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Predicting the Demand for Central Bank Digital Currency: A Structural Analysis with Survey Data

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Abstract

This paper predicts households' demand for a central bank digital currency (CBDC) with different design attributes by applying a structural demand model to a unique Canadian survey dataset. CBDC and its close alternatives, cash and demand deposits, are viewed as product bundles of different attributes. I estimate households' preferences towards these attributes from how they allocate their liquid assets between cash and demand deposits. The estimated preferences are used to predict the demand for CBDC with a set of design attributes and quantify the impacts of CBDC design choices on CBDC demand. Under a baseline design for CBDC, the aggregate CBDC holdings out of households' liquid assets could range from 4 to 52%, depending on whether households would perceive CBDC to be closer to cash or deposits. I find that important design attributes include budgeting usefulness, anonymity, bundling of bank services and rate of return.

Topics: Central bank research, Digital currencies and fintech
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1 Introduction

Many central banks around the world are contemplating the issuance of a central bank digital currency (CBDC), a digital form of central-bank-issued money. According to a Bank for International Settlements (BIS) survey in 2020, 86% of central banks are engaging in CBDC work and 14% have already reached the pilot stage.[1] To decide whether to issue a CBDC,[2] a central bank needs to consider three important questions: What would be the demand for CBDC? How would the design attributes of CBDC affect the demand? To what extent would CBDC impact the demand for cash and deposits? This paper helps answer these questions empirically.

Serving as a store-of-value asset and a payment instrument, CBDC is an alternative to cash and demand deposits. According to a recent BIS report, one foundational principle for CBDC issuance is that CBDC should complement and co-exist with cash and deposits (BIS, 2020). This paper represents the first attempt to empirically quantify households' potential CBDC holdings relative to cash and demand deposits, the impacts of different design attributes on CBDC holdings, and the extent to which CBDC may crowd out the demand for cash and deposits.

While there is emerging theoretical literature on the implications of CBDC (e.g., Andolfatto, 2021; Williamson, 2021*b*; Chiu et al., 2020; Brunnermeier and Niepelt, 2019; Keister and Sanches, 2019), the lack of data on CBDC poses a constraint to the empirical work. This paper provides a framework to predict the potential demand for CBDC relative to its close alternatives, cash and demand deposits. The key idea is to view CBDC, cash, and demand deposits as product bundles of different attributes based on a structural demand model. I estimate households' preferences for the attributes by applying the model to survey data on the existing products. Provided that the estimated preferences remain the same after CBDC issuance, I can predict the demand for CBDC based on its design attributes and how much households value each attribute, and study how the CBDC demand would be affected by different design attributes.

More specifically, a household obtains an utility from holding each product, which de-

[1]Respondents to the BIS survey include 21 advanced economies and 44 emerging market economies, covering 91% of the world economic output (Boar and Wehrli, 2021). Examples of retail CBDC pilots include the DCEP in China, the e-krona in Sweden, and the e-peso in Uruguay.

[2]This paper focuses on the retail CBDC that is available to the general public and can be used for retail transactions. For some countries including Canada, the motivation for considering the issuance of a retail CBDC is in part driven by declining cash usage as documented in Engert, Fung and Segendorff (2019), which could lead to financial exclusion of certain groups of people, and in part as a response to the potential risks posed by privately issued e-money (e.g., Adrian and Mancini-Griffoli, 2019; Brunnermeier, James and Landau, 2019; Zhu and Hendry, 2019). For other motivations for issuing CBDC, see Kahn, Rivadeneyra and Wong (2018), Engert and Fung (2017), and Fung and Halaburda (2016), among others.

pends on the attributes of the product, the household characteristics, and the product fixed effect that captures the average impact of unobserved households' idiosyncratic preferences. Without CBDC, the household decides how to allocate the endowment of liquid assets between cash and demand deposits based on the relative utilities from holding cash and deposits, which in turn depend on the differences in the product attributes. Using a unique Canadian survey dataset that contains households' cash and deposit shares out of their liquid assets and the product attributes of cash and deposits, I can estimate households' preferences towards each product attribute.

To predict the demand for CBDC with a certain design, apart from the chosen design attributes of CBDC and the estimated preference parameter for each attribute, I also need to make assumptions on the CBDC-specific effects that consist of the impacts of the household characteristics and the CBDC fixed effect on the utilities for holding CBDC. The effects related to the household characteristics reflect how households from a given demographic group would value CBDC relative to cash and demand deposits, while the CBDC fixed effect reflects the average impact of households' idiosyncratic preferences on their utilities for CBDC. In the counterfactual analyses, I assume these CBDC-specific effects can range from being cash-like, in which case households would perceive CBDC to be closer to cash, to being deposit-like, in which case they would perceive CBDC to be closer to deposits.

I find that under a baseline design for CBDC, where CBDC is non-interest-bearing, unbundled with bank services, and achieves 70% of cash budgeting usefulness and anonymity, the total CBDC holdings out of households' liquid assets could range from 4–52% of their liquid assets. The exact level of CBDC demand in this range depends on the assumptions for CBDC-specific effects. The lower (upper) bound prediction is obtained when assuming CBDC-specific effects are cash-like (deposit-like).[3] Since a median household only holds around 4% of their liquid assets in cash, the demand for CBDC would also be low if households perceive CBDC to be closer to cash. Similarly, this paper finds that households with higher income, older age, or that are home owners tend to hold more CBDC balance if CBDC-specific effects are more cash-like, since these groups tend to hold more cash.

Unlike the predicted level of CBDC demand, the percentage change in CBDC demand in response to a change in a given attribute would rely much less on CBDC-specific effects. By studying the impacts of different design attributes, this paper provides useful insights on how much each design attribute would matter for CBDC demand. I find that important design attributes include usefulness for budgeting, anonymity, bundling of bank services, and rate of return, which are ranked in a decreasing order of importance, except for the rate of

[3] With more information on whether households would perceive CBDC to be closer to cash or deposits, it could be possible to take a stance on the CBDC-specific effects and thus narrow down this range.

return whose impact depends on the magnitude of the rate change.[4]

I measure the impact of each product attribute using the percentage change in CBDC demand in response to a change in the given attribute relative to the baseline design, while keeping everything else unchanged. I find that reducing the budgeting usefulness of CBDC from 70% of cash usefulness to deposit usefulness would lower CBDC demand by around 7–14%, depending on different assumptions for CBDC-specific effects. Reducing CBDC anonymity from 70% of cash anonymity to 0% like deposits would lower CBDC demand by around 5–10%. If CBDC becomes bundled with bank services, its demand would increase by around 4–8%. Finally, increasing the CBDC rate from 0% to 0.1% could raise its demand by around 10–23%.[5] The estimated model also allows for studying the impacts of changes in CBDC designs where a combination of different attributes change at the same time. For example, moving from a cryptocurrency design with a full degree of cash anonymity to the Sand Dollar design with a low level of anonymity could reduce CBDC demand by around 6–10%.

In this framework, the demand for CBDC comes from households' liquid assets, so it is natural to examine the crowding-out effects of CBDC on the demand for cash and deposits. Since a higher demand for CBDC tends to reduce cash and deposit demand by more, CBDC-specific effects also play a large role here. When CBDC-specific effects are deposit-like (cash-like), CBDC with a baseline design can reduce the demand for deposits and cash each by around 52% (4%) on average across households.

The empirical literature on CBDC is scarce. To the best of my knowledge, there are two empirical papers on CBDC (Bijlsma et al., 2021; Huynh et al., 2020). Huynh et al. (2020) focuses on consumers' choices of using CBDC to pay at the point of sale. They study consumers' payment choices among cash, debit cards, and credit cards and use the estimated demand parameters to predict the adoption and usage of CBDC as a new payment instrument. In contrast, this paper focuses on households' potential holdings of CBDC, taking into account the role of CBDC as both a store-of-value asset and a payment instrument. Predicting the potential holdings of CBDC is important for understanding how much CBDC would affect bank deposits, which are a relatively low-cost and stable funding source for banks. Bijlsma et al. (2021) conducted a survey on the adoption and usage intention for hypothetical CBDC accounts in the Netherlands. In the absence of a CBDC or a concrete design for CBDC, this survey approach is challenging because the results would rely heavily on people's understanding of CBDC based on a broad description for CBDC. The key

[4] Other product attributes that are studied in this paper include cost of use, ease of use/convenience, security, capability of online purchase, and merchant acceptance.

[5] The median demand deposit rate after tax was around 0.08% across households during 2010–2017. Therefore, the change of 0.1 percentage points in CBDC interest rate is a large change.

difference here is that I use households' preferences that are revealed from their allocation decisions on cash and demand deposits to predict their potential holdings of CBDC with a set of design attributes.

The paper is also related to the growing literature on how CBDC could affect bank deposits and thus financial intermediation (e.g., Andolfatto, 2021; Garratt and Zhu, 2021; Chiu et al., 2020; Keister and Sanches, 2019).[6] This literature often assumes CBDC to be a perfect substitute for deposits and focuses on the rate of return differences, which directly implies the substitution pattern between the demand for deposits and CBDC. That is, the one that offers a lower rate of return would face a zero demand. In contrast, this paper models CBDC as an imperfect substitute for deposits, where CBDC can differ from deposits in a variety of product attributes, including the rate of return. In doing so, the paper provides empirical evidence on the extent to which the demand for CBDC would be affected by different design attributes of CBDC.[7] Since the demand for CBDC would come from the liquid assets like deposits, the paper also sheds light on the crowding-out effect of CBDC on the demand for deposits under different CBDC designs.

The rest of this paper is organized as follows. Section 2 describes the structural demand model and then introduces CBDC into the model. Section 3 discusses the data sources and how to measure different product attributes using the survey data. Section 4 shows the estimated demand parameters. Section 5 uses the estimated model to predict the demand for CBDC relative to cash and demand deposits, the crowding-out effects on the demand for cash and deposits, the impacts of different design choices on CBDC demand, and the CBDC holdings across different demographic groups. Section 6 concludes.

[6] Existing theoretical literature also looks at the impact of CBDC on financial stability (e.g., Fernández-Villaverde et al., 2021; Williamson, 2021*a*; Schilling, Fernández-Villaverde and Uhlig, 2020; Brunnermeier and Niepelt, 2019; Skeie, 2019), monetary policy (e.g., Davoodalhosseini, 2021; Jiang and Zhu, 2021; Bordo and Levin, 2017), macroeconomic volatility (e.g., Barrdear and Kumhof, 2021; Ferrari, Mehl and Stracca, 2020), and welfare (e.g., Assenmacher et al., 2021; Williamson, 2021*b*; Piazzesi and Schneider, 2020). For policy discussions on the macro implications of CBDC issuance, see Davoodalhosseini, Rivadeneyra and Zhu (2020), García et al. (2020), Berentsen and Schar (2018), Mancini-Griffoli et al. (2018), Meaning et al. (2018), Engert and Fung (2017), etc.

[7] There are a few theoretical papers focusing on certain design features of CBDC, such as anonymity and security in Agur, Ari and Dell'Ariccia (2021), automation of personal loss recovery via an expiry date on offline CBDC balances proposed in Kahn, van Oordt and Zhu (2021), and asymmetric privacy between the receiver and the sender of money in Tinn and Dubach (2021). Kahn, Rivadeneyra and Wong (2020) look at the trade-offs between safety and convenience of digital currencies in general, which provides guidance for the design of CBDC. For policy discussions on the technical design choices and the design principles, see Allen et al. (2020), Auer and Böhme (2020), Kumhof and Noone (2018), etc.

2 Model

Section 2.1 introduces a logit demand model to study how households allocate their liquid assets between cash and demand deposits. I use this structural demand model to study asset allocation because households' utilities are modeled in terms of the product attributes, which facilitates the counterfactual analysis of introducing a CBDC with a set of design attributes. The model can be equivalently written in terms of an asset allocation problem with money-in-the-utility assumptions and a constant-elasticity-of-substitution (CES) utility function, as shown in Appendix A.1.

Section 2.2 introduces CBDC and discusses how to predict the potential demand for CBDC based on a logit model and a nested logit model. Under the logit model, there are no common factors that drive the unobserved idiosyncratic preferences for CBDC, cash, and deposits. In contrast, the nested logit model allows CBDC to be a closer substitute for cash (deposits) due to the correlated idiosyncratic preferences for CBDC and cash (deposits). Appendix A.2 shows that the nested logit model can be equivalently represented by an asset allocation problem with money-in-the-utility assumptions and a nested CES utility function.

2.1 Logit Model of Cash and Deposit Demand

Assume each household i is endowed with $w_{i,t}$ dollars in period t. For each dollar, household i chooses to hold it in cash c or demand deposits d. Household i's indirect utility u for product $j \in \{c, d\}$ depends on the product attributes $\boldsymbol{x}_{i,j,t}$, household characteristics $\boldsymbol{z}_{i,t}$, a product-specific constant η_j, and an i.i.d. utility shock $\epsilon_{i,j,t}$:

$$u_{i,j,t} = \boldsymbol{\alpha}'\boldsymbol{x}_{i,j,t} + \boldsymbol{\gamma}_j'\boldsymbol{z}_{i,t} + \eta_j + \epsilon_{i,j,t} = V_{i,j,t} + \epsilon_{i,j,t} \tag{1}$$

where $V_{i,j,t} \equiv \boldsymbol{\alpha}'\boldsymbol{x}_{i,j,t} + \boldsymbol{\gamma}_j'\boldsymbol{z}_{i,t} + \eta_j$ is the observable part of the indirect utility. The vector $\boldsymbol{\alpha}$ consists of the preference parameters for the product attributes. Parameters $\boldsymbol{\gamma}_j$ reflect the effects of household characteristics on the utility for holding product j. The utility shock $\epsilon_{i,j,t}$ captures the unobserved idiosyncratic preferences and the constant η_j reflects the average impact of these unobserved preferences on the utility for product j. In the presence of η_j, the mean of the unobserved part of the utility $\epsilon_{i,j,t}$ is zero.

Since the utility shock $\epsilon_{i,j,t}$ is randomly drawn from a given distribution, even if the observed utility for holding the one dollar in cash is higher, that is, $V_{i,c,t} > V_{i,d,t}$, there is a probability that the unobserved portion of the utility for deposits $\epsilon_{i,d,t}$ is sufficiently higher to overcome the lower $V_{i,d,t}$ such that household i chooses to hold it in deposits instead. Let $f(\boldsymbol{\epsilon}_{i,t})$ denote the joint density of the random vector $\boldsymbol{\epsilon}_{i,t} = (\epsilon_{i,c,t}, \epsilon_{i,d,t})$. The probability that household i chooses product j is:

$$P_{i,j,t} = \int_{\epsilon} I(\epsilon_{i,k,t} - \epsilon_{i,j,t} < V_{i,j,t} - V_{i,k,t} \ \forall \ k \neq j) f(\boldsymbol{\epsilon}_{i,t}) d\boldsymbol{\epsilon}_{i,t} \tag{2}$$

where k denotes the product other than j and $I(.)$ is an indicator that equals one if the condition inside the brackets is true and zero otherwise. Assuming the i.i.d. utility shock follows a Type I extreme value distribution, the choice probability of holding the one dollar in product j is:

$$P_{i,j,t} = \frac{\exp(V_{i,j,t})}{\exp(V_{i,c,t}) + \exp(V_{i,d,t})} \in (0,1) \tag{3}$$

where $j \in \{c, d\}$. When the observed attributes of product j improves such that the observed utility $V_{i,j,t}$ increases, the probability of choosing product j also increases, given everything else remains the same.

With the endowment of $w_{i,t}$ dollars, household i makes $w_{i,t}$ number of choices. By the law of large numbers, the probability $P_{i,j,t}$ of holding the one dollar in asset j is equivalent to the share $s_{i,j,t} \equiv \frac{q_{i,j,t}}{w_{i,t}}$ of asset j out of the liquid asset $w_{i,t}$, where $q_{i,j,t}$ denotes the balance of asset j and $w_{i,t} = q_{i,c,t} + q_{i,d,t}$ is the total liquid asset (sum of cash and demand deposit balances) held by household i.[8] After taking the difference between the logs of deposit and cash shares, the log of deposit-to-cash ratio can be written as:

$$\ln \frac{q_{i,d,t}}{q_{i,c,t}} = V_{i,d,t} - V_{i,c,t} = \boldsymbol{\alpha}'(\boldsymbol{x}_{i,d,t} - \boldsymbol{x}_{i,c,t}) + (\boldsymbol{\gamma}_d - \boldsymbol{\gamma}_c)'\boldsymbol{z}_{i,t} + \eta_d - \eta_c \tag{4}$$

which depends on the difference between the observed utilities for deposits and cash. This utility difference in turn depends on the differences in the product attributes $(\boldsymbol{x}_{i,d,t} - \boldsymbol{x}_{i,c,t})$, the household characteristics $\boldsymbol{z}_{i,t}$, and the difference in the product-specific constants $(\eta_d - \eta_c)$.

The choice probability (2) shows that only the utility difference matters for households' choices, so the effects of household characteristics can only be identified if they are product-specific (i.e., $\boldsymbol{\gamma}_d \neq \boldsymbol{\gamma}_c$). Since different values of $\boldsymbol{\gamma}_d$ and $\boldsymbol{\gamma}_c$ that result in the same differences $(\boldsymbol{\gamma}_d - \boldsymbol{\gamma}_c)$ will give the same choices, the overall level of $(\boldsymbol{\gamma}_d - \boldsymbol{\gamma}_c)$ needs to be set and the same applies to $(\eta_d - \eta_c)$. I follow a common approach to normalize the parameters for cash,

[8]The interpretation of choice probabilities as asset shares is also used in Wang et al. (2020) and Xiao (2020). They assume that each agent is endowed with one dollar and makes a discrete choice among different assets. They point out that this one-dollar one-choice assumption can be interpreted as a situation where agents make multiple discrete choices for their one-dollar endowment and the probability of choosing each asset can be interpreted as the portfolio weight. Similarly, Ellickson, Grieco and Khvastunov (2020) study the discrete choice for each unit of the consumer's grocery expenditure and the probability for choosing a particular store is interpreted as the share of the consumer's expenditure spent at that store.

$\boldsymbol{\gamma}_c$ and η_c, to zero. After this normalization, the estimated $\widehat{\eta}_d$ reflects the average impact of the unobserved idiosyncratic preferences on the utility for deposits relative to cash and the estimated $\widehat{\boldsymbol{\gamma}}_d$ reflects the effects of household characteristics $\boldsymbol{z}_{i,t}$ on the utility for deposits relative to cash.

2.2 Introducing CBDC

To predict the demand for CBDC, one key step is to calculate each household's observed utility $V_{i,cbdc,t}$ for CBDC. Provided that the estimated preference parameters $\widehat{\boldsymbol{\alpha}}$ remain the same after CBDC issuance, the utility for CBDC can be calculated using the CBDC attributes $\boldsymbol{x}_{i,cbdc}$ and the assumptions on the CBDC-specific effects (i.e., $\boldsymbol{\gamma}_{cbdc}$ and η_{cbdc}) as below:

$$V_{i,cbdc,t} = \widehat{\boldsymbol{\alpha}}'\boldsymbol{x}_{i,cbdc} + \boldsymbol{\gamma}'_{cbdc}\boldsymbol{z}_{i,t} + \eta_{cbdc} \tag{5}$$

In the counterfactual analyses, I assume these CBDC-specific effects, $\boldsymbol{\gamma}_{cbdc}$ and η_{cbdc}, can range from being cash-like (i.e., taking the normalized parameter values for cash $\boldsymbol{\gamma}_c = 0$ and $\eta_c = 0$) to deposit-like (i.e., taking the estimated values for deposits $\widehat{\boldsymbol{\gamma}}_d$ and $\widehat{\eta}_d$). In reality, the parameters $\boldsymbol{\gamma}_{cbdc}$ and η_{cbdc} could lie outside this range, but this paper does not consider these cases that require extrapolation. Instead, it predicts the potential demand for CBDC relative to cash and demand deposits by focusing on the values of $\boldsymbol{\gamma}_{cbdc}$ and η_{cbdc} in between the corresponding values for cash and deposits.

If households perceive CBDC to be closer to cash (deposits), then the CBDC-specific effects are likely to be more cash-like (deposit-like). More specifically, assuming $\boldsymbol{\gamma}_{cbdc} = \boldsymbol{\gamma}_c$ implies that the household characteristics have identical effects on the utilities for cash and CBDC. In other words, households from a given demographic group would equally value CBDC and cash. Assuming $\eta_{cbdc} = \eta_c$ means that the average impact of the unobserved idiosyncratic preferences on the utility for CBDC is identical to that for cash. In contrast, assuming $\boldsymbol{\gamma}_{cbdc} = \widehat{\boldsymbol{\gamma}}_d$ and $\eta_{cbdc} = \widehat{\eta}_d$ implies that the household characteristics and the unobserved idiosyncratic preferences have identical effects on the utilities for deposits and CBDC.

2.2.1 Predictions Based on Logit Model

Apart from the observed utility $V_{i,cbdc,t}$ (5), another key component for predicting the demand for CBDC is the distribution of the random utility shock $\epsilon_{i,j,t}$, where $j \in \{c, d, cbdc\}$. This section introduces CBDC into the logit demand model described in Section 2.1, where $\epsilon_{i,j,t}$ is assumed to be i.i.d Type I extreme value. After CBDC issuance, household i allocates the endowment of the liquid asset $w_{i,t}$ into CBDC, cash, and demand deposits. With the distributional assumption on $\epsilon_{i,j,t}$, the probability of allocating each dollar of the endowment $w_{i,t}$ into CBDC, or equivalently, the share of CBDC holding, is:

$$s_{i,cbdc,t} = \frac{\exp(V_{i,cbdc,t})}{\exp(V_{i,c,t}) + \exp(V_{i,d,t}) + \exp(V_{i,cbdc,t})} \tag{6}$$

A higher observed utility $V_{i,cbdc,t}$ leads to a larger share of CBDC holding, keeping everything else the same. Given that $w_{i,t}$ is unaffected by the CBDC issuance, the demand for CBDC comes from the substitution away from cash and deposits.[9] In this logit framework, the demand for CBDC draws proportionally from cash and deposits so that the deposit-to-cash ratio remains unchanged as in (4).

This independence of irrelevant alternatives (IIA) property – the deposit-to-cash ratio being unaffected by the introduction of CBDC – is due to the assumption that the unobserved factors are i.i.d. across products. The resulting substitution patterns can be restrictive in some cases. For example, supposing CBDC and deposits are perfect substitutes, the demand for CBDC should only draw from deposits while cash demand is unaffected. However, this perfect substitute case cannot be captured in the logit framework. Even if CBDC and deposits have an identical observed utility, they are still imperfect substitutes due to the unobserved idiosyncratic preferences. To allow for different degrees of substitutability between CBDC and the existing products and thus more flexible substitution patterns, Section 2.2.2 introduces a nested logit framework which avoids the IIA property.

2.2.2 Predictions Based on Nested Logit Model

This section introduces CBDC into a nested logit framework to capture more general substitution patterns. The unobserved utilities $\boldsymbol{\epsilon}_{i,t} = (\epsilon_{i,c,t}, \epsilon_{i,d,t}, \epsilon_{i,cbdc,t})$ that capture the idiosyncratic preferences are now jointly distributed as generalized extreme value and can be correlated across products that are closer substitutes. Suppose CBDC and deposits are closer substitutes due to the correlated unobserved utilities, then the demand for CBDC would mainly draw from deposits. This section discusses, in turn, the cases where CBDC is a closer substitute for deposits or cash.

[9] In this paper, the liquid asset only consists of cash and demand deposits because they are close alternatives to CBDC. The assumption that the liquid asset holding is unaffected by CBDC issuance is realistic as long as the CBDC interest rate is lower than the deposit rate, in which case the introduction of CBDC is unlikely to cause substitution away from other types of liquid assets into CBDC. For the counterfactual analyses in Section 5, I assume that CBDC is non-interest-bearing under the baseline design.

Case I. CBDC as a closer substitute for deposits

Suppose the unobserved utilities for CBDC and deposits are correlated and hence they are in the same nest B_{d_cbdc}. This could be because households value the feature of digital payments, which cannot be identified empirically since there are no data on their perceptions towards this feature. Since CBDC and deposits can both be used for digital payments, this feature could drive the correlation between their unobserved utilities. The probability of household i allocating each dollar into CBDC is the conditional probability of choosing CBDC from the nest B_{d_cbdc} multiplied by the probability of choosing the nest B_{d_cbdc}:

$$P_{i,cbdc,t} = \underbrace{\frac{\exp\left(\frac{V_{i,cbdc,t}}{\tau_d}\right)}{\exp\left(\frac{V_{i,cbdc,t}}{\tau_d}\right)+\exp\left(\frac{V_{i,d,t}}{\tau_d}\right)}}_{\text{Prob}(j=cbdc|j\in B_{d\_cbdc})} \underbrace{\frac{\left[\exp\left(\frac{V_{i,cbdc,t}}{\tau_d}\right)+\exp\left(\frac{V_{i,d,t}}{\tau_d}\right)\right]^{\tau_d}}{\left[\exp\left(\frac{V_{i,cbdc,t}}{\tau_d}\right)+\exp\left(\frac{V_{i,d,t}}{\tau_d}\right)\right]^{\tau_d}+\exp\left(V_{i,c,t}\right)}}_{\text{Prob}(j\in B_{d\_cbdc})} \tag{7}$$

where $\tau_d \equiv \sqrt{1-\rho_{d\_cbdc}} \in (0,1]$ is an inverse measure of the correlation $\rho_{d\_cbdc} \in [0,1)$ between the unobserved utilities for deposits and CBDC. The observed utilities for CBDC and deposits are scaled by a factor of $\frac{1}{\tau_d}$. Intuitively, this is because a positive correlation between their unobserved utilities implies a greater role of the observed utilities in explaining the choices between deposits and CBDC.[10] When the unobserved utilities are uncorrelated (i.e., $\tau_d = 1$), this reduces to the logit model where the CBDC share (7) would be identical to (6).

