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

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Preliminary and Incomplete: Please do not cite without prior permission

May 10, 2021

Abstract

This paper predicts households' demand for central bank digital currency (CBDC) under different design scenarios by applying a structural model of demand to a unique Canadian household survey dataset. More specifically, households' utilities from holding each asset are represented in the product attribute space and their preferences towards these attributes are estimated by studying how they allocate their liquid assets between cash and demand deposit, which are close alternatives to CBDC. The paper predicts the CBDC demand using the estimated preferences and the design attributes of CBDC. Under a baseline design, households hold around 4% to 55% of their liquid assets in CBDC, depending on how households with different characteristics value CBDC. Important attributes affecting the demand for CBDC include usefulness for budgeting, anonymity, cost of use, bundling of financial advice service, and rate of return.

JEL Classification: E50, E58

Keywords: Central bank digital currency; Demand estimation; Design attributes

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I am grateful to Jonathan Chiu and Yu Zhu for the constructive feedback and useful guidance throughout the development of this paper. I want to thank Kim Huynh for the helpful suggestions at various stages of this project and the Economic Research and Analysis team of the Currency Department at the Bank of Canada for providing the cleaned payment survey data. I thank Shutao Cao, Marie-Hélèn Felt, Sofia Lu, Adi Mordel and Yaz Terajima for sharing their knowledge about the datasets. I am also grateful to my colleagues, Narayan Bulusu, Heng Chen, Mohammad Davoodalhosseini, Rod Garratt, Paul Grieco, Xing Guo, Scott Hendry, Janet Jiang, Charles Kahn, Anneke Kosse, Zhentong Lu, Maarten Van Oordt, Edona Reshidi, Francisco Rivadeneyra, Oleksandr Shcherbakov, Andrew Usher, Angelika Welte, and Erhao Xie, for their insightful comments. Finally, I thank the seminar participants at the Bank of Canada. The views expressed in this paper are those of the author and not necessarily the views of the Bank of Canada.

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 recent 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, a central bank needs to consider three important questions: What would be the demand for the CBDC? How would the design attributes of CBDC affect the demand? How would CBDC impact the demand for cash and deposits? This paper helps answer these questions empirically.[2]

Serving as a store-of-value asset and a payment instrument, CBDC is a close alternative to cash and demand deposit. 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). By studying how households allocate their liquid assets between cash, demand deposit and CBDC in a structural demand model, this paper makes three contributions. It predicts the potential demand for CBDC, evaluates the contributions of different design attributes, and assesses the impacts of CBDC on cash and demand deposit.

This paper represents the first attempt to empirically quantify households' demand for CBDC relative to cash and demand deposit. While there is an emerging theoretical literature on the impact of CBDC, the lack of data on CBDC poses a constraint on the empirical work. This paper proposes a solution by modeling CBDC, cash, and demand deposit as product bundles of attributes and estimating households' preferences for different product attributes. Given that these preferences will likely remain the same after CBDC issuance, the estimated model can be used to predict the demand for CBDC with given design attributes.

More specifically, using a structural demand model, households' utilities obtained from holding cash and demand deposit are determined by their preferences towards different product attributes. As a result, how households allocate their liquid assets between demand deposit and cash depends on their utility differences between the two assets, which in turn depends on the differences in each attribute of the two assets. I estimate households' preferences towards these attributes using a unique Canadian household survey dataset which

[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, etc.

[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 the 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 the privately issued e-money (e.g., Adrian and Mancini-Griffoli, 2019; Brunnermeier, James and Landau, 2019; Zhu and Hendry, 2019). For other motivations of issuing CBDC, see Kahn, Rivadeneyra and Wong (2018), Engert and Fung (2017), and Fung and Halaburda (2016), etc.

contains information on their asset holdings as well as their perceptions towards different product attributes.

The paper clarifies the main difficulty in predicting the CBDC demand. That is, apart from the design attributes, how households with different characteristics value CBDC would also affect their utilities from holding CBDC. Since CBDC does not exist in Canada, these effects cannot be identified without the data on CBDC.[3] To predict the demand for CBDC with certain design attributes, I assume these unidentified effects for CBDC range from being cash-like, in which case households in different demographic groups value CBDC and cash in the same way, to being deposit-like, in which case they value CBDC and deposit in the same way. For instance, when the unidentified effects for CBDC are cash-like, it means that if old people obtain a certain utility from holding cash, they will obtain the same utility from holding CBDC.

Despite the structural approach and the rich dataset used, there is still a lot of uncertainty in the potential demand for CBDC because I find that the unidentified effects for CBDC play a large role. As a consequence, the predicted range for the CBDC demand, which is measured by the share of CBDC holdings out of the liquid assets, is broad.[4] Under a baseline design of CBDC, households hold around 4–55% of their liquid assets in CBDC, depending on whether the unidentified effects for CBDC are more cash-like or deposit-like. Since a median household only holds around 4% of their liquid assets in cash, their demand for CBDC would also be low if the unidentified effects are more cash-like. Similarly, this paper finds that households with older age, higher income, or are home owners tend to hold more CBDC balance if the unidentified effects are more cash-like, since these groups tend to hold more cash balance.

Although it is difficult to pin down the level of CBDC demand, this paper still provides useful insights on which attributes would matter more for CBDC demand. This is because the impacts of design attributes rely much less on the unidentified effects for CBDC. Important design attributes that affect CBDC demand include the usefulness for budgeting, anonymity, cost of use, bundling of financial planning advice, and the rate of return.[5]

Under the baseline design, CBDC is non-interest-bearing, unbundled with financial advice service, as cheap to use as cash, and achieves 70% of the cash anonymity and budgeting usefulness. The impact of each product attribute is measured by the percentage change in

[3] Besides, the unidentified effects for CBDC also include a CBDC-specific constant that captures the average impact of all the unmodeled factors on the utilities from holding CBDC. One example of the unmodeled factors is that people could have preferences for the tangibility of cash as opposed to cards or smartphones, but this feature cannot be identified without the data related to this feature and hence is unmodeled.

[4] The liquid assets are defined as the sum of cash and demand deposit holdings in this paper.

[5] Other product attributes that are studied in this paper include ease, security, capability of online purchase, and merchant acceptance.

CBDC demand relative to that under the baseline design as the given attribute changes, while keeping everything else unchanged. I find that reducing the budgeting usefulness of CBDC from 70% of cash budgeting usefulness to deposit usefulness would reduce the CBDC demand by around 8–16%, depending on the unidentified effects for CBDC. Changing CBDC anonymity from 70% of cash anonymity to 0% like deposit would reduce the CBDC demand by around 5–10%. If CBDC becomes bundled with financial planning advice like deposit, its demand would increase by around 4–9%. If CBDC becomes more costly to use like credit cards, then its demand would drop by around 4–8%. Finally, increasing the CBDC rate from 0% to 0.1% could raise its demand by around 8–18%.[6]

This paper also examines the crowding-out effects of CBDC on cash and deposit demand. Given that a higher demand for CBDC tends to reduce the cash and deposit demand by more, the unidentified effects for CBDC also play a large role in the crowding-out effects. The extent to which cash or deposit is reduced also depends on their substitutability with CBDC. For example, if people perceive CBDC and deposit to be closer substitutes, the demand for CBDC would mainly draw from deposit instead of cash. As deposit and CBDC become more substitutable, the mean percentage reduction in deposit demand across households can increase from 55% to 87%, while the crowding-out effect on cash demand would decrease from 56% to 25%, after introducing a CBDC with the baseline design and deposit-like unidentified effects.[7]

Regarding the empirical prediction of the CBDC demand, this paper is closely related to Huynh et al. (2020), which predicts the adoption and usage of CBDC as a new payment instrument.[8] They study consumers' payment choices between cash, debit cards and credit cards at the point of sale and use the estimated demand parameters to conduct counterfactual analyses for CBDC. In contrast, this paper focuses on households' holdings of CBDC as a store of value and studies how households allocate their liquid assets between CBDC, cash, and demand deposit, taking into account the payment features of these assets.

While there are some theoretical papers discussing the design choices of CBDC (e.g., Garratt and Zhu, 2021; Chiu et al., 2020; Agur, Ari and Dell'Ariccia, 2019; Keister and

[6]The median demand deposit rate after tax is around 0.04% across households. Therefore, the change of 0.1 percentage point in CBDC interest rate is a large change.

[7]When the baseline CBDC has cash-like unidentified effects, the demand for CBDC is much lower and hence deposit and cash demand are crowded out by only around 4% or less, depending on the substitutability between CBDC and deposit.

[8]More recently, Bijlsma et al. (2021) conducted a survey on the adoption and usage intention for hypothetical CBDC accounts in the Netherlands. For the CBDC current account, people are asked to choose how much money they want to put into this account, while for the CBDC savings account, people are asked to divide 40K euros between a standard savings account and a CBDC savings account. One key difference from their paper is that here I quantify households' potential holdings of CBDC relative to their cash and demand deposit holdings.

Sanches, 2019),[9] they often study CBDC as a perfect substitute for deposit or cash, or only focus on the rate of return differences across products. This paper captures a variety of product attributes and models CBDC as an imperfect substitute for deposit or cash due to differences in both the modeled and unmodeled factors, which is important for understanding how CBDC could affect bank deposit. Besides, there lacks empirical evidence on the importance of different design features of CBDC. In particular, the anonymity feature is frequently discussed in the literature (e.g., Tinn and Dubach, 2021; Agur, Ari and Dell'Ariccia, 2019; Davoodalhosseini, 2018; Bech and Garratt, 2017), but there is no empirical evidence on the extent to which anonymity affects the potential CBDC demand. This paper fills this gap by quantifying the demand for CBDC with various attributes.

The paper is also related to the growing literature on how CBDC could affect bank deposits and thus financial intermediation (e.g., Chiu et al., 2020; Fernández-Villaverde et al., 2020; Niepelt, 2020; Brunnermeier and Niepelt, 2019; Keister and Sanches, 2019; Andolfatto, 2018).[10] This literature has produced mixed results depending on the model assumptions. Keister and Sanches (2019) find that CBDC could crowd out bank deposits in a model with a perfectly competitive banking sector. By contrast, when banks have market power and CBDC is a perfect substitute to bank deposit, banks would raise their deposit rates to match the CBDC rate in order to retain their deposits. In this case, CBDC serves as an outside option and deposits can increase due to the higher deposit rate (e.g., Chiu et al., 2020; Andolfatto, 2018). This paper contributes to the literature by providing a framework to study CBDC designs that can differ from bank deposits in a variety of dimensions including the interest rate on CBDC. In doing so, the paper sheds light on the crowding-out effect of CBDC on deposit demand.

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 and Section 5 uses these parameters to predict the demand

[9] 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), and Kumhof and Noone (2018), etc.

[10] Existing theoretical literature also looks at the impact of CBDC on financial stability (e.g., Schilling, Fernández-Villaverde and Uhlig, 2020; Williamson, 2020; Skeie, 2019), monetary policy (e.g., Davoodalhosseini, 2018; Bordo and Levin, 2017), and macroeconomic volatility (e.g., Barrdear and Kumhof, 2016). There are also other implications of CBDC issuance. For instance, Williamson (2019) points out that CBDC could drive out physical currency and hence eliminate the associated illegal activities. For policy discussions on the macro implications of CBDC issuance, see García et al. (2020), Davoodalhosseini, Rivadeneyra and Zhu (2020), Berentsen and Schar (2018), Mancini-Griffoli et al. (2018), Meaning et al. (2018), and Engert and Fung (2017), etc.

for CBDC under different design scenarios and across different demographic groups. Section 6 concludes.

2 Model

Section 2.1 introduces a logit demand model to study how households allocate their liquid assets between cash and demand deposit. I focus on these two assets because they can be used as store-of-value assets as well as payment instruments and thus are close alternatives to CBDC. I use this structural demand model to study asset allocation because households' utilities are modeled in the product attribute space, which facilitates the counterfactual analysis of introducing a CBDC with a given design. The model can be equivalently written in terms of a standard 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 respectively. Under the logit model, there are no common unobserved factors that drive the utilities for CBDC, cash, and deposit, whereas the nested logit model allows CBDC to be a closer substitute to cash or deposit along the unobserved dimensions. 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 deposit 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. Although the choice of allocating the one dollar to cash or deposit is deterministic from the point of view of a given household, it is indeterministic to econometricians given that it is impossible to model all the factors. The utility shock $\epsilon_{i,j,t}$ captures all the unobserved factors and the constant η_j measures the average impact of these unobserved factors 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. The variance of the utility shock $\epsilon_{i,j,t}$ is $\pi^2/6$ after normalising the scale of the utility.

Since the utility shock $\epsilon_{i,j,t}$ is random and draws from a given distribution, even if the observed utility for holding the one dollar in cash is higher, i.e., $V_{i,c,t} > V_{i,d,t}$, there is a probability that the unobserved portion of the utility for deposit $\epsilon_{i,d,t}$ is sufficiently higher to overcome the lower $V_{i,d,t}$ such that household i chooses to hold it in deposit 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 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 of holding cash or deposit is equivalent to the share $s_{i,j,t}$ of asset j out of the liquid asset $w_{i,t}$:[11]

$$P_{i,j,t} = \frac{q_{i,j,t}}{w_{i,t}} \equiv s_{i,j,t} \tag{4}$$

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.

Using (3) and (4), take the difference between the logs of deposit and cash shares to get the log of deposit-to-cash ratio:

$$\ln \frac{q_{i,d,t}}{q_{i,c,t}} = V_{i,d,t} - V_{i,c,t} = \boldsymbol{\alpha}'(\boldsymbol{x}_{i,d,t} - \boldsymbol{x}_{i,c,t}) + (\boldsymbol{\gamma}_d - \boldsymbol{\gamma}_c)'\boldsymbol{z}_{i,t} + \eta_d - \eta_c \tag{5}$$

[11] 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 endowment of one dollar 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 consumers' expenditure spent at that store.

which depends on the difference between the observed utilities for deposit and cash. This utility difference in turn depends on the differences in product attributes ($\boldsymbol{x}_{i,d,t} - \boldsymbol{x}_{i,c,t}$), the household characteristics $\boldsymbol{z}_{i,t}$, and the difference in product-specific constants ($\eta_d - \eta_c$). Appendix A.1 shows that a similar expression for the log of deposit-to-cash ratio can be derived from an asset allocation problem.

According to the choice probabilities (2), 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, only the differences ($\boldsymbol{\gamma}_d - \boldsymbol{\gamma}_c$) can be identified. Hence, the overall levels of ($\boldsymbol{\gamma}_d - \boldsymbol{\gamma}_c$) and ($\eta_d - \eta_c$) need to be set and one common approach is to normalize the parameters for cash $\boldsymbol{\gamma}_c$ and η_c to zero. After this normalization, the estimated $\widehat{\eta}_d$ would capture the average impact of unobserved factors on the utility for deposit relative to cash and the estimated $\widehat{\boldsymbol{\gamma}}_d$ would reflect the effects of household characteristics $\boldsymbol{z}_{i,t}$ on the utility for deposit relative to cash.

2.2 Introducing CBDC

To predict the demand for CBDC, the first step is to calculate each household's observed utility $V_{i,cbdc,t}$ for CBDC. The estimated preference parameters $\widehat{\boldsymbol{\alpha}}$ are likely to remain the same after CBDC issuance. If the utility $V_{i,cbdc,t}$ were determined by the product attributes only, then knowing $\widehat{\boldsymbol{\alpha}}$ and the attributes $\boldsymbol{x}_{i,cbdc}$ would be sufficient to predict households' demand for CBDC. However, the utility $V_{i,cbdc,t}$ also depends on the CBDC-specific parameters $\boldsymbol{\gamma}_{cbdc}$ and η_{cbdc}:

$$V_{i,cbdc,t} = \widehat{\boldsymbol{\alpha}}' \boldsymbol{x}_{i,cbdc} + \boldsymbol{\gamma}'_{cbdc} \boldsymbol{z}_{i,t} + \eta_{cbdc} \tag{6}$$

Given that CBDC does not exist in Canada, these parameters for CBDC cannot be identified without having data on CBDC. To predict the demand for CBDC, I assume these unidentified effects for CBDC, $\boldsymbol{\gamma}_{cbdc}$ 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 deposit $\widehat{\boldsymbol{\gamma}}_d$ and $\widehat{\eta}_d$). In reality, the parameters $\boldsymbol{\gamma}_{cbdc}$ and η_{cbdc} could lie outside this range, but this paper neglects these cases that require extrapolation. Instead, this paper predicts the potential demand for CBDC relative to cash and demand deposit by focusing on the values of $\boldsymbol{\gamma}_{cbdc}$ and η_{cbdc} in between the corresponding values for cash and deposit.

Different assumptions on the unidentified effects for CBDC (i.e., $\boldsymbol{\gamma}_{cbdc}$ and η_{cbdc}) entail different implications. Assuming $\boldsymbol{\gamma}_{cbdc} = \boldsymbol{\gamma}_c$ implies that the household characteristics have identical effects on the utilities for cash and CBDC. For instance, if old people obtain a certain utility from holding cash, then they will obtain the same utility from holding CBDC.

Assuming $\eta_{cbdc} = \eta_c$ means that the average impact of the unobserved factors on the utility for CBDC is identical to that for cash. By contrast, assuming $\boldsymbol{\gamma}_{cbdc} = \widehat{\boldsymbol{\gamma}}_d$ and $\eta_{cbdc} = \widehat{\eta}_d$ implies that the household characteristics and the unobserved factors have identical effects on the utilities for deposit and CBDC.

2.2.1 Predictions Based on Logit Demand

Apart from the observed utility $V_{i,cbdc,t}$ (6), 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 deposit. Under the logit demand model, the probability of allocating each dollar of the endowment $w_{i,t}$ into CBDC, or equivalently, the share of CBDC holding is:

$$s_{i,cbdc,t} = \frac{\exp(V_{i,cbdc,t})}{\exp(V_{i,c,t}) + \exp(V_{i,d,t}) + \exp(V_{i,cbdc,t})} \tag{7}$$

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 introduction of CBDC crowds out the demand for cash and deposit.[12] As a result, the household's shares of cash and deposit are reduced to:

$$s'_{i,c,t} = \frac{q'_{i,c,t}}{w_{i,t}} = \frac{\exp(V_{i,c,t})}{\exp(V_{i,c,t}) + \exp(V_{i,d,t}) + \exp(V_{i,cbdc,t})} \tag{8}$$

$$s'_{i,d,t} = \frac{q'_{i,d,t}}{w_{i,t}} = \frac{\exp(V_{i,d,t})}{\exp(V_{i,c,t}) + \exp(V_{i,d,t}) + \exp(V_{i,cbdc,t})} \tag{9}$$

where $s'_{i,c,t}$ and $s'_{i,d,t}$ denote the cash and deposit shares after CBDC issuance, respectively. In this logit framework, the demand for CBDC draws proportionally from cash and deposit so that the deposit-to-cash ratio $\frac{q'_{i,d,t}}{q'_{i,c,t}} = \exp(V_{i,d,t} - V_{i,c,t})$ remains unchanged as in (5).

This independence of irrelevant alternatives (IIA) property – the deposit-to-cash ratio is unaffected by the introduction of CBDC – is due to the assumption that the unobserved factors are i.i.d. across products. The resulting substitution pattern can be restrictive in some cases. For example, suppose CBDC and deposit are perfect substitutes, the demand

[12] In this paper, the liquid asset only consists of cash and demand deposit because they are the close alternatives to CBDC. The assumption that the size of liquid asset 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 a baseline design.

for CBDC should only draw from deposit while cash demand is unaffected. However, this perfect substitute case cannot be captured in the logit framework. Even if CBDC and deposit have an identical observed utility, they are still imperfect substitutes due to the unobserved factors. To allow for more flexible substitution patterns and different degrees of substitutability between CBDC and the existing product, Section 2.2.2 introduces a nested logit framework, which can capture the similarity between products along the unobserved dimensions. When there is no correlation between the unobserved utilities, the nested logit model reduces to the standard logit model.

