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Cash in the Pocket, Cash in the Cloud: Cash Holdings of Bitcoin Owners

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Abstract

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

Topics: Bank notes, Digital currencies and fintech, Econometric and statistical methods
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1 Introduction

In a speech in February 2020, Bank of Canada Deputy Governor Tim Lane discussed two potential reasons for issuing Central Bank Digital Currency (CBDC): (1) if cash demand falls to a negligible level, and (2) if private digital currencies make serious inroads. In Canada, there has been a documented decline in the use of cash by consumers for undertaking point-of-sale transactions over the last decade. The Bank of Canada's 2017 Methods-of-Payment (MOP) survey shows that the share of cash used for retail transactions declined from 54 percent in 2009 to 33 percent in 2017 (see Henry et al. (2018b)). Even so, cash remains popular among certain demographic groups (i.e., older, less-educated, and lower-income) and for certain types of transactions (e.g., small-value transactions or payments at bars/restaurants). For some demographic groups, cash is also commonly used as a convenient store of value. Other advanced economies have witnessed similar patterns of cash use at the POS. For example, Bagnall et al. (2016) undertake an international comparison across seven countries showing that cash is resilient.[1]

The country that has been touted as being closest to a cashless society is Sweden, due primarily to a lack of consumer demand for cash (see Riksbank (2017), Riksbank (2018a), and Riksbank (2018b)). Engert et al. (2019) undertake a cross-country comparison of Canada and Sweden to understand the potential drivers of the differences between the two countries. They find that both countries have similar payment infrastructures, so the difference in cash use is due to (1) the legal tender status of bank notes, and (2) banking regulations related to secure deposits in Sweden. In addition, they argue that cash demand has two components: transactional and non-transactional. In Canada and many other countries, banknotes in circulation continue to grow at pace with GDP, while at the same time cash used for payments is declining. The overall stable or increasing demand for cash is therefore thought of as primarily a store-of-value motive.

Two key considerations are relevant for assessing whether the criteria for issuing CBDC will be met in the future. First is the role of consumer preferences in driving the demand for cash and alternatives.[2] What characteristics of cash do consumers value, and would these translate to cash as manifested in a digital form? Why might consumers 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. For example, Huynh et al. (2020) estimate the demand for payment services and find that a CBDC could

[1] The seven countries are Australia, Austria, Canada, France, Germany, Netherlands, and the United States of America.

[2] Kennickell and Kwast (1997) presciently and accurately summarized the point almost 25 years earlier in distinguishing from a supply-side approach to studying electronic payments: "What types of products are consumers likely to be actually willing to pay for? What are the characteristics of current and likely future purchasers of electronic products and services? How quickly will consumers adopt electronic technologies?"

potentially substitute for cash and debit card payments up to a 25 percent market share, however this would require it to combine the best features of both cash and debit cards and be compelling enough for widespread acceptance by merchants.

Second, to assess whether private digital currencies are making inroads, it is important to understand the extent to which they function for consumers as a method of payment versus a store of value or 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 currency (Nakamoto (2008)); that is, it would provide economic agents with the ability to make digital peer-to-peer payments without the need for a trusted third party (Böhme et al. (2015)). However, the stunning increase in the price of Bitcoin, which rose from $1,000 USD in late 2016 to a peak of almost $20,000 USD in late 2017, has led many to view Bitcoin as something more akin to a "cryptoasset" than a cryptocurrency.

To better understand consumer adoption and use of the most popular private digital currency, Bitcoin, the Bank of Canada commissioned the Bitcoin Omnibus Survey (BTCOS) in 2016 (see Henry et al. (2018a)). The survey has been administered annually in subsequent years (see Henry et al. (2019a) and Henry et al. (2020)).[3] In the current paper we use data from the 2017 and 2018 BTCOS. The 2017 BTCOS introduced a question designed to measure Canadian consumers' cash holdings – that is, cash held in the 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 are necessarily displacing cash in an increasingly digital world, and it also corroborates a similar finding by Fujiki and Tanaka (2014). However, it naturally raises questions about how to properly interpret this finding, specifically in terms of whether there may be factors driving *both* cash holdings and Bitcoin ownership. For example, Bitcoin owners may prefer anonymous liquidity, and hence cash may be a hedge (or vice versa); or, some Bitcoin owners may not trust institutions such as government or banks, leading to large cash holdings outside of traditional financial institutions. These sources of selection induce endogeneity that is likely to bias estimates of the effect of Bitcoin ownership on cash holdings.

Therefore, considering these potential sources of endogeneity, this paper aims to estimate the effect of Bitcoin ownership on the level of consumer cash holdings in Canada. In doing so, we also examine whether there are distributional effects present in the relationship between cash holdings and Bitcoin ownership. Anticipating possible sources of selection, both the 2017 and 2018 BTCOS were designed with a question that can be used as an exclusion restriction/instrumental variable: "What percentage of Canadians do you think will be using

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

Bitcoin 15 years from now?" This variable works well as an exclusion restriction because owners are more optimistic about the prevalence of future Bitcoin use; however, there is no obvious direct relationship with the current level of cash holdings. To further improve identification, we exploit differences in the functional form of age effects between the model for Bitcoin ownership and the model for cash holdings.[4]

Based on the results that control for selection, we find that the difference in cash holdings between Bitcoin owners and non-owners varies from 39 percent (in 2018) to 63 percent (in 2017) at the 25th quantile of cash, and from 176 percent (in 2017) to 203 percent (in 2018) at the 95th quantile of cash. The mean effect varies from 82 percent in 2018 to 95 percent in 2017. These results suggest that adoption of cryptocurrencies, such as Bitcoin, may not necessarily lead to a decrease in the demand for cash.

The paper is organized as follows: Section 2 describes the 2017 and 2018 BTCOS, Section 3 discusses the identification strategy, while Section 4 presents our findings. Section 5 concludes.

2 Data Overview

2.1 The Bitcoin Omnibus Surveys

Our analysis uses data from the 2017 and 2018 Bitcoin Omnibus Surveys (BTCOS), commissioned by the Currency Department at the Bank of Canada and conducted by market research firm Ipsos. The 2017 BTCOS is an extension to what was considered a pilot survey in 2016. This pilot, conducted in two waves in December 2016, was designed primarily to obtain basic measurements concerning public awareness and ownership of Bitcoin in Canada. As the price of Bitcoin increased rapidly over the course of 2017, the Bank of Canada decided to conduct a follow-up to the pilot with additional questions. The 2017 BTCOS was in the field December 12–15, 2017, corresponding to a (then) historical peak in the price of Bitcoin. By contrast, the 2018 survey was conducted in November and early December 2018, when the price of Bitcoin was close to a minimum following a year-long decline.

Respondents to the BTCOS are recruited via an online panel managed by Ipsos and complete the survey in an online format. The core components of the survey based on the 2016 pilot are as follows: awareness of Bitcoin; ownership/non-ownership of Bitcoin; amount of Bitcoin holdings; and reasons for ownership/non-ownership. The 2017 and 2018 surveys contain additional content aimed at providing a deeper understanding of the motivation of Bitcoin owners and their usage behaviour, including beliefs about the future adoption and

[4]Using nonlinearities as an identification mechanism for two-stage models was suggested by Dong (2010) and Escanciano et al. (2016).

survival of Bitcoin; knowledge of Bitcoin features; price expectations; use of Bitcoin for payments or person-to-person transfers; preferred methods of payment for online purchases; and ownership of other cryptocurrencies. Most importantly for the purposes of this paper, the 2017 and 2018 BTCOS ask respondents to report the amount of *cash on hand*, that is, the cash currently held in their wallet, purse, or pockets. We refer to this throughout the paper as a respondent's *cash holdings*.

In 2017, a total of 2,623 Canadians completed the BTCOS, of which 117 self-identified as Bitcoin owners. In 2018, the BTCOS was answered by 1,987 Canadians, of which 99 reported they own Bitcoin. In addition to content questions, respondents are also asked to provide demographic information. Sampling for the survey is conducted to meet quota targets for the Canadian population relative to age, gender, and region. Once the sample is collected, the Bank of Canada conducts an in-depth calibration procedure to ensure that the sample is representative of the adult Canadian population across a variety of dimensions (see Henry et al. (2019b) for details).

2.2 Descriptive Statistics

Table 1 presents the main finding that motivates our subsequent empirical analysis – namely, that Bitcoin adopters hold noticeably more cash than non-adopters.[5] Specifically, Bitcoin adopters in the BTCOS hold at least three times more cash, on average, than non-adopters, and anywhere from \$60 to \$80 more cash at the median. As a point of comparison, we also consider data from the Bank of Canada's Methods-of-Payment (MOP) survey, a more general and comprehensive consumer payments survey conducted in 2013 and 2017 (see Henry et al. (2015) and Henry et al. (2018b)). The MOP has the exact same cash holdings question and also includes a question in 2017 to identify Bitcoin adopters. The MOP results are in line with the findings from the 2017 and 2018 BTCOS: adopters hold just under three times more cash than non-adopters, and \$25 more cash at the median. We further note that on the extensive margin, non-adopters in the BTCOS are more likely to hold zero dollars in cash (8 percent) compared with adopters (6 percent in 2018; 5 percent in 2017); however, this finding is not as strong in the MOP data.

