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Predicting the demand for central bank digital currency: A structural analysis with survey data[☆]

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ABSTRACT

What would be the potential demand for central bank digital currency (CBDC)? Which design attributes would affect the demand for CBDC? By applying a structural model to a unique Canadian survey dataset, I find that the aggregate CBDC holdings as a percentage of the total household liquid assets could range from 4–52%, based on households' demand perspective. Allowing banks to respond to CBDC would substantially constrain the take-up of CBDC, reducing the upper bound prediction to below 20%. Important design attributes of CBDC identified are budgeting usefulness, anonymity, bundling of bank services, and rate of return.

1. Introduction

Many central banks around the world are contemplating the issuance of a central bank digital currency (CBDC), a digital form of central-bank-issued money. According to a Bank for International Settlements (BIS) survey in 2020, 86% of central banks are engaging in CBDC work and 14% have already reached the pilot stage.[1] To decide whether to issue a CBDC,[2] a

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[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).

[2] This paper focuses on the retail CBDC that is available to the general public and can be used for retail transactions. For some countries including Canada, the motivation for considering the issuance of a retail CBDC is in part driven by declining cash usage as documented in Engert et al. (2019), which could lead to financial exclusion of certain groups of people, and in part as a response to the potential risks posed by privately issued e-money (e.g., Adrian and Mancini-Griffoli, 2019; Brunnermeier et al., 2019; Zhu and Hendry, 2019).

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central bank needs to consider three important questions: What would be the demand for CBDC? How would the design attributes of CBDC affect the demand? To what extent would CBDC impact the demand for cash and deposits? This paper helps answer these questions empirically.

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

While there is emerging theoretical literature on the implications of CBDC (e.g., Andolfatto, 2021; Brunnermeier and Niepelt, 2019; Chiu et al., 2022; Keister and Sanches, 2022; Williamson, 2022), the lack of data on CBDC poses a constraint to the empirical work. This paper provides a framework to predict the potential demand for CBDC relative to its close alternatives, cash and demand deposits. The key idea is to view CBDC, cash, and demand deposits as product bundles of different attributes based on a structural demand model. I estimate households' preferences for the attributes by applying the model to survey data on the existing products. Provided that the estimated preferences remain the same after CBDC issuance, I can predict the demand for CBDC based on its design attributes and how much households value each attribute, and study how the CBDC demand would be affected by different design attributes.

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

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

I find that under a baseline design for CBDC, where CBDC is non-interest-bearing, unbundled with bank services, and achieves 70% of cash budgeting usefulness and anonymity, the share of CBDC in the total household holdings of liquid assets could range from 4–52%. The exact level of CBDC demand in this range depends on the assumptions for CBDC-specific effects. The lower (upper) bound prediction is obtained when assuming CBDC-specific effects are cash-like (deposit-like). Since a median household only holds around 4% of their liquid assets in cash, the demand for CBDC would also be low if households perceive CBDC to be closer to cash. In an extension of the paper, I introduce a simple Cournot banking model in the deposit market to account for banks' responses to CBDC. Once allowing banks to respond to CBDC, the upper bound prediction can be reduced to below 20%. This is because the presence of an attractive CBDC makes the bank deposit demand much more elastic compared to the case without CBDC, which induces banks to make deposits more attractive via a much higher deposit rate to avoid losing a lot of deposits.

Unlike the predicted level of CBDC demand, the percentage change in CBDC demand in response to a change in a given attribute would rely much less on CBDC-specific effects. By studying the impacts of different design attributes, this paper provides useful insights on how much each design attribute would matter for CBDC demand. I find that important design attributes include usefulness for budgeting, anonymity, bundling of bank services, and rate of return, which are ranked in a decreasing order of importance, except for the rate of return whose impact depends on the magnitude of the rate change.[3]

The empirical literature on CBDC is scarce (Bijlsma et al., 2021; Huynh et al., 2020; Whited et al., 2022). Whited et al. (2022) study the impact of a CBDC on bank lending using US bank-level data. This paper focuses on households' demand perspective and provides insights on which design attributes would matter for the CBDC demand. Huynh et al. (2020) use a structural demand model to study consumers' choices of using CBDC to pay at the point of sale. In contrast, this paper focuses on households' potential holdings of CBDC, taking into account the role of CBDC as both a store-of-value asset and a payment instrument. Bijlsma et al. (2021) conduct a survey on the adoption intention for hypothetical CBDC accounts in the Netherlands. This paper uses households' revealed preferences from their allocation decisions on cash and demand deposits, which does not rely on survey respondents' understanding of CBDC.

The paper is also related to the growing literature on how CBDC could affect bank deposits and thus financial intermediation (e.g., Andolfatto, 2021; Chiu et al., 2022; Garratt et al., 2022; Keister and Sanches, 2022).[4] This literature often assumes

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

[4] Existing theoretical literature also looks at the impact of CBDC on financial stability (e.g., Brunnermeier and Niepelt, 2019; Fernández-Villaverde et al., 2021; Schilling et al., 2020; Skeie, 2019; Williamson, 2021), monetary policy (e.g., Bordo and Levin, 2017; Davoodalhosseini, 2021; Jiang and Zhu, 2021),

CBDC to be a perfect substitute for deposits and focuses on the rate of return differences, which directly implies the substitution patten between the demand for deposits and CBDC. That is, the one that offers a lower rate of return would face a zero demand. In contrast, this paper models CBDC as an imperfect substitute for deposits, where CBDC can differ from deposits in a variety of product attributes, including the rate of return. In doing so, the paper provides empirical evidence on the extent to which the demand for CBDC would be affected by different design attributes of CBDC.[5] Since the demand for CBDC would come from the liquid assets like deposits, the paper also sheds light on the crowding-out effect of CBDC on the demand for deposits under different CBDC designs.

The rest of this paper is organized as follows. Section 2 describes the structural demand model and then introduces CBDC into the model. Section 3 discusses the data sources and how to measure different product attributes using the survey data. Section 4 shows the estimated demand parameters. Section 5 uses the estimated model to conduct counterfactual analyses on CBDC. Section 6 incorporates banks' endogenous responses to CBDC and studies the role of the network effects. Section 7 concludes.