Due to the correlated unobserved utilities within the nest, cash and deposits no longer substitute proportionally into CBDC. Appendix B.1 shows that the deposit-to-cash ratio $\frac{s'_{i,d,t}}{s'_{i,c,t}}$ after CBDC issuance becomes:

$$\frac{s'_{i,d,t}}{s'_{i,c,t}} = \left[1+\exp\left(\frac{V_{i,cbdc,t}-V_{i,d,t}}{\tau_d}\right)\right]^{\tau_d-1}\frac{s_{i,d,t}}{s_{i,c,t}} \tag{8}$$

where $\frac{s_{i,d,t}}{s_{i,c,t}} = \exp\left(V_{i,d,t}-V_{i,c,t}\right)$ is the deposit-to-cash ratio before the CBDC issuance. When CBDC is a perfect substitute for deposits (i.e., $V_{i,cbdc,t} = V_{i,d,t}$ and τ_d approaches 0), the deposit-to-cash ratio after CBDC issuance is reduced by a half, since half of the deposits would be substituted into CBDC while cash is unaffected. Appendix B.1 shows that when $0 < \tau_d < 1$, the deposit-to-cash ratio $\frac{s'_{i,d,t}}{s'_{i,c,t}}$ becomes smaller than that before the CBDC issuance,

[10] A higher correlation between the unobserved utilities for deposits and CBDC lowers the variance of $(\epsilon_{i,cbdc,t}-\epsilon_{i,d,t})$. Let $\text{Var}(\epsilon_{i,d,t}) = \text{Var}(\epsilon_{i,cbdc,t}) = \sigma^2$ denote the variance of the unobserved utilities, where the logit model implicitly scales the utilities for all products such that the unobserved utilities have a variance of $\sigma^2 = \frac{\pi^2}{6}$. Under the logit model, $\text{Var}(\epsilon_{i,cbdc,t}-\epsilon_{i,d,t}) = 2\sigma^2$, while under the nested logit model, $\text{Var}(\epsilon_{i,cbdc,t}-\epsilon_{i,d,t}) = 2\sigma^2 - 2\sigma^2\rho_{d\_cbdc} = 2\sigma^2(1-\rho_{d\_cbdc})$, which is reduced by a factor of $(1-\rho_{d\_cbdc})$.

since the demand for CBDC draws more than proportionally from deposits. Furthermore, the crowding-out effect on deposits is stronger if CBDC has a higher observed utility than deposits (i.e., $V_{i,cbdc,t} - V_{i,d,t} > 0$), as shown in Appendix B.1.

How the correlation impacts the CBDC share depends on the difference in the observed utilities for CBDC and deposits, as shown in Appendix B.1. When the observed utility for CBDC is higher than that for deposits, it is ambiguous how the correlation affects the CBDC share. On the one hand, a higher correlation ρ_{d_cbdc} makes CBDC and deposits more substitutable and thus leads to greater substitution from deposits to CBDC when $(V_{i,cbdc,t} - V_{i,d,t}) > 0$, which tends to raise the CBDC share. On the other hand, the higher correlation implies that the demand for CBDC would mainly draw from its closer substitute, deposits. As the cash demand is reduced by less, the share that can be allocated to deposits and CBDC is smaller, which tends to reduce the CBDC share. In contrast, when $(V_{i,cbdc,t} - V_{i,d,t}) \leqslant 0$, the former effect reinforces the latter and it is unambiguous that a higher correlation reduces the CBDC share.

Case II. CBDC as a closer substitute for cash

Suppose CBDC and cash are closer substitutes along the unobserved dimensions and hence they are in the same nest. One example of the unobserved factor could be that people value the central-bank-issued money. Since CBDC and cash are both issued by the central bank and this feature cannot be identified empirically due to the lack of data, this can lead to a positive correlation between the unobserved utilities for CBDC and cash. Appendix B.2 shows that in this case, the deposit-to-cash ratio after CBDC issuance becomes:

$$\frac{s'_{i,d,t}}{s'_{i,c,t}} = \left[1 + \exp\left(\frac{V_{i,cbdc,t} - V_{i,c,t}}{\tau_c}\right)\right]^{1-\tau_c} \frac{s_{i,d,t}}{s_{i,c,t}} \tag{9}$$

where $\tau_c \equiv \sqrt{1 - \rho_{c\_cbdc}} \in (0, 1]$ is an inverse measure of the correlation $\rho_{c\_cbdc} \in [0, 1)$ between the unobserved utilities for CBDC and cash. Appendix B.2 shows that the deposit-to-cash ratio is greater than or equal to that before CBDC issuance, since the demand for CBDC mainly draws from its closer substitute, which is cash in this case.

How the CBDC share changes with the correlation depends on the sign of the observed utility difference, as shown in Appendix B.2. If the observed utility for CBDC is higher than that for cash, it is ambiguous how the CBDC share is affected by the correlation. On the one hand, when $(V_{i,cbdc,t} - V_{i,c,t})$ is positive, a higher correlation ρ_{c_cbdc} tends to raise the CBDC share by making CBDC and cash more substitutable. On the other hand, as the demand for CBDC draws mainly from its closer substitute (i.e., cash), deposits become less affected and thus the total share of CBDC and cash is lower, which tends to lower the CBDC share. In contrast, when $(V_{i,cbdc,t} - V_{i,c,t}) \leqslant 0$, the former effect is reversed and the CBDC share unambiguously decreases in ρ_{c_cbdc}.

3 Data

This paper uses the Canadian Financial Monitor (CFM) survey and the Methods-of-Payment (MOP) survey. The former is a syndicated survey run by Ipsos, while the latter is a Bank of Canada survey. The CFM survey provides detailed information on households' deposit and cash holdings and has some repeated cross sections.[11] The MOP survey is a cross-sectional dataset and has two components: a survey questionnaire that contains information on people's perceptions towards different payment features, and a payment diary that records detailed transaction-level data for each respondent during a three-day period.

In this paper, cash is measured as the sum of cash in wallet and the precautionary holding of cash. The paper focuses on the sample period of 2010–2017 for the CFM data because the survey questions on cash holdings are consistent across years during this period.[12] It focuses on the demand deposits, which can be readily used for transactions and thus are a close alternative to CBDC. Therefore, deposits are measured by the sum of chequing, chequing/saving, and saving account balances for each household. Figure 10 in Appendix C.1 shows the usage of all the bank account types that are classified in the CFM data. Detailed information on the measures of cash and deposit holdings can be found in Appendix C.1.1 and C.1.2.

The MOP survey in 2013 consisted of three subsamples, one of which was formed by recruiting the respondents who had recently filled out the CFM survey. These two datasets are matched using the common ID documented by the survey company Ipsos.[13] Apart from

[11] Although CFM has repeated observations for some households, this panel dimension is not intentional. There is a high attrition rate, so the survey company recruits new participants to maintain a nationally representative survey in each year, as discussed in Chen, Felt and Huynh (2014).

[12] During 2010–2017, the question on cash in wallet is: "How much cash do you have in your purse or wallet right now?" and the question on precautionary cash holding is: "(On average), how much cash on hand does your household hold for emergencies, or other precautionary reasons?". Note that the phrase "on average" is included in the question for 2010–2012, while it is not included for 2013–2017. This difference is less of a concern after controlling for the year fixed effects. The results are robust to using the sample period of 2013–2017 only.

[13] Note that the MOP survey questions are addressed to a given individual, while the CFM is a household-level survey where the questions are often addressed to a given household. Without having data on everyone's perceptions in the same household, this paper assumes that the individual's perceptions are representative of the given household and would affect the household's asset allocation decision. Felt (2017) also uses information from both the CFM and MOP data in 2013 to study the influence of the spouse on a person's payment method usage in Chapter 3, adopting the method proposed in Felt (2020) to deal with the unob-

the product attributes, household characteristics can also affect the utilities from holding cash and deposits. When estimating the demand parameters in Section 4, this paper also includes household income, household head age and education, household size, home ownership, whether the household has a female head, region, rural area, whether there is internet access at work, households' attitudes towards investing in the stock market, the extent to which they feel difficulty in paying off debt, and whether anyone from the household was behind debt obligations in the past year. These variables are from the CFM data except for the internet access which is from the MOP survey questionnaire. Table 7 in Appendix C.5 shows the summary statistics of the key variables of interest.

To predict the demand for CBDC with a set of design attributes and assess how different attributes would affect the demand for CBDC, a key step is to estimate households' preferences for these product attributes. This paper uses the MOP survey to measure most of the product attributes, including the cost of use, ease of use/convenience, security, anonymity, usefulness for budgeting, capability of online purchase, and merchant acceptance rate. In addition, rate of return and bundling of bank services are measured using the CANNEX and CFM data, respectively. The details for each attribute are discussed below.

Rate of Return

The return on deposits tends to differ across households as they save at different banks. One unique feature of the CFM data is that there is information on the main financial institution of a given household.[14] I use this information together with the bank-level deposit rates from CANNEX to construct the household-specific deposit rates.[15] However, among the main financial institutions on the CFM choice list that households can choose from, only the big six and Laurentian Bank have the demand deposit rates available from CANNEX during the sample period. Hence, I use the rates for these seven banks and assume the deposit rates of other banks to be the average across these seven banks.[16]

served behavior of the person's spouse in a given household due to the lack of data. In contrast, this paper focuses on decisions at the household level.

[14] Details on the construction of the main financial institution for each household can be found in Appendix C.1.3.

[15] Mulligan and Sala-i-Martin (2000) use the marginal tax rate facing each household to proxy for the rate of return, assuming households face the same pretax interest rate. However, they only have three different marginal tax rates in their dataset (1989 Survey of Consumer Financial for the US). In addition, the marginal tax rates do not provide much more information once income is controlled for. Attanasio, Guiso and Jappelli (2002) avoid this problem using the regional variation in the interest rates for their cross-sectional dataset of Italian households during 1989–1995. In contrast, this paper uses the cross-bank and over-time variation instead, since there are no data for the Canadian deposit rates at a regional level.

[16] The results in this paper are robust to dropping the households whose main financial institutions are not the big six or Laurentian Bank, accounting for about 33% of the observations. More information about

Since the interest earned on savings is taxed at the same marginal rate as income, I multiply the net interest rate by one minus the marginal tax rate on household income using the federal and provincial income tax rates during 2010–2017 published on the website of the Government of Canada. Figure 12 in Appendix C.3 shows the average deposit rates across households over the period of 2010–2017.

Cost, Ease of Use, and Security

To measure the cost, ease of use, and security features of cash and deposits, I use the respondents' ratings for each of these features from the MOP survey questionnaire. For a given payment feature, each individual chooses a rating from one to five on a Likert scale for each of the payment instruments, including cash, debit card, and credit card.[17] For instance, the survey question on cost asks people how costly they think it is (or would be) to use each payment instrument, taking fees and interest payments into account. Similarly, the questions on ease of use and security ask people how easy or hard and how risky or secure it is (or would be) to use each payment instrument, respectively. I use the debit card ratings to measure the cost, ease, and security of using deposits to make payments. Table 6 in Appendix C.5 shows that most people perceive cash to be a very low-cost, easy-to-use, and secure payment instrument compared to other payment instruments in the MOP 2013 survey.

Following Arango, Huynh and Sabetti (2015), I standardize the ratings by the respondent's overall level of perceptions over cash, debit card, and credit card for each payment feature. For example, a respondent who rates 5, 2, 2 for the ease-of-use feature of cash, debit card, and credit card, respectively, has a standardized rating of 5/9 for cash and thus perceives cash to be easier to use compared to a respondent who rates 5 for all three payment instruments.[18]

Bundling of Bank Services

Deposits are often bundled with other services provided by banks. To capture this complementarity between deposits and other bank services, this paper uses households' attitudes

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the demand deposit rates from CANNEX can be found in Appendix C.3.

[17] The ratings for each feature are also available for prepaid card, mobile payment application, the tap and go feature of a credit/debit card, online payment account (e.g., PayPal), and online payment from a credit card/bank account.

[18] Instead of standardising by the overall perception across all payment instruments as in Arango, Huynh and Sabetti (2015), I calculate the overall perception across cash, debit card, and credit card, which are most frequently used, as shown in Figure 11 in Appendix C.1.4. The perceptions based on usage experience are likely to be more informative.

towards other services provided by their banks in the CFM survey. More specifically, each household can choose a number from one (strongly disagree) to ten (strongly agree) for the statement, "I would go to my bank for any financial planning advice." The scale of these ratings is adjusted from 1–10 to 0–5, where ratings below (and including) five on the original scale are treated as zero. This is because households that disagree with or are neutral about the statement should be indifferent between holding cash and deposits when considering this feature. The more they value the services provided by their banks, the more utility they would obtain from holding deposits.

Since deposits are exclusively tied to the bank, unlike cash that can be obtained through banks or other sources, they tend to have a higher degree of bundling with bank services than cash. For simplicity of interpretation, I assume this feature takes a value of one for deposits and zero for cash. The exact numbers do not matter because the impact of this feature is identified by interacting with households' attitudes towards bank services and the degree of bundling for deposits relative to cash only scales up/down the preference parameter. In the counterfactual analysis, I look at the changes in the degree of bundling for CBDC relative to the degrees for cash and deposits.

Anonymity and Usefulness for Budgeting

Cash tends to be more anonymous and useful for budgeting than deposits. When using cash to make payments, the user's identity does not need to be revealed and the transactions would be traceless. The latter implies that it would be impossible to use the transaction patterns to determine the user's identity. People may perceive cash to be useful for budgeting because cash gives a signal of the remaining budget via a glance into one's pocket (von Kalckreuth, Schmidt and Stix, 2014) or serves as a commitment device to avoid overspending (Hernandez, Jonker and Kosse, 2017). With online and mobile banking, deposits may also be useful for budgeting to some extent. However, this still requires some extra effort in terms of logging into the mobile app or memorizing the pre-set budget. Given that cash has higher levels of anonymity and budgeting usefulness, I set these two features to take a value of one for cash and zero for deposits.[19]

To identify the impacts of these features on households' utilities, these features are combined with individuals' perceptions of importance towards these features from the MOP survey questionnaire. More specifically, the survey asks each respondent to choose a rating from one (not at all important) to seven (very important) for anonymity (in terms of

[19]Similar to the discussion on the bundling feature, there is no need to assume that deposits are not useful for budgeting at all by taking a value of zero. The prior is that cash is more useful for budgeting than deposits, which is confirmed by the empirical results in Section 4.

not having to provide the name/information) and budgeting usefulness, respectively, when considering which payment method to use. The scale of the ratings is adjusted from 1–7 to 0–6 by subtracting one from the original ratings. This is because the rating of one on the original scale means that people think the given feature is not important at all, in which case they should be indifferent from holding cash or deposits when considering these features. If people think anonymity and budgeting usefulness are more important, they should obtain more utility from holding cash relative to deposits.

Online Purchase Capability

Since cash cannot be used for online purchases while deposits can, this online purchase capability feature takes a value of one for deposits and zero for cash. To identify its impact on households' utilities, it is combined with households' online transaction frequency. Households that shop online more often should obtain more utility from holding deposits.

From the MOP payment diary in 2013, each respondent records their transactions over a three-day period. A transaction is counted as online whenever the purchase is made online using a computer or a smartphone/tablet.[20] For each respondent, the online transaction frequency is calculated as the number of online transactions over the total number of transactions recorded by this individual.

Card Unacceptance Rate

To calculate the cards' unacceptance rate using the MOP payment diary, I divide the number of transactions where debit/credit cards are not accepted or the store is cash-only by the total number of transactions recorded for each respondent.[21] What matters for households' allocation between cash and deposits is not the aggregate-level merchant acceptance for cash or cards, but rather their own experience of the acceptance rate after optimizing which stores to visit. For example, if households prefer to visit the stores that do not accept cards after taking into account the factors such as the store location and the quality of the goods, they are likely to obtain more utility from holding cash and thus hold more cash relative to deposits.

[20] Other choice categories for the location of purchase include at a store, over the phone, to another person, and by mail.

[21] The MOP survey questionnaire also provides information on merchant acceptance. Appendix C.2 explains why this paper uses the information from the MOP payment diary to measure this feature.

4 Demand Estimation

This section estimates the demand-side parameters based on the logit model described in Section 2.1 and shows the estimated preference parameters and the relative importance of each attribute in explaining households' allocation of liquid assets between cash and deposits. The demand-side parameters (i.e., $\boldsymbol{\alpha}$, $\boldsymbol{\gamma}_d$, and η_d) are estimated using the log of deposit-to-cash ratio (4) derived from the logit model:[22]

$$\ln \frac{q_{i,d,t}}{q_{i,c,t}} = \boldsymbol{\alpha}'(\boldsymbol{x}_{i,d,t} - \boldsymbol{x}_{i,c,t}) + \boldsymbol{\gamma}_d' \boldsymbol{z}_{i,t} + \eta_d + \varepsilon_{i,t} \tag{10}$$

The vector $\boldsymbol{x}_{i,j,t}$ consists of different product attributes that are household-specific (i.e., interest rate, cost of use, ease of use, security, and card unacceptance rate), as well as the attributes that have no variation over households (i.e., bundling of bank services, anonymity, usefulness for budgeting, and online purchase capability) and are identified using the related household-specific variables, as discussed in Section 3. The parameters $\boldsymbol{\gamma}_d$ reflect the effects of household characteristics on the utility for deposits relative to cash and the deposit-specific constant η_d reflects the average impact of the unobserved idiosyncratic preferences on the utility for deposits relative to cash, as discussed in Section 2.1.

Table 1 shows the estimated preference parameters $\widehat{\boldsymbol{\alpha}}$ for different product attributes and the deposit-specific constant $\widehat{\eta}_d$. The latter is the constant term in the regression, which is positive as shown in Table 1 and thus increases the utility from holding deposits relative to cash. The effects $\widehat{\boldsymbol{\gamma}}_d$ of the household characteristics on the utilities of deposits relative to cash can be found in Table 8 in Appendix D.

From the last column in Table 1, when the post-tax deposit rate rises by 0.1 percentage points, the deposit-to-cash ratio increases by around 21.9%. This means when the median post-tax deposit rate across households increases from 0.08% to 0.18%, the median deposit-to-cash ratio increases from 23 to 28. This semi-elasticity is estimated using the variation in deposit rates from the big six banks and Laurentian Bank, for which the data are available. Since there is not much over-time variation in the deposit rates for some of the big six banks, the fixed effects of groups of banks are applied. More specifically, I include the indicators for the two largest banks by assets (i.e., TD and RBC), the indicator of the small bank (i.e., Laurentian Bank), and the indicator of banks that are not the big six or Laurentian Bank. The bundling of bank services also has a significant positive effect on the deposit-to-

[22] This paper focuses on the intensive margin and does not study the extensive margin in terms of whether to hold an asset, because it is difficult to know whether the zero asset holdings are true values or due to non-responses (i.e., missing values) in the survey data. There are around 7% (15%) of household-year observations with zero or missing cash (demand deposit) balances.

cash ratio. When households more strongly agree that they would go to their bank for any financial planning advice, implying that they trust their bank a lot and value the services provided by their bank, they would hold more deposits relative to cash.

Table 1: Households' Preferences for Product Attributes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Deposit rate	2.114**	2.175**	2.208**	2.176**	2.167**	2.098**	2.263**	2.297**	2.191**
	(1.035)	(1.033)	(1.035)	(1.035)	(1.036)	(1.034)	(1.033)	(1.034)	(1.036)
Bank service		0.052***	0.051***	0.050***	0.050***	0.054***	0.060***	0.060***	0.059***
		(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Cost of use			-0.204	-0.150	-0.080	-0.087	-0.087	-0.102	-0.101
			(0.189)	(0.195)	(0.201)	(0.201)	(0.201)	(0.202)	(0.202)
Ease/Convenience				0.490	0.371	0.402	0.437	0.423	0.374
				(0.460)	(0.466)	(0.466)	(0.465)	(0.465)	(0.466)
Security					0.402	0.366	0.453*	0.444*	0.457*
					(0.256)	(0.256)	(0.256)	(0.256)	(0.256)
Anonymity						-0.058***	-0.039**	-0.038**	-0.038**
						(0.018)	(0.018)	(0.018)	(0.018)
Budgeting							-0.063***	-0.063***	-0.062***
							(0.018)	(0.017)	(0.017)
Online payment								0.425	0.439
								(0.312)	(0.314)
Card unacceptance									-0.282
									(0.181)
Constant	1.372***	1.318***	1.348***	1.391***	1.385***	1.594***	1.690***	1.672***	1.695***
	(0.381)	(0.380)	(0.382)	(0.384)	(0.384)	(0.389)	(0.387)	(0.388)	(0.388)
Observations	4,352	4,352	4,352	4,352	4,352	4,352	4,352	4,352	4,352
Adjusted R^2	0.062	0.064	0.064	0.064	0.064	0.067	0.069	0.069	0.070

Robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Data sources: CFM 2010–2017, MOP 2013, CANNEX 2010–2017, Government of Canada website

Note: The dependent variable is the log of deposit-to-cash ratio. Bank, region, and year fixed effects are included in each regression. Household characteristics included in each regression consist of household income, household head age, female head indicator, household head education, home ownership, household size, rural area indicator, internet access at work, attitudes towards stock market investment, feeling difficulty in paying off debt, and the indicator of being behind debt obligations in the past year.

Cost, ease of use, and security in Table 1 each refers to the difference in the standardized ratings between debit cards and cash, as discussed in Section 3. Cost of use has a much smaller effect on the deposit-to-cash ratio compared to ease of use and security. When debit cards are perceived to be more easy and secure to use, households would hold more deposits relative to cash.[23] Anonymity and budgeting in Table 1 refer to the individual-specific ratings

[23]The standard error is large for the ease feature, which is likely due to the lack of variation as the ratings for the ease of debit cards and cash are identical for around 65% of the observations. Note that only the

on the importance of anonymity and budgeting usefulness as payment features, respectively. Given that cash is anonymous while deposits are not, when people think anonymity is more important, they would obtain more utility from holding cash and hence would hold more cash relative to deposits. Similarly, the table shows that when people think budgeting usefulness is more important, they would hold more cash relative to deposits. This is consistent with the prior that cash is more useful for budgeting than deposits.[24]

Online payment frequency measured by the fraction of transactions made online has a positive effect on the deposit-to-cash ratio, as expected. Since cash cannot be used to make online purchases, the more frequently households shop online, the more deposits they will hold relative to cash. However, the coefficient is not significant, which is likely due to the lack of variation in the online transaction frequency across households as only around 12% of people made online purchases during a three-day period in the MOP 2013 payment diary. Card unacceptance in Table 1 refers to the fraction of transactions where the store is cash-only or the cards are not accepted at the individual level. As shown in the table, the card unacceptance rate has a negative effect on the deposit-to-cash ratio.

Figure 1 shows the relative importance of different product features in explaining the deposit-to-cash ratio. For a given feature, its importance is measured by its contribution to the utility difference between deposits and cash, which then affects the deposit-to-cash ratio (4). The bar chart plots the average contribution of each product feature across households and years. As can be seen, the most important attributes that affect the deposit-to-cash ratio are budgeting usefulness, anonymity, rate of return, and bundling of bank services. Ease of use and security features do not contribute a lot to the utility difference between deposits and cash because debit cards and cash are perceived to be relatively similar in terms of these attributes.

Table 9 in Appendix D compares the baseline OLS regression with the weighted least squares (WLS) estimation by applying the sample weights.[25] The estimated preference parameters are similar, although the standard errors are higher under the WLS. I find that there is no significant difference between WLS and OLS, following the method in Deaton (2019, p. 72).[26] This indicates that the sampling is independent of the dependent variable

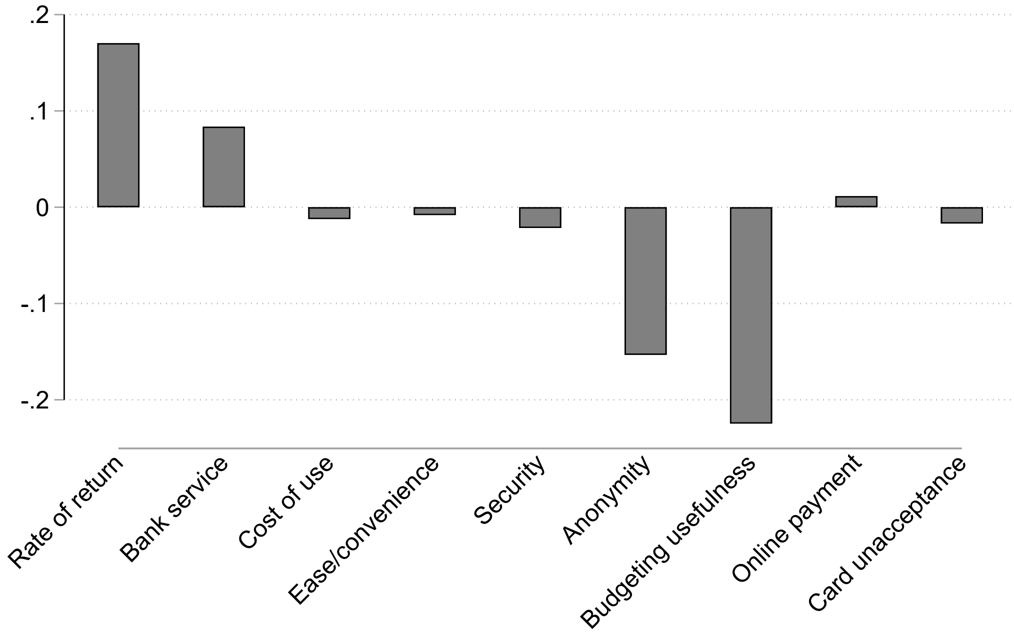
difference in ratings between deposits and cash matters, so these features can only be identified if people perceive debit cards and cash to be different in these features.

