Agent-Based Simulation of Central Bank Digital Currencies∗

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Abstract
This paper presents a multi-period agent-based model for the study of macro-financial effects related to the introduction of a retail Central Bank Digital Currency (CBDC). Calibrating it with aggregate statistics of the German retail payment market, we exemplify how the model can be used to quantify the impact of a CBDC on i) the usage of alternative means of payments, ii) the composition of consumer’s wealth, and iii) the banking sector disintermediation. We find that CBDC can be configured without largely impacting the banking sector balance sheet. However, we also find that card companies may suffer a substantial decline in their transaction revenues. We see this model as a framework that can be enriched and tuned to answer a myriad of questions relevant to different jurisdictions from a macro-financial angle. The model is publicly available in the FNA simulation platform for running other policy experiments i.e., testing the efficacy of alternative configurations of CBDCs.

Keywords: CBDC, payment systems, agent-based model, economic impact, disintermediation

JEL Classification: C63, E41, G21, G28

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1 Introduction

Central banks around the world are actively exploring central bank digital currencies (CBDCs). A recent survey from Boar and Wehrli (2021) finds that more than 80% of the 65 central banks surveyed are undertaking extensive work on CBDCs. The survey also points out that, in the next three years, central banks representing about 20% of the world’s population are expected to issue a retail (general purpose) CBDC. The implementation of a retail CBDC has the potential to fundamentally reshape our current monetary and financial systems, with implications not yet fully understood and currently actively researched. The Federal Reserve Bank of Boston, for example, is undertaking work on retail CBDC research with the MIT Digital Currency Initiative (Federal Reserve Bank of Boston, 2020). Additionally, as reported in Reuters (2021), European Central Bank (ECB) policymaker Ignazio Visco has stated that ECB is exploring ways to launch a digital euro. At the same time, a live CBDC has been fully deployed. The Central Bank of The Bahamas launches its Sand Dollar to the general public in October 2020 (Central Bank of the Bahamas, 2019).

Despite the rising interest, many central banks appear not yet convinced that the benefits of CBDC issuance will predominate the costs (Barontini and Holden, 2019). One of the major roadblocks is the fact that the implications of CBDC on the financial and economic system, as well as the behavior of players within a CBDC ecosystem, remain unknown. Accordingly, the literature on CBDC has been growing rapidly for the past few years (see e.g., Kiff et al. (2020) for the recent survey). Some, for example, have studied the possibility of different CBDC designs and discussed various approaches to cope with the banking disintermediation. Bindseil (2021) and Panetta (2018) propose imposing holding limits, while Kumhof and Noone (2018) suggest a more progressive proposal that would restrict on-demand convertibility of deposits into CBDC. Gross and Schiller (2021) shows that, unless central banks decide to provide additional funds, CBDC will crowd out bank deposits. Others focus on the CBDC implication on systemic risk (Fernández-Villaverde et al., 2020) and its impact on monetary policy (Keister and Monnet, 2020).

This paper offers, to the best of our knowledge, the first Agent-Based model of an economy with a CBDC. While a number of features are still simplistic, our model already includes several key ingredients needed to discuss the main issues related to a CBDC. Its modular structure makes it amenable to extensions and modifications, making it a tool for enquiry & a modelling platform for a “user” to run policy experiments. Some of the issues that can already be looked into in this stylized framework are: CBDC adoption, disintermediation, leverage of the banking sector (and thus, by extension, financial stability), conduct of monetary policy. At the moment, agents and their interactions are highly simplified, while complex concepts are reduced to simple variables or ratios. However, as we rely on simulations as opposed to numerical solutions, nothing will stop us from adding parts to it, to make it more realistic and capable to address additional questions related to a CBDC. For now, we show what we can obtain with this minimal structure; future expansions will be relatively easy, exploiting a number of “plugs” that we embedded in the model in a long-term development view.
The remainder of the paper is organised as follows: in Section 2 we provide an overview of prior research in payment simulation and agent-based simulation. We present the details of the agent based model in section 3, and describe the parameter calibration in section 4. We then present and discuss the results in section 5. Finally, we discuss our conclusions and further works in section 6.

2 Relevant Literature

The literature on CBDC is in constant and rapid evolution. So, instead of attempting a review that would necessarily be incomplete and soon become outdated, we give a short overview of two families of studies this paper draws on: the literature on payments and the one in agent-based modeling.