2.2.2 Predictions Based on Nested Logit Demand

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

Case I. CBDC as a closer substitute for deposit

Suppose the unobserved utilities for CBDC and deposit 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 peoples' perceptions towards this feature. 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}:

$$P_{i,cbdc,t} = \underbrace{\frac{\exp\left(\frac{V_{i,cbdc,t}}{\tau_d}\right)}{\exp\left(\frac{V_{i,cbdc,t}}{\tau_d}\right) + \exp\left(\frac{V_{i,d,t}}{\tau_d}\right)}}_{\text{Prob}(j=cbdc|j\in B_{d\_cbdc})} \underbrace{\frac{\left[\exp\left(\frac{V_{i,cbdc,t}}{\tau_d}\right) + \exp\left(\frac{V_{i,d,t}}{\tau_d}\right)\right]^{\tau_d}}{\left[\exp\left(\frac{V_{i,cbdc,t}}{\tau_d}\right) + \exp\left(\frac{V_{i,d,t}}{\tau_d}\right)\right]^{\tau_d} + \exp\left(V_{i,c,t}\right)}}_{\text{Prob}(j\in B_{d\_cbdc})} \tag{10}$$

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 of deposit and CBDC. The observed utilities of CBDC and deposit 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 deposit and CBDC.[13] When the unobserved utilities are uncorrelated (i.e., $\tau_d = 1$), this reduces to the logit demand model where the CBDC share (10) is identical to (7).

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

$$\frac{s'_{i,d,t}}{s'_{i,c,t}} = \left[1 + \exp\left(\frac{V_{i,cbdc,t} - V_{i,d,t}}{\tau_d}\right)\right]^{\tau_d - 1} \frac{s_{i,d,t}}{s_{i,c,t}} \tag{11}$$

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. Equation (11) shows that when the unobserved utilities are uncorrelated (i.e., $\tau_d = 1$), the deposit-to-cash ratio $\frac{s'_{i,d,t}}{s'_{i,c,t}}$ is unaffected by CBDC issuance, since cash and deposit are crowded out by the same proportion. When CBDC is a perfect substitute to deposit (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 deposit 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, since the demand for CBDC draws more than proportionally from deposit. Furthermore, the crowding-out effect on deposit is stronger if CBDC is perceived to be a better product than deposit along the observed dimensions (i.e., $V_{i,cbdc,t} - V_{i,d,t} > 0$), as shown in Appendix B.1.

The impact of the correlation on the CBDC share depends on the difference in the observed utilities of CBDC and deposit, as shown in Appendix B.1. When the observed utility of CBDC is higher than that of deposit, it is ambiguous how the correlation affects the CBDC share. On the one hand, a higher correlation ρ_{d_cbdc} (or lower τ_d) makes CBDC and deposit more substitutable and thus leads to a greater substitution from deposit 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 means that the demand for CBDC would mainly draw from its closer substitute, deposit. As the cash demand is reduced by less, the share that can be allocated to deposit and CBDC is smaller, which tends to reduce the CBDC share. By 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.

[13] A higher correlation between the unobserved utilities for deposit and CBDC lowers the variance of $(\epsilon_{i,cbdc,t} - \epsilon_{i,d,t})$. Let $\mathrm{Var}(\epsilon_{i,d,t}) = \mathrm{Var}(\epsilon_{i,cbdc,t}) = \sigma^2$ denote the variances of the unobserved utilities, where the logit model implicitly scales all the product utilities such that the unobserved utilities have a variance of $\sigma^2 = \frac{\pi^2}{6}$. Hence, $\mathrm{Var}(\epsilon_{i,cbdc,t} - \epsilon_{i,d,t}) = 2\sigma^2$ under the logit model. By contrast, under the nested logit where the unobserved utilities are positively correlated within the nest, $\mathrm{Var}(\epsilon_{i,cbdc,t} - \epsilon_{i,d,t}) = 2\sigma^2 - 2\sigma^2\rho_{d\_cbdc} = 2\sigma^2(1 - \rho_{d\_cbdc})$, which is reduced by a factor of $(1 - \rho_{d\_cbdc})$.

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 unmodeled factor could be that people value 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 of CBDC and cash. Appendix B.2 shows that in this case, the deposit-to-cash ratio after CBDC issuance becomes:

$$\frac{s'_{i,d,t}}{s'_{i,c,t}} = \left[1 + \exp\left(\frac{V_{i,cbdc,t} - V_{i,c,t}}{\tau_c}\right)\right]^{1-\tau_c} \frac{s_{i,d,t}}{s_{i,c,t}} \tag{12}$$

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 of CBDC and cash. Equation (12) shows that the deposit-to-cash ratio is greater than or equal to that before CBDC issuance $\frac{s_{i,d,t}}{s_{i,c,t}}$, since the demand for CBDC mainly draws from its closer substitute, which is cash in this case.

Conditional on the level of correlation, a higher observed utility of CBDC leads to a higher demand for CBDC. However, how the CBDC demand changes with the level of correlation depends on the sign of the observed utility difference, as shown in Appendix B.2. If the observed utility of CBDC is higher than that of cash, it is ambiguous how the CBDC share is affected by the correlation. On the one hand, a higher correlation ρ_{c_cbdc} (lower τ_c) makes CBDC and cash more substitutable and thus leads to a greater substitution from cash to CBDC when $(V_{i,cbdc,t} - V_{i,c,t})$ is positive, which tends to raise the CBDC share. On the other hand, a greater substitutability between CBDC and cash implies that the demand for CBDC draws mainly from cash. As deposit becomes less affected, the total share that can be allocated to CBDC and cash is lower, which tends to lower the CBDC share. By contrast, when $(V_{i,cbdc,t} - V_{i,c,t}) \leqslant 0$, the former effect is reversed and the CBDC share unambiguously decreases in the correlation coefficient.

3 Data

This paper uses two Canadian household survey datasets, Canadian Financial Monitor (CFM) during the period of 2010–2017 and the Methods of Payment (MOP) survey for year 2013. CFM is an unbalanced panel and covers around 12,000 households each year, while MOP survey is a cross-sectional dataset.[14] CFM provides detailed information on

[14]Although CFM has repeated observations for some households, there ia a high attrition rate and hence the survey company recruits new participants to maintain a nationally representative survey in each year, as discussed in Chen, Felt and Huynh (2014). They exploit the panel dimension of the CFM to estimate the

households' deposit and cash holdings, while the MOP survey contains information on people's perceptions towards different payment features that can be used to measure the product attributes of cash and demand deposit. The MOP survey is accompanied by a three-day shopping diary which records detailed transaction-level data for each respondent, such as the choice of payment instruments used and the location of purchase for each transaction.

In this paper, cash is measured as the sum of cash in wallet and the precautionary holding of cash. I focus on the sample period of 2010–2017 in CFM because the survey questions on cash holdings are consistent across years during this period.[15] This paper focuses on the demand deposit, which can be readily used for transactions and thus is a close alternative to CBDC. Therefore, deposit is measured by the sum of chequing, chequing/saving, and saving account balances for each household. Figure 8 in Appendix C.1 shows the usage of all the bank account types that are classified in CFM data. Detailed information on the measures of cash and deposit holdings can be found in Appendix C.1.

The MOP survey in 2013 targeted people who have recently participated in CFM and the survey company Ipsos Reid documented the conversion between the respondent identification (ID) in MOP and the household ID in CFM.[16] I match these two datasets using the common ID to obtain households' holdings of financial assets from CFM as well as the product attributes from MOP.[17] Apart from the product attributes, household characteristics can also affect the utilities from holding cash and deposit. When estimating the demand parameters in Section 4, I control for household income, household head age and education, household size, home ownership, female head, region, rural area, whether the household has internet access via phone or at work, and households' payment habit measured by the frequency of cash transactions. These variables are from the CFM data except for the internet access and the payment habit which are from the MOP survey and the diary data, respectively. Table

impact of retail payment innovations on cash usage after correcting for the attrition bias.

[15] 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.

[16] 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.

[17] 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 unobserved behavior of the person's spouse in a given household due to the lack of data. By contrast, this paper focuses on decisions at the household level and assumes the perceptions of the individual within the household would matter for the household's decision.

5 in Appendix C shows the summary statistics of the key variables of interest.

To predict the demand for CBDC under a given design and assess how different design features of CBDC affect its demand, a key step is to estimate the households' preferences for these product attributes. This paper uses the MOP survey and the diary data to capture most of the product attributes, including the cost of use, ease/convenience, security, anonymity, usefulness for budgeting, capability of online purchase, and individual-level merchant acceptance rate. In addition, the attributes of return and bundling are captured using the CANNEX and CFM data, respectively. The details for each attribute are discussed below.

Rate of return

The return on deposit 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.[18] I use this information together with the bank-level deposit rates from CANNEX to construct the household-specific deposit rates.[19] However, CANNEX only provides the demand deposit rates for the big six banks before late 2020, so I use the variation in the deposit rates across the big six and assume the deposit rates of other banks to be the average of the big-six deposit rates.[20]

Since the interests earned on savings are taxed at the same marginal rate on 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 10 in Appendix C.3 plots the average deposit rate before and after taxes across households over the period 2010–2017.

[18] There are multiple pieces of information on the main financial institution in CFM. Details on the construction of main financial institution for each household can be found in Appendix C.1.3.

[19] 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 offer 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 variation instead, since there is no regional variation in the Canadian deposit rates.

[20] The paper mainly uses cross-bank variation in the deposit rates to identify the effect the rate of return. The standard deviation of the deposit rates compared to the mean is around 60% in each year from 2010–2015. The results in this paper are robust to dropping the non-big-six banks. More information about the demand deposit rates from CANNEX can be found in Appendix C.3.

Cost, ease and security

To measure the cost, ease and security features of cash and deposit, I use the respondents' ratings for each of these features from the MOP survey. 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.[21] 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 ease and security features are measured by individual-level perceptions on how easy or hard and how risky or secure it is (or would be) to use each payment instrument, respectively. Table 3 in Appendix C.2 shows that most people perceive cash to be a very low cost, easy-to-use and secure payment instrument relative to debit and credit cards. The ratings for credit card are used to proxy for the features of deposit because credit cards are the most frequently used payment instrument by Canadian households, as shown in Figure 9 in Appendix C.1. Besides, around 91% of households have credit cards throughout the period of 2010–2017 in the CFM data.

Following Arango, Huynh and Sabetti (2015), I standardise the ratings by the respondent's overall level of perceptions over cash, debit card and credit card for each payment feature. As a consequence, a respondent that rates 5, 2, 2 for the ease feature of cash, debit card, and credit card, respectively, has a standardised rating of 5/9 for cash and thus perceives cash to be easier to use compared to a respondent that rates 5 for all three payment instruments.[22]

Bundling of financial planning advice

Unlike cash, deposit is often bundled with other services provided by banks. Hence, this product bundling feature takes a value of zero for cash and one for deposit. Given that this feature does not have any variation across households, to identify its impact on households' utilities, it is interacted with households' attitudes towards financial advice offered by banks in CFM data. The more households value the bundling of financial advice service, the more utility they would obtain from holding deposit. In contrast, this feature does not contribute to the utility from holding cash since cash does not have the bundling feature.

[21] 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.

[22] 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, and the perceptions based on usage experience are likely to be more informative. The results in this paper are robust to non-standardised ratings or ratings that are standardised by the overall level of perceptions across all payment instruments.

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 changed 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 the statement or are neutral about the statement should be indifferent between holding cash and deposit when considering this feature.

Anonymity and usefulness for budgeting

Cash is anonymous and more useful for budgeting than deposit, so the anonymity and budgeting usefulness features take a value of one for cash and zero for deposit.[23] 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 cash serves as a commitment device to avoid overspending.[24] Different motives can imply different technical designs for CBDC. However, it is hard to distinguish between these motives using the current data.

To identify the impacts of these features on households' utilities, the features are interacted with households' perceptions of importance towards these features from the MOP survey. 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 not having to provide the name/information) and budgeting usefulness when considering which payment method to use. The scale of the ratings is shifted from 1–7 to 0–6 by subtracting one from the original ratings, since the rating of one on the original scale means that people think the given feature is not important at all. In this case, they should be indifferent from holding cash and deposit when considering these features. If households think anonymity and/or the usefulness for budgeting are more important, they should obtain more utility from holding cash relative to deposit.

[23] Although the budgeting usefulness feature takes a value of zero for deposit, There is no need to assume that deposit is not useful for budgeting at all. When studying the impact of the change in this feature on CBDC demand in Section 5.2, I focus on the change in CBDC budgeting usefulness on a relative scale (i.e., bounded by the degrees of usefulness for cash and deposit).

[24] Hernandez, Jonker and Kosse (2017) find that both cash and debit cards are perceived to be useful for checking the amount left to spend using a unique Dutch survey in 2012. Since I use the payment features of credit card to proxy for those of deposit (as Canadians use credit cards most frequently), the assumption here is that cash is more useful for budgeting than credit cards.

Online purchase capability

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

From the MOP diary data in 2013, each respondent records their transactions within a 3-day period. A transaction is counted as online whenever the respondent makes the purchase using an online payment account or Interac online, or whenever the location of purchase is online using a computer or a smartphone/tablet.[25] The latter takes into account the online card payments. 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 diary data, I divide the number of transactions where credit/debit cards are not accepted or the store is cash-only by the total number of transactions recorded for each respondent. Households that often encounter the situations with card unacceptance are expected to obtain more utility from holding cash relative to deposit.[26]

4 Demand Estimation

This section estimates the demand-side parameters based on the logit demand model described in Section 2.1. It shows the estimated preference parameters and the contributions of each attribute to households' utilities from holding cash and deposit. These demand-side parameters are used to predict the potential demand for CBDC in Section 5.

Households' utility preference parameters $\boldsymbol{\alpha}$ are estimated using the log of deposit-to-cash

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

[26] The MOP survey also has some other information on the acceptance of payment instruments. Appendix C.2 explains why this paper uses the information from the MOP diary data to measure this feature.

ratio (5) derived from the logit model:[27]

$$\ln \frac{q_{i,d,t}}{q_{i,c,t}} = \boldsymbol{\alpha}'(\boldsymbol{x}_{i,d,t} - \boldsymbol{x}_{i,c,t}) + \boldsymbol{\gamma}_d' \boldsymbol{z}_{i,t} + \eta_d + \varepsilon_{i,t} \tag{13}$$

The vector $\boldsymbol{x}_{i,j,t}$ consists of different product attributes that are household-specific (i.e., interest rate, cost of use, ease, security, and card unacceptance rate), as well as the attributes that are indicator variables and have no variation over households (i.e., bundling of financial planning advice service, anonymity, usefulness for budgeting, and online purchase capability). To identify the impacts of these binary features, I use households' perceptions or attitudes towards these features, as discussed in Section 3. The parameters $\boldsymbol{\gamma}_d$ reflect the effects of household characteristics on the utility for deposit relative to cash and the deposit-specific constant η_d captures the average impact of all the unobserved factors on the utility for deposit 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 $\widehat{\eta}_d$ based on (13). The latter is the constant term in the regression, which is positive as shown in Table 1 and thus increases the utility from holding deposit relative to cash. Apart from the preference parameters and the product-specific constant, the effects $\widehat{\boldsymbol{\gamma}}_d$ of the household characteristics also matter for the utilities of deposit relative to cash, which can be found in Table 6 in Appendix D.

From the last column in Table 1, when the post-tax deposit rate rises by 0.1 percentage point, the deposit-to-cash ratio increases by around 17.6%.[28] This means when the median post-tax deposit rate across households increases from 0.04% to 0.14%, the median deposit-to-cash ratio increases from 23 to 27. The bundling of financial advice service also has a significant positive effect on the deposit to cash ratio. When households more strongly agree that they would go to their bank for any financial planning advice, they would hold more deposit relative to cash.

Cost, ease, and security in Table 1 each refers to the difference in the standardised ratings between credit card and cash, as discussed in Section 3. Cost of use has a significantly

[27]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.

[28]This semi-elasticity is estimated using mainly the cross-bank variation in deposit rates across the big six banks. The rates for non-big six (about 35% of the observations) are imputed using the average deposit rates for the big six banks. The results are robust to excluding the households that bank with the non-big six. Besides, there is not much over time variation in the deposit rates for some of the big six banks, so the fixed effects of groups of banks are applied. More specifically, I include the indicator for the top two banks by assets (TD and RBC) and the indicator for the non-big six.

negative effect on the deposit-to-cash ratio as expected.[29] When credit cards are perceived to be more costly in terms of fees and interest payments, households would hold less deposit relative to cash. By contrast, households' perceptions for the ease and security features matter less for their choices between deposit and cash as the coefficients are much smaller in magnitude compared to the coefficient for the cost of use.

Table 1: Households' Preferences for Product Attributes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Deposit rate	1.659*	1.697*	1.658*	1.653*	1.653*	1.567	1.801*	1.819*	1.759*
	(0.989)	(0.985)	(0.982)	(0.985)	(0.985)	(0.981)	(0.983)	(0.983)	(0.983)
Bundling of service		0.052***	0.053***	0.053***	0.053***	0.057***	0.064***	0.063***	0.063***
		(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Cost of use			-0.582***	-0.580***	-0.572***	-0.535***	-0.517***	-0.519***	-0.527***
			(0.148)	(0.148)	(0.151)	(0.150)	(0.150)	(0.150)	(0.150)
Ease/Convenience				0.042	0.026	0.018	0.065	0.052	0.036
				(0.468)	(0.471)	(0.471)	(0.471)	(0.471)	(0.472)
Security					0.064	0.025	0.110	0.093	0.103
					(0.233)	(0.233)	(0.233)	(0.233)	(0.234)
Anonymity						-0.063***	-0.039**	-0.039**	-0.039**
						(0.018)	(0.018)	(0.018)	(0.018)
Budgeting							-0.074***	-0.074***	-0.074***
							(0.017)	(0.017)	(0.017)
Online payment								0.280	0.286
								(0.228)	(0.228)
Card unacceptance									-0.183
									(0.179)
Constant	1.159***	1.079***	1.233***	1.238***	1.238***	1.449***	1.593***	1.585***	1.588***
	(0.402)	(0.402)	(0.400)	(0.402)	(0.402)	(0.408)	(0.409)	(0.409)	(0.408)
Observations	4,399	4,399	4,399	4,399	4,399	4,399	4,399	4,399	4,399
Adjusted R^2	0.059	0.061	0.064	0.064	0.064	0.067	0.070	0.070	0.070

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

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, indicators of internet access at work or via cell phone, and the fraction of purchases paid using cash.

Anonymity and budgeting in Table 1 refer to the household-specific ratings on the importance of anonymity and the usefulness for budgeting as payment features, respectively.

[29]The results are robust even if the ratings are not standardised by the overall perceptions (sum of ratings) for cash, debit card and credit card. However, if the ratings for debit card are used to proxy for the deposit features, the cost of use is no longer significant. This is likely because Canadian households use credit cards most often, so the ratings for credit card are better proxies for these payment features of deposit.

Given that cash is anonymous and more useful for budgeting than deposit, a higher rating implies that the household thinks these features are more important and hence obtains more utility from holding cash relative to deposit. As a result, they would want to hold more cash relative to deposit in this case.[30]

Online payment frequency (i.e., 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 deposit 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 15% of people made online purchases during a three-day period in MOP 2013 diary data.

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. What matters for households' choices cash and deposit is not the aggregate-level merchant acceptance for cash or cards, but rather their own experience of the acceptance rate. For example, if households prefer to visit cash-only stores or often find that their debit or credit cards are not accepted at the point of sale, they are likely to hold more cash relative to deposit. The card unacceptance rate has a negative effect on the deposit-to-cash ratio but is not significant potentially due to the lack of variation, as only around 21% of people encountered card unacceptance situations during a three-day period in MOP 2013 diary data.

Table 7 in Appendix D compares the baseline OLS regression with the weighted least squares (WLS) estimation by applying the sample weights.[31] 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).[32] This indicates that the sampling is independent of the dependent variable conditional on the explanatory variables, in which case weighting is unnecessary and harmful for the precision (Solon, Haider and Wooldridge, 2013).

