitcoin, the Bank of Canada commissioned the Bitcoin Omnibus Survey (BTCOS) in 2016 (Henry et al. (2017)); the survey has been running annually in subsequent years (Henry et al. (2018a); Henry et al. (2019)). The BTCOS was among the first in terms of consumer focused surveys dedicated to Bitcoin, inspired by other early work on the topic such as Schuh and Shy (2016), and Polasik (2015). In the current paper, we use data from the 2017 BTCOS consisting of survey responses from 2,623 Canadians, selected from an online panel and post-stratified to be representative of Canadian consumers with respect to age, gender and region. The survey asks about: respondents' overall awareness of Bitcoin, ownership and level of Bitcoin holdings, reasons for ownership/non-ownership, use of Bitcoin for making payments or other transfers, ownership of other cryptocurrencies, knowledge of the features of Bitcoin as a technology, future expectations on the survival / adoption level of Bitcoin, level of cash holdings. In addition the survey collects standard demographic information about each respondent.

The year 2017 was particularly notable for Bitcoin for several reasons. For one, as mentioned previously, the price of Bitcoin reached a peak in late 2017 of almost $20,000USD; this peak happened to coincide with when the BTCOS was in the field. The survey results certainly reflect this timing. Awareness of Bitcoin among Canadians increased to 83%, from 62% in 2016. Further, a majority of Bitcoin owners cited investment related reasons for holding

Bitcoin, a shift from 2016 wherein payment related reasons were most popular. In addition, cryptocurrencies received increased attention from investment and government institutions in 2017. For example, Japan issued laws requiring cryptocurrencies to register with the financial services agency. By June 2017, Goldman Sachs had started to cover Bitcoin in their market division, while at the end of October the Chicago Mercantile Exchange began issuing Bitcoin derivatives.

The 2017 iteration of the BTCOS included a new question designed to measure consumer cash holdings of Canadians (i.e., cash held in the person's wallet, purse, or pockets). 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; it also corroborates a similar finding by Fujiki and Tanaka (2014). However, it also raises questions about how to properly interpret this fact; more specifically, whether there may be factors driving both cash holdings *and* Bitcoin ownership. This simultaneity may potentially drive selection into holding Bitcoin, for which there are several plausible explanations: 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, the goal of this paper is to estimate the effect of Bitcoin ownership on the level of consumer cash holdings. In doing so, we also examine whether any distributional effects are present, and explore how consumer preferences may account for the relationship between cash holdings and Bitcoin ownership. To account for potential endogeneity due to selection, the BTCOS was designed with instrumental variables in mind. Here, we employ the question on expected future adoption: *"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 current level of cash holdings. With instrument in hand, we address the endogeneity of Bitcoin ownership using two different methods: via propensity score weighting and via control function approach. Finally, we estimate quantile models using a control function approach to investigate whether Bitcoin ownership has varying affects at different levels of cash holdings.

In the first stage of estimation, we find that age, gender and employment status are significant predictors of Bitcoin ownership. Adding our proposed instrument into the model produces superior predictability based on logit specification tests, and the coefficient is both economically and statistically significant in its positive correlation with cash holdings.

In the second stage, a baseline model which does not take into account selection shows that switching from being a non-owner to an owner of Bitcoin increases cash holdings by 143%. However, controlling for endogeneity via the two methods described above yields consistent results: the effect of Bitcoin ownership is still significant, but smaller, ranging from 95% to 104%. Quantile estimates show that the effect of Bitcoin ownership is highly non-linear. There is little difference in cash holdings between owners and non-owners of Bitcoin at lower quantiles, whereas the difference is large and increasing starting with the 25 percentile (about 80%), reaching about 183% at the 90 percentile of cash. Correcting for selection in the quantile models reduces the impact of Bitcoin ownership at higher quantiles.

Next, we quantify the effects of a set of preferences that are relevant for Bitcoin adoption on amounts of Bitcoin holdings. We find that the observed heterogeneity of these preferences for Bitcoin adoption become indistinguishable. This suggests that at this time we cannot answer in a meaningful way whether Bitcoin is technically a complement or substitute for cash.

Finally, we do a series of robustness checks of our results. We first address whether missing data associated to our instrument (about 15% of the data is missing at random) has any impact by performing imputation and then redoing our analysis. The results are not statistically different after applying this missing data correction. We also checked what drives the observed selection changes at high quantiles of cash by employing a counterfactual analysis that looks at gender differences in knowledge about Bitcoin. We found that at high quantiles of cash, female Bitcoin owners have similar knowledge about Bitcoin as males. This equivalence result explains both the selection of Bitcoin ownership associated to the high quantiles of cash and the lack of significance between males and females at high quantiles of cash.

3.2 Data

We based our analysis on the 2017 Bitcoin Omnibus Survey (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, which is the core of our analysis, extended the 2016 survey by adding questions that were used to identify the reasons for holding Bitcoin. The two important questions of the 2017 survey 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.

Between 2016 and 2017 there was a shift in reasons for holding Bitcoin; in 2016 the reasons for holding Bitcoin were for transnational purposes and the new technology associated with it, wile in 2017 the weight shifted towards investment interests (see Henry et al ., 2017 and 2018). Also, in 2017, the awareness of Bitcoin reached 85 per cent while ownership was only at 5 percent. However, compared to 2016 when ownership was at 2.9 percent, the jump in ownership over an year was almost 75 percent and was driven by new entrants in the Bitcoin market that got awareness in the past year. The transition towards Bitcoin was driven also by the higher test score on knowledge that both owner and no owners have compared to the similar groups from 2016. These information about new owners and past owners suggest that selection into Bitcoin ownership is an important mechanism that one needs to take into consideration when the relationship of Bitcoin ownership is linked to cash holdings.

The chosen sample for the 2017 BTCOS was post-stratified by region, age and gender to match the population totals observed in the 2016 Canadian census, comprising of 2623 individuals answers. 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 fallow up to one in 2013). While this survey, focused on methods of payments had an important question that relates to the outcome of interest in this analysis (the cash on hand), but also one about no cash. Additionally, these questions also are addressed to Bitcoin adopters (both current and past owners) and those that used digital currency at least once in the past year. What we can see from both surveys (BTCOS and MOP) is that there is a big difference between Bitcoin adopters and non adopters in terms of cash holdings (the adopters of Bitcoin an average hold at least three time 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 increased also from 84 dollars in 2013 to 105 in 2017, increase probably driven by increase in holding of higher notes (see Table 1).

A look at the demographics of Bitcoin owners versus non owners (see Table 2) shows that owners are dominated by young employed males. In particular looking at the within group numbers we see that for owners, the age group 18 to 24 represents 63 percent of the owners, while for the age group 34 to 64, 32 percent are owners, the remaining Bitcoin owners (5 percent) are above 64 years old. Also, we see that 73 percent of the owners are males and 85 percent of the owners are employed (see Table 2). There is no difference between Bitcoin holders and non holders in terms of income. If we look at the cash side we see that the Bitcoin owners hold about 4 times more cash than non owners (for the young and mid age categories) and about 40 percent more cash for the highest age category. 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 results is that the unemployed Bitcoin owners hold with 30 percent 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 to 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 1) 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). 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 Bitcoin owners 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.

3.3 Identification strategy

The identification of the relationship that links the cash holdings to Bitcoin adopters builds on the information available in the Bitcoin Omnibus Survey (2017 BTCOS), characteristics of the data and the interactions that are 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, while the initial submission of the survey was random, the collected answers were not random. Therefore, the identification strategy should consider the selection into answering, which can be a source of endogeneity.

In particular, we already saw from summary statistics that Bitcoin users hold more cash comparing with non Bitcoin users. This raises the possibility that in the data may be some simultaneity that links cash holding and Bitcoin ownership due to the anonymity of both. This simultaneity, may potentially drive selection into holding bitcoin as Bitcoin can be used as a hedge for anonymous liquidity; additionally another selection mechanism may be also linked to the fact that some of 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. Additionally, for robustness, we propose an alternative method that corrects for this selection (we employ program evaluation techniques based on Inverse Probability Weighting) The control function approach is further used to quantify the effect of Bitcoin ownership on quantiles of cash.

The control function requires for identification an exclusion restriction. The BTCOS 2017 survey was designed to have a question that addresses the need for this exclusion restriction. The variable is based on the question that quantifies the beliefs about adoption of Bitcoin in 15 years: Expected adoption rate (EAR15)[4]. The EAR15 cannot be correlated to current cash holdings, but it is correlated with Bitcoin ownership as most of the current owners of bitcoin believe in the future of the bitcoin. The proposed program evaluation technique is suggested as an alternative in case an exclusion restriction is not available from the survey data and to check if using two roads for identification are leading us to similar results. Two types of hypotheses that link Bitcoin ownership to cash holdings are tested.

3.3.1 First Hypothesis of Interest

A 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:

$$Cash_i = \alpha + \beta Btc_i + \gamma X_i + \delta P_j + u_i,$$

where $Cash_i$ is the log of cash holdings of individual i, Btc_i is an indicator for the treatment

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

(takes the value of 1 if the individual is Bitcoin owner and zero otherwise), X_i is a set of individual characteristics named above, and P_j are province fixed effects.

Endogenous Selection

As the estimated parameter of interest may suffer from the potential bias due to endogeneous selection on Bitcoin ownership we consider three alternative approaches that are addressing this issue.

1. Correction via Propensity Score Firstly, we assume that there is no instrument available in the data. In this case we can base the identification of the selection effects by estimating an Average Treatment Effect (ATE) that measures the difference $E(Cash|Btc, X) - E(Cash|No{-}Btc, X)$ by employing an Adaptive Inverse Propensity Score Weighting (IPSW) approach. The IPSW is based on the Inverse Probability Weighting introduced by Horvitz and Thompson (1952) to address the nonrandom sampling problems associated to policy evaluation. More recently, the IPW approach was introduced in the treatment effects literature by Wooldridge (2002) and Hirano et al. (2003). A positive ATE will not reject the H_{01}. This procedure requires the existence of a propensity score ($0 < PS = Pr(Btc_i = 1|X_i, P_j) < 1$), which is the probability of holding Bitcoin conditional on observed demographics and province fixed effects. This method of identification of the ATE is useful for two reasons: firstly, by weighting the observations it corrects the problem of data selection allowing for designs with a disparate sampling population and targeted population and secondly, the inverse probability weighting can also be used to account for missing data when subjects with missing data cannot be included in the primary analysis, in this case the inverse probability weighs can be used to inflate the weight for subjects who are under-represented due to a large degree of missing data. By employing the inverse propensity score weighting, we can identify ATE as follows:

$$ATE = \mathbb{E}\left[\frac{Cash \times Btc}{PS} - \frac{Cash \times (1 - Btc)}{1 - PS}\right],$$

where PS is the propensity score or in other words the probability of selecting to be a Bitcoin holder given the individual observables X_i and province fixed effects P_j. The estimated treatment effect is obtained by replacing the PS with an estimate obtained via an adaptive procedure as in Weber et al. (2019) as the adaptive procedure provides an improved estimate of the final matching rate.

2. Correction via Control Function (CF). The CF approach , firstly introduced by Heckman and Robb (1985), corrects the endogenous selection by modeling the endogeneity in the error term using a two stage estimation procedure as it requires an exclusion restriction for identification of the impact of Bitcoin ownership on individual cash holdings. In the first stage the endogeneous variable is projected on an exclusion restriction and a set of observed characteristics at individual and province level:

$$Btc_i = Pr(Z_i, X_i, P_j) + \epsilon_i,$$

where Z_i is the exclusion restriction, which is a variable that is correlated with the endogenous variable but not correlated with the error on the main equation, here we consider Z_i to be the EAR15. The 15 years adoption rate of Bitcoin cannot be correlated to current cash holdings, but it is correlated with Bitcoin ownership as most of the current owners of bitcoin believe in the future of the bitcoin. In other words the Bitcoin expected adoption rate can work as a clean separator between the Bitcoin holders and non owners. Indeed, a CDF plot of Bitcoin expected adoption rate for the Bitcoin owners versus non owners (Fig. 2), shows that the two distributions do not intersect [5]and therefore the Bitcoin expected adoption rate acts as a clear separation between the two groups. Also, there is no obvious direct relationship of the expected adoption rate of Bitcoin with current level of cash holdings. Consequently, the 15 years expected adoption rate can be used as an exclusion restriction (IV) tool necessary for the identification of the Probability of Bitcoin ownership. The exclusion restriction also satisfies the conditional independence assumption as in Abadie, Angrist, and Imbens (2002).

The residuals from this stage (CF) are further used as a correction term in the second stage

[5]In particular looking at the median of the distribution we see that non owners believe that expected adoption rate will be around 30%, while owners believe that the expected adoption rate will be around 60%.

that defines the main equation of interest. As the endogenous variable is binary we have to choose appropriate residuals (that are not correlated with the error in the main equation) and have statistical properties that are similar with the ones used in 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 as their distribution is closer to the distribution of residuals from the least squares regression models. The deviance residual (CF) is computed as fallows:

$$CF = devresid(\widehat{Btc_i}) = sign_i\sqrt{-2(Btc_i \log(Pr(\widehat{Z_i, X_i}, P_j)) + (1 - Btc_i)\log(1 - Pr(\widehat{Z_i, X_i}, P_j))},$$

where $sign_i$ is positive if Btc_i takes the value of one and is negative if Btc_i takes the value of zero. The testable hypothesis in this case is:

$$H_{01}^{'} : E(Cash|Btc, E[Adopt], X, P) > E(Cash|No - Btc, E[Adopt], X, P),$$

where , $E[Adopt]$ is the EAR15 variable. 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:

$$Cash_i = \alpha + \beta Btc_i + \gamma X_i + +\delta P_j + \phi CF_i + u_i.$$

3.3.2 Second Hypothesis of Interest

As the distribution of the outcome (cash holdings), as seen in Figure 1, 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:

$$Q_{Cash}(\tau)_i = \alpha^\tau + \beta^\tau Btc_i + \gamma^\tau X_i + \delta^\tau P_j + u_i^\tau.$$

This model can be viewed as a conditional quantile treatment effects type model. The underlying assumption required for identification of the quantile treatment effects is that the errors are orthogonal to the treatment (Btc indicator) and the selection on observables is exogenous.

Endogenous selection at the quantile level

An alternative way at quantifying the quantile effects in the presence of endogenous selection is to test the following hypothesis:

$$H_{02}^{'} : Q_\tau(Cash|Btc, E[Adopt], X) > Q_\tau(Cash|No - Btc, E[Adopt], X),$$

where, the Bitcoin holders are entering in the quantile equation also via a control function as suggested in the linear specification above.

This hypothesis is thesited via the following equation:

$$Q_{Cash}(\tau)_i = \alpha^\tau + \beta^\tau Btc_i + \gamma^\tau X_i + \delta^\tau P_j + \phi^\tau CF_i + u_i^\tau.$$

where CF is the deviance residual from the $Pr(Z_i, X_i, P_j)$ estimation.

3.4 Results

To test our hypotheses of interest we group the discussion of the results on four separated parts. To test the first hypothesis of interest we require to estimate a linear model of log of cash holdings on our variable of interest (Bitcoin ownership), demographic charactersistics and province fixed effects. However, to control for the endogenous selection we need to augment this model with a correction term that require the estimation the probability of Bitcoin ownership. Consequently, we start the presentation of the results with the extensive margin analysis that quantifies the effects of the demographics and province fixed effects on the probability of holding Bitcoin. This analysis matches with the estimation of the propensity score required in the AIPW methodology. 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 to 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 (2002).