Table 2 provides a demographic breakdown of Bitcoin owners[6] versus non-owners, along with their average cash holdings. In both 2017 and 2018, Bitcoin owners tend to be younger

[5]For the purposes of this table only, we consider an "adopter" to be anyone who currently owns *or* previously owned Bitcoin. This allows for an increased sample size for the calculation, as the BTCOS has a question that allows us to identify past owners. Further, in the Methods-of-Payment (MOP) survey, a Bitcoin adopter is identified as anyone who used Bitcoin within the past year; since we don't know whether or not the respondent still owns Bitcoin, this definition of "adopter" for the BTCOS is more comparable with the MOP.

[6]From this point on we consider Bitcoin owners to mean *current* owners.

in age, employed, and male. For example, the 18- to 34-year-old age group accounts for 71 percent of Bitcoin owners in 2017 and 55 percent in 2018. By contrast, among non-owners this demographic group represents only about a quarter of the sample. Similarly, males are noticeably over-represented among Bitcoin owners (75 percent in 2017; 63 percent in 2018) when compared with non-owners (47 and 48 percent in 2017 and 2018, respectively). As one might expect, more Bitcoin owners are categorized as "high" in Bitcoin knowledge. Only 5 percent of non-owners achieve a perfect score on the three questions designed to test Bitcoin knowledge, whereas more than a quarter of Bitcoin owners achieve this score in both years. Finally, looking at changes from 2017 to 2018, there are notable differences in the composition of Bitcoin owners with respect to their level of income and education. In 2017 there is little difference between Bitcoin owners and non-owners in terms of their income profile, while in 2018 Bitcoin owners are relatively more likely to have a household income over $70K. Similarly, there is a shift in the profile of Bitcoin owners from low education (high school) to higher levels of education (college and university) between 2017 and 2018.

Looking at cash holdings, we find that demographic groups associated with Bitcoin ownership also tend to have higher cash holdings. For example, in both 2017 and 2018, Bitcoin owners aged 18 to 34 years hold more than five times more cash on hand, on average, than owners aged 55 and older. This contrasts with patterns among non-owners, where older respondents tend to hold similar (in 2018) or more (in 2017) cash than younger age groups. Similarly, Bitcoin owners with the highest levels of income and education (over $70K and university-educated, respectively) hold noticeably more cash than their lower income and education counterparts. One particularly stark association from 2018 involves financial literacy.[7] Bitcoin owners are more likely to have low financial literacy relative to non-owners and are also one of the most cash intensive groups, holding $1,123 on average.

Finally, Figure 1 shows the distribution of log-transformed cash holdings by Bitcoin owners and non-owners. We see that in both 2017 and 2018, Bitcoin owners hold more cash across almost the entire support, except for lower levels of cash (roughly, below the 15th quantile) where the distributions are similar for the two groups. The figure also demonstrates that not only do Bitcoin owners hold higher levels of cash at the mean, the distribution is also skewed heavily to the right. Further, the distribution of non-owners is heterogeneous with multiple modes. These two observations suggest that any estimation approach 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 also analyze the quantiles of cash.

[7] The 2018 BTCOS includes three standardized questions that measure respondents' financial literacy; see Lusardi and Mitchell (2014).

3 Identification Strategy

Identifying the relationship that links cash holdings to Bitcoin ownership builds on information available from the BTCOS, certain characteristics of the data, and the interactions present in the data. Naively, we can use the question about Bitcoin ownership to separate owners from non-owners and, as a benchmark, estimate an ordinary least squares (OLS) linear regression model where the explanatory variable of interest is Bitcoin ownership. However, our demographic analysis suggests that ownership of Bitcoin is *not* exogenous. To confirm this fact, Table 3 shows the statistical differences in means for certain demographic characteristics, namely age, gender, employment, education, number of children, and marital status.

These differences suggest that the unconditional mean effects of Bitcoin ownership on cash holdings should not be identical with the conditional mean effects. In particular, for 2017, Bitcoin owners are younger (almost 13 years mean age difference), 60 percent more likely to be male,[8] and more likely to be employed and have higher education (43 percent more likely to be employed and 55 percent more likely to have completed some university-level education). In 2018, while there are still observed differences between Bitcoin owners and non-owners, some of these differences are reduced – there is only an 11-year difference in age and owners are only 31 percent more likely to be male. At the same time, in 2018 there are increased differences between Bitcoin owners and non-owners relative to education (84 percent more likely to be university-educated) and income categories. The differences in the distribution of observable characteristics suggest that owning Bitcoin is selective, and therefore we should account for the selection in our identification strategy. The difference in findings between 2017 and 2018 may imply that the selection effect is stronger in 2017 than 2018.

We have seen from summary statistics that Bitcoin adopters hold more cash compared to non-adopters. This raises the possibility of some simultaneity that links cash holdings and Bitcoin ownership – that is, unobservable factors that drive people to *both* adopt Bitcoin and also hold high levels of cash. For example, Bitcoin owners may prefer anonymous liquidity, and hence cash may be a hedge (or vice versa); or, some Bitcoin owners may not trust institutions such as government or banks, leading to large cash holdings outside of traditional financial institutions. To solve these selection issues, we propose using identification methods that account for endogenous selection via a control function approach.[9] The control function approach is further used to quantify the effect of Bitcoin ownership on quantiles of cash.

In what follows, we describe our two main hypotheses of interest regarding the link

[8] To compute the percentage change between male owners and male non-owners we use: (proportion of owners (75)-proportion of non-owners (47))/proportion of non-owners (47).

[9] Wooldridge (2015) provides an excellent overview.

between Bitcoin ownership and cash holdings; for each hypothesis, we consider a version that does not account for selection, as well as one that does account for selection. Then, we outline the models used for testing each hypothesis.

3.1 Expected Cash Holdings

The first question of interest relates to average (or mean) cash holdings, and tests the following hypothesis:

$$H_{01} : E(Cash|Btc, X, P) > E(Cash|No - Btc, X, P), \tag{1}$$

where X includes individual characteristics of gender, age, education, marital status, number of children, employment status, household grocery shopping participation, and income, and P is 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 a benchmark, we estimate a simple linear OLS model of the form:

$$cash_{i,t} = \alpha + \beta Btc_{i,t} + \gamma X_{i,t} + \delta P_j + u_{i,t}, \tag{2}$$

where $cash_{i,t}$ is the log of cash holdings of individual i at time $t \in \{2017, 2018\}$[10]; $Btc_{i,t}$ is equal to 1 if the respondent i from period t is a Bitcoin owner and zero otherwise; $X_{i,t}$ is a set of respondent characteristics for individual i from period t; P_j is regional fixed effects; and $u_{i,t}$ is the cross-section specific error term.

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

$$Btc_{i,t} = Pr(Z_{i,t}, X_{i,t}, P_j) + \epsilon_{i,t}, \tag{3}$$

where $Z_{i,t}$ is the exclusion restriction of individual i from period t, and $\epsilon_{i,t}$ is the error term that has an independent and identically distributed (i.i.d.) logistic distribution.

The exclusion restriction we utilize is based on the survey question about expectations of the future adoption rate of Bitcoin, namely: *"What percentage of Canadians do you predict will be using Bitcoin 15 years from now?"*. We call this variable $EAR15$. It is positively

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

correlated with Bitcoin ownership, as owners tend to have a more optimistic outlook on the future adoption of Bitcoin.[11] However, $EAR15$ does not directly influence a respondent's current level of cash holdings – the survey question specifically asks respondents to count the amount of cash in their wallet, purse, or person during the survey, and they cannot re-optimize their cash holdings. Therefore, $EAR15$ should not be correlated with cash holdings and indeed the correlation coefficient between $EAR15$ and cash holdings is 0.06.

Additionally, Figure 2 illustrates the cumulative distribution function (CDF) plot of $EAR15$ for Bitcoin owners versus non-owners in both 2017 and 2018. The CDF of the two distributions do not intersect. In more technical terms, $EAR15$ of Bitcoin owners First Order Stochastic Dominates (FOSD) the distribution of $EAR15$ for non-owners.[12]. The medians of the distributions show that non-owners believe the expected adoption rate will be around 30 percent, while owners believe it will be around 60 percent. The $EAR15$ variable also satisfies the conditional independence assumption as in Abadie et al. (2002). Consequently, $EAR15$ acts as a valid exclusion restriction to delineate between Bitcoin owners and non-owners.

To further improve identification, we exploit differences in age effects between the model for Bitcoin ownership (Equation 3) and the model for cash holdings (Equation 2). Figure 3 shows the predicted probabilities of Bitcoin ownership in 2017 and 2018 (top panels), as well as predicted cash holdings (bottom panels), as a function of age. The graph clearly shows that age has a nonlinear effect on ownership while it has a linear effect on cash holdings. This nonlinearity in the first stage can be exploited in identification as suggested by Dong (2010) and Escanciano et al. (2016).