2. Model

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

2.1. Logit model of cash and deposit demand

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

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

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

Since the utility shock $\epsilon_{i,j,t}$ is randomly drawn from a given distribution, even if the observed utility for holding the one dollar in cash is higher, that is, $V_{i,c,t} > V_{i,d,t}$, there is a probability that the unobserved portion of the utility for deposits $\epsilon_{i,d,t}$ is sufficiently higher to overcome the lower $V_{i,d,t}$ such that household i chooses to hold it in deposits instead. Assuming the i.i.d. utility shock follows a Type I extreme value distribution, the choice probability of holding the one dollar in product $j \in \{c, d\}$ is:

$$P_{i,j,t} = \frac{\exp(V_{i,j,t})}{\exp(V_{i,c,t}) + \exp(V_{i,d,t})} \in (0, 1) \tag{2}$$

When the observed attributes of product j improves such that the observed utility $V_{i,j,t}$ increases, $P_{i,j,t}$ 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 the one dollar in asset j is equivalent to the asset j's share $s_{i,j,t} \equiv \frac{q_{i,j,t}}{w_{i,t}}$, where $q_{i,j,t}$ denotes the balance of asset j and $w_{i,t} = q_{i,c,t} + q_{i,d,t}$ is liquid asset balance (sum of cash and demand deposit balances) held by household i.[6] After taking the difference between the logged deposit and cash shares, the log of deposit-to-cash ratio can be written as:

$$\ln\frac{q_{i,d,t}}{q_{i,c,t}} = V_{i,d,t} - V_{i,c,t} = \boldsymbol{\alpha}'(\boldsymbol{x}_{i,d,t} - \boldsymbol{x}_{i,c,t}) + (\boldsymbol{\gamma}_d - \boldsymbol{\gamma}_c)'\boldsymbol{z}_{i,t} + \eta_d - \eta_c \tag{3}$$

macroeconomic volatility (e.g., Barrdear and Kumhof, 2021; Minesso et al., 2022), and welfare (e.g., Assenmacher et al., 2021; Piazzesi and Schneider, 2020; Williamson, 2022). For policy discussions on the macro implications of CBDC issuance, see Berentsen and Schar (2018), Davoodalhosseini et al. (2020), Engert and Fung (2017), García et al. (2020), Mancini-Griffoli et al. (2018), Meaning et al. (2018), etc.

[5] There are a few theoretical papers focusing on certain design features of CBDC, such as anonymity and security in Agur et al. (2022), automation of personal loss recovery via an expiry date on offline CBDC balances proposed in Kahn et al. (2021), and asymmetric privacy between the receiver and the sender of money in Tinn and Dubach (2021).

[6] The interpretation of choice probabilities as asset shares is also used in Wang et al. (2022) and Xiao (2020). They assume that each agent is endowed with one dollar and makes a discrete choice among different assets. They point out that this one-dollar one-choice assumption can be interpreted as a situation where agents make multiple discrete choices for their one-dollar endowment and the probability of choosing each asset can be interpreted as the portfolio weight. Similarly, Ellickson et al. (2020) study the discrete choice for each unit of the consumer's grocery expenditure and the probability for choosing a particular store is interpreted as the share of the consumer's expenditure spent at that store.

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

As shown in (3), only the utility difference matters for households' choices, so the effects of household characteristics can only be identified if they are product-specific (i.e., $\boldsymbol{\gamma}_d \neq \boldsymbol{\gamma}_c$). Since different values of $\boldsymbol{\gamma}_d$ and $\boldsymbol{\gamma}_c$ that result in the same differences $(\boldsymbol{\gamma}_d - \boldsymbol{\gamma}_c)$ will give the same choices, the overall level of $(\boldsymbol{\gamma}_d - \boldsymbol{\gamma}_c)$ needs to be set and the same applies to $(\eta_d - \eta_c)$. I follow a common approach to normalize the parameters for cash, $\boldsymbol{\gamma}_c$ and η_c, to zero. After this normalization, the estimated $\widehat{\eta}_d$ reflects the average impact of the unobserved idiosyncratic preferences on the utility for deposits relative to cash and the estimated $\widehat{\boldsymbol{\gamma}}_d$ reflects the effects of household characteristics $\boldsymbol{z}_{i,t}$ on the utility for deposits relative to cash.

2.2. Introducing CBDC

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

$$V_{i,cbdc,t} = \widehat{\boldsymbol{\alpha}}'\boldsymbol{x}_{i,cbdc} + \boldsymbol{\gamma}'_{cbdc}\boldsymbol{z}_{i,t} + \eta_{cbdc} \tag{4}$$

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

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

2.2.1. Predictions based on logit model

Apart from the observed utility $V_{i,cbdc,t}$ (4), another key component for predicting the demand for CBDC is the distribution of the random utility shock $\epsilon_{i,j,t}$, where $j \in \{c, d, cbdc\}$. This section introduces CBDC into the logit demand model described in Section 2.1, where $\epsilon_{i,j,t}$ is assumed to be i.i.d. Type I extreme value. After CBDC issuance, household i allocates the endowment of the liquid asset $w_{i,t}$ into CBDC, cash, and demand deposits. With the distributional assumption on $\epsilon_{i,j,t}$, the probability of allocating each dollar of the endowment $w_{i,t}$ into CBDC, or equivalently, the share of CBDC holding, is:

$$s_{i,cbdc,t} = \frac{\exp(V_{i,cbdc,t})}{\exp(V_{i,c,t}) + \exp(V_{i,d,t}) + \exp(V_{i,cbdc,t})} \tag{5}$$

A higher observed utility $V_{i,cbdc,t}$ leads to a larger share of CBDC holding, keeping everything else the same. Given that $w_{i,t}$ is unaffected by the CBDC issuance, the demand for CBDC comes from the substitution away from cash and deposits.[7] In this logit framework, the demand for CBDC draws proportionally from cash and deposits. This substitution patterns can be restrictive in some cases. For example, if CBDC and deposits are perfect substitutes, the demand for CBDC should only draw from deposits while cash demand is unaffected. To allow for more flexible substitution patterns, Section 2.2.2 introduces CBDC into a nested logit framework.