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. Forth, to understand the factors that drive not only the ownership of Bitcoin but also the amounts of Bitcoin the holders chose to have, we quantify the effects of different preferences associated to Bitcoin ownership on the amounts of Bitcoin the owners chose to have. For this analysis we use the questions in BTCOS 2017 survey that are linked to preferences which are grouped in four categories: non trust in institutions, technology related, payment related and investment related.

3.4.1 Extensive Margin

The results are presented in Table 3. The first column refers to the results of the probability of Bitcoin ownership when accounting for demographic characteristics and province fixed effects, the second column augments the model with the EAR15 variable, the third and forth columns are equivalent models but are accounting for the possibility that Bitcoin ownership to be a rare event. While in Table 3 we present the estimated parameter form all these probability models, in the appendix (Table 11) we report the associated marginal effects for the first two columns from Table 3 as the models that account for the possibility that Bitcoin is a rare event in the data provide very close results with the equivalent logit models. Consequently, the correction for rare events does not provide any additional information and we will continue the analysis using as main results for the extensive margin analysis the first two columns from Table 3. The results emphasize the role of gender, age, employment status , number of kids and the type of grocery shopping on Bitcoin ownership, while only two provinces (Prairies and Atlantic) have a significant different impact when compared to the benchmark, British Columbia province. In particular, the age, being female, having kids and being from Prairies or Atlantic provinces have a significant negative impact on the Bitcoin ownership, while being employed has a positive effect on Bitcoin ownership.

When we augmented the model with the EAR15 variable (column two of Table 3) we observe the predictability power of this exclusion restriction as it increases the probability of Bitcoin ownership. We see that the model that augments with EAR15, has a smaller sample size (15% smaller) due to the fact that some of the respondents did not answer to this question. We check if the reduced sample suffers from additional selection issues, by checking if the average observables are significantly different in the two samples. The results are presented in Table 12 from the appendix. These results show that there is no additional selection due to non-answering the EAR15 question.

Given the fact that only 5 percent of the sample represents the owners of Bitcoin (117 observations), we check if each cell associated to the variables used in the analyses have sufficient observations to do a proper analysis. Table 13 in the appendix provides information about these counts. Wilson VanVoorhis et al (2007) pointed out that for a chi-square test 5 observations per cell are minimum while for a mean comparison a 7 observations per cell are minimum. We have for almost all the cells much more than 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.

Further, we check the predictability power of the two model specifications. The results are presented in Table 4. While both models show a good predictability of Bitcoin ownership, the model with EAR15 dominates the model 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 0.8615), see Metz (1978).

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 5). Actually, the variable itself gives an area under the ROC of 0.78, which underlines the importance of this variable to discriminate between Bitcoin owners and non owners.

A graphical representation of the cumulative distribution function of the current adoption rate of Bitcoin by Bitcoin owners and non owners using EAR15 as a separator between the two distributions (see Figure 2), shows that the adoption rate of Bitcoin owners First Order Stochastic Dominate (FOSD) the adoption rate of non owners (FOSD test based on Kolmogorov-Smirnov has a p-value =1), confirming the power of discrimination between the Bitcoin owners and non owners of ERA15. This motivates again to use this predictor as an exclusion restriction in the model of interest (cash holdings) when we control for selection.

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.

3.4.2 Intensive Margin Analysis

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, than we extend the linear analysis assuming that adoption is selective. The results of these analyses are presented in Table 6.

Column 1 of Table 6 presents the results of the benchmark model. Here we see that the parameter estimate of Bitcoin ownership is statistical significant and equal to 1.42, and can be interpreted that in average Bitcoin owners hold a 142 percent higher amount of cash than non owners when we control for age, gender, income, education, marital status, number of kids and province of origin.

We do not assume that adoption of Bitcoin is exogenous. We base our assumption on the fact that the two subpopulations (owners and non owners) are different in distributions (see Table 7 for differences in means for different demographic characteristics: age, gender, employment, education, number of kids and marital status).

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, the Bitcoin adopters are younger (almost 14 years mean age difference), almost 75 % males, and more likely to be unemployed than the non owners counterparts. These difference in distribution of observables suggests that the owning Bitcoin is selective and, therefore we should account for the selection in our estimation.

The next two columns of Table 6 present different ways to account for the selection: a) via PS weighting - AIPW, b) via CF approach. The first method assume there are no instruments to address the endogeneity and estimates a propensity score that is further used to weight the observed data of owners and non-owners. The last two methods assume the existence of an instrument (exclusion restriction, here EAR15) that separates the Bitcoin owners from non owners without affecting the current cash holdings.

The results show that all three types of proposed corrections give close results for the difference of average cash holdings between the Bitcoin owners and non owners (AIPW estimates a value of 1.037, CF a value of 0.944). These results suggest that after correcting for selection while controlling for the demographic characteristics and the province of origin the average difference in cash holdings between the Bitcoin owners and non owners is about 100 percent higher (varying from 95 to 104 percent). 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 50000 Ca Dollars).

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, thefore we focus our attention to the quantiles of cash holdings.

Quantile Effects of Cash Holdings

To test the second hypothesis of interest we follow the same logic as for the first hypothesis (which estimates a conditional mean effect of log cash holdings). First we assume that the estimated quantiles are not affected by the selection into Bitcoin ownership and second we assume the selection into Bitcoin is present and estimate bias correction type quantiles using the CF approach, where the CF is the same as the one used to correct for selection for the first test hypothesis.

The results of the two analyses are presented in Table 8 (simple quantile estimates - benchmark) and Table 9 (quantiles estimates corrected for selection).

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, the lower quantile effects to be insignificant, while the higher quantile effects to be strongly in favor of Bitcoin owners. Indeed the estimated median effect (estimated at 1.053) of Bitcoin owner on log cash is below the conditional mean effect estimated via the linear benchmark model and it is close withe estimated mean effect estimated via AIPW method. Also, at low quantiles of cash (10 percentile) there is a slight difference between Bitcoin owners and non-owners of about 13%, this difference is decreasing towards the median and increasing after the median, for high quantiles (95 percentile) the difference is about 3 times higher. The pattern across quantiles in the benchmark quantile model is not monotonically increasing as it was expected.

As in the case of the linear model we think the estimated quantile results (that do not account for selection) are overestimates of the conditional quantiles as the two sub populations are not the same across different quantiles. Therefore, to get a correct conditional quantile effect we estimate a model that accounts for the selection at the quantile level. In particular the corrected quantile model adds an additional correction term which is our proposed CF. The results of this estimation are presented in Table 9.

The results, as in the linear case with correction for selection, emphasize that indeed the estimated conditional median effect is smaller (estimated at 0.922) than the one obtained using the benchmark quantile estimates and also the unconditional median. The same holds for any other estimated quantiles. The demographic characteristics that were relevant for linear model are also relevant for the quantile model: age (positive effect, with a marginal effect that very across quantiles), gender-female (negative effect, with marginal effects that are higher at lower quantiles and lower at high quantiles of cash, at 95 percentile gender cash holdings differences become insignificant) and higher income categories that show positive effects over the benchmark category (0 to 50000 Ca Dollars), effect that is maintained across all quantiles. A graphical representation of the differences between the simple quantiles estimated and the corrected for selection quantile estimates are presented in Figure 3, to show how selection affects the quantile estimates, especially the highest ones. Another interesting finding finding about the highes quantiles of cash is that the difference in cash holdings between males and females disappear at very high quantiles (95 percentile). To understand what drives these results at high quantiles of cash we further explore the findings in the Robustness check section.

3.4.3 Preferences and Quantities of Bitcoin

This subsection quantifies the effects of different preferences associated to 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 the BTCOS 2017 survey: non trust in institutions, technology related, payment related and investment related [6]. We estimate the effect of these preferences on the amounts of Bitcoins own in the subsample of Bitcoin owners controlling for the demographic characteristics, considering the preferences one by one and jointly. The

[6]To measure the effect of investment preferences on the amount of Bitcoin, we created a dummy variable that takes value of one if respondents chose to own it as an investment and zero otherwise. Technology related index would take value one if respondents chose one of the following: he is interested in new technology, Bitcoin uses secured blockchain technology to prevent loss and fraud, and it is a cost-saving technology. The non-trust/ anonymously related 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. 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; for further detalis on these measures see Henry et al. (2018a)

results are presented in Table 10.

The first four columns are showing the results with individual preferences: non-trust in institutions, technology related, payment related and investment related taken one by one. The only significant result is observed when we consider the investment related preference. This suggest that at the time of the survey, the dominant characteristic of bitcoin ownership (as a volume) was the investment motive. However, when the preferences are taken jointly, none of these preferences are significant.

These results suggest that while there are different reasons for holding Bitcoins these reasons are indistinguishable when they relate to volumes of bitcoin owned. For this reason, 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, but we can say that Bitcoin holders are also cash lovers.

3.5 Robustness Analysis

We conduct a series of robustness checks to assess the sensitivity of our results to various factors; tables of results are found in the Appendix - Robustness Checks Section.

1. First, we check if the results change after accounting for missing data in our instrumental variable, EAR15 [7]; recall that EAR15 is the variable containing the response to the question about expected Bitcoin adoption rate among the Canadian population, fifteen years from now. To do this we use an imputation method based on the assumption that EAR15 is missing at random (MAR), i.e., we assume that the probability of being missing depends only on observed data (e.g. respondent-level demographics). We base our imputation on Lee and Carlin (2010). As we see in Table 12, there is a slight difference in the means of observables between the sample that answered the question and the total sample. Also, when we compare those that answer with those that do not answer the differences are more pronounced, in particular for: age, gender, employment, university

[7] About 15 % of the respondents did not answer the EAR15 (398 out of 2623 total respondents)

level degree and income above \$100k and Quebec province. Consequently, we look at the probability of not answering EAR15 conditioning on these observables. We also add into the model variables for the day and hour of answering the survey, as these variables may help explain non-response. Results are presented in Table 14.

The results indeed show that the three observables mentioned above (age, gender, university level degree and income) help explain the observed EAR15 data. Females and older persons are more likely to be non-respondents to this question, while university-educated and high-income respondents are more likely to have answered.

Using this first step analysis, we base our MAR imputation on these observables and implement the multiple imputation procedure in STATA (mi impute chained). The result of this imputation is a new EAR15 variable that corrects for the missing data, ($EAR15\_imp$). We then proceed in using the imputed EAR15 variable to conduct again the extensive and intensive margin analysis, see Tables 15, 17, 21. The results on both margins are very similar, with the models that correct for missing data providing marginally higher estimates.

2. Using $EAR15\_imp$, we also tested the impact of non-response to EAR15 in determining the role of preferences in Bitcoin ownership and holdings. The results are presented in Table 16.

   We see that the data adjustment on EAR15 does not play a significant role on how preferences are related to Bitcoin ownership, the results emphasizing again that we cannot distinguish between these preferences.

3. Third, we tested the role of zero cash holdings on the average effect of Bitcoin ownership on cash holdings. To do so, we treat zero cash holdings as censored observations. Consequently, we re-estimate a censored linear model without and with control function, using a Tobit approach based on Tobin (1958). The results are presented in Table 18.

   The results obtained via a censored linear regression are in line with our previously discussed results (there is a slight non-significant increase in the parameter estimates on

Bitcoin ownership if the zeros are censored: from 0.97 in the model without censoring to 0.99 model with censoring).

4. Fourth, we checked if polynomials of the CF are impacting our results. The introduction of polynomials of CF is done to test if the CF has additional effects besides its mean on the cash holdings. In Table 19, we add quadratic and cubic functions of CF and see that the effect of Bitcoin ownership on cash holdings stays stable across these specifications. This suggests that there are no additional effects on CF that are not controlled by our correction term.

5. Fifth, we do interactions between the CF and some of the individual characteristics (age, gender, income categories) to see if there are unmeasured interactions between our CF and these observables. None of these interactions are significant.

6. Finally, to understand what drives potential selection at high quantiles of cash, observed in the corrected quantile model, we decompose the differences in cash holdings between: men and women; individuals with high versus low Bitcoin literacy scores[8]; and, between males and females with high literacy scores (similarly to Bannier et al., 2019) for high percentiles of cash holdings, using Chernozhukov et al. (2013) method (see Table 22).

   The results show that the differences between males and females are driven neither by the unobervables nor changes in the distribution of other observables, but by the weights (parameters) associated with these variables. The same holds true when we compare the differences in Bitcoin literacy. When we interact high Bitcoin literacy with the gender (at high quantiles of cash holdings) we do not see differences between males and females with high literacy scores. This lack of difference is also observed in the data (the proportion of male Bitcoin holders with high literacy score and high cash holdings is similar to that of female Bitcoin holders with high literacy score and high cash holdings. These

[8]Bitcoin knowledge score is a dummy variable that takes one if respondents answered correctly at least two of three questions, and zero otherwise. The questions, which could be answered with true, false, or don't know, tested knowledge about the total supply of Bitcoin, whether Bitcoin is backed by a government, and its public ledger (Henry et al. (2019)).

results suggest that the selection observed at high quantiles of cash may be driven by the fact that females that are Bitcoin literate are also inclined to have high cash holdings.

3.6 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. 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 Canadas 2017 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, 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 [9]. 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

[9] The Bitcoin Omnibus Survey is an ongoing survey program of the Bank of Canada. For e.g., the 2018 iteration of the BTCOS included new questions on financial literacy, plans to go cashless, and consumer rankings of features of online payments

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?

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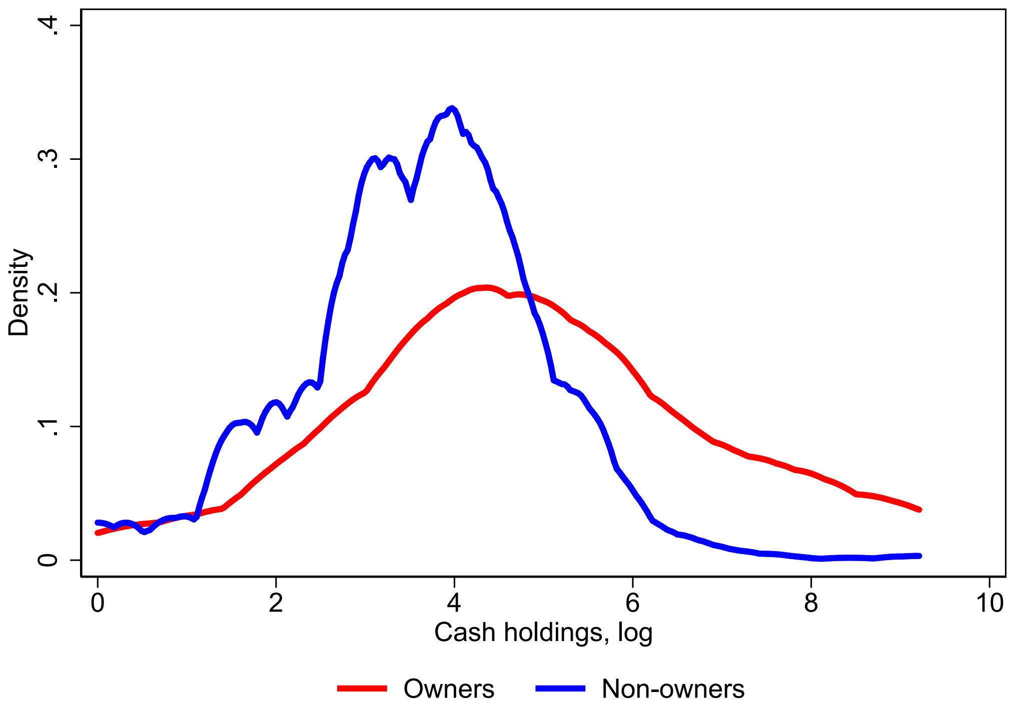
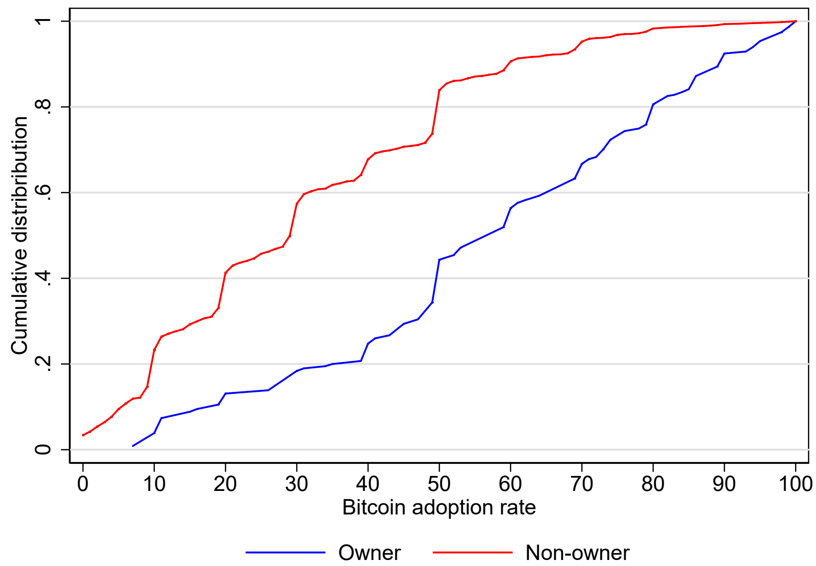
Tables and Figures