2.1 Payment Simulation

As discussed in Leinonen and Soramäki (2004), simulation techniques allow one to build models that closely imitate the real world. This approach is particularly useful when generic econometric models are limited to deal in complex economic or financial systems. In this respect, simulation techniques have long enjoyed success in modelling payment and settlement systems. Koponen and Soramäki (1998) present the first Payment Simulator to assess liquidity impact of Finnish banks when joining the Pan-European interbank payment system TARGET. Simulation approaches are well established for understanding large-value payments systems probably since the regulatory approval process of the CLS system for settling FX trades, as simulations were extensively used to understand behaviour of the system both in normal and abnormal circumstances. Today, the majority of systemically important FMIs employ simulators to stress test and validate changes to their systems as well as to guide them on design choices.

In a study published by the Bank of Finland, for example, Hellqvist and Koskinen (2005) apply a stress testing simulation to the Finnish Bond clearing and settlement system. Furthermore, in Soramäki et al. (2007) and Beyeler et al. (2007), the approach was joined with network theory to understand the topology of the Fedwire system and to simulate failures in critical financial infrastructures. The Eurosystem has also recently embraced payment system simulations as an ongoing oversight tool by specifying how the transaction level data may be used (EU, 2010) and developing a TARGET2 simulation platform. Another recent example is the project to develop new features for CHAPS interbank payment system in the UK. McLafferty and Edward (2013) use real payment data to quantify the liquidity efficiency that could be obtained in CHAPS, the UK’s large-value payment system, by the implementation of a liquidity saving mechanism. A more recent example is Byck and Heijmans (2021) who study liquidity in the Canadian large value payment system. The simulation of retail payment systems or the cash cycle have not been studied to the same extent. However, agent-based modelling (ABM) approaches have been deployed to understand these more granular systems.
2.2 Agent-Based Modelling

Agent-based modelling is a computational modelling paradigm that enables the description of how agents behave and interact in a system. The methodology of ABM encodes the behavior of individual agents in simple rules so that we can observe the emergent results of these agents’ interactions (Wilensky and Rand, 2015). Figure 1 shows the schematic representation of the typical elements of ABM. There are a number of agents in an environment who are interacting with each other and also with the environment.

An ABM is suited to modelling complex systems such as the economy, where complexity, heterogeneity, networks and heuristics combine to produce emergent behaviour. ABMs have already delivered strong results on different applications, such as financial system stress-test (Farmer et al., 2020), funding risk (Halaj, 2018), housing market (Geanakoplos et al., 2012), payment system (Galbiati and Soramäki, 2011) and financial market simulation (Markose et al., 2005). As described in Turrell (2016), the characteristics of ABM may make it a well-suited approach for exploring the impact of different possible CBDC specifications.

3 An Agent-Based Model of CBDC

This section lays out a parsimonious set of building blocks to investigate recurring issues in the CBDC debate: i) digital currency adoption, ii) credit and disintermediation, iii) bank leverage, iv) monetary policy. We aim at a minimum sufficient structure i.e. we try to introduce only what is strictly needed, in terms of agents, assets, prices, choices, rules, to model these issues. We take inspiration from existing models, from which we borrow the gist of the argument rather than assumptions and formalism, and assemble these modelling blocks into a simple, modular model, with a view to scale it up in the future.

Fig. 1: Schematic representation of an agent-based model (ABM).
The model is cast in discrete time, with each $t$ ($t = 1, 2, \ldots$) representing a “day”. The model features 4 classes of agents: consumers, merchants, a commercial bank, a central bank. There is also an underlying ‘economy’, represented by risky projects undertaken by the commercial bank. Agents interact in time according to given rules, generating dynamics for the model’s key outputs: i) composition of consumer’s wealth (allocated between cash, CBDC, financial assets), ii) diffusion of means of payments and thus percentage of transactions settled via cash, cards and CBDC, iii) bank deposits, iv) interest rates, iv) the size of the economy.

