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 94 percent more cash than nonowners. Focusing on the quantiles of cash holdings, we find that Bitcoin ownership has a highly nonlinear effect: the difference in cash holdings between Bitcoin owners and nonowners varies from 78 percent at the 25^{th} quantile to 172 percent at the 95^{th} quantile. Our results provide evidence against the narrative that certain new technologies, such as Bitcoin will necessarily lead to a decline in cash usage.

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1 Introduction

There has been a documented decline in the use of cash by consumers for undertaking point-of-sale (POS) transactions over the last decade in Canada. The Bank of Canada's 2017 Methods-of-Payment (MOP) survey reports that the share of cash used for retail transactions declined from 54 per cent in 2009 to 33 per cent in 2017, see Henry et al. (2018a). However, cash remains popular among certain demographic groups (older, less-educated, and lower-income) and certain types of transactions (small-value transactions). For some demographic groups, it is commonly used as a convenient store-of-value. Similarly, most advanced economies have witnessed a similar pattern of cash usage at the POS. Bagnall et al. (2016) undertakes an international comparison and shows that cash is resilient across seven countries.[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: Sveriges Riksbank (2017, 2018a, 2018b). Engert et al. (2019) undertake a cross-country comparison of Canada and Sweden to understand the potential drivers of the difference between the two countries. They find that both countries have similar payment infrastructures, so the difference in cash usage is due to bank notes' legal tender status and banking regulations to secure deposits in Sweden. In addition, they argue that cash demand has two components: transactional and non-transactional. In Canada and many other countries, banknotes in circulation continue to grow at pace with GDP while at the same time, cash used for payments is declining. The stable or increasing demand for cash is thought of as a store-of-value motive. The prospect of a cashless society is driving a flurry of research and policy analysis into Central Bank Digital Currency (CBDC) – a digital form of central bank money. Lane (2020) discusses two potential reasons for issuing CBDC: one, if cash demand falls to negligible amount and two if a private digital currency threatens to takeover payments in Canada. The two conditions may be inter-related as some pundits argue that privately-issued digital currencies, such as Bitcoin, may supplant cash. First, is the role of consumer preferences in driving the demand for cash and alternatives, see Van Hove (2005). Questions like: What characteristics of cash do consumers value, and would these translate to cash in a digital form? Why consumers want a digital form of cash? are becoming relevant. Characteristics that consumers deem important for in-person transactions – such as speed, ease of use, etc. – may not be as relevant in an online setting. Huynh et al. (2020) estimate the demand for payment services and find that a CBDC that reflects the best of both cash and debit cards would not have wide adoption and usage despite widespread merchant acceptance. Second, it is important to understand the extent to which existing private digital currencies function for consumers

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

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 , which rose from US$1,000 (late of 2016) to a peak of almost US$20,000 (late 2017) has led many to reassess whether Bitcoin should be considered as something more akin to a 'cryptoasset' than a cryptocurrency. To better understand consumer adoption and use of Bitcoin, the Bank of Canada commissioned the Bitcoin Omnibus Survey (BTCOS) in 2016 (Henry et al. (2017)); the survey has been running annually in subsequent years (Henry et al. (2018a); Henry et al. (2019))[2]. In the current paper, we use data from the 2017 BTCOS. The 2017 BTCOS included a new question designed to measure Canadians' consumer cash holdings (i.e., cash held in the person's wallet, purse, or pockets). A striking finding was that Bitcoin owners tend to hold noticeably more cash, both on average and at the median, compared with non-owners. This finding alone challenges the assumption that digital currencies will necessarily displace cash in an increasingly digital world, and it also corroborates a similar finding by Fujiki and Tanaka (2014). However, it also raises questions about how to properly interpret this fact, specifically whether there may be factors driving both cash holdings and Bitcoin ownership. This simultaneity may potentially drive selection into holding Bitcoin for the following possible reasons: Bitcoin owners may prefer anonymous liquidity, and hence cash may be a hedge (or vice versa); some Bitcoin owners may not trust institutions (e.g. government or banks), leading to large cash holdings outside of traditional financial institutions. These sources of selection induce endogeneity that is likely to bias estimates of the effect of Bitcoin ownership on cash holdings.