Figure 1 summarizes the estimated preference parameters in terms of how different prod-

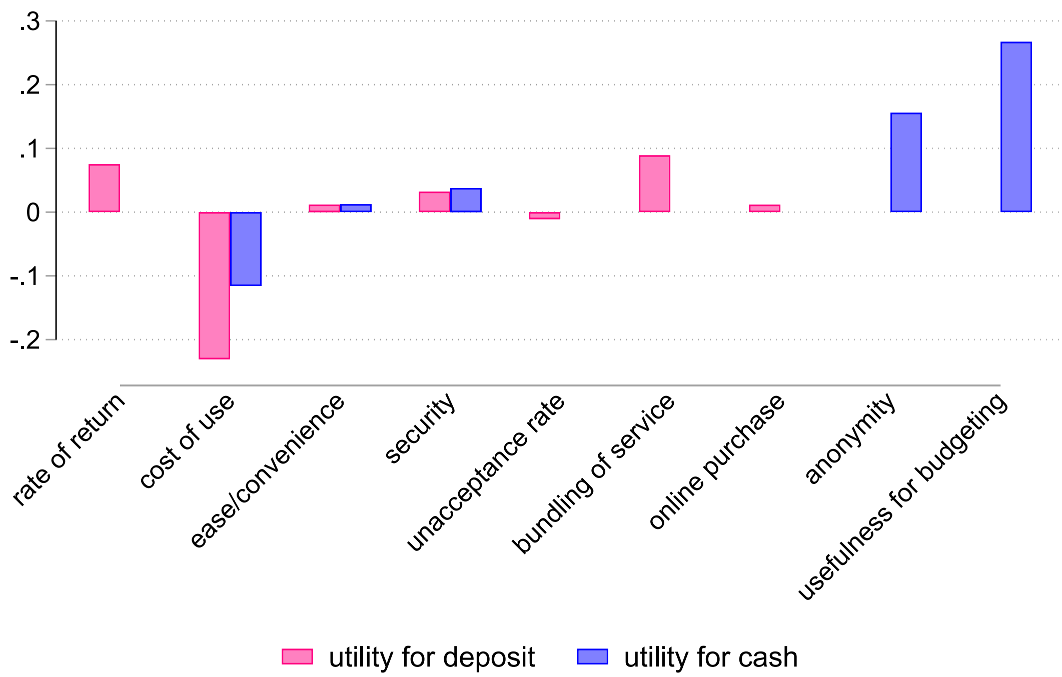
[30] Garratt and van Oordt (2019) point out that commercial payment platforms can use the payments data for price discrimination, but as individuals do not bear the full cost, they may not choose to preserve their information by using cash. This implies that the estimated impact of the anonymity feature might have been higher if households had taken into account the full cost of failing to protect their privacy.

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

[32] Deaton (2019, p. 72) point out that the easiest way to test the difference between the WLS and OLS 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, I find that the P-value is 0.29 and hence the null cannot be rejected at the 5% level.

uct features contribute to the utilities for cash and deposit. The bar chart shows the contributions of each feature to the utilities for a given product that are averaged across households and years. For some features, one bar is missing because the feature of that product takes a value of zero. Since cash has a nominal rate of return of zero, the rate of return does not contribute to the utility from holding cash. Similarly, the bundling of financial planning advice service and the online purchase capability are also zero for cash. Given data availability, I assume cash is always accepted, so the unacceptance rate for cash is zero. Figure 1 shows that the most important attributes that affect the utility from holding deposit are the cost of use, the bundling of financial advice service, and the rate of return, while the usefulness of budgeting, anonymity and the cost of use affect the utility from holding cash the most.

Figure 1: Contributions of Product Attributes to Households' Utilities



Data sources: CFM 2010–2017, MOP 2013, CANNEX 2010–2017, Government of Canada website
Note: The bar chart plots the contributions of different product features to the utilities of cash and deposit, where the y-axis is in utils. For each attribute x, the pink (blue) bar is computed as the attribute for deposit (cash) multiplied by the corresponding preference parameter $\widehat{\alpha}x_{i,d,t}$ ($\widehat{\alpha}x_{i,c,t}$) that is averaged across households and years. Missing bars are due to the given feature of cash or deposit taking a value of zero.

5 Counterfactual Analysis

This section predicts the potential demand for CBDC relative to cash and demand deposit using the estimated preference parameters shown in the last column of Table 1. The utility

$V_{i,cbdc,t}$ from holding CBDC (6) can be calculated after designing the CBDC attributes $\boldsymbol{x}_{cbdc}$ and setting the unidentified CBDC-specific effects ($\boldsymbol{\gamma}_{cbdc}$ and η_{cbdc}) based on the known values for deposit ($\widehat{\boldsymbol{\gamma}}_d$ and $\widehat{\eta}_d$) or cash ($\boldsymbol{\gamma}_c$ and η_c).

Table 2 summarises the CBDC attributes under three different designs, i.e., a deposit design, a cash design and a realistic design, where the latter is treated as the baseline design. Under the deposit (cash) design, CBDC attributes are assumed to be identical to those of deposit (cash). Under the realistic design, CBDC attributes consist of a mixture of cash and deposit attributes, as shown in the last row of Table 2. With the realistic design, CBDC is assumed to be non-interest-bearing and unbundled with financial planning advice services. In addition, the cost of use, ease, and security features of CBDC take the ratings for cash, meaning that people perceive CBDC to be as cheap, easy, and secure to use as cash. Given that the central bank needs to conform to public policy objectives such as anti-money laundering, CBDC cannot be fully anonymous like cash. I assume it can achieve 70% of cash anonymity by making transactions below a 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 and its unacceptance rate is zero.

Table 2: CBDC Attributes under Different Design Scenarios

CBDC design	Return	Bundling	Cost	Ease	Security	Anonymity	Budgeting	Online	Unacceptance
$\boldsymbol{x}_{cbdc} = \boldsymbol{x}_d$	deposit rate	1	credit card	credit card	credit card	0	0	1	cards
$\boldsymbol{x}_{cbdc} = \boldsymbol{x}_c$	0	0	cash	cash	cash	1	1	0	0
$\boldsymbol{x}_{cbdc} = \boldsymbol{x}_{real}$	0	0	cash	cash	cash	0.7	0.7	1	0

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 realistic design ($\boldsymbol{x}_{cbdc} = \boldsymbol{x}_{real}$). 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.

Section 5.1 shows the predicted demand for CBDC under the three different designs described in Table 2. Section 5.2 examines the impacts of each design attribute on the CBDC demand. Section 5.3 shows how the demand for CBDC differs across social demographic groups.

5.1 Demand for CBDC

This section predicts the potential demand for CBDC if it were issued in 2017, based on the logit and nested logit models described in Section 2.2.1 and 2.2.2, respectively. The demand for CBDC is measured by its aggregate share, which is the total predicted CBDC holdings over total liquid assets held by households, where liquid assets are defined as the sum of cash and demand deposit holdings in this paper.

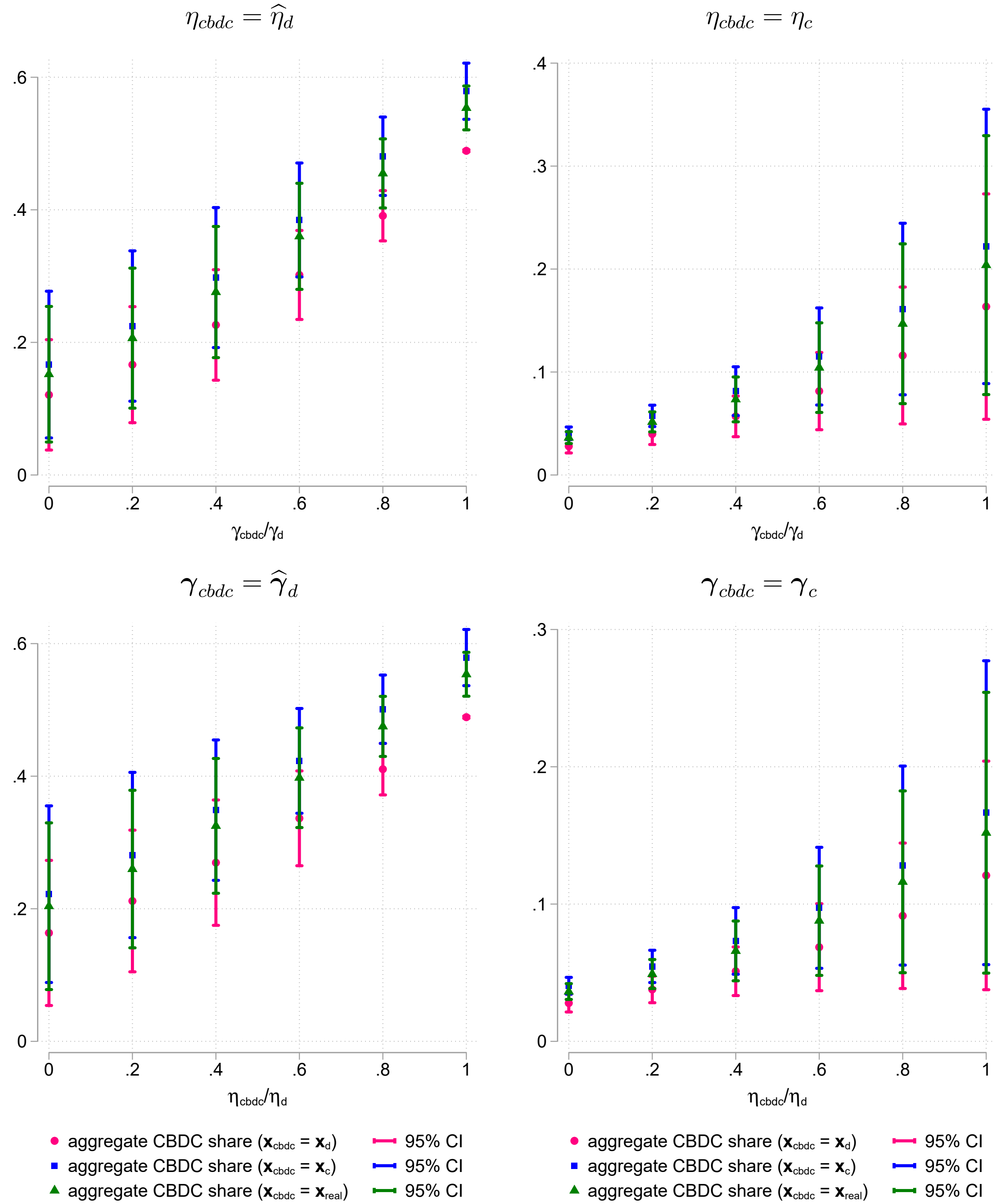
5.1.1 Predicted Demand for CBDC under Logit Framework

The utility for CBDC (6) 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 all the unobserved factors captured by η_{cbdc}. As discussed in Section 2.2, parameters $\boldsymbol{\gamma}_{cbdc}$ and η_{cbdc} cannot be identified, so their values need to be assumed in order to predict the demand for CBDC. To avoid extrapolation, I assume the unidentified effects for CBDC ($\boldsymbol{\gamma}_{cbdc}$ and η_{cbdc}) 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 $\eta_{cbdc} = \widehat{\eta}_d$). Therefore, Figure 2 plots 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. In each graph, three different designs for CBDC are plotted, i.e., the deposit design ($\boldsymbol{x}_{cbdc} = \boldsymbol{x}_d$), the cash design ($\boldsymbol{x}_{cbdc} = \boldsymbol{x}_c$), and the realistic design ($\boldsymbol{x}_{cbdc} = \boldsymbol{x}_{real}$).

There are two main findings from Figure 2. First, the unidentified effects for CBDC play an important role in predicting the potential demand for CBDC. When these effects become more deposit-like (i.e., $\boldsymbol{\gamma}_{cbdc}$ and η_{cbdc} increase), the aggregate CBDC share increases. Intuitively, since a median household holds around 96% of their liquid assets in deposit and 4% in cash in the CFM data, if households value CBDC in a similar way as they value deposit, they would also hold more CBDC. The upper panel of Figure 2 shows that as $\boldsymbol{\gamma}_{cbdc}$ increases from zero to $\widehat{\boldsymbol{\gamma}}_d$, the aggregate CBDC share increases from around 15% to 55% (4% to 20%) when $\eta_{cbdc} = \widehat{\eta}_d$ ($\eta_{cbdc} = \eta_c$). The lower panel of Figure 2 shows that the value of product-specific constant η_{cbdc} also contributes a lot to the predicted CBDC demand. Second, conditional on the unidentified effects for CBDC, the differences between the three designs are relatively small.

A higher demand for CBDC implies larger crowding-out effects on deposit and cash. Under the logit model, the demand for CBDC draws proportionally from deposit and cash, so the percentage drops in deposit and cash relative to the holdings prior to CBDC issuance are identical. Figure 11 in Appendix D shows that the mean percentage drop across households in deposit (or cash) is only around 4% when the unidentified effects for CBDC are cash-like and hence the predicted CBDC demand is low. This mean percentage drop increases to around 56% when the unidentified effects for CBDC are deposit-like and hence the predicted CBDC demand is high. Section 5.1.2 shows that in a nested logit model, the crowding-out effects on deposit and cash would differ depending on which one is a closer substitute for CBDC.

Figure 2: Aggregate CBDC Shares for Different Values of $\boldsymbol{\gamma}_{cbdc}$ and η_{cbdc}



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, i.e., 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 ($\boldsymbol{x}_{cbdc} = \boldsymbol{x}_{real}$). 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 Framework

In the previous section, CBDC is treated as a distinct product where households possess a unique set of unobserved preferences for CBDC. In other words, there are no common factors driving the unobserved utilities for different products. This assumption is relaxed in this section, so that CBDC can be a closer substitute to deposit or cash in an unobserved way, 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 3 plots the aggregate CBDC shares against different levels of correlation ranging from 0 to 0.99, assuming the unobserved utility of CBDC is correlated with that for deposit (left panel) or cash (right panel). When the correlation is zero, the predictions are identical to those based on the logit model. In each graph of Figure 3, three different designs are plotted, i.e., the deposit design, the cash design and the realistic design.

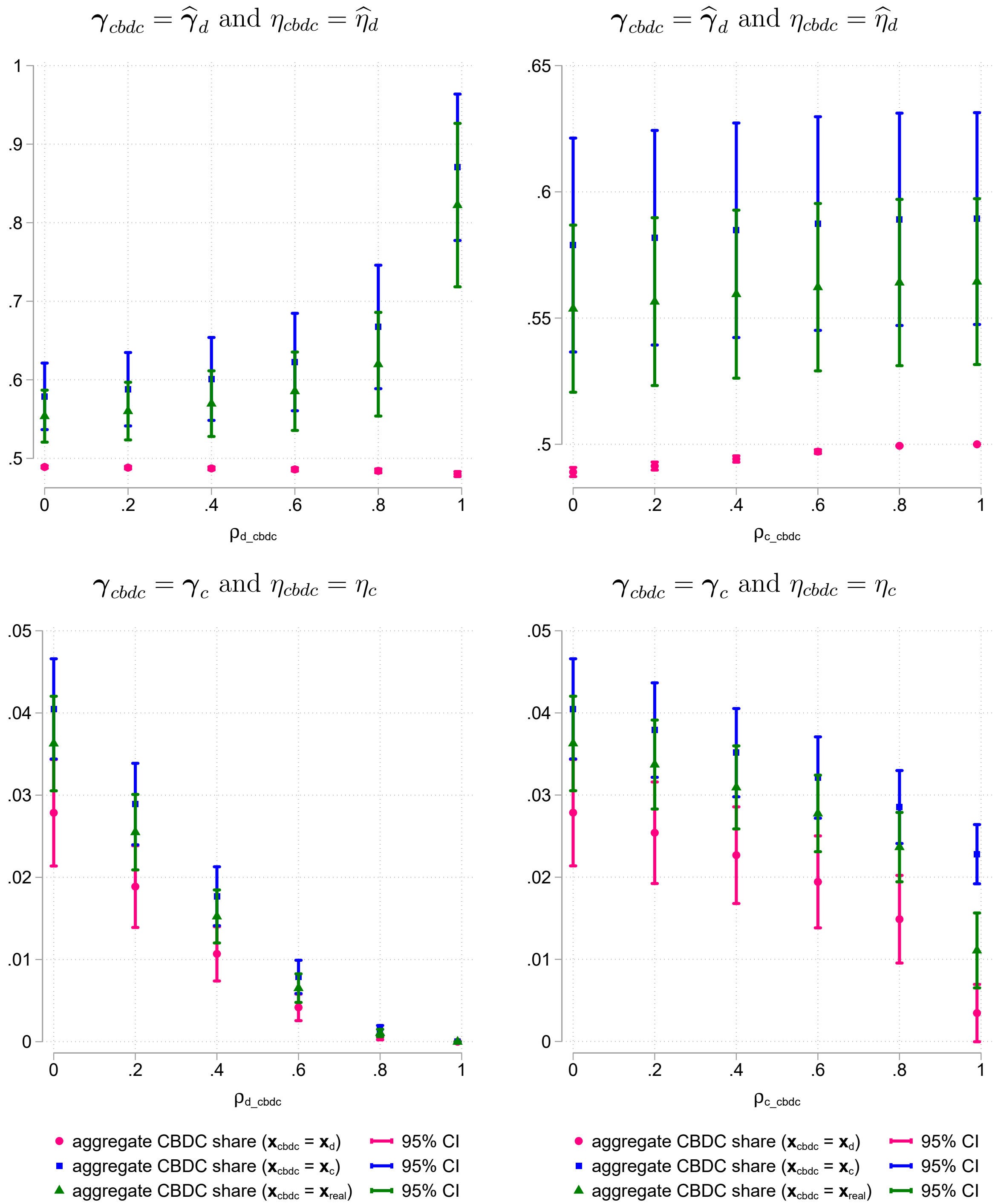
Figure 3 provides three main implications. First, the predicted aggregate CBDC shares are robust to a wide range of correlation coefficients. When the correlation is below 0.8, the level changes in the aggregate CBDC shares across different levels of correlation are small, which holds for all three designs.

Second, the correlation between the unobserved utilities of CBDC and cash ρ_{c_cbdc} has a much smaller impact compared to ρ_{d_cbdc}. The right panel of Figure 3 shows that the level changes in aggregate CBDC shares are small even when the correlation ρ_{c_cbdc} approaches one. This is because households only hold a small fraction of their liquid assets in cash. Even if CBDC has a higher observed utility than cash due to $\boldsymbol{\gamma}_{cbdc} = \widehat{\boldsymbol{\gamma}}_d$ and $\eta_{cbdc} = \widehat{\eta}_d$ in the top right graph, the greater substitution from cash into CBDC as ρ_{c_cbdc} increases would not add much extra demand for CBDC.

Third, the impact of the correlation on the aggregate CBDC share depends on the observed utility difference between CBDC and its closer substitute.[33] More specifically, the deposit design (pink line) in the first graph of Figure 3 shows the case when there is no observed utility difference between CBDC and deposit, as both the CBDC attributes and the unidentified effects are identical to those of deposit. In this case, as ρ_{d_cbdc} increases, CBDC demand draws more than proportionally from its closer substitute, deposit. Since cash becomes less affected, the total asset share that can be allocated to CBDC and deposit is smaller, which leads to a smaller CBDC share. By contrast, when there is a difference in the observed utilities of CBDC and deposit, the substitution between them also plays a role, which could outweigh the effect above. Under the cash design (blue line) or the realistic design (green line) in the first graph, CBDC has a higher observed utility than deposit due

[33] As discussed in Section 2.2.2, how the CBDC share changes with the correlation depends on the sign of the utility difference in the nested logit model.

Figure 3: Aggregate CBDC Shares for Different Levels of Correlation ρ_{d_cbdc} or ρ_{c_cbdc}



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 of CBDC and deposit (cash), conditional on different values of γ_{cbdc} and η_{cbdc}. The correlation coefficient ranges from 0 to 0.99. 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, i.e., 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 ($\boldsymbol{x}_{cbdc} = \boldsymbol{x}_{real}$). The standard errors for calculating the 95% confidence intervals are computed using the delta method.

to better anonymity and budgeting usefulness features, so a higher ρ_{d_cbdc} that makes them more substitutable can lead to greater substitution from deposit into CBDC. Therefore, the first graph shows that under these two designs, the aggregate CBDC share increases in ρ_{d_cbdc}.

Similarly, the cash design in the bottom right graph of Figure 3 shows the case when there is no observed utility difference between CBDC and cash, as both the CBDC attributes and the unidentified effects are identical to those of cash. In this case, the aggregate CBDC share decreases as ρ_{c_cbdc} increases, due to less substitution from deposit to the nest of similar products (CBDC and cash). By contrast, under the deposit design or the realistic design, CBDC has a lower observed utility compared to cash due to worse anonymity and budgeting usefulness features, so there will be greater substitution from CBDC into cash as ρ_{c_cbdc} increases. This additional substitution effect reinforces the first mechanism, causing a large drop in the CBDC share under these two designs as ρ_{c_cbdc} increases.

Apart from the design attributes, the unidentified effects for CBDC can also contribute to the observed utility difference between CBDC and deposit. The bottom left graph of Figure 3 shows that when CBDC has a lower observed utility than deposit due to $\boldsymbol{\gamma}_{cbdc} = \boldsymbol{\gamma}_c$ and $\eta_{cbdc} = \eta_c$, the aggregate CBDC share approaches zero as ρ_{d_cbdc} increases and results in greater substitution from CBDC to deposit.