As summarizes in Figure 2, the consumers make daily purchases from the merchants using either cash, deposit (card) or CBDC. The decision regarding the means of payment is based on both the consumers’ wealth allocation and the merchant’s acceptance. Moreover, we assume that the commercial bank adjust its balance sheet by borrowing CBDC from the central bank to face consumers’ withdrawals and to fund risky projects. Meanwhile, the central bank conducts monetary policy (e.g., sets the maximum allowed CBDC balance and determines the rate of CBDC borrowing) and issues CBDC based bank demand. The following subsections describe in more detail the 4 classes of agents and their actions.

3.1 Consumers

There is a large, fixed number of consumers, indexed by $i = 1\ldots N_C$. At any given day $t$, each consumer $i$ has overall wealth $W_i(t)$ allocated between i) cash, ii) CBDC, iii) an interest-bearing current account, or deposit, used for payments (say via debit or credit card), and iv) an otherwise unspecified asset. The latter is not liquid i.e. cannot be used for payments before being liquidated into the current account, and is be used as store of value. In sum,

$$W_i(t) = C_i(t) + K_i(t) + B_i(t) + A_i(t)$$

1The commercial bank does not charge any usage fees for both CBDC and card transactions. When transaction fees exist, there would be some bargaining powers between consumers and merchants (Bolt and Soramäki, 2008).
where $W$ is wealth, $C$ is cash, $K$ is CBDC, $B$ is bank deposit and $A$ is illiquid asset. At each $t$, every $i$ does two things: she decides on the allocation of her wealth and she makes purchases.

**Purchases & payments** Daily purchases are represented by a weighted bipartite network of $N_c$ consumers and $N_m$ retailers. Randomly drawn at each $t$, this network is denoted by:

$$\Pi(t) = \left\{ \{p_{i,j}^\alpha(t)\}_{j \in M^i} \right\}_{i=1..N_c}$$

(2)

where $p_{i,j}^\alpha$ is the value of the $\alpha$-th purchase that $i$ makes from retailer $j$ and $M^i$ is the set of retailers from which $i$ makes purchases. We build $\Pi(.)$ in steps$^2$:

1. Draw a total number of purchases in the network: $\eta(t) \sim \text{Poisson}$
2. For each purchase, draw a pair of consumer $i$ (from the set of all consumers) and merchant $j$ (from the set of all merchants)
3. Randomly draw the purchases’ size as $\log(p_{i,j}^\alpha) \sim \text{Normal [truncated]}$ for all $i,j$ and $\alpha$

Each of the $\eta$ purchases is either ‘online’ or ‘offline’, according to independent random draws with probabilities $p_{\text{online}}$ and $1 - p_{\text{online}}$. Only ‘offline’ purchases can be settled in cash. The settlement of each purchase takes place according to the following rule (where overlap means a set of liquid assets of which the consumer has enough for the purchase and are accepted by the merchant):

**Online**

- overlap is $\emptyset$:
  - merchant accepts CBDC & consumer has CBDC wallet: CBDC
  - otherwise: no purchase
- otherwise: random draw

**Offline**

- overlap is $\emptyset$: no purchase
- otherwise: random draw

Let first consider an online purchase. If the consumer has not enough $B$ nor CBDC to pay for the purchase, but CBDC is accepted by the merchant, the consumer immediately ‘tops up’ its CBDC wallet and uses that. Otherwise the purchase fails. Topups, however, are possible only if the consumer holds a CBDC wallet. Initially, no consumer holds one but, at each $t$, those who do not have a wallet will acquire one with probability:

$$\text{prob}_i(\text{openWallet}(t)) = g(w_i(t-1), y_j(t-1)),$$

$^2$The network is exogenous. However, we could make it part of the adoption ‘story’ assuming a different network formation rule. For example, retailers may decide to offer a number of payment options, in order to attract consumers. And vice-versa, consumers would decide purchases (also) on the basis of the payment means accepted by retailers.
where \( w_i(t) \) and \( y_j(t) \) (resp. \( y_j(t) \)) is the percentage of consumers (merchants) who hold (accept) CBDC.\(^3\)

Let’s now look at the offline purchase case. If no payment option is available, the purchase fails. Otherwise, any available liquid asset (\( C, K \) or \( B \)) is used according to a random draw. Online and offline purchases thus differ because: i) offline purchases may be settled with any liquid asset, while online ones purchases admit \( B \) or \( K \) but not \( C \); ii) a consumer may top up her CBDC wallet ‘on the spot’ for online purchases, but not for offline ones.