[24] Garratt and Van Oordt (2021) point out that commercial payment platforms can use the payments data for price discrimination, but as individuals do not bear the full cost, they may not choose to preserve their information by using cash. This implies that the estimated impact of the anonymity feature might have been higher if households had taken into account the full cost of failing to protect their privacy.

[25] Detailed information on the sample weights for the matched sample of MOP and CFM can be found in Appendix C.4.

[26] Deaton (2019, p. 72) points out that the easiest way to test the difference between the WLS and OLS

Figure 1: Relative Importance of Different Product Attributes



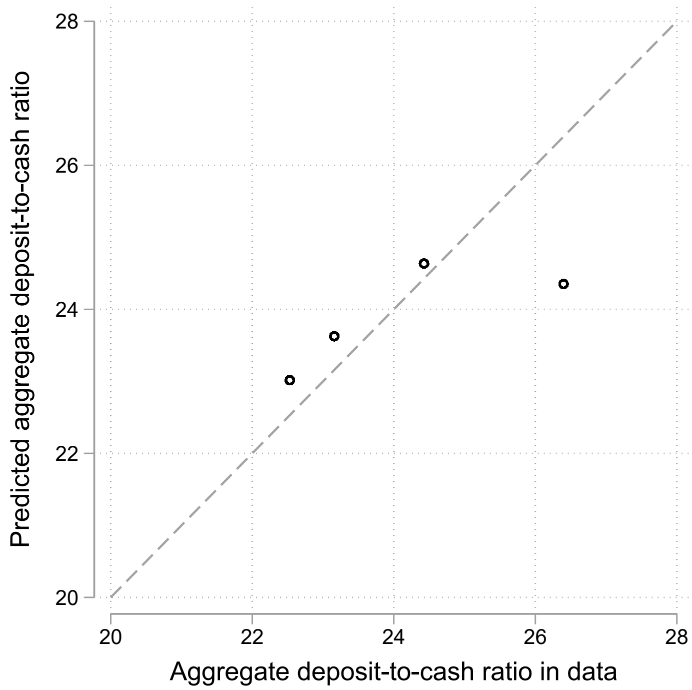
Data sources: CFM 2010–2017, MOP 2013, CANNEX 2010–2017, Government of Canada website
Note: The bar chart shows the relative importance of different product attributes in explaining the deposit-to-cash ratio by plotting the contribution of each attribute to the utility difference between deposits and cash, where the y-axis is in utils. For each attribute x, the bar is computed as the attribute difference between deposits and cash multiplied by the corresponding preference parameter $\widehat{\alpha}(x_{i,d,t} - x_{i,c,t})$ that is averaged across households and years.

conditional on the explanatory variables, in which case weighting is unnecessary and harmful for precision (Solon, Haider and Wooldridge, 2013).

The adjusted R squared in Table 1 is only around 0.07 and the correlation between the predicted deposit-to-cash ratio and the data values is around 0.28, which indicates that it is difficult to have precise predictions for each household due to a lot of variability in the deposit-to-cash ratios across households. Since the counterfactual analyses focus on the aggregate CBDC share instead of aiming to precisely predict each household's CBDC holding, I check how well the model can predict the aggregate deposit-to-cash ratio. More specifically, I look at the out-of-sample model fit by estimating the model using data from 2010–2013 only and predicting the aggregate deposit-to-cash ratio during 2014–2017 using the estimated model. Figure 2 plots the predicted values of the aggregate deposit-to-cash

estimators is to use an auxiliary regression approach. More specifically, this is done by (1) adding the sample weight and the interaction terms between each explanatory variable and the sample weight into the baseline regression and (2) using an F-test to test the joint significance of these added variables. If the null that these variables are jointly zero cannot be rejected, then there is no significant difference between WLS and OLS. Using this method, the P-value is 0.21 and hence the null cannot be rejected at the 5% level.

Figure 2: Out-of-Sample Prediction of Aggregate Deposit-to-Cash Ratio



Data sources: CFM 2010–2017, MOP 2013, CANNEX 2010–2017, Government of Canada website
Note: The graph plots the predicted aggregate deposit-to-cash ratio against the corresponding data values from 2014 to 2017. Each point is associated with a given year. The predicted values are calculated based on the model parameters that are estimated using the subsample from 2010 to 2013. The dashed line is a 45-degree line.

ratio against the corresponding data values in each year from 2014 to 2017. These model-predicted values outperform the naive estimates based on different ways of averaging the past data values, as shown in Figure 13 in Appendix D.[27]

5 Counterfactual Analysis

This section conducts the counterfactual analyses using the estimated demand-side parameters from the last column of Table 1 and Table 8 in Appendix D. Section 5.1 shows the predicted demand for CBDC under three different designs and discusses the crowding-out effects on cash and deposit demand. Section 5.2 examines the impacts of each design attribute on CBDC demand. Section 5.3 discusses three additional CBDC designs that are frequently discussed and their impacts on CBDC demand. Section 5.4 shows how the demand for

[27] The naive estimates are often negatively correlated with the data values. Besides, the root mean squared errors of the naive estimates (i.e., using simple average over 2010–2013, past-year value, or past two-/three-/four-year average to predict the aggregate deposit-to-cash ratios from 2014 to 2017) are around 63–169% larger than those of the model-predicted values, depending on which naive estimate is used.

CBDC differs across social demographic groups.

5.1 Demand for CBDC

I predict the potential demand for CBDC if it were issued in 2017 and to what extent it could affect the demand for cash and deposits based on the logit model in Section 5.1.1 and nested logit model in Section 5.1.2. The demand for CBDC is measured by the aggregate CBDC share, which is the total CBDC holdings over the total liquid assets held by households. This section shows the CBDC demand under three different designs, that is, deposit design, cash design, and baseline design.

Table 2 summarizes the attributes of CBDC under each design. With the deposit (cash) design, CBDC attributes are assumed to be identical to the deposit (cash) attributes. Under the baseline design, CBDC is assumed to be non-interest-bearing, unbundled with bank services, and perceived to be as cheap, easy, and secure to use as cash.[28] CBDC cannot be fully anonymous like cash due to know-your-customer and anti-money laundering requirements. I assume it can achieve 70% of cash anonymity by making transactions below a certain threshold fully anonymous, for example. Similarly, I assume CBDC can achieve 70% of the budgeting usefulness for cash by enabling people to easily see their balance, for instance. CBDC can be used for online transactions, so the feature of online purchase capability takes a value of one. Lastly, I assume CBDC will be widely accepted by merchants like cash with an acceptance rate of one since merchants will likely face a much lower interchange fee with CBDC.

Table 2: CBDC Attributes under Different Design Scenarios

CBDC design	Return	Bundling	Cost	Ease	Security	Anonymity	Budgeting	Online	Acceptance
Deposit design	deposit rate	1	debit card	debit card	debit card	0	0	1	cards
Cash design	0	0	cash	cash	cash	1	1	0	1
Baseline design	0	0	cash	cash	cash	0.7	0.7	1	1

Note: The table shows the product attributes of CBDC under three different designs: deposit design ($\boldsymbol{x}_{cbdc} = \boldsymbol{x}_d$), cash design ($\boldsymbol{x}_{cbdc} = \boldsymbol{x}_c$), and baseline design ($\boldsymbol{x}_{cbdc} = \boldsymbol{x}_{base}$). In each case, CBDC attributes $\boldsymbol{x}_{cbdc}$ are assumed to be identical to the deposit attributes, cash attributes, or a mixture of both cash and deposit attributes, respectively. Cost, ease of use, and security are each measured by the ratings for debit cards or cash depending on the design.

[28] According to the core CBDC features outlined in BIS (2020), CBDC should be at very low or no cost to end users, as easy as using cash, and extremely resistant to cyber attacks or other threats. As shown in Table 6 in Appendix C.5, most people perceive cash to be a low-cost, easy-to-use, and secure payment instrument, so I use the cash ratings to measure the cost, ease, and security of using CBDC to make payments under the baseline design.

5.1.1 Predicted Demand for CBDC under Logit Model

The utility $V_{i,cbdc,t}$ for CBDC (5) consists of three main components: how households value different attributes of CBDC captured by $\widehat{\boldsymbol{\alpha}}' \boldsymbol{x}_{i,cbdc,t}$, how households with different characteristics value CBDC captured by $\boldsymbol{\gamma}'_{cbdc} \boldsymbol{z}_{i,t}$, and the average impact of the unobserved idiosyncratic preferences captured by η_{cbdc}. To calculate the utility for CBDC and thus predict the demand for CBDC, I assume the CBDC-specific effects range from being cash-like (i.e., $\boldsymbol{\gamma}_{cbdc} = \boldsymbol{\gamma}_c = 0$ and $\eta_{cbdc} = \eta_c = 0$) to being deposit-like (i.e., $\boldsymbol{\gamma}_{cbdc} = \widehat{\boldsymbol{\gamma}}_d$ and $\eta_{cbdc} = \widehat{\eta}_d$), as discussed in Section 2.2. Therefore, Figure 3 shows the aggregate CBDC shares against the values of $\boldsymbol{\gamma}_{cbdc}/\widehat{\boldsymbol{\gamma}}_d$ and $\eta_{cbdc}/\widehat{\eta}_d$, ranging from zero to one. Each graph plots the aggregate CBDC shares under the three designs shown in Table 2.

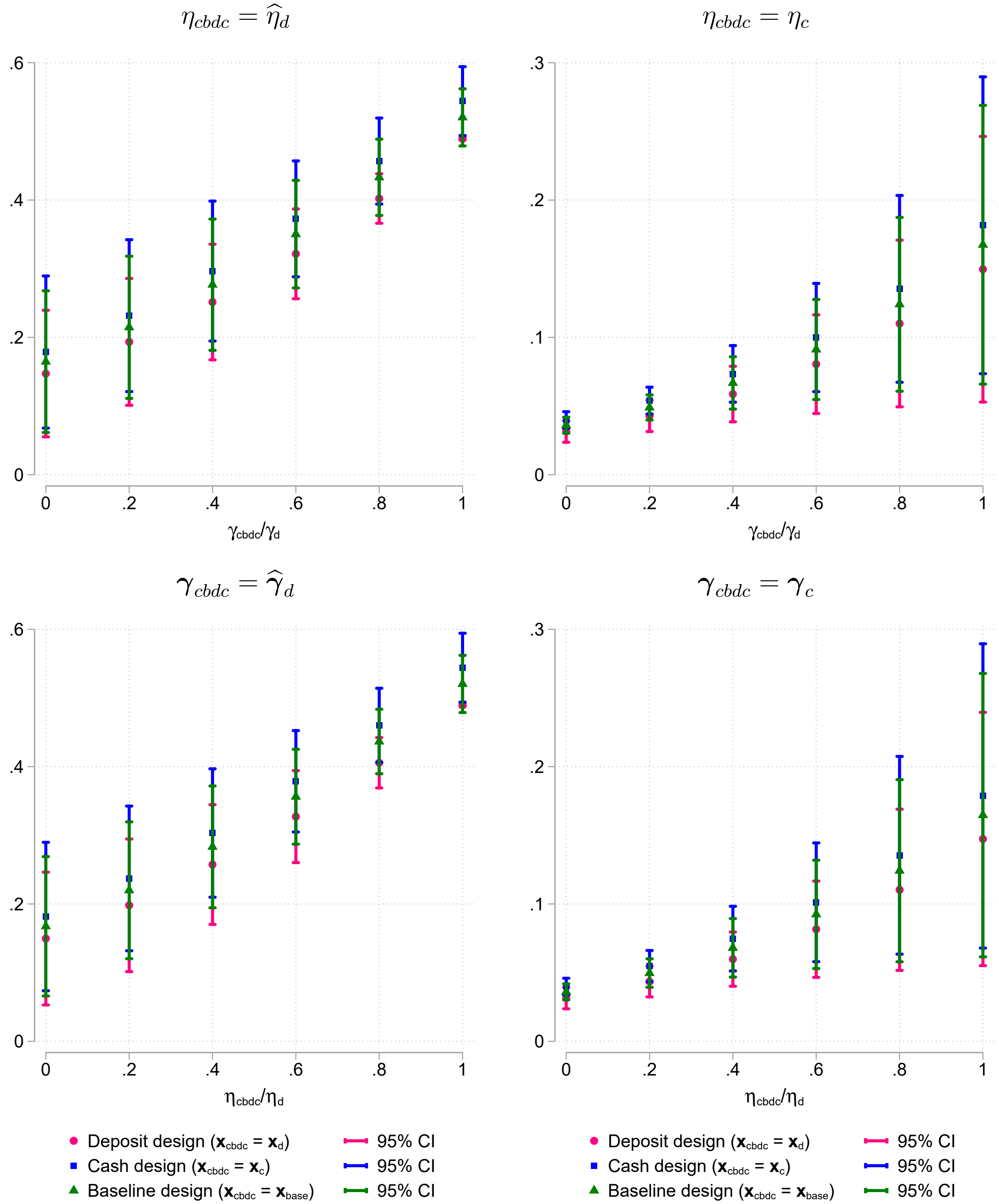
There are three main findings from Figure 3. First, when CBDC-specific effects are cash-like (deposit-like), the aggregate CBDC share is around 4% (52%). Intuitively, since a median household holds around 96% of their liquid assets in deposit and 4% in cash in the CFM data, if CBDC-specific effects are closer to being deposit-like, implying that households would perceive CBDC to be closer to deposit, they would also hold more CBDC.

Second, the two components of the CBDC-specific effects, that is, the demographics-related effects $\boldsymbol{\gamma}_{cbdc}$ and the CBDC fixed effect η_{cbdc}, are equally important in determining the potential level of CBDC demand. The upper panel shows that as $\boldsymbol{\gamma}_{cbdc}$ approaches $\widehat{\boldsymbol{\gamma}}_d$, the aggregate CBDC share increases from around 16% to 52% (4% to 17%) conditional on $\eta_{cbdc} = \widehat{\eta}_d$ ($\eta_{cbdc} = \eta_c$). Similarly, the lower panel shows that as η_{cbdc} approaches $\widehat{\eta}_d$, the aggregate CBDC share increases from around 17% to 52% (4% to 16%), conditional on $\boldsymbol{\gamma}_{cbdc} = \widehat{\boldsymbol{\gamma}}_d$ ($\boldsymbol{\gamma}_{cbdc} = \boldsymbol{\gamma}_c$).

Third, the aggregate CBDC shares under the cash design are the highest among the three designs mainly due to the higher levels of anonymity and budgeting usefulness under the cash design. Although the deposit design is better in terms of the rate of return and bundling of bank services, it is not enough to compensate for its low level of anonymity and budgeting usefulness, so the CBDC demand is lower under the deposit design.

A higher demand for CBDC implies larger crowding-out effects on the demand for deposits and cash. Under the logit model, the demand for CBDC draws proportionally from deposits and cash, so the percentage drops in deposit and cash demand are identical. Figure 14 in Appendix D shows that the mean percentage drop in deposits and cash across households is around 4% (52%) when CBDC-specific effects are cash-like (deposit-like).

Figure 3: Aggregate CBDC Shares for Different Assumptions on CBDC-specific Effects



Note: The graphs in the upper (lower) panel plot the aggregate CBDC shares against different values of γ_{cbdc} (η_{cbdc}) as a fraction of the estimated parameters $\widehat{\gamma}_d$ ($\widehat{\eta}_d$) conditional on the value of η_{cbdc} (γ_{cbdc}). The aggregate CBDC share refers to the share of CBDC holdings out of households' liquid assets. In each graph, three different designs for CBDC are plotted, that is, when CBDC attributes $\boldsymbol{x}_{cbdc}$ are identical to deposit attributes ($\boldsymbol{x}_{cbdc} = \boldsymbol{x}_d$), cash attributes ($\boldsymbol{x}_{cbdc} = \boldsymbol{x}_c$), or a mixture of both ($\boldsymbol{x}_{cbdc} = \boldsymbol{x}_{base}$). The standard errors for calculating the 95% confidence intervals are computed using the delta method.

5.1.2 Predicted Demand for CBDC under Nested Logit Model

Under the logit model, CBDC is treated as a distinct product in the sense that households possess a unique set of unobserved idiosyncratic preferences for CBDC. In other words, there are no common factors driving the unobserved idiosyncratic preferences for different products. This assumption is relaxed in this section, so that CBDC can be a closer substitute for deposits or cash due to the correlated idiosyncratic preferences, as discussed in Section 2.2.2. This section examines to what extent the predictions from the logit model are robust to the correlated unobserved utilities across products.

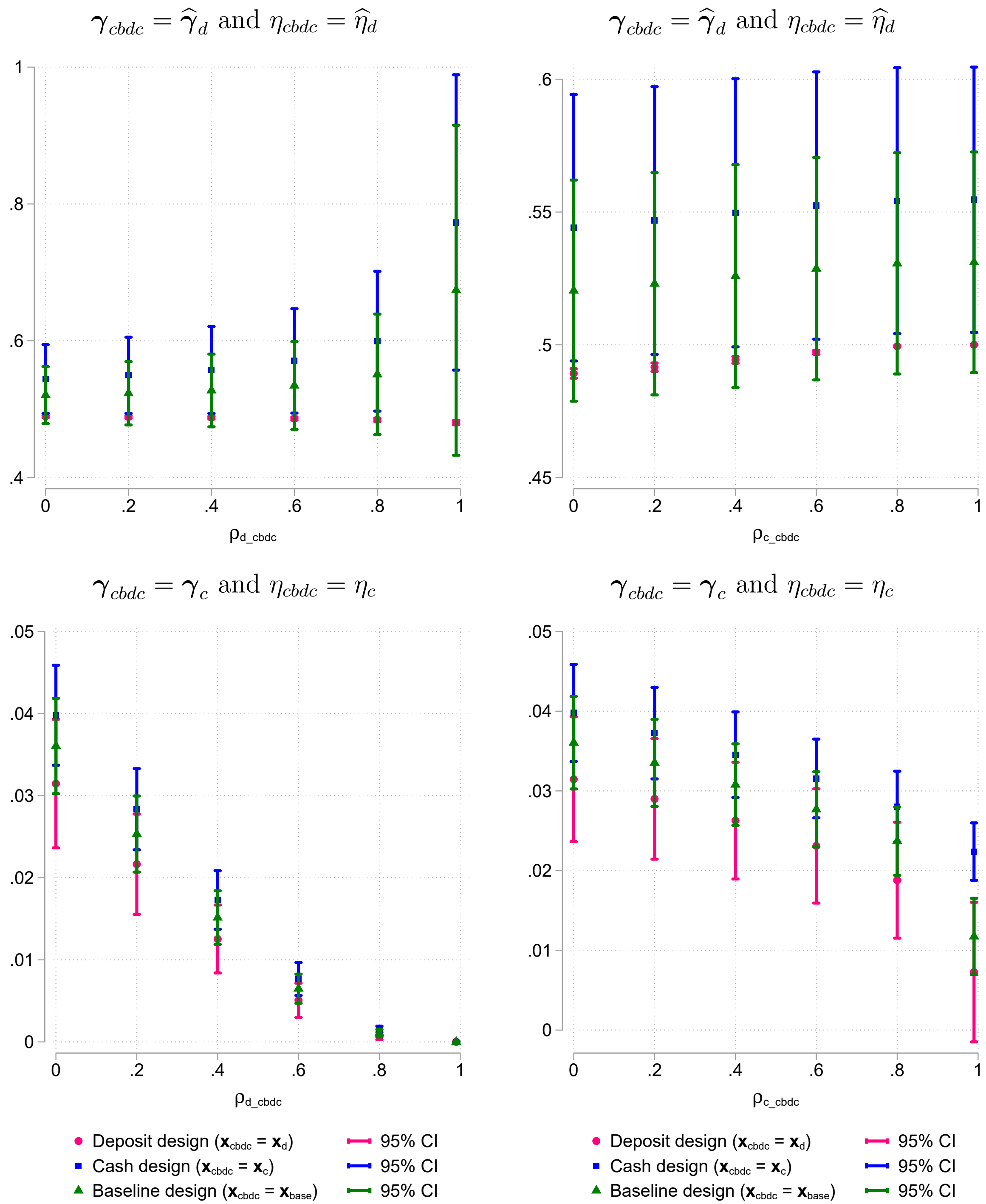
Figure 4 plots the aggregate CBDC shares against different levels of correlation ranging from 0 to 0.99, assuming the unobserved utility for CBDC is correlated with that for deposits (left panel) or cash (right panel). A higher correlation between the unobserved utilities for CBDC and deposits (cash) implies greater substitutability between CBDC and deposits (cash). When the correlation is zero, the predictions are identical to those based on the logit model. Each graph plots the aggregate CBDC shares under the deposit design, the cash design, and the baseline design.

There are three main implications from Figure 4. First, the predicted aggregate CBDC shares are robust to a wide range of correlation coefficients. When the correlation is below 0.8, the level changes in the aggregate CBDC shares across different levels of correlation are small, conditional on a given CBDC design.

Second, the impact of the correlation on the aggregate CBDC share depends on the utility difference between CBDC and its closer substitute, as discussed in Section 2.2.2. For example, under the deposit design in the first graph, CBDC and deposits have the same observed utility, as both the design of CBDC and the CBDC-specific effects are identical to those of deposits. In this case, as ρ_{d_cbdc} increases, cash is reduced by less as CBDC demand draws more than proportionally from deposits. As a consequence, the remaining asset share that can be allocated to CBDC and deposits is smaller, which leads to a lower CBDC share. This effect can be reversed (reinforced) by the substitution between CBDC and deposits when CBDC has a higher (lower) observed utility than deposits. Under the cash design or the baseline design, CBDC has a higher observed utility than deposits due to better anonymity and budgeting usefulness features, so a higher ρ_{d_cbdc} that makes them more substitutable can lead to greater substitution from deposits into CBDC and hence a higher aggregate CBDC share.

In contrast, in the bottom right graph, CBDC with the deposit design or the baseline design has a lower observed utility than that with the cash design, so a higher ρ_{c_cbdc} leads to greater substitution from CBDC into cash and larger drops in the CBDC shares compared to the drop under the cash design. Apart from the design, the CBDC-specific effects can also

Figure 4: Aggregate CBDC Shares for Different Degrees of Substitutability



Note: The left (right) panel plots the aggregate CBDC shares against different levels of correlation ρ_{d_cbdc} (ρ_{c_cbdc}) between the unobserved utilities for CBDC and deposits (cash), conditional on different values of γ_{cbdc} and η_{cbdc}. The correlation coefficient ranges from 0–0.99. A higher correlation ρ_{d_cbdc} (ρ_{c_cbdc}) implies greater substitutability between CBDC and deposits (cash). The aggregate CBDC share refers to the share of CBDC holdings out of households' liquid assets. In each graph, three different designs for CBDC are plotted, that is, when CBDC attributes $\boldsymbol{x}_{cbdc}$ are identical to deposit attributes ($\boldsymbol{x}_{cbdc} = \boldsymbol{x}_d$), cash attributes ($\boldsymbol{x}_{cbdc} = \boldsymbol{x}_c$), or a mixture of both ($\boldsymbol{x}_{cbdc} = \boldsymbol{x}_{base}$). The standard errors for calculating the 95% confidence intervals are computed using the delta method.

lead to an observed utility difference. The bottom left graph shows that when CBDC has a much lower observed utility than deposits due to the CBDC-specific effects being cash-like (i.e., $\boldsymbol{\gamma}_{cbdc} = \boldsymbol{\gamma}_c$ and $\eta_{cbdc} = \eta_c$), there is greater substitution from CBDC to deposits and the aggregate CBDC share approaches zero as ρ_{d_cbdc} increases.

Third, the correlation ρ_{c_cbdc} between the unobserved utilities for CBDC and cash has a much smaller impact compared to ρ_{d_cbdc}. The right panel of Figure 4 shows that the level changes in aggregate CBDC shares are small even when ρ_{c_cbdc} approaches one. This is because households only hold a small fraction of their liquid assets in cash. Hence, even if CBDC has a much higher observed utility than cash due to the CBDC-specific effects being deposit-like (i.e., $\boldsymbol{\gamma}_{cbdc} = \widehat{\boldsymbol{\gamma}}_d$ and $\eta_{cbdc} = \widehat{\eta}_d$), the greater substitution from cash into CBDC as ρ_{c_cbdc} increases would not add much extra demand for CBDC, as shown in the top right graph.

Similar to the logit model, the crowding-out effects on the demand for deposits and cash depend a lot on CBDC-specific effects. Suppose CBDC has a baseline design and is a closer substitute to deposits. The left panels of Figure 15 and 16 in Appendix D show that when CBDC-specific effects are cash-like, deposit and cash demand would only be reduced by around 0–4%. In contrast, when CBDC-specific effects are deposit-like, the demand for deposits (cash) can be crowded out by around 52–70% (15–52%), as ρ_{d_cbdc} increases from 0 to 0.99.

When CBDC is a closer substitute to cash, the crowding out on deposit demand is robust to changes in the correlation ρ_{c_cbdc}, whereas the crowding out on cash demand is more sensitive to ρ_{c_cbdc}, as shown in the right panels of Figure 15 and 16 in Appendix D. Intuitively, the latter is because people only hold a small amount of cash, so even a small level change can be a large percentage change. As ρ_{c_cbdc} increases from 0 to 0.99, implying that CBDC and cash become more substitutable, deposit (cash) demand would be reduced by 50–52% (52–100%) when CBDC-specific effects are deposit-like, and 0–4% (4–26%) when CBDC-specific effects are cash-like.

5.2 The Impacts of CBDC Design Attributes

In this section, I quantify how each design attribute would impact CBDC demand. While CBDC-specific effects (i.e., $\boldsymbol{\gamma}_{cbdc}$ and η_{cbdc}) play a large role in determining the exact level of CBDC demand, this section shows that the impacts of the design attributes on the percentage changes in CBDC demand would rely much less on these assumptions.