Under the nested logit model, the crowding-out effects on deposit and cash not only depends on the demand for CBDC, but also depends on whether CBDC is a closer substitute to deposit or cash. Figure 12 in Appendix D shows the crowding-out effects on deposit. The upper panel shows that when the unidentified effects for CBDC are deposit-like (i.e., $\boldsymbol{\gamma}_{cbdc} = \widehat{\boldsymbol{\gamma}}_d$ and $\eta_{cbdc} = \widehat{\eta}_d$), the demand for CBDC is high and hence deposit can be crowded out by around 55–87% under the realistic design of CBDC. This contrasts with the lower panel where the demand for CBDC is low due to $\boldsymbol{\gamma}_{cbdc} = \boldsymbol{\gamma}_c$ and $\eta_{cbdc} = \eta_c$, and hence deposit is only crowded out by around 0–4% under the realistic CBDC design in this case.

The exact magnitude of the crowding out on deposit also depends on the degree of substitutability between CBDC, deposit, and cash. If CBDC and deposit are similar products (left panel), a higher correlation ρ_{d_cbdc} between their unobserved utilities can make them more substitutable, leading to greater crowding out on deposit if CBDC has a higher observed utility. This explains why as ρ_{d_cbdc} increases, the deposit holding drops by more due to better CBDC attributes under the cash design or the realistic design in the top left graph, whereas it drops by less due to the cash-like unidentified effects for CBDC in the bottom left graph. If CBDC and cash are similar products (right panel), as the correlation ρ_{c_cbdc} between their unobserved utilities increases, the demand for CBDC would draw more than proportionally from cash, leading to less crowding out on deposit.

The crowding-out effects on cash are more sensitive to the degree of substitutability, as shown in Figure 13 in Appendix D. This is mainly because people only hold a small amount of cash so the percentage change in cash can be large. When the demand for CBDC is high due to the deposit-like unidentified effects for CBDC in the upper panel, cash can be crowded out by 25–56% (56–100%) under the realistic CBDC design, depending on the level of correlation ρ_{d_cbdc} (ρ_{c_cbdc}). When the demand for CBDC is low due to the cash-like unidentified effects for CBDC in the lower panel, cash is crowded out by 0–4% (4–28%) under the realistic CBDC design, depending on the level of correlation ρ_{d_cbdc} (ρ_{c_cbdc}).

5.2 The Impacts of CBDC Design Attributes

This section studies the impacts of each product attribute on the percentage change in the aggregate CBDC share relative to the baseline CBDC share under the realistic design described in Table 2. While the unidentified effects for CBDC ($\boldsymbol{\gamma}_{cbdc}$ and η_{cbdc}) play a large role in predicting the level of CBDC demand, this section shows that the impacts of design attributes rely much less on these assumptions.

This section identifies some important attributes that affect the CBDC demand, including the rate of return, anonymity, usefulness for budgeting, cost of use, and bundling of financial planning advice service, which are discussed in turn below. This is consistent with Figure 1, which shows that these attributes tend to contribute more to households' utilities. The predicted impacts of attributes are robust to a wide range of correlation ρ_{d_cbdc} between the unobserved utilities of CBDC and deposit. This section does not look at the values of ρ_{c_cbdc} because it has a much smaller impact on the impacts of design attributes compared to ρ_{d_cbdc}.[34]

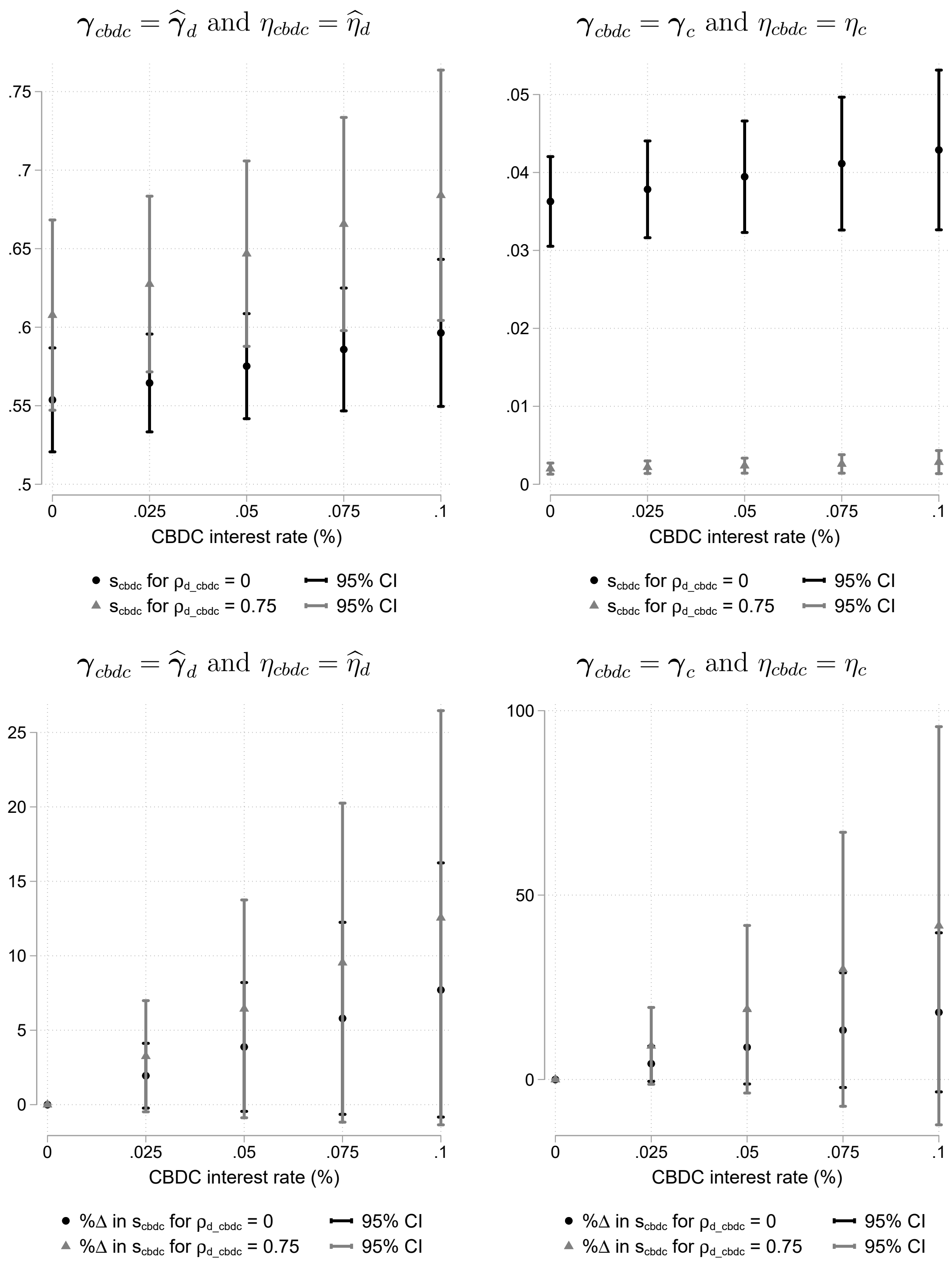
CBDC interest rate

Figure 4 shows how changes in CBDC interest rates would impact the aggregate CBDC shares (upper panel) and the percentage changes in aggregate CBDC shares relative to those under the realistic design (lower panel), conditional on the unidentified effects for CBDC ($\boldsymbol{\gamma}_{cbdc}$ and η_{cbdc}) and the correlation ρ_{d_cbdc} between the unobserved utilities of CBDC and deposit. The range 0–0.1% is chosen because the median (95th percentile) deposit rate after tax is around 0.04% (0.1%) across households and years in the sample.

Focusing on the predictions based on $\rho_{d\_cbdc} = 0$ (i.e., logit model) in the upper panel, the aggregate CBDC share increases from 55% to 60% (3.6% to 4.3%) as the CBDC rate increases

[34] Intuitively, a higher correlation ρ_{c_cbdc} increases the substitutability between CBDC and cash. Given that people tend to hold a small amount of cash, even when CBDC has better attributes, the greater substitution from cash to CBDC would not increase the CBDC demand much.

Figure 4: 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 in the aggregate CBDC share $\%\Delta s_{cbdc}$ relative to the baseline value (lower panel) for different levels of CBDC interest rate ranging from 0% 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 of CBDC and deposit are plotted. The standard errors for calculating the 95% confidence intervals are computed using the delta method.

from 0% to 0.1%, when the unidentified effects for CBDC are assumed to be deposit-like (cash-like). As shown in the upper panel, the predicted levels of CBDC demand differ a lot depending on the unidentified effects for CBDC. To summarize the impacts of CBDC interest rates across different assumptions on the unidentified effects, I look at the percentage changes in aggregate CBDC shares relative to the baseline shares under the realistic design for CBDC in the lower panel of Figure 4.

In the lower panel, when the CBDC is non-interest-bearing as in the realistic design, there is a zero percentage change in the aggregate CBDC share. Focusing on $\rho_{d\_cbdc} = 0$, when the CBDC rate rises to 0.1%, the aggregate CBDC share increases by around 8% (18%) when the unidentified effects for CBDC are deposit-like (cash-like). When the correlation is high (e.g., $\rho_{d\_cbdc} = 0.75$), the percentage changes in aggregate CBDC shares are slightly larger due to the greater substitutability between deposit and CBDC that enlarges the impact of the attribute change.[35] This section treats the predictions based on the logit model as baseline estimates since they are more conservative and have narrower confidence intervals.

Figure 4 shows that the percentage changes in CBDC demand are less affected by the unidentified effects for CBDC, since the two graphs in the lower panel are on a much similar scale compared to the upper panel. This suggests that despite the difficulty of predicting the level of CBDC demand, it is relatively more precise to gauge the impacts of the design features on the percentage changes in the CBDC demand.

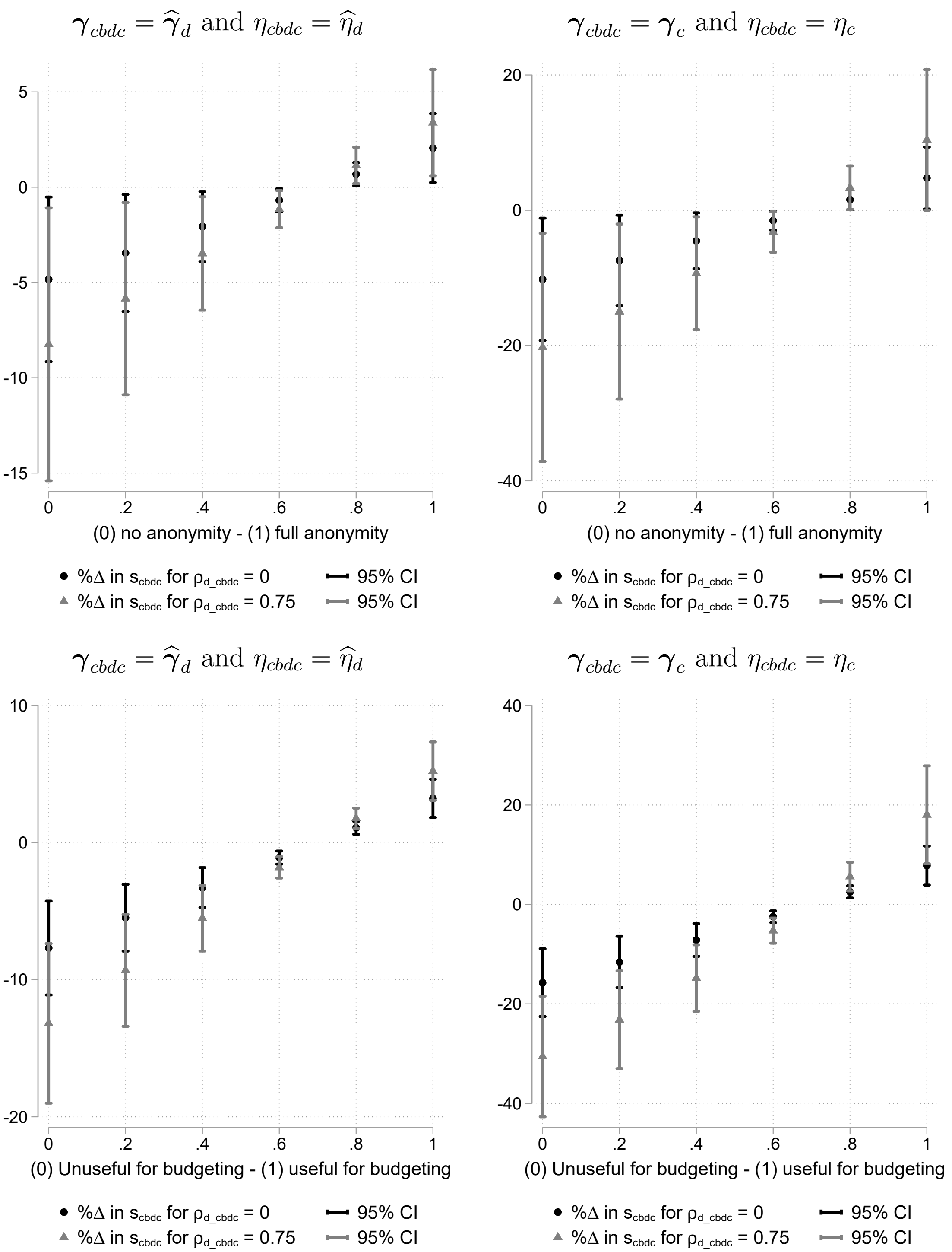
CBDC anonymity and usefulness for budgeting

Figure 5 shows the impacts of the anonymity and the budgeting usefulness features on the percentage changes in aggregate CBDC shares. Under the realistic design, CBDC is assumed to achieve 70% of the cash anonymity and the budgeting usefulness for cash. Relative to the realistic design, if CBDC becomes non-anonymous like deposit, the aggregate CBDC share drops by around 5–10% (8–20%) when $\rho_{d\_cbdc} = 0$ (0.75), depending on the unidentified effects for CBDC ($\boldsymbol{\gamma}_{cbdc}$ and η_{cbdc}). If CBDC can achieve the cash anonymity, i.e., the degree of anonymity increases from 0.7 to 1, the aggregate CBDC share increases by around 2–5% (3–10%) when $\rho_{d\_cbdc} = 0$ (0.75).

Usefulness for budgeting has a slightly larger effect compared to anonymity. Relative to the realistic design where CBDC can achieve 70% of the budgeting usefulness for cash, if CBDC becomes not useful for budgeting like deposit, its aggregate share will drop by around 8–16% (depending on the values of $\boldsymbol{\gamma}_{cbdc}$ and η_{cbdc}) when $\rho_{d\_cbdc} = 0$. If CBDC becomes as

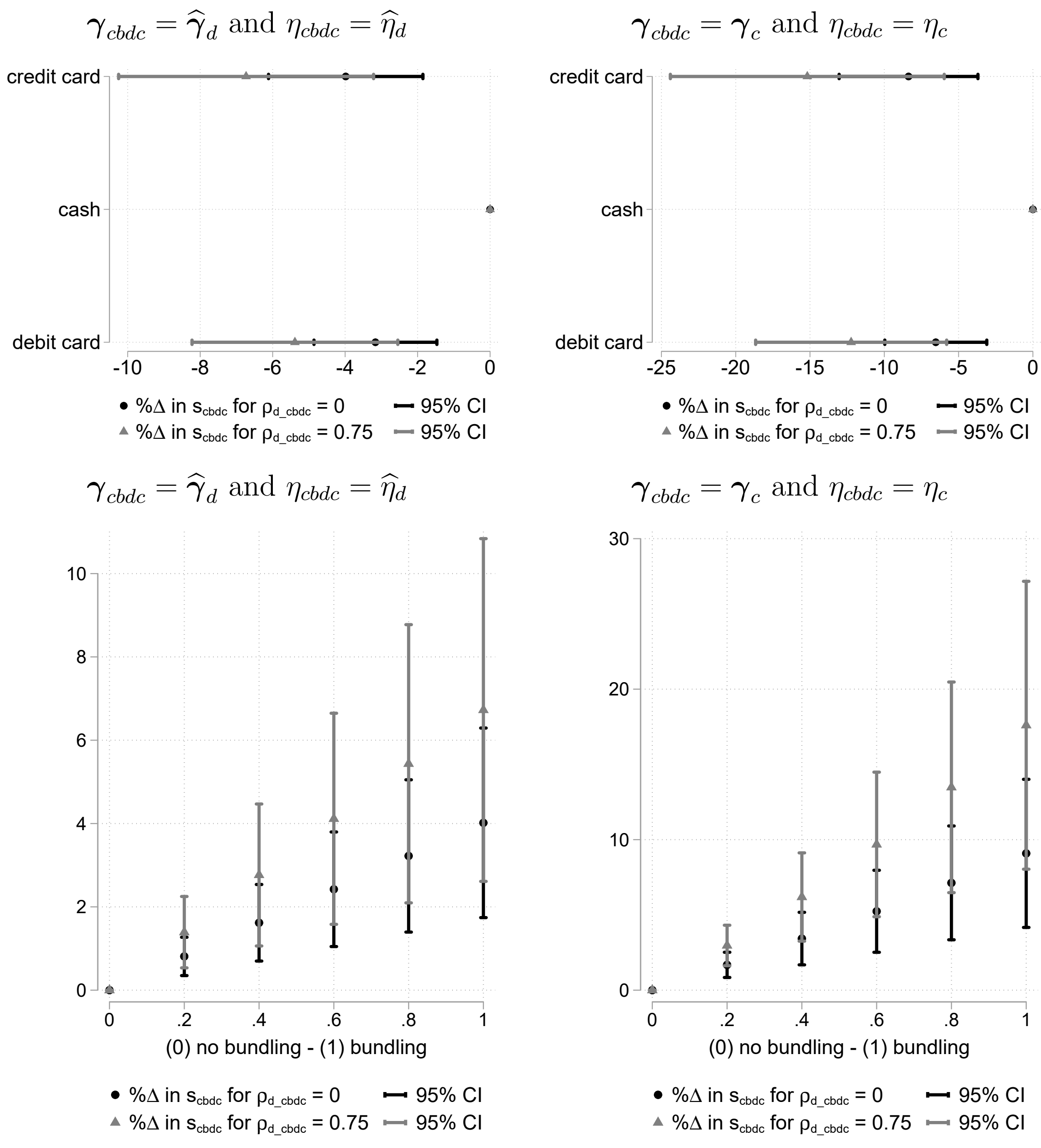
[35] In the top right graph, the aggregate CBDC share is lower under $\rho_{d\_cbdc} = 0.75$ because CBDC has a lower observed utility than deposit due to $\boldsymbol{\gamma}_{cbdc} = \boldsymbol{\gamma}_c$ and $\eta_{cbdc} = \eta_c$. With greater substituability between CBDC and deposit, this leads to more substitution from CBDC to deposit.

Figure 5: The Impacts of Anonymity and Usefulness for Budgeting on CBDC Demand



Note: The graph plots the percentage change in the aggregate CBDC share $\%\Delta s_{cbdc}$ relative to the baseline value against different levels of anonymity (upper panel) and degrees of usefulness for budgeting (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 of CBDC and deposit are plotted. The standard errors for calculating the 95% confidence intervals are computed using the delta method.

Figure 6: The Impacts of Cost of Use and Product Bundling on CBDC Demand



Note: The graph plots the percentage change in the aggregate CBDC share $\%\Delta s_{cbdc}$ relative to the baseline value for different cost of use (upper panel) and degrees of product bundling (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 of CBDC and deposit are plotted. The standard errors for calculating the 95% confidence intervals are computed using the delta method.

useful as cash in terms of the budgeting feature, its share increases by around 3–8% when $\rho_{d\_cbdc} = 0$.