The total amounts paid with the three liquid assets in a day are indicated respectively by \( \hat{K}, \hat{B}, \hat{C} \), whose sum \( \hat{P} \) may turn out to be less than \( \sum_j p_{ij}^\alpha \) as purchases will fail if settlement is not possible (when e.g., the consumer runs out of cash or CBDC cannot be used).

**Wealth allocation** At \( t = 0 \), no consumer holds CBDC. \( C, B \) and \( A \) are attributed to consumers according to an observed empirical distribution:

\[
W_i(0) = C_i(0) + B_i(0) + A_i(0), \quad [C, B, A] \sim f(.)
\]  
(3)

In this section, we omit the consumer’s index as this is not needed and all the equations hold in the aggregate too.

At each \( t > 0 \), before purchases are made, consumers move part of their \( B \) into CBDC (‘top-up’), provided that both: i) they hold a wallet (as they have encountered merchants using CBDC)\(^4\), and ii) at \( t-1 \) they found themselves constrained in CBDC.

The top-up is set to \( \tau \) times the daily average CBDC payments that the consumer could have made, up to \( t \). The CBDC top-up is also limited by design to a maximum \( \beta \) so the consumer’s CBDC balance evolves as

\[
K(t + 1) = K(t) + \Delta K(t) = \begin{cases} 
\min \left[ \tau \bar{K}, \beta \right] - K(t) & \text{if there is a top-up} \\
- K(t) & \text{otherwise}
\end{cases}
\]  
(4)

where \( \bar{K} \) is average daily amount of CBDC payments the consumer could have made. We have \( \bar{K} \geq \text{mean}(\bar{K}) \) but, if the consumer holds enough CBDC as to never be constrained, the two number come close as time goes by.

The consumer buys and sells \( A \) using the bank account, thus shifting wealth between \( A \) and \( B \). This latter can be used for payments, but \( A \) yields a fixed \( r_A \) (paid into the bank account) possibly higher than the rate paid on deposits \( r_B \). We do not explicitly model consumer preferences but assume that the consumer targets a certain

\(^3\)This contributes to the CBDC adoption story. For example, the adoption rate is higher the larger the proportion of consumers and merchants in the system using CBDC.

\(^4\)Note that the first time top up depends on a random draw.

\(^5\)Note that the first time top up depends on a random draw.
ratio $A/W$, which depends on the spread in the returns offered by the illiquid asset and the bank account. We assume this target to be:

$$\left( \frac{A}{W} \right)^* = 1 - \frac{1}{r_A/r_B(t)}$$ (5)

and we posit a ‘gradual & approximate’ adjustment towards it. That is, the consumer chooses $A(t+1)$ so that:

$$\frac{A(t+1)}{W(t)} - \frac{A(t)}{W(t)} = -\frac{1}{\nu} \left( \frac{A(t)}{W(t)} - \left( \frac{A}{W} \right)^* \right).$$ (6)

The term ‘approximate’ refers to the fact that $\frac{A(t+1)}{W(t)}$ is an approximation to the ratio to be targeted $\frac{A(t+1)}{W(t+1)}$, and $\nu \geq 1$ makes the adjustment gradual. For example, if $\nu = 2$, the distance between the (approximate) current value and the target is halved. The target converges to 1 (i.e., all wealth is held in $A$) when $r_A/r_B(t) \to \infty$, and instead it converges to 0 as $r_B(t) \to r_A$, as indeed there is no reason to hold the non-liquid asset, if this does not offer superior returns).

The bank account $B$ goes up as: i) returns from $A$ are received, and ii) $A$ is liquidated. It instead falls when: i) $A$ is invested into, ii) CBDC is topped up, iii) cash is withdrawn, and iv) card payments are made. We also assume that each consumer receives an exogenous amount of salary, denoted by $\kappa$. So $B$ changes as follows:

$$B(t+1) - B(t) = \Delta B(t) = [A(t)r_A + B(t)r_B] - [\Delta K(t) + \dot{K}(t)] - [\Delta C(t) + \dot{C}(t)] - \Delta A(t) - B(t) + \kappa$$ (7)

where the terms in square brackets are respectively interest income, CBDC top-ups (see above Equation (4)), cash withdrawals (Equation (8) below), while $\Delta A(t)$ is the additional investment into $A$, and $\dot{B}$ are card payments.