Therefore, considering this potential source of endogeneity, this paper aims to estimate the effect of Bitcoin ownership on the level of consumer cash holdings. In doing so, we also examine whether any distributional effects are present and explore how consumer preferences may account for the relationship between cash holdings and Bitcoin ownership. Anticipating the sources of selection, the 2017 BTCOS was designed with a question that can be used as an exclusion restriction or an instrumental variable: "What percentage of Canadians do you think will be using Bitcoin 15 years from now?". This variable works well as an exclusion restriction because owners are more optimistic about the prevalence of future Bitcoin use; however, there is no obvious direct relationship with the current level of cash holdings. Based on the results that are controlling for selection, we found that the difference in cash holdings between Bitcoin holders and non-holders varies from 71.4 % at the 25 quantile of cash to

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

171 % at the 95 quantile of cash, with a mean effect of 97 %. These results suggest that adoption of cryptocurrencies, such as Bitcoin, may not lead to a decrease in the demand for cash.

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

2 2017 Bitcoin Omnibus Survey

We base our analysis on the 2017 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. Also, the survey collects standard demographic information about each respondent. Between 2016 and 2017 there was a shift in reasons for holding Bitcoin; in 2016 the reasons for holding Bitcoin were for transactional purposes and the new technology associated with it, while 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 a year was almost 75 percent. This jump was driven by new entrants in the Bitcoin market that got awareness in the past year and got a higher test score on the Bitcoin knowledge. This information about new owners and past owners suggests that selection into Bitcoin ownership is an important mechanism that one needs to consider when the relationship of Bitcoin ownership is linked to cash holdings.

The chosen 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 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, it has an important question that relates to the outcome of interest in this analysis (the cash

on hand)[3], but also one about no cash. Additionally, these questions are also addressed to Bitcoin adopters (both current and past owners) and to those that used digital currency at least once in the past year.

2.1 Descriptive statistics

What we can see from both surveys (BTCOS and MOP, see Table 1) 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 times more cash). Also, an interesting finding from all these surveys is that while the no cash users increased by 50 % from 2013 (from 6% to 9%) the average cash on hands also increased from 84 dollars in 2013 to 105 in 2017, increase probably driven by the increase in holdings of higher notes.

- insert Table 1 here -

Table 2 provides a demographic breakdown of Bitcoin owners versus non-owners. Bitcoin owners are dominated by young, employed, or males. In particular, looking at the within-group numbers we see that for owners, the age group 18 to 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. 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 four times more cash than non-owners (for the young and mid-age categories) and about 40 percent more cash for the highest age category.

- insert Table 2 here -

Also, we observe that male owners hold more cash than their female counterparts (25 percent more). What is also interesting to point out from Table 2 results is that the unemployed Bitcoin owners hold 30 per cent more cash than their employed counterparts. These observations also suggest that demographic characteristics are important to our analysis as there are important differences between the demographics associated with Bitcoin owners and non-owners.

Finally, if we look at the distribution of cash by Bitcoin owners and non-owners (here we look at the log of cash, see Figure 1 below) we see that Bitcoin owners hold more cash across almost all the support of cash (except at lower levels of cash, below 15th quantile, where the holding of cash is similar across the two groups). The figure also emphasizes that

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

Bitcoin owners hold high levels of cash, the distribution of cash holding for Bitcoin owners is heavy-tailed to the right. We also see that the distribution of non-holders of Bitcoin after the log transformation is heterogeneous (with multiple modes). These two observations suggest that an estimation that is based on mean average responses of cash holdings by Bitcoin holders will be affected by this observed skewness and heterogeneity. Consequently, while we look at the mean responses of cash holdings as a benchmark model, we analyze also the quantiles of cash.

- insert Figure 1 here -

2.2 Preferences and Quantities of Bitcoin

This subsection quantifies the effects of different preferences associated with Bitcoin ownership on the amount of Bitcoins the owners chose to have. Understanding the role of these preferences is also of relevance as increased amounts of Bitcoin owned may signal shifts in investments towards these speculative assets with implications to the role the Bitcoin may have when it is compared to cash (substitute versus complement). We construct four categories of preferences using the questions from 2017 BTCOS:[4]

1. The non-trust related (or anonymity) index takes one if Bitcoin users mention that they do not trust either the banks, the government, or the Canadian dollar and Bitcoin allows making anonymous payments.