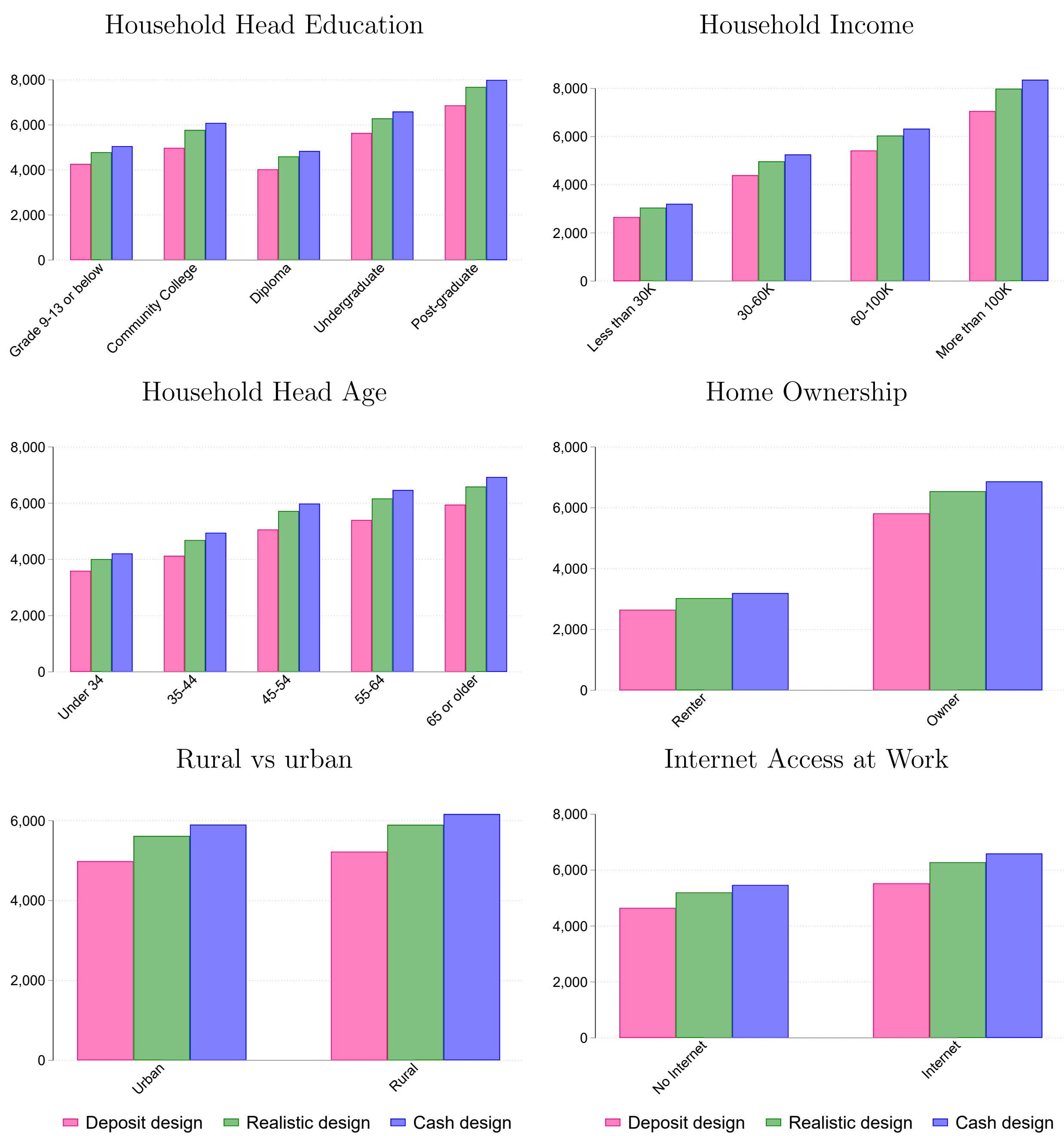
Cost of use and product bundling

Figure 6 shows the impacts of the cost of use and the product bundling features. Under the realistic design, CBDC is assumed to be unbundled with financial planning advice service and as cheap to use as cash. The latter is implemented by using the cost-of-use ratings for cash to measure the cost of use for CBDC. The upper panel shows that if the cost of use for CBDC changes from cash ratings to credit card (debit card) ratings, implying that CBDC is perceived to be more costly to use, then its aggregate share would drop by around 4–8% (3–7%) when $\rho_{d\_cbdc} = 0$, depending on the unidentified effects for CBDC ($\boldsymbol{\gamma}_{cbdc}$ and η_{cbdc}). The lower panel shows that if CBDC becomes bundled with the service of financial planning advice, unlike under the realistic design, then its aggregate share would increase by around 4–9% (depending on the values of $\boldsymbol{\gamma}_{cbdc}$ and η_{cbdc}) when $\rho_{d\_cbdc} = 0$. When $\rho_{d\_cbdc} = 0.75$, the changes are slightly larger while the confidence intervals are also wider.

Other features of CBDC

The impacts of ease and security features on CBDC demand are small. As shown in Table 1 in Section 4, the preference parameters for these two features are much smaller compared to the parameter for the cost of use. The impacts of online purchase capability and unacceptance rate are shown in Figure 14 in Appendix D. The upper panel of Figure 14 shows that relative to the realistic design where CBDC can be used for online purchase, losing this feature only reduces its aggregate share by around 1%. This small impact is partly because only around 15% of households use online payment for one or more transactions during the three-day shopping diary recorded in 2013. Those who do not use online payment will not obtain any utility from this feature, so this online feature does not contribute much to the aggregate CBDC share. The lower panel of Figure 14 shows that relative to the realistic 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, then the aggregate CBDC share drops by around 2–4% when $\rho_{d\_cbdc} = 0$.

Figure 7: 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 assumptions that the CBDC-specific effects of household characteristics and CBDC fixed effect are identical to the estimated parameters for deposit. The predicted CBDC holdings are deflated by CPI in each year.

5.3 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.[36] Figure 7 shows the unweighted mean predicted CBDC holdings in Canadian dollars across groups with different education levels, income, age, internet access, home ownership, and area of living (rural vs urban). Within each demographic group, the predicted holdings under three different designs are shown, i.e. the deposit design, the cash design, and the realistic design. Detailed information about the designs can be found in Table 2. The predictions in this section are based on the logit model.[37]

Figure 7 shows that households with higher education, higher income, older age, or home ownership, tend to hold more CBDC on average. In contrast, there are no notable differences in CBDC holdings between groups living in rural vs. urban areas or having vs. not having internet access. These patterns are similar under different designs of CBDC, although the magnitude of the CBDC holdings differs slightly across designs. When the product attributes of CBDC are identical to the cash (deposit) attributes, CBDC holdings across different groups are slightly higher (lower) compared to the realistic design, since the cash design is better in terms of anonymity and budgeting usefulness features, whereas the deposit design is worse in terms of these two features.

Since the observed utility for CBDC depends on both the design of CBDC and the unidentified effects for CBDC (i.e., $\boldsymbol{\gamma}_{cbdc}$ and η_{cbdc}), the fact that the patterns are similar across different designs indicates that they are driven by the unidentified effects. Figure 7 assumes that the unidentified effects for CBDC are deposit-like (i.e., $\boldsymbol{\gamma}_{cbdc} = \widehat{\boldsymbol{\gamma}}_d$ and $\eta_{cbdc} = \widehat{\eta}_d$), implying that the observed utility of CBDC is similar to that of deposit. In this case, if households in a given demographic group prefer to hold more deposit, they would also want to hold more CBDC. Figure 16 in Appendix D shows that households with higher education, older age, higher income, or are homeowners tend to hold more deposit over 2014–2017 in CFM data. As a result, households in these demographics groups also hold more CBDC as shown in Figure 7.

Similarly, when assuming that the unidentified effects for CBDC are cash-like (i.e., $\boldsymbol{\gamma}_{cbdc} = \boldsymbol{\gamma}_c$ and $\eta_{cbdc} = \eta_c$), the observed utility of CBDC is close to that of cash. Figure 17 in

[36] 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.

[37] 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 of CBDC and cash. This is because ρ_{c_cbdc} only has a very small impact on the CBDC holdings, as discussed in Section 5.1.2. The results are also robust to different values of ρ_{d_cbdc}, as long as the unidentified effects for CBDC are close to being deposit-like (i.e., $\boldsymbol{\gamma}_{cbdc}$ and η_{cbdc} are close to the estimated values for deposit, $\widehat{\boldsymbol{\gamma}}_d$ and $\widehat{\eta}_d$).

Appendix D shows that households with older age, higher income, or home ownership, tend to hold more cash in the data. Therefore, those demographic groups also tend to hold more CBDC in this case, as shown in Figure 15 in Appendix D.

The patterns in Figure 7 are robust to different time periods (or years) except for the level of education. There is no clear pattern across groups with different levels of education during the period of 2010–2013. This is consistent with Figure 16 in Appendix D that shows no clear pattern in deposit holdings across different education levels during this period. The patterns for the unweighted mean CBDC holdings in Figure 7 are also robust to those for the median or weighted mean holdings.

This section examines the holdings of CBDC holdings 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 higher liquid assets. If the two effects cancel out with each other, the CBDC shares should be similar to those held by households in younger age groups. If this wealth effect dominates, households in older age groups that hold more CBDC in balances can have lower CBDC shares. I find that when assuming that the unidentified effects for CBDC are deposit-like, the are no differences in CBDC shares across different demographic groups. In contrast, when assuming that the unidentified effects for CBDC are cash-like, households with higher education, higher income, home ownership, or internet access at work have lower CBDC shares.

6 Conclusions

In light of the declining cash usage and the potential threat from the privately issued e-money, many central banks around the world are exploring the possibility of issuing their own digital currencies (CBDC) that allow the public to continue having access to the central bank issued money even if the society becomes cashless.

Since CBDC can be used as both a payment instrument and a store-of-value asset, it is a close alternative to cash and demand deposit. There are concerns that CBDC will crowd out a lot of bank deposit, which has financial stability implications. Given that a higher demand for CBDC tends to imply greater crowding out on deposit demand, it is important to predict the likely holdings of CBDC by households. This paper represents the first attempt to empirically estimate the potential demand for CBDC relative to cash and demand deposit, as well as the impacts of different design features on the potential demand for CBDC.

Using a structural demand model, households' utilities for different products are represented in the product attribute space and hence their liquid asset allocation depends on the differences in these attributes between assets. Using a unique Canadian household survey dataset, the paper estimates how households value these product attributes when allocating their liquid assets between cash and demand deposit. The estimated preference parameters for the product attributes are used to predict the demand for CBDC with a given design.

This paper finds that there is a lot of uncertainty about the potential level of CBDC demand, because the unidentified effects for CBDC play a large role in determining the potential level of CBDC demand. Therefore, the paper only predicts a broad range for the CBDC demand. Under a realistic design of CBDC, households would hold around 4–55% of their liquid assets in CBDC, depending on whether the unidentified effects for CBDC are more cash-like or deposit-like.

Despite the difficulty in predicting the exact level of CBDC demand, this paper still provides a better understanding of which design attributes of CBDC would matter more for CBDC demand, since the impacts of design attributes rely much less on the unidentified effects. The important product attributes identified in this paper include the budgeting usefulness, anonymity, cost of use, bundling of financial planning advice, and the rate of return.

Appendices

A Asset Allocation Problem

Section A.1 shows that the log of deposit-to-cash ratio (5) 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 found in an asset allocation problem with a nested CES utility function.

A.1 CES Utility

Under the money-in-the-utility assumptions, households obtain utility from holding cash c and deposit d since they can use money holdings to facilitate transactions. Each household i maximizes the following CES utility function:[38]

$$u_{i,t}(q_{i,c,t}, q_{i,d,t}, \boldsymbol{x}_{i,c,t}, \boldsymbol{x}_{i,d,t}, \boldsymbol{z}_{i,t}) = \left[\nu_{i,c,t} q_{i,c,t}^{\theta} + \nu_{i,d,t} q_{i,d,t}^{\theta}\right]^{\frac{1}{\theta}} \tag{14}$$

subject to a budget constraint:

$$q_{i,c,t} + q_{i,d,t} = w_{i,t} \tag{15}$$

where $\theta \in (0, 1]$ is the substitution parameter and $\nu_{i,j,t}$ is a share parameter that 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 deposit 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 1, the two assets are perfect substitutes, in which case if the marginal utility $\nu_{i,j,t}$ from asset j is higher, then the entire wealth 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:

$$\frac{1}{\theta}\left[\nu_{i,c,t} q_{i,c,t}^{\theta} + \nu_{i,d,t} q_{i,d,t}^{\theta}\right]^{\frac{1}{\theta}-1} \nu_{i,j,t} \theta q_{i,j,t}^{\theta-1} = \lambda \quad \forall\ j \in \{c, d\} \tag{16}$$

[38]See Kurlat (2019) and Drechsler, Savov and Schnabl (2017) for this type of utility specification.

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

$$\frac{q_{i,d,t}}{q_{i,c,t}} = \left(\frac{\nu_{i,d,t}}{\nu_{i,c,t}}\right)^{\frac{1}{1-\theta}} \tag{17}$$

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 demand framework before normalising the scale of the utility.[39]

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:

$$\ln \frac{q_{i,d,t}}{q_{i,c,t}} = \frac{1}{1-\theta}\left(V^*_{i,d,t} - V^*_{i,c,t}\right) = \frac{1}{1-\theta}\left[\boldsymbol{\alpha}^{*'}(\boldsymbol{x}_{i,d,t} - \boldsymbol{x}_{i,c,t}) + \boldsymbol{\gamma}^{*'}_d \boldsymbol{z}_{i,t} + \eta^*_d\right] \tag{18}$$

which is equivalent to the log of deposit-to-cash ratio (5) under the logit framework 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 deposit and cash. In contrast, under the logit framework, these parameters are scaled by the standard deviation of the unobserved factors to normalise the scale of the utility.

A.2 Nested CES Utility

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

$$u_{i,t}(q_{i,c,t}, q_{i,d,t}, q_{i,cbdc,t}, \boldsymbol{x}_{i,c,t}, \boldsymbol{x}_{i,d,t}, \boldsymbol{x}_{i,cbdc,t}, \boldsymbol{z}_{i,t}) = \left[\nu_{i,c,t} q^{\theta}_{i,c,t} + \nu_{i,d,t}\left[q^{\varphi}_{i,d,t} + \frac{\nu_{i,cbdc,t}}{\nu_{i,d,t}} q^{\varphi}_{i,cbdc,t}\right]^{\frac{\theta}{\varphi}}\right]^{\frac{1}{\theta}} \tag{19}$$

and the budget constraint becomes:

$$q_{i,c,t} + q_{i,d,t} + q_{i,cbdc,t} = w_{i,t} \tag{20}$$

where $\varphi \in (0,1]$ is the substitution parameter between CBDC and deposit, $\theta \in (0,1]$ 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 $q_{i,c,t}$, deposit $q_{i,d,t}$ and CBDC $q_{i,cbdc,t}$ holdings.

[39]Let $\mathrm{Var}(\epsilon_{i,j,t}) = \sigma^2$ denote the variance of the error term in the logit model. This variance is often normalised to $\pi^2/6$, so the parameters $\boldsymbol{\alpha}$, $\boldsymbol{\gamma}_j$, and η_j in (1) are the corresponding parameters $\boldsymbol{\alpha}^*$, $\boldsymbol{\gamma}^*_j$, and η^*_j scaled by $\sqrt{\pi^2/6}/\sigma$.

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:

$$\frac{1}{\theta}\left[\nu_{i,c,t}q_{i,c,t}^{\theta}+\nu_{i,d,t}\left[q_{i,d,t}^{\varphi}+\frac{\nu_{i,cbdc,t}}{\nu_{i,d,t}}q_{i,cbdc,t}^{\varphi}\right]^{\frac{\theta}{\varphi}}\right]^{\frac{1}{\theta}-1}\nu_{i,c,t}\theta q_{i,c,t}^{\theta-1}=\lambda \tag{21}$$

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

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

Divide the first order conditions with respect to $q_{i,d,t}$ (22) and $q_{i,cbdc,t}$ (23) to get:

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

Divide the first order conditions with respect to $q_{i,d,t}$ (22) and $q_{i,c,t}$ (21) to get:

$$\frac{\nu_{i,d,t}\left[q_{i,d,t}^{\varphi}+\frac{\nu_{i,cbdc,t}}{\nu_{i,d,t}}q_{i,cbdc,t}^{\varphi}\right]^{\frac{\theta}{\varphi}-1}q_{i,d,t}^{\varphi-1}}{\nu_{i,c,t}q_{i,c,t}^{\theta-1}}=1 \tag{25}$$

which can be rearranged to:

$$\frac{\nu_{i,d,t}\left[1+\frac{\nu_{i,cbdc,t}}{\nu_{i,d,t}}\frac{q_{i,cbdc,t}^{\varphi}}{q_{i,d,t}^{\varphi}}\right]^{\frac{\theta}{\varphi}-1}q_{i,d,t}^{\theta-1}}{\nu_{i,c,t}q_{i,c,t}^{\theta-1}}=1 \tag{26}$$

Using (24) and (26), the deposit-to-cash ratio after CBDC issuance can be written as:

$$\frac{q_{i,d,t}}{q_{i,c,t}}=\left(1+\frac{q_{i,cbdc,t}}{q_{i,d,t}}\right)^{\frac{\varphi-\theta}{\varphi(\theta-1)}}\left(\frac{\nu_{i,d,t}}{\nu_{i,c,t}}\right)^{\frac{1}{1-\theta}} \tag{27}$$

Note that when $\varphi=\theta$, this reduces to the CES utility case and the deposit-to-cash ratio is identical to (17), which is independent from CBDC. This resembles the independence of irrelevant alternative property under the standard 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 (27) after CBDC issuance under the nested CES utility here is equivalent to that under the nested logit model (11) when

$\tau_d - 1 = \frac{\varphi-\theta}{\varphi(\theta-1)}$, where τ_d is the inverse correlation measure between the unobserved utilities of similar products under the nested logit. Similar to (11), the deposit-to-cash ratio after the CBDC issuance is a fraction of that before the CBDC issuance,[40] where the fraction depends on how CBDC is valued against deposit (indicated by $\frac{q_{i,cbdc,t}}{q_{i,d,t}}$) and the degree of substitutability between CBDC and deposit $\frac{\varphi-\theta}{\varphi(\theta-1)}$.

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 of similar products. This section shows the cases when CBDC is a closer substitute for deposit and cash in turn.

B.1 CBDC and Deposit are Closer Substitutes

Suppose CBDC and deposit are in the same nest B_{d_cbdc}, then the deposit share is:

$$s'_{i,d,t} = \underbrace{\frac{\exp\left(\frac{V_{i,d,t}}{\tau_d}\right)}{\exp\left(\frac{V_{i,cbdc,t}}{\tau_d}\right) + \exp\left(\frac{V_{i,d,t}}{\tau_d}\right)}}_{\text{Prob}(j=d|j\in B_{d\_cbdc})} \underbrace{\frac{\left[\exp\left(\frac{V_{i,cbdc,t}}{\tau_d}\right) + \exp\left(\frac{V_{i,d,t}}{\tau_d}\right)\right]^{\tau_d}}{\left[\exp\left(\frac{V_{i,cbdc,t}}{\tau_d}\right) + \exp\left(\frac{V_{i,d,t}}{\tau_d}\right)\right]^{\tau_d} + \exp\left(V_{i,c,t}\right)}}_{\text{Prob}(j\in B_{d\_cbdc})} \tag{28}$$

and the cash share is:

$$s'_{i,c,t} = \frac{\exp\left(V_{i,c,t}\right)}{\left[\exp\left(\frac{V_{i,cbdc,t}}{\tau_d}\right) + \exp\left(\frac{V_{i,d,t}}{\tau_d}\right)\right]^{\tau_d} + \exp\left(V_{i,c,t}\right)} \tag{29}$$

[40]It can be seen from Appendix A.1 that the deposit-to-cash ratio before the CBDC issuance is $\left(\frac{\nu_{i,d,t}}{\nu_{i,c,t}}\right)^{\frac{1}{1-\theta}}$, which is equivalent to that derived from the logit model, after assuming that the share parameter in the CES utility function $\nu_{i,j,t}$ is an exponential function of the product attributes and household characteristics captured by $V^*_{i,j,t}$.