Figure 1: Kernel density, log of cash holdings by BTC ownership



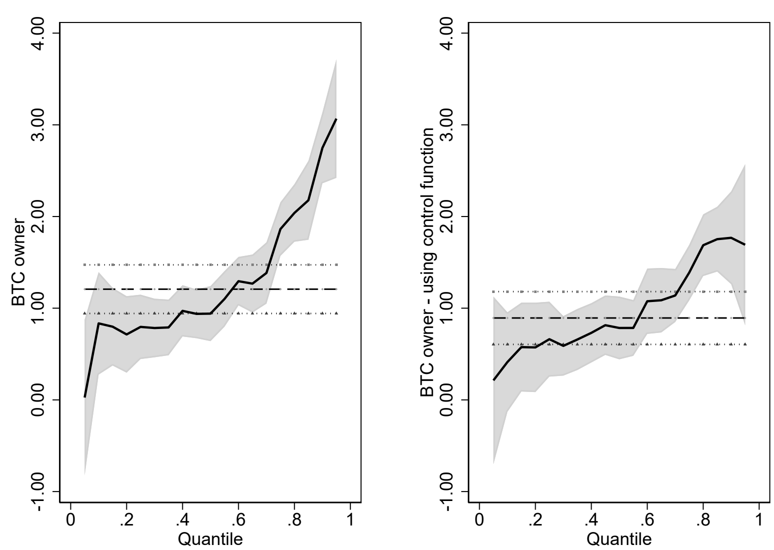
Note: Data are from the Bitcoin Omnibus Survey 2017. The red density is for Bitcoin owners and the blue density is for non owners.

Figure 2: BTC Expected Adoption Rate as an instrument



Note: Data are from the Bitcoin Omnibus Survey 2017. The red CDF is for non-owners of Bitcoin and the blue CDF is for Bitcoin owners.

Figure 3: Quantile and Control-Function Quantile Results



Note: Left graph presents the quantile results without correction for selection, while the right graph presents the quantile results for the model with correction for selection.

Table 1: Cash and Ownership of Bitcoin in Canada

	Cash on hand		**No cash**	**N**
	mean	median	percentage	
Bitcoin adopters				
2017 BTCOS	451	100	4	154
2017 MOP	320	65	8	93
Non Adopters				
2013 MOP	84	40	6	3,663
2017 BTCOS	105	40	8	2,469
2017 MOP	108	40	9	3,127

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.

Table 2: Demographics of Bitcoin owners in Canada and their holdings of cash

	Proportion		**Cash holdings, median**	
Demographic	BTC_no	BTC_yes	BTC_no	BTC_yes
18-34 years	0.23	0.63	20	100
35-54 years	0.41	0.32	33	125
55+ years	0.35	0.05	50	70
Male	0.45	0.73	45	100
Female	0.55	0.27	30	75
$<$ 50k	0.37	0.38	25	100
50k-99k	0.40	0.40	40	100
100k+	0.23	0.21	50	110
Retired	0.23	0.03	50	83
Employed	0.58	0.85	35	100
Unemployed/NILF	0.18	0.12	20	129
N	2506	117	2506	117

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

Table 3: Probability of Bitcoin ownership

	(1)	(2)	(3)	(4)
VARIABLES	Logit	Logit with Instrument	Rare Events	Rare Events with Instrument
Age	-0.0682***	-0.0549***	-0.0671***	-0.0537***
	(0.00910)	(0.00948)	(0.00901)	(0.00936)
Gender: Female	-1.303***	-1.234***	-1.278***	-1.202***
	(0.221)	(0.233)	(0.219)	(0.230)
Income: 50k-99k	-0.158	-0.133	-0.155	-0.129
	(0.243)	(0.258)	(0.241)	(0.255)
Income: 100k+	-0.402	-0.372	-0.390	-0.358
	(0.309)	(0.328)	(0.306)	(0.324)
Region: Prairies	-0.703**	-0.767**	-0.689**	-0.748**
	(0.337)	(0.356)	(0.332)	(0.350)
Region: Ontario	-0.367	-0.489	-0.369	-0.486
	(0.285)	(0.304)	(0.282)	(0.300)
Region: Quebec	-0.304	-0.491	-0.305	-0.485
	(0.303)	(0.326)	(0.300)	(0.321)
Region: Atlantic	-0.772*	-0.839*	-0.719	-0.783*
	(0.457)	(0.477)	(0.444)	(0.463)
Employment: employed	0.871***	0.709**	0.842***	0.678**
	(0.286)	(0.293)	(0.282)	(0.288)
Education: College/CEGEP/Trade school	-0.127	-0.0762	-0.132	-0.0809
	(0.311)	(0.326)	(0.307)	(0.320)
Education: University	0.234	0.291	0.217	0.272
	(0.293)	(0.310)	(0.289)	(0.305)
Number of kids: No kids	-0.469**	-0.302	-0.463**	-0.297
	(0.235)	(0.246)	(0.233)	(0.243)
Marital status: Not married/CL	-0.286	-0.236	-0.282	-0.231
	(0.252)	(0.263)	(0.250)	(0.260)
HH grocery shopping: Not all of it	-0.641***	-0.278	-0.627***	-0.268
	(0.220)	(0.235)	(0.218)	(0.232)
EAR15		0.0401***		0.0393***
		(0.00455)		(0.00449)
Constant	0.740	-1.560**	0.766	-1.498**
	(0.554)	(0.649)	(0.546)	(0.640)
Observations	2,623	2,225	2,623	2,225

Note: The first column is the benchmark probability model of Bitcoin ownership, the second column is the benchmark augmented with the EAR15, the third and forth columns are the same models but when accounting that Bitcoin ownership is treated as a rare event Baseline categories are Male, <50k income, from BC, unemployed, conducts all HH grocery shopping. EAR15 = What percentage of Canadians do you predict will be using Bitcoin 15 years. Significance stars ***, **, and * represent 1%, 5% and 10% significance, respectively.

Table 4: Logit Specification Tests

Logit Model	Btc Own	Coef.	Std. Err.	z	
1	Prediction	1.60	0.29	5.49	0.00
	Prediction squared	0.10	0.05	2.25	0.03
	Constant	0.70	0.40	1.73	0.08
	LROC	0.82			
2	Prediction	1.19	0.19	6.09	0.00
	Prediction squared	0.04	0.037	1.10	0.271
	Constant	0.14	0.23	0.60	0.54
	LROC	0.86			
3	Prediction	1.67	0.29	5.67	0.00
	Prediction squared	0.11	0.05	2.47	0.014
	Constant	0.74	0.39	1.86	0.014
	LROC	0.82			
4	Prediction	1.23	0.20	6.14	0.00
	Prediction squared	0.047	0.039	1.21	0.22
	Constant	0.131	0.23	0.57	0.557
	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 5: Logit EAR15 Estimation and Specification Tests

Logit Model with EAR15 only	(1)
VARIABLES	Estimates
EAR15	0.0458***
	(0.00419)
Constant	-4.918***
	(0.251)
Linktest	
Prediction	1.238***
Prediction squared	0.047
LROC	0.78
Observations	2,225

Note: Similar specification tests as in Table 4. Significance stars ***, **, and * represent 1%, 5% and 10% significance, respectively.

Table 6: Cash Holdings modeled: linearly, as a treatment and with CF

VARIABLES	OLS	AIPW	CF
BTC_owner	1.423***	1.037***	0.944***
	(0.212)	(0.339)	(0.220)
Age	0.0204***		0.0265***
	(0.00225)		(0.00262)
Gender: Female	-0.277***		-0.0711
	(0.0661)		(0.0737)
Income: 50k-99k	0.266***		0.312***
	(0.0762)		(0.0822)
Income: 100k+	0.559***		0.599***
	(0.0954)		(0.103)
Region: Prairies	0.127		0.221*
	(0.113)		(0.117)
Region: Ontario	0.0991		0.148
	(0.0991)		(0.103)
Region: Quebec	0.155		0.262**
	(0.105)		(0.112)
Region: Atlantic	0.0435		0.131
	(0.145)		(0.157)
Employment: employed	0.0324		-0.0384
	(0.0708)		(0.0775)
Education: College/CEGEP/Trade school	-0.0324		-0.00364
	(0.0868)		(0.0984)
Education: University	0.0940		0.0417
	(0.0872)		(0.0970)
Number of kids: No kids	-0.0533		0.0587
	(0.0832)		(0.0908)
Marital status: Not married/CL	0.00336		-0.00866
	(0.0777)		(0.0841)
HH grocery shopping: Not all of it	-0.185***		-0.118
	(0.0706)		(0.0766)
CF			3.343***
			(0.555)
Constant	2.268***		1.619***
	(0.190)		(0.226)
Observations	2,623	2,623	2,225
R-squared	0.084		0.103

Note: Column 1 is for benchmark OLS model; Column 2 is AIPW (ATE) model; Column 3 is the model with CF correction. Baseline categories are Male, <50k income, from BC, unemployed, conducts all HH grocery shopping. Significance stars ***, **, and * represent 1%, 5% and 10% significance, respectively.

Table 7: Mean Differences in observables between Bitcoin owners and non owners

Variable	Bitcoin owners Mean	Bitcoin owners Std. Dev.	Non owners Mean	Non owners Std. Dev.	Difference
Age	34.78	11.20	48.18	15.54	- 13.39***
Gender: Female	0.27	0.45	0.55	0.50	-0.27***
Income: 50k-99k	0.38	0.49	0.36	0.48	-0.03
Income: 100k +	0.21	0.41	0.21	0.40	0.00
Employment: employed	0.85	0.36	0.58	0.49	0.27***
Education: College/CEGEP/Trade school	0.27	0.45	0.35	0.48	-0.07 *
Education: University	0.56	0.50	0.42	0.49	0.13***
Number of kids	0.60	0.49	0.76	0.42	-0.17***
Marital status: Not married/CL	0.45	0.50	0.41	0.49	0.04

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 8: Quantiles of Cash Holdings

VARIABLES	Q10	Q25	Q50	Q75	Q90	Q95
BTC owner	1.136*	1.164***	1.053***	1.662***	2.725***	3.026***
	(0.594)	(0.269)	(0.155)	(0.166)	(0.204)	(0.282)
Age	0.0371***	0.0333***	0.0177***	0.0157***	0.0158***	0.0123***
	(0.00874)	(0.00395)	(0.00228)	(0.00244)	(0.00300)	(0.00415)
Gender: Female	0.0599	-0.302***	-0.308***	-0.306***	-0.426***	-0.356***
	(0.245)	(0.111)	(0.0640)	(0.0685)	(0.0843)	(0.117)
Income: 50k-99k	0.163	0.356***	0.296***	0.214***	0.384***	0.356***
	(0.284)	(0.129)	(0.0743)	(0.0795)	(0.0978)	(0.135)
Income: 100k+	0.845**	0.648***	0.593***	0.408***	0.568***	0.506***
	(0.361)	(0.163)	(0.0942)	(0.101)	(0.124)	(0.171)
Region: Prairies	0.357	0.123	0.159	0.0475	0.183	0.239
	(0.420)	(0.190)	(0.110)	(0.117)	(0.144)	(0.200)
Region: Ontario	0.237	0.147	0.168*	-0.0404	-0.0820	-0.0883
	(0.376)	(0.170)	(0.0983)	(0.105)	(0.129)	(0.179)
Region: Quebec	0.437	0.167	0.154	0.0299	-0.100	-0.0950
	(0.397)	(0.180)	(0.104)	(0.111)	(0.137)	(0.189)
Region: Atlantic	-0.111	0.171	0.0969	-0.110	0.271	0.310
	(0.516)	(0.234)	(0.135)	(0.144)	(0.177)	(0.245)
Employment: employed	0.163	-0.0320	-0.0601	0.0656	0.0513	0.182
	(0.272)	(0.123)	(0.0711)	(0.0761)	(0.0936)	(0.129)
Education: College/CEGEP/Trade school	-0.177	-0.0359	0.0486	-0.0522	-0.199*	-0.0527
	(0.329)	(0.149)	(0.0860)	(0.0920)	(0.113)	(0.156)
Education: University	0.00853	0.123	0.133	0.0671	-0.0703	0.00475
	(0.329)	(0.149)	(0.0859)	(0.0919)	(0.113)	(0.156)
Number of kids: No kids	0.200	-0.153	-0.0398	-0.0282	-0.204*	-0.137
	(0.307)	(0.139)	(0.0802)	(0.0858)	(0.105)	(0.146)
Marital status: Not married/CL	-0.140	0.0754	0.0548	0.0331	0.136	0.0898
	(0.294)	(0.133)	(0.0767)	(0.0821)	(0.101)	(0.140)
HH grocery shopping: Not all of it	-0.200	-0.195	-0.172**	-0.126*	-0.0492	-0.0765
	(0.268)	(0.121)	(0.0700)	(0.0749)	(0.0921)	(0.127)
Constant	-1.418**	0.808**	2.531***	3.645***	4.528***	4.923***
	(0.722)	(0.327)	(0.189)	(0.202)	(0.248)	(0.343)
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. Significance stars ***, **, and * represent 1%, 5% and 10% significance, respectively.