The last variable to be specified is $C$, for which we imagine similar choices as for CBDC: when she runs out of it, the consumer withdraw $\tau_c$ days worth of expected cash payments. That is:

$$C(t+1) - C(t) = \Delta C(t) = \begin{cases} 
\min \left[ \tau_c \dot{C}, \beta_c \right] - \dot{C}(t) & \text{if there is a cash withdrawal} \\
-\dot{C}(t) & \text{otherwise}
\end{cases}$$ (8)

where the cash withdrawal, $\min \left[ \tau_c \dot{C}, \beta_c \right]$, equals $\Delta C(t) + \dot{C}(t)$ when a withdrawal is made.

In summary, wealth grows due to the return on $A$ and the interest paid on $B$. This, along with salary $\kappa$, allows a stream of purchases, modeled as a random networks. Payments are made by using liquid assets $B$, $C$, or $K$. Bank account $B$ is also the source of cash (via withdrawals) and CBDC (via top-ups). It is also used to buy $A$, which can then be liquidated back into $B$. The demand for $C$ and $K$ (withdrawals and
top-ups) is a function of previous usage. The demand for $A$ depends on the spread $r_A - r_B(t)$ and on $\frac{A}{W}$.

### 3.2 Merchants

All merchants accept cash and at $t = 0$ a percentage of them accepts card ($P_B$) and CBDC payments ($P_K$) too. As time goes by, each merchant start accepting CBDC at a random time, which depends on their customers’ previous demands:

All merchants accept cash and at $t = 0$ a fraction $P_B$ of them accepts card. A subset of these merchants, amounting to a fraction $P_K < P_B$ of the total, accepts CBDC payments too. As time goes by, each merchant start accepting CBDC at a random time, which depends on their customers’ previous demands:

$$\text{prob}_j(\text{accepts}(t)) = h(z_j(t - 1))$$

where $z_j(t)$ is the percentage of consumers that visited merchant $j$ and were able to pay via CBDC up to $t$, and $h$ is some function such that $h(0) = 0$ and $h(1) \leq 1$. There is no feedback from the merchants’ sales into the economy: from a modelling perspective, their purpose is only to contribute to a CBDC adoption story.

### 3.3 Commercial Bank

The bank does the following:

- Issues $B$ to consumers. In particular, the bank sets rate $r_B$ and the amount of deposits is determined by the consumers’ demand (Equation (7))
- Borrows CBDC from the central bank ($K_{\text{bank}}$), paying rate $r$
- Uses the above funds to:
  - face consumers’ withdrawals
  - fund risky projects $X$, which yield a daily random return $r_X(t)$ distributed according to a distribution $\Lambda$

We imagine the following timing: given $X(t), \sum_i B_i(t) = B(t)$ and $K_{\text{bank}}(t)$, the return $r_X(t)$ is drawn, the bank pays the due interest and time-$t$ profit is computed. Then, the bank sets $r_B(t+1)$ to which consumers react choosing $B(t+1)$, causing the deposits inflow $\Delta B(t)$. To this, the bank responds setting $X(t+1)$ and $K_{\text{bank}}(t+1)$. And so on.

The bank’s time-$t$ profit is:

$$X(t)r_X(t) - B(t)r_B(t) - K_{\text{bank}}(t)r(t), \quad (10)$$
which we assume to be distributed to (un-modelled) shareholders. The bank faces two constraints. First, it cannot exceed a leverage ratio of \( \bar{\Gamma} \). i.e., at all \( t \), it must be:

\[
\frac{\text{debt}}{\text{assets} - \text{debt}} = \frac{B(t) + K_{\text{bank}}(t)}{X(t) - [B(t) + K_{\text{bank}}(t)]} = \Gamma(t) \leq \bar{\Gamma} \tag{11}
\]

where \( \Gamma \) denotes the bank’s actual leverage, defined here as debt to equity. We assume that breaching the constraint entails a ‘default’, so the bank stops operating. We do not model what happens in this event, as this model is supposed to describe a normal functioning of the economy. We can, however, imagine that a breach of the constraint brings about a bank run, or special intervention from the central bank, and leave this for future investigation.