2. Technology related index would take value one if respondents chose one of the following: they are interested in new technology, Bitcoin uses secured blockchain technology to prevent loss and fraud, and is a cost-saving technology.

3. Canadians usage of Bitcoin to pay for goods and services, either online or in physical stores, or to sent peer-to-peer payments reflect their preferences related to transactions.

4. To measure the effect of investment preferences on the amount of Bitcoin, we created a dummy variable that takes the value of one if respondents chose to own it as an investment and zero otherwise.

We tabulate these preferences on the amounts of Bitcoins owned by the subsample of Bitcoin owners using an ordered logit model. We account for the demographic characteristics, considering the preferences one by one and jointly. The results are presented in Table 3.

- insert Table 3 here -

[4]For further details on these measures, see Henry et al. (2018b).

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 tabulation is the investment-related preference. This suggests that at the time of the survey, the dominant characteristic of Bitcoin ownership (quantitatively) was the investment motive. However, when the preferences are taken jointly, none of these preferences is significant.

These results suggest that while there are different reasons for holding Bitcoins, these reasons are indistinguishable when they relate to the amount 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, even if we observe that Bitcoin owners are owning more cash than non-owners.

3 Identification Strategy

Identifying the relationship that links the cash holdings to Bitcoin adopters builds on the information available in the 2017 BTCOS, characteristics of the data, and the interactions present in the data. Given that the survey is based on a random assignment, we can use a Bitcoin ownership question to separate the Bitcoin owners from the non-owners and, as a benchmark we estimate a simple linear model where the variable of interest (or the treatment variable) is Bitcoin ownership. However, we do not assume that the adoption of Bitcoin is exogenous. We base our assumption that the two subpopulations (owners and non-owners) are different in distributions. Table 4 demonstrates the differences in means for different demographic characteristics: age, gender, employment, education, number of kids and marital status.

- insert Table 4 here -

These differences suggest that the unconditional mean effects on cash usage should not be identical with the conditional mean effects of cash usage. In particular, the Bitcoin adopters are younger (almost 14 years mean age difference), almost 75 per cent males, and more likely to be unemployed than the non-owners counterparts. These differences in the distribution of observables suggest that the owning Bitcoin is selective and, therefore, we should account for the selection in our identification strategy.

We already saw from summary statistics that Bitcoin users hold more cash comparing with non-Bitcoin users. This raises the possibility of some simultaneity that links cash holding and Bitcoin ownership, simultaneity that can drive selection into holding Bitcoin as it can be used as a hedge for anonymous liquidity, or alternatively, the Bitcoin holders may not like institutions and avoid reporting their Bitcoin holdings. To solve these selection

issues, we propose to use identification methods that are accounting for the endogenous selection via a control function approach. The control function approach is further used to quantify the effect of Bitcoin ownership on quantiles of cash.

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

3.1 Expected cash holdings

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

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

where X includes individual characteristics as gender, age, education, marital status, number of kids, employment status, household grocery shopping and income, while P are province fixed effects. In other words, this hypothesis tests if the average holdings of cash are higher for Bitcoin owners than for non-owners.

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

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

where $cash_i$ is the log of cash holdings of individual i, Btc_i is equal to 1 if the respondent is Bitcoin owner and zero otherwise, X_i is a set of respondent characteristics for individual i, P_j are regional fixed-effects, while u_i is the error term.

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

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

where Z_i is the exclusion restriction and ϵ_i is the error term that has an i.i.d. logistic distribution. The exclusion restriction is the survey question on a respondent's expectation

of the adoption rate of Bitcoin in 15 years (EAR15)[5]. The EAR15 is positively correlated with Bitcoin ownership as the owners have a positive outlook on the adoption of Bitcoin. EAR15 is not correlated with cash holdings as the survey question asks respondents to count the amount of cash on their wallet, purse, or person during the survey. They cannot re-optimize their cash holdings. Therefore, EAR15 should not be correlated with Bitcoin ownership.