The predicted impacts of attributes from both the logit and nested logit models are shown in this section. When the unobserved utilities for CBDC and deposits are correlated under the nested logit model, the impact of a given attribute on CBDC demand is larger. Intuitively, when CBDC and deposits are closer substitutes, any attribute change will lead to greater substitution between the two. Hence, the predictions based on the logit model can be viewed as a lower bound.

The correlation ρ_{c_cbdc} between the unobserved utilities for CBDC and cash has a much smaller impact on the impacts of design attributes compared to ρ_{d_cbdc}, so the results are not shown in this section. Intuitively, a higher correlation ρ_{c_cbdc} increases the substitutability between CBDC and cash, which leads to greater substitution from cash into CBDC if CBDC has better attributes than cash. However, this would not add much to the CBDC demand since people tend to hold a small amount of cash.

I find that except for the rate of return whose impact depends on the magnitude of the rate change, the most important attribute is budgeting usefulness, followed by anonymity and bundling of bank services. This is consistent with Figure 1, which shows that these attributes are relatively more important in explaining the allocation between deposits and cash. The rest of this section discusses the impact of each attribute in turn.

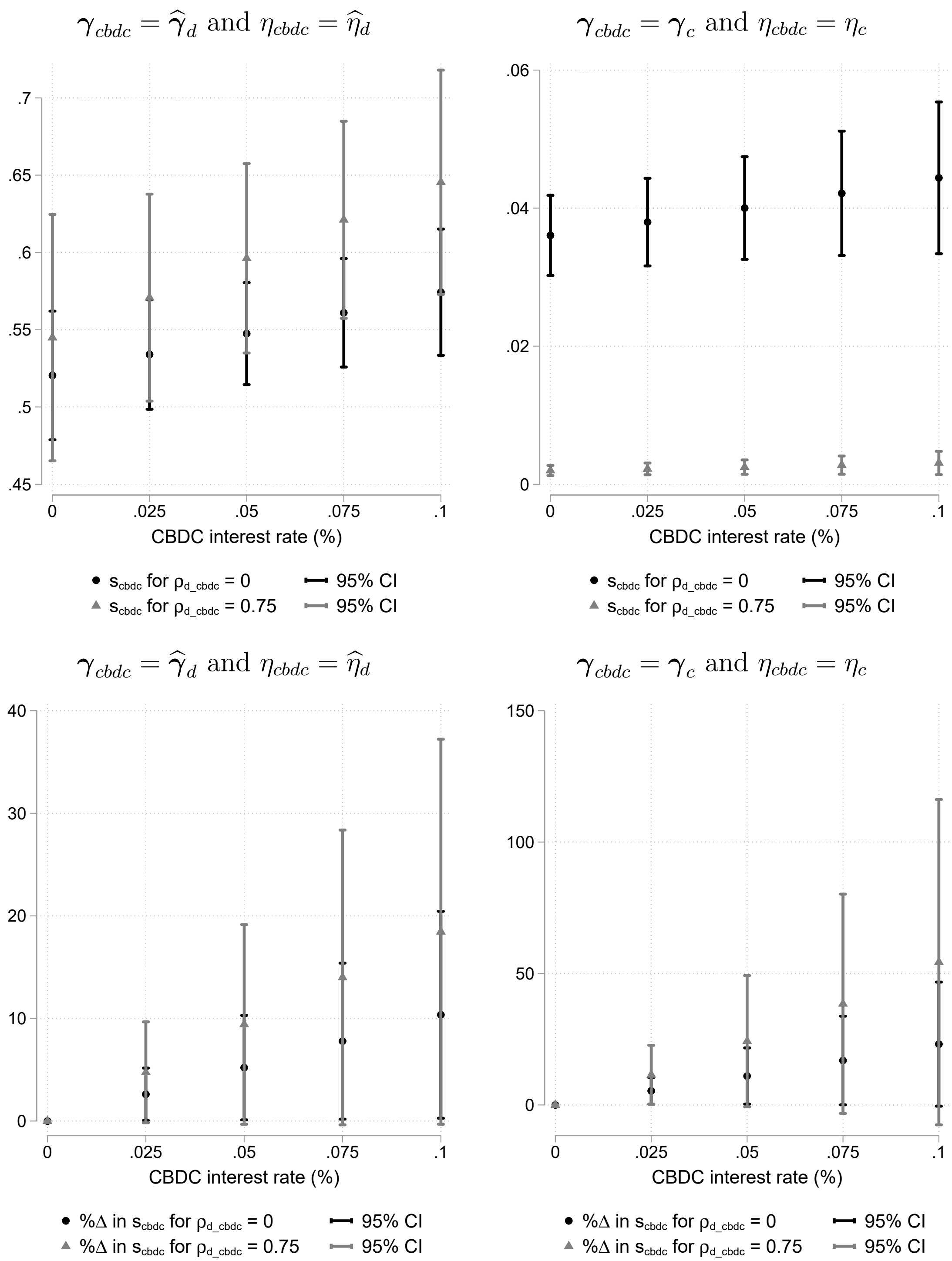
CBDC Interest Rate

Figure 5 shows how changes in the CBDC interest rate would impact the aggregate CBDC shares (upper panel) and the percentage changes in aggregate CBDC shares relative to those under the baseline design (lower panel), conditional on the CBDC-specific effects (i.e., γ_{cbdc} and η_{cbdc}) and the correlation ρ_{d_cbdc} between the unobserved utilities for CBDC and deposits. The range 0–0.1% is chosen because the median (75th percentile) deposit rate after tax is around 0.08% (0.1%) across households during 2010–2017.

The upper panel of Figure 5 shows that as the CBDC rate increases from 0% to 0.1%, the aggregate CBDC share increases from 52% to 57% (3.6% to 4.4%), when CBDC-specific effects are deposit-like (cash-like) under the logit model. As can be seen, the predicted levels of CBDC demand differ a lot depending on CBDC-specific effects. To summarize the impacts of the CBDC interest rate across different assumptions on CBDC-specific effects, I look at the percentage changes in the aggregate CBDC shares relative to the shares under the baseline design in the lower panel.

As shown in the lower panel of Figure 5, when CBDC is non-interest-bearing as in the baseline design, there is a zero percentage change in the aggregate CBDC share. Based on the logit model where $\rho_{d\_cbdc} = 0$, as the CBDC rate rises to 0.1%, the aggregate CBDC share increases by around 10% (23%) if CBDC-specific effects are deposit-like (cash-like). The 0.1 percentage point increase in CBDC rate is a large change as most households face a post-tax deposit rate that is below 0.1%. When the correlation is high (e.g., $\rho_{d\_cbdc} = 0.75$), the

Figure 5: The Impact of Rate of Return on CBDC Demand



Note: The graph plots the aggregate CBDC share s_{cbdc} (upper panel) and the percentage change $\%\Delta$ in the aggregate CBDC share s_{cbdc} relative to the baseline value (lower panel) for different levels of CBDC interest rate ranging from 0% to 0.1%, conditional on different values of γ_{cbdc} and η_{cbdc}. In each graph, two different levels of the correlation ρ_{d_cbdc} between the unobserved utilities for CBDC and deposits are plotted. The standard errors for calculating the 95% confidence intervals are computed using the delta method.

percentage changes in aggregate CBDC shares are larger due to the greater substitutability between deposits and CBDC that enlarges the impact of the attribute change.

The range of 10% to 23% is much narrower compared to the range for the predicted level of CBDC demand, implying that the percentage changes in CBDC demand depend much less on CBDC-specific effects. This is because by looking at the percentage changes in demand in response to the attribute change, the level effects can be largely canceled out. For the rest of this section, I focus on the impacts of design attributes on the percentage changes in CBDC demand.

CBDC Anonymity and Usefulness for Budgeting

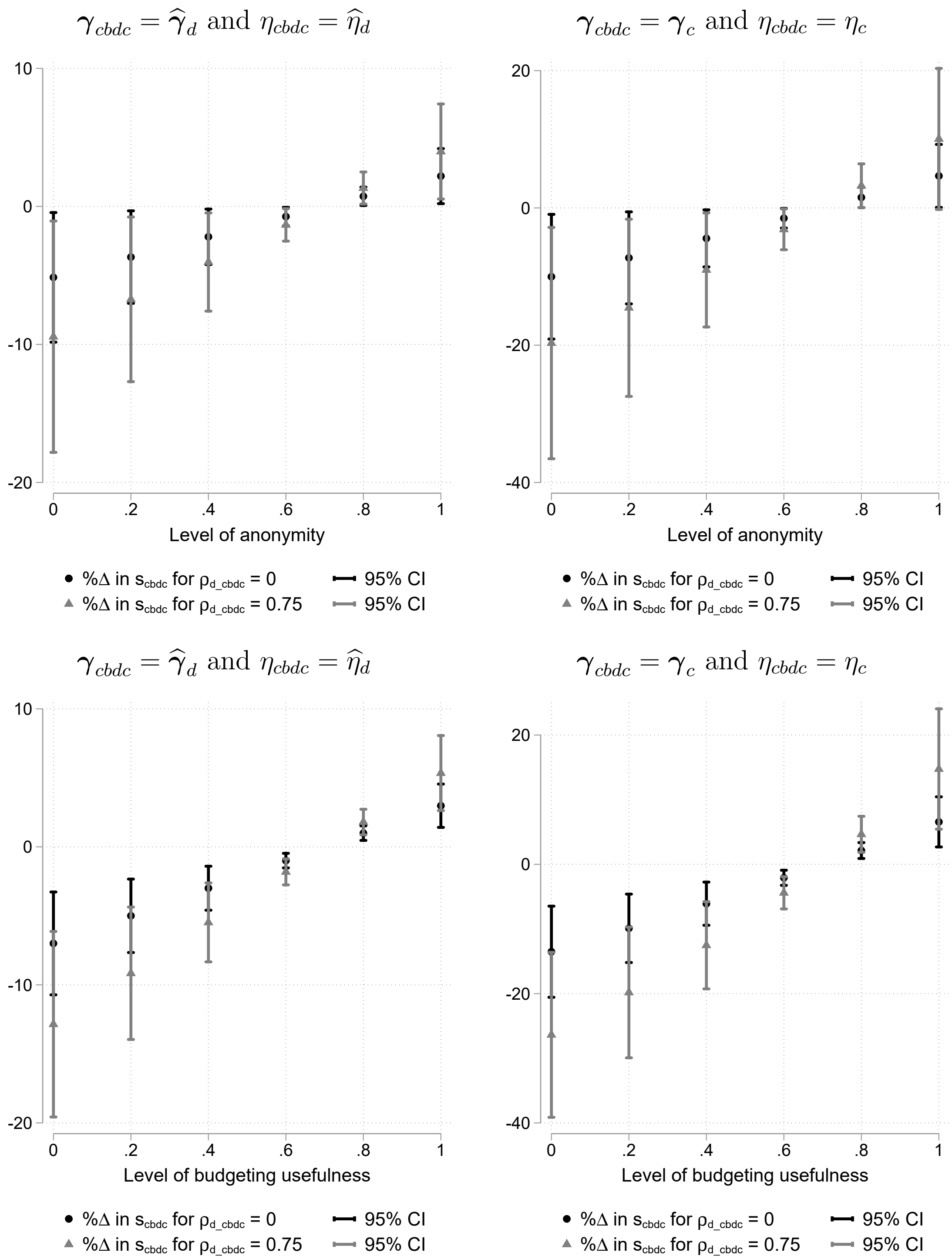
Figure 6 shows the impacts of anonymity and budgeting usefulness on the percentage changes in aggregate CBDC shares. The point of zero (one) on the x-axis refers to the level of anonymity or budgeting usefulness for deposits (cash). Under the baseline design, CBDC is assumed to achieve 70% of the cash anonymity and budgeting usefulness. Relative to the baseline design, if the anonymity level of CBDC reduces to the deposit anonymity level, the aggregate CBDC share would drop by around 5–10% under the logit model, where the range is due to different assumptions on CBDC-specific effects (i.e., $\boldsymbol{\gamma}_{cbdc}$ and η_{cbdc}). Under the nested logit model where the correlation ρ_{d_cbdc} is assumed to be 0.75, the aggregate CBDC share would drop by around 9–20%. If CBDC under the baseline design could achieve the cash anonymity, that is, the level of anonymity increases from 0.7 to 1, the aggregate CBDC share would increase by around 2–5% (4–10%) when $\rho_{d\_cbdc} = 0$ (0.75).

Budgeting usefulness has a larger impact than anonymity. Relative to the baseline design where CBDC can achieve 70% of the cash budgeting usefulness, if CBDC becomes less useful for budgeting like deposits, its aggregate share would drop by around 7–14% under the logit model where $\rho_{d\_cbdc} = 0$. If CBDC becomes as useful for budgeting as cash, its aggregate share would increase by around 3–7% when $\rho_{d\_cbdc} = 0$.

Bundling of Bank Services

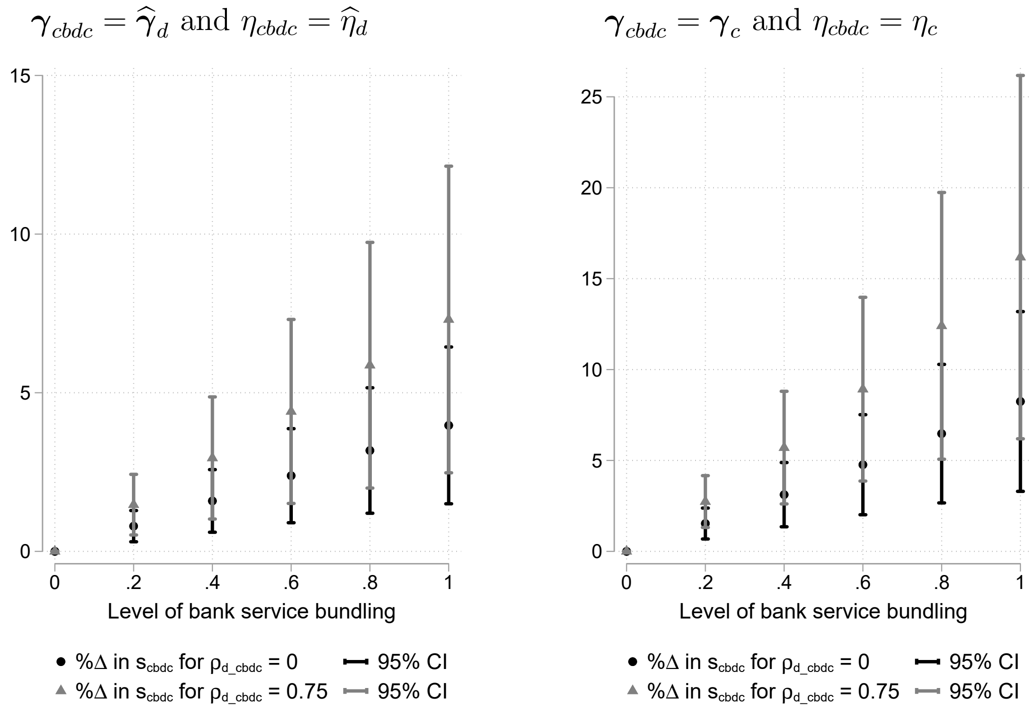
Figure 7 shows the impact of the bundling of the financial planning advice service. Under the baseline design, CBDC is assumed to have the same level of bundling as cash. If CBDC has a higher degree of bundling like deposits, then its aggregate share would increase by around 4–8% relative to the share under the baseline design, depending on CBDC-specific effects. When $\rho_{d\_cbdc} = 0.75$, the changes in CBDC demand are larger while the confidence intervals are also wider.

Figure 6: The Impacts of Anonymity and Budgeting Usefulness on CBDC Demand



Note: The graph plots the percentage change $\%\Delta$ in the aggregate CBDC share s_{cbdc} relative to the share under the baseline design against different levels of anonymity (upper panel) and usefulness for budgeting (lower panel), conditional on different values of γ_{cbdc} and η_{cbdc}. The point of zero (one) on the x-axis refers to the level of anonymity or budgeting usefulness for deposits (cash). In each graph, two different levels of the correlation ρ_{d_cbdc} between the unobserved utilities for CBDC and deposits are plotted. The standard errors for calculating the 95% confidence intervals are computed using the delta method.

Figure 7: The Impact of Bank Service Bundling on CBDC Demand



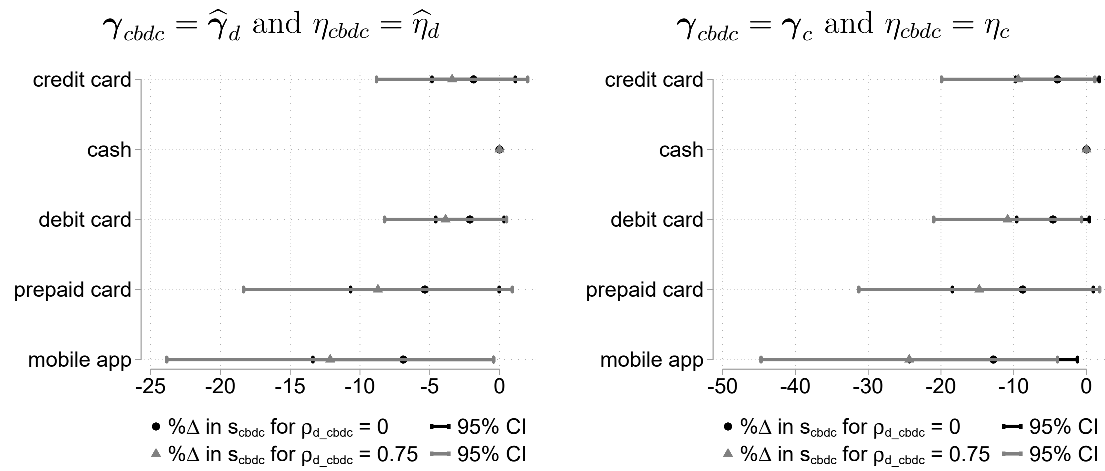
Note: The graph plots the percentage change $\%\Delta$ in the aggregate CBDC share s_{cbdc} relative to the share under the baseline design against different levels of bank service bundling, conditional on different values of γ_{cbdc} and η_{cbdc}. The point of zero (one) on the x-axis refers to the level of bundling for cash (deposits). In each graph, two different levels of the correlation ρ_{d_cbdc} between the unobserved utilities for CBDC and deposits are plotted. The standard errors for calculating the 95% confidence intervals are computed using the delta method.

Cost, Ease of Use, and Security

Figure 8 shows the changes in the aggregate CBDC share when the cost, ease of use, and security features of CBDC are each measured by the ratings for a given payment instrument. The changes are mainly driven by the ease-of-use and security features because the preference parameter associated with the cost feature is much smaller in magnitude, as shown in Table 1. Apart from the most frequently used payment instruments (i.e., cash, debit cards, and credit cards), I also look at the ratings for mobile payment apps and prepaid cards because CBDC may be accessed through a smartphone or a physical payment card. Hence, the ratings for these payment instruments may be better proxies for people's perceptions towards how easy or secure it is when using CBDC to make payments.

Under the baseline design, CBDC is perceived to be as cheap, easy, and secure to use as cash. If these payment features of CBDC change from cash ratings to debit card or credit card ratings, the changes in the aggregate CBDC share are very small, as shown in Figure 8. However, if these CBDC features are measured by the ratings for prepaid cards (mobile

Figure 8: The Impacts of Cost, Ease, and Security on CBDC Demand



Note: The graph plots the percentage change %Δ in the aggregate CBDC share s_{cbdc} relative to the share under the baseline design for different levels of cost of use, ease of use, and security, conditional on different values of γ_{cbdc} and η_{cbdc}. The y-axis refers to the ratings for different payment instruments that are used to measure the cost, ease, and security of using CBDC to make payments. In each graph, two different levels of the correlation ρ_{d_cbdc} between the unobserved utilities for CBDC and deposits are plotted. The standard errors for calculating the 95% confidence intervals are computed using the delta method.

apps), then the aggregate CBDC share would drop by around 5–9% (7–13%) under the logit model where $\rho_{d\_cbdc} = 0$, depending on CBDC-specific effects. This is because people perceive prepaid cards or mobile apps to be much less easy and secure to use than cash, while their perceptions towards debit or credit cards are relatively similar to those for cash, as shown in Table 6 in Appendix C.5.

Other Features of CBDC

The impacts of online purchase capability and unacceptance rate are shown in Figure 17 in Appendix D. The upper panel of Figure 17 shows that relative to the baseline design where CBDC can be used for online purchases, losing this feature only reduces its aggregate share by around 1%. This small impact is partly because only around 12% of people shopped online for one or more transactions from the three-day shopping diary in MOP 2013. Those who do not shop online will not obtain any utility from this feature, so this online feature does not contribute much to the aggregate CBDC share. The lower panel shows that relative to the baseline design where CBDC is assumed to be universally accepted by merchants, if all households find that there is a 25% probability that CBDC is unaccepted,[29] then the aggregate CBDC share would drop by around 3–7% under the logit model.

[29] Note that this is a large change because the mean and median unacceptance rates across households are around 0.06 and 0, respectively.

5.3 Applications to CBDC Design Scenarios

This section shows the impacts of designs on CBDC demand. Similar to the impacts of the design attributes discussed in Section 5.2, the impacts of changes in CBDC designs on percentage changes in CBDC demand also rely much less on the CBDC-specific effects (i.e., γ_{cbdc} and η_{cbdc}). Table 3 shows the CBDC attributes under three different design scenarios, where CBDC is designed to capture some prominent features of a cryptocurrency, the Bahamian Sand Dollar, or a synthetic CBDC, respectively. The three designs differ in terms of anonymity, bundling of bank services, cost, ease of use, and security. For features such as the rate of return, budgeting usefulness, and merchant acceptance, it is more difficult to ascertain their relative levels without enough information, so I set them equal across the designs for simplicity of interpretation.

Table 3: CBDC Attributes under Different Design Scenarios

CBDC design	Return	Bundling	Cost	Ease	Security	Anonymity	Budgeting	Online	Acceptance
Cryptocurrency	0	0	very low	mobile app	mobile app	1	0	1	1
Sand Dollar	0	0	very low	mobile app prepaid card	mobile app prepaid card	0.2	0	1	1
Synthetic CBDC	0	1	debit card	debit card	debit card	0	0	1	1

Note: The table shows the product attributes of CBDC when designing CBDC to capture certain features of a cryptocurrency, the Bahamian Sand Dollar, or a synthetic CBDC, respectively. Cost, ease of use, and security are each measured by the ratings for mobile payment applications, prepaid cards, or debit cards, depending on the design. For the Sand Dollar, I use the average ratings for mobile apps and prepaid cards to measure its ease and security features. "Very low" means that the cost takes the lowest rating of one (i.e., very low cost) on a Likert scale of 1–5.

Across the three designs, only the cryptocurrency design is able to reach the full degree of cash anonymity, where anonymity refers to the separation of users' identities from their transactions.[30] I assume that a CBDC with a cryptocurrency design would be perceived as a very low-cost payment instrument because some cryptocurrencies can have very low transaction fees. For example, during the past year up to August 2021, the average transaction fee for Dash is often below 0.005 US dollars and even the highest point is below 0.04 US dollars.[31] I use the ratings for mobile payment apps to measure the ease and security of using CBDC with the cryptocurrency design to make payments as it can be accessed via

[30] Unlike bitcoin that is pseudonymous, some cryptocurrencies such as Monero, Zcash, and Dash can better conceal users' identities by shielding the transaction information and thus making it difficult to analyze the transaction patterns to back out the user identity. Although it is unlikely for a central bank to issue a fully anonymous CBDC, it is still useful to compare a "central bank cryptocurrency" (Berentsen and Schar, 2018; Bech and Garratt, 2017) design with other designs.

[31] The average transaction fees can be found on the website: https://bitinfocharts.com/comparison/dash-transactionfees.html#1y.

mobile wallets.

The synthetic CBDC proposed in Adrian and Mancini-Griffoli (2019) is not a CBDC and is similar to deposits provided by a narrow bank that are fully backed by reserves at the central bank (BIS, 2020). Hence, the design for the synthetic CBDC is similar to the deposit design shown in Table 2, where the debit card ratings are used to measure the cost, ease-of-use, and security features. In addition, CBDC under this design is assumed to have the same level of bank service bundling and anonymity as deposits.

The Sand Dollar is the world's first nationwide CBDC issued by the central bank of the Bahamas. Although it is not designed to replicate the anonymity feature of cash, it tends to have a slightly higher degree of anonymity than deposits due to the tiered know-your-customer requirements. For example, the Tier I wallet with a holding limit of $500 does not require an official ID, which is designed for the unbanked, non-residents, or visitors.[32] Since the unbanked account for around 20% of the adult population in the Bahamas (IMF, 2019, p. 13) and these people would likely use the Tier I wallet, I assume that the Sand Dollar can achieve 20% of the cash anonymity. According to the official website, the Sand Dollar has zero transaction fees for individuals, so I assume it would be perceived as a very low cost payment instrument. Since the digital wallet for the Sand Dollar can be accessed via a mobile phone or a physical smart card, I use the average ratings for mobile payment apps and prepaid cards to measure the ease and security features.

Table 4: Percentage Changes in CBDC Demand when CBDC Design Changes

Design	Cryptocurrency	Sand Dollar	Synthetic CBDC
Cryptocurrency	0	-6 to -10	-1 to -2
Sand Dollar	6 to 11	0	6 to 9
Synthetic CBDC	1 to 2	-6 to -8	0

Data sources: MOP 2013, CANNEX 2010–2017, CFM 2010–2017
Note: The table shows the percentage changes in CBDC demand when the CBDC design changes from each design in the first column to each design in the first row under the logit model. The three designs represent the scenarios where CBDC is designed to replicate certain features of a cryptocurrency, the Bahamian Sand Dollar, or a synthetic CBDC, respectively. The first (second) number in each cell refers to the prediction based on the assumption that CBDC-specific effects are deposit-like (cash-like).