2.2.2. Predictions based on nested logit model

Under a nested logit model, the unobserved utilities $\boldsymbol{\epsilon}_{i,t} = (\epsilon_{i,c,t}, \epsilon_{i,d,t}, \epsilon_{i,cbdc,t})$ that capture the idiosyncratic preferences are now jointly distributed as generalized extreme value and can be correlated across products that are closer substitutes. In this case, the demand for CBDC would mainly draw from its closer substitute.

Suppose the unobserved utilities for CBDC and deposits are correlated. In this case, CBDC and deposits are closer substitutes and they are in the same nest. This could be because households value the feature of digital payments, which cannot be identified empirically since there are no data on their perceptions towards this feature. Since CBDC and deposits can both be used for digital payments, this feature could drive the correlation between their unobserved utilities. The CBDC share $s_{i,cbdc,t}$ is the conditional probability of choosing CBDC from the nest multiplied by the probability of choosing the

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

nest:

$$s_{i,cbdc,t} = \frac{\exp\left(\frac{V_{i,cbdc,t}}{\tau_d}\right)}{\exp\left(\frac{V_{i,cbdc,t}}{\tau_d}\right)+\exp\left(\frac{V_{i,d,t}}{\tau_d}\right)} \frac{\left[\exp\left(\frac{V_{i,cbdc,t}}{\tau_d}\right)+\exp\left(\frac{V_{i,d,t}}{\tau_d}\right)\right]^{\tau_d}}{\left[\exp\left(\frac{V_{i,cbdc,t}}{\tau_d}\right)+\exp\left(\frac{V_{i,d,t}}{\tau_d}\right)\right]^{\tau_d}+\exp(V_{i,c,t})} \tag{6}$$

where $\tau_d \equiv \sqrt{1-\rho_{d\_cbdc}} \in (0,1]$ is an inverse measure of the correlation $\rho_{d\_cbdc} \in [0,1)$ between the unobserved utilities for deposits and CBDC. The observed utilities for CBDC and deposits are scaled by a factor of $\frac{1}{\tau_d}$. Intuitively, this is because a positive correlation between their unobserved utilities implies a greater role of the observed utilities in explaining the choices between deposits and CBDC. When $\rho_{d\_cbdc} = 0$, this reduces to the logit model where the CBDC share (6) would be identical to (5). When $\rho_{d\_cbdc} > 0$, the demand for CBDC draws more than proportionally from deposits and the impact of ρ_{d_cbdc} on the CBDC share depends on the sign of the observed utility difference between CBDC and deposits, $\left(V_{i,cbdc,t} - V_{i,d,t}\right)$. Appendix A provides derivations and discussions on the nested logit model, including the case on CBDC and cash being closer substitutes.

3. Data

This paper uses the Canadian Financial Monitor (CFM) survey and the Methods-of-Payment (MOP) survey. The former is a syndicated survey run by Ipsos, while the latter is a Bank of Canada survey. The CFM survey provides detailed information on households' deposit and cash holdings and has some repeated cross sections.[8] The MOP survey is a cross-sectional dataset that contains information on people's perceptions towards different payment features and a payment diary that records detailed transaction-level data for each respondent during a three-day period. Most of the product attributes are measured using the MOP survey, however, MOP does not provide detailed information on cash and deposit holdings. I merge the two datasets using the common ID documented by the survey company Ipsos.[9]

In this paper, cash is measured as the sum of cash in wallet and the precautionary holding of cash. The sample period of 2010–2017 is chosen because the CFM survey questions on cash holdings are consistent across years during this period. Deposits are measured by the sum of chequing, chequing/saving, and saving account balances, which can be readily used for transactions and thus are a close alternative to CBDC. More details on these measures can be found in Appendix C.1. Household characteristics are measured using the CFM data. Appendix C.5 shows the summary statistics of the key variables of interest. Since estimating households' preferences for the product attributes is a key step in predicting the demand for CBDC, the rest of this section discusses how each attribute is measured.

Rate of Return

One unique feature of the CFM data is that there is information on the main financial institution of a given household.[10] I use this information together with the bank-level deposit rates from CANNEX to construct the household-specific deposit rates.[11] Given the data availability, I use the bank-specific rates for the big six banks and Laurentian Bank, and assume the deposit rates of other banks to be the average across these seven banks.[12] Since the interest earned on savings is taxed at the same marginal rate as income, the net interest rate is multiplied by one minus the marginal tax rate on household income, where the latter is obtained using the federal and provincial income tax rates during 2010–2017 published on the website of the Government of Canada.

Cost, Ease of Use, and Security

To measure the cost, ease of use, and security features of cash and deposits, I use the respondents' ratings for each of these features from the MOP survey questionnaire. For 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. Each individual chooses a rating from one to five on a Likert scale for each of the payment instruments, including cash, debit card, and

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

[9] The 2013 MOP survey consisted of three subsamples, one of which was formed by recruiting the respondents who had recently filled out the CFM survey. 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. More details on the datasets can be found in Felt (2017).

[10] More details can be found in Appendix C.1.3.

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

[12] The results in this paper are robust to dropping the households whose main financial institutions are not the big six or Laurentian Bank, accounting for about 33% of the observations. More information about the demand deposit rates from CANNEX can be found in Appendix C.3.

credit card. Similarly, the questions on ease of use and security ask people how easy or hard and how risky or secure it is (or would be) to use each payment instrument, respectively.

The debit card ratings are used to measure the cost, ease, and security of using deposits to make payments.[13] Following Arango et al. (2015), I standardize the ratings by the respondent's overall level of perceptions over cash, debit card, and credit card for each payment feature. For example, a respondent who rates 5, 2, 2 for the ease-of-use feature of cash, debit card, and credit card, respectively, has a standardized rating of 5/9 for cash and thus perceives cash to be easier to use compared to a respondent who rates 5 for all three payment instruments.

Bundling of Bank Services

Deposits are often bundled with other services provided by banks. To capture this complementarity between deposits and other bank services, this paper uses households' attitudes towards other services provided by their banks in the CFM survey. More specifically, each household can choose a number from one (strongly disagree) to ten (strongly agree) for the statement, "I would go to my bank for any financial planning advice." The more they value the services provided by their banks, the more utility they would obtain from holding deposits. Households that disagree with or are neutral about the statement (i.e., rate below 6) should be indifferent between holding cash and deposits when considering this feature, so the scale of these ratings is adjusted from 1–10 to 0–5 by treating the ratings smaller than 6 on the original scale as zero.