Table 9: Quantiles of Cash Holdings corrected for Selection via a Control Function

VARIABLES	Q10	Q25	Q50	Q75	Q90	Q95
BTC owner	0.191	0.782***	0.922***	1.098***	1.826***	1.718***
	(0.515)	(0.266)	(0.172)	(0.178)	(0.245)	(0.352)
Age	0.0446***	0.0366***	0.0220***	0.0196***	0.0219***	0.0192***
	(0.00823)	(0.00425)	(0.00275)	(0.00284)	(0.00391)	(0.00562)
Gender: Female	0.518**	-0.111	-0.134*	-0.162**	-0.232**	-0.0513
	(0.224)	(0.116)	(0.0747)	(0.0773)	(0.106)	(0.153)
Income: 50k-99k	0.390	0.393***	0.245***	0.252***	0.341***	0.326*
	(0.248)	(0.128)	(0.0829)	(0.0857)	(0.118)	(0.170)
Income: 100k+	0.783**	0.643***	0.556***	0.464***	0.547***	0.473**
	(0.310)	(0.160)	(0.104)	(0.107)	(0.147)	(0.212)
Region: Prairies	0.583	0.133	0.137	0.0467	0.201	0.390
	(0.357)	(0.184)	(0.119)	(0.123)	(0.169)	(0.243)
Region: Ontario	0.204	0.138	0.119	0.0186	0.0380	0.221
	(0.315)	(0.163)	(0.105)	(0.109)	(0.150)	(0.215)
Region: Quebec	0.609*	0.229	0.170	0.0559	0.0799	0.196
	(0.343)	(0.177)	(0.115)	(0.118)	(0.163)	(0.234)
Region: Atlantic	-0.0464	0.141	0.0519	0.0966	0.253	0.550*
	(0.450)	(0.233)	(0.150)	(0.155)	(0.214)	(0.307)
Employment: employed	-0.199	-0.0901	-0.0767	0.0297	0.0484	0.0598
	(0.239)	(0.124)	(0.0797)	(0.0824)	(0.113)	(0.163)
Education: College/CEGEP/Trade school	-0.203	0.0633	0.0900	-0.0439	-0.0949	-0.187
	(0.300)	(0.155)	(0.100)	(0.103)	(0.142)	(0.205)
Education: University	0.0287	0.0844	0.111	0.00130	-0.0983	-0.246
	(0.295)	(0.153)	(0.0984)	(0.102)	(0.140)	(0.201)
Number of kids: No kids	0.230	-0.102	0.0271	0.0932	0.000123	0.0173
	(0.269)	(0.139)	(0.0898)	(0.0929)	(0.128)	(0.184)
Marital status: Not married/CL	-0.328	-0.0298	0.0194	0.0298	0.139	0.182
	(0.257)	(0.133)	(0.0859)	(0.0888)	(0.122)	(0.176)
HH grocery shopping: Not all of it	-0.346	-0.151	-0.150*	-0.0766	0.0395	0.110
	(0.237)	(0.123)	(0.0791)	(0.0818)	(0.113)	(0.162)
CF	6.041***	3.260***	1.857***	2.692***	3.448***	4.488***
	(1.435)	(0.742)	(0.479)	(0.495)	(0.681)	(0.980)
Constant	-1.993***	0.464	2.193***	3.166***	3.707***	4.076***
	(0.694)	(0.359)	(0.232)	(0.239)	(0.330)	(0.474)
Observations	2,225	2,225	2,225	2,225	2,225	2,225

Note: Baseline categories are Male, <50k income, from BC, unemployed, conducts all HH grocery shopping. Significance stars ***, **, and * represent 1%, 5% and 10% significance, respectively.

Table 10: Order Logit Model for Quantities of Bitcoin as a function of Prefrences

VARIABLES	Ologit	Ologit	Ologit	Ologit	Ologit
Nontrust	0.389				-0.258
	(0.907)				(1.207)
Tehnology		0.444			-0.151
		(0.600)			(0.957)
Payment			0.471		-0.0990
			(0.506)		(0.880)
Investment				-0.907**	-1.027
				(0.457)	(0.827)
EAR15	0.0191**	0.0189**	0.0174*	0.0152*	0.0145
	(0.00942)	(0.00918)	(0.00935)	(0.00876)	(0.00948)
Age	0.0362*	0.0374*	0.0370*	0.0465**	0.0473**
	(0.0212)	(0.0212)	(0.0211)	(0.0227)	(0.0222)
Gender: Female	0.366	0.245	0.322	0.0943	0.0751
	(0.553)	(0.567)	(0.543)	(0.577)	(0.605)
Income: 50k-99k	0.715	0.708	0.666	0.802	0.799
	(0.533)	(0.513)	(0.530)	(0.502)	(0.502)
Income: 100k+	1.299**	1.279**	1.275**	1.466**	1.461**
	(0.653)	(0.635)	(0.626)	(0.627)	(0.630)
Region: Prairies	-0.471	-0.514	-0.528	-0.676	-0.667
	(0.609)	(0.610)	(0.615)	(0.627)	(0.643)
Region: Ontario	-0.110	-0.0687	-0.0589	-0.226	-0.208
	(0.514)	(0.499)	(0.503)	(0.510)	(0.529)
Region: Quebec	-0.285	-0.269	-0.255	-0.293	-0.272
	(0.556)	(0.548)	(0.546)	(0.572)	(0.573)
Region: Atlantic	-1.312	-1.522	-1.340	-1.634	-1.611
	(1.310)	(1.223)	(1.276)	(1.155)	(1.141)
Employment: employed	0.286	0.259	0.299	0.108	0.116
	(0.625)	(0.631)	(0.622)	(0.654)	(0.648)
Education: College/CEGEP/Trade school	-0.0263	0.0283	0.0546	0.0788	0.0941
	(0.594)	(0.591)	(0.569)	(0.598)	(0.592)
Education: University	0.284	0.353	0.381	0.404	0.395
	(0.605)	(0.611)	(0.593)	(0.621)	(0.606)
Number of kids: No kids	0.281	0.316	0.231	0.414	0.384
	(0.538)	(0.527)	(0.515)	(0.521)	(0.554)
Marital status: Not married/CL	0.0801	0.0403	0.116	0.0785	0.0924
	(0.441)	(0.454)	(0.445)	(0.460)	(0.463)
HH grocery shopping: Not all of it	-0.101	-0.121	-0.0569	-0.211	-0.244
	(0.483)	(0.475)	(0.478)	(0.471)	(0.553)
Observations	110	110	110	110	110

Note: The first four columns are showing the results with individual prefrences: nontrust, technology, payment, investment, takken individually; the last column presents the results with the preferences taken jointly. Significance stars ***, **, and * represent 1%, 5% and 10% significance, respectively.

Table 11: Marginal Effects - Probability of Bitcoin Ownership

	(1)	(2)
VARIABLES	ME Logit	ME Logit with Instrument
Age	-0.0013***	-0.0009***
	0.0002	0.0002
Gender: Female	-0.0273***	-0.0232***
	0.0043	0.0055
Income: 50k-99k	-0.0029	-0.0023
	0.0043	0.0044
Income: 100k+	-0.0067	-0.0059
	0.0047	0.0049
Region: Prairies	-0.0109**	-0.0110**
	0.0045	0.0044
Region: Ontario	-0.0065	-0.0082
	0.0049	0.0049
Region: Quebec	-0.0053	-0.0077
	0.005	0.0046
Region: Atlantic	-0.0109**	-0.0109**
	0.0049	0.0047
Employment: employed	0.0156***	0.0119**
	0.0048	0.0047
Education: College/CEGEP/Trade school	-0.0023	-0.0013
	0.0056	0.0056
Education: University	0.0045	0.0052
	0.0057	0.0057
Number of kids: No kids	-0.0099*	-0.0058
	0.0056	0.0051
Marital status: Not married/CL	-0.0052	-0.0041
	0.0046	0.0045
HH grocery shopping: Not all of it	-0.0119***	-0.0049
	0.0043	0.0042
EAR15		0.0007***
		0.0001
Observations	2,623	2,225

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

Table 12: Means of Demographic Characteristics for total sample, EAR15 subsample and EAR15 non-respondents

	All		Respondents		Non-Respondents		Difference
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	
Age	47.58	15.62	47.25	15.64	49.44	15.37	-2.20 ***
Gender: Female	0.54	0.50	0.50	0.50	0.74	0.44	-0.23***
Income: 50k-99k	0.36	0.48	0.36	0.48	0.32	0.47	0.04*
Income: 100k+	0.21	0.40	0.22	0.41	0.13	0.33	0.09***
Region: Prairies	0.19	0.39	0.19	0.39	0.17	0.38	0.02
Region: Ontario	0.34	0.47	0.35	0.48	0.27	0.44	0.08**
Region: Quebec	0.24	0.43	0.22	0.41	0.39	0.49	-0.17***
Region: Atlantic	0.09	0.28	0.08	0.27	0.11	0.31	-0.03*
Employment: employed	0.59	0.49	0.60	0.49	0.52	0.50	0.08***
Education: College/CEGEP/Trade school	0.35	0.48	0.34	0.47	0.37	0.48	-0.02
Education: University	0.43	0.49	0.46	0.50	0.24	0.43	0.23***
Number of kids: No kids	0.76	0.43	0.76	0.43	0.76	0.43	0.00
Marital status: Not married/CL	0.41	0.49	0.41	0.49	0.39	0.49	0.02
HH grocery shopping: Not all of it	0.46	0.50	0.46	0.50	0.43	0.50	0.03
Observations	2623		2225		398		

Note: The last column is the difference in means between the respondents and non-respondents of EAR15 question. The stars are associated with a t-test for difference in means. Significance stars ***, **, and * represent 1%, 5% and 10% significance, respectively.

Table 13: Counts of Bitcoin Owners by Cells of Demographic Characteristics and Province

Variable	Category	Counts
Gender	Female	32
	Male	85
Income	Between 50-99	45
	Higher than 100	24
	Less than 50	43
Region	British Columbia	24
	Praires	18
	Ontario	39
	Quebec	29
	Atlantic	7
Employment	Retired/NILF	4
	Employed	99
	Unemployed	14
Education	Highschool	20
	College	32
	Univ	65
Kids	Kids	47
	No kids	70
Marital status	Married	64
	Not married	53
Grocery shop	All	76
	Not at all	41
NonTrust/Anonimity		7
Technology related		21
Investment related		14
Payment related		61

Appendix - Robustness checks

Table 14: Probability of Not Answering EAR15

VARIABLES	Logit
Age	0.00872**
	(0.00409)
Gender: Female	1.036***
	(0.126)
Income: 50k-99k	-0.275**
	(0.130)
Income: 100k+	-0.423**
	(0.178)
Region: Prairies	0.930***
	(0.255)
Region: Ontario	0.788***
	(0.241)
Region: Quebec	1.592***
	(0.237)
Region: Atlantic	1.299***
	(0.280)
Employment: employed	-0.0255
	(0.126)
Education: University	-0.906***
	(0.132)
Hour	-0.00696
	(0.00869)
Day	-0.0485
	(0.0371)
Constant	-2.591***
	(0.624)
Observations	2,623

Note: The choice of observables for the selection into answering EAR15 are based on the characteristics from Table 12 that show differences between sample of non-respondents and respondents of EAR15 variable. In addition, we consider the hour and the day of the answers. Significance stars ***, **, and * represent 1%, 5% and 10% significance, respectively.

Table 15: Probability of Bitcoin ownership - with sample correction

VARIABLES	Logit	Logit (EAR15_imp)	Rare Events	Rare Events (EAR15_imp)
Age	-0.0682***	-0.0575***	-0.0671***	-0.0562***
	(0.00933)	(0.00959)	(0.00901)	(0.00932)
Gender: Female	-1.303***	-1.299***	-1.278***	-1.268***
	(0.210)	(0.221)	(0.219)	(0.228)
Income: 50k-99k	-0.158	-0.102	-0.155	-0.0989
	(0.252)	(0.265)	(0.241)	(0.253)
Income: 100k+	-0.402	-0.353	-0.390	-0.340
	(0.294)	(0.311)	(0.306)	(0.323)
Region: Prairies	-0.703**	-0.845**	-0.689**	-0.826**
	(0.340)	(0.364)	(0.332)	(0.350)
Region: Ontario	-0.367	-0.584*	-0.369	-0.580*
	(0.277)	(0.299)	(0.282)	(0.300)
Region: Quebec	-0.304	-0.638**	-0.305	-0.631**
	(0.292)	(0.313)	(0.300)	(0.320)
Region: Atlantic	-0.772*	-0.916**	-0.719	-0.860*
	(0.445)	(0.457)	(0.444)	(0.461)
Employment: employed	0.871***	0.695**	0.842***	0.665**
	(0.308)	(0.307)	(0.282)	(0.287)
Education: College/CEGEP/Trade school	-0.127	0.0169	-0.132	0.0103
	(0.316)	(0.318)	(0.307)	(0.316)
Education: University	0.234	0.411	0.217	0.390
	(0.288)	(0.299)	(0.289)	(0.301)
Number of kids: No kids	-0.469**	-0.287	-0.463**	-0.282
	(0.228)	(0.234)	(0.233)	(0.243)
Marital status: Not married/CL	-0.286	-0.219	-0.282	-0.215
	(0.249)	(0.260)	(0.250)	(0.260)
HH grocery shopping: Not all of it	-0.641***	-0.264	-0.627***	-0.254
	(0.221)	(0.229)	(0.218)	(0.231)
EAR15_imp		0.0414***		0.0406***
		(0.00442)		(0.00452)
Constant	0.740	-1.651**	0.766	-1.587**
	(0.553)	(0.647)	(0.546)	(0.639)
Observations	2,623	2,623	2,623	2,623

Note: The first column is the benchmark probability model of Bitcoin ownership, the second column is the benchmark augmented with the imputed EAR15, the third and forth columns are the same models but when accounting that Bitcoin ownership is treated as a rare event. Significance stars ***, **, and * represent 1%, 5% and 10% significance, respectively.

Table 16: Order Logit Model for Quantities of Bitcoin as a function of Prefrences - with sample correction for EAR15

VARIABLES	Ologit	Ologit	Ologit	Ologit	Ologit
Nontrust	0.126				-0.719
	(0.794)				(1.107)
Tehnology		0.375			-0.467
		(0.583)			(0.962)
Payment			0.670		-0.248
			(0.510)		(0.925)
Investment				-1.035**	-1.363
				(0.459)	(0.851)
EAR15_imp	0.0603	0.0151	0.105	0.0462	0.0500
	(0.627)	(0.641)	(0.614)	(0.604)	(0.612)
Age	0.0538	0.0407	0.0691	0.0610	0.0643
	(0.199)	(0.203)	(0.195)	(0.189)	(0.192)
Gender: Female	0.0146	0.0482	-0.132	-0.199	-0.232
	(1.891)	(1.928)	(1.884)	(1.856)	(1.867)
Income: 50k-99k	0.630	0.575	0.662	0.778	0.787
	(0.989)	(0.999)	(0.963)	(0.931)	(0.937)
Income: 100k+	1.146	1.108	1.203	1.410*	1.417*
	(0.827)	(0.819)	(0.792)	(0.788)	(0.777)
Region: Prairies	-0.325	-0.345	-0.432	-0.563	-0.560
	(0.677)	(0.671)	(0.666)	(0.633)	(0.650)
Region: Ontario	0.121	0.207	0.0443	-0.0855	-0.0772
	(1.162)	(1.175)	(1.123)	(1.065)	(1.097)
Region: Quebec	-0.287	-0.0836	-0.492	-0.305	-0.295
	(2.860)	(2.906)	(2.771)	(2.697)	(2.744)
Region: Atlantic	-1.506	-1.509	-1.698	-1.813	-1.754
	(2.376)	(2.377)	(2.321)	(2.243)	(2.264)
Employment: employed	0.275	0.321	0.198	0.0785	0.0906
	(1.280)	(1.295)	(1.258)	(1.211)	(1.229)
Education: College/CEGEP/Trade school	0.263	0.118	0.521	0.296	0.354
	(2.466)	(2.505)	(2.410)	(2.350)	(2.393)
Education: University	0.526	0.347	0.884	0.595	0.600
	(3.156)	(3.207)	(3.108)	(3.055)	(3.113)
Number of kids: No kids	0.254	0.140	0.409	0.437	0.384
	(2.283)	(2.311)	(2.225)	(2.144)	(2.170)
Marital status: Not married/CL	0.304	0.152	0.463	0.264	0.311
	(1.702)	(1.754)	(1.676)	(1.682)	(1.708)
HH grocery shopping: Not all of it	-0.00658	-0.270	0.343	-0.144	-0.183
	(3.553)	(3.628)	(3.485)	(3.396)	(3.463)
Observations	110	110	110	110	110

Note: The first four columns are showing the results with individual prefrences: nontrust, technology, payment, investment, takken individually; the last column presents the results with the preferences taken jointly. Significance stars ***, **, and * represent 1%, 5% and 10% significance, respectively.