Table 4 shows the percentage change in the aggregate CBDC share when changing from each design in the first column to each design in the first row under the logit model. As

[32]Details for the Tier I wallet can be found from https://www.sanddollar.bs/individual and who can use it can be found from https://www.sanddollar.bs/getinvolved.

can be seen, when changing from the cryptocurrency design to the Sand Dollar design with a much lower level of anonymity, CBDC demand would drop by around 6–10%, depending on different assumptions for CBDC-specific effects. Although the synthetic CBDC design has better features in terms of the bundling of bank services, ease of use, and security,[33] this is still not enough to compensate for its low anonymity level. As a result, moving from the cryptocurrency design with a high level of anonymity to the synthetic CBDC design would reduce the CBDC demand by around 1–2%. In contrast, when changing from the Sand Dollar design with a low level of anonymity to the synthetic CBDC design, the CBDC demand would increase by 6–9%.

Under the nested logit model, the impacts of the design changes on CBDC demand would be larger. For instance, a higher correlation between the unobserved utilities for CBDC and deposit implies that CBDC and deposit are more substitutable, so any changes in CBDC designs would lead to greater substitution between them and hence larger changes in CBDC demand. When the correlation is high (i.e., $\rho_{d\_cbdc} = 0.75$), the magnitude of the changes in CBDC demand is roughly twice as large.

5.4 CBDC Demand across Different Demographic Groups

This section studies how CBDC holdings differ across social demographic groups if CBDC were present during the period of 2014–2017.[34] Figure 9 shows the unweighted mean predicted CBDC holdings in Canadian dollars across different demographic groups based on the logit model.[35] Within each demographic group, the predicted holdings under three different designs are shown, that is, the deposit design, the cash design, and the baseline design, as described in Table 2.

Figure 9 shows that households with higher education, higher income, older age, or home ownership tend to hold more CBDC on average. In contrast, the differences in CBDC holdings between groups living in rural vs. urban areas or having vs. not having internet access are small. These patterns are similar across the three CBDC designs, although the magnitude of the CBDC holdings differs slightly across designs. Under the cash (deposit) design, CBDC holdings across different groups are slightly higher (lower) compared to the

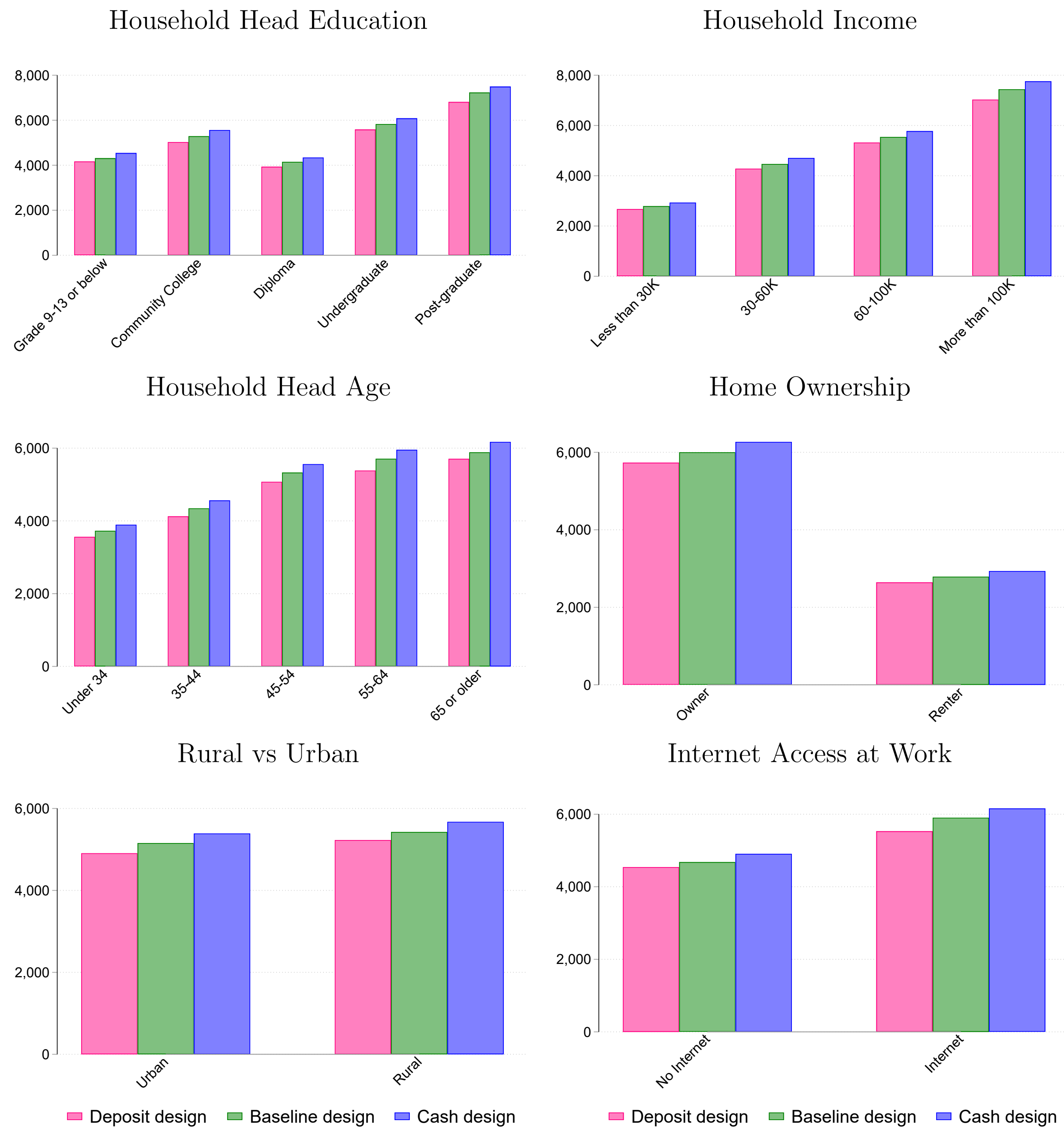
[33] As shown in Table 6 in Appendix C.5, more people perceive debit cards to be easy and secure to use compared to mobile apps or prepaid cards.

[34] This section shows the predictions over a few years to ensure that there are sufficient observations to calculate the mean predicted CBDC holding within each demographic group.

[35] For robustness checks, I also look at the predictions based on the nested logit model. The results in this section are robust to different degrees of correlation ρ_{c_cbdc} between the unobserved utilities for CBDC and cash. This is because ρ_{c_cbdc} only has a very small impact on the level of CBDC holdings, as discussed in Section 5.1.2. The results are also robust to different values of ρ_{d_cbdc}, as long as CBDC-specific effects are close to being deposit-like (i.e., γ_{cbdc} and η_{cbdc} are close to the estimated values for deposits, $\widehat{\gamma}_d$ and $\widehat{\eta}_d$).

baseline design, since the cash (deposit) design is better (worse) in terms of anonymity and budgeting usefulness features.

Figure 9: CBDC holdings in Canadian Dollars across Demographic Groups



Note: The bar charts show the unweighted mean predicted CBDC holdings across households and over the period of 2014–2017 for different demographic groups. For a given demographic group, the predicted CBDC holdings under three different designs are plotted. The CBDC holdings are predicted from the logit model based on the assumption that CBDC-specific effects are deposit-like. The predicted CBDC holdings are deflated by CPI in each year.

Since the observed utility for CBDC depends on both the design and the CBDC-specific effects (i.e., $\boldsymbol{\gamma}_{cbdc}$ and η_{cbdc}), the patterns being similar across the designs indicates that they are driven by the CBDC-specific effects. Figure 9 assumes that CBDC-specific effects are deposit-like (i.e., $\boldsymbol{\gamma}_{cbdc} = \widehat{\boldsymbol{\gamma}}_d$ and $\eta_{cbdc} = \widehat{\eta}_d$), implying that households tend to perceive CBDC to be closer to deposits. In this case, if households in a given demographic group prefer to hold more deposits, they would also want to hold more CBDC. Figure 18 in Appendix D shows that the types of households that tend to hold more CBDC in Figure 9 also hold more deposits during 2014–2017 in the CFM data. Similarly, Figure 19 in Appendix D shows that households with older age, higher income, or home ownership tend to hold more cash in the data. I find that when assuming CBDC-specific effects are cash-like (i.e., $\boldsymbol{\gamma}_{cbdc} = \boldsymbol{\gamma}_c$ and $\eta_{cbdc} = \eta_c$), those groups also tend to hold more CBDC in this case, as shown in Figure 20 in Appendix D.

The patterns in Figure 9 are robust to different time periods (or years) except for the level of education and are robust to different ways of summarizing the CBDC holdings (e.g., median or weighted mean holdings). This section examined the holdings of CBDC instead of the shares because the latter is entangled with the effects of wealth. For example, households in older age groups tend to hold more CBDC, but they also have more liquid assets. If the two effects cancel out each other, the CBDC shares between the older and younger age groups should be similar. If this wealth effect dominates, households in older age groups that hold more CBDC balances can have lower CBDC shares. I find that when assuming that CBDC-specific effects are deposit-like, there is not much difference in CBDC shares across different demographic groups. In contrast, when assuming that CBDC-specific effects are cash-like, households with higher education, higher income, home ownership, or internet access at work tend to have lower CBDC shares.

6 Conclusions

This paper provides a framework to empirically quantify the potential demand for CBDC relative to cash and demand deposits. Using a structural demand model, households decide how to allocate their liquid assets between cash and deposits based on the relative utilities from holding cash and deposits, which in turn depend on the differences in the product attributes between the two. I then estimate households' preferences for the product attributes using a unique Canadian survey dataset that contains households' asset holdings and the product attributes of cash and demand deposits. Provided that these estimated preference parameters remain the same after CBDC issuance, they can be used to predict the demand for CBDC with a set of chosen design attributes and quantify the impacts of the design choices on CBDC demand.

I find that under a baseline design for CBDC, where CBDC is non-interest-bearing, unbundled with bank services, and achieves 70% of cash budgeting usefulness and anonymity, the total CBDC holdings out of households' liquid assets could range from 4–52%. To pin down the exact level of CBDC demand in this range, I need to make assumptions on the CBDC-specific effects that consist of two equally important components, the demographics-related effects and the CBDC fixed effect. The former captures how households from a given demographic group would value CBDC relative to cash and demand deposits, while the latter captures the average impact of the unobserved idiosyncratic preferences on the utilities for CBDC. With more information from survey data, it could be possible to take a stance on these effects and thus narrow down the range of the estimates.

In this paper, CBDC can differ from deposits and cash in a variety of product attributes, which allows for analyzing the impacts of CBDC design choices. By studying the percentage change in CBDC demand in response to the change in a given attribute, the level effects would largely be canceled out and thus CBDC-specific effects would matter much less. In doing so, I find that some attributes are more important for CBDC demand, which include budgeting usefulness, anonymity, bundling of bank services, and rate of return.

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Appendices

A Asset Allocation Problem

Section A.1 shows that the log of deposit-to-cash ratio (4) derived from the logit model can also be derived from an asset allocation problem with a constant-elasticity-of-substitution (CES) utility function. Section A.2 shows that the predictions from the nested logit model in Section 2.2.2 can be equivalently derived from an asset allocation problem with a nested CES utility function.

A.1 CES Utility

With the money-in-the-utility assumptions, households obtain the utility from holding cash c and deposits d since they can use the money holdings to facilitate transactions. Each household i maximizes the following CES utility function:[36]

$$u_{i,t}(q_{i,c,t}, q_{i,d,t}, \boldsymbol{x}_{i,c,t}, \boldsymbol{x}_{i,d,t}, \boldsymbol{z}_{i,t}) = \left[\nu_{i,c,t} q_{i,c,t}^{\theta} + \nu_{i,d,t} q_{i,d,t}^{\theta}\right]^{\frac{1}{\theta}} \tag{11}$$

subject to a budget constraint:

$$q_{i,c,t} + q_{i,d,t} = w_{i,t} \tag{12}$$

where $\theta \in (0, 1]$ is the substitution parameter and the estimate of the share parameter $\nu_{i,j,t}$ depends on the product attributes $\boldsymbol{x}_{i,j,t}$ and the household characteristics $\boldsymbol{z}_{i,t}$ for product $j \in \{c, d\}$. The interest on deposits or the opportunity cost of holding cash is included in the product attributes $\boldsymbol{x}_{i,j,t}$. The cash and deposit holdings are denoted by $q_{i,c,t}$ and $q_{i,d,t}$, respectively. This type of budget constraint, where wealth $w_{i,t}$ is allocated between different assets, follows Perraudin and Sørensen (2000). When θ approaches 0, the utility function becomes Cobb-Douglas. When θ is equal to one, the two assets are perfect substitutes, in which case if $\nu_{i,j,t}$ from asset j is higher, then the entire wealth $w_{i,t}$ will be allocated to this asset.

Let λ denote the Lagrange multiplier associated with the budget constraint. Taking the first order conditions with respect to $q_{i,j,t}$ gives:

$$\frac{1}{\theta}\left[\nu_{i,c,t} q_{i,c,t}^{\theta} + \nu_{i,d,t} q_{i,d,t}^{\theta}\right]^{\frac{1}{\theta}-1} \nu_{i,j,t} \theta q_{i,j,t}^{\theta-1} = \lambda \quad \forall\ j \in \{c, d\} \tag{13}$$

[36]See Kurlat (2019) and Drechsler, Savov and Schnabl (2017) for this type of asset allocation problem.

Divide the first order conditions with respect to $q_{i,d,t}$ and $q_{i,c,t}$ to get:

$$\frac{q_{i,d,t}}{q_{i,c,t}} = \left(\frac{\nu_{i,d,t}}{\nu_{i,c,t}}\right)^{\frac{1}{1-\theta}} \tag{14}$$

Suppose $\nu_{i,j,t}$ can be represented by an exponential function of product attributes and household characteristics $\exp(V^*_{i,j,t})$, where $V^*_{i,j,t} = \boldsymbol{\alpha}^{*'}\boldsymbol{x}_{i,j,t} + \boldsymbol{\gamma}^{*'}_j \boldsymbol{z}_{i,t} + \eta^*_j$ is the observed part of the household's indirect utility (1) in the logit model before normalizing the scale of the utility.

Use $\nu_{i,j,t} = \exp(V^*_{i,j,t})$ and take logs of the deposit-to-cash ratio $\frac{q_{i,d,t}}{q_{i,c,t}}$ to get:

$$\ln\frac{q_{i,d,t}}{q_{i,c,t}} = \frac{1}{1-\theta}\left(V^*_{i,d,t} - V^*_{i,c,t}\right) = \frac{1}{1-\theta}\left[\boldsymbol{\alpha}^{*'}(\boldsymbol{x}_{i,d,t} - \boldsymbol{x}_{i,c,t}) + \boldsymbol{\gamma}^{*'}_d \boldsymbol{z}_{i,t} + \eta^*_d\right] \tag{15}$$

which is equivalent to the log of deposit-to-cash ratio (4) under the logit model except for the interpretation of the parameters. In this CES utility framework, the parameters (i.e., $\boldsymbol{\alpha}^*$, $\boldsymbol{\gamma}^*_d$, and η^*_d) are scaled by the degree of substitutability $(1-\theta)$ between deposits and cash. In contrast, under the logit model, these parameters are scaled by the standard deviation of the unobserved factors to normalize the scale of the utility. More specifically, the logit model implicitly scales the utilities for all products such that the variance of the unobserved factors is $\pi^2/6$. Let σ^* denote the original standard deviation of the unobserved factors in the logit model. The parameters $\boldsymbol{\alpha}^*$, $\boldsymbol{\gamma}^*_j$, and η^*_j are scaled by $\sqrt{\pi^2/6}/\sigma^*$.

A.2 Nested CES Utility

After introducing CBDC, suppose CBDC and deposits are closer substitutes and households hold them in bundles. The utility function has the following nested structure:

$$u_{i,t}(q_{i,c,t}, q_{i,d,t}, q_{i,cbdc,t}, \boldsymbol{x}_{i,c,t}, \boldsymbol{x}_{i,d,t}, \boldsymbol{x}_{i,cbdc,t}, \boldsymbol{z}_{i,t}) = \left[\nu_{i,c,t} q^{\theta}_{i,c,t} + \nu_{i,d,t}\left[q^{\varphi}_{i,d,t} + \frac{\nu_{i,cbdc,t}}{\nu_{i,d,t}} q^{\varphi}_{i,cbdc,t}\right]^{\frac{\theta}{\varphi}}\right]^{\frac{1}{\theta}} \tag{16}$$

and the budget constraint becomes:

$$q_{i,c,t} + q_{i,d,t} + q_{i,cbdc,t} = w_{i,t} \tag{17}$$

where $\varphi \in (0,1]$ is the substitution parameter between CBDC and deposits, $\theta \in (0,1]$ is the substitution parameter between cash and the bundle, and $\nu_{i,j,t}$ is a share parameter for product $j \in \{c, d, cbdc\}$. When $\varphi = \theta$, the nest structure disappears. Here, the wealth $w_{i,t}$ is allocated into cash $q_{i,c,t}$, deposits $q_{i,d,t}$, and CBDC $q_{i,cbdc,t}$.

Let λ denote the Lagrange multiplier associated with the budget constraint. Take the first order conditions with respect to $q_{i,c,t}$, $q_{i,d,t}$, and $q_{i,cbdc,t}$ to get:

$$\frac{1}{\theta}\left[\nu_{i,c,t}q_{i,c,t}^{\theta}+\nu_{i,d,t}\left[q_{i,d,t}^{\varphi}+\frac{\nu_{i,cbdc,t}}{\nu_{i,d,t}}q_{i,cbdc,t}^{\varphi}\right]^{\frac{\theta}{\varphi}}\right]^{\frac{1}{\theta}-1}\nu_{i,c,t}\theta q_{i,c,t}^{\theta-1}=\lambda \tag{18}$$

$$\frac{1}{\theta}\left[\nu_{i,c,t}q_{i,c,t}^{\theta}+\nu_{i,d,t}\left[q_{i,d,t}^{\varphi}+\frac{\nu_{i,cbdc,t}}{\nu_{i,d,t}}q_{i,cbdc,t}^{\varphi}\right]^{\frac{\theta}{\varphi}}\right]^{\frac{1}{\theta}-1}\nu_{i,d,t}\frac{\theta}{\varphi}\left[q_{i,d,t}^{\varphi}+\frac{\nu_{i,cbdc,t}}{\nu_{i,d,t}}q_{i,cbdc,t}^{\varphi}\right]^{\frac{\theta}{\varphi}-1}\varphi q_{i,d,t}^{\varphi-1}=\lambda \tag{19}$$

$$\frac{1}{\theta}\left[\nu_{i,c,t}q_{i,c,t}^{\theta}+\nu_{i,d,t}\left[q_{i,d,t}^{\varphi}+\frac{\nu_{i,cbdc,t}}{\nu_{i,d,t}}q_{i,cbdc,t}^{\varphi}\right]^{\frac{\theta}{\varphi}}\right]^{\frac{1}{\theta}-1}\nu_{i,d,t}\frac{\theta}{\varphi}\left[q_{i,d,t}^{\varphi}+\frac{\nu_{i,cbdc,t}}{\nu_{i,d,t}}q_{i,cbdc,t}^{\varphi}\right]^{\frac{\theta}{\varphi}-1}\frac{\nu_{i,cbdc,t}}{\nu_{i,d,t}}\varphi q_{i,cbdc,t}^{\varphi-1}=\lambda \tag{20}$$

Divide the first order conditions with respect to $q_{i,d,t}$ (19) and $q_{i,cbdc,t}$ (20) to get:

$$\frac{q_{i,d,t}}{q_{i,cbdc,t}}=\left(\frac{\nu_{i,d,t}}{\nu_{i,cbdc,t}}\right)^{\frac{1}{1-\varphi}} \tag{21}$$

Divide the first order conditions with respect to $q_{i,d,t}$ (19) and $q_{i,c,t}$ (18) to get:

$$\frac{\nu_{i,d,t}\left[q_{i,d,t}^{\varphi}+\frac{\nu_{i,cbdc,t}}{\nu_{i,d,t}}q_{i,cbdc,t}^{\varphi}\right]^{\frac{\theta}{\varphi}-1}q_{i,d,t}^{\varphi-1}}{\nu_{i,c,t}q_{i,c,t}^{\theta-1}}=1 \tag{22}$$

which can be rearranged to:

$$\frac{\nu_{i,d,t}\left[1+\frac{\nu_{i,cbdc,t}}{\nu_{i,d,t}}\frac{q_{i,cbdc,t}^{\varphi}}{q_{i,d,t}^{\varphi}}\right]^{\frac{\theta}{\varphi}-1}q_{i,d,t}^{\theta-1}}{\nu_{i,c,t}q_{i,c,t}^{\theta-1}}=1 \tag{23}$$

Using (21) and (23), the deposit-to-cash ratio after CBDC issuance can be written as:

$$\frac{q_{i,d,t}}{q_{i,c,t}}=\left(1+\frac{q_{i,cbdc,t}}{q_{i,d,t}}\right)^{\frac{\varphi-\theta}{\varphi(\theta-1)}}\left(\frac{\nu_{i,d,t}}{\nu_{i,c,t}}\right)^{\frac{1}{1-\theta}} \tag{24}$$

Note that when $\varphi=\theta$, this reduces to the CES utility case and the deposit-to-cash ratio is identical to (14), which is independent from CBDC. This resembles the independence of irrelevant alternative property under the logit model.

Suppose $\nu_{i,j,t}$ is an exponential function of the product attributes and household characteristics, as in Appendix A.1. The deposit-to-cash ratio (24) after CBDC issuance under the nested CES utility here is equivalent to that under the nested logit model (8) when $\tau_d-1=\frac{\varphi-\theta}{\varphi(\theta-1)}$, where τ_d is the inverse measure of the correlation between the unobserved utilities for similar products under the nested logit.

It can be seen from Appendix A.1 that the deposit-to-cash ratio before the CBDC issuance is $\left(\frac{\nu_{i,d,t}}{\nu_{i,c,t}}\right)^{\frac{1}{1-\theta}}$. Hence, similar to the prediction from the nested logit model (8), the deposit-to-cash ratio after the CBDC issuance is a fraction of that before the CBDC issuance, where the fraction depends on how CBDC is valued against deposits (indicated by $\frac{q_{i,cbdc,t}}{q_{i,d,t}}$) and the degree of substitutability between CBDC and deposits $\frac{\varphi-\theta}{\varphi(\theta-1)}$.

B Choice Probabilities under Nested Logit Model

This section shows the probabilities of holding each dollar in each asset/product under the nested logit model, where the choice probabilities are interpreted as the portfolio shares as discussed in Section 2.1. It also shows how the deposit-to-cash ratio and the CBDC share are affected by the correlation between the unobserved utilities for similar products. This section shows the cases when CBDC is a closer substitute for deposits and cash in turn.

B.1 CBDC and Deposits are Closer Substitutes

Suppose CBDC and deposits are in the same nest B_{d_cbdc}, then the deposit share is the conditional probability of choosing deposits from the nest B_{d_cbdc} multiplied by the probability of choosing the nest B_{d_cbdc}:

$$s'_{i,d,t} = \underbrace{\frac{\exp\left(\frac{V_{i,d,t}}{\tau_d}\right)}{\exp\left(\frac{V_{i,cbdc,t}}{\tau_d}\right) + \exp\left(\frac{V_{i,d,t}}{\tau_d}\right)}}_{\text{Prob}(j=d|j\in B_{d\_cbdc})} \underbrace{\frac{\left[\exp\left(\frac{V_{i,cbdc,t}}{\tau_d}\right) + \exp\left(\frac{V_{i,d,t}}{\tau_d}\right)\right]^{\tau_d}}{\left[\exp\left(\frac{V_{i,cbdc,t}}{\tau_d}\right) + \exp\left(\frac{V_{i,d,t}}{\tau_d}\right)\right]^{\tau_d} + \exp\left(V_{i,c,t}\right)}}_{\text{Prob}(j\in B_{d\_cbdc})} \tag{25}$$

and the cash share is:

$$s'_{i,c,t} = \frac{\exp\left(V_{i,c,t}\right)}{\left[\exp\left(\frac{V_{i,cbdc,t}}{\tau_d}\right) + \exp\left(\frac{V_{i,d,t}}{\tau_d}\right)\right]^{\tau_d} + \exp\left(V_{i,c,t}\right)} \tag{26}$$

where $\tau_d \equiv \sqrt{1-\rho_{d\_cbdc}} \in (0,1]$ is an inverse measure of the correlation $\rho_{d\_cbdc} \in [0,1)$ between the unobserved utilities for deposits and CBDC.

Divide the deposit share (25) by the cash share (26) to get the deposit-to-cash ratio after

CBDC issuance:

$$\begin{aligned}\frac{s'_{i,d,t}}{s'_{i,c,t}} &= \frac{\exp\left(\frac{V_{i,d,t}}{\tau_d}\right)\left[\exp\left(\frac{V_{i,d,t}}{\tau_d}\right)+\exp\left(\frac{V_{i,cbdc,t}}{\tau_d}\right)\right]^{\tau_d-1}}{\exp\left(V_{i,c,t}\right)} \\ &= \exp\left(V_{i,d,t}-V_{i,c,t}\right)\exp\left(\frac{V_{i,d,t}}{\tau_d}-V_{i,d,t}\right)\left[\exp\left(\frac{V_{i,d,t}}{\tau_d}\right)+\exp\left(\frac{V_{i,cbdc,t}}{\tau_d}\right)\right]^{\tau_d-1} \\ &= \left[1+\exp\left(\frac{V_{i,cbdc,t}-V_{i,d,t}}{\tau_d}\right)\right]^{\tau_d-1}\exp\left(V_{i,d,t}-V_{i,c,t}\right)\end{aligned} \tag{27}$$

where $\exp\left(V_{i,d,t}-V_{i,c,t}\right)=\frac{s_{i,d,t}}{s_{i,c,t}}$ is the deposit-to-cash ratio before the CBDC issuance, as can be seen from (4). Since $\left[1+\exp\left(\frac{V_{i,cbdc,t}-V_{i,d,t}}{\tau_d}\right)\right]>1$ and $(\tau_d-1)\leqslant 0$, the fraction is $0<\left[1+\exp\left(\frac{V_{i,cbdc,t}-V_{i,d,t}}{\tau_d}\right)\right]^{\tau_d-1}\leqslant 1$. As a consequence, $\frac{s'_{i,d,t}}{s'_{i,c,t}}\leqslant\frac{s_{i,d,t}}{s_{i,c,t}}$.