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

Anonymity and Usefulness for Budgeting

Cash tends to be more anonymous and useful for budgeting than deposits. When using cash to make payments, the user's identity does not need to be revealed and the transactions would be traceless. People may perceive cash to be more useful for budgeting because cash gives a signal of the remaining budget via a glance into one's pocket (von Kalckreuth et al., 2014) or serves as a commitment device to avoid overspending (Hernandez et al., 2017). I set these two features to take a value of one for cash and zero for deposits and study the budgeting usefulness of CBDC relative to the degrees for cash and deposits in Section 5.2. The prior that cash is more useful for budgeting than deposits is confirmed by the empirical results in Section 4.

To identify the impacts of these features on households' utilities, these features are interacted with individuals' perceptions of importance towards these features from the MOP survey. The survey asks people how important they think anonymity (in terms of not having to provide the name/information) or budgeting usefulness is when considering which payment method to use. Each respondent chooses a rating from one (not at all important) to seven (very important) for each feature. Those that choose the rating of one should be indifferent from holding cash or deposits when considering these features, so the scale of the ratings is adjusted from 1–7 to 0–6 by subtracting one from the original ratings. If people think anonymity and budgeting usefulness are more important, they should obtain more utility from holding cash relative to deposits.

Online Purchase Capability and Card Unacceptance Rate

Since cash cannot be used for online purchases while deposits can, this online purchase capability feature takes a value of one for deposits and zero for cash. To identify its impact on households' utilities, it is combined with the online transaction frequency, which is calculated as the number of online transactions over the total number of transactions recorded during a three-day period by each respondent in the MOP payment diary. Households that shop online more often should obtain more utility from holding deposits.

The card unacceptance rate is measured by the number of transactions where debit/credit cards are not accepted or the store is cash-only over the total number of transactions recorded for each respondent in the MOP payment diary. If households prefer to visit the stores that do not accept cards after taking into account the factors such as the store location and the quality of the goods, they are likely to obtain more utility from holding cash and thus hold more cash relative to deposits. More details on the measures can be found in Appendix C.2.

4. Demand estimation

This section estimates the demand-side parameters (i.e., $\boldsymbol{\alpha}$, $\boldsymbol{\gamma}_d$, and η_d) using the log of deposit-to-cash ratio (3) derived from the logit model.[14] Table 1 only reports the estimated parameters $\widehat{\boldsymbol{\alpha}}$ for different product attributes and the deposit-

[13] This paper uses debit card instead of credit card ratings because the cost ratings of credit cards also reflect the borrowing cost, which could overestimate the cost of using deposits to pay, even though credit cards are used more frequently by Canadians as shown in Figure C2 of Appendix C.1.4.

[14] 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.

Table 1
Estimated Preference Parameters for Product Attributes.

	Interest rate	Bundling	Cost	Ease	Security	Anonymity	Budgeting	Online	Card unacceptance
Estimates	2.191**	0.059***	-0.101	0.374	0.457*	−0.038**	−0.062***	0.439	-0.282
	(1.036)	(0.018)	(0.202)	(0.466)	(0.256)	(0.018)	(0.017)	(0.314)	(0.181)

Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Data sources: CFM 2010–2017, MOP 2013, CANNEX 2010–2017, Government of Canada website. Note: The table shows the estimated preference parameters for the product attributes from regressing the log of deposit-to-cash ratio on the product attributes and household characteristics (i.e., household income, household head age, female head indicator, household head education, home ownership, household size, rural area indicator, internet access at work, attitudes towards stock market investment, feeling difficulty in paying off debt, and the indicator of being behind debt obligations in the past year, as well as the bank, region, and year fixed effects). The parameters for household characteristics are shown in Table D5 of Appendix D.1. The intercept of the regression is 1.695 and is significant at 1% level. The sample consists of 4352 household-year observations during 2010–2017. The adjusted R^2 is 0.07.

specific constant $\widehat{\eta}_d$ (i.e., intercept of the regression reported in table footnote), while the effects $\widehat{\boldsymbol{\gamma}}_d$ of the household characteristics on the utilities of deposits relative to cash are shown in Table D5 in Appendix D.1. I include bank fixed effects,[15] measured using households' main financial institutions, to control for unobserved bank quality that may be correlated with the bank-specific deposit rates. Region and year fixed effects are also included to control for the regional-level and the macro-level shocks, respectively. In the counterfactual analysis, all fixed effects are treated as households characteristics, so $\widehat{\boldsymbol{\gamma}}_d$ also includes the estimated fixed effects.

Table 1 shows that when the post-tax deposit rate rises by 0.1 percentage points, the deposit-to-cash ratio increases by around 21.9%. This means when the median post-tax deposit rate across households increases from 0.08% to 0.18%, the median deposit-to-cash ratio increases from 23 to 28. The bundling of bank services 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, implying that they trust their bank and value the services provided by their bank, they would hold more deposits relative to cash.

Cost, ease, and security in Table 1 each refers to the difference in the standardized ratings between debit cards and cash, as discussed in Section 3. Cost of use has a much smaller effect on the deposit-to-cash ratio compared to ease and security. When debit cards are perceived to be more easy and secure to use, households would hold more deposits relative to cash.[16] Anonymity and budgeting refer to the individual-specific ratings on the importance of anonymity and budgeting usefulness as payment features, respectively. The table shows that when people think anonymity or budgeting usefulness is more important, they would hold more cash relative to deposits. This is consistent with the prior that cash is more anonymous and useful for budgeting than deposits.

Online payment frequency has a positive effect on the deposit-to-cash ratio and card unacceptance rate has a negative effect, as expected. The insignificance of the coefficients likely due to the lack of variation, as only around 12% of people made online purchases and around 20% of people visited stores that were cash-only or did not accept cards during a three-day period in the 2013 MOP payment diary.

More details on the estimation, robustness checks, and the out-of-sample model fit are shown in Appendix D. I find that there is no significant difference between the baseline OLS regression and the weighted least squares (WLS) estimation by applying the sample weights. In addition, the baseline results are largely robust to excluding bank, region, or year fixed effects. I also check how well the model can predict the aggregate deposit-to-cash ratio. More specifically, I estimate the model using data from 2010–2013 and then predict the aggregate deposit-to-cash ratio during 2014–2017 using the estimated parameters excluding the estimated year fixed effects. I find that these model-predicted values outperform the naive estimates based on different ways of averaging the past data values, as shown in Figure D5 in Appendix D.3.