Divide the deposit share (28) by the cash share (29) to get:

$$
\begin{aligned}
\frac{s'_{i,d,t}}{s'_{i,c,t}} &= \frac{\exp\left(\frac{V_{i,d,t}}{\tau_d}\right)\left[\exp\left(\frac{V_{i,d,t}}{\tau_d}\right)+\exp\left(\frac{V_{i,cbdc,t}}{\tau_d}\right)\right]^{\tau_d-1}}{\exp\left(V_{i,c,t}\right)} \\
&= \exp\left(V_{i,d,t}-V_{i,c,t}\right)\exp\left(\frac{V_{i,d,t}}{\tau_d}-V_{i,d,t}\right)\left[\exp\left(\frac{V_{i,d,t}}{\tau_d}\right)+\exp\left(\frac{V_{i,cbdc,t}}{\tau_d}\right)\right]^{\tau_d-1} \\
&= \left[1+\exp\left(\frac{V_{i,cbdc,t}-V_{i,d,t}}{\tau_d}\right)\right]^{\tau_d-1}\exp\left(V_{i,d,t}-V_{i,c,t}\right)
\end{aligned}
\tag{30}
$$

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. 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 (30) with respect to τ_d:

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

where the last two steps use (30) and the derivative of $\frac{s_{i,cbdc,t}}{s'_{i,d,t}}=\exp\left(\frac{V_{i,cbdc,t}-V_{i,d,t}}{\tau_d}\right)$ with respect to τ_d is:

$$
\frac{\partial\frac{s_{i,cbdc,t}}{s'_{i,d,t}}}{\partial\tau_d}=\exp\left(\frac{V_{i,cbdc,t}-V_{i,d,t}}{\tau_d}\right)\left(-\frac{V_{i,cbdc,t}-V_{i,d,t}}{\tau_d^2}\right)
\tag{32}
$$

Hence, how the deposit-to-cash ratio changes with τ_d depends on how the CBDC-to-deposit ratio changes with τ_d, 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. By 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 in terms of the deposit-to-cash ratio:

$$s_{i,cbdc,t} = \frac{\frac{s_{i,cbdc,t}}{s'_{i,d,t}}}{1 + \frac{s'_{i,c,t}}{s'_{i,d,t}} + \frac{s_{i,cbdc,t}}{s'_{i,d,t}}} \tag{33}$$

To see how $s_{i,cbdc,t}$ changes with τ_d, differentiate $s_{i,cbdc,t}$ (33) with respect to τ_d:

$$\begin{aligned}
\frac{\partial s_{i,cbdc,t}}{\partial \tau_d} &= \frac{\frac{\partial \frac{s_{i,cbdc,t}}{s'_{i,d,t}}}{\partial \tau_d}}{1 + \frac{s'_{i,c,t}}{s'_{i,d,t}} + \frac{s_{i,cbdc,t}}{s'_{i,d,t}}} - \frac{\frac{s_{i,cbdc,t}}{s'_{i,d,t}}}{\left(1 + \frac{s'_{i,c,t}}{s'_{i,d,t}} + \frac{s_{i,cbdc,t}}{s'_{i,d,t}}\right)^2} \left[-\left(\frac{s'_{i,d,t}}{s'_{i,c,t}}\right)^{-2} \frac{\partial \frac{s'_{i,d,t}}{s'_{i,c,t}}}{\partial \tau_d} + \frac{\partial \frac{s_{i,cbdc,t}}{s'_{i,d,t}}}{\partial \tau_d} \right] \\
&= \frac{\partial \frac{s_{i,cbdc,t}}{s'_{i,d,t}}}{\partial \tau_d} \frac{1 + \frac{s'_{i,c,t}}{s'_{i,d,t}}}{\left(1 + \frac{s'_{i,c,t}}{s'_{i,d,t}} + \frac{s_{i,cbdc,t}}{s'_{i,d,t}}\right)^2} + \frac{\partial \frac{s'_{i,d,t}}{s'_{i,c,t}}}{\partial \tau_d} \frac{\frac{s_{i,cbdc,t}}{s'_{i,d,t}} \left(\frac{s'_{i,d,t}}{s'_{i,c,t}}\right)^{-2}}{\left(1 + \frac{s'_{i,c,t}}{s'_{i,d,t}} + \frac{s_{i,cbdc,t}}{s'_{i,d,t}}\right)^2}
\end{aligned} \tag{34}$$

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 (31) into (34) to get:

$$\begin{aligned}
\frac{\partial s_{i,cbdc,t}}{\partial \tau_d} &= \frac{\partial \frac{s_{i,cbdc,t}}{s'_{i,d,t}}}{\partial \tau_d} \frac{1 + \frac{s'_{i,c,t}}{s'_{i,d,t}}}{\Lambda^2} + \frac{\frac{s_{i,cbdc,t}}{s'_{i,d,t}} \left(\frac{s'_{i,d,t}}{s'_{i,c,t}}\right)^{-2}}{\Lambda^2} \frac{s'_{i,d,t}}{s'_{i,c,t}} \left[\ln\left(1 + \frac{s_{i,cbdc,t}}{s'_{i,d,t}}\right) + (\tau_d - 1) \frac{1}{1 + \frac{s_{i,cbdc,t}}{s'_{i,d,t}}} \frac{\partial \frac{s_{i,cbdc,t}}{s'_{i,d,t}}}{\partial \tau_d} \right] \\
&= \frac{\partial \frac{s_{i,cbdc,t}}{s'_{i,d,t}}}{\partial \tau_d} \frac{1}{\Lambda^2} \left[1 + \frac{s'_{i,c,t}}{s'_{i,d,t}} + \left(\frac{s'_{i,d,t}}{s'_{i,c,t}}\right)^{-1} \frac{(\tau_d - 1)}{\frac{s'_{i,d,t}}{s_{i,cbdc,t}} + 1} \right] + \frac{\frac{s_{i,cbdc,t}}{s'_{i,d,t}} \left(\frac{s'_{i,d,t}}{s'_{i,c,t}}\right)^{-1}}{\Lambda^2} \ln\left(1 + \frac{s_{i,cbdc,t}}{s'_{i,d,t}}\right) \\
&= \frac{\partial \frac{s_{i,cbdc,t}}{s'_{i,d,t}}}{\partial \tau_d} \frac{1}{\Lambda^2} \left[1 + \frac{s'_{i,c,t}}{s'_{i,d,t}} \left(1 + \frac{(\tau_d - 1)}{\frac{s'_{i,d,t}}{s_{i,cbdc,t}} + 1}\right) \right] + \frac{\frac{s_{i,cbdc,t}}{s'_{i,d,t}} \left(\frac{s'_{i,d,t}}{s'_{i,c,t}}\right)^{-1}}{\Lambda^2} \ln\left(1 + \frac{s_{i,cbdc,t}}{s'_{i,d,t}}\right)
\end{aligned} \tag{35}$$

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. The only term that has an ambiguous sign in (35) is $\frac{\partial \frac{s_{i,cbdc,t}}{s'_{i,d,t}}}{\partial \tau_d}$. 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 (32), 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:

$$\frac{s'_{i,d,t}}{s'_{i,c,t}} = \left[1 + \exp\left(\frac{V_{i,cbdc,t} - V_{i,c,t}}{\tau_c}\right)\right]^{1-\tau_c} \exp\left(V_{i,d,t} - V_{i,c,t}\right) \tag{36}$$

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. 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 (36) with respect to τ_c and simplify to get:

$$\frac{\partial \frac{s'_{i,d,t}}{s'_{i,c,t}}}{\partial \tau_c} = \frac{s'_{i,d,t}}{s'_{i,c,t}} \left[-\ln\left(1 + \frac{s_{i,cbdc,t}}{s'_{i,c,t}}\right) + (1 - \tau_c)\frac{1}{1 + \frac{s_{i,cbdc,t}}{s'_{i,c,t}}} \frac{\partial \frac{s_{i,cbdc,t}}{s'_{i,c,t}}}{\partial \tau_c}\right] \tag{37}$$

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:

$$\frac{\partial \frac{s_{i,cbdc,t}}{s'_{i,c,t}}}{\partial \tau_c} = \exp\left(\frac{V_{i,cbdc,t} - V_{i,c,t}}{\tau_c}\right)\left(-\frac{V_{i,cbdc,t} - V_{i,c,t}}{\tau_c^2}\right) \tag{38}$$

Since the sign of $\frac{\partial \frac{s_{i,cbdc,t}}{s'_{i,c,t}}}{\partial \tau_c}$ is ambiguous depending on how the observed utility of CBDC compares with that of deposit, it is unclear how the deposit-to-cash ratio changes with τ_c (37). 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 in terms of the deposit-to-cash ratio:

$$s_{i,cbdc,t} = \frac{\frac{s_{i,cbdc,t}}{s'_{i,c,t}}}{1 + \frac{s'_{i,d,t}}{s'_{i,c,t}} + \frac{s_{i,cbdc,t}}{s'_{i,c,t}}} \tag{39}$$

To see how $s_{i,cbdc,t}$ changes with τ_c, differentiate $s_{i,cbdc,t}$ (39) with respect to τ_c:

$$\begin{aligned}\frac{\partial s_{i,cbdc,t}}{\partial \tau_c} &= \frac{\frac{\partial \frac{s_{i,cbdc,t}}{s'_{i,c,t}}}{\partial \tau_c}}{1+\frac{s'_{i,d,t}}{s'_{i,c,t}}+\frac{s_{i,cbdc,t}}{s'_{i,c,t}}} - \frac{\frac{s_{i,cbdc,t}}{s'_{i,c,t}}}{\left(1+\frac{s'_{i,d,t}}{s'_{i,c,t}}+\frac{s_{i,cbdc,t}}{s'_{i,c,t}}\right)^2}\left(\frac{\partial \frac{s'_{i,d,t}}{s'_{i,c,t}}}{\partial \tau_c}+\frac{\partial \frac{s_{i,cbdc,t}}{s'_{i,c,t}}}{\partial \tau_c}\right) \\ &= \frac{\partial \frac{s_{i,cbdc,t}}{s'_{i,c,t}}}{\partial \tau_c}\frac{1+\frac{s'_{i,d,t}}{s'_{i,c,t}}}{\left(1+\frac{s'_{i,d,t}}{s'_{i,c,t}}+\frac{s_{i,cbdc,t}}{s'_{i,c,t}}\right)^2} - \frac{\partial \frac{s'_{i,d,t}}{s'_{i,c,t}}}{\partial \tau_c}\frac{\frac{s_{i,cbdc,t}}{s'_{i,c,t}}}{\left(1+\frac{s'_{i,d,t}}{s'_{i,c,t}}+\frac{s_{i,cbdc,t}}{s'_{i,c,t}}\right)^2}\end{aligned} \tag{40}$$

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 (37) into (40) and simplify to get:

$$\frac{\partial s_{i,cbdc,t}}{\partial \tau_c} = \frac{\partial \frac{s_{i,cbdc,t}}{s'_{i,c,t}}}{\partial \tau_c}\frac{1}{\Omega^2}\left[1+\frac{s'_{i,d,t}}{s'_{i,c,t}}\left(1-\frac{(1-\tau_c)}{\frac{s'_{i,c,t}}{s_{i,cbdc,t}}+1}\right)\right] + \frac{\frac{s_{i,cbdc,t}}{s'_{i,c,t}}\frac{s'_{i,d,t}}{s'_{i,c,t}}}{\Omega^2}\ln\left(1+\frac{s_{i,cbdc,t}}{s'_{i,c,t}}\right) \tag{41}$$

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. The only term that has an ambiguous sign in (41) is $\frac{\partial \frac{s_{i,cbdc,t}}{s'_{i,c,t}}}{\partial \tau_c}$. 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 (38), 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. By 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

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. Besides, the CFM survey became an online survey after 2018, so the most recent data are less comparable with those from the offline surveys in previous years. This section discusses how to construct the measures of cash holding, deposit holding, and the main financial institution using CFM data in the matched sample of CFM and MOP.

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 precautionary cash holding only, since the demand deposit balance is also answered in categories and is calculated at the household level. The baseline results in the paper are robust to 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.

Changes in survey questions over time

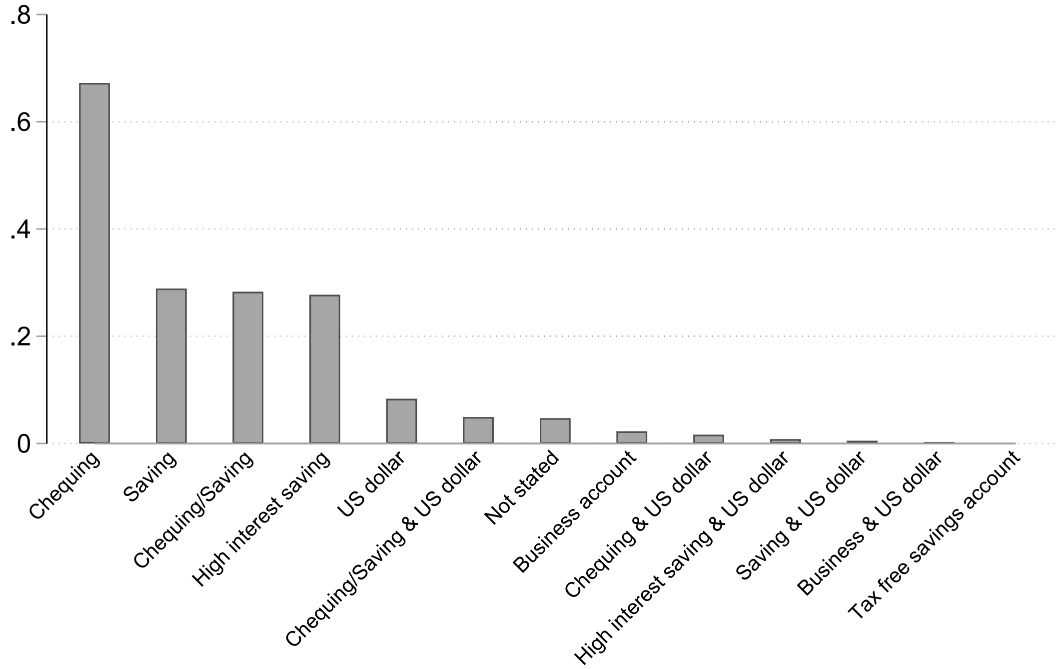
In 2009, the question on cash in wallet is: "On average, how much cash on hand was held for regular day-to-day use?". After 2009, the question changed to: "How much cash do you have in your purse or wallet right now?". Besides, the question on precautionary cash holding changed in 2018: "How much cash does your household hold outside your purse, wallet, or pockets right now?". Prior to 2018, the question is "(On average), how much cash on hand does your household hold for emergencies, or other precautionary reasons?".

C.1.2 Deposit Holding

The CFM survey asks respondent to list all 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 answers for the current balance in each bank account are in terms of the following categories (in Canadian dollars): non/zero, under 100, 100–499, 500–999, ..., 600000–749999, 750000 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 the baseline analysis, I focus on the household's balance in demand deposit accounts (including chequing, saving, chequing/saving accounts), where the maximum demand deposit balance across households is around \$526K.

Figure 8: Fraction of Observations with a Positive Balance in Different Bank Accounts



Data source: CFM 2010–2017

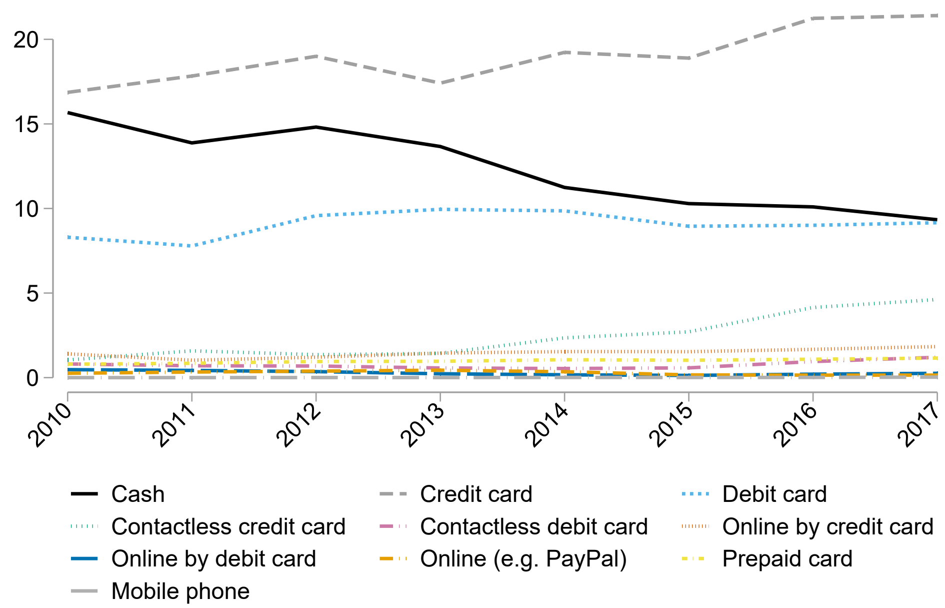
Note: The bar chart shows the fraction of household-year observations that have a positive balance in a given type of bank account in the matched sample of CFM and MOP.

C.1.3 Main Financial Institution

There are two sections asking about the financial institutions (FIs) in the CFM survey. One question in section 1 of the survey is: "What is your main financial institution?". Each household can enter three different main FIs, although around 71% of household-year observations only write one main FI in this section. In section 4 of the survey that asks about detailed information on chequing and saving accounts, where the respondent needs to write down the FI associated with each bank account owned by each individual in the household.

Since this paper focuses on the demand deposit, I construct the main FI for each household using the information from section 4 of the survey. 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, then one of these FIs is treated as the main FI if it also coincides with the main FI answered in section 1 of survey.

Figure 9: Weighted Mean Number of Transactions (Past Month) across Households



Data source: CFM 2010–2017

Note: The graph plots weighted mean number of transactions (in the past month) via each payment instrument across households in the matched 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 expenditure 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

This section explains the construction of the merchant acceptance variable. There are several pieces of information on merchant acceptance from the MOP survey data. For example, the survey asks 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 cause simultaneous causality problem. A household that prefers to use deposit to pay and hence holds more deposit may think acceptance is more important. The survey also asks people whether they think a given payment instrument is widely accepted. These perceptions tend to depend on which payment instrument is often used and hence is less accurate than the acceptance rate encountered in transactions. Therefore, this paper uses the information from the MOP diary data to construct the individual-level acceptance rate.

Table 3: 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
Credit card	0.17	0.22	0.17	0.29	0.14
Debit card	0.27	0.37	0.20	0.12	0.02
Ease/Convenience	Very hard to use				Very easy to use
Cash	0.00	0.01	0.04	0.17	0.76
Credit card	0.01	0.01	0.07	0.31	0.60
Debit card	0.00	0.01	0.10	0.29	0.59
Security/Risk	Very risky				Very secure
Cash	0.01	0.07	0.11	0.26	0.54
Credit card	0.02	0.13	0.16	0.53	0.15
Debit card	0.01	0.11	0.16	0.53	0.18

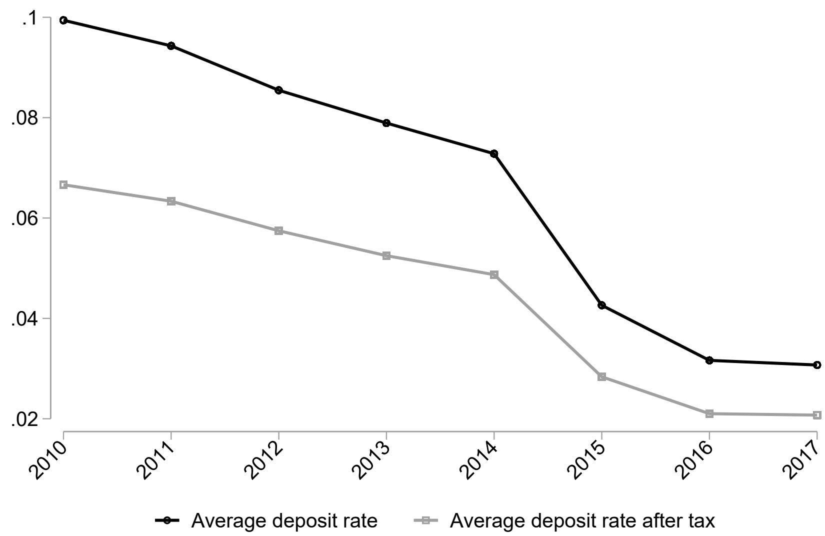
Data source: MOP 2013

Note: The table summarises 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 datasets. The ratings of 1 to 5 represent very low to very high cost for the cost of use feature, very hard to very easy to use for the ease of use feature, and very risky to very secure for the security feature.

C.3 CANNEX Deposit Rates

Historical rates for deposit accounts are only available for the big six banks, whereas historical term deposit rates are available for more financial institutions in CANNEX data. For other financial institutions, demand deposit rates are available from October 2020. Since this paper

Figure 10: 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 rate before and after income taxes across households in the matched sample of CFM and MOP data. Households face different deposit rates (after taxes) as they save at different banks (and they have different marginal income tax rates). The bank-level deposit rates are from CANNEX data and the federal and provincial tax rates are from the Government of Canada website.

focuses on the demand deposit during 2010–2017, I can only use the deposit rates for the big six. CANNEX data are at the bank-product level on a weekly frequency. I take average of the weekly rates to get the annual rates. For each bank, I calculate the mean deposit rate across different deposit account products, which include interest chequing account, daily interest saving account, tier savings account (i.e., higher balance tier gives higher interest rate), etc. Each balance tier of the tier savings account is treated as a different product.

C.4 Sample Weights

To construct the sample weights for the matched 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 or estimating the weighted regression to be compared with the baseline OLS estimation.