Additionally, Figure 2 illustrates the cumulative distribution function (CDF) plot of Bitcoin expected adoption rate for the Bitcoin owners versus non-owners. The CDF of the two distributions do not intersect (The adoption rate of Bitcoin owners First Order Stochastic Dominate (FOSD) the adoption rate of non-owners[6]).[7] The EAR15 restriction also satisfies the conditional independence assumption as in Abadie, Angrist, and Imbens (2002). Consequently, $EAR15$ acts as an exclusion restriction to delineate between the bitcoin owners and non-owners

- insert Figure 2 here -

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

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

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 for this control function is:

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

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

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

[6]FOSD test based on Kolmogorov-Smirnov has a p-value =1

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

the following model:

$$cash_i = \alpha + \beta Btc_i + \gamma X_i + + \delta P_j + \phi \widehat{\epsilon_i} + u_i.$$

3.2 Quantiles of cash holdings

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

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

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

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

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

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

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

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

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

4 Empirical Results

To test our hypotheses of interest, we group the discussion of the results on three separate parts. To test the first hypothesis of interest, we require to estimate the log-linear model of cash holdings on our variable of interest (Bitcoin ownership), demographic characteristics and regional fixed-effects. However, to control the endogenous selection, we need to augment this model with a correction term that requires estimating the probability of Bitcoin

ownership. Consequently, we start presenting the results with the extensive margin analysis that quantifies the effects of the demographics and province fixed effects on the probability of holding Bitcoin (propensity score).

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

4.1 Probability of owning Bitcoin

The results are presented in Table 5. The first column refers to the results of the probability of Bitcoin ownership (propensity score) when accounting for demographic characteristics and province fixed effects, the second column augments the model with the $EAR15$ variable, the third and fourth columns are equivalent models but are accounting for the possibility that Bitcoin ownership to be a rare event. 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 5.

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 significantly different impact when compared to the benchmark, British Columbia province (both regions have the lowest Bitcoin ownership, half of BC: 2% versus 4%, see Henry et al. (2018)). 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.

- insert Table 5 here -

When we augmented the model with the $EAR15$ variable, we observe the predictability power of this exclusion restriction as it increases the probability of Bitcoin ownership. [8]

[8]The model that augments with $EAR15$, has a smaller sample size (15% smaller) because 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. We model the missing data with missing-at-random imputation model. We find that this item non-response does not have

Given that only 5 per cent of the sample represents the owners of Bitcoin (117 observations), we check if each cell associated to the variables used in the analyses has sufficient observations to do a proper analysis. Wilson VanVoorhis et al. (2007) pointed out that for a chi-square test, 5 observations per cell are minimal, while a 7 observations per cell are minimum for a mean comparison. We have for almost all the cells much more than the required minimum. One cell with problems was the retired cell, therefore, we combine retired with unemployed and not in labour force to obtain a relevant comparison cell with employed.[9]

Further, we check the predictability power of the two model specifications. The results are presented in Table 6. 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).

- insert Table 6 here -

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 7. 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.

- insert Table 7 here -

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

4.2 Cash Holdings

4.2.1 Mean Effects of Cash Holdings

To test the first hypothesis of interest, we estimate the benchmark linear specification that treats the adoption of Bitcoin as exogenous, then we extend the linear analysis assuming that adoption is selective. [10] The results of these analyses are presented in Table 8.

a material effect on the outcomes. The result of this imputation is a new EAR15 variable that corrects for the missing data, which is further used in the analysis.

[9]We provide empirical estimates to demonstrate that these minimum cells doe not affect the estimation results.

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

- insert Table 8 here -

Column 1 of Table 8 presents the results of the benchmark model. Here we see that the parameter estimate of Bitcoin ownership is statistically significant and equal to 1.42, and can be interpreted that in average, Bitcoin owners hold a 142 per cent higher amount of cash than non-owners when we control for age, gender, income, education, marital status, number of kids and province of origin.

The next column of Table 8 presents the conditional mean of cash holdings model that accounts for the selection via the CF approach. The results show that the proposed correction estimates an average difference of log-cash holdings between the Bitcoin owners and non-owners of 0.971, which imply that the average difference in cash holdings between the Bitcoin owners and non-owners is about 97 per cent higher (after controlling for selection). The demographic characteristics that are relevant for cash holdings are: age (positive effect), gender-female (negative effect) and medium and higher income categories show positive effects over the benchmark category (0 to CAN$50,000). The Prairies, Ontario and Quebec are also showing positive effects over the benchmark region (British Columbia)., The introduction of the CF also removes the effects of not doing grocery shopping[11].