5. Counterfactual analysis

This section conducts the counterfactual analyses on CBDC using the estimated demand-side parameters from Table 1 and Table D5 in Appendix D.1,[17] and assuming there are no endogenous changes in the attributes of deposits and cash after the CBDC issuance to focus on the demand perspective.[18] Section 5.1 shows the predicted demand for CBDC and discusses

[15] Since there is not much over-time variation in the deposit rates for some of the big six banks, the fixed effects of groups of banks are applied. More specifically, I include the indicators for the two largest banks by assets (i.e., TD and RBC), the indicator of the small bank (i.e., Laurentian Bank), and the indicator of banks that are not the big six or Laurentian Bank.

[16] The large standard error for the ease feature is likely due to the lack of variation as the ratings for the ease of debit cards and cash are identical for around 65% of the observations. Note that only the difference in ratings between deposits and cash matters, so these features can only be identified if people perceive debit cards and cash to be different in these features.

[17] In Appendix E.7, I study how the preference parameters differ across different demographic groups by estimating them separately in different subsamples. I find that although the parameters can be significantly different across certain demographic groups, these differences are largely canceled out on an aggregate level and do not affect the aggregate-level predictions shown in this section.

[18] Endogenous changes in the deposit rate are examined in Section 6.1. Appendix E.8 discusses the potential changes in the cost and merchant acceptance features of deposits and cash after CBDC issuance.

Table 2
CBDC Attributes under Different Design Scenarios.

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

Note: The table shows the product attributes of CBDC under three different designs: deposit design, cash design, and baseline design. Cost, ease, and security features are each measured by the ratings for debit cards or cash depending on the design. Under the deposit design, merchant acceptance for CBDC is assumed to equal that for deposits, which is measured by the fraction of transactions where cards are accepted, while under the cash design or baseline design, CBDC is assumed to be always accepted by merchants.

the crowding-out effects on cash and deposit demand. Section 5.2 examines the impacts of each design attribute on CBDC demand. Appendix E.5 discusses the applications of the estimated model in studying CBDC design proposals. Appendix E.6 shows how the predicted CBDC holdings differ across demographic groups.

5.1. Demand for CBDC

This section predicts the potential demand for CBDC if it were issued in 2017 and to what extent it could affect the demand for cash and deposits based on the logit model in Section 5.1.1 and nested logit model in Section 5.1.2. The demand for CBDC is measured by the aggregate CBDC share s_{cbdc}, which is the total CBDC holdings $\sum_i s_{i,cbdc} w_i$ over total household liquid assets $w = \sum_i w_i$ in a given year. This can be equivalently written as the weighted sum of each household's CBDC share:

$$s_{cbdc} = \sum_i \frac{w_i}{w} s_{i,cbdc} \tag{7}$$

where the weight $\frac{w_i}{w}$ is the ratio of each household's liquid assets over total household liquid assets. I focus on the measure of s_{cbdc} because it provides a direct reference for how much CBDC to issue for a central bank and the model can predict the aggregate asset share well, as discussed in Appendix E.1.

Table 2 outlines three different CBDC designs that will be studied in this section. With the deposit (cash) design, CBDC attributes are assumed to be identical to the deposit (cash) attributes. Under the baseline design, CBDC is assumed to be non-interest-bearing, unbundled with bank services, and perceived to be as cheap, easy, and secure to use as cash.[19] CBDC cannot be fully anonymous like cash due to know-your-customer and anti-money laundering requirements. I assume it can achieve 70% of cash anonymity by allowing users not to reveal their identification when opening a CBDC account that has a low holding limit, for example. CBDC is assumed to achieve 70% of the budgeting usefulness for cash by replicating the budgeting functions of cash that are discussed in Section 3. For example, by enabling people to preset their budgets on various spending categories and reminding people of their remaining budgets after each transaction can help CBDC achieve some degree of cash budgeting usefulness and perform better than the existing budgeting functions of deposit accounts. CBDC can be used for online transactions, so the feature of online purchase capability takes a value of one. Lastly, I assume CBDC will be widely accepted by merchants like cash with an acceptance rate of one since merchants will likely face a much lower interchange fee with CBDC.

5.1.1. Predicted demand for CBDC under logit model

The utility $V_{i,cbdc,t}$ for CBDC (4) consists of three main components: how households value different attributes of CBDC captured by $\widehat{\boldsymbol{\alpha}}'\boldsymbol{x}_{i,cbdc,t}$, how households with different characteristics value CBDC captured by $\boldsymbol{\gamma}'_{cbdc}\boldsymbol{z}_{i,t}$, and the average impact of the unobserved idiosyncratic preferences captured by η_{cbdc}. To calculate $V_{i,cbdc,t}$ and thus predict the demand for CBDC, I assume the CBDC-specific effects range from being cash-like (i.e., $\boldsymbol{\gamma}_{cbdc} = \boldsymbol{\gamma}_c = 0$ and $\eta_{cbdc} = \eta_c = 0$) to being deposit-like (i.e., $\boldsymbol{\gamma}_{cbdc} = \widehat{\boldsymbol{\gamma}}_d$ and $\eta_{cbdc} = \widehat{\eta}_d$), as discussed in Section 2.2. Therefore, Fig. 1 shows the aggregate CBDC shares against the values of $\boldsymbol{\gamma}_{cbdc}/\widehat{\boldsymbol{\gamma}}_d$ and $\eta_{cbdc}/\widehat{\eta}_d$, ranging from zero to one.[20]

There are two main findings from Fig. 1. First, when CBDC-specific effects are cash-like (deposit-like), the aggregate CBDC share is around 4% (52%) under the baseline design of CBDC. Intuitively, since a median household holds around 96% of their liquid assets in deposits and 4% in cash in the CFM data, if CBDC-specific effects are closer to being deposit-like, implying that households would perceive CBDC to be closer to deposits, they would also hold more CBDC.