To see how the inverse correlation measure τ_d affects the deposit-to-cash ratio, differentiate (27) with respect to τ_d to get:

$$\begin{aligned}\frac{\partial\frac{s'_{i,d,t}}{s'_{i,c,t}}}{\partial\tau_d} &= \left[1+\exp\left(\frac{V_{i,cbdc,t}-V_{i,d,t}}{\tau_d}\right)\right]^{\tau_d-1}\ln\left(1+\exp\left(\frac{V_{i,cbdc,t}-V_{i,d,t}}{\tau_d}\right)\right)\frac{s_{i,d,t}}{s_{i,c,t}} \\ &\quad+(\tau_d-1)\left[1+\exp\left(\frac{V_{i,cbdc,t}-V_{i,d,t}}{\tau_d}\right)\right]^{\tau_d-2}\exp\left(\frac{V_{i,cbdc,t}-V_{i,d,t}}{\tau_d}\right)\left(-\frac{V_{i,cbdc,t}-V_{i,d,t}}{\tau_d^2}\right)\frac{s_{i,d,t}}{s_{i,c,t}} \\ &= \left(1+\frac{s_{i,cbdc,t}}{s'_{i,d,t}}\right)^{\tau_d-1}\frac{s_{i,d,t}}{s_{i,c,t}}\left[\ln\left(1+\frac{s_{i,cbdc,t}}{s'_{i,d,t}}\right)+(\tau_d-1)\frac{1}{1+\frac{s_{i,cbdc,t}}{s'_{i,d,t}}}\frac{\partial\frac{s_{i,cbdc,t}}{s'_{i,d,t}}}{\partial\tau_d}\right] \\ &= \frac{s'_{i,d,t}}{s'_{i,c,t}}\left[\ln\left(1+\frac{s_{i,cbdc,t}}{s'_{i,d,t}}\right)+(\tau_d-1)\frac{1}{1+\frac{s_{i,cbdc,t}}{s'_{i,d,t}}}\frac{\partial\frac{s_{i,cbdc,t}}{s'_{i,d,t}}}{\partial\tau_d}\right]\end{aligned} \tag{28}$$

As can be seen from (28), how the deposit-to-cash ratio changes with τ_d depends on how the CBDC-to-deposit ratio $\frac{s_{i,cbdc,t}}{s'_{i,d,t}}=\exp\left(\frac{V_{i,cbdc,t}-V_{i,d,t}}{\tau_d}\right)$ changes with τ_d:

$$\frac{\partial\frac{s_{i,cbdc,t}}{s'_{i,d,t}}}{\partial\tau_d}=\exp\left(\frac{V_{i,cbdc,t}-V_{i,d,t}}{\tau_d}\right)\left(-\frac{V_{i,cbdc,t}-V_{i,d,t}}{\tau_d^2}\right) \tag{29}$$

which in turn depends on the sign of the observed utility difference $(V_{i,cbdc,t}-V_{i,d,t})$. When $V_{i,cbdc,t}-V_{i,d,t}\geqslant 0$, the deposit-to-cash ratio increases in τ_d. In contrast, when $V_{i,cbdc,t}-V_{i,d,t}<0$, the deposit-to-cash ratio can decrease in τ_d.

Since the asset shares sum to one, i.e., $s'_{i,c,t}+s'_{i,d,t}+s_{i,cbdc,t}=1$, divide this identity by

$s'_{i,d,t}$ and rearrange to write the CBDC share $s_{i,cbdc,t}$ in terms of the deposit-to-cash ratio:

$$s_{i,cbdc,t} = \frac{\frac{s_{i,cbdc,t}}{s'_{i,d,t}}}{1 + \frac{s'_{i,c,t}}{s'_{i,d,t}} + \frac{s_{i,cbdc,t}}{s'_{i,d,t}}} \tag{30}$$

To see how $s_{i,cbdc,t}$ changes with τ_d, differentiate $s_{i,cbdc,t}$ (30) with respect to τ_d:

$$\begin{aligned} \frac{\partial s_{i,cbdc,t}}{\partial \tau_d} &= \frac{\frac{\partial \frac{s_{i,cbdc,t}}{s'_{i,d,t}}}{\partial \tau_d}}{1 + \frac{s'_{i,c,t}}{s'_{i,d,t}} + \frac{s_{i,cbdc,t}}{s'_{i,d,t}}} - \frac{\frac{s_{i,cbdc,t}}{s'_{i,d,t}}}{\left(1 + \frac{s'_{i,c,t}}{s'_{i,d,t}} + \frac{s_{i,cbdc,t}}{s'_{i,d,t}}\right)^2} \left[- \left(\frac{s'_{i,d,t}}{s'_{i,c,t}}\right)^{-2} \frac{\partial \frac{s'_{i,d,t}}{s'_{i,c,t}}}{\partial \tau_d} + \frac{\partial \frac{s_{i,cbdc,t}}{s'_{i,d,t}}}{\partial \tau_d} \right] \\ &= \frac{\partial \frac{s_{i,cbdc,t}}{s'_{i,d,t}}}{\partial \tau_d} \frac{1 + \frac{s'_{i,c,t}}{s'_{i,d,t}}}{\left(1 + \frac{s'_{i,c,t}}{s'_{i,d,t}} + \frac{s_{i,cbdc,t}}{s'_{i,d,t}}\right)^2} + \frac{\partial \frac{s'_{i,d,t}}{s'_{i,c,t}}}{\partial \tau_d} \frac{\frac{s_{i,cbdc,t}}{s'_{i,d,t}} \left(\frac{s'_{i,d,t}}{s'_{i,c,t}}\right)^{-2}}{\left(1 + \frac{s'_{i,c,t}}{s'_{i,d,t}} + \frac{s_{i,cbdc,t}}{s'_{i,d,t}}\right)^2} \end{aligned} \tag{31}$$

Define $\Lambda \equiv \left(1 + \frac{s'_{i,c,t}}{s'_{i,d,t}} + \frac{s_{i,cbdc,t}}{s'_{i,d,t}}\right)$ and substitute (28) into (31) to get:

$$\begin{aligned} \frac{\partial s_{i,cbdc,t}}{\partial \tau_d} &= \frac{\partial \frac{s_{i,cbdc,t}}{s'_{i,d,t}}}{\partial \tau_d} \frac{1 + \frac{s'_{i,c,t}}{s'_{i,d,t}}}{\Lambda^2} + \frac{\frac{s_{i,cbdc,t}}{s'_{i,d,t}} \left(\frac{s'_{i,d,t}}{s'_{i,c,t}}\right)^{-2}}{\Lambda^2} \frac{s'_{i,d,t}}{s'_{i,c,t}} \left[\ln\left(1 + \frac{s_{i,cbdc,t}}{s'_{i,d,t}}\right) + (\tau_d - 1) \frac{1}{1 + \frac{s_{i,cbdc,t}}{s'_{i,d,t}}} \frac{\partial \frac{s_{i,cbdc,t}}{s'_{i,d,t}}}{\partial \tau_d} \right] \\ &= \frac{\partial \frac{s_{i,cbdc,t}}{s'_{i,d,t}}}{\partial \tau_d} \frac{1}{\Lambda^2} \left[1 + \frac{s'_{i,c,t}}{s'_{i,d,t}} + \left(\frac{s'_{i,d,t}}{s'_{i,c,t}}\right)^{-1} \frac{(\tau_d - 1)}{\frac{s'_{i,d,t}}{s_{i,cbdc,t}} + 1} \right] + \frac{\frac{s_{i,cbdc,t}}{s'_{i,d,t}} \left(\frac{s'_{i,d,t}}{s'_{i,c,t}}\right)^{-1}}{\Lambda^2} \ln\left(1 + \frac{s_{i,cbdc,t}}{s'_{i,d,t}}\right) \\ &= \frac{\partial \frac{s_{i,cbdc,t}}{s'_{i,d,t}}}{\partial \tau_d} \frac{1}{\Lambda^2} \left[1 + \frac{s'_{i,c,t}}{s'_{i,d,t}} \left(1 + \frac{(\tau_d - 1)}{\frac{s'_{i,d,t}}{s_{i,cbdc,t}} + 1}\right) \right] + \frac{\frac{s_{i,cbdc,t}}{s'_{i,d,t}} \frac{s'_{i,c,t}}{s'_{i,d,t}}}{\Lambda^2} \ln\left(1 + \frac{s_{i,cbdc,t}}{s'_{i,d,t}}\right) \end{aligned} \tag{32}$$

Since $\tau_d \in (0, 1]$ and $\frac{s'_{i,d,t}}{s_{i,cbdc,t}} > 0$, the term $\left(1 + \frac{(\tau_d - 1)}{\frac{s'_{i,d,t}}{s_{i,cbdc,t}} + 1}\right)$ is positive. Hence, the sign of the derivative $\frac{\partial s_{i,cbdc,t}}{\partial \tau_d}$ depends on how the CBDC-to-deposit ratio $\frac{s_{i,cbdc,t}}{s'_{i,d,t}}$ changes with τ_d (29), which in turn depends on the sign of the observed utility difference $(V_{i,cbdc,t} - V_{i,d,t})$. When $V_{i,cbdc,t} - V_{i,d,t} > 0$, it is ambiguous how the CBDC share changes with τ_d. When $V_{i,cbdc,t} - V_{i,d,t} \leqslant 0$, it is unambiguous that the CBDC share increases in τ_d.

B.2 CBDC and Cash are Closer Substitutes

If CBDC and cash are in the same nest, following similar steps in B.1, the deposit-to-cash ratio after CBDC issuance is:

$$\frac{s'_{i,d,t}}{s'_{i,c,t}} = \left[1 + \exp\left(\frac{V_{i,cbdc,t} - V_{i,c,t}}{\tau_c}\right)\right]^{1-\tau_c} \exp\left(V_{i,d,t} - V_{i,c,t}\right) \tag{33}$$

where $\tau_c \equiv \sqrt{1 - \rho_{c\_cbdc}} \in (0, 1]$ is an inverse measure of the correlation $\rho_{c\_cbdc} \in [0, 1)$ and $\exp\left(V_{i,d,t} - V_{i,c,t}\right) = \frac{s_{i,d,t}}{s_{i,c,t}}$ is the deposit-to-cash ratio before the CBDC issuance. Since $\left[1 + \exp\left(\frac{V_{i,cbdc,t} - V_{i,c,t}}{\tau_c}\right)\right] > 1$ and $(1 - \tau_c) \geqslant 0$, the factor $\left[1 + \exp\left(\frac{V_{i,cbdc,t} - V_{i,c,t}}{\tau_c}\right)\right]^{1-\tau_c} \geqslant 1$. As a consequence, $\frac{s'_{i,d,t}}{s'_{i,c,t}} \geqslant \frac{s_{i,d,t}}{s_{i,c,t}}$.

To see how the inverse correlation measure τ_c affects the deposit-to-cash ratio, differentiate (33) with respect to τ_c and simplify to get:

$$\frac{\partial \frac{s'_{i,d,t}}{s'_{i,c,t}}}{\partial \tau_c} = \frac{s'_{i,d,t}}{s'_{i,c,t}} \left[-\ln\left(1 + \frac{s_{i,cbdc,t}}{s'_{i,c,t}}\right) + (1 - \tau_c)\frac{1}{1 + \frac{s_{i,cbdc,t}}{s'_{i,c,t}}} \frac{\partial \frac{s_{i,cbdc,t}}{s'_{i,c,t}}}{\partial \tau_c}\right] \tag{34}$$

where $\frac{s_{i,cbdc,t}}{s'_{i,c,t}} = \exp\left(\frac{V_{i,cbdc,t} - V_{i,c,t}}{\tau_c}\right)$ and the derivative of $\frac{s_{i,cbdc,t}}{s'_{i,c,t}}$ with respect to τ_c is:

$$\frac{\partial \frac{s_{i,cbdc,t}}{s'_{i,c,t}}}{\partial \tau_c} = \exp\left(\frac{V_{i,cbdc,t} - V_{i,c,t}}{\tau_c}\right)\left(-\frac{V_{i,cbdc,t} - V_{i,c,t}}{\tau_c^2}\right) \tag{35}$$

As can be seen from (34), how the deposit-to-cash ratio changes with τ_c depends on how the CBDC-to-cash ratio $\frac{s_{i,cbdc,t}}{s'_{i,c,t}}$ changes with τ_c (35), which in turn depends on how the observed utility for CBDC compares with that for cash. When $V_{i,cbdc,t} - V_{i,c,t} \geqslant 0$, the deposit-to-cash ratio unambiguously decreases in τ_c. When $V_{i,cbdc,t} - V_{i,c,t} < 0$, the deposit-to-cash ratio can increase in τ_c.

Divide the identity $s'_{i,c,t} + s'_{i,d,t} + s_{i,cbdc,t} = 1$ by $s'_{i,c,t}$ and rearrange to write the CBDC share $s_{i,cbdc,t}$ in terms of the deposit-to-cash ratio:

$$s_{i,cbdc,t} = \frac{\frac{s_{i,cbdc,t}}{s'_{i,c,t}}}{1 + \frac{s'_{i,d,t}}{s'_{i,c,t}} + \frac{s_{i,cbdc,t}}{s'_{i,c,t}}} \tag{36}$$

To see how $s_{i,cbdc,t}$ changes with τ_c, differentiate $s_{i,cbdc,t}$ (36) with respect to τ_c:

$$\begin{aligned}\frac{\partial s_{i,cbdc,t}}{\partial \tau_c} &= \frac{\frac{\partial \frac{s_{i,cbdc,t}}{s'_{i,c,t}}}{\partial \tau_c}}{1+\frac{s'_{i,d,t}}{s'_{i,c,t}}+\frac{s_{i,cbdc,t}}{s'_{i,c,t}}} - \frac{\frac{s_{i,cbdc,t}}{s'_{i,c,t}}}{\left(1+\frac{s'_{i,d,t}}{s'_{i,c,t}}+\frac{s_{i,cbdc,t}}{s'_{i,c,t}}\right)^2}\left(\frac{\partial \frac{s'_{i,d,t}}{s'_{i,c,t}}}{\partial \tau_c}+\frac{\partial \frac{s_{i,cbdc,t}}{s'_{i,c,t}}}{\partial \tau_c}\right) \\ &= \frac{\partial \frac{s_{i,cbdc,t}}{s'_{i,c,t}}}{\partial \tau_c}\frac{1+\frac{s'_{i,d,t}}{s'_{i,c,t}}}{\left(1+\frac{s'_{i,d,t}}{s'_{i,c,t}}+\frac{s_{i,cbdc,t}}{s'_{i,c,t}}\right)^2} - \frac{\partial \frac{s'_{i,d,t}}{s'_{i,c,t}}}{\partial \tau_c}\frac{\frac{s_{i,cbdc,t}}{s'_{i,c,t}}}{\left(1+\frac{s'_{i,d,t}}{s'_{i,c,t}}+\frac{s_{i,cbdc,t}}{s'_{i,c,t}}\right)^2}\end{aligned} \tag{37}$$

Define $\Omega \equiv \left(1+\frac{s'_{i,d,t}}{s'_{i,c,t}}+\frac{s_{i,cbdc,t}}{s'_{i,c,t}}\right)$. Substitute (34) into (37) and simplify to get:

$$\frac{\partial s_{i,cbdc,t}}{\partial \tau_c} = \frac{\partial \frac{s_{i,cbdc,t}}{s'_{i,c,t}}}{\partial \tau_c}\frac{1}{\Omega^2}\left[1+\frac{s'_{i,d,t}}{s'_{i,c,t}}\left(1-\frac{(1-\tau_c)}{\frac{s'_{i,c,t}}{s_{i,cbdc,t}}+1}\right)\right] + \frac{\frac{s_{i,cbdc,t}}{s'_{i,c,t}}\frac{s'_{i,d,t}}{s'_{i,c,t}}}{\Omega^2}\ln\left(1+\frac{s_{i,cbdc,t}}{s'_{i,c,t}}\right) \tag{38}$$

Since $\tau_c \in (0,1]$ and $\frac{s'_{i,c,t}}{s_{i,cbdc,t}} > 0$, the term $\left(1-\frac{(1-\tau_c)}{\frac{s'_{i,d,t}}{s_{i,cbdc,t}}+1}\right)$ is positive. Hence, how the CBDC share changes with τ_c depends on how the CBDC-to-deposit ratio $\frac{s_{i,cbdc,t}}{s'_{i,c,t}}$ changes with τ_c (35), which in turn depends on the sign of the observed utility difference $(V_{i,cbdc,t} - V_{i,c,t})$. When $V_{i,cbdc,t} - V_{i,c,t} > 0$, it is ambiguous how the CBDC share changes with the inverse correlation measure τ_c. In contrast, when $V_{i,cbdc,t} - V_{i,c,t} \leqslant 0$, it is unambiguous that the CBDC share increases in τ_c.

C Data

This section discusses the main data sources used in this paper. Section C.1 discusses the measures of cash holding, deposit holding, and the main financial institution, and shows the transaction frequency for different payment instruments using the CFM data. Section C.2 explains the construction of the merchant acceptance rate using the MOP 2013 data. Section C.3 discusses the demand deposit rates from CANNEX data. Section C.4 shows the construction of the sample weights in the merged sample of CFM and MOP survey data. Section C.5 shows the summary statistics.

C.1 Canadian Financial Monitor Survey

The CFM survey data are available from 1999, but the information on cash holding is only available from 2009. In addition, the CFM survey became an online survey after 2018, so the most recent data are less comparable with the offline surveys from previous years. This paper uses the sample period of 2010–2017 because the survey questions on cash changed in 2009 and 2018. In 2009, the question on cash in wallet is, "On average, how much cash on hand was held for regular day-to-day use?". After 2009, the question changed to: "How much cash do you have in your purse or wallet right now?". The question on precautionary cash holding also changed in 2018: "How much cash does your household hold outside your purse, wallet, or pockets right now?". Prior to 2018, the question was, "(On average), how much cash on hand does your household hold for emergencies, or other precautionary reasons?".

C.1.1 Cash Holding

In the baseline analysis, cash is measured by the sum of cash in wallet and precautionary cash holdings using the CFM data. There are two caveats: (1) cash in wallet is at an individual level while the precautionary cash holding is at a household level; (2) the answer for cash in wallet is in the nearest Canadian dollar, while that for the precautionary cash holding is in one of the following categories in Canadian dollars: none/zero, 1–49, 50–99, 100–249, 250–499, 500–999, 1000–2999, 3000 or more. I take the middle point of each category and if a household is in the top category (i.e., 3000 or more), I assume the precautionary cash holding for that household is 3000. Taking the upper bound at \$3000 is similar to winsorizing the data at the 96th percentile, since around 4% of observations are in the top category during 2010–2017.

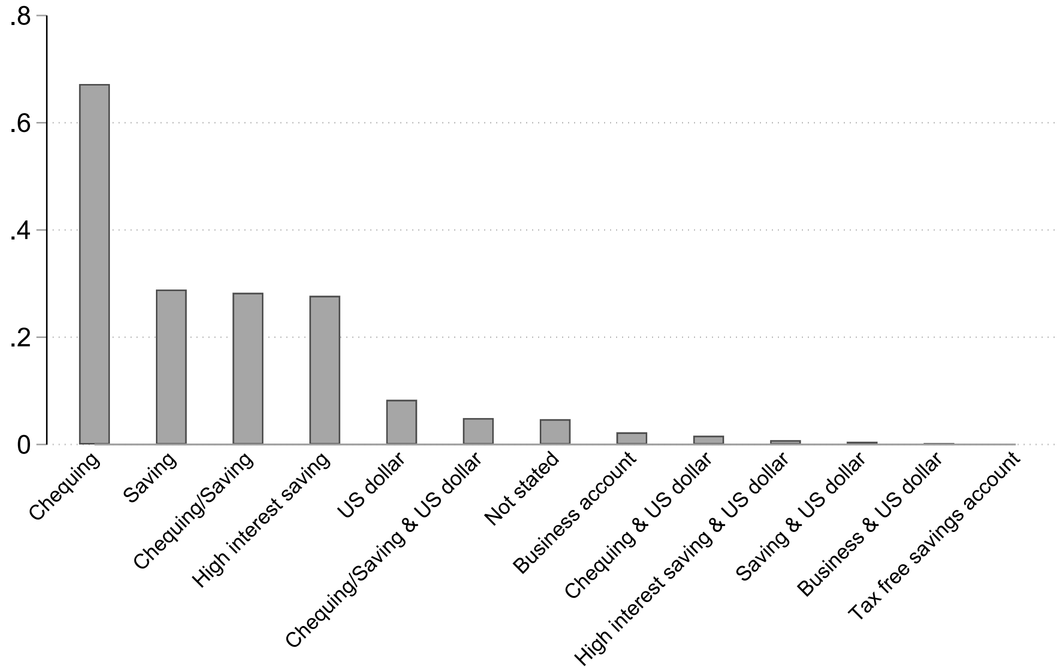
To address these two caveats, I check the results using the precautionary cash holding only, since the demand deposit balance is calculated at the household level and is also answered in one of the balance categories. The baseline results in the paper are robust using this alternative measure of cash. This is not surprising since the correlation between the total cash holding and the precautionary cash holding is around 0.98.

C.1.2 Deposit Holding

The CFM survey asks respondents to provide information on bank accounts (including the current balance, the type of account, associated financial institution, etc.) owned by each person in the household. The types of account include: chequing, saving, chequing/saving, high interest saving, chequing & US dollars, saving & US dollars, chequing/saving & US dollars, high interest saving & US dollars, etc.

The current balance in each bank account is answered in one of the following categories in Canadian dollars: non/zero, under 100, 100–499, 500–999, ..., 600,000–749,999, 750,000 or above. There are 38 categories between the smallest category (none/zero) and the highest category ($750K or over). I take the middle point of each category and if a household is in the top category (i.e., $750K or over), I assume the balance in the given bank account is $750K. In this paper, I focus on households' balances in demand deposit accounts (i.e., chequing, saving, chequing/saving accounts), where the maximum demand deposit balance across households is around $526K during 2010–2017.

Figure 10: Fraction of Household-year Observations for Different Bank Accounts



Data source: CFM 2010–2017

Note: The bar chart shows the fraction of household-year observations that have a positive balance in a given type of bank account in the merged sample of CFM and MOP.

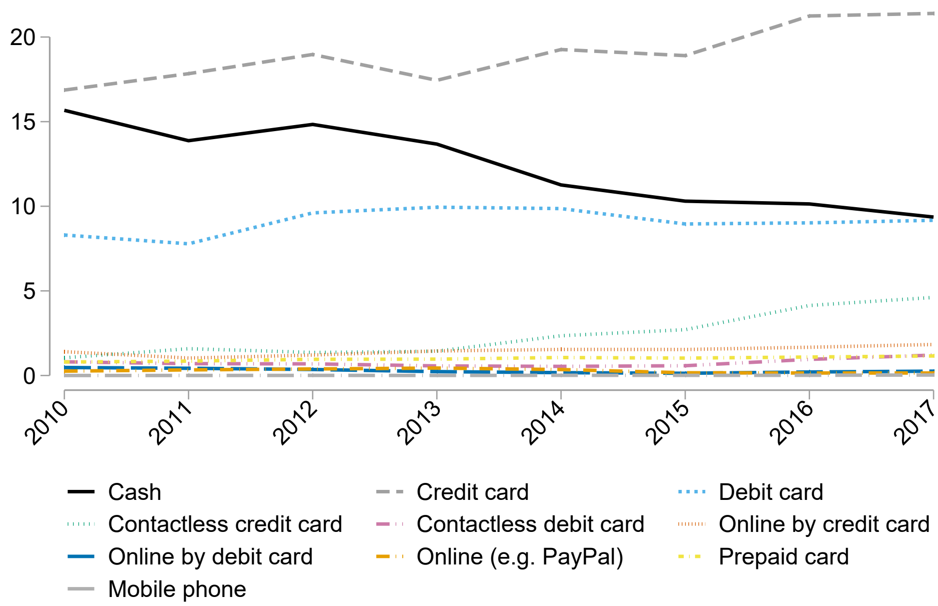
C.1.3 Main Financial Institution

There are two questions asking about the financial institutions (FIs) in the CFM survey. One question from section 1 of the survey is, "What is your main financial institution?". Each household can enter a maximum of three different main FIs, although around 67% of the household-year observations only enter one main FI. The other question on FIs is from the section on bank accounts in the survey, where the respondent needs to enter the FI associated with each bank account owned by each individual in the household.

Since this paper focuses on the demand deposits, I construct the main FI for each household using the information from the section on bank accounts. For each household, the FI that has the highest demand deposit balance is treated as the main FI. When different FIs have equal balances for a given household, the one that is treated as the main FI is the one that coincides with the main FI answered in section 1 of the survey.