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

The last column of Table 8 presents the conditional median of cash holdings model that accounts for the selection via the CF approach. The conditional median results are similar with the ones of conditional mean, with some differences: the median effect is smaller than the mean effect in magnitude (0.934 vs 0.971) and Ontario is no longer significant.

4.2.2 Quantile Effects of Cash Holdings

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

The results of the two analyses are presented in Table 9 (simple quantile estimates - benchmark) and Table 10 (quantiles estimates corrected for selection).

- insert Table 9 here -

Given the observed distribution of log cash for Bitcoin owners and non-owners we expect that median estimate to be below the estimated mean effect, the lower quantile effects to

[11] A discussion about this results is found in the subsection Bitcoin Selection

be insignificant, while the higher quantile effects to be strongly in favour of Bitcoin owners. Indeed, for the first 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. Also, at low quantiles of cash (10 percentile) there is a higher difference between Bitcoin owners and non-owners of about 136 per cent, this difference is decreasing towards the median and increasing after the median; at high quantiles (95 percentile) of cash the difference is about three times higher. The pattern across quantiles in the benchmark quantile model is not monotonically increasing as it was expected, with higher estimated values at lower quantiles than expected..

As in the linear model, where we the endogeneity test suggested that Btc variable is endogeneous, we expect to be endogeneous also in the quantile model. Therefore, to get a correct conditional quantile effect, we estimate a model that accounts for the selection at the quantile leve with the same CF. The results of this estimation are presented in Table 10.

- insert Table 10 here -

As in the linear case with correction for selection, the results emphasize that indeed the estimated conditional median effect is smaller (estimated at 0.934) than the one obtained using the benchmark quantile estimates and the unconditional median. Once we control for selection the conditional quantiles are showing the expected patterns: not significant effects at lower quantiles and increased difference in cash holdings between Bitcoin owners and non-owners over the quantiles up the 95 percentile.

The demographic characteristics that were relevant for the linear model are also relevant for the quantile model: age (positive effect, with a marginal effect that varies 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 CAN$50,000), an effect that is maintained across all quantiles.

A graphical representation of the differences between the benchmark quantiles estimates and the corrected for selection quantile estimates are presented in Figure 3. The results show how selection affects the quantile estimates, especially the lowest and the highest ones. Another interesting finding is that the difference in cash holdings between males and females disappear at very high quantiles (95 percentile) of cash. The next subsection is discussing the possible explanations of the selection correction.

4.3 Bitcoin Selection

To understand what drives potential selection we observe that once the control function is introduced in the conditional mean and conditional quantile models, few interesting results

are observed: first, at the conditional mean model, the introduction of the CF removes the effects of not doing grocery shopping and second at the conditional quantile analysis two results are to be mentioned: at high quantiles of cash there is no difference between males and females and the effect of no grocery shopping become again significant at the conditional median, while disappearing at the other quantiles.

To understand these results we look at the role of our exclusion restriction on capturing these effects. In particular, how the gender differences in EAR15 between the individuals that do and not do grocery shopping are captured by the excluded restriction (EAR15) in the first stage.

The gender difference in expectations for grocery shopping can be linked to the latest work of D'Acunto et al. (2020), which emphasize the role of gender differences in capturing economic expectations. They also suggest that females tend to have significantly more distorted beliefs than males about economic outcomes and these gender differences in beliefs are linked to participation in grocery shopping.

The difference in expected Bitcoin adoption between the ones that do grocery versus the ones that do not do grocery is of 5.4 percent and significant,[12], while the gender difference(males versus females) in EAR15 is of 4.24 percent and significant [13]. Also, at high quantiles of cash (above 90 percentile), the EAR15 gender difference disappears[14]

Further, by looking at the unconditional relationship between the grocery shopping choices and cash holdings by gender and by Bitcoin ownership we observe that while there is no difference in cash holdings between the grocery shoppers and non shoppers, once we look by gender and Bitcoin ownership we start to see differences.