Table 4 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 matched 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 4, 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 4. For example, the weighted fraction of households with a household size of one in Quebec should 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/number of households in the sample for each income-region category as initial weights.[41] 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.

[41]Using population totals/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.

Table 4: 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.

Table 5: 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)	5282	0.04	0.03	0.00	0.02	0.04	0.06	0.20
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	0.22	0.21	-0.50	0.00	0.22	0.40	0.57
Difference in ratings for ease of use	6243	-0.02	0.07	-0.50	-0.07	0.00	0.00	0.40
Difference in ratings for security	6264	-0.05	0.13	-0.57	-0.08	-0.08	0.00	0.50
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	0.04	0.13	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								
Fraction of cash transactions	5910	0.38	0.34	0.00	0.00	0.33	0.64	1.00
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
Rent a home	6200	0.27	0.44	.	.	.	.	.
Female head	6327	0.77	0.42	.	.	.	.	.
Internet access via phone	6332	0.35	0.48	.	.	.	.	.
Internet access at work/school/elsewhere	6332	0.40	0.49	.	.	.	.	.
Live in rural area	6332	0.16	0.37	.	.	.	.	.
Main financial institution is TD/RBC	5364	0.34	0.47	.	.	.	.	.
Main financial institution is non-big six	5364	0.34	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 service and the ratings for anonymity and budgeting usefulness are changed as discussed in Section 3. The statistics reported are based on the adjusted scales. Difference in ratings refers to the difference in the standardised ratings between credit card and cash for a given feature. Household income and household head education are categorical variables. The last seven household characteristics are indicator variables that take a value of zero or one, hence some statistics are omitted in the table.

D Additional Results

Table 6: Estimated Parameters for Household Characteristics

	$\widehat{\gamma}_d$	se
Fraction of transactions using cash	-0.565***	(0.094)
Household head age	0.006**	(0.003)
Household income \$15,000 - \$19,999	0.483***	(0.172)
Household income \$20,000 - \$24,999	0.627***	(0.182)
Household income \$25,000 - \$29,999	0.298*	(0.180)
Household income \$30,000 - \$34,999	0.757***	(0.166)
Household income \$35,000 - \$44,999	0.746***	(0.155)
Household income \$45,000 - \$54,999	0.473***	(0.152)
Household income \$55,000 - \$59,999	0.808***	(0.182)
Household income \$60,000 - \$69,999	0.712***	(0.162)
Household income \$70,000 - \$99,999	0.836***	(0.146)
Household income \$100,000 - \$149,999	0.911***	(0.154)
Household income $\geqslant$ \$15,000	0.727***	(0.177)
Household size = 2	-0.202**	(0.082)
Household size = 3	-0.088	(0.105)
Household size $\geqslant$ 4	-0.472***	(0.106)
Grade 9-13	0.437	(0.275)
Community College	0.445	(0.281)
Diploma	0.574**	(0.279)
Undergraduate	0.535*	(0.279)
Post-graduate	0.672**	(0.286)
Rent a home	-0.238***	(0.078)
Female head	0.289***	(0.082)
Have internet access on cell phone	0.028	(0.068)
Have internet access at work/school/elsewhere	0.172**	(0.071)
Live in rural area	0.175**	(0.083)
Main financial institution is TD/RBC	0.155**	(0.072)
Main financial institution is non-big six	0.191***	(0.071)
Year 2011	-0.051	(0.139)
Year 2012	-0.121	(0.132)
Year 2013	-0.001	(0.124)
Year 2014	0.073	(0.128)
Year 2015	-0.009	(0.131)
Year 2016	0.083	(0.136)
Year 2017	-0.044	(0.140)
Quebec	0.236*	(0.129)
Ontario	0.407***	(0.122)
Prairies	0.472***	(0.134)
British Columbia	0.467***	(0.137)
Observations	4,399	
Adjusted R^2	0.070	

Robust standard errors in parentheses

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

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

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

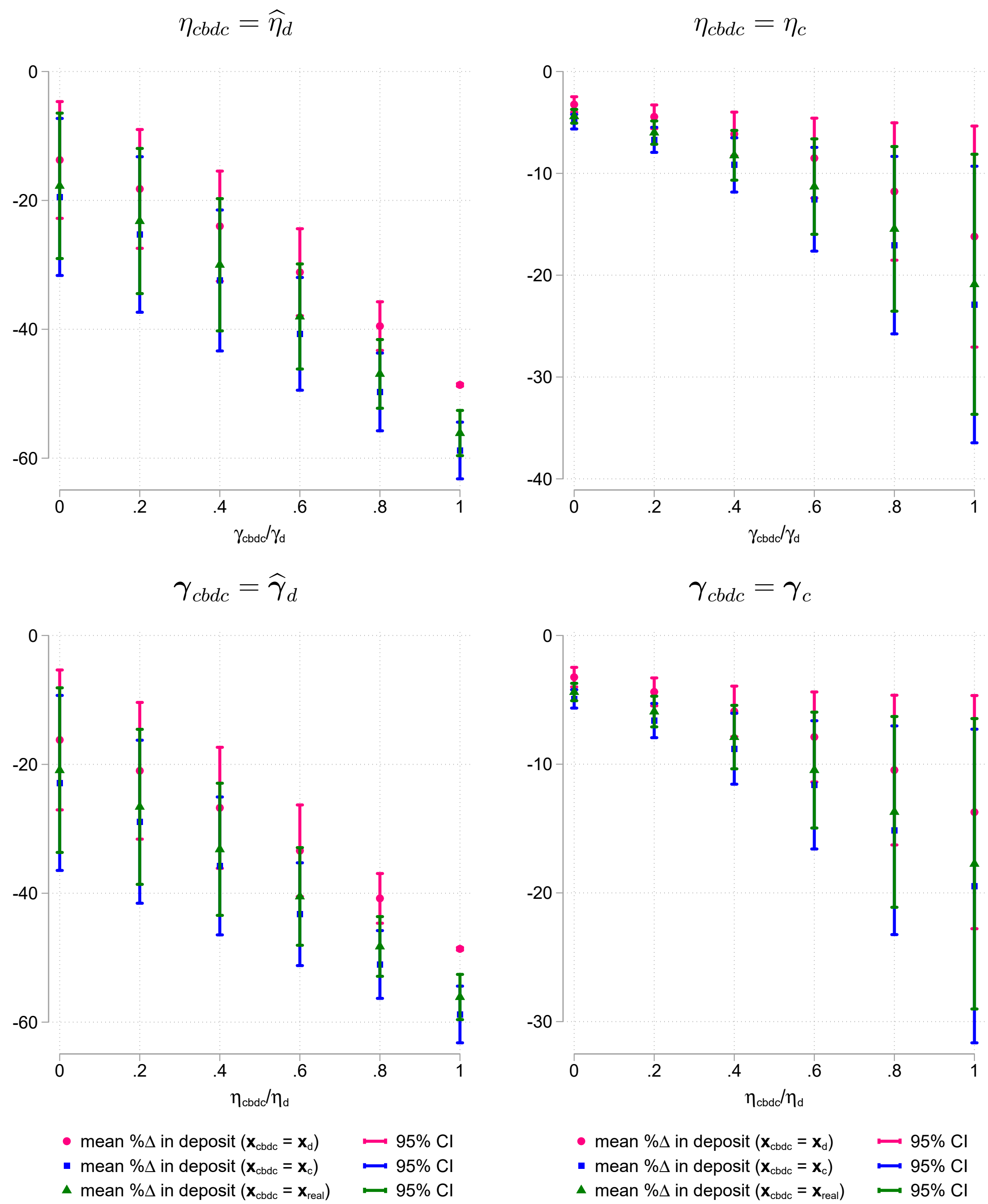
Table 7: Baseline Regression vs Weighted Least Squares

	(1) Baseline	(2) WLS
Deposit rate (after tax)	1.759*	2.908**
	(0.983)	(1.212)
Attitudes towards bundling of service	0.063***	0.048**
	(0.017)	(0.019)
Difference in ratings for cost of use	-0.527***	-0.570***
	(0.150)	(0.183)
Difference in ratings for ease of use	0.036	0.622
	(0.472)	(0.532)
Difference in ratings for security	0.103	-0.175
	(0.234)	(0.285)
Ratings for anonymity	-0.039**	-0.016
	(0.018)	(0.021)
Ratings for budgeting usefulness	-0.074***	-0.081***
	(0.017)	(0.022)
Fraction of online transactions	0.286	0.321
	(0.228)	(0.337)
Fraction of transactions cards unaccepted	-0.183	-0.081
	(0.179)	(0.227)
Constant	1.588***	1.440***
	(0.408)	(0.451)
Observations	4,399	4,399
Adjusted R^2	0.070	0.083
Bank Fixed Effect	Yes	Yes
Region Fixed Effect	Yes	Yes
Year Fixed Effect	Yes	Yes

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

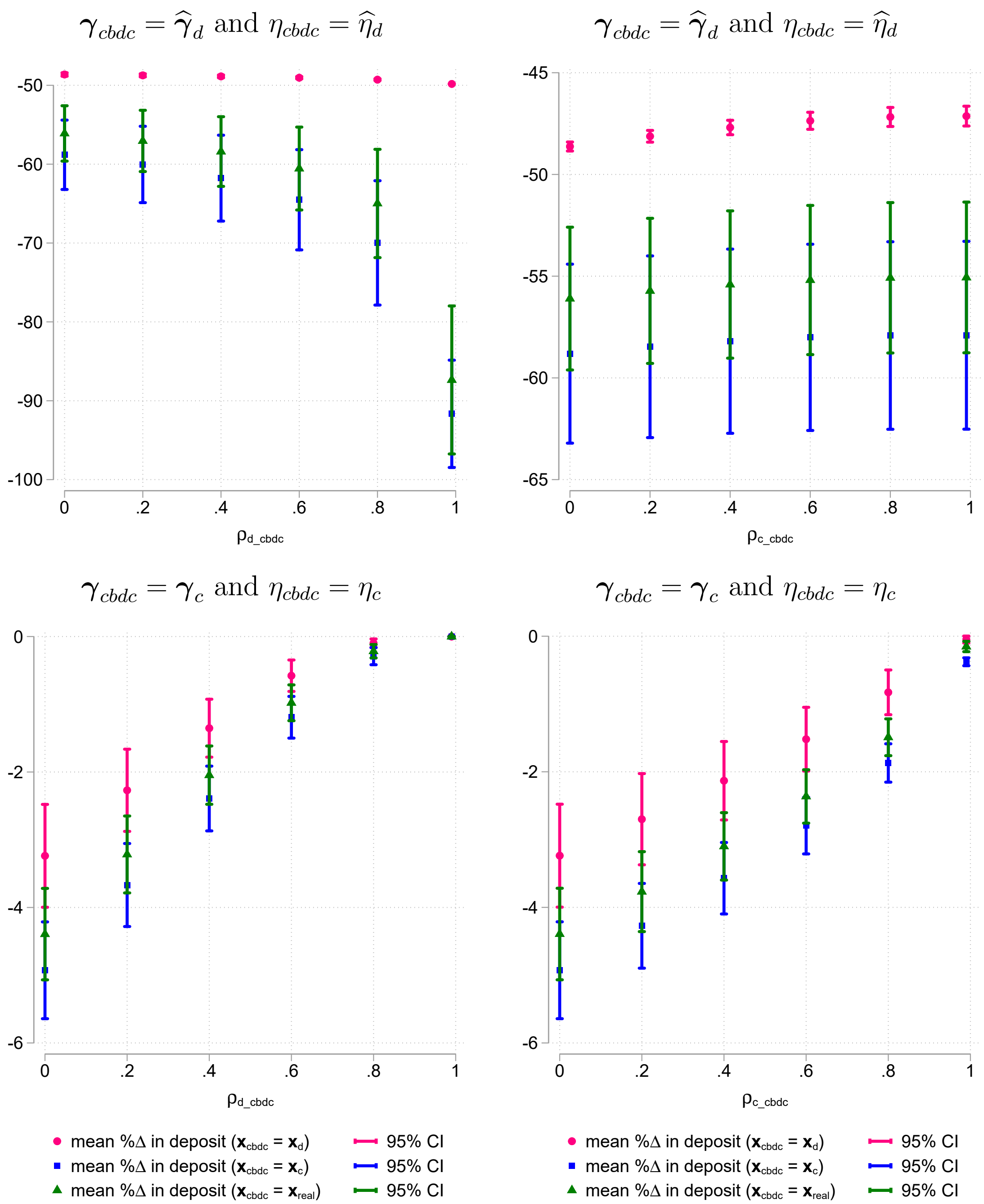
Note: Column (1) shows the baseline results, which are identical to column (9) in Table 1. Column (2) shows the results from a weighted regression where the sample weights are applied. Household characteristics, including household income, household head age, female head indicator, household head education, home ownership, household size, rural area indicator, indicators of internet access at work or via cell phone, and the fraction of purchases paid using cash, are also controlled for in each regression.

Figure 11: Mean Percentage Change in Deposit for Different Values of $\boldsymbol{\gamma_{cbdc}}$ and η_{cbdc}



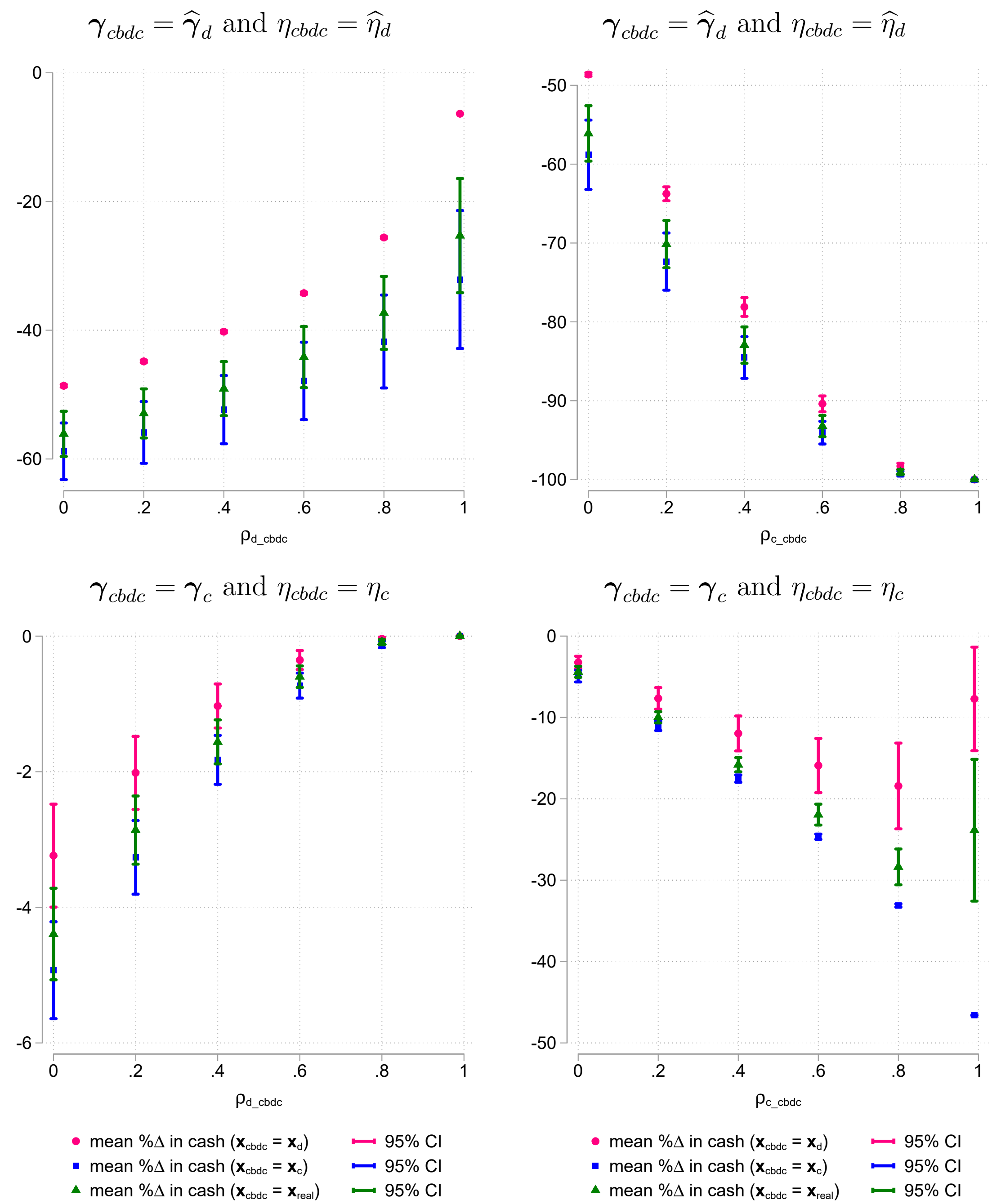
Note: The graphs in the upper (lower) panel plot the mean percentage change in deposit relative to the deposit holding before CBDC issuance for different values of $\boldsymbol{\gamma}_{cbdc}$ (η_{cbdc}) as a fraction of the estimated parameters $\widehat{\boldsymbol{\gamma}}_d$ ($\widehat{\eta}_d$), conditional on different values of η_{cbdc} ($\boldsymbol{\gamma}_{cbdc}$). Since deposit 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, i.e., 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 ($\boldsymbol{x}_{cbdc} = \boldsymbol{x}_{real}$). The standard errors for calculating the 95% confidence intervals are computed using the delta method.

Figure 12: Mean Percentage Change in Deposit against ρ_{d_cdbc} and ρ_{c_cdbc}



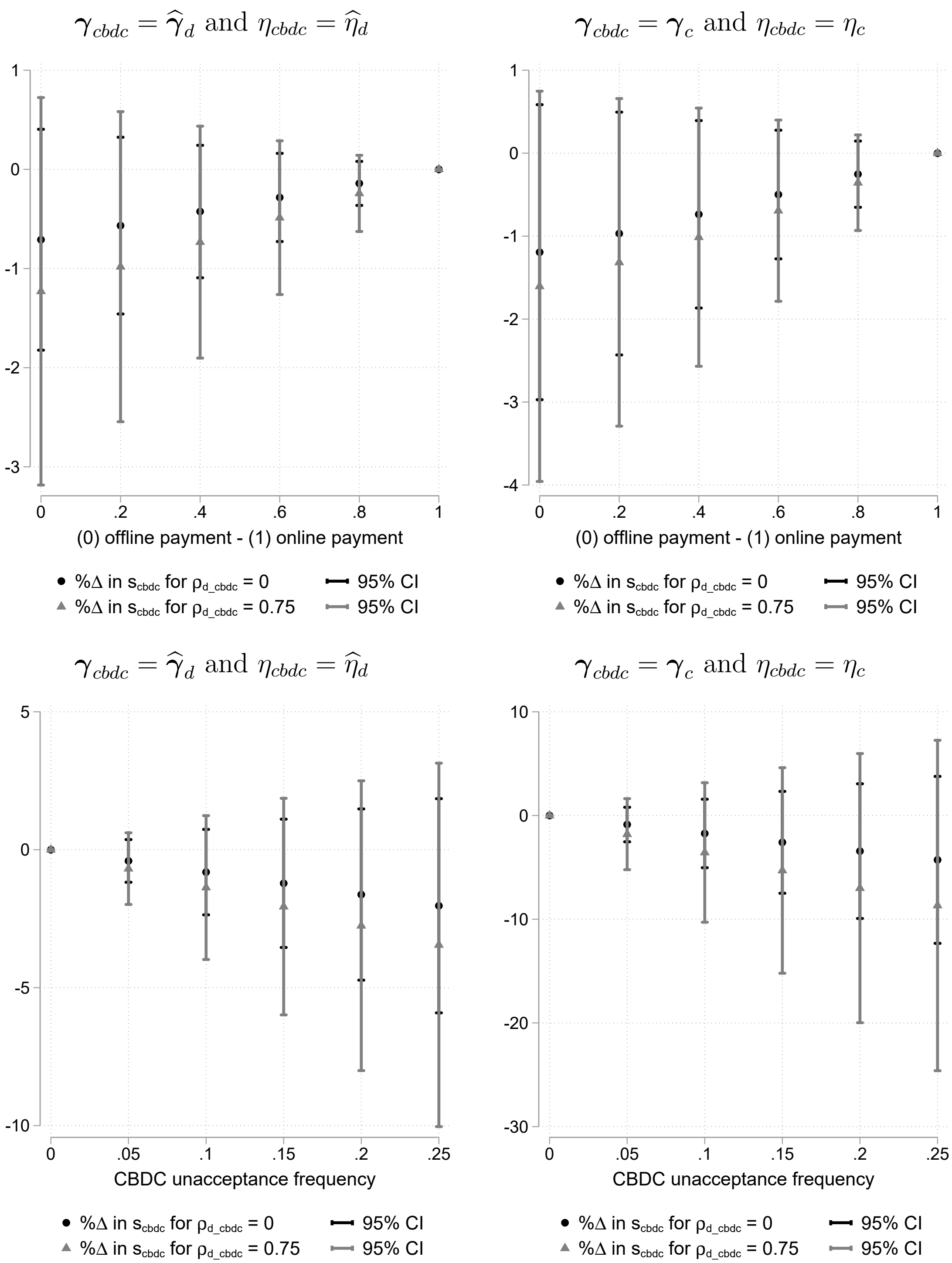
Note: The graphs in the left (right) column plot the mean percentage change in deposit holding relative to that before the CBDC issuance for different levels of correlation $\rho_{d\_cbdc}(\rho_{c\_cbdc}) \in [0, 0.99]$ between the unobserved utilities of CBDC and deposit (cash), conditional on different values of γ_{cbdc} and η_{cbdc}. In each graph, three different designs for CBDC are plotted, i.e., 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 ($\boldsymbol{x}_{cbdc} = \boldsymbol{x}_{real}$). The standard errors for calculating the 95% confidence intervals are computed using the delta method.