To exploit the nonlinear effect of age on Bitcoin ownership, we introduce fractional polynomial (FP) terms of age. The use of FP as a method to obtain a more robust nonlinear representation of the relationship between the explanatory variable of interest and a binary choice outcome was previously studied by Williams (2011). This study suggests that use of FP is a better alternative to other methods designed to capture nonlinearity in discrete choice settings. Consequently, we augment our first stage model with FP terms as follows:

$$Btc_{i,t} = Pr(Z_{i,t}, X_{i,t}, Age^{p_k}_{i,t}, P_j) + \epsilon_i, \tag{4}$$

where $Age^{p_k}_{i,t}$ represents the FP terms of age for individual i in period t. In our specification, the selected FP is of order two and is provided by Royston and Altman (1994)'s algorithm, which provides the best fit between the predictor (here, age) and the outcome (here, Bitcoin ownership).

Finally, to account for the endogenous selection into Bitcoin ownership as well as possible sources of simultaneity, we estimate a second stage model that augments Equation 2 with a

[11] The correlation coefficient between $EAR15$ and Bitcoin ownership is 0.24.

[12] We conducted a FOSD test based on Kolmogorov-Smirnov that resulted in a p-value equal to 1.

CF. The estimated residuals from the first stage with FP age terms (Equation 4) are used as a correction term in this second stage; as the endogenous variable is binary, we have to construct appropriate residuals that are not correlated with the error term in the main equation, and also have statistical properties similar to those used in a least squares approach. As we chose the logit link function to estimate the probability of Bitcoin ownership, we chose as a CF the deviance residuals ($\widehat{\epsilon_{i,t}}$) since their distribution is closer to the distribution of residuals from OLS regression models:

$$\widehat{\epsilon_{i,t}} = sign_{i,t}\sqrt{-2(Btc_{i,t}\log(Pr(Z_{i,t},\widehat{X_{i,t},A}ge^{p_k}_{i,t},P_j)) + (1-Btc_{i,t})\log(1-Pr(Z_{i,t},\widehat{X_{i,t},A}ge^{p_k}_{i,t},P_j))}, \tag{5}$$

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

The first testable hypothesis is therefore modified as follows:

$$H^{'}_{01} : E(Cash|Btc, EAR15, X, P) > E(Cash|No-Btc, EAR15, X, P), \tag{6}$$

where $EAR15$ is the exclusion restriction. This hypothesis is tested by estimating the following second stage model, where the CF term is introduced as a correction:

$$cash_{i,t} = \alpha + \beta Btc_{i,t} + \gamma X_{i,t} + +\delta P_j + \phi\widehat{\epsilon_{i,t}} + u_{i,t}. \tag{7}$$

3.2 Quantiles of Cash Holdings

Recall that Figure 1 shows that the distribution of cash holdings has a heavy right tail for Bitcoin owners and is multimodal for non-owners. The average cash holding amount is affected by these characteristics of the data, and therefore an additional hypothesis of interest tests if Bitcoin owners hold more cash than non-owners across all quantiles of cash:

$$H_{02} : Q_\tau(Cash|Btc, X, P) > Q_\tau(Cash|No-Btc, X, P), \tag{8}$$

where Q_τ is the τ-th quantile and X and P are defined previously. This hypothesis can be tested using the following reduced form specification:

$$Q_{Cash}(\tau)_{i,t} = \alpha^\tau + \beta^\tau Btc_{i,t} + \gamma^\tau X_{i,t} + \delta^\tau P_j + u^\tau_{i,t}. \tag{9}$$

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

$$H_{02}^{'} : Q_\tau(Cash|Btc, EAR15, X) > Q_\tau(Cash|No - Btc, EAR15, X), \tag{10}$$

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

$$Q_{Cash}(\tau)_{i,t} = \alpha^\tau + \beta^\tau Btc_{i,t} + \gamma^\tau X_{i,t} + \delta^\tau P_j + \phi^\tau \widehat{\epsilon_{i,t}} + u_{i,t}^\tau, \tag{11}$$

where $\widehat{\epsilon_i}$ is the deviance residual specified in Equation 5.

4 Empirical Results

For the first hypothesis of interest, H_{01}, we estimate an OLS model of log cash holdings on Bitcoin ownership, demographic characteristics, and regional fixed effects. However, as discussed in Section 3, to properly account for endogenous selection we need to augment this model with a correction term that requires first estimating the probability of Bitcoin ownership, in order to test H_{01}'. Consequently, we start by presenting results from the *extensive margin* analysis, which quantifies the effects of observable characteristics on the probability of owning Bitcoin (also referred to as the propensity score). We further augment the propensity score model with the exclusion restriction ($EAR15$) and nonlinear age terms, to estimate the probability of owning Bitcoin that is ultimately used for the first stage of the two-stage CF approach. Following this, we present results related to both the first and second hypotheses of interest (mean effects and quantile effects, respectively), both with and without the correction for selection.

4.1 Probability of Owning Bitcoin

The results of the extensive margin analysis are presented in Table 4; the first four columns are results for the year 2017, while the last four columns are for 2018. The first column models the probability of Bitcoin ownership accounting for demographic characteristics and regional fixed effects; the second column augments the model with the $EAR15$ variable; the third column adds a quadratic age term; finally, the fourth column adds FP of age (see Section 3). The fifth to eighth columns are the equivalent models for the 2018 data.[13]

[13]Given that only 5 percent of the sample represents owners of Bitcoin (117 observations in 2017 and 99 in 2018), we check if each cell associated to the variables used in the analyses has sufficient observations to do a proper analysis. VanVoorhis and Morgan (2007) point out that for a chi-squared test, five observations per cell are minimal, while seven observations per cell are the minimum needed for a mean comparison.

A concern associated with this estimation is that Bitcoin ownership can be considered a "rare event," as only around 5 percent of Canadians are Bitcoin owners. To address this potential issue, the probability models are adjusted to account for rare events 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). The correction for rare events does not provide any additional information, being similar to the classical logistic model, and therefore we report only the logistic results.[14]

The results from 2017 emphasize the role of gender, age, employment status, and number of children on Bitcoin ownership. In particular, being older, female, and having children have a significant and negative impact on the likelihood of owning Bitcoin, while being employed has a significant and positive effect.[15] With respect to region, only the Prairies and Atlantic provinces have a significantly different (negative) effect when compared with the benchmark, British Columbia. Compared with the 2018 results (columns 5 to 8), we see a change in the demographics of Bitcoin owners, as income and education become statistically significant for Bitcoin ownership – higher education and income levels are associated with increased likelihood of owning Bitcoin.

When we augment the model with the $EAR15$ variable, we observe the predictability power of this exclusion restriction as measured by adjusted R^2 (54 percent higher adjusted R^2 in 2017 due to $EAR15$; 52 percent higher in 2018).[16] In addition to the $EAR15$ variable, recall that to improve identification in the second stage we add regressors that capture the nonlinearity of age in relationship with Bitcoin ownership. Consequently, in column 3 (for 2017) and column 7 (for 2018), age squared is included as an additional explanatory variable. We see that this addition does not provide any improvement for 2017 relative to increased predictive power as measured by the adjusted R^2, and only a marginal improvement for 2018. However, when the FP of order two are added to the model along with $EAR15$ (column 4

For almost all the cells we have much more than the minimum as suggested by these guidelines. One cell with problems is the retired cell, therefore we combine retired with unemployed and not in labour force to obtain a relevant comparison cell with employed. We provide empirical estimates to demonstrate that these minimum cells do not affect the estimation results.

[14] The penalized likelihood results are available in an online Appendix.

[15] Some of these findings are consistent with respect to other literature on the adoption and use of digital technologies more generally. For example, an OECD report from 2018 documents a persistent gap between men and women in terms of the "access, use and ownership of digital technologies" in many G20 countries (OECD (2018)). Rogers (2010) documents that early adopters of new technologies are typically young, live in urban areas, and are educated and socially active.

[16] The model that augments with $EAR15$ initially has a smaller sample size (by about 15 percent) because, in both years, some of the respondents did not answer this question. We therefore check if the reduced sample suffers from additional selection issues by seeing if the average observables are significantly different in the two samples. Ultimately, this leads to modelling the missing data with a missing-at-random (MAR) imputation model where we conclude that the item non-response does not have a significant effect on outcomes. As a result of this imputation, Table 4 utilizes a new $EAR15$ variable that corrects for the missing data and the entire sample is used in the estimation.

for 2017 and column 8 for 2018), we see an increase in predictability of Bitcoin ownership for both years. Consequently, we retain this last specification as the one needed to generate the control function for the second stage regression model.

Finally, we check the predictability power of the model specifications using logit specification tests. Results are presented at the bottom of Table 4. The model with $EAR15$ dominates the model without it by showing that there are no remaining unobservables that can improve the predictability of Bitcoin ownership. More specifically, the prediction is significant while its square is not. In terms of discrimination between owners and non-owners, the area under receiver operating characteristic (ROC) curve is 0.86 versus 0.81 without $EAR15$ (see Metz (1978)). For both years, when the model with $EAR15$ is augmented with nonlinear FP terms of age, there is a marginal increase in the predictability of Bitcoin ownership, while there is no increase if only the square of age is added.

An analysis using only $EAR15$ as an explanatory variable for Bitcoin ownership shows the importance of this variable for predicting the probability of owning Bitcoin, as shown in Table 5. The variable itself gives an area under the ROC of 0.78 for 2017 and 0.77 for 2018. This underlines the importance of this variable for discriminating between Bitcoin owners and non-owners.