Second, the aggregate CBDC shares under the cash design are the highest among the three designs mainly due to the higher levels of anonymity and budgeting usefulness under the cash design. Although the deposit design is better in terms

[19] According to the core CBDC features outlined in BIS (2020), CBDC should be at very low or no cost to end users, as easy as using cash, and extremely resistant to cyber attacks or other threats. As shown in Table C2 in Appendix C.5, most people perceive cash to be a low-cost, easy-to-use, and secure payment instrument, so I use the cash ratings to measure the cost, ease, and security of using CBDC to make payments under the baseline design.

[20] Figure E7 in Appendix E.2 shows that the two components of the CBDC-specific effects, i.e., the demographics-related effects $\boldsymbol{\gamma}_{cbdc}$ and the CBDC fixed effect η_{cbdc}, are equally important in determining the potential level of CBDC demand.

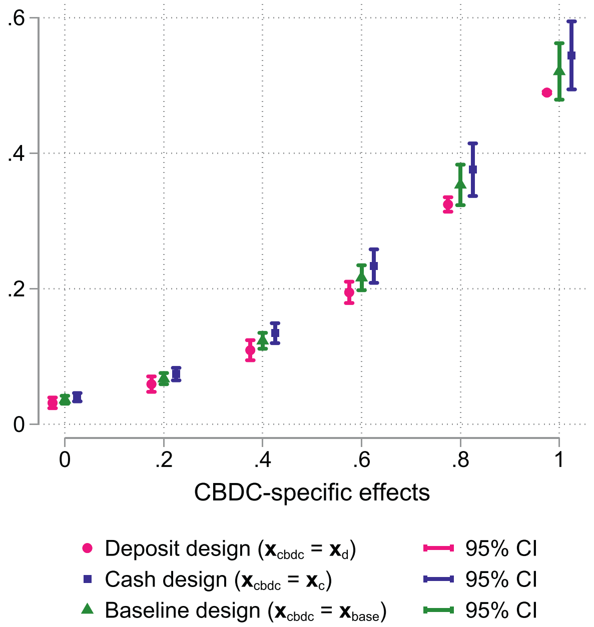

Fig. 1. Aggregate CBDC Shares under Different Assumptions for CBDC-specific Effects. Note: The graph plots the aggregate CBDC shares against different assumptions of the CBDC-specific effects (captured by the values of $\boldsymbol{\gamma}_{cbdc}/\widehat{\boldsymbol{\gamma}}_d$ and $\eta_{cbdc}/\widehat{\eta}_d$). At point of zero (one) on the x-axis, CBDC-specific effects are assumed to be cash-like (deposit-like), i.e., $\boldsymbol{\gamma}_{cbdc}$ and η_{cbdc} take the normalised values for cash (estimated values for deposits), so that $\boldsymbol{\gamma}_{cbdc}/\widehat{\boldsymbol{\gamma}}_d$ and $\eta_{cbdc}/\widehat{\eta}_d$ are both equal to zero (one). Each line is associated with a different design for CBDC, that is, when CBDC attributes $\boldsymbol{x}_{cbdc}$ are identical to deposit attributes ($\boldsymbol{x}_{cbdc} = \boldsymbol{x}_d$), cash attributes ($\boldsymbol{x}_{cbdc} = \boldsymbol{x}_c$), or a mixture of both ($\boldsymbol{x}_{cbdc} = \boldsymbol{x}_{base}$). The standard errors for calculating the 95% confidence intervals are computed using the delta method.

of the rate of return and bundling of bank services, it is not enough to compensate for its low level of anonymity and budgeting usefulness, so the CBDC demand is lower under the deposit design.

A higher demand for CBDC implies larger crowding-out effects on the demand for deposits and cash. Under the logit model, the demand for CBDC draws proportionally from deposits and cash, so the percentage drops in deposit and cash demand are identical. The mean percentage drop in deposits and cash across households is around 4% (52%) when CBDC-specific effects are cash-like (deposit-like), as shown in Appendix E.2.

5.1.2. Predicted demand for CBDC under nested logit model

Under the nested logit model, CBDC can be a closer substitute for deposits or cash due to the correlated idiosyncratic preferences, as discussed in Section 2.2.2. I find that the predicted aggregate CBDC shares and the crowding-out effects on deposit demand are robust to a wide range of correlation coefficients. The crowding-out effects on cash demand are more sensitive. Intuitively, as people only hold a small amount of cash, even a small level change can be a large percentage change. Detailed results are discussed in Appendix E.3.

5.2. The impacts of CBDC design attributes

While CBDC-specific effects (i.e., $\boldsymbol{\gamma}_{cbdc}$ and η_{cbdc}) play a large role in determining the level of CBDC demand, this section shows that the impacts of the design attributes on the percentage changes in CBDC demand would rely much less on these assumptions, since the level effects are largely canceled out.

Table 3 summarises the impacts of the important CBDC attributes on the percentage changes in aggregate CBDC shares based on the logit model. Except for the rate of return whose impact depends on the magnitude of the rate change, the most important attribute is budgeting usefulness, followed by anonymity and bundling of bank services. This is consistent with Figure D4 in Appendix D.1, which shows that these attributes are relatively more important in explaining the allocation between deposits and cash.

Table 3 shows that if the CBDC rate increases from 0% under the baseline design to 0.1%,[21] the aggregate CBDC share s_{cbdc} increases by 10% to 23%, where the range is due to different assumptions for the CBDC-specific effects and is much narrower compared to that for the level of CBDC demand. More specifically, when the CBDC-specific effects are deposit-like (cash-like), the level of s_{cbdc} increases from 0.52 to 0.57 (0.036 to 0.044), resulting in a percentage change of around 10% (23%), which is a lower (upper) bound estimate of the percentage change in s_{cbdc}.

[21] The 0.1 percentage point increase in CBDC rate is a large change as most households face a post-tax deposit rate of below 0.1% in 2017.

Table 3
Percentage Changes in CBDC Demand when CBDC Attribute Changes.

Design attribute	Change in attribute relative to baseline design	% change in s_{cbdc} logit model
Interest rate	0% → 0.1%	10 to 23
Budgeting usefulness	0.7 → 0	-7 to -14
Anonymity	0.7 → 0	-5 to -10
Bundling of bank service	0 → 1	4 to 8

Note: The table shows the percentage changes in aggregate CBDC shares s_{cbdc} in response to a change in CBDC attribute based on the logit model. The middle column describes the change in CBDC attribute relative to the baseline design, while keeping all the other attributes unchanged. The last column shows the percentage change in s_{cbdc} in response to the attribute change. The lower (upper) bound estimate in each cell of the last column is obtained using the assumption that CBDC-specific effects are deposit-like (cash-like).