- insert Table 11 here -

In particular, we see that more females (in proportion) do grocery shopping than males and also that females that are doing grocery shopping are holding more cash than the ones that are not doing (for males the differences in log cash being smaller). Additionally, more Bitcoin owners (proportionally) are doing grocery shopping (when compared to non-owners), also, we see that the owners that are doing grocery shopping are actually holding much more cash than the Bitcoin owners that are not doing grocery shopping, especially at higher quantiles of cash.

This observation may suggest that ownership of cash of Bitcoin holders is not driven by the complementary of cash (Fujiki (2020) showed that Bitcoin owners also invest in safe assets, and in his view cash is a safe asset.), but rather this ownership of cash is a preference.

[12] t-test of the difference is 5.59 with a p-value of 0.00.
[13] t-test of the difference is 4.39 with a p-value of 0.00.
[14] t-test of the difference is 0.78 with a p-value of 1.00.

Bitcoin owners that are family oriented hold more cash to buy larger quantities of groceries to minimize the time spent at groceries.

To further dive into this finding about the lack of difference on cash holdings between females and males at high conditional quantiles of cash, we decompose the differences in cash holdings between: males and females of individuals with high versus low Bitcoin literacy scores [15]; 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.

The results found in Table 12 show that the differences between males and females are driven neither by the unobervables nor by changes in the distribution of other observables, but by the weights (parameters) associated with these variables.

- insert Table 12 here -

The same holds true when we compare the differences in Bitcoin literacy. When we interact with 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 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.

5 Conclusion

The year 2017 was pivotal in the evolution of cryptocurrencies. As the price of Bitcoin skyrocketed, 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 Canada's 2017 Bitcoin Omnibus Survey, this paper sheds light on a surprising finding which suggests that digital currencies may in fact play a role

[15] 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 a government backs Bitcoin, and its public ledger (Henry et al. (2019)).

in supplementing existing payment methods and financial systems, rather than supplanting them. Controlling for observable factors, and most importantly selection into Bitcoin ownership (driven by gender difference in expectations of future Bitcoin ownership), we show that cash holdings of Bitcoin owners are substantially higher than non-owners. Further, this difference is most drastic among consumers that hold large amounts of cash.

To build on this work, we suggest several directions for future research [16]. First, it is necessary to identify the specific features that Bitcoin owners deem relevant for determining their adoption and usage – this may help explain what is driving large cash holdings among owners. Second, it would be useful to classify Bitcoin owners into various types, e.g. investors, casual users, etc. It is not unreasonable to assume that Bitcoin owners themselves are heterogeneous, and this needs to be factored into any analysis that attempts to explain the relationship between Bitcoin ownership and cash holdings. Finally, it would be useful to examine evidence from other countries. Canada may be considered relatively advanced in terms of financial inclusion and the structure of its financial institutions – how would our results differ in countries where this is not the case?

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[16] 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

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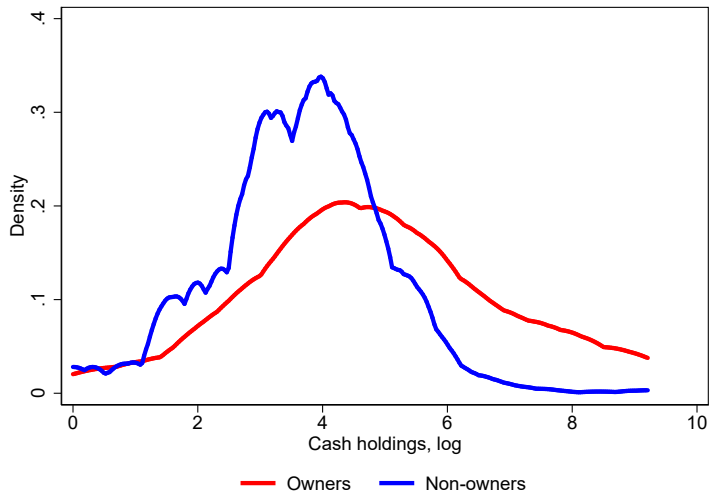
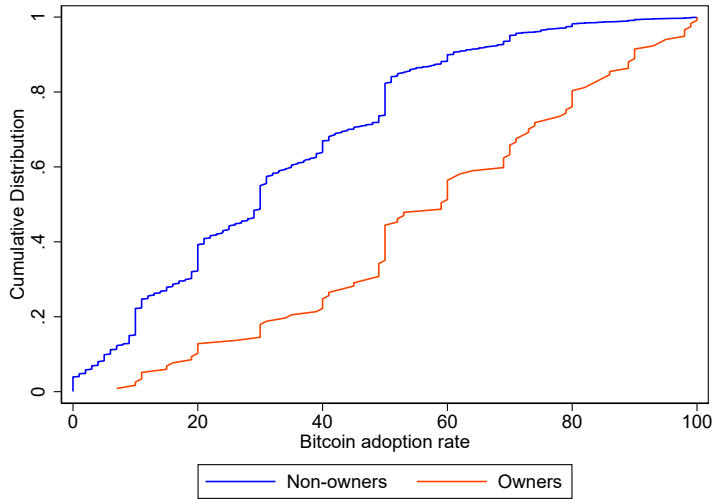
Figure 1: **Kernel density, log of cash holdings by BTC ownership**