4.2 Mean Effects of Cash Holdings

Next, we focus on the *intensive margin* of our analysis, which is designed to answer the question of interest regarding the effect of Bitcoin ownership on the usage of cash. To test the first hypothesis of interest, H_{01}, we estimate a benchmark linear specification that treats the ownership of Bitcoin as exogenous. Then, we extend the linear analysis assuming that ownership is in fact selective using a CF approach and use this model to test H'_{01}.[17] The results of these analyses are presented in Table 6.

Column 1 of Table 6 presents the results of the benchmark model for the year 2017. The parameter estimate of Bitcoin ownership is statistically significant and equal to 1.36. This can be interpreted as, on average, Bitcoin owners hold 136 percent more cash than non-owners after controlling for age, gender, income, education, marital status, number of children, and region. Column 2 of Table 6 presents the conditional mean of cash holdings model that accounts for selection via a CF approach. The results show that the proposed correction estimates an average difference of log-cash holdings between Bitcoin owners and non-owners of 0.948. This result implies that the average cash holdings are about 95 percent higher for Bitcoin owners after controlling for selection. The demographic characteristics

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

that are relevant for cash holdings are age (positive effect), gender-female (negative effect), and medium and higher income categories that show positive effects over the benchmark category (less than \$50,000 household income). The Prairies, Ontario, and Quebec regions show positive effects over the benchmark region (British Columbia). The last two columns are the symmetric results for the year 2018. In general, the results are consistent across the two years, however the mean effects of cash holdings are lower in 2018 than in 2017 (1.18 in 2018 vs 1.36 in 2017 for the model without correction for selection; 0.825 in 2018 vs 0.948 in 2017 for the model with correction).

4.3 Quantile Effects of Cash Holdings

Finally, we consider that the mean log-cash estimates are affected by the observed distributions having a heavy right tail for Bitcoin owners and being multimodal for non-owners – therefore we focus our attention on the quantiles of cash holdings. To investigate the effects of Bitcoin ownership across the distribution, we first estimate benchmark quantile models allowing us to test H_{02}. Then we introduce the CF correction term (as in the linear case) so that we can test H'_{02}. The results of the conditional quantile model without selection (benchmark) for 2017 and 2018 are presented in Table 7 and Table 8; results correcting for endogenous selection via the add CF term are presented in Table 9 and Table 10.

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

For 2018 we observe four differences: at lower quantiles the estimated cash holdings are not significant between Bitcoin owners and non-owners; the median is higher than the median estimate from 2017 by about 30 percent; the high quantiles of cash are lower than in 2017 as we see a bigger bending down at the highest quantiles[18]; and there is a change in significance for gender and age at high quantiles of cash (gender remains significant while age becomes insignificant). These changes can be explained by the observed changes in demographics for Bitcoin owners in 2018.

As in the linear case with correction for selection, the results emphasize that indeed the estimated conditional median effect is smaller (estimated at 0.907 for 2017 and 1.052 for 2018) than the one obtained using the benchmark quantile estimates and the unconditional

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

median. Once we control for selection, the conditional quantiles show the expected patterns: no significant effects at lower quantiles and an increased difference in cash holdings between Bitcoin owners and non-owners over the quantiles up the 90 percentile, with a correction down at the 95 percentile.

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

A graphical representation of the differences between the benchmark quantiles estimates and the corrected for selection quantile estimates is presented in Figure 4. The results show how selection affects the quantile estimates, especially the lowest and the highest ones.

5 Conclusion

The year 2017 was significant 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. This was followed by a steep decline in the price of Bitcoin over the course of 2018, bottoming out in early 2019. Against this background, much of the discussion on Bitcoin came down to how people were actually using it: Was it a vehicle for speculation and investment, or a convenient way for criminals to transact online? Were people using Bitcoin as it was originally designed – that is, a decentralized currency that opens up new avenues for making transactions that would otherwise not have taken place? The answers to these questions are still largely unclear even now, but they have become increasingly relevant via-à-vis proposals for Central Bank Digital Currency and the so-called death of cash.

Using data from the Bank of Canada's 2017 and 2018 Bitcoin Omnibus Survey, this paper sheds light on a surprising finding that 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 the cash holdings of Bitcoin owners are substantially higher than for non-owners. Further, this difference is most drastic among consumers who hold large amounts of cash.

Our analysis does raise further questions about the specific factors that are driving Bitcoin owners to hold more cash, and in general it is clear that there are limitations to our data set. For example, Fujiki (2020) uses Japanese survey data containing information about financial asset holdings in addition to Bitcoin ownership. This research finds that Bitcoin owners are likely using cash to serve as a hedge for a relatively larger share of conventional risky assets in their overall portfolio. In a different vein, Stix (2021) documents survey evidence from Austria showing that beliefs about the future may be relevant. Specifically, although Bitcoin owners are extremely confident about the advantages of Bitcoin over conventional payment methods, only about half of them have actually used it to make a payment. In other words, while Bitcoin owners currently have a preference for cash, they may shift to using Bitcoin for payments in the event that it is more widely adopted in the future. See also Balutel et al. (2022) on the importance of beliefs about the future and the role of network effects in Bitcoin adoption.

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

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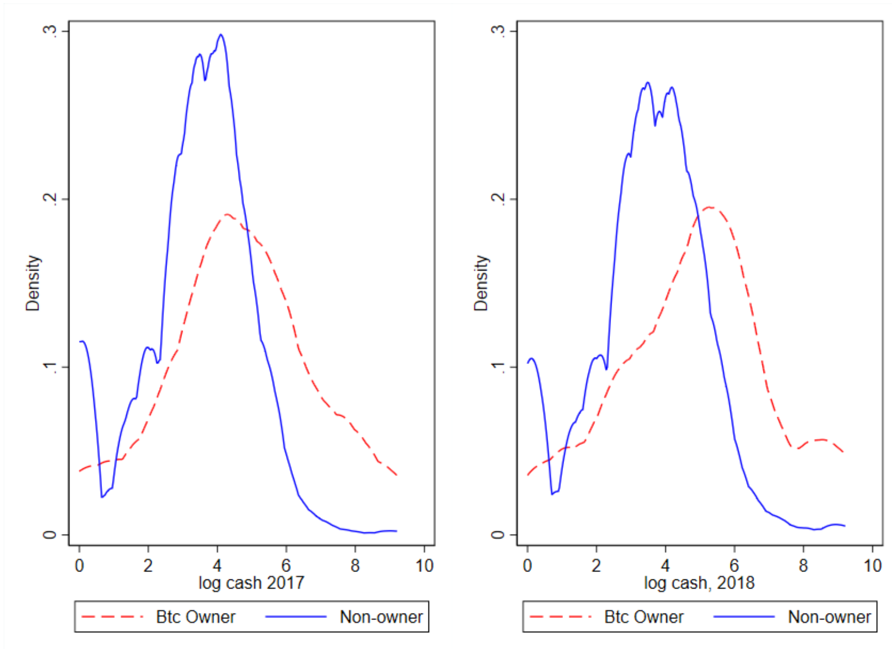
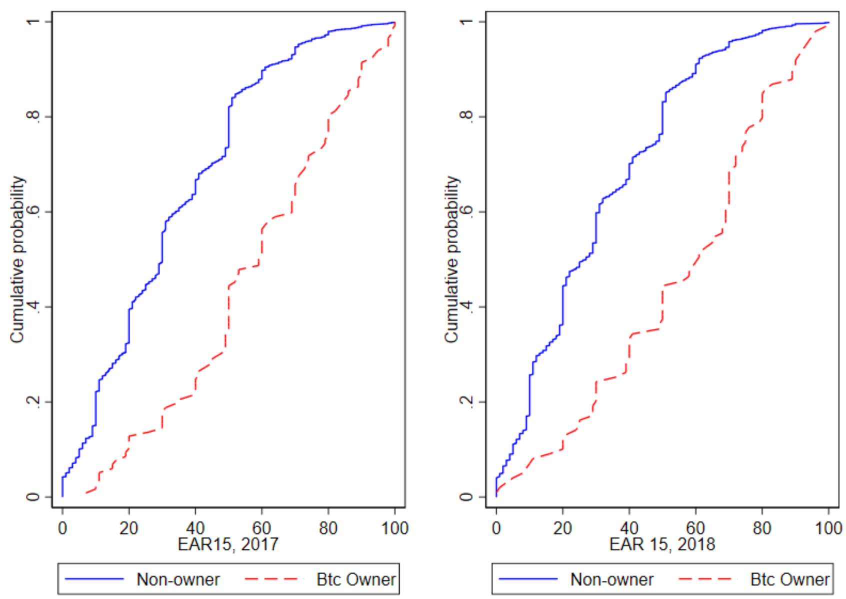
Figure 1: **Density of cash holdings (in logs) for Bitcoin owners and non-owners**