Table 17: Cash Holdings modeled: linearly, with selection and as a treatment, with sample correction

VARIABLES	OLS	AIPW	CF
BTC owner	1.423***	1.037***	0.971***
	(0.212)	(0.339)	(0.219)
Age	0.0204***		0.0268***
	(0.00225)		(0.00239)
Gender: Female	-0.277***		-0.118*
	(0.0661)		(0.0685)
Income: 50k-99k	0.266***		0.283***
	(0.0762)		(0.0752)
Income: 100k+	0.559***		0.606***
	(0.0954)		(0.0949)
Region: Prairies	0.127		0.228**
	(0.113)		(0.111)
Region: Ontario	0.0991		0.168*
	(0.0991)		(0.0984)
Region: Quebec	0.155		0.220**
	(0.105)		(0.105)
Region: Atlantic	0.0435		0.158
	(0.145)		(0.144)
Employment: employed	0.0324		-0.0222
	(0.0708)		(0.0707)
Education: College/CEGEP/Trade school	-0.0324		-0.0109
	(0.0868)		(0.0863)
Education: University	0.0940		0.0588
	(0.0872)		(0.0864)
Number of kids: No kids	-0.0533		-0.00414
	(0.0832)		(0.0830)
Marital status: Not married/CL	0.00336		0.0436
	(0.0777)		(0.0767)
HH grocery shopping: Not all of it	-0.185***		-0.100
	(0.0706)		(0.0703)
Pr(btc_own)			3.388***
			(0.550)
Constant	2.268***		1.610***
	(0.190)		(0.209)
Observations	2,623	2,623	2,623
R-squared	0.084		0.102

Note: The estimates in this table are repeats of the estimates in Table 6, but with sample correction for EAR15. Column 1 is for benchmark OLS model; Column 2 is AIPW (ATE) model; Column 3 is the model with CF correction. Baseline categories are Male, <50k income, from BC, unemployed, conducts all HH grocery shopping. Significance stars ***, **, and * represent 1%, 5% and 10% significance, respectively.

Table 18: Cash Holdings modeled: Tobit (lower bound at 0)

VARIABLES	log_cash	log_cash - with EAR15
BTC owner	1.477***	0.991***
	(0.222)	(0.230)
Age	0.0222***	0.0291***
	(0.00249)	(0.00265)
Gender: Female	-0.272***	-0.102
	(0.0728)	(0.0757)
Income: 50k-99k	0.285***	0.302***
	(0.0843)	(0.0832)
Income: 100k+	0.599***	0.649***
	(0.104)	(0.103)
Region: Prairies	0.129	0.237*
	(0.125)	(0.123)
Region: Ontario	0.104	0.178
	(0.110)	(0.109)
Region: Quebec	0.170	0.239**
	(0.116)	(0.115)
Region: Atlantic	0.0444	0.166
	(0.160)	(0.160)
Employment: employed	0.0352	-0.0231
	(0.0784)	(0.0782)
Education: College/CEGEP/Trade school	-0.0254	-0.00202
	(0.0962)	(0.0955)
Education: University	0.104	0.0660
	(0.0964)	(0.0954)
Number of kids: No kids	-0.0648	-0.0117
	(0.0914)	(0.0911)
Marital status: Not married/CL	-0.00685	0.0363
	(0.0855)	(0.0844)
HH grocery shopping: Not all of it	-0.197**	-0.105
	(0.0776)	(0.0774)
CF		3.628***
		(0.572)
Constant	2.097***	1.392***
	(0.211)	(0.232)
var(e.log_cash)	3.152***	3.090***
	(0.120)	(0.116)
Observations	2,623	2,623

Note: First column presents the estimates of the benchmark linear model assuming censoring at 0, using Tobit, while the second column augments the first model with the imputed ERA15 variable. Baseline categories are Male, <50k income, from BC, unemployed, conducts all HH grocery shopping. Significance stars ***, **, and * represent 1%, 5% and 10% significance, respectively.

Table 19: Cash Holdings with polynomials of CF - with sample correction

VARIABLES	log_cash	log_cash	log_cash
BTC owner	0.971***	0.974***	0.971***
	(0.219)	(0.219)	(0.219)
Age	0.0268***	0.0252***	0.0271***
	(0.00239)	(0.00253)	(0.00268)
Gender: Female	-0.118*	-0.146**	-0.119*
	(0.0685)	(0.0701)	(0.0710)
Income: 50k-99k	0.283***	0.278***	0.281***
	(0.0752)	(0.0751)	(0.0750)
Income: 100k+	0.606***	0.594***	0.600***
	(0.0949)	(0.0950)	(0.0951)
Region: Prairies	0.228**	0.211*	0.238**
	(0.111)	(0.112)	(0.113)
Region: Ontario	0.168*	0.157	0.177*
	(0.0984)	(0.0984)	(0.0989)
Region: Quebec	0.220**	0.209**	0.232**
	(0.105)	(0.105)	(0.105)
Region: Atlantic	0.158	0.140	0.169
	(0.144)	(0.145)	(0.145)
Employment: employed	-0.0222	-0.00601	-0.0259
	(0.0707)	(0.0713)	(0.0720)
Education: College/CEGEP/Trade school	-0.0109	-0.0133	-0.00876
	(0.0863)	(0.0863)	(0.0862)
Education: University	0.0588	0.0623	0.0597
	(0.0864)	(0.0863)	(0.0863)
Number of kids: No kids	-0.00414	-0.0159	-0.00193
	(0.0830)	(0.0830)	(0.0828)
Marital status: Not married/CL	0.0436	0.0398	0.0505
	(0.0767)	(0.0767)	(0.0769)
HH grocery shopping: Not all of it	-0.100	-0.107	-0.0950
	(0.0703)	(0.0703)	(0.0703)
CF	3.388***	1.665	5.023***
	(0.550)	(1.115)	(1.921)
CF2		3.402*	-12.75
		(1.877)	(7.847)
CF3			17.42**
			(7.905)
Constant	1.610***	1.765***	1.568***
	(0.209)	(0.224)	(0.240)
Observations	2,623	2,623	2,623
R-squared	0.102	0.103	0.105

Note: CF2 and CF3 ar polynomials of degree 2 and 3 of CF. Baseline categories are Male, <50k income, from BC, unemployed, conducts all HH grocery shopping. Significance stars ***, **, and * represent 1%, 5% and 10% significance, respectively.

Table 20: Cash Holdings with Interactions of CF - with sample correction

VARIABLES	log_cash	log_cash	log_cash	log_cash	log_cash
BTC owner	0.971***	0.966***	0.972***	0.967***	
	(0.219)	(0.220)	(0.219)	(0.220)	
Age	0.0268***	0.0276***	0.0270***	0.0266***	
	(0.00239)	(0.00247)	(0.00245)	(0.00239)	
Gender: Female	-0.118*	-0.127*	-0.130*	-0.118*	
	(0.0685)	(0.0694)	(0.0749)	(0.0684)	
Income: 50k-99k	0.283***	0.284***	0.285***	0.254***	
	(0.0752)	(0.0752)	(0.0755)	(0.0821)	
Income: 100k+	0.606***	0.605***	0.609***	0.570***	
	(0.0949)	(0.0950)	(0.0958)	(0.102)	
Region: Prairies	0.228**	0.227**	0.232**	0.230**	
	(0.111)	(0.112)	(0.111)	(0.111)	
Region: Ontario	0.168*	0.168*	0.169*	0.168*	
	(0.0984)	(0.0985)	(0.0983)	(0.0983)	
Region: Quebec	0.220**	0.221**	0.222**	0.222**	
	(0.105)	(0.104)	(0.104)	(0.105)	
Region: Atlantic	0.158	0.157	0.161	0.158	
	(0.144)	(0.144)	(0.144)	(0.144)	
Employment: employed	-0.0222	-0.00856	-0.0243	-0.0200	
	(0.0707)	(0.0725)	(0.0712)	(0.0706)	
Education: College/CEGEP/Trade school	-0.0109	-0.00983	-0.0108	-0.00828	
	(0.0863)	(0.0862)	(0.0863)	(0.0863)	
Education: University	0.0588	0.0624	0.0582	0.0570	
	(0.0864)	(0.0864)	(0.0864)	(0.0864)	
Number of kids: No kids	-0.00414	-0.0191	-0.00325	0.00479	
	(0.0830)	(0.0836)	(0.0831)	(0.0838)	
Marital status: Not married/CL	0.0436	0.0396	0.0464	0.0442	
	(0.0767)	(0.0770)	(0.0771)	(0.0767)	
HH grocery shopping: Not all of it	-0.100	-0.107	-0.0989	-0.0988	
	(0.0703)	(0.0707)	(0.0702)	(0.0704)	
CF	3.388***	4.775***	3.354***	2.933***	
	(0.550)	(1.617)	(0.560)	(0.742)	
CF*age		-0.0460			
		(0.0488)			
CF*female			0.478		
			(1.404)		
CF*income: 50k-99k				0.863	
				(1.113)	
CF*income: 100k+				1.584***	
				(0.211)	
Constant	1.610***	1.595***	1.599***	1.629***	
	(0.209)	(0.209)	(0.211)	(0.208)	
Observations	2,623	2,623	2,623	2,623	
R-squared	0.102	0.103	0.102	0.103	

Note: First column is the linear model with CF correction, second column adds the interaction between CF and age, column three adds the interaction CF with Female, while column four add interacctions of CF with income categories that are not benchmark categories. Baseline categories are Male, <50k income, from BC, unemployed, conducts all HH grocery shopping. Significance stars ***, **, and * represent 1%, 5% and 10% significance, respectively.

Table 21: Quantiles of Cash Holdings corrected for Selection via a Control Function - with sample correction

VARIABLES	Q10	Q25	Q50	Q75	Q90	Q95
BTC_owner	0.202	0.714**	0.934***	1.189***	1.874***	1.711***
	(0.525)	(0.284)	(0.169)	(0.177)	(0.219)	(0.347)
Age	0.0450***	0.0388***	0.0221***	0.0198***	0.0213***	0.0160***
	(0.00770)	(0.00417)	(0.00247)	(0.00259)	(0.00321)	(0.00509)
Gender: Female	0.282	-0.211*	-0.189***	-0.203***	-0.249***	-0.171
	(0.213)	(0.115)	(0.0683)	(0.0715)	(0.0886)	(0.141)
Income: 50k-99k	0.322	0.332***	0.276***	0.246***	0.347***	0.319**
	(0.234)	(0.127)	(0.0750)	(0.0786)	(0.0974)	(0.155)
Income: 100k+	0.970***	0.662***	0.580***	0.470***	0.571***	0.538***
	(0.297)	(0.161)	(0.0953)	(0.0999)	(0.124)	(0.196)
Region: Prairies	0.572	0.162	0.199*	0.0439	0.263*	0.348
	(0.348)	(0.188)	(0.112)	(0.117)	(0.145)	(0.230)
Region: Ontario	0.233	0.191	0.160	0.00661	0.0466	0.0722
	(0.311)	(0.168)	(0.0997)	(0.104)	(0.129)	(0.205)
Region: Quebec	0.502	0.164	0.181*	0.0457	0.0329	0.0917
	(0.328)	(0.177)	(0.105)	(0.110)	(0.136)	(0.217)
Region: Atlantic	-0.0289	0.244	0.110	-0.0188	0.343*	0.558**
	(0.427)	(0.231)	(0.137)	(0.144)	(0.178)	(0.282)
Employment: employed	0.0727	-0.0430	-0.0872	0.0385	-0.0149	0.0595
	(0.225)	(0.122)	(0.0722)	(0.0756)	(0.0936)	(0.149)
Education: College/CEGEP/Trade school	-0.134	-0.00160	0.0654	-0.0317	-0.138	-0.0810
	(0.271)	(0.146)	(0.0868)	(0.0910)	(0.113)	(0.179)
Education: University	-0.0171	0.0848	0.119	0.0433	-0.133	-0.165
	(0.271)	(0.147)	(0.0868)	(0.0910)	(0.113)	(0.179)
Number of kids: No kids	0.335	-0.142	-0.0156	0.0138	-0.0699	-0.0621
	(0.253)	(0.137)	(0.0812)	(0.0851)	(0.105)	(0.167)
Marital status: Not married/CL	-0.179	0.0659	0.0738	0.0669	0.136	0.214
	(0.242)	(0.131)	(0.0776)	(0.0813)	(0.101)	(0.160)
HH grocery shopping: Not all of it	-0.285	-0.123	-0.150**	-0.0385	-0.0244	0.0641
	(0.223)	(0.121)	(0.0716)	(0.0751)	(0.0930)	(0.148)
Pr(btc_own)	5.751***	3.453***	1.881***	2.642***	3.296***	4.274***
	(1.463)	(0.792)	(0.469)	(0.492)	(0.609)	(0.968)
Constant	-2.226***	0.340	2.157***	3.182***	3.878***	4.389***
	(0.658)	(0.356)	(0.211)	(0.221)	(0.274)	(0.435)
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. Significance stars ***, **, and * represent 1%, 5% and 10% significance, respectively.

Table 22: Counterfactual experiments by selected demographics

	Gender	High_score	Gender_high_score
VARIABLES	log_cash1	log_cash1	log_cash1
t_q1	-0.0125	-0.613**	-0.498
	(0.219)	(0.256)	(0.437)
t_q2	0.429***	-0.382***	-0.163
	(0.134)	(0.134)	(0.371)
t_q5	0.382***	-0.243***	0.160
	(0.0596)	(0.0598)	(0.189)
t_q7	0.412***	-0.280***	0.359**
	(0.0596)	(0.0524)	(0.160)
t_q8	0.435***	-0.268***	0.436**
	(0.0713)	(0.0606)	(0.191)
t_q9	0.453***	-0.259***	0.518
	(0.0786)	(0.0931)	(0.330)
x_q1	0.0742	-0.00439	0.355
	(0.0749)	(0.0569)	(0.290)
x_q2	0.0807**	0.0298	0.198
	(0.0400)	(0.0435)	(0.240)
x_q5	0.0299	-0.0223	0.0968
	(0.0236)	(0.0273)	(0.153)
x_q7	0.0101	-0.0419*	0.0531
	(0.0241)	(0.0230)	(0.145)
x_q8	0.0104	-0.0385	0.0254
	(0.0280)	(0.0264)	(0.156)
x_q9	-0.00161	-0.0348	0.0898
	(0.0397)	(0.0306)	(0.201)
b_q1	0.323***	-0.236	0.0570
	(0.123)	(0.152)	(0.477)
b_q2	0.357***	-0.185**	-0.0318
	(0.0873)	(0.0826)	(0.455)
b_q5	0.347***	-0.153**	0.0974
	(0.0764)	(0.0734)	(0.311)
b_q7	0.378***	-0.162**	0.0734
	(0.0728)	(0.0704)	(0.285)
b_q8	0.348***	-0.201***	0.0579
	(0.0775)	(0.0777)	(0.296)
b_q9	0.327***	-0.193**	0.0552
	(0.0825)	(0.0824)	(0.356)
r_q1	-0.410**	-0.373*	-0.910**
	(0.196)	(0.192)	(0.438)
r_q2	-0.00869	-0.226*	-0.330
	(0.125)	(0.118)	(0.312)
r_q5	0.00471	-0.0673	-0.0337
	(0.0373)	(0.0417)	(0.189)
r_q7	0.0244	-0.0766	0.233
	(0.0540)	(0.0510)	(0.183)
r_q8	0.0765	-0.0284	0.352
	(0.0694)	(0.0734)	(0.246)
r_q9	0.127	-0.0314	0.373
	(0.0997)	(0.103)	(0.383)
Observations	2,623	2,623	283

Note: The first column presents counterfactual results based on gender, second column compares the people with high Bitcoin literacy scores with the others, while the last column looks at the interaction between the gender and high literacy score people at high quantiles of cash holdings. t_q*- presents the quantile treatment effects. x_q*- refers to the differences in quatiles due to observables X. b_q*- refers to the differences in quatiles due to the β parameters . r_q*- refers to the differences in quatiles due to unobservables, residuals. Significance stars ***, **, and * represent 1%, 5% and 10% significance, respectively.