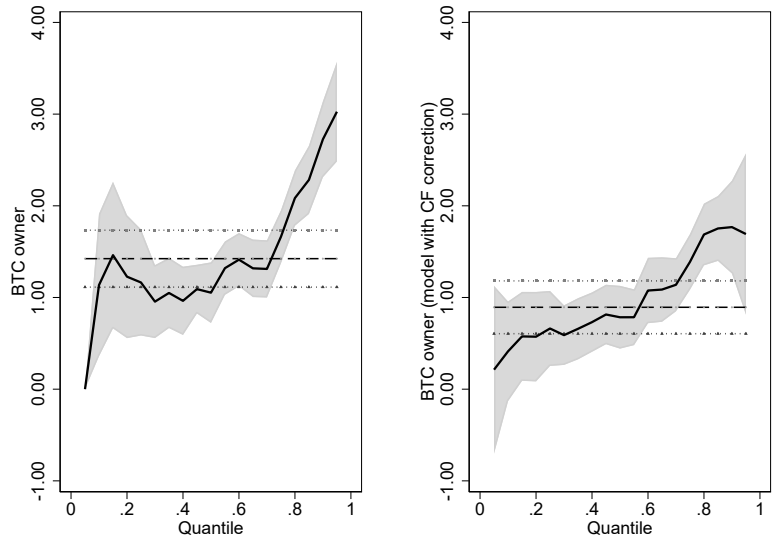
Note: Data are from the 2017 BTCOS. The red density is for Bitcoin owners and the blue density is for non-owners.

Figure 2: BTC Expected Adoption Rate as an instrument



Note: Data are from the 2017 BTCOS. The the blue CDF is for Bitcoin owners and the red CDF is for non-owners. FIX THIS GRAPH!!! -¿ as previous figure red should be owners while blue is non-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: **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	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 4: **Mean Differences in observables between Bitcoin owners and non-owners**

Variable	Bitcoin owners Mean	Std. Dev.	Non owners Mean	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 5: **Probability of Bitcoin ownership - with sample correction**

VARIABLES	Logit	Logit with EAR15	Rare Events	Rare Events with EAR15
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		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 6: **Logit Specification Tests**

Logit Model	Btc Own	Coef.	Std. Err.	z	p-value
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 7: **Logit EAR15 Estimation and Specification Tests**

Logit Model with EAR15 only	(1)
VARIABLES	Estimates
EAR15	0.0468***
	(0.0042)
Constant	-5.14***
	(0.253)
Linktest	
Prediction	1.375***
Prediction squared	0.07
LROC	0.78
Observations	2,623