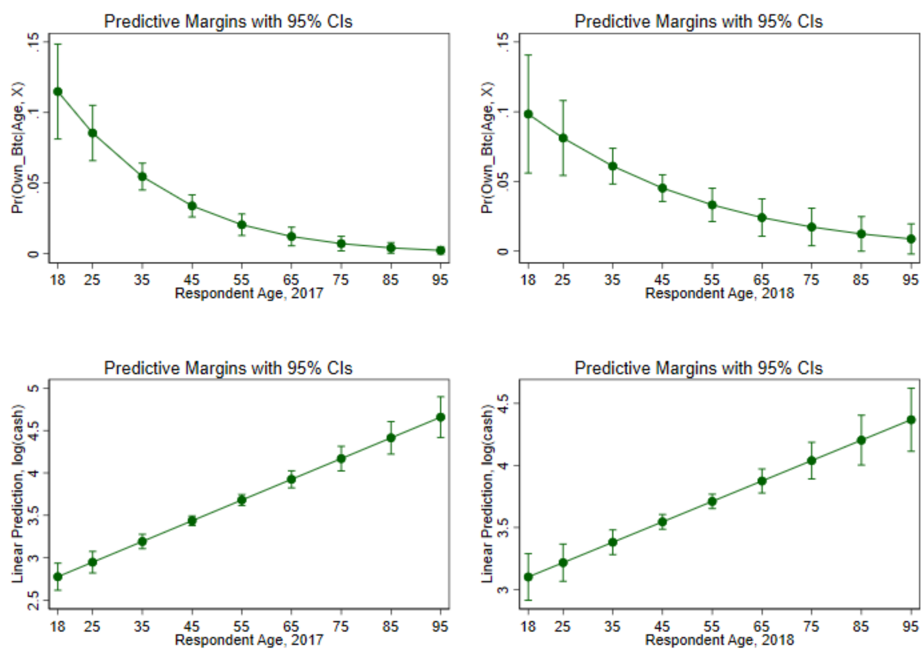
Note: The panels plot the density of cash holdings (in logs) for Bitcoin owners (red line) and non-owners (blue line) for 2017 (left) and 2018 (right). Data are from the 2017 and 2018 BTCOS.

Figure 2: **Cumulative distribution function of the expected adoption rate by Bitcoin owners and non-owners**



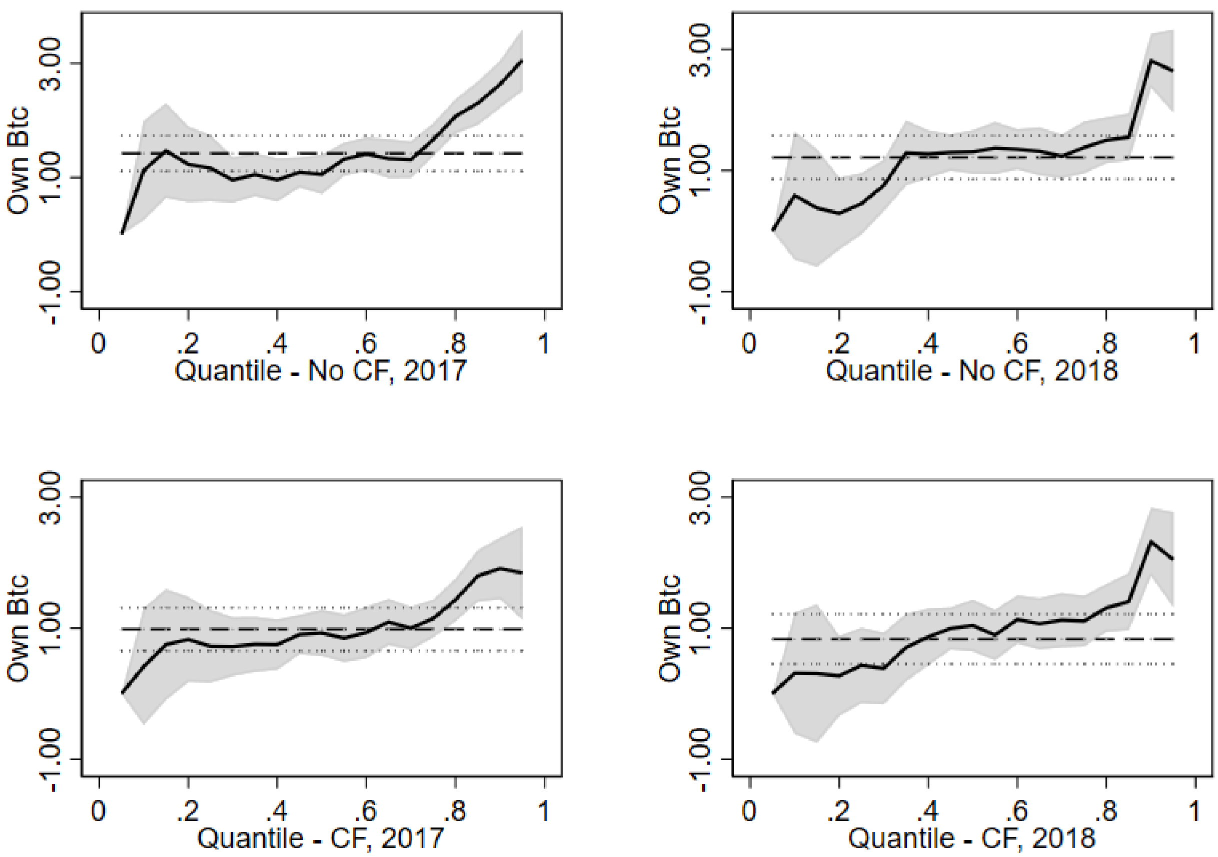
Note: The panels plot the cumulative distribution functions (CDF) of expected adoption rate of Bitcoin (EAR15) for Bitcoin owners (red line) and non-owners (blue line) for 2017 (left) and 2018 (right). The two distributions are statistically different. Data are from the 2017 and 2018 BTCOS.

Figure 3: **Predictive margins of Bitcoin ownership and cash holdings as functions of age**



Note: The top panels plot the predicted margins of the probability of Bitcoin adoption as a function of age (first stage equation) for 2017 (top left) and 2018 (top right). The bottom panels plot the predicted margins of the cash holdings (log cash) as a function of age (second stage equation) for 2017 (bottom left) and 2018 (bottom right). Data are from the 2017 and 2018 BTCOS.

Figure 4: **Predicted quantiles of the difference in cash holdings (in logs) between Bitcoin owners and non-owners.**



Note: The panels plot the predicted margins for the quantiles of the difference in cash holdings (in logs) between Bitcoin owners and non-owners. The top graphs plot the predicted quantiles when we do not account for the endogenous selection for 2017 (top left) and 2018 (top right). The bottom graphs plot the predicted quantiles when we account for the endogenous selection for 2017 (bottom left) and 2018 (bottom right).

Table 1: **Cash and Bitcoin adoption in Canada**

	Cash on hand mean	median	No cash percentage	N
Bitcoin Adopters				
2018 BTCOS	518	120	6%	144
2017 BTCOS	434	100	5%	154
2017 MOP	320	65	8%	93
Non Adopters				
2018 BTCOS	171	40	8%	1,843
2017 BTCOS	104	40	8%	2,469
2017 MOP	108	40	9%	3,127
2013 MOP	84	40	6%	3,663

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 and non-owners in Canada and their cash holdings**

Demographic	2017 non-owners		owners		2018 non-owners		owners	
	proportion	mean cash	proportion	mean cash	proportion	mean cash	proportion	mean cash
Male	0.47	99	0.75	599	0.48	160	0.63	565
Female	0.53	68	0.25	590	0.52	78	0.37	884
18-34	0.25	72	0.71	711	0.26	130	0.55	849
35-54	0.34	78	0.25	445	0.34	103	0.32	716
55+	0.40	92	0.04	137	0.40	109	0.13	120
High School	0.43	74	0.36	415	0.44	119	0.19	694
College	0.31	73	0.22	248	0.30	101	0.33	461
University	0.27	93	0.42	835	0.26	116	0.48	840
<30K	0.30	68	0.34	370	0.31	116	0.16	458
30k-69K	0.44	85	0.38	718	0.41	101	0.46	748
70K+	0.27	107	0.27	904	0.28	148	0.38	798
Employed	0.60	86	0.86	603	0.60	128	0.83	715
Not employed	0.40	75	0.14	560	0.40	88	0.17	647
British Columbia	0.13	71	0.16	369	0.13	87	0.17	1039
Prairies	0.18	83	0.17	1002	0.18	114	0.21	1130
Ontario	0.39	79	0.34	735	0.38	116	0.38	605
Quebec	0.23	91	0.28	298	0.24	115	0.21	376
Atlantic	0.07	78	0.05	741	0.07	114	0.04	342
Btc literacy: Low	0.57	79	0.24	356	0.63	116	0.19	631
Btc literacy: Medium	0.38	94	0.49	699	0.32	115	0.52	624
Btc literacy: High	0.05	99	0.27	623	0.05	64	0.29	861
FL literacy: Low					0.26	143	0.38	1123
FL literacy: Medium					0.36	84	0.33	570
FL literacy: High					0.37	115	0.29	330
N	2,506		117		1,987		99	

Note: The table presents the proportion of Bitcoin owners and non-owners by demographic characteristics and the mean of cash holdings of Bitcoin owners and non-owners by demographic characteristics. The first four columns (1–4) are the results for the year 2017 and last four columns (5–8) are for the year 2018. For each year the first two columns are the proportion of Bitcoin non-owners (1, 5) and the cash holdings for Bitcoin non-owners (2, 6), while the last two columns are the proportions of Bitcoin owners (3, 7) and the cash holdings of Bitcoin owners (4, 8).