4 Drivers of Bitcoin diffusion in Canada: the role of beliefs and network externalities

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4.1 Introduction

It is well-established that many adoption processes - also known in the literature as 'diffusion' - follow an s-curve pattern, wherein: adoption growth is slow initially, followed by a period of rapid expansion, and eventually levelling off once the technology has saturated the market. During the initial stage of this process it may appear that a given technology is not particularly relevant, due to the associated period of slow growth and low adoption. However, the nature of the s-curve is that this can quickly change, and a period of exponential growth can seem to come out of nowhere. Driving these dynamics is the concept of network externalities - as the number of users increases there is a feedback effect, such that a marginal adopter provides added benefit to the system, over and above their individual contribution.

Bass (1969) provided the first mathematical description of the diffusion process, a remarkably simple differential equation that provided insights which have remained relevant to this day, namely: that the rate of adoption in part depends on the current aggregate level of adoption in the population; and, that diffusion is initiated by 'early adopters' that drive adoption to a certain level, following which 'imitators' begin to catch on and the technology spreads rapidly. Over time many other models of diffusion have been proposed and studied which highlight or emphasize other mechanisms for diffusion.

From available empirical evidence, it would seem that Bitcoin remains in an early stage of diffusion. Surveys conducted across the world put estimates of Bitcoin ownership in the range of 1.5% to 5% (see: Stix (2019); Henry et al. (2018); Financial Conduct Authority (2019); Hundtofte et al. (2019)). It remains to be seen whether Bitcoin will follow an s-curve pattern and ultimately achieve widespread adoption, or whether it will fizzle out. Bitcoin certainly has its' doubters. Budish (2018), for example, argues that were Bitcoin to achieve a broad level of acceptance/success as a digital currency, this would only result in certain economic incentives becoming strong enough that would ultimately cause the system to collapse. On the other hand, central banks across the world are taking Bitcoin and other private digital currencies quite seriously, as evidenced in part by research and policy initiatives geared towards exploring Central Bank Digital Currency – a digital form of cash to compete with private counterparts.

In late 2016, the Bank of Canada commissioned the Bitcoin Omnibus Survey (BTCOS) to gather information on the awareness and use of Bitcoin among Canadians. The survey has been conducted annually since (see Henry et al (2017, 2018, 2019)). In this paper, we make use of these novel data, and in particular having two available observations (2016 and 2017), to conduct an empirical study on the diffusion of Bitcoin. We follow the approach of Goolsbee and Klenow (2002) who studied the diffusion of personal computers. They estimate the Bass model by interpreting the aggregate level of adoption as a so-called 'local network' variable: the city-level adoption rate of personal computers in the previous time period. In our case, we calculate a similar local network variable based on the level of Bitcoin adoption in 2016, and use it measure the impact of network effects on diffusion.

In addition to this approach, we add to our study an analysis on the effect of beliefs about the future of Bitcoin survival on an individual's adoption decision. Survey evidence shows that beliefs about the future potential of Bitcoin may play an important role in its diffusion as a nascent technology. For example, in an Austrian survey (see Stix (2019)) of digital currencies it is found that owners believe these instruments provide relative benefits in terms of making payments, compared with other conventional payment methods. However, only 50% of these owners report having used the digital currencies to make an actual payment. The implication is that these owners believe that Bitcoin and other digital currencies will have benefits in the future. Similarly, the 2018 BTCOS identified that Bitcoin owners are much more likely to state that they plan to go 'cashless' in the future (c.f. Engert et al (2018)). Our study of beliefs makes use of a question introduced in the 2017 BTCOS that asks respondents how likely they think it is that Bitcoin will survive in 15 years.

We find robust evidence that beliefs about Bitcoin's future survival are strongly associated with an individual's adoption decision. There is limited evidence that network effects currently play a role in diffusion, suggesting that Bitcoin remains in an early stage of diffusion wherein early adopters play a key role.

4.2 Data

4.2.1 Overview of dataset

We use data from the Bank of Canada's Bitcoin Omnibus Survey (BTCOS). Initiated in November/December of 2016, the primary purpose of the BTCOS was to serve as a monitoring tool, obtaining basic measurements of Bitcoin awareness and ownership among the Canadian population. The Currency Department of the Bank of Canada conducts a wide range of economic research into the use of payment methods to better understand the use and possible evolution of banknotes (cash). To that end, it is necessary to understand and assess the potential for new payment innovations, including cryptocurrencies, to impact the demand for cash. The success of the inaugural 2016 BTCOS led to follow-up waves of the survey being conducted on an annual basis from 2017 to present.

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 survey instrument is brief, taking on average five minutes to complete, with core components as follows: awareness of Bitcoin; ownership/past ownership of Bitcoin; amount of Bitcoin holdings; reasons for ownership/non-ownership. As the survey has evolved over time, its' scope has broadened based on demand for more detailed information about the motivation of Bitcoin owners and their usage behaviour. Our analysis relies mostly on the 2017 BTCOS, wherein the following questions were added to the core components: beliefs about the future 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 addition to content questions, respondents are also asked to provide demographic information, see Table 1. Most 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 the sample is representative of the adult Canadian population along a variety of dimensions (see Henry et al (2019)).

4.2.2 Key variables of interest

Our analysis concerns three main variables of interest which we now discuss.

Adoption (A_i): Each respondent answers the question: "Do you currently have or own any Bitcoin?". Therefore, $A_i = 1$ if a respondent has adopted Bitcoin in 2017 and 0 otherwise. Table 2 shows the adoption rates of Bitcoin in 2016 and 2017, both overall, as well as by demographic categories determined by age, gender and region. Adoption is noticeably higher among younger Canadians aged 18-34 years old with 11.1% self-reporting as Bitcoin owners in 2017, compared with just 3.2% of those aged 35-54 and only 0.5% among those over 55. Adoption is also higher among males versus females (6.6% versus 2.1% in 2017). Regional variation is less stark, but adoption is observed to be higher in British Columbia and Quebec, and lowest in the Atlantic provinces.

Local network variable ($LN_{i,2016}$)**:** Column 1 of Table 2 provides examples of so-called 'local network' variables. For a given individual i observed in 2017, we calculate the level of adoption among their cohort in 2016 and assign this value to $LN_{i,2016}$; the value of course depends on the particular variable we choose to define the cohort. For example, if we choose the cohorts to be defined by the three age categories as given in Table 2, then a respondent j who is aged

45 will be assigned $LN_{j,2016} = 0.016$.

This is motivated by Goolsbee and Klenow (2002) where they model the diffusion of personal computers. In their paper, Goolsbee and Klenow use the city-level adoption of personal computers in the previous time period to measure network effects, i.e., the extent to which diffusion of technology in a person's social network affects their adoption decision. In a similar vein, we seek to use past period (2016) adoption of Bitcoin as measured by the 2016 BTCOS for our local network variable. The main limitation with our data is that Bitcoin is still in the early stages of adoption – in 2016 there were only $N = 58$ Bitcoin owners observed in our sample. This makes it difficult to use a fine distinction on the possible cohort (e.g. using city-level data) since we would have many zero observations. By contrast, choosing as coarser distinction (e.g. gender) means that little variation is observed.

Beliefs ($ES15_i$): Respondents 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. The scale by default is initiated at 50, so the respondent must slide it right or left to express a positive or negative opinion, respectively, about the future of Bitcoin . We construct the variable $ES15$, the expected survival of Bitcoin in 15 years, by dividing the answer to this question by 100 and interpreting it as a probability. Figure 1 shows the distribution of $ES15$. It has mean value of 0.45 and median of 0.5; 17% of respondents left the slider at 50 ($ES15 = 0.5$), suggesting they were essentially unsure about the future survival of Bitcoin.

4.3 Empirical strategy

In this section, we discuss the empirical strategy for estimating the effect of beliefs and network externalities on Bitcoin adoption.

4.3.1 Baseline models

We first consider two baseline models.

Ba-C (Beliefs as continuous):

$$Prob(A_i = 1|ES15_i) = \beta_0^c + \beta_1^c ES15_i + \beta_2^c LN_{i,2016} + \beta_3^c [LN_{i,2016} * ES15_i] + \alpha^c X_i + \epsilon_i^c$$

Ba-D (Beliefs made discrete):

$$Prob(A_i = 1|E_i) = \beta_0^d + \beta_1^d E_i + \beta_2^d LN_{i,2016} + \beta_3^d [LN_{i,2016} * E_i] + \alpha^d X_i + \epsilon_i^d$$

We can estimate Ba-D and Ba-C using a probit or logit model. In Ba-D, we transform the beliefs variable $ES15$ into a discrete indicator variable, E, as follows: we assign the value $E_i = 1$ if $ES15_i > 0.5$ and 0 otherwise. The purpose of this is to account for the fact that $ES15$ has a highly non-linear distribution, and therefore to explore whether this fact has any impact on the qualitative or quantitative results for the coefficient on beliefs. The interpretation of E_i is that beliefs may be considered as 'high' or 'low'; the 0.5 threshold classifies those with uncertain beliefs (i.e. those who left the slider at 50) as having low beliefs.

In both Ba-C and Ba-D, we define the local network variable $LN_{i,2016}$ to be determined by the cohort of age by gender, where we take two categories for age (18 to 34 years old; 35 years old and above) and two categories for gender (male; female), for a total of four categories. This strikes a balance between parsimony – which is necessary due to the fact that there are such a small number of Bitcoin adopters in 2016 – and having a reasonable amount of variation, since we know from Table 2 that age and gender are unconditionally correlated with adoption.

For X_i, we utilize available demographic characteristics about the respondent as control variables to limit omitted variable bias (see again Table 1). Specifically we have: age (continuous), gender (2 categories), income (3 categories), region (5 categories), employment (2 categories), education (3 categories), number of kids in HH (2 categories), marital status (2 categories), HH grocery shopping responsibilities (2 categories).

Finally, with respect to the coefficients β_i^j for $i \in \{1,2,3\}$ and $j \in \{c,d\}$, we give the following interpretations: β_1^j measures the direct effects of a person's beliefs on their adoption decision; β_2 measures network externalities, i.e. the extent to which an individual's adoption decision is affected by the level of adoption within their cohort; β_3^j measures the interaction between network effects and beliefs.

4.3.2 Identification via an exclusion restriction

It is reasonable to suspect that a person's beliefs may be co-determined with their adoption decision, or perhaps more relevantly, that the direction of causality is unclear. On one hand, a person may research Bitcoin and form positive beliefs about its' future utility and survival, which would then drive them to adopt. Conversely, it could also be the case that a person's adoption decision is reflective of experimentation with Bitcoin; initially they have low or uncertain beliefs about its' future, but adopting causes their beliefs to increase. Possible mechanisms for the latter explanation could be due to confirmation or hindsight bias, or simply due to learning more about the technology from using it directly.

Therefore, it is advisable to use an exclusion restriction that can help us identify the true effect of beliefs about Bitcoin survival on an individual's adoption decision – something correlated with beliefs, but not directly with adoption. We construct such a variable by exploiting design features of the BTCOS survey instrument. Specifically, we utilize other surveys questions where respondents are asked to express an opinion about Bitcoin:

1. Respondents were asked a series of five questions testing their knowledge of various aspects of the Bitcoin system, see Tables 3 and 4. These were 'True/False' type questions but the respondent was also allowed to answer with 'Don't know'.

2. In addition to beliefs about survival, respondents were also asked to report their beliefs about the level of future Bitcoin adoption: "What percentage of Canadians do you think will be using Bitcoin 15 years from now?" This question was similar to the question about the future survival of Bitcoin in that a sliding scale from 0 to 100 was used, with

the slider initiated at 50, where 0 means no Canadians will adopt and 100 means all Canadians will adopt. From this question we derive a variable called $EAR15$ in a manner similar to $ES15$.

From this set of questions, we construct a variable called $unsure$, that measures how frequently respondents choose to provide a 'non-answer' regarding Bitcoin:

$$unsure = \sum_{i=1}^{5} \mathbb{1}\{Know_i = \text{"Don't know"}\} + [1 - 2 * abs(EAR15 - 0.5)],$$

where $Know_i$ is the i-th knowledge question. The rationale for the second term is as follows: if a respondent left the slider unchanged, then the deviation of $EAR15$ from 0.5 is zero and this adds a score of 1 to $unsure$; if they expressed the strongest possible preference (0 or 1), the absolute deviation is 0.5 and therefore this contributes 0 to $unsure$; preferences in between these values contribute linearly to $unsure$ based on how far the respondent moved the slider from 0.5.

Conditioning on $unsure$ demonstrates a correlation with $ES15$, see Figure 3. Respondents who have a high value of $unsure$ are very likely to have kept the slider at or near 50. By contrast, for those who demonstrate a willingness to respond / express an opinion about Bitcoin in other questions found in the BTCOS, the distribution of beliefs does not exhibit a heaping feature. Additionally, whereas Bitcoin owners tend to express high beliefs about Bitcoin (see Figure2), those with a low unsure score have a wide range of beliefs, skewing only slightly positive. This provides evidence that $unsure$ is correlated with adoption only indirectly through its' relationship with $ES15$.

4.3.3 Accounting for possible endogeneity of beliefs

To account for the fact that beliefs may be endogenous, our approach is to first model beliefs separately using the exclusion restriction we have just defined. In both the discrete and continuous case we can then apply a control function approach to correct for the estimate on beliefs. As an additional robustness check, we also estimate a bivariate probit model in the case of discrete beliefs. Details are provided below.

Control Function: In comparison with our baseline model, we now seek to estimate two-stage models:

CF-C (Beliefs as continuous):

$$(1) ES15_i = \delta^c X_i + \gamma^c Z_i + u_i^c$$

$$(2) Prob(A_i = 1|ES15_i) = \beta_0^c + \beta_1^c ES15_i + \beta_2^c LN_{i,2016} + \beta_3^c [LN_{i,2016} * ES15_i] + \alpha^c X_i + \eta^c CF_i^c + \epsilon_i^c$$

CF-D (Beliefs made discrete):

$$(1) Prob(E_i = 1) = \delta^d x_i + \gamma^d Z_i + u_i^d$$

$$(2) Prob(A_i = 1|E_i) = \beta_0^d + \beta_1^d E_i + \beta_2^d LN_{i,2016} + \beta_3^d [LN_{i,2016} * E_i] + \alpha^d X_i + + \eta^d CF_i^d + \epsilon_i^d$$

In both cases, for brevity, we use the notation Z_i for the exclusion restriction described above, i.e. $Z_i = unsure_i$. In CF-C, Equation 1 is estimated using OLS and CF_i^c is then the usual estimated residual from OLS. In CF-D, Equation 1 is estimated using a probit model and CF_i^d is taken to be the deviance residual.