Under the baseline design, CBDC is assumed to achieve 70% of the cash anonymity and budgeting usefulness. Relative to the baseline design, if the budgeting usefulness of CBDC reduces to the level for deposits, then the aggregate share s_{cbdc} would drop by 7–14%. Similarly, if the anonymity of CBDC reduces to that of deposits, s_{cbdc} would drop by 5–10%. Lastly, if CBDC has a higher degree of bundling like deposits, s_{cbdc} would increase by 4–8%.

Suppose CBDC and deposits are closer substitutes due to correlated unobserved utilities under the nested logit model. In this case, the percentage changes in s_{cbdc} are larger due to the greater substitutability between deposits and CBDC that enlarges the impact of the attribute change. Therefore, the predictions based on the logit model are more conservative. The results for the nested logit model and the impacts of other attributes not shown in this section can be found in Appendix E.4.

6. Extensions

This section introduces two extensions of the model and investigates how the baseline predictions based on the households' demand side would change. First, the attributes of the existing products are assumed to be unchanged by the presence of CBDC in the baseline analysis. However, if banks respond to CBDC through a higher deposit rate to make deposits more attractive, then the rate of return attribute of deposits would change after CBDC issuance. Section 6.1 incorporates the endogenous responses by banks.

Second, network effects can exist in the medium of exchange role of cash, deposits, and CBDC. Given data availability, this paper focuses on the direct network effects in Section 6.2, i.e., the value of a product to a user increases in the number of other users in the same network, which can exist in peer-to-peer transactions.[22]

6.1. Incorporating banks' responses

Assume N identical banks with a marginal cost c compete for deposits *à la* Cournot and earn an exogenous return r^l on loans. Each bank n chooses its deposit quantity D_n, taking all the other banks' quantities as given, to maximize the profit π_n:

$$\pi_n = \left[r^l - r^d (D_n + \sum_{k \neq n} D_k) - c \right] D_n \tag{8}$$

where $r_d(.)$ is the deposit rate as a function of the total deposit quantity. Let D denote the aggregate deposit demand. Appendix F.1 shows that in equilibrium,

$$r^l - r^d - c = \frac{1}{N} \left(\frac{\partial D}{\partial r^d} \frac{1}{D} \right)^{-1} \tag{9}$$

where the left hand side is each bank's inverse semi-elasticity of deposit demand. Appendix F.2 shows that the semi-elasticity of the aggregate deposit demand is:

$$\frac{\partial D}{\partial r^d} \frac{1}{D} = \alpha \sum_i \frac{s_{i,d} w_i}{D} (1 - s_{i,d})(1 - T_i) \tag{10}$$

where $D = \sum_i s_{i,d} w_i$ and T_i is the marginal tax rate on household income. The semi-elasticity (10) is calculated using the estimated parameter α, the predicted deposit share $s_{i,d}$, the household-level liquid assets w_i, and the marginal tax rates.

[22] The other type of network effects is the indirect network effects, where the more consumers are using a payment instrument, the more merchants would want to accept it, and vice versa. With data on the universe of POS terminal adoptions by retailers and number of debit cards at issuer-municipality level in Mexico, Higgins (2020) used the Mexican government's rollout of one million debit cards to cash transfer recipients during 2009–2012 as a natural experiment to estimate the indirect network effects.