Table 3: **Mean differences for demographic characteristics between Bitcoin owners and non-owners**

	2017		2018	
	$\overline{X_{NoBtc}} - \overline{X_{Btc}}$	t-test	$\overline{X_{NoBtc}} - \overline{X_{Btc}}$	t-test
Age	13.40***	12.39	11.11***	7.55
Gender: Female	0.276***	6.48	0.153***	2.99
Income: <30k	-0.035	-0.76	0.164***	4.05
Income: 30k-69k	-0.029	-0.64	- 0.148***	-2.86
Income: >70k	0.000	-0.001	-0.129***	-2.70
BC	-0.064	-1.68	-0.026	-0.70
Prairies	0.035	1.01	-0.023	-0.59
Ontario	0.007	0.15	-0.020	-0.39
Quebec	-0.004	-0.11	0.053*	1.30
Atlantic	0.027	1.19	0.016	0.71
Employed	- 0.262***	-7.50	-0.229***	-5.53
Education: High school	0.057*	1.59	0.157***	5.37
Education: College/CEGEP/Trade school	0.076**	1.79	0.030	-0.614
Education: University	- 0.133***	-2.83	-0.187***	-3.67
Number of kids: No kids	0.166***	3.60	0.261***	5.12
Marital status: Not married/CL	-0.047	-1.01	0.052	1.04
Grocery shopping: Not all of it	-0.110***	-2.43	-0.092**	-1.83

Note: Columns 1 and 3 present the difference in means between Bitcoin non-owners and owners for years 2017 and 2018, while columns 2 and 4 present the t-test for the difference in means for the two years. ***, **, and * represent 1%, 5%, and 10% significance, respectively. Data are from the Bitcoin Omnibus Survey 2017 and 2018.

Table 4: **Probability of Bitcoin ownership**

Variables	(1,2017)	(2, 2017)	(3, 2017)	(4, 2017)	(5, 2018)	(6, 2018)	(7 2018)	(8, 2018)
Respondent Age	-0.0680***	-0.0563***	-0.0646		-0.0558***	-0.0363***	-0.139***	
	(0.00926)	(0.00944)	(0.0561)		(0.0108)	(0.0116)	(0.0388)	
Age^2			0.000103				0.00117***	
			(0.000691)				(0.000423)	
Age^{p_1}				-19.31***				-0.058***
				(6.373)				(0.012)
Age^{p_2}				49.23***				0.027***
				(11.07)				(0.006)
Gender: Female	-1.300***	-1.357***	-1.357***	-1.355***	-0.928***	-0.802***	-0.787***	-0.796***
	(0.210)	(0.222)	(0.222)	(0.225)	(0.223)	(0.238)	(0.243)	(0.242)
Income: 50k-99k	-0.138	-0.110	-0.109	-0.111	0.956***	1.018***	1.053***	1.070***
	(0.253)	(0.265)	(0.264)	(0.264)	(0.304)	(0.311)	(0.303)	(0.313)
Income: 100k+	-0.377	-0.353	-0.350	-0.300	0.976***	0.908**	1.000***	1.020***
	(0.294)	(0.311)	(0.309)	(0.316)	(0.365)	(0.374)	(0.366)	(0.372)
Prairies	-0.678**	-0.818**	-0.815**	-0.859**	-0.0698	-0.0359	-0.00114	0.017
	(0.339)	(0.361)	(0.360)	(0.358)	(0.370)	(0.382)	(0.385)	(0.393)
Ontario	-0.353	-0.558*	-0.557*	-0.563*	-0.210	-0.292	-0.265	-0.213
	(0.278)	(0.298)	(0.299)	(0.298)	(0.320)	(0.335)	(0.336)	(0.344)
Quebec	-0.279	-0.610**	-0.608*	-0.637**	-0.395	-0.459	-0.355	-0.327
	(0.293)	(0.311)	(0.311)	(0.311)	(0.363)	(0.384)	(0.388)	(0.395)
Atlantic	-0.759*	-0.931**	-0.928**	-0.929**	-0.387	-0.501	-0.419	-0.387
	(0.447)	(0.458)	(0.457)	(0.463)	(0.570)	(0.609)	(0.614)	(0.614)
Employment	0.783***	0.623**	0.635**	0.526*	0.121	0.173	0.353	0.251
	(0.303)	(0.307)	(0.320)	(0.318)	(0.279)	(0.286)	(0.300)	(0.306)
College/CEGEP/Trade school	-0.0980	0.0834	0.0878	0.0289	0.864**	0.911**	1.015**	0.931**
	(0.317)	(0.321)	(0.326)	(0.323)	(0.412)	(0.423)	(0.423)	(0.422)
University	0.264	0.494	0.498	0.373	0.986**	0.971**	1.054**	0.954**
	(0.288)	(0.302)	(0.306)	(0.311)	(0.396)	(0.414)	(0.416)	(0.414)
Number of kids: No kids	-0.468**	-0.296	-0.303	-0.352	-0.713***	-0.608**	-0.700**	-0.593**
	(0.228)	(0.234)	(0.238)	(0.237)	(0.249)	(0.271)	(0.272)	(0.275)
Marital status: Not married/CL	-0.299	-0.196	-0.200	-0.0801	-0.201	0.002	-0.0259	-0.018
	(0.249)	(0.257)	(0.261)	(0.269)	(0.289)	(0.291)	(0.294)	(0.294)
Grocery Shopping: Not all of it	-0.657***	-0.275	-0.280	-0.209	-0.529**	-0.242	-0.301	-0.244
	(0.221)	(0.229)	(0.235)	(0.236)	(0.235)	(0.241)	(0.245)	(0.242)
EAR15		0.0405***	0.0405***	0.0404***		0.0378***	0.0373***	0.0368***
		(0.00433)	(0.00434)	(0.00433)		(0.00538)	(0.00538)	(0.0054)
Constant	0.756	-1.671**	-1.526	-6.912***	-0.593	-3.348***	-1.534	-3.712***
	(0.558)	(0.658)	(1.161)	(3.522)	(0.697)	(0.943)	(1.186)	(0.843)
Observations	2,623	2,623	2,623	2,623	1,987	1,987	1,987	1,987
LR χ^2	110.4	171.3	172.9	183.4	92.43	167.5	182.4	178.2
Adj. R^2	0.175	0.270	0.270	0.276	0.162	0.246	0.254	0.260
Logit specification tests								
Prediction	1.56***	1.19***	1.18***	1.17***	1.65***	1.098***	1.05***	1.056***
Prediction squared	0.098**	0.39	0.038	0.035	0.12**	0.021	0.04	0.01
LROC	0.81	0.866	0.866	0.869	0.79	0.85	0.854	0.86

Notes:
1. The first column is the benchmark probability model of Bitcoin ownership for year 2017, the second column is the benchmark augmented with EAR15, the third column adds age squared, the fourth column is the benchmark with EAR15 and augmented with two fractional polynomial terms; columns 5, 6, 7 and 8 are the symmetrical models for the year 2018. Baseline categories are male, <50k income, British Columbia region, unemployment, high school education, having children, married, and conducting all the household grocery shopping. 2. Two additional specification tests were provided at the bottom of the Table: a) a linktest that regresses Bitcoin ownership on its prediction and squared prediction, where a significant square prediction may emphasize missing information in the Bitcoin ownership model; b) a test that quantifies the power of discrimination between Bitcoin owners and non-owners, where the LROC is the value of the area under receiver operating characteristic (ROC) curve. A value close to 1 suggests a high power of discrimination between Bitcoin owners and non-owners. 3. ***, **, and * represent 1%, 5%, and 10% significance, respectively.

Table 5: **Probability of Bitcoin ownership as a function of the exclusion restriction only**

Logit Model with EAR15 only	2017	2018
VARIABLES	Estimates 2017	Estimates 2018
EAR15	0.0454***	0.0456***
	(0.0042)	(0.0048)
Constant	-5.079***	-4.878
	(0.255)	(0.282)
Linktest	2017	2018
Prediction	1.248***	1.589***
Prediction squared	0.046	0. 114
LROC	0.78	0.77
Observations	2,623	1,987

Note: Similar specification tests as at the bottom of Table 4. ***, **, and * represent 1%, 5%, and 10% significance, respectively.