Bivariate Probit: By making beliefs discrete we naturally have two equations with outcome variables that are binary. This lends itself to estimation using a bivariate probit, which estimates the coefficients jointly, allowing for correlation in the error terms across equations:

BP-D (Beliefs made discrete):

$$(1) Prob(E_i = 1) = \delta^d X_i + \gamma^d Z_i + u_i^d$$

$$(2) Prob(A_i = 1|E_i) = \beta_0^d + \beta_1^d E_i + \beta_2^d LN_{i,2016} + \beta_3^d [LN_{i,2016} * E_i] + \alpha^d X_i + + \epsilon_i^d$$

4.4 Results

4.4.1 Modelling beliefs about Bitcoin survival

Tables 5 and 6 present results from the first stage of estimation, i.e. modelling beliefs about the future of Bitcoin survival as the dependent variable. As described above we examine two scenarios – first where beliefs are treated as continuous ($ES15$ as the dependent variable) and second where beliefs are transformed to be discrete (E as the dependent variable). In the continuous case, Table 5 contains four columns: we estimate a model of $ES15$ with and without the exclusion restriction; and, we use two estimation procedures, OLS as well as a fractional linear regression using a logit link function. The fractional linear regression (implemented as *fracreg* in Stata) is used in cases where the dependent variable is a probability constrained between 0 and 1. Likewise in the discrete case there are also four columns in Table 6: we estimate a model for E with and without the exclusion restriction; and, we estimate both a probit and logit specification.

Taking up the continuous beliefs scenario, we first note that both estimation procedures (OLS and fractional regression) produce similar results. There are no differences in the statistical significance of the coefficients between the two procedures; further, significant coefficients are very similar in magnitude. Age is significant and negatively correlated with future beliefs about Bitcoin survival, meaning that older respondents think that Bitcoin is less likely to survive. Regional effects are also present – relative to the base category of British Columbia, all other regions except the Prairies hold more positive views about Bitcoin survival. Interestingly, those without kids are less optimistic about Bitcoin's future survival than those with children. Our exclusion restriction $unsure$ is significant at the 1% level and negatively correlated with beliefs. This means that those who are more likely to provide answers about Bitcoin on the BTCOS also have higher expectations for Bitcoin's survival, conditional on all other factors considered.

Taking beliefs to be discrete yields a similar pattern of results to the continuous case, though there are slight differences. Age, region and having children are significant predictors of beliefs about survival, with the same directions as in the continuous case. By contrast, employment effects do not show up in the discrete case (though they are only weakly significant in the continuous model). Another notable difference is that household shopping responsibilities are significantly associated with beliefs in the discrete case – those who are responsible for all of the grocery shopping duties have higher beliefs, though the significance is weak in the model with the exclusion restriction. The exclusion restriction is again highly significant and negatively correlated with having high beliefs about the survival of Bitcoin in 15 years. Finally, the results are not sensitive to the choice of specification (probit vs logit), as significant coefficients are similar in magnitude across the two specifications.

4.4.2 Bitcoin adoption, beliefs and network effects

Table 7 presents results from the Bitcoin adoption models described in Section 3, including both baseline and control function models with beliefs as continuous or discrete, as well as a bivariate probit model in the discrete case. We report marginal effects in all cases. Across the board, it is clear that beliefs about the survival of Bitcoin in 15 years are correlated with Bitcoin adoption. The coefficient on beliefs is significant at the 1% level in each of the models considered; higher beliefs about Bitcoin survival indicate a greater likelihood of being a Bitcoin owner. This effect is amplified when we use a control function to account for the endogeneity of beliefs – the magnitude of the marginal effect is roughly 10 times greater in the discrete case compared with that of the baseline model, and roughly 20 times greater in the continuous case. The control function variables themselves are highly significant indicating that the baseline models provide a biased estimate of the effect of beliefs on adoption.

With respect to network effects the relationship is not quite as clear. Taking beliefs as continuous, the coefficient on the local network variable is not significant; however, there is significance at the 5% level for the baseline discrete model (Ba-D) and weak significance (10% level) for the control function discrete model (CF-D). The marginal effects coefficients on the local network variable are positive and fairly consistent, ranging from 0.429 to 0.577. This indicates that a higher level of Bitcoin adoption among your peers, as defined by age and gender, is associated with a greater propensity to adopt. Finally, we see little evidence that there is a social learning effect related to beliefs, as measured by the interaction term. Across the models the coefficient is negative and it is only significant in the bivariate probit model.

Our interpretation of these results is as follows. Being in an early stage of diffusion, network effects on Bitcoin adoption are weak because the level of adoption is low and therefore one is less likely to interact with a Bitcoin owner in their normal social circle. Furthermore, the strong correction by the control function suggests that experimentation with Bitcoin is also low; early adopters have already formed strong beliefs about Bitcoin's future, which drives their adoption. Additionally, beliefs are formed on an individual basis and not (at this juncture) reinforced by network effects as indicated by the lack of significance on the interaction term.

4.5 Conclusion

In this paper, we utilized a unique dataset from Canada on Bitcoin use across multiple years to gain insight into the process of diffusion of Bitcoin as a technology. We find evidence that Bitcoin is still in an early stage of diffusion, in the sense that aggregate adoption is low and we do not yet see strong evidence for network effects relative to the effects of individual characteristics. Beliefs about Bitcoin's future survival are highly correlated with adoption, suggesting that early adopters are not just experimenting but rather are heavily invested in the technology. In future work, we plan to extend our analysis using additional waves of the survey (2018 and 2019) with the aim of assessing whether the present results are robust, as well as constructing an estimate for the s-curve in order to obtain predictions on when Bitcoin may enter a period of more rapid diffusion.

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Tables and Figures

Figure 1: **Beliefs about BTC survival, kernel density:** This figure shows the kernel density of responses to the following question: "How likely do you think it is that the Bitcoin system will fail or survive in the next 15 years?". Respondents used a sliding scale from 0 to 100, initiated at 50, where 0 means that Bitcoin will certainly fail and 100 means that Bitcoin will certainly survive. The question was asked of respondents who indicated they were aware of Bitcoin. We divide responses by 100 and interpret as a probability.

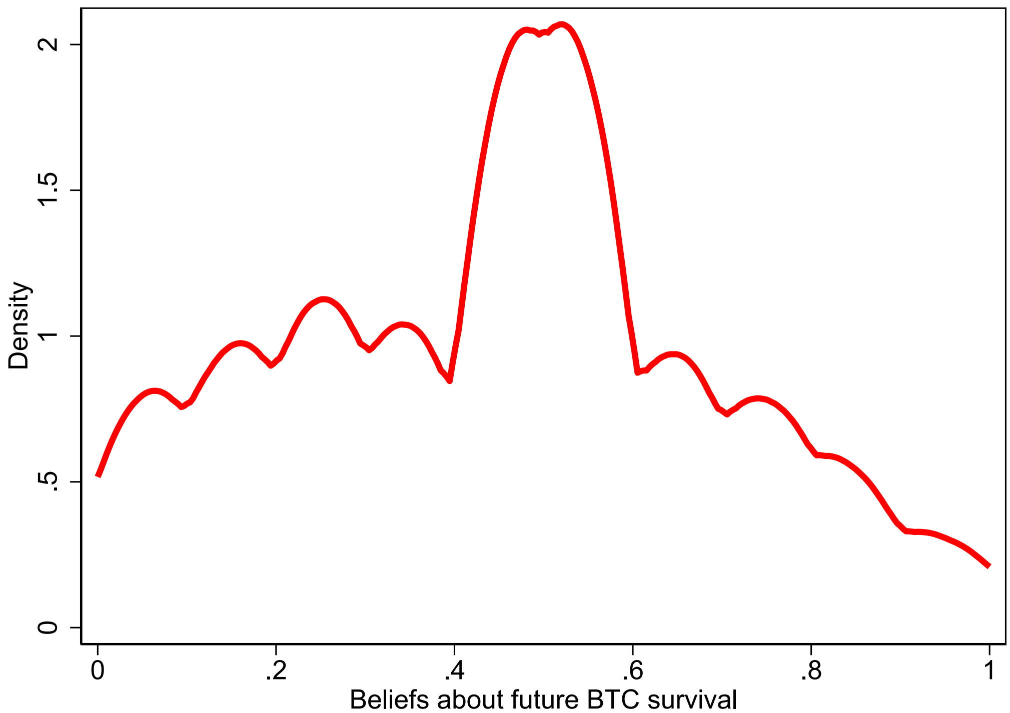

Figure 2: **Beliefs about BTC survival by BTC ownership, kernel density:** This figure shows the kernel density of responses to the following question: "How likely do you think it is that the Bitcoin system will fail or survive in the next 15 years?". Respondents used a sliding scale from 0 to 100, initiated at 50, where 0 means that Bitcoin will certainly fail, and 100 means that Bitcoin will certainly survive. The question was asked of respondents who indicated they were aware of Bitcoin. We divide responses by 100 and interpret as a probability. The distributions shown are for Bitcoin owners in green compared with Bitcoin non-owners in blue.

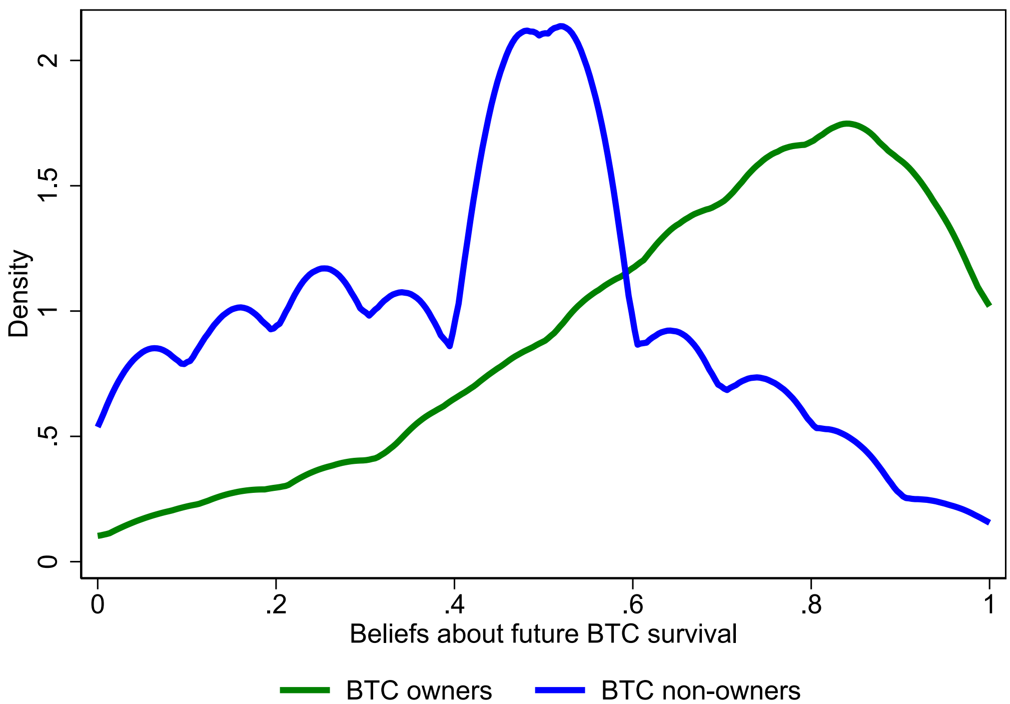

Figure 3: **Beliefs about BTC survival by $unsure$, kernel density:** This figure shows the kernel density of responses to the following question: "How likely do you think it is that the Bitcoin system will fail or survive in the next 15 years?". Respondents used a sliding scale from 0 to 100, initiated at 50, where 0 means that Bitcoin will certainly fail, and 100 means that Bitcoin will certainly surive. The question was asked of respondents who indicated they were aware of Bitcoin. We divide responses by 100 and interpret as a probability. The distributions shown are for those with a high value of $unsure$ (greater than or equal to 4) versus those with a low value of $unsure$ (less than or equal to 2). The propensity to give a so-called 'non-answer' to the BTCOS survey questions is correlated with beliefs but not directly with Bitcoin adoption.

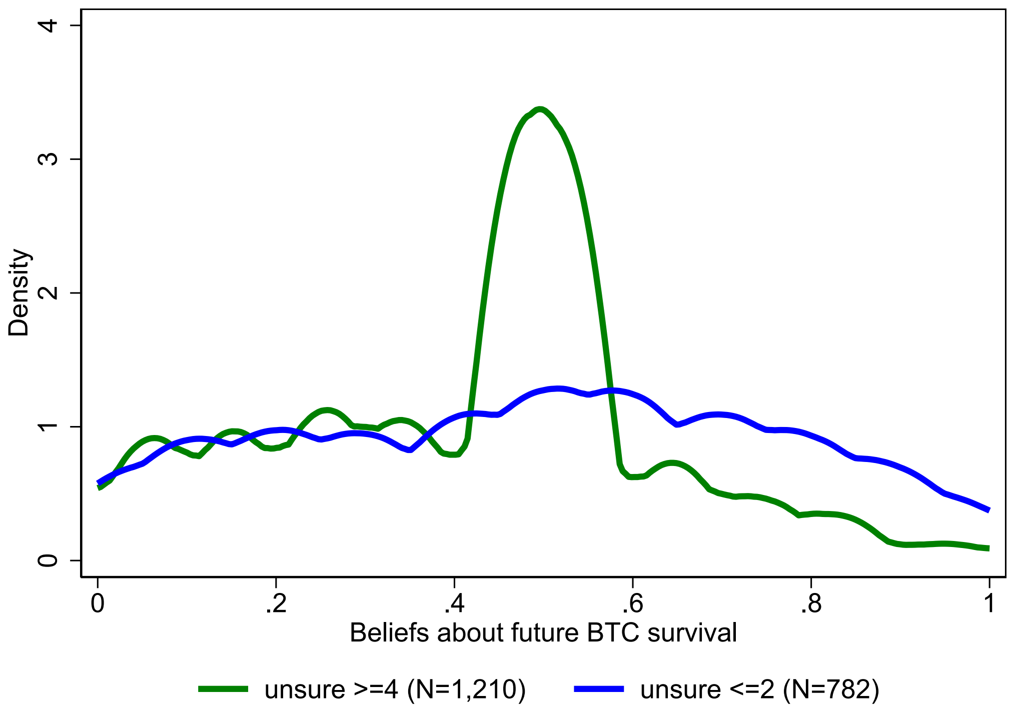

Table 1: **Sample description / observable characteristics, 2017 Bitcoin Omnibus Survey:** This table shows the distribution (proportion) and counts of demographic variables associated to respondents from the 2017 Bitcoin Omnibus Survey. The total sample size was $N = 2,623$. The first column shows the proportion of respondents in each category, while the second column reports total counts. Respondents were not forced to respond to sensitive questions about income and employment, hence there are missing data for these variables. We use these individual level characteristics as control variables in subsequent regressions.

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

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

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

Table 3: **Knowledge of Bitcoin – description of questions** This table describes the set of five true/false questions put to respondents in the 2017 Bitcoin Omnibus Survey, to test their knowledge of the underlying technology/economics behind the Bitcoin system. Respondents were allowed to answer with 'Don't know', and we utilize such responses in creating an exclusion restriction.

Question	Text	Answer
1	Bitcoin allows for direct transactions between two parties, without the need for a trusted third party involved.	TRUE
2	The total supply of Bitcoin is fixed.	TRUE
3	All Bitcoin transactions are recorded on a distributed ledger that is publicly accessible.	TRUE
4	Bitcoin is backed by a government.	FALSE
5	The security (i.e. immutability) of the Bitcoin system relies solely on cryptography.	FALSE

Table 4: **Knowledge of Bitcoin – distribution of responses:** This table shows the distribution of responses to the five knowledge questions. These questions were asked of the $N = 2,225$ respondents who indicated that they were aware of Bitcoin. We utilized 'Don't know' responses in creating an exclusion restriction for estimating the impact of beliefs on adoption.