Second, the bank must continuously meet its obligations i.e., pay interest and satisfy bank withdrawals.\(^6\) That is, at each time it needs at each time liquidity for an amount equal to \([B(t)r_B(t) + K_{\text{bank}}(t)r(t)] - \Delta B(t)\). To do so, the bank borrows new funds from the central bank (\( \Delta K_{\text{bank}} \)) and/or liquidates \( X \) (\( \Delta X \)) which, we assume, is illiquid in the sense that part of it is lost when liquidating it.\(^7\) The liquidity constraint of the bank then is as follows:

\[
[B(t)r_B(t) + K_{\text{bank}}(t)r(t)] - \Delta B(t) = \Delta K_{\text{bank}}(t) + \begin{cases} 
\Delta X(t)\xi & \text{if } \Delta X(t) < 0 \\
\Delta X(t) & \text{otherwise}
\end{cases} \tag{12}
\]

where \( \xi \in (0, 1) \) indicates that, in order to obtain £1 of liquidity, the bank has to sell £1/\( \xi > 1 \) worth of \( X \).

In the above equation, on the l.h.s is the bank’s liquidity need and on the r.h.s is the amount of new funds. If the need is positive, funds are obtained by borrowing from the central bank and/or by changing \( X \). If the liquidity need is negative, the bank can instead pay back to the central bank and/or invest into \( X \).\(^8\) As the liquidity need is fixed at \( t \), the bank chooses \( K(t+1) \) or \( X(t+1) \), and the other quantity is determined by difference, according to Equation (12).

When choosing between \( X \) and \( K_{\text{bank}} \) in response to changes in \( B \), the bank faces a trade off between profitability and leverage. When the bank chose to liquidate \( X \), the difference between assets and debt (denominator in Equation (11)) is unchanged but debt (numerator) falls, thus the bank de-leverages. If the bank instead prefers to borrow \( K_{\text{bank}} \), the bank substitutes central bank debt for consumer debt, so debt is unchanged. As assets are unchanged too, leverage thus remains constant. From a leverage perspective, liquidating \( X \) is thus preferable. However, from a profitability perspective, borrowing from the central bank is preferable: by substituting central bank debt for consumer deposits, the bank can preserve the lucrative asset \( X \).\(^9\)

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\(^6\)These include cash withdrawals and CBDC top-ups, as per Equation (7).

\(^7\)We assume that the commercial bank holds no cash. It can either get it instantly from the central bank using CBDC reserves, or sell part of \( X \) against CBDC, which is then instantly converted into cash.

\(^8\)So far, the bank can also increase \( X \) when facing a positive liquidity need, in which case it would borrow from the central bank to both meet the liquidity need and invest in \( X \). And vice versa: it could decrease \( X \) even when not needed i.e when facing a negative liquidity need.

\(^9\)We assume that \( r \) is lower than the return offered by \( X \). This is true in the current low rates environment, and is probably also true historically, as \( X \) represents the overall portfolio of the financial
Given a path of central bank interest rates $r(t)$, the bank could maximize the expected discounted future stream of profits (Equation (10)) under constraints (Equation (11) and Equation (12)), choosing optimal paths of $r_B$ and $X$ or, alternatively, $K$. However, in the spirit of the ABM method, we assume here that the bank follows simple rules instead of precisely maximizing profits. As for the consumer, however, we imagine that the bank slowly adjusts its leverage ratio towards a target that depends on $\sigma$, the spread between the expected return on $X$ and the average cost of debt: $\sigma(t) = \frac{\Lambda B(t) + K_{bank}(t)}{r_B(t) + K_{bank}(t)} - 1$. We assume this target to be:

$$\Gamma^*(t) = \bar{\Gamma} \left(1 - \frac{1}{\sigma(t)}\right),$$

so if $\sigma$ drops below 1 (the expected return on $X$ falls below the cost of financing it) the bank targets 0 leverage. If instead $\sigma$ goes to infinity, the bank asymptotically targets the maximum allowed leverage $\bar{\Gamma}$ (beyond which it would 'default'). The target is approached again ‘slowly and approximately’ according to the following equation (where, to reduce clutter, we write $K$ for $K_{bank}$ and we omit time $(t)$ except for $(t + 1)$ variables so, e.g., $B$ alone stands for $B(t)$):

$$B + K(t + 1) - B + K(t + 1) = -\frac{1}{\mu} (\Gamma - \Gamma^*). \quad (13)$$

As for the consumers’ equation in Equation (6), ‘approximately’ refers to the fact that the first ratio is an approximation of the true leverage to be targeted (which would have $t + 1$ for $B$ too): the bank myopically acts as if deposits at $t + 1$ will be the same as at $t$. Parameter $\mu \geq 1$ again determines the speed of adjustment towards target.