Table 6: **Cash holdings estimates modelled by using OLS; OLS with CF; Q50 with CF**

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Own Bitcoin	1.362***	0.948***	0.907***	1.179***	0.825***	1.052***
	(0.203)	(0.211)	(0.195)	(0.230)	(0.239)	(0.265)
Respondent Age	0.0185***	0.0244***	0.0210***	0.0114***	0.0165***	0.0192***
	(0.00197)	(0.00219)	(0.00257)	(0.00273)	(0.00296)	(0.00342)
Gender: Female	-0.271***	-0.127**	-0.195***	-0.393***	-0.290***	-0.351***
	(0.0609)	(0.0621)	(0.0718)	(0.0765)	(0.0783)	(0.0912)
Income: 50k-99k	0.244***	0.258***	0.263***	0.251***	0.167**	0.270***
	(0.0679)	(0.0690)	(0.0793)	(0.0798)	(0.0810)	(0.0921)
Income: 100k+	0.511***	0.552***	0.567***	0.455***	0.371***	0.420***
	(0.0866)	(0.0866)	(0.0977)	(0.110)	(0.107)	(0.132)
Prairies	0.125	0.216**	0.216*	0.0498	0.0750	0.110
	(0.103)	(0.0979)	(0.121)	(0.134)	(0.139)	(0.166)
Ontario	0.0940	0.156*	0.151	0.0134	0.0485	0.0994
	(0.0863)	(0.0850)	(0.0963)	(0.104)	(0.107)	(0.115)
Quebec	0.142	0.200**	0.187	-0.0301	0.0328	0.0565
	(0.0949)	(0.0926)	(0.119)	(0.110)	(0.118)	(0.124)
Atlantic	0.0434	0.147	0.107	-0.117	-0.0635	-0.123
	(0.129)	(0.130)	(0.134)	(0.174)	(0.171)	(0.167)
Employment	0.0419	-0.000747	-0.0690	-0.000752	0.00125	-0.0340
	(0.0630)	(0.0635)	(0.0738)	(0.0760)	(0.0737)	(0.0819)
College/CEGEP/Trade school	-0.0337	-0.0154	0.0592	-0.0374	-0.0736	0.0412
	(0.0780)	(0.0810)	(0.0979)	(0.0957)	(0.0965)	(0.103)
University	0.0843	0.0515	0.111	0.231**	0.163*	0.301***
	(0.0775)	(0.0799)	(0.0964)	(0.0988)	(0.0927)	(0.105)
Number of kids: No kids	-0.0445	-0.000459	0.00768	-0.118	-0.00573	0.0138
	(0.0749)	(0.0743)	(0.0835)	(0.101)	(0.101)	(0.110)
Marital status: Not married/CL	0.00622	0.0435	0.0831	0.0958	0.134	0.142
	(0.0690)	(0.0679)	(0.0759)	(0.0968)	(0.0924)	(0.102)
Grocery shopping: Not all of it	-0.174***	-0.0963	-0.112	-0.168**	-0.0907	-0.250***
	(0.0631)	(0.0642)	(0.0744)	(0.0854)	(0.0816)	(0.0927)
$\widehat{\epsilon_i}$		3.067***	1.914***		2.716***	1.550**
		(0.524)	(0.556)		(0.560)	(0.788)
Constant	2.481***	1.877***	2.212***	3.098***	2.581***	2.516***
	(0.167)	(0.196)	(0.231)	(0.235)	(0.250)	(0.281)
Observations	2,623	2,623	2,623	1,987	1,987	1,987
R-squared	0.089	0.108		0.080	0.093	

Note:
Column 1 is for benchmark OLS model for year 2017; column 2 is OLS with CF correction for year 2017; column 3 is the Median model with CF correction for year 2017. Columns 4, 5, 6 are symmetrical models for year 2018.
Baseline categories are male, <50k income, British Columbia region, unemployment, high school education, have children, married, and conducts all household grocery shopping.
$\widehat{\epsilon_i}$ is the Control Function (CF).

***, **, and * represent 1%, 5%, and 10% significance, respectively. Bootstrap standard errors in parenthesis.

Table 7: **Quantiles of cash holdings, 2017**

VARIABLES	(1) Q10_2017	(2) Q25_2017	(3) Q50_2017	(4) Q75_2017	(5) Q90_2017	(6) Q95_2017
Own Bitcoin	0.874*	1.063***	1.038***	1.654***	2.629***	3.051***
	(0.461)	(0.238)	(0.244)	(0.444)	(0.405)	(0.433)
Respondent Age	0.0261***	0.0304***	0.0169***	0.0156***	0.0170***	0.0134***
	(0.00458)	(0.00353)	(0.00238)	(0.00238)	(0.00347)	(0.00422)
Gender: Female	0.0400	-0.282***	-0.293***	-0.301***	-0.455***	-0.350***
	(0.129)	(0.101)	(0.0655)	(0.0699)	(0.104)	(0.121)
Income: 50k-99k	0.0981	0.312***	0.287***	0.210***	0.366***	0.347***
	(0.152)	(0.115)	(0.0757)	(0.0763)	(0.116)	(0.133)
Income: 100k+	0.559***	0.574***	0.572***	0.403***	0.588***	0.493***
	(0.193)	(0.136)	(0.0978)	(0.0949)	(0.130)	(0.187)
Prairies	0.248	0.123	0.155	0.0489	0.227	0.237
	(0.236)	(0.205)	(0.114)	(0.111)	(0.157)	(0.171)
Ontario	0.169	0.145	0.152*	-0.0389	-0.0536	-0.100
	(0.225)	(0.162)	(0.0903)	(0.0959)	(0.133)	(0.153)
Quebec	0.286	0.154	0.146	0.0312	-0.0297	-0.110
	(0.258)	(0.159)	(0.113)	(0.101)	(0.144)	(0.173)
Atlantic	-0.0714	0.142	0.0835	-0.122	0.324	0.294
	(0.258)	(0.251)	(0.126)	(0.170)	(0.216)	(0.288)
Employment	0.115	-0.0178	-0.0607	0.0684	0.130	0.214*
	(0.137)	(0.117)	(0.0724)	(0.0690)	(0.109)	(0.124)
College/CEGEP/Trade school	-0.0868	-0.0376	0.0413	-0.0494	-0.211	-0.0306
	(0.158)	(0.132)	(0.0943)	(0.0855)	(0.147)	(0.158)
University	0.0662	0.0913	0.132	0.0684	-0.116	0.0331
	(0.157)	(0.135)	(0.0942)	(0.0875)	(0.132)	(0.129)
Number of kids: No kids	0.133	-0.144	-0.0343	-0.0314	-0.172	-0.153
	(0.148)	(0.131)	(0.0831)	(0.0800)	(0.118)	(0.157)
Marital status: Not married/CL	-0.116	0.0786	0.0590	0.0327	0.132	0.0808
	(0.132)	(0.119)	(0.0753)	(0.0842)	(0.103)	(0.137)
Grocery shopping: Not all of it	-0.155	-0.174*	-0.156**	-0.122	-0.0564	-0.0864
	(0.141)	(0.104)	(0.0735)	(0.0776)	(0.0958)	(0.122)
Constant	-0.340	1.062***	2.598***	3.662***	4.414***	4.857***
	(0.364)	(0.324)	(0.200)	(0.197)	(0.303)	(0.330)
Observations	2,623	2,623	2,623	2,623	2,623	2,623

Note: Baseline categories are male, <50k income, British Columbia region, unemployment, high school education, have children, married, and conducts all household grocery shopping.
***, **, and * represent 1%, 5%, and 10% significance, respectively. Bootstrap standard errors in parenthesis.

Table 8: **Quantiles of cash holdings, 2018**

VARIABLES	(1) Q10_2018	(2) Q25_2018	(3) Q50_2018	(4) Q75_2018	(5) Q90_2018	(6) Q95_2018
Own Bitcoin	0.422	0.459	1.314***	1.367***	2.811***	2.642***
	(0.432)	(0.433)	(0.210)	(0.308)	(0.664)	(0.354)
Respondent Age	0.0235***	0.0226***	0.0155***	0.00818**	-4.05e-05	-0.00472
	(0.00624)	(0.00415)	(0.00285)	(0.00376)	(0.00423)	(0.00640)
Gender: Female	0.0717	-0.351***	-0.372***	-0.474***	-0.535***	-0.608***
	(0.172)	(0.116)	(0.0835)	(0.0910)	(0.110)	(0.199)
Income: 50k-99k	0.284	0.424***	0.331***	0.216**	0.143	-0.00868
	(0.211)	(0.124)	(0.0814)	(0.0999)	(0.122)	(0.178)
Income: 100k+	0.415	0.570***	0.466***	0.488***	0.368**	0.212
	(0.277)	(0.157)	(0.122)	(0.140)	(0.174)	(0.243)
Prairies	-0.483	-0.270	0.0602	0.339**	0.331	0.315
	(0.306)	(0.179)	(0.165)	(0.156)	(0.208)	(0.252)
Ontario	-0.127	-0.0494	0.0838	0.101	0.0488	-0.102
	(0.308)	(0.138)	(0.114)	(0.121)	(0.174)	(0.201)
Quebec	-0.0809	-0.153	0.0509	0.0724	-0.168	-0.200
	(0.344)	(0.155)	(0.125)	(0.122)	(0.191)	(0.262)
Atlantic	-0.379	-0.600*	-0.144	-0.0580	0.0271	0.183
	(0.345)	(0.317)	(0.160)	(0.223)	(0.365)	(0.504)
Employment	0.0199	0.0215	-0.0602	-0.0936	0.0383	0.0758
	(0.177)	(0.114)	(0.0819)	(0.0931)	(0.124)	(0.178)
College/CEGEP/Trade school	-0.0108	-0.0753	0.0569	0.0529	0.114	-0.0426
	(0.196)	(0.164)	(0.101)	(0.112)	(0.164)	(0.245)
University	0.442**	0.215	0.320***	0.268**	0.202	-0.0473
	(0.217)	(0.156)	(0.105)	(0.119)	(0.165)	(0.217)
Number of kids: No kids	-0.0634	-0.174	-0.0401	-0.0774	0.0895	-0.147
	(0.210)	(0.155)	(0.104)	(0.138)	(0.165)	(0.263)
Marital status: Not married/CL	0.219	0.296**	0.110	0.0265	-0.107	-0.0778
	(0.185)	(0.143)	(0.0973)	(0.125)	(0.125)	(0.181)
Grocery shopping: Not all of it	0.183	-0.132	-0.321***	-0.230**	-0.123	-0.113
	(0.156)	(0.130)	(0.0919)	(0.109)	(0.119)	(0.169)
Constant	-0.144	1.623***	2.846***	4.203***	5.339***	6.615***
	(0.548)	(0.338)	(0.251)	(0.302)	(0.372)	(0.523)
Observations	1,987	1,987	1,987	1,987	1,987	1,987