	Correct	Incorrect	Don't know
Q1			
%	0.509	0.046	0.445
N	1,132	102	991
Q2			
%	0.213	0.228	0.560
N	473	507	1,245
Q3			
%	0.181	0.194	0.625
N	403	432	1,390
Q4			
%	0.591	0.040	0.369
N	1,314	90	821
Q5			
%	0.040	0.414	0.546
N	89	922	1,214

Table 5: **Modelling beliefs about Bitcoin – continuous:** This table presents the results from several models of $ES15$ as a dependent variable. Columns labelled (1) and (2) use OLS to estimate the model while columns (3) and (4) use a fractional linear regression (marginal effects are reported); columns (2) and (4) augment the model with our exclusion restriction $unsure$, denoted in short by Z. Of the $N = 2,225$ respondents who answered the beliefs question, there were $N = 1,992$ observations due to missing data.

	(1)	(2)	(3)	(4)
VARIABLES	OLS	OLS w/ Z	fracreg	fracreg w/ Z
Age	-0.00246***	-0.00241***	-0.00246***	-0.00241***
	(0.000405)	(0.000405)	(0.000385)	(0.000384)
Female	0.00139	0.00871	0.00146	0.00878
	(0.0112)	(0.0116)	(0.0111)	(0.0114)
Income 50k-99k	1.58e-05	-0.000773	4.41e-05	-0.000742
	(0.0136)	(0.0136)	(0.0137)	(0.0137)
Income 100k+	-0.0132	-0.0140	-0.0130	-0.0137
	(0.0169)	(0.0168)	(0.0170)	(0.0170)
Prairies	0.00629	0.00717	0.00675	0.00763
	(0.0189)	(0.0188)	(0.0189)	(0.0189)
Ontario	0.0426**	0.0429**	0.0430**	0.0433**
	(0.0168)	(0.0168)	(0.0170)	(0.0170)
Quebec	0.0469***	0.0448**	0.0474***	0.0452**
	(0.0182)	(0.0182)	(0.0183)	(0.0184)
Atlantic	0.0632***	0.0669***	0.0635***	0.0671***
	(0.0238)	(0.0238)	(0.0227)	(0.0226)
Employed	0.0244*	0.0231*	0.0247**	0.0234*
	(0.0128)	(0.0128)	(0.0125)	(0.0125)
College/CEGEP/Trade school	-0.0291*	-0.0297*	-0.0291*	-0.0297*
	(0.0160)	(0.0160)	(0.0156)	(0.0155)
University	-0.0301*	-0.0350**	-0.0302**	-0.0351**
	(0.0160)	(0.0161)	(0.0153)	(0.0155)
No kids	-0.0403***	-0.0397***	-0.0400***	-0.0393***
	(0.0140)	(0.0140)	(0.0142)	(0.0142)
Not married or CL	-4.22e-05	0.00108	0.000110	0.00125
	(0.0137)	(0.0137)	(0.0139)	(0.0138)
HH groc shop, Not all	-0.0129	-0.0104	-0.0130	-0.0104
	(0.0124)	(0.0125)	(0.0126)	(0.0126)
unsure		-0.00731**		-0.00729**
		(0.00313)		(0.00311)
Constant	0.582***	0.599***		
	(0.0326)	(0.0334)		
Observations	1,992	1,992	1,992	1,992
R-squared	0.051	0.054		

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: **Modelling beliefs about Bitcoin – discrete:** This table presents the results from several models of E(discretized version of $ES15$ as a dependent variable. Columns labelled (1) and (2) use a probit model while columns (3) and (4) use a logit (marginal effects are reported everywhere); columns (2) and (4) augment the model with our exclusion restriction $unsure$, denoted in short by Z. Of the $N = 2,225$ respondents who answered the beliefs question, there were $N = 1,992$ observations due to missing data. Data are from the 2016 and 2017 Bitcoin Omnibus Survey.

VARIABLES	(1) probit	(2) probit w/ Z	(3) logit	(4) logit w/ Z
Age	-0.00584***	-0.00553***	-0.00587***	-0.00556***
	(0.000744)	(0.000739)	(0.000740)	(0.000735)
Female	-0.0224	0.0162	-0.0227	0.0158
	(0.0212)	(0.0218)	(0.0211)	(0.0217)
Income 50k-99k	0.0117	0.00809	0.0101	0.00616
	(0.0259)	(0.0257)	(0.0260)	(0.0257)
Income 100k+	-0.0201	-0.0228	-0.0198	-0.0234
	(0.0322)	(0.0319)	(0.0323)	(0.0320)
Prairies	0.0255	0.0300	0.0244	0.0289
	(0.0369)	(0.0367)	(0.0375)	(0.0373)
Ontario	0.0715**	0.0730**	0.0727**	0.0743**
	(0.0325)	(0.0322)	(0.0328)	(0.0325)
Quebec	0.0896***	0.0787**	0.0909***	0.0802**
	(0.0348)	(0.0346)	(0.0349)	(0.0347)
Atlantic	0.0703	0.0895**	0.0711	0.0908**
	(0.0454)	(0.0448)	(0.0457)	(0.0448)
Employed	0.0286	0.0214	0.0311	0.0242
	(0.0243)	(0.0242)	(0.0244)	(0.0243)
College/CEGEP/Trade school	-0.0428	-0.0479	-0.0436	-0.0468
	(0.0302)	(0.0301)	(0.0302)	(0.0301)
University	-0.0584*	-0.0848***	-0.0605**	-0.0856***
	(0.0304)	(0.0305)	(0.0305)	(0.0306)
No kids	-0.0667***	-0.0639**	-0.0665***	-0.0634**
	(0.0258)	(0.0256)	(0.0255)	(0.0253)
Not married or CL	-0.0292	-0.0222	-0.0294	-0.0228
	(0.0258)	(0.0255)	(0.0257)	(0.0253)
HH groc shop, Not all	-0.0552**	-0.0424*	-0.0559**	-0.0421*
	(0.0234)	(0.0232)	(0.0232)	(0.0230)
unsure		-0.0376***		-0.0376***
		(0.00577)		(0.00574)
Observations	1,992	1,992	1,992	1,992

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: **Modelling Bitcoin adoption:** This table presents several models of Bitcoin adoption as presented in Section 3. Marginal effects are reported. The local network variable is determined by the adoption rate of Bitcoin in 2016 among a respondent's cohort as defined by age (two categories – 18 to 34 years old and 35+) by gender (two categories – female and male), for a total of four categories. For the continuous version the beliefs variable is $ES15$; for the discrete model it is E. Data are from the 2016 and 2017 Bitcoin Omnibus Survey.

	Continuous beliefs		Beliefs made discrete		
	Ba-C	CF-C	Ba-D	CF-D	BP-D
VARIABLES					
Beliefs	0.165***	3.196***	0.0728***	0.717***	0.147***
	(0.0365)	(0.490)	(0.0158)	(0.105)	(0.0301)
Local network	0.577	0.429	0.487**	0.435*	0.467***
	(0.366)	(0.306)	(0.245)	(0.235)	(0.154)
Interaction	-0.162	-0.0252	-0.0107	-0.0361	-0.315**
	(0.459)	(0.383)	(0.209)	(0.203)	(0.144)
Control function		-3.066***		-0.275***	
		(0.489)		(0.0432)	
Age	-0.00129**	0.00615***	-0.00128**	0.00163**	-0.000532**
	(0.000587)	(0.00134)	(0.000615)	(0.000772)	(0.000227)
Female	-0.0296**	-0.0375***	-0.0323**	-0.0239**	-0.00530
	(0.0124)	(0.0120)	(0.0126)	(0.0121)	(0.00478)
Income 50k-99k	-0.0109	-0.0105	-0.0143	-0.0203*	-0.00682
	(0.0116)	(0.0113)	(0.0120)	(0.0117)	(0.00443)
Income 100k+	-0.0205	0.0199	-0.0233*	-0.0140	-0.00931*
	(0.0138)	(0.0140)	(0.0141)	(0.0137)	(0.00563)
Prairies	-0.0277*	-0.0438***	-0.0286*	-0.0399***	-0.00500
	(0.0159)	(0.0155)	(0.0159)	(0.0154)	(0.00632)
Ontario	-0.0204	-0.150***	-0.0205	-0.0596***	-0.00191
	(0.0136)	(0.0237)	(0.0136)	(0.0144)	(0.00554)
Quebec	-0.0159	-0.153***	-0.0167	-0.0600***	-0.00299
	(0.0142)	(0.0256)	(0.0146)	(0.0155)	(0.00597)
Atlantic	-0.0355*	-0.228***	-0.0333	-0.0718***	-0.00867
	(0.0201)	(0.0378)	(0.0207)	(0.0226)	(0.00851)
Employed	0.0281**	-0.0490***	0.0301**	0.0126	0.00912**
	(0.0127)	(0.0162)	(0.0129)	(0.0130)	(0.00448)
College/CEGEP/Trade school	-0.00707	0.0823***	-0.00921	0.0152	-0.00523
	(0.0141)	(0.0197)	(0.0144)	(0.0145)	(0.00554)
University	0.00612	0.104***	0.00755	0.0438***	-0.00323
	(0.0132)	(0.0193)	(0.0135)	(0.0141)	(0.00547)
No kids	-0.0216**	0.105***	-0.0258**	0.0115	-0.0101**
	(0.0105)	(0.0214)	(0.0106)	(0.0111)	(0.00435)
Not married or CL	-0.00936	-0.00905	-0.00881	0.00465	-0.00626
	(0.0110)	(0.0102)	(0.0112)	(0.0107)	(0.00450)
HH groc shop, Not all	-0.0206**	0.0197*	-0.0218**	0.00705	-0.00990**
	(0.0104)	(0.0118)	(0.0105)	(0.0109)	(0.00416)
Observations	1,992	1,992	1,992	1,992	1,992

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Conclusion

Summary

This thesis has contributed to the literature on payment surveys and to a greater understanding of the economics of payments for nascent financial technologies.

In the first chapter, we analysed electronic payment card acceptance and payment card usage decisions, using a unique data set from Hungary. First, by comparing different stratification variables we were able to simulate the approach of conventional merchant surveys, and provide practical guidance on which variables should be most effective for obtaining accurate measurements of card acceptance.

Second, we estimated logistic regression models of both card acceptance and usage at the point of sale. Our results confirm that many of the determinants of payment choice identified in the payments survey literature hold true when analyzing the full universe of payments. This suggests that surveys can be a useful and relevant methodology for studying payments going forward.

Moving to the second chapter, we reported on findings from the 2018 Bitcoin Omnibus Survey (BTCOS), and explained innovations to the survey intended to deepen an understanding of the motivation of Bitcoin owners.

Bitcoin ownership continued to grow in 2018, but can be considered low overall at just around 5%. Consistent with dramatic drops in the price of Bitcoin in 2018, we observed an increase in the number of *past* Bitcoin owners, and those who continued to own Bitcoin did so in smaller quantities. The main reason for owning Bitcoin remained as an investment, suggesting that Bitcoin adopters treat it more as an asset versus a currency. However, Bitcoin owners in 2018 also reported using it more often for buying goods and services or making person-to-person transfers, compared with past years.

Developments to the BTCOS in 2018 were built on lessons learned from the previous waves. One key addition was of the “Big Three” financial literacy questions, originally proposed by Lusardi and Mitchell, which have become prevalent in many surveys as a standardized methodology for quantifying financial literacy. Despite the fact that higher-literacy individuals were more likely to have heard of Bitcoin, it turns out that they were less likely to own it.

Also new to the survey were questions related to cash and online payment preferences. While Bitcoin owners held more cash in their pockets at the median, they were more likely to say they had already stopped using cash and to plan to go 'cashless' in the future. Canadians rated security the most important feature for making online payments, while privacy, acceptance and ease of use were much less common. These preferences did not appear to distinguish the subset of Bitcoin adopters, as they expressed much more varied preferences compared with non-owners.

In the third chapter we delved deeper into the economics of Bitcoin via the relationship between cash holdings and Bitcoin ownership. Using data from the 2017 BTCOS, this chapter shed light on a surprising finding which suggests that digital currencies may 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, we showed 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. We explored possible mechanisms that could potentially explain why Bitcoin owners hold more cash.

Finally, in the fourth chapter, we again utilized several years' worth of data from the BTCOS to gain insight into the process of diffusion of Bitcoin as a technology. The evidence suggests that Bitcoin is still in an early stage of diffusion, in the sense that aggregate adoption is low, and we do not yet see strong evidence for network effects relative to the effects of individual characteristics. Beliefs about Bitcoin's future survival are highly correlated with adoption, suggesting that early adopters are not simply experimenting, but rather are heavily invested in the technology which drives them to adopt.

Future work

Along the way, within each chapter, we have provided related suggestions for future work. To conclude, we offer a more comprehensive vision for linking developments in payment survey methodology to an increased understanding of the economics behind Bitcoin.

Our work has demonstrated that, from a survey methodology perspective, Bitcoin users can be considered as a *hard-to-reach* population. By this we mean the following: To accurately measure the adoption of Bitcoin using a consumer payment survey, it is desirable to use sampling methods that will produce a representative sample; from there, we can calculate unbiased point estimates with known variability.

However, as we have seen in our study and use of the BTCOS, a problem with this approach is that because the target population is so small, we may expend considerable resources obtaining a large overall sample with only a small subpopulation of Bitcoin users. Over the three waves of the BTCOS the sample size was roughly $N = 2,000$, meaning that the sample of Bitcoin owners was only around $N = 100$. This makes it challenging to conduct in-depth analysis on the subpopulation of Bitcoin owners. In addition, due to constraints on survey length, the survey instrument must be in some sense geared towards *non-owners*, since they constitute the bulk of respondents

Bitcoin owners may also be considered hard-to-reach for other reasons. For example, they may be holding Bitcoin because of a desire for anonymity, or, a lack of trust in governments or traditional financial institutions. This means that they may be hesitant to respond to surveys conducted by established survey companies or market research firms. Further, those that do respond to such surveys would likely reflect a selected sample of Bitcoin users, who are using Bitcoin primarily due to other motivations such as speculative investment.

Additionally, Bitcoin users may belong to complex and difficult-to-define social networks, which inform the diffusion process itself. Whereas physical location (geography) has historically been used to study the network effects of technology diffusion, it is not clear that geographical distinctions are as relevant in the Internet age. To truly understand Bitcoin diffusion we need to know more about how its network of users is constituted.

There are existing statistical methods available to address the problems associated with sampling of hard-to-reach populations. In future work, we plan to address the challenges of surveying Bitcoin users by employing such an approach, called *respondent-driven sampling* (RDS).

In RDS, survey respondents recruit others in their network to also complete the survey; and, respondents receive incentives both for completing the survey themselves (primary incentive), as well as for completed surveys of people they recruit (secondary incentives). In this way, the survey sampling process ‘drives itself.

Some benefits of RDS are: 1] If conducted properly, and under certain assumptions, we can obtain unbiased estimates of quantities of interest for the target population of Bitcoin users; 2] Through the sampling process we gain information on the network of Bitcoin users; 3] Since respondents are recruited by others they know and trust, certain types of Bitcoin users may be more likely to complete the survey versus a more traditional approach.

In sum, to further our study of Bitcoin we propose to undertake an RDS study of Bitcoin users. This will allow us to obtain a large sample on which to conduct in-depth analysis, as well as design a detailed survey instrument allowing for a better understanding of the economic trade-offs involved in owning and using Bitcoin.