C.1.4 Household Payment Patterns

Figure 11: Weighted Mean Number of Transactions (Past Month) across Households



Data source: CFM 2010–2017
Note: The graph plots the weighted mean number of transactions (in the past month) via each payment instrument across households in the merged sample of CFM and MOP, where the sample weights are applied. The survey question for each payment instrument usage (except for cash) is, "How many times has your household completed each of these transactions in the past month?". The survey question for cash usage is, "How many times did your household use cash to make purchases in the past week?". The answers for cash usage are multiplied by four to reflect the number of transactions in the past month.

C.2 Methods-of-Payment Survey 2013

Both the MOP survey questionnaire and the payment diary contain information on merchant acceptance. This section explains why I use the MOP payment diary to construct the merchant acceptance rate. There are two questions related to merchant acceptance from the MOP survey questionnaire. One question is to ask people whether they think acceptance is an important feature when considering how to pay. However, using these perceptions on the importance of acceptance feature could potentially lead to simultaneous causality. A person that prefers to use deposits to pay and hence holds more deposits may think acceptance is more important.

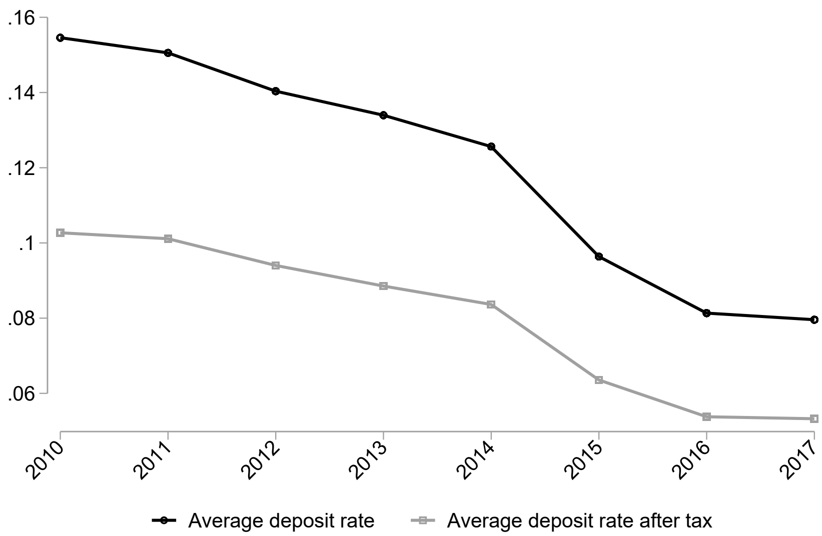
Another question from the survey questionnaire is to ask people whether they think a given payment instrument is widely accepted. The categories that people can choose from include: rarely accepted, occasionally accepted, often accepted, almost always accepted, and not sure. These perceptions tend to be less informative than the acceptance rate calculated using the payment diary because the perceptions of acceptance are not the only determinant for which stores people want to visit. They will also consider factors such as the location and the quality of the goods. For example, when some people perceive debit cards to be less widely accepted, this does not necessarily mean they would hold more cash and use cash to pay since they can avoid the cash-only stores or they may prefer to shop in the stores that accept cards anyway. In contrast, the card acceptance rates experienced by individuals through their own transactions tend to result from the individuals' optimal decisions in terms of which stores to visit, which are likely to matter more for their allocation between deposits and cash. Therefore, this paper uses the information from the MOP payment diary to construct the individual-level acceptance rate.

C.3 CANNEX Deposit Rates

CANNEX data are at a bank-product-week level. I average the weekly rates to get the annual rates. I use the deposit products from the high interest chequing category classified in CANNEX, because they are likely to be the most relevant for the demand deposit rates. Other categories of deposit products during the sample period include daily interest savings which are non-chequable and offer much higher deposit rates, daily interest chequing which tend to have rates close to zero throughout the sample period, daily interest investment for large balances, and senior and junior accounts that target particular groups of people. The high interest chequing accounts offer different tiers of interest rates, where the rate is higher for a larger balance. I take the average rate across different tiers to get the deposit rate of a given product. Each of the banks that I use has one product in this high interest chequing category except for CIBC which has two. To get the deposit rate at a bank-year level for CIBC, I average the deposit rates across the two products.

The deposit rates for the high interest chequing accounts are available for the big six, Laurentian Bank, Alterna Bank, Alterna Savings, and Manulife Bank over the sample period of 2010–2017. However, the latter three are not on the CFM choice list, so I use the deposit rates for the big six and Laurentian Bank which can be matched to the CFM data.

Figure 12: Average Deposit Rates across Households over Time



Data sources: CANNEX 2010–2017, CFM 2010–2017, Government of Canada website
Note: The graph plots the average deposit rates before and after income taxes across households in the merged sample of CFM and MOP data. Households face different deposit rates (after taxes) as they save at different banks (and have different marginal income tax rates). The bank-level deposit rates are from CANNEX data and the federal and provincial income tax rates are from the Government of Canada website.

C.4 Sample Weights

To construct the sample weights for the merged sample of CFM 2010–2017 and MOP 2013, I use the population targets from National Household Survey 2011, Census 2011, and Census 2016 from StatCan. The sample weights are mainly used in calculating the descriptive statistics and estimating the weighted regression for robustness checks.

Table 5 in this section shows the population statistics in 2011 and 2016 only, due to the infrequency of the census data. The sample weights for the merged sample (covering the period of 2010–2017) of MOP and CFM are calibrated to target the statistics in year 2011 (2016) for the period of 2010–2013 (2014–2017). The population targets used in the weight calibration include household size, household income, household home ownership, and household head age, each nested within a given region (i.e., Atlantic and Prairies, Quebec, Ontario, British Columbia). As shown in Table 5, Atlantic region only accounts for 7% of the population, so it is combined with Prairies to ensure there are enough households in each stratum. The weighted sample data would match the population targets in Table 5. For example, the weighted fraction of households with a household size of one in Quebec would be 0.33.

I use the iterative proportional fitting to calibrate the weights in each year, which is commonly used in sample calibration as documented in Kolenikov (2014) and Vincent (2013). The first step is to specify the initial weights. I use the population totals over the number of households in the sample for each income-region category as initial weights. Using population totals over the number of households in the sample to generate the same initial weight for everyone does not affect the raking procedure and gives the same calibrated weights. The second step is to update the sample weights for each targeted demographic category in turn such that the weighted totals (of households) match the population counts in the given demographic category. The second step is repeated until the distances between the weighted totals and the population totals are minimized for all the targeted demographic categories.

Table 5: StatCan Targets for Private Households

(a) Population Statistics in 2016

	Atlantic	Quebec	Ontario	Prairies	BC	Canada
Region						
	0.07	0.25	0.37	0.17	0.13	1.00
Household Size						
1	0.28	0.33	0.26	0.25	0.29	0.28
2	0.40	0.35	0.33	0.34	0.35	0.34
3	0.16	0.14	0.16	0.15	0.15	0.15
4 or more	0.17	0.18	0.25	0.25	0.21	0.22
Household Income						
Less than 30K	0.21	0.21	0.17	0.14	0.19	0.18
30-60K	0.28	0.29	0.23	0.21	0.24	0.25
60-100K	0.25	0.25	0.25	0.24	0.25	0.25
More than 100K	0.26	0.24	0.35	0.41	0.32	0.32
Household Home Ownership						
Rent	0.27	0.39	0.30	0.27	0.32	0.32
Own	0.73	0.61	0.70	0.73	0.68	0.68
Household Head Age						
Under 34	0.15	0.17	0.16	0.21	0.17	0.17
35-44	0.15	0.17	0.17	0.19	0.16	0.17
45-54	0.20	0.19	0.22	0.20	0.20	0.20
55-64	0.21	0.21	0.20	0.19	0.21	0.20
65 or older	0.28	0.25	0.25	0.21	0.26	0.25

(b) Population Statistics in 2011

	Atlantic	Quebec	Ontario	Prairies	BC	Canada
Region						
	0.07	0.26	0.37	0.17	0.13	1.00
Household Size						
1	0.26	0.32	0.25	0.26	0.28	0.28
2	0.39	0.35	0.32	0.34	0.35	0.34
3	0.17	0.15	0.16	0.15	0.15	0.16
4 or more	0.19	0.18	0.26	0.24	0.22	0.23
Household Income						
Less than 30K	0.26	0.27	0.20	0.19	0.23	0.22
30-60K	0.29	0.30	0.26	0.24	0.26	0.27
60-100K	0.25	0.24	0.25	0.25	0.25	0.25
More than 100K	0.20	0.19	0.29	0.32	0.25	0.26
Household Home Ownership						
Rent	0.26	0.39	0.28	0.26	0.30	0.31
Own	0.74	0.61	0.72	0.74	0.70	0.69
Household Head Age						
Under 34	0.16	0.19	0.16	0.22	0.17	0.18
35-44	0.17	0.17	0.19	0.19	0.18	0.18
45-54	0.22	0.22	0.24	0.22	0.22	0.23
55-64	0.21	0.20	0.19	0.18	0.20	0.19
65 or older	0.25	0.23	0.23	0.19	0.23	0.22

Data sources: StatCan (Census 2016, Census 2011, National Household Survey 2011)
Note: Each cell represents the fraction of households under the given category.

C.5 Summary Statistics

Table 6: Ratings for Payment-specific Features

Ratings	1	2	3	4	5
Cost of use	Very low cost				Very high cost
Cash	0.74	0.14	0.10	0.02	0.00
Debit card	0.27	0.37	0.20	0.12	0.02
Credit card	0.17	0.22	0.17	0.29	0.14
Mobile payment app	0.05	0.10	0.71	0.10	0.02
Prepaid card	0.12	0.17	0.49	0.15	0.05
Ease/Convenience	Very hard to use				Very easy to use
Cash	0.00	0.01	0.04	0.17	0.76
Debit card	0.00	0.01	0.10	0.29	0.59
Credit card	0.01	0.01	0.07	0.31	0.60
Mobile payment app	0.04	0.13	0.63	0.13	0.04
Prepaid card	0.02	0.06	0.45	0.28	0.18
Security/Risk	Very risky				Very secure
Cash	0.01	0.07	0.11	0.26	0.54
Debit card	0.01	0.11	0.16	0.53	0.18
Credit card	0.02	0.13	0.16	0.53	0.15
Mobile payment app	0.09	0.22	0.54	0.11	0.02
Prepaid card	0.02	0.09	0.41	0.32	0.15

Data source: MOP 2013

Note: The table summarizes the weighted fraction of households choosing each rating (from a scale of one to five) for each feature of a given payment instrument, where the sample weights are applied to the merged sample of CFM 2013 and MOP 2013. For the cost, ease of use, and security features, the ratings of 1 to 5 represent very low- to very high-cost, very hard to very easy to use, and very risky to very secure, respectively.

Table 7: Summary Statistics

Variable	Obs	Mean	sd	Min	p25	p50	p75	Max
Dependent variable								
ln(deposit/cash)	5025	3.05	1.96	-4.20	1.84	3.10	4.31	10.13
Product Attributes								
Deposit rate (after tax)	5756	0.08	0.04	0.00	0.04	0.09	0.11	0.34
Attitudes towards bundling of service	6235	1.45	1.76	0.00	0.00	1.00	3.00	5.00
Difference in ratings for cost of use	6251	0.12	0.15	-0.50	0.00	0.13	0.20	0.57
Difference in ratings for ease of use	6243	-0.02	0.07	-0.50	-0.07	0.00	0.00	0.36
Difference in ratings for security	6264	-0.05	0.12	-0.57	-0.08	-0.07	0.00	0.57
Ratings for anonymity	6296	4.10	1.72	0.00	3.00	4.00	6.00	6.00
Ratings for budgeting usefulness	6279	3.70	1.82	0.00	3.00	4.00	5.00	6.00
Fraction of online transactions	5910	0.03	0.09	0.00	0.00	0.00	0.00	1.00
Fraction of transactions cards unaccepted	5910	0.06	0.14	0.00	0.00	0.00	0.00	1.00
Household Characteristics								
Household head age	6332	52.28	14.58	18.00	41.00	53.00	63.00	95.00
Household income	6208	7.55	3.36	1.00	5.00	8.00	10.00	12.00
Household size	6332	2.14	1.19	1.00	1.00	2.00	3.00	8.00
Household head education	6310	3.82	1.39	1.00	2.00	4.00	5.00	6.00
Dislike investing in stock market	6261	6.11	2.93	1.00	4.00	6.00	9.00	10.00
Have difficulty in paying off debt	6248	3.33	2.82	1.00	1.00	2.00	5.00	10.00
Behind debt obligations in the past year	6202	0.04	0.20	.	.	.	.	.
Rent a home	6200	0.27	0.44	.	.	.	.	.
Household has a female head	6332	0.77	0.42	.	.	.	.	.
Internet access at work/school/elsewhere	6332	0.40	0.49	.	.	.	.	.
Live in rural area	6332	0.16	0.37	.	.	.	.	.
Main financial institution (FI) is TD	5864	0.18	0.38	.	.	.	.	.
Main FI is RBC	5864	0.16	0.36	.	.	.	.	.
Main FI is Laurentian Bank	5864	0.01	0.09	.	.	.	.	.
Main FI is non-big six or Laurentian Bank	5864	0.33	0.47	.	.	.	.	.

Data sources: MOP 2013, CANNEX 2010–2017, CFM 2010–2017

Note: The table summarizes the number of observations, mean, standard deviation, minimum value, 25th percentile, median, 75th percentile, and maximum value for each given variable in the merged sample of CFM 2010–2017 and MOP 2013. The original scales for attitudes towards bundling of services and the ratings for anonymity and budgeting usefulness are changed, as discussed in Section 3. Difference in ratings refers to the difference in the standardized ratings between debit card and cash for a given feature. Household income and household head education are categorical variables. General attitudes towards stock market investment and debt obligations are on a scale of 1 (strongly disagree) to 10 (strongly agree), measuring the extent to which the respondent agrees with the corresponding statement. The last nine household characteristics are indicator variables that take a value of zero or one.

D Additional Results

Table 8: Estimated Parameters for Household Characteristics

	$\widehat{\gamma}_d$	se
Household head age 35–44	-0.277***	(0.106)
Household head age 45–54	-0.289***	(0.099)
Household head age 55–64	-0.223**	(0.105)
Household head age $\geqslant$ 65	-0.170	(0.122)
Household income \$15,000 - \$19,999	0.432**	(0.178)
Household income \$20,000 - \$24,999	0.476**	(0.187)
Household income \$25,000 - \$29,999	0.201	(0.185)
Household income \$30,000 - \$34,999	0.695***	(0.170)
Household income \$35,000 - \$44,999	0.648***	(0.155)
Household income \$45,000 - \$54,999	0.424***	(0.152)
Household income \$55,000 - \$59,999	0.713***	(0.184)
Household income \$60,000 - \$69,999	0.632***	(0.164)
Household income \$70,000 - \$99,999	0.768***	(0.148)
Household income \$100,000 - \$149,999	0.860***	(0.157)
Household income $\geqslant$ \$15,000	0.684***	(0.178)
Household size = 2	-0.239***	(0.084)
Household size = 3	-0.077	(0.106)
Household size $\geqslant$ 4	-0.421***	(0.108)
Grade 9-13	0.644**	(0.277)
Community College	0.664**	(0.283)
Diploma	0.759***	(0.279)
Undergraduate	0.767***	(0.280)
Post-graduate	0.918***	(0.286)
Rent a home	-0.261***	(0.078)
Household has a female head	0.283***	(0.086)
Have internet access at work/school/elsewhere	0.136*	(0.070)
Live in rural area	0.175**	(0.082)
Dislike investing in stock market	0.029**	(0.011)
Have difficulty in paying off debt	-0.075***	(0.012)
Behind debt obligations in the past year	-0.326*	(0.168)
Main financial institution (FI) is TD	0.152*	(0.091)
Main FI is RBC	-0.016	(0.106)
Main FI is Laurentian Bank	-0.852**	(0.397)
Main FI is not big six or Laurentian Bank	0.022	(0.092)
Year 2011	-0.042	(0.140)
Year 2012	-0.148	(0.133)
Year 2013	0.004	(0.124)
Year 2014	0.073	(0.129)
Year 2015	0.003	(0.134)
Year 2016	0.111	(0.139)
Year 2017	-0.023	(0.144)
Quebec	0.308**	(0.133)
Ontario	0.418***	(0.126)
Prairies	0.508***	(0.137)
British Columbia	0.560***	(0.140)
Observations	4,352	
Adjusted R^2	0.070	

Robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Data sources: CFM 2010–2017, MOP 2013, CANNEX 2010–2017, Government of Canada website

Note: The table shows the estimated parameters $\widehat{\gamma}_d$ and their standard errors (se), which represent the effects of household characteristics on the utilities from holding deposits relative to cash. These results follow from the specification in column (9) of Table 1.

Table 9: Baseline Regression vs Weighted Least Squares

	(1) Baseline	(2) WLS
Deposit rate (after tax)	2.191**	3.293**
	(1.036)	(1.318)
Attitudes towards bank service	0.059***	0.044**
	(0.018)	(0.020)
Difference in ratings for cost of use	-0.101	-0.300
	(0.202)	(0.253)
Difference in ratings for ease of use	0.374	0.205
	(0.466)	(0.549)
Difference in ratings for security	0.457*	0.009
	(0.256)	(0.321)
Ratings for anonymity	-0.038**	-0.017
	(0.018)	(0.021)
Ratings for budgeting usefulness	-0.062***	-0.067***
	(0.017)	(0.022)
Fraction of online transactions	0.439	0.359
	(0.314)	(0.529)
Fraction of transactions cards unaccepted	-0.282	-0.187
	(0.181)	(0.225)
Constant	1.695***	1.346***
	(0.388)	(0.429)
Observations	4,352	4,352
Adjusted R^2	0.070	0.082
Bank Fixed Effect	Yes	Yes
Region Fixed Effect	Yes	Yes
Year Fixed Effect	Yes	Yes

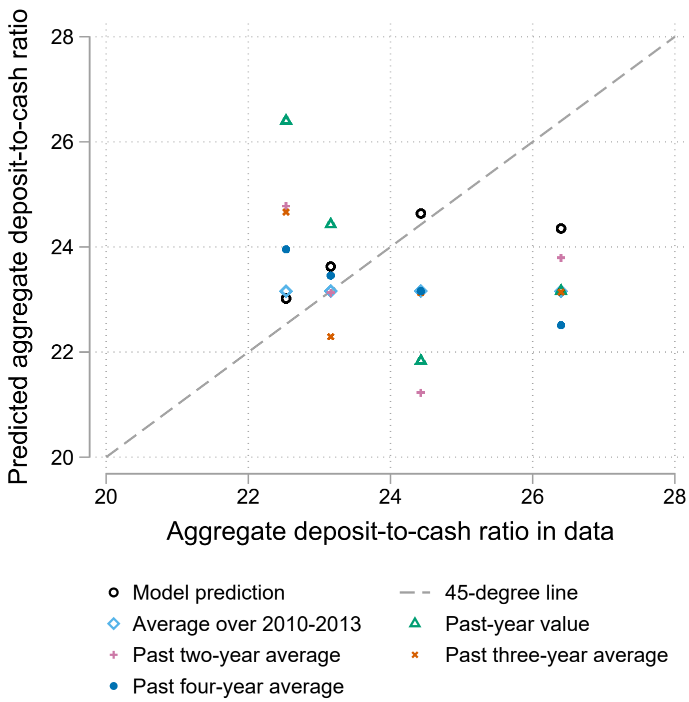
Robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Data sources: CFM 2010–2017, MOP 2013, CANNEX 2010–2017, Government of Canada website

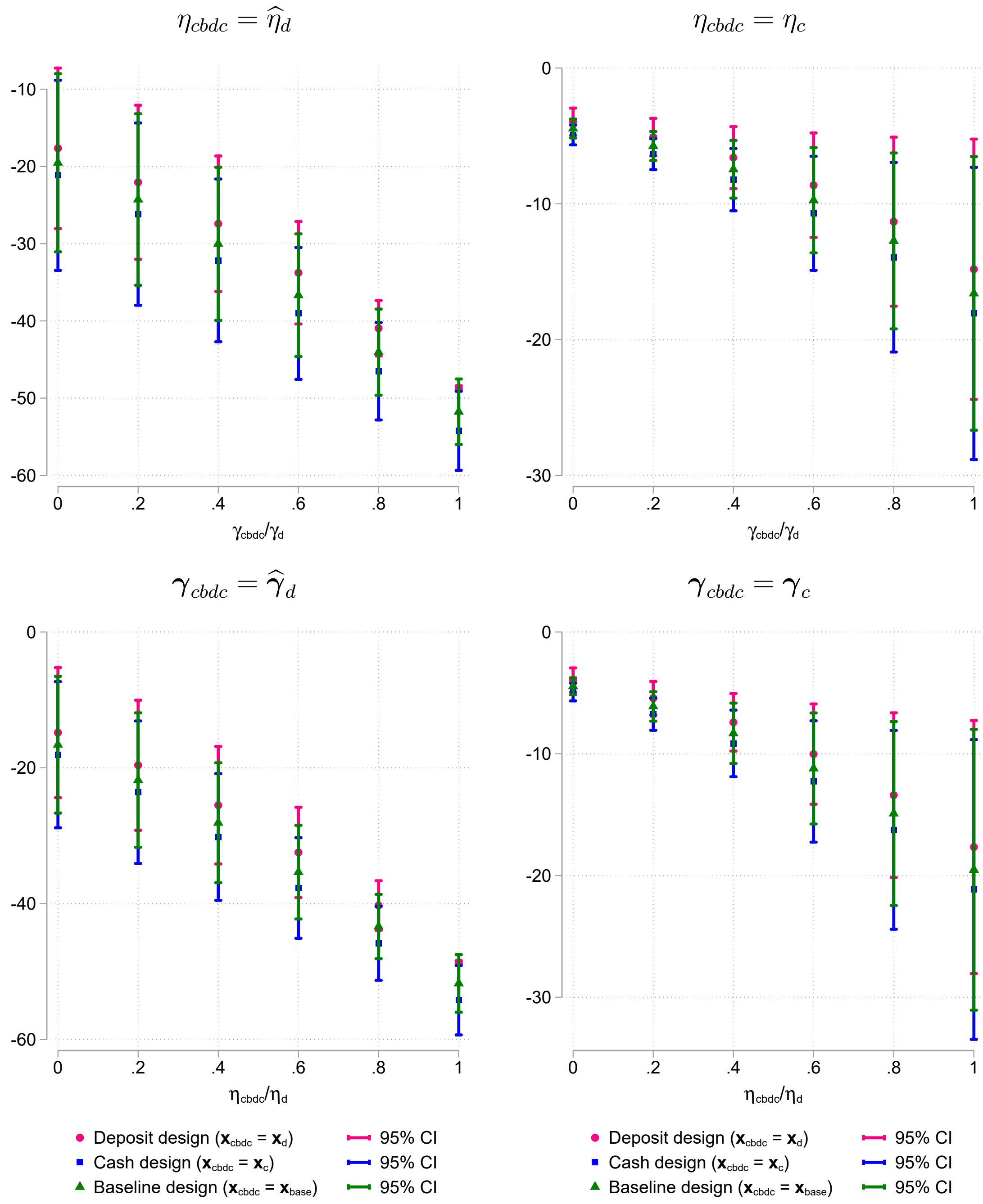
Note: Column (1) shows the baseline results, which are identical to column (9) in Table 1. Column (2) shows the results from a weighted regression where the sample weights are applied. Household characteristics included in each regression consist of household income, household head age, female head indicator, household head education, home ownership, household size, rural area indicator, internet access at work, attitudes towards stock market investment, feeling difficulty in paying off debt, and the indicator of being behind debt obligations in the past year.

Figure 13: Model-Predicted Aggregate Deposit-to-Cash Ratio vs. Naive Estimates



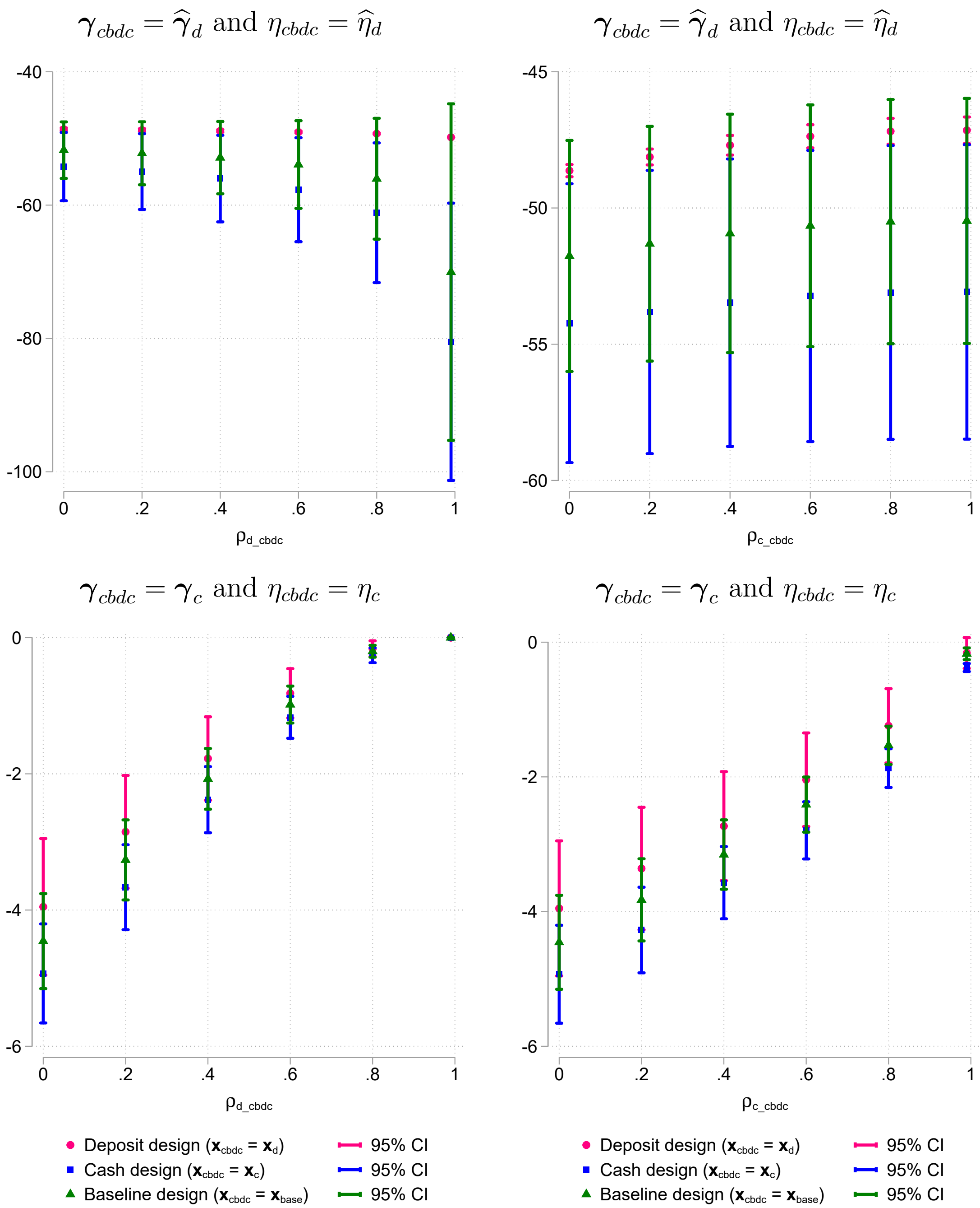
Data sources: CFM 2010–2017, MOP 2013, CANNEX 2010–2017, Government of Canada website
Note: The graph plots the predicted values of the aggregate deposit-to-cash ratio based on the model and different naive estimates against the corresponding data values for years from 2014 to 2017. Each point is associated with a given year. The model-predicted values are calculated based on the model parameters that are estimated using the subsample from 2010 to 2013. The naive estimates (i.e., average over 2010–2013, past-year value, past two-/three-/four-year average) use the data values of the aggregate deposit-to-cash ratio in the past to predict the aggregate deposit-to-cash ratio for each year from 2014 to 2017. The dashed line is a 45-degree line.