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

Table 8: **Cash Holdings modeled by: OLS; OLS with CF; Q50 with CF**

VARIABLES	OLS	OLS-CF	Q50-CF
BTC owner	1.423***	0.971***	0.934***
	(0.212)	(0.219)	(0.169)
Age	0.0204***	0.0268***	0.0221***
	(0.00225)	(0.00239)	(0.00247)
Gender: Female	-0.277***	-0.118*	-0.189***
	(0.0661)	(0.0685)	(0.0683)
Income: 50k-99k	0.266***	0.283***	0.276***
	(0.0762)	(0.0752)	(0.0750)
Income: 100k+	0.559***	0.606***	0.580***
	(0.0954)	(0.0949)	(0.0953)
Region: Prairies	0.127	0.228**	0.199*
	(0.113)	(0.111)	(0.112)
Region: Ontario	0.0991	0.168*	0.160
	(0.0991)	(0.0984)	(0.0997)
Region: Quebec	0.155	0.220**	0.181*
	(0.105)	(0.105)	(0.105)
Region: Atlantic	0.0435	0.158	0.110
	(0.145)	(0.144)	(0.137)
Employment: employed	0.0324	-0.0222	-0.0872
	(0.0708)	(0.0707)	(0.0722)
Education: College/CEGEP/Trade school	-0.0324	-0.0109	0.0654
	(0.0868)	(0.0863)	(0.0868)
Education: University	0.0940	0.0588	0.119
	(0.0872)	(0.0864)	(0.0868)
Number of kids: No kids	-0.0533	-0.00414	-0.0156
	(0.0832)	(0.0830)	(0.0812)
Marital status: Not married/CL	0.00336	0.0436	0.0738
	(0.0777)	(0.0767)	(0.0776)
HH grocery shopping: Not all of it	-0.185***	-0.100	-0.150**
	(0.0706)	(0.0703)	(0.0716)
$\widehat{\epsilon_i}$		3.388***	1.881***
		(0.550)	(0.469)
Constant	2.268***	1.610***	2.157***
	(0.190)	(0.209)	(0.211)
Observations	2,623	2,623	2,623
R-squared	0.084	0.102	

Note:
Column 1 is for benchmark OLS model; Column 2 is OLS with CF; Column 3 is the Median with CF correction.
Baseline categories are Male, <50k income, from BC, unemployed, conducts all HH grocery shopping.
$\widehat{\epsilon_i}$ is the CF.

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

Table 9: **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:	-0.177	-0.0359	0.0486	-0.0522	-0.199*	-0.0527
College/CEGEP/Trade school	(0.329)	(0.149)	(0.0860)	(0.0920)	(0.113)	(0.156)
Education:	0.00853	0.123	0.133	0.0671	-0.0703	0.00475
University	(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	-0.140	0.0754	0.0548	0.0331	0.136	0.0898
	(0.294)	(0.133)	(0.0767)	(0.0821)	(0.101)	(0.140)
Household grocery shopping:	-0.200	-0.195	-0.172**	-0.126*	-0.0492	-0.0765
Not all of it	(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 household grocery shopping. Significance stars ***, **, and * represent 1%, 5% and 10% significance, respectively.

Table 10: **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)
$\widehat{\epsilon_i}$	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.
$\widehat{\epsilon_i}$ is the CF.
Significance stars ***, **, and * represent 1%, 5% and 10% significance, respectively.

Table 11: **Grocery Shoppings by Gender and Bitcoin Ownership**

Percentile	log cash	log cash	log cash Female	log cash Female	log cash Male	log cash Male	log cash Own Btc	log cash	log cash Not Own Btc	log cash
	No Grocery	Grocery	No Grocery	Grocery	No Grocery	Grocery	No Grocery	Grocery	No Grocery	Grocery
10	0.00	0.69	0.00	0.69	0.00	0.00	1.75	1.10	0.00	0.69
25	2.30	2.48	2.30	2.30	3.00	3.00	3.00	3.57	2.30	2.30
50	3.56	3.69	3.22	3.56	3.81	3.91	4.61	4.61	3.56	3.69
75	4.38	4.61	4.09	4.38	4.61	4.61	5.63	6.21	4.38	4.44
90	5.30	5.30	4.96	5.23	5.42	5.54	6.91	8.44	5.30	5.30
95	5.70	5.79	5.31	5.70	5.99	6.34	7.53	9.02	5.70	5.70
Obs	1196	1427	557	852	639	575	41	76	1155	1351

Table 12: **Counterfactual experiments by: gender, high literacy score, gender interacted with high literacy score**

VARIABLES	Gender log_cash	High_score log_cash	Gender_high_score log_cash
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.