Given history up to $t$, either $X(t + 1)$ can be freely determined, or $K_{bank}(t + 1)$, but not both, because of the cash flow constraint in Equation (12). Using then Equation (13), we write $K_{bank}(t + 1)$ as a function of $X(t + 1)$ (writing again $K$ for $K_{bank}$ and omitting time $(t)$ except for $(t + 1)$ variables):

$$K(t + 1) = \frac{D}{1 + D} X(t + 1) - B \quad (14)$$

where $D = \frac{B + K}{X - [B + K]} - \frac{1}{\mu} (\Gamma - \Gamma^*)$. Plugging this into Equation (12), we obtain $X(t + 1)$:

$$X(t + 1) = [B(1 + r_B) + K(1 + r) + X\xi] \frac{1 + D}{D + \xi(1 + D)} \quad (15)$$

In reality, the above Equation (15) should have $B(t + 1)$ in the place of $B$. However, we assume that at $t$ the bank does not know $B(t + 1)^{10}$, so $X(t + 1)$ is set using $B(t)$ as an approximation.

Finally, regarding the choice of $r_B$, we assume that the bank applies a mark-up on sector.

10After all, our single bank is a metaphor for the whole financial sector, so it is reasonable to assume that this does not have perfect knowledge of the demand for deposits.
the cost of borrowing CBDC, $r$, set by the central bank:

$$r_B(t) = r(t) + \epsilon$$  \hfill (16)$$

with $\epsilon > 0$ (and in the region of approx 1%).

3.4 Central Bank

The central bank has two traditional tools at its disposal: i) the max leverage $\bar{\Gamma}$ and ii) the cost of borrowing CBDC $r$. It also sets iii) the maximum CBDC top-up $\beta_c$ and cash withdrawal $\beta$. With the first, the central bank tweaks the commercial bank’s leverage constraint. With the second, it determines the cost of borrowing CBDC. Together, these two affects the commercial bank’s choices, i.e., i) the amount of financed projects $X$ and the commercial bank reserves $K_{bank}$ (because the target leverage depends on the average cost of debt) and ii) the interest paid on deposits $r_B$, affecting in turn consumers’ choices.

In theory we could explicitly model an objective function for the central bank and solve for a (game-theoretic) equilibrium between the commercial bank and the central bank, whereby each agent chooses mutually optimal actions. At this stage, however, the model will primarily be used to shed light onto the effects of central bank choices, so the central bank variables are left free, to be provided as an exogenous input. In order to close the model and provide some first results, the following rules will be used as baselines central bank policies:

1. Constant policy: $\bar{\Gamma}$, $r$ constant in time, and set to levels which indicatively reflect current conditions. Limit $\beta$ is also constant and set to typical maximum cash withdrawal level.

2. Growth-targeting rate policy: $\bar{\Gamma}$ and $\beta$ as above; $r(t)$ set as an increasing function of $X(t) - X(t-1)$.

3. Macroprudential policy: $\beta$ and $r$ as per “constant policy”; $\bar{\Gamma}$ set, at long intervals, as a decreasing function of the mean $X(t) - X(t-1)$ over the period.

4 Model Calibration & Simulation Engine

In order to run our model we need to pin down its many parameters and the system’s initial conditions. We do not attempt any rigorous calibration here because our objective is to exemplify how the model can be used, rather than provide definitive answers. However, we adopt the following strategy to minimize the impact from a necessarily approximate calibration of the initial conditions.

First, we calibrate a stripped down version of the model that does not include the CBDC - we do so looking at data from the German retail market and other stylized facts (e.g. long-term returns on equity). Having set these parameters and some realistic initial values for the state variables, we then perform a “model burn-in”
i.e. we simulate the model until a steady state is reached, while keeping switched off all the CBDC-related variables\textsuperscript{11}. Finally, we introduce the CBDC. By so doing, we ensure that any subsequent change is attributable to the introduction of the CBDC.