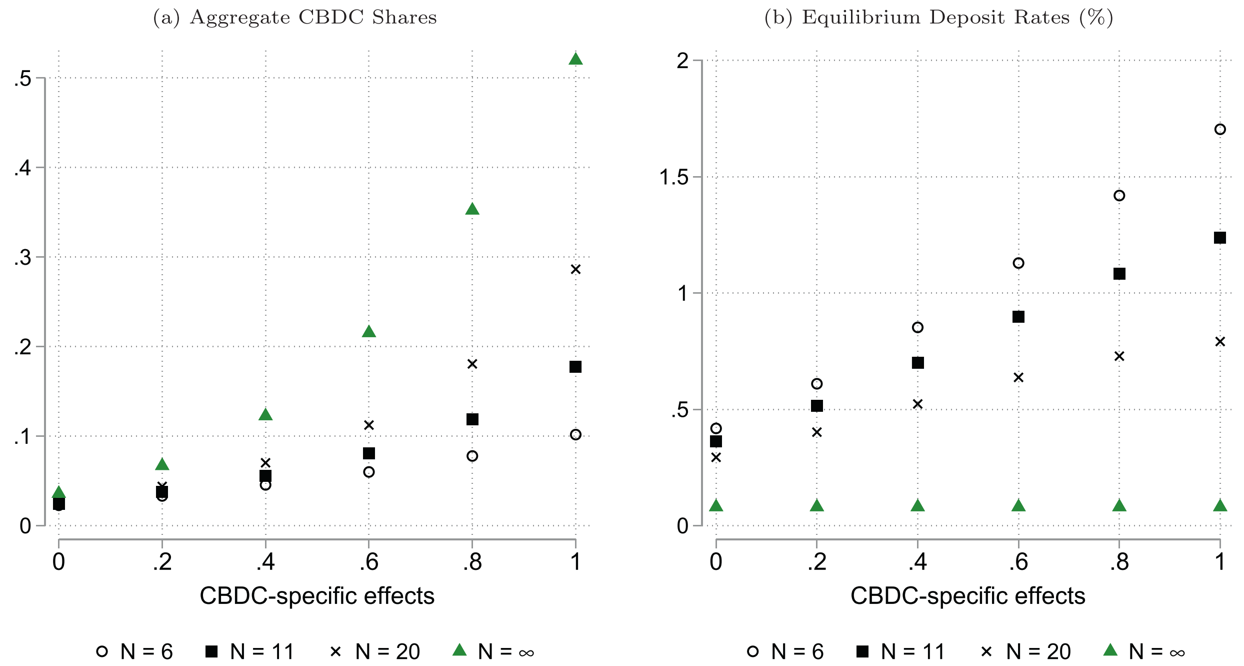

Fig. 2. Equilibrium Outcomes under Different CBDC-specific Effects and Number of Banks. Note: The left (right) panel plots the aggregate CBDC shares (equilibrium deposit rates) against different CBDC-specific effects after introducing a CBDC with a baseline design in 2017. The x-axis shows the values of $\boldsymbol{\gamma}_{cbdc}/\widehat{\boldsymbol{\gamma}}_d$ and $\eta_{cbdc}/\widehat{\eta}_d$. At point of zero (one) on the x-axis, CBDC-specific effects are assumed to be cash-like (deposit-like), i.e., $\boldsymbol{\gamma}_{cbdc}$ and η_{cbdc} take the normalised values for cash (estimated values for deposits), so that $\boldsymbol{\gamma}_{cbdc}/\widehat{\boldsymbol{\gamma}}_d$ and $\eta_{cbdc}/\widehat{\eta}_d$ are both equal to zero (one). Each line corresponds to a different number of banks N. Note that $N = 11$ is the only calibration that matches the bank profit margin. When N is infinity, the results nest with the baseline predictions based on demand side only.

I find that the inverse semi-elasticity $\left(\frac{\partial D}{\partial r^d}\frac{1}{D}\right)^{-1}$ is around 16.6 in year 2017, implying that the profit margin $(r^l - r^d - c)$ would be 16.6% if the banking sector was a monopoly (i.e., $N = 1$). I calibrate $N = 11$ to get a profit margin of around 1.5% (16.6/11), which matches the weighted average of net interest income over total assets ratios across the big six banks and Laurentian Bank, where the weight is each bank's market share by total assets.

The marginal cost c in (9) is calculated using the calibrated N, the estimated $\left(\frac{\partial D}{\partial r^d}\frac{1}{D}\right)^{-1}$, the loan return r^l measured by the weighted average of the 5-year closed mortgage rates across the big six banks, and the equilibrium deposit rate r^d measured by the average pre-tax deposit rates across households.[23] With $r^l = 4.78\%$ and $r^d = 0.08\%$ in 2017, c is around 3.2%. When CBDC is introduced, r^d and $\left(\frac{\partial D}{\partial r^d}\frac{1}{D}\right)^{-1}$ are endogenously changing, while r^l, c, and N are treated as exogenous and unchanged. The new equilibrium deposit rate in the presence of a CBDC is solved using (9).

Fig. 2 shows the aggregate CBDC shares s_{cbdc} and equilibrium deposit rates r^d under different degrees of bank market power reflected by N. Under the calibration of $N = 11$ discussed above, Fig. 2a shows that the range of aggregate CBDC shares is narrowed to 2–18%. The upper bound of the baseline prediction is now reduced to below 20% because the presence of an attractive CBDC tends to make the deposit demand more elastic by lowering $s_{i,d}$, as shown in (10). As a consequence, banks have to make deposits more attractive through a higher deposit rate to avoid losing a lot of deposits. As shown in Fig. 2b, the equilibrium deposit rates are much higher compared to the 0.08% in the absence of CBDC, suggesting the importance of CBDC despite a lower take-up.

When N increases and banks have less market power, the equilibrium aggregate CBDC share is higher. In the limiting case when N is infinity, each bank faces a perfectly elastic deposit demand and does not respond to CBDC, so the results are identical to the baseline predictions. The impacts of design attributes on the percentage changes in s_{cbdc} tend to be reduced slightly. Results are discussed in Appendix F.3.

6.2. Incorporating network effects

To incorporate the direct network effects, I introduced a social utility term, $\mu_i^e(a_{-i,j})$, into each household's utility (1) to capture household i's belief about the actions by others in i's group $g(i)$, following the literature on modeling social interac-

[23] This is equivalent to the weighted average of bank deposit rates, where each bank's weight is in terms of the number of customers in the sample.

tions in structural models (e.g., Blume et al., 2011; Brock and Durlauf, 2002):

$$u_{i,j} = V_{i,j} + \beta\mu_i^e(a_{-i,j}) + \epsilon_{i,j} \qquad \forall i \in g(i), \quad j \in \{c, d, cbdc\} \tag{11}$$

where a positive β reflects the network effects, i.e., each household's utility depends on the others' choices within the same group. When $\beta = 0$, this is reduced to the baseline model without network effects. Since the same β is assumed to apply to all three products, the presence of network effects does not necessarily lead to a higher aggregate CBDC share. Rather, the aggregate CBDC share depends on the private utilities $V_{i,cbdc}$ from CBDC relative to those of the other products and the role of the network effects is to amplify these private utility differences across products.

For a given level of β that determines the magnitude of the amplification, the network effects tend to matter more when the top two products give similar private utilities. Intuitively, if the winner gives much higher private utilities than the runner-up, then the winner would attract a lot of demand anyway, in which case the network effects are less important in determining the asset shares. I find that the baseline results are robust under the empirically estimated $\widehat{\beta}$ and a wide range of exogenously set β values. However, when β is extremely high, implying strong network effects, even if CBDC only provides slightly higher (lower) private utilities than deposits, the aggregate CBDC share can approach one (zero). Detailed analyses and results can be found in Appendix G.

7. Conclusions

By applying a structural demand model to a unique Canadian survey dataset, this paper predicts households' potential demand for CBDC with different design attributes. CBDC and its close alternatives, cash and demand deposits, are viewed as product bundles of different attributes. Households' preferences towards these attributes are estimated from how they allocate their liquid assets between deposits and cash. Provided that these estimated preference parameters remain the same after CBDC issuance, they can be used to predict the demand for CBDC and how the demand depends on CBDC design choices.

Focusing on households' demand perspective, the aggregate holdings of a baseline CBDC as a percentage of the total household liquid assets could range from 4% to 52%, depending on whether households would perceive CBDC to be closer to cash or deposits. This range would be greatly narrowed once supply-side responses are incorporated. I find that allowing banks to respond to CBDC can substantially constrain the take-up of CBDC, reducing the upper bound prediction to below 20%. In addition, by studying the impact of changing each CBDC attribute on the percentage change in CBDC demand, the paper identifies some important design attributes that could affect the demand for CBDC, which include budgeting usefulness, anonymity, bundling of bank services, and rate of return.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jmoneco.2022.11.007

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