Note: Baseline categories are male, <50k income, British Columbia region, unemployment, high school education, have children, married and conducts all the household grocery shopping.
***, **, and * represent 1%, 5%, and 10% significance, respectively. Bootstrap standard errors in parenthesis.

Table 9: **Quantiles of cash holdings, 2017: corrected for selection via a control function**

VARIABLES	(1) Q10CF_2017	(2) Q25CF_2017	(3) Q50CF_2017	(4) Q75CF_2017	(5) Q90CF_2017	(6) Q95CF_2017
Own Bitcoin	0.257	0.634***	0.907***	1.150***	1.960***	1.759***
	(0.435)	(0.226)	(0.195)	(0.357)	(0.465)	(0.598)
Respondent Age	0.0351***	0.0355***	0.0210***	0.0196***	0.0202***	0.0168***
	(0.00484)	(0.00369)	(0.00257)	(0.00258)	(0.00351)	(0.00452)
Gender: Female	0.234*	-0.189*	-0.195***	-0.187**	-0.266**	-0.208*
	(0.134)	(0.101)	(0.0718)	(0.0730)	(0.105)	(0.126)
Income: 50k-99k	0.234	0.312***	0.263***	0.226***	0.347***	0.324**
	(0.149)	(0.113)	(0.0793)	(0.0763)	(0.120)	(0.136)
Income: 100k+	0.665***	0.602***	0.567***	0.444***	0.538***	0.533***
	(0.197)	(0.129)	(0.0977)	(0.0997)	(0.129)	(0.196)
Prairies	0.358*	0.146	0.216*	0.0708	0.206	0.275
	(0.205)	(0.190)	(0.121)	(0.119)	(0.149)	(0.188)
Ontario	0.134	0.168	0.151	0.0184	0.0192	-0.0168
	(0.200)	(0.143)	(0.0963)	(0.0987)	(0.131)	(0.160)
Quebec	0.316	0.165	0.187	0.0674	0.0179	0.0359
	(0.231)	(0.143)	(0.119)	(0.102)	(0.150)	(0.183)
Atlantic	-0.0177	0.218	0.107	-0.0250	0.309	0.508
	(0.234)	(0.236)	(0.134)	(0.173)	(0.217)	(0.316)
Employment	0.0272	-0.0441	-0.0690	0.0681	-0.0143	0.145
	(0.139)	(0.116)	(0.0738)	(0.0713)	(0.105)	(0.133)
College/CEGEP/Trade school	-0.0120	0.00606	0.0592	-0.0301	-0.154	-0.0315
	(0.159)	(0.138)	(0.0979)	(0.0858)	(0.145)	(0.161)
University	0.0579	0.0974	0.111	0.0540	-0.122	-0.0815
	(0.149)	(0.135)	(0.0964)	(0.0901)	(0.133)	(0.142)
Number of kids: No kids	0.160	-0.142	0.00768	0.0237	-0.0954	-0.115
	(0.142)	(0.137)	(0.0835)	(0.0811)	(0.131)	(0.159)
Marital status: Not married/CL	-0.0730	0.0505	0.0831	0.0525	0.133	0.229
	(0.144)	(0.113)	(0.0759)	(0.0827)	(0.107)	(0.144)
Grocery shopping: Not all of it	-0.178	-0.127	-0.112	-0.0479	-0.0142	0.0361
	(0.148)	(0.104)	(0.0744)	(0.0759)	(0.0974)	(0.134)
$\widehat{\epsilon_i}$	4.068***	3.216***	1.914***	2.539***	3.002***	3.753**
	(0.951)	(0.613)	(0.556)	(0.611)	(1.164)	(1.600)
Constant	-1.078***	0.631*	2.212***	3.178***	4.020***	4.379***
	(0.411)	(0.340)	(0.231)	(0.220)	(0.334)	(0.397)
Observations	2,623	2,623	2,623	2,623	2,623	2,623

Note: Baseline categories are male, <50k income, British Columbia region, unemployment, high school education, have children, married, and conducts all the household grocery shopping. $\widehat{\epsilon_i}$ is the CF. ***, **, and * represent 1%, 5%, and 10% significance, respectively. Bootstrap standard errors in parenthesis.

Table 10: **Quantiles of cash holdings, 2018: corrected for selection via a control function**

VARIABLES	(1) Q10CF_2018	(2) Q25CF_2018	(3) Q50CF_2018	(4) Q75CF_2018	(5) Q90CF_2018	(6) Q95CF_2018
Own Bitcoin	0.0916	0.387	1.052***	1.094***	2.485***	2.029***
	(0.388)	(0.366)	(0.280)	(0.280)	(0.800)	(0.782)
Respondent Age	0.0261***	0.0258***	0.0192***	0.0113***	0.00307	-0.000224
	(0.00616)	(0.00430)	(0.00344)	(0.00386)	(0.00462)	(0.00581)
Gender: Female	0.0407	-0.199*	-0.351***	-0.381***	-0.468***	-0.668***
	(0.166)	(0.117)	(0.0865)	(0.0946)	(0.118)	(0.166)
Income: 50k-99k	0.174	0.385***	0.270***	0.185*	0.124	-0.113
	(0.199)	(0.130)	(0.0924)	(0.100)	(0.132)	(0.176)
Income: 100k+	0.356	0.516***	0.420***	0.416***	0.361**	0.0454
	(0.243)	(0.155)	(0.135)	(0.133)	(0.176)	(0.229)
Prairies	-0.202	-0.294	0.110	0.441***	0.420*	0.350
	(0.323)	(0.198)	(0.167)	(0.156)	(0.226)	(0.263)
Ontario	0.126	-0.0504	0.0994	0.125	0.147	0.115
	(0.328)	(0.139)	(0.115)	(0.122)	(0.187)	(0.197)
Quebec	0.123	-0.126	0.0565	0.145	-0.0890	0.107
	(0.343)	(0.164)	(0.127)	(0.127)	(0.198)	(0.256)
Atlantic	-0.0870	-0.593**	-0.123	-0.0749	0.131	0.378
	(0.358)	(0.273)	(0.171)	(0.195)	(0.385)	(0.422)
Employment	0.0281	0.0174	-0.0340	-0.104	-0.0185	0.179
	(0.167)	(0.117)	(0.0805)	(0.101)	(0.127)	(0.162)
College/CEGEP/Trade school	-0.0989	-0.0584	0.0412	0.0164	0.0316	-0.205
	(0.193)	(0.167)	(0.103)	(0.107)	(0.167)	(0.235)
University	0.276	0.179	0.301***	0.254**	0.0735	-0.189
	(0.212)	(0.151)	(0.106)	(0.118)	(0.165)	(0.208)
Number of kids: No kids	0.0805	-0.137	0.0138	0.0478	0.150	0.315
	(0.195)	(0.167)	(0.116)	(0.135)	(0.170)	(0.280)
Marital status: Not married/CL	0.207	0.347**	0.142	0.0293	-0.0738	-0.0281
	(0.175)	(0.145)	(0.101)	(0.126)	(0.130)	(0.166)
Grocery shopping: Not all of it	0.258*	-0.0813	-0.250**	-0.151	-0.0901	-0.0436
	(0.156)	(0.129)	(0.0995)	(0.118)	(0.128)	(0.177)
$\widehat{\epsilon_i}$	3.546***	2.021**	1.550**	2.011***	1.873	4.009
	(0.819)	(0.802)	(0.790)	(0.655)	(1.518)	(2.694)
Constant	-0.646	1.236***	2.516***	3.793***	5.044***	5.774***
	(0.566)	(0.370)	(0.289)	(0.337)	(0.391)	(0.527)
Observations	1,987	1,987	1,987	1,987	1,987	1,987

Note: Baseline categories are male, <50k income, British Columbia region, unemployment, high school education, have children, married, and conducts all the household grocery shopping. $\widehat{\epsilon_i}$ is the CF. ***, **, and * represent 1%, 5%, and 10% significance, respectively. Bootstrap standard errors in parenthesis.