Figure 14: Mean Percentage Change in Deposits for Different CBDC-specific Effects



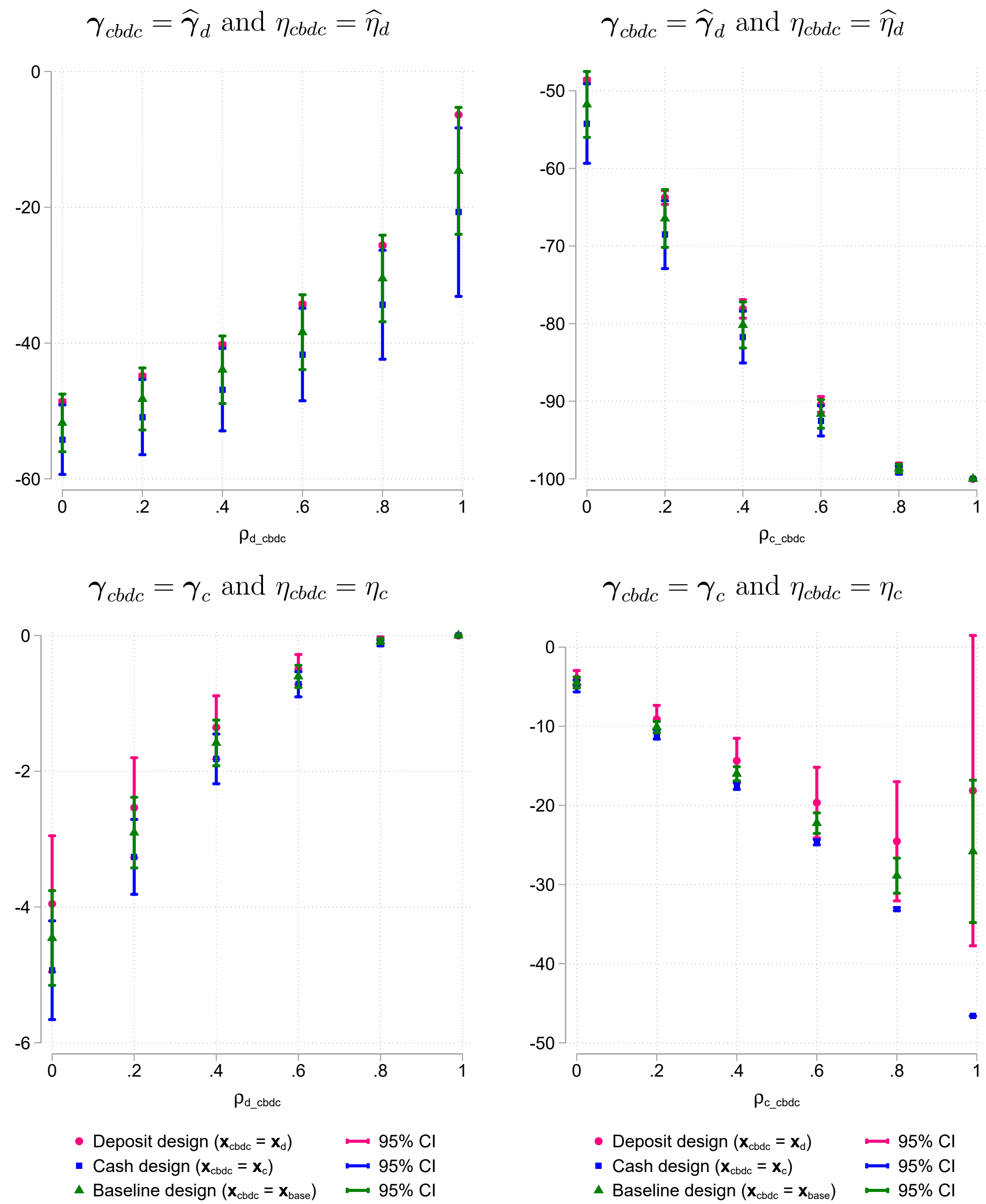
Note: The graphs in the upper (lower) panel plot the mean percentage change in deposits relative to the deposit holding before CBDC issuance for different values of γ_{cbdc} (η_{cbdc}) as a fraction of the estimated parameters $\widehat{\gamma}_d$ ($\widehat{\eta}_d$), conditional on different values of η_{cbdc} (γ_{cbdc}). Since deposits and cash are substituted proportionally into CBDC under the logit model, these graphs also represent the mean percentage changes in cash. In each graph, three different designs for CBDC are plotted, that is, when CBDC attributes $\boldsymbol{x}_{cbdc}$ are identical to deposit attributes ($\boldsymbol{x}_{cbdc} = \boldsymbol{x}_d$), cash attributes ($\boldsymbol{x}_{cbdc} = \boldsymbol{x}_c$), or a mixture of both ($\boldsymbol{x}_{cbdc} = \boldsymbol{x}_{base}$). The standard errors for calculating the 95% confidence intervals are computed using the delta method.

Figure 15: Mean Percentage Change in Deposits for Different Degrees of Substitutability



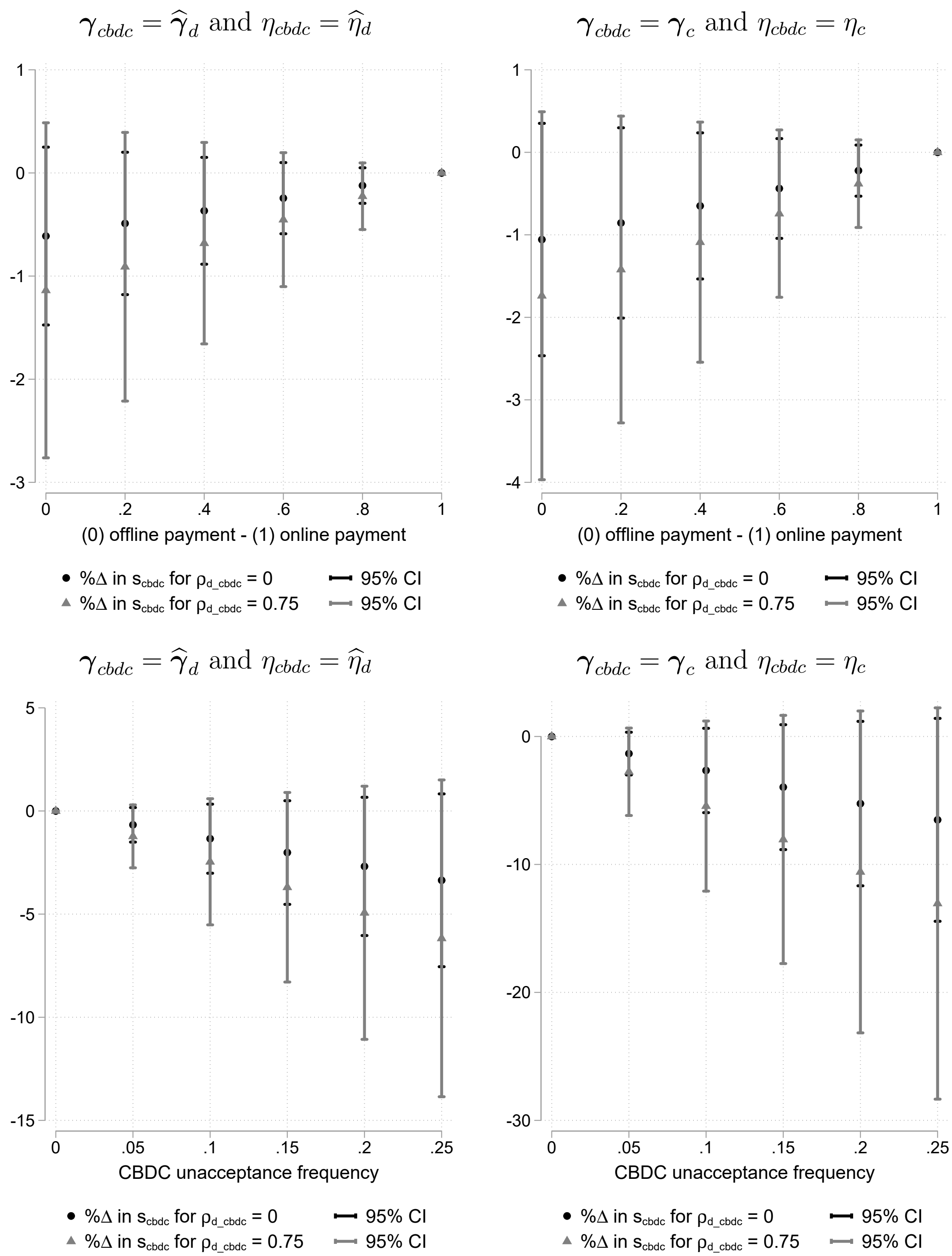
Note: The graphs in the left (right) column plot the mean percentage change in deposit holding relative to that before the CBDC issuance for different levels of correlation $\rho_{d\_cbdc}(\rho_{c\_cbdc}) \in [0, 0.99]$ between the unobserved utilities for CBDC and deposits (cash), conditional on different values of γ_{cbdc} and η_{cbdc}. A higher correlation $\rho_{d\_cbdc}(\rho_{c\_cbdc})$ implies greater substitutability between CBDC and deposits (cash). In each graph, three different designs for CBDC are plotted, that is, when CBDC attributes $\boldsymbol{x}_{cbdc}$ are identical to deposit attributes ($\boldsymbol{x}_{cbdc} = \boldsymbol{x}_d$), cash attributes ($\boldsymbol{x}_{cbdc} = \boldsymbol{x}_c$), or a mixture of both ($\boldsymbol{x}_{cbdc} = \boldsymbol{x}_{base}$). The standard errors for calculating the 95% confidence intervals are computed using the delta method.

Figure 16: Mean Percentage Change in Cash for Different Degrees of Substitutability



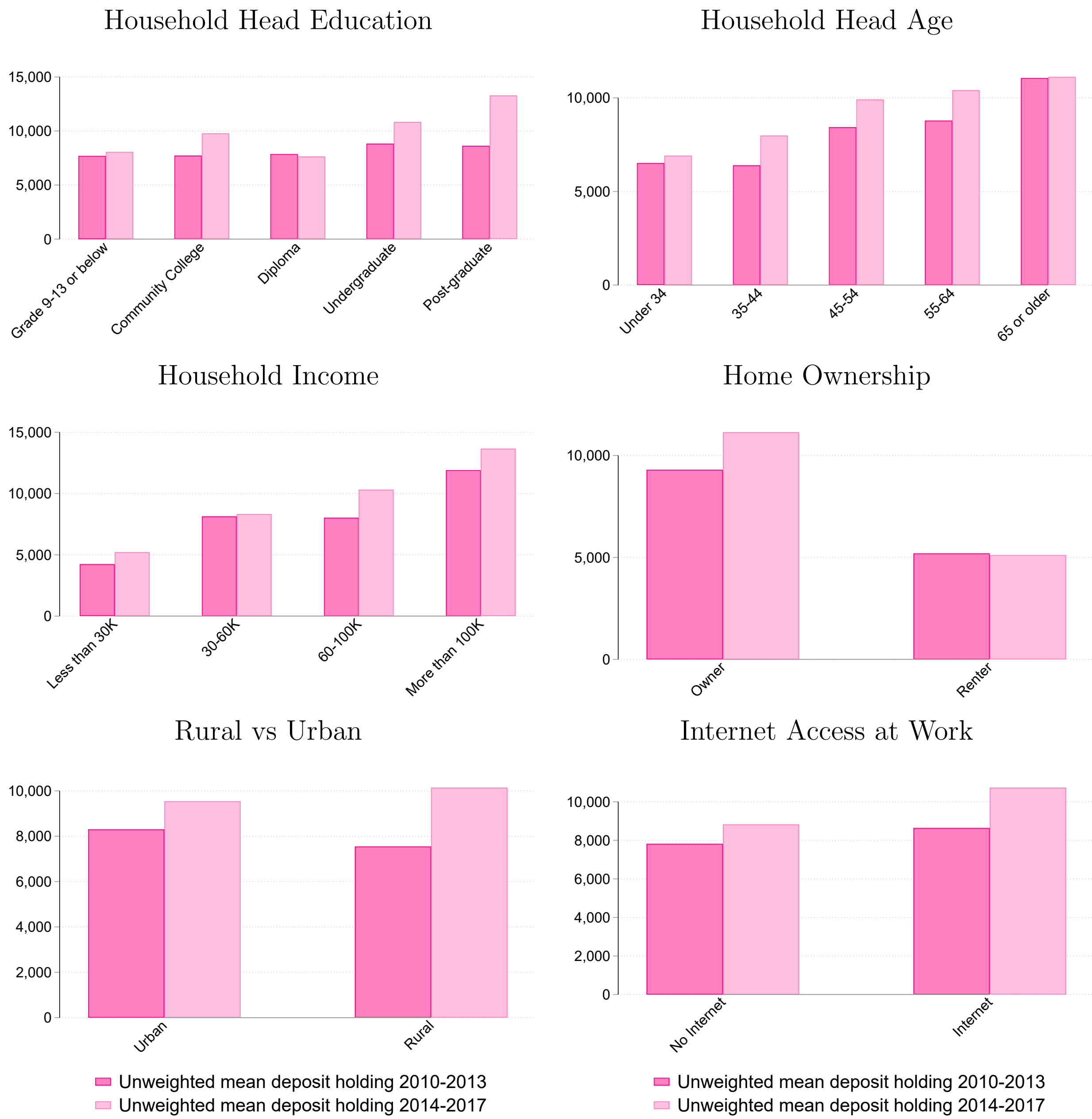
Note: The graphs in the left (right) column plot the mean percentage change in cash holding relative to that before the CBDC issuance for different levels of correlation $\rho_{d\_cbdc}(\rho_{c\_cbdc}) \in [0, 0.99]$ between the unobserved utilities for CBDC and deposits (cash), conditional on different values of γ_{cbdc} and η_{cbdc}. A higher correlation $\rho_{d\_cbdc}(\rho_{c\_cbdc})$ implies greater substitutability between CBDC and deposits (cash). In each graph, three different designs for CBDC are plotted, that is, when CBDC attributes $\boldsymbol{x}_{cbdc}$ are identical to deposit attributes ($\boldsymbol{x}_{cbdc} = \boldsymbol{x}_d$), cash attributes ($\boldsymbol{x}_{cbdc} = \boldsymbol{x}_c$), or a mixture of both ($\boldsymbol{x}_{cbdc} = \boldsymbol{x}_{base}$). The standard errors for calculating the 95% confidence intervals are computed using the delta method.

Figure 17: The Impacts of Online Purchase Capability and Unacceptance Rate



Note: The graphs plot the percentage changes $\%\Delta$ in the aggregate CBDC share s_{cbdc} relative to the share under the baseline design against different degrees of online purchase capability (upper panel) and CBDC unacceptance frequency (lower panel), conditional on different values of γ_{cbdc} and η_{cbdc}. In each graph, two different levels of the correlation ρ_{d_cbdc} between the unobserved utilities for CBDC and deposits are plotted. The standard errors for calculating the 95% confidence intervals are computed using the delta method.

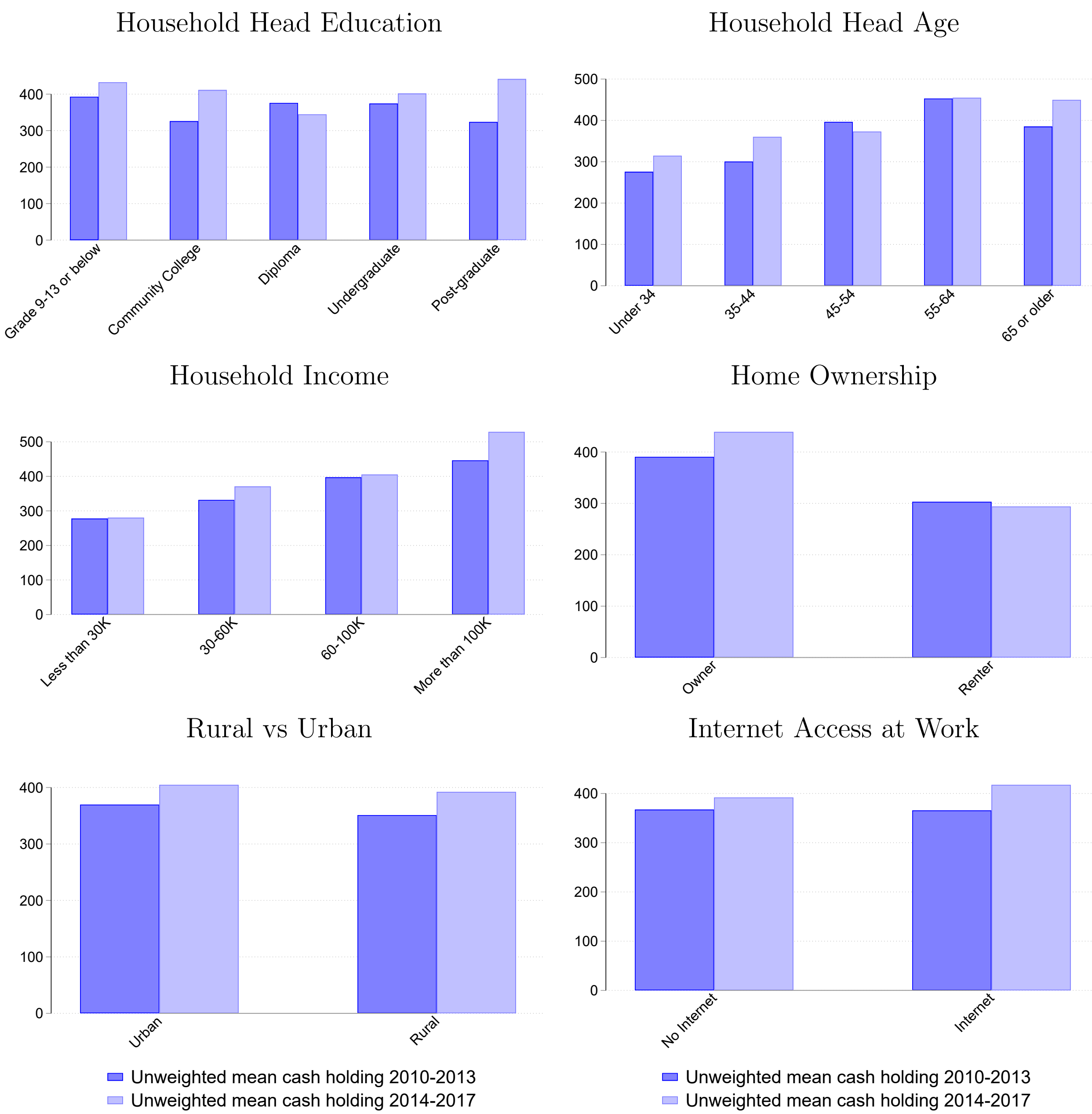
Figure 18: Deposit Holdings in Canadian Dollars across Demographic Groups



Data sources: CFM 2010–2017

Note: The bar charts show the unweighted mean deposit holdings across households and over the periods of 2010–2013 and 2014–2017 for different demographic groups in the merged sample of CFM and MOP data. The deposit holdings are deflated by CPI in each year.

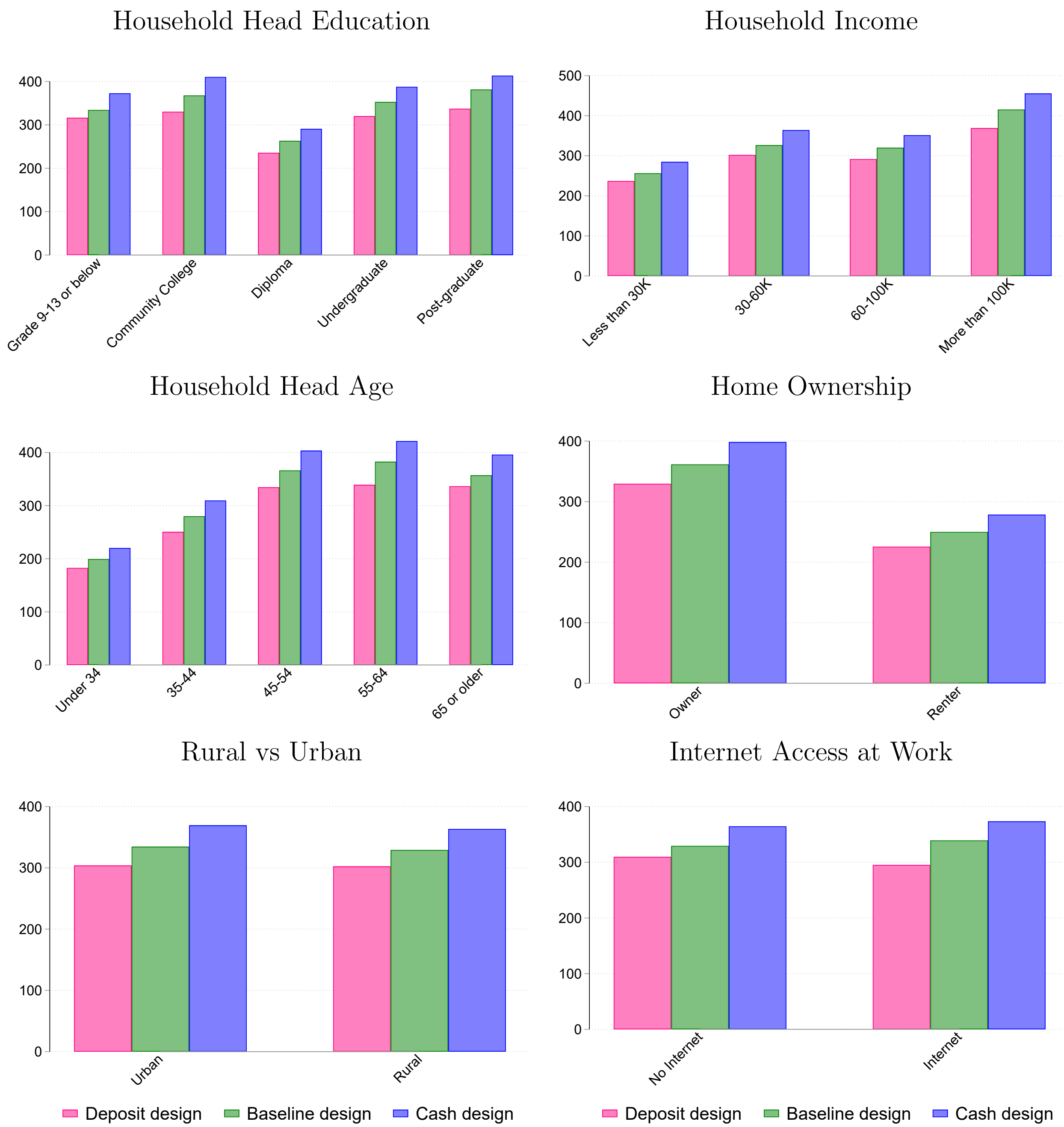
Figure 19: Cash Holdings in Canadian Dollars across Demographic Groups



Data sources: CFM 2010–2017

Note: The bar charts show the unweighted mean cash holdings across households and over the periods of 2010–2013 and 2014–2017 for different demographic groups in the merged sample of CFM and MOP data. The cash holdings are deflated by CPI in each year.

Figure 20: CBDC holdings in Canadian Dollars across Demographic Groups



Note: The bar charts show the unweighted mean predicted CBDC holdings across households and over the period of 2014–2017 for different demographic groups. For a given demographic group, the predicted CBDC holdings under three different designs are plotted. The CBDC holdings are predicted based on the logit model with the assumption that CBDC-specific effects are cash-like. The predicted CBDC holdings are deflated by CPI in each year.