4.1 Consumers

The model calibration for the consumers is illustrated in Table 1. In what follows, we describe the parameterization of variables related to i) purchases & payments, and ii) wealth allocation.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value</th>
<th>Data Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>$N_c$</td>
<td>Number of consumers</td>
<td>1500</td>
<td>Model assumption</td>
</tr>
<tr>
<td>$\bar{\eta}$</td>
<td>Average number of daily purchases</td>
<td>1500</td>
<td>Cabinakova et al. (2019)</td>
</tr>
<tr>
<td>$\bar{\bar{p}}<em>{i,j}, \bar{p}</em>{i,j}, \bar{\bar{p}}_{i,j}$</td>
<td>Mean, median and max purchase value</td>
<td>EUR 21.11, 14.21, 1000</td>
<td>Cabinakova et al. (2019)</td>
</tr>
<tr>
<td>$p_{\text{online}}$</td>
<td>The proportion of online purchases</td>
<td>20%</td>
<td>E-commerce data</td>
</tr>
<tr>
<td>$g(w, y)$</td>
<td>Adoption function, where $w (y)$ is the proportion of consumers (merchants) who have adopted CBDC</td>
<td>$0.25(w + y)$</td>
<td>Model assumption</td>
</tr>
<tr>
<td>$[C, B, A] \sim f(.)$</td>
<td>Initial wealth distribution</td>
<td>See text.</td>
<td>Deutsche Bundesbank (2019)</td>
</tr>
<tr>
<td>$\kappa$</td>
<td>Exogenous salary</td>
<td>EUR 18</td>
<td>Comparable to median purchase value</td>
</tr>
<tr>
<td>$r_A$</td>
<td>Return on asset</td>
<td>$\frac{3%}{365}$</td>
<td>Moody’s</td>
</tr>
<tr>
<td>$\tau$</td>
<td>CBDC top-up horizon</td>
<td>10</td>
<td>Bagnall et al. (2016)</td>
</tr>
<tr>
<td>$\tau_c$</td>
<td>Cash withdrawal horizon</td>
<td>10</td>
<td>Bagnall et al. (2016)</td>
</tr>
<tr>
<td>$\nu$</td>
<td>Adjustment on target wealth</td>
<td>1</td>
<td>Model assumption</td>
</tr>
</tbody>
</table>

Table 1: Model calibration for the consumers.

4.1.1 Purchases & payments

- Distribution of the total number of purchases. For a total number of consumer $N_C = 1500$ in the model, we assume that the total number of purchases is

\textsuperscript{11}In practice, it is sufficient to assume that no merchant accepts CBDC, and that no CBDC is borrowed from the central bank.
distributed according to the Poisson distribution with mean $\bar{\eta} = 1500$. The parameterization is based on Cabinakova et al. (2019) who find that there are roughly 20 billion transactions in German retail market per year (54.8 million per day). Taking into account that the German’s working population is about 53 million, this imply that each consumer makes approximately 1 payment per day.

- **Distribution of purchase value.** The value of $\tilde{P}_{i,j}^u$ and $\tilde{P}_{i,j}^\ell$ are calibrated from Cabinakova et al. (2019).

- **Probabilities involved in the “settlement rule” (to determine which payment instrument is used).** In the case where consumers needs to perform a random draw, we assume that each asset has the same probability to be chosen.

- **Probability of online purchases.** By comparing the value of retail\(^{12}\) versus e-commerce spending\(^{13}\), we assume that $p_{\text{online}} = 20\%$.

### 4.1.2 Wealth allocation

- **Initial wealth allocation** ($[C, B, A] \sim f(.)$). Deutsche Bundesbank (2019). We generate the consumers initial deposits from a (truncated) log-normal distribution with parameters mean EUR 7,100 and median EUR 1,800; and maximum EUR 10,000. These numbers are based on the distribution of German households’ portfolio structure in 2017 published in Deutsche Bundesbank (2019). We also assume each consumer initially holds EUR 200 cash and EUR 0 CBDC\(^{14}\). The consumers assets are then obtained by scaling