Figure 13: Mean Percentage Change in Cash against ρ_{d_cdbc} and ρ_{c_cdbc}



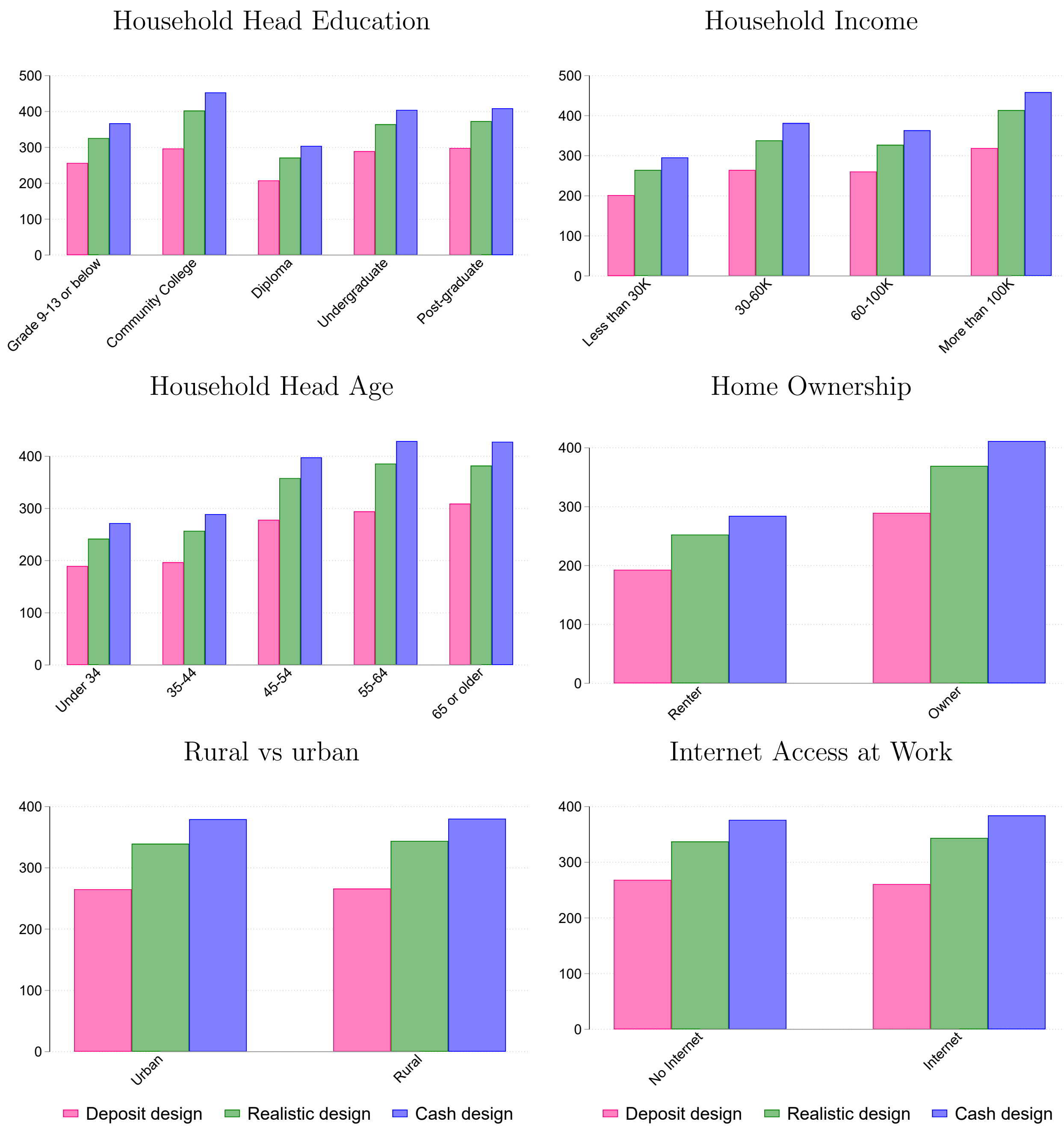
Note: The graphs in the left (right) column plot the mean percentage change in cash holding relative to that before the CBDC issuance for different levels of correlation $\rho_{d\_cbdc}(\rho_{c\_cbdc}) \in [0, 0.99]$ between the unobserved utilities of CBDC and deposit (cash), conditional on different values of γ_{cbdc} and η_{cbdc}. In each graph, three different designs for CBDC are plotted, i.e., 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 ($\boldsymbol{x}_{cbdc} = \boldsymbol{x}_{real}$). The standard errors for calculating the 95% confidence intervals are computed using the delta method.

Figure 14: The Impacts of Online Purchase Capability and Unacceptance Rate



Note: The graph plots the percentage change in the aggregate CBDC share $\%\Delta s_{cbdc}$ relative to the baseline value 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 of CBDC and deposit are plotted. The standard errors for calculating the 95% confidence intervals are computed using the delta method.

Figure 15: CBDC holdings in Canadian Dollars across Demographic Groups



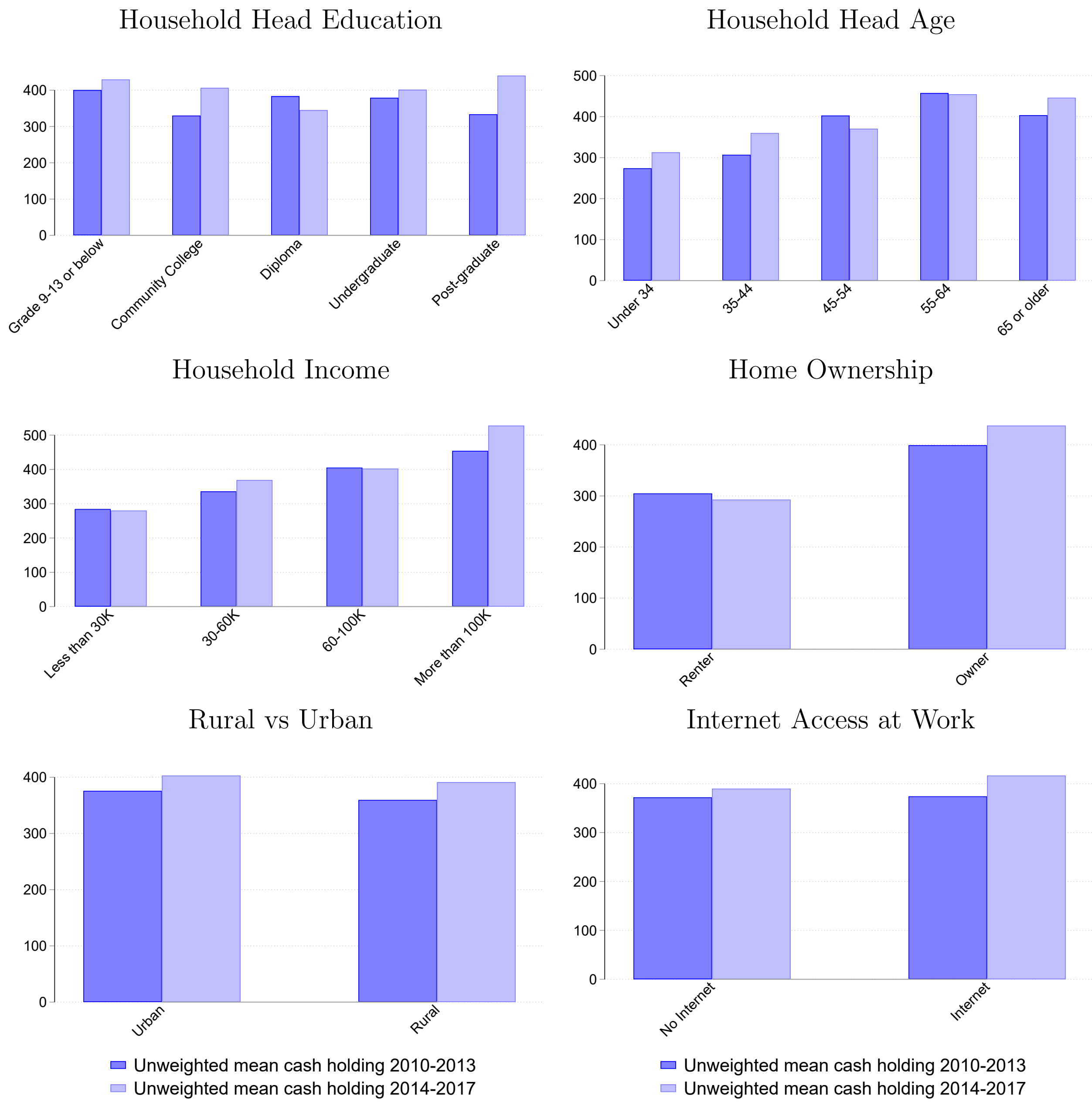
Note: The bar charts show the unweighted mean predicted CBDC holdings across households and over the period of 2014–2017 for different demographic groups. For a given demographic group, the predicted CBDC holdings under three different designs are plotted. The CBDC holdings are predicted based on the assumptions that the CBDC-specific effects of household characteristics and CBDC fixed effect are identical to the normalised parameters for cash. The predicted CBDC holdings are deflated by CPI in each year.

Figure 16: Deposit Holdings in Canadian Dollars across Demographic Groups

Data sources: matched sample of CFM 2010–2017 and MOP 2013

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

Figure 17: Cash Holdings in Canadian Dollars across Demographic Groups



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

References

Adrian, Tobias, and Tommaso Mancini-Griffoli. 2019. "The rise of digital money." IMF Fintech Notes 19/01, International Monetary Fund.

Agur, Itai, Anil Ari, and Giovanni Dell'Ariccia. 2019. "Designing central bank digital currencies." IMF Working Paper 19/252.

Allen, Sarah, Srdjan Capkun, Ittay Eyal, Giulia Fanti, Bryan A Ford, James Grimmelmann, Ari Juels, Kari Kostiainen, Sarah Meiklejohn, Andrew Miller, et al. 2020. "Design choices for central bank digital currency: Policy and technical considerations." National Bureau of Economic Research Working Paper 27634.

Andolfatto, David. 2018. "Assessing the impact of central bank digital currency on private banks." FRB St. Louis Working Paper 2018-25.

Arango, Carlos, Kim P Huynh, and Leonard Sabetti. 2015. "Consumer payment choice: Merchant card acceptance versus pricing incentives." *Journal of Banking & Finance*, 55: 130–141.

Attanasio, Orazio P, Luigi Guiso, and Tullio Jappelli. 2002. "The demand for money, financial innovation, and the welfare cost of inflation: An analysis with household data." *Journal of Political Economy*, 110(2): 317–351.

Auer, Raphael, and Rainer Böhme. 2020. "The technology of retail central bank digital currency." BIS Quarterly Review March pp85-100.

Barrdear, John, and Michael Kumhof. 2016. "The macroeconomics of central bank issued digital currencies." Bank of England Staff Working Paper No. 605.

Bech, Morten L, and Rodney Garratt. 2017. "Central bank cryptocurrencies." BIS Quarterly Review September 2017.

Berentsen, Aleksander, and Fabian Schar. 2018. "The case for central bank electronic money and the non-case for central bank cryptocurrencies." Available at SSRN: https://ssrn.com/abstract=3194981.

Bijlsma, Michiel, Carin van der Cruijsen, Nicole Jonker, and Jelmer Reijerink. 2021. "What triggers consumer adoption of central bank digital currency?" De Nederlandsche Bank Working Paper No. 709.

BIS. 2020. "Central bank digital currencies: foundational principles and core features." Joint work by Bank of Canada, European Central Bank, Bank of Japan, Sveriges Riksbank, Swiss National Bank, Bank of England, Board of Governors Federal Reserve System, and Bank for International Settlements. Available at: https://www.bis.org/publ/othp33.pdf.

Boar, Codruta, and Andreas Wehrli. 2021. "Ready, steady, go? - Results of the third BIS survey on central bank digital currency." BIS Papers No 114.

Bordo, Michael D, and Andrew T Levin. 2017. "Central bank digital currency and the future of monetary policy." National Bureau of Economic Research Working Paper 23711.

Brunnermeier, Markus K, and Dirk Niepelt. 2019. "On the equivalence of private and public money." *Journal of Monetary Economics*, 106: 27–41.

Brunnermeier, Markus K, Harold James, and Jean-Pierre Landau. 2019. "The digitalization of money." National Bureau of Economic Research Working Paper 26300.

Chen, Heng, Marie-Hélène Felt, and Kim P Huynh. 2014. "Retail payment innovations and cash usage: Accounting for attrition using refreshment samples." Bank of Canada Working Paper 2014-27.

Chiu, Jonathan, Seyed Mohammadreza Davoodalhosseini, Janet Hua Jiang, and Yu Zhu. 2020. "Bank market power and central bank digital currency: Theory and quantitative assessment."

Davoodalhosseini, Mohammad, Francisco Rivadeneyra, and Yu Zhu. 2020. "CBDC and monetary policy." Bank of Canada Staff Analytical Notes 2020-4.

Davoodalhosseini, Seyed Mohammadreza. 2018. "Central bank digital currency and monetary policy." Available at SSRN 3011401.

Deaton, Angus. 2019. *The analysis of household surveys: A microeconometric approach to development policy.* World Bank Publications.

Drechsler, Itamar, Alexi Savov, and Philipp Schnabl. 2017. "The deposits channel of monetary policy." *The Quarterly Journal of Economics*, 132(4): 1819–1876.

Ellickson, Paul B, Paul LE Grieco, and Oleksii Khvastunov. 2020. "Measuring competition in spatial retail." *The RAND Journal of Economics*, 51(1): 189–232.

Engert, Walter, and Ben Siu-Cheong Fung. 2017. "Central bank digital currency: Motivations and implications." Bank of Canada Staff Discussion Paper No. 2017-16.

Engert, Walter, Ben Fung, and Björn Segendorff. 2019. "A tale of two countries: Cash demand in Canada and Sweden." Bank of Canada Staff Discussion Paper 2019-7.

Felt, Marie-Hélène. 2017. "Three essays on identification and estimation using sample combination in a missing data context." PhD diss. Carleton University.

Felt, Marie-Hélène. 2020. "On the identification of joint distributions using marginals and aggregates." *Economics Letters*, 194: 109431.

Fernández-Villaverde, Jesús, Daniel Sanches, Linda Schilling, and Harald Uhlig. 2020. "Central bank digital currency: Central banking for all?" National Bureau of Economic Research Working Paper 26753.

Fung, Ben SC, and Hanna Halaburda. 2016. "Central bank digital currencies: A framework for assessing why and how." Bank of Canada Staff Discussion Paper No. 2016-22.

García, Alejandro, Bena Lands, Xuezhi Liu, and Joshua Slive. 2020. "The potential effect of a central bank digital currency on deposit funding in Canada." Bank of Canada Staff Analytical Note 2020-15.

Garratt, Rodney, and Haoxiang Zhu. 2021. "On interest-bearing central bank digital currency with heterogeneous banks." *Available at SSRN 3802977.*

Garratt, Rodney J, and Maarten RC van Oordt. 2019. "Privacy as a public good: A case for electronic cash." Bank of Canada Staff Working Paper 2019-24.

Hernandez, Lola, Nicole Jonker, and Anneke Kosse. 2017. "Cash versus debit card: The role of budget control." *Journal of Consumer Affairs*, 51(1): 91–112.

Huynh, Kim, Jozsef Molnar, Oleksandr Shcherbakov, and Qinghui Yu. 2020. "Demand for payment services and consumer welfare: The introduction of a central bank digital currency." Bank of Canada Staff Working Paper 2020-7.

Kahn, Charles M, Francisco Rivadeneyra, and Tsz-Nga Wong. 2018. "Should the central bank issue e-money?" Bank of Canada Staff Working Paper 2018-58.

Kahn, Charles M, Francisco Rivadeneyra, and Tsz-Nga Wong. 2020. "Eggs in one basket: Security and convenience of digital currencies." Federal Reserve Bank of St. Louis Working Paper 2020-032A.

Keister, Todd, and Daniel R Sanches. 2019. "Should central banks issue digital currency?" Federal Reserve Bank of Philadelphia Working Paper 19-26.

Kolenikov, Stanislav. 2014. "Calibrating survey data using iterative proportional fitting (raking)." *The Stata Journal*, 14(1): 22–59.

Kumhof, Michael, and Clare Noone. 2018. "Central bank digital currencies-design principles and balance sheet implications." Bank of England Staff Working Paper No. 725, Bank of England working paper.

Kurlat, Pablo. 2019. "Deposit spreads and the welfare cost of inflation." *Journal of Monetary Economics*, 106: 78–93.

Mancini-Griffoli, Tommaso, Maria Soledad Martinez Peria, Itai Agur, Anil Ari, John Kiff, Adina Popescu, and Celine Rochon. 2018. "Casting light on central bank digital currency." IMF Staff Discussion Notes 18-08.

Meaning, Jack, Ben Dyson, James Barker, and Emily Clayton. 2018. "Broadening narrow money: monetary policy with a central bank digital currency." Bank of England Working Paper No.724, Bank of England Working Paper.

Mulligan, Casey B, and Xavier Sala-i-Martin. 2000. "Extensive margins and the demand for money at low interest rates." *Journal of political Economy*, 108(5): 961–991.

Niepelt, Dirk. 2020. "Reserves for all? Central bank digital currency, deposits, and their (non)-equivalence." *International Journal of Central Banking*, 16(3): 211–238.

Perraudin, William RM, and Bent E Sørensen. 2000. "The demand for risky assets: Sample selection and household portfolios." *Journal of Econometrics*, 97(1): 117–144.

Schilling, Linda, Jesús Fernández-Villaverde, and Harald Uhlig. 2020. "Central Bank Digital Currency: When Price and Bank Stability Collide." National Bureau of Economic Research Working Paper 28237.

Skeie, David R. 2019. "Digital currency runs." Available at SSRN 3294313.

Solon, Gary, Steven J. Haider, and Jeffrey Wooldridge. 2013. "What are we weighting for?" National Bureau of Economic Research Working Paper 18859.

Tinn, Katrin, and Christophe Dubach. 2021. "Central bank digital currency with asymmetric privacy." *Available at SSRN 3787088*.

Vincent, K. 2013. "Methods-of-payment survey: Sample calibration analysis." Bank of Canada Technical Report No. 103.

von Kalckreuth, Ulf, Tobias Schmidt, and Helmut Stix. 2014. "Using cash to monitor liquidity: Implications for payments, currency demand, and withdrawal behavior." *Journal of Money, Credit and Banking*, 46(8): 1753–1786.

Wang, Yifei, Toni M Whited, Yufeng Wu, and Kairong Xiao. 2020. "Bank market power and monetary policy transmission: Evidence from a structural estimation." National Bureau of Economic Research Working Paper No.27258.

Williamson, Stephen. 2019. "Central bank digital currency: Welfare and policy implications." Available at: https://ideas.repec.org/p/red/sed019/386.html.

Williamson, Stephen D. 2020. "Central bank digital currency and flight to safety." Available at: https://sammf.com/joint-workshop-the-economics-of-digital-currencies/.

Xiao, Kairong. 2020. "Monetary transmission through shadow banks." *The Review of Financial Studies*, 33(6): 2379–2420.

Zhu, Yu, and Scott Hendry. 2019. "A framework for analyzing monetary policy in an economy with e-money." Bank of Canada Staff Working Paper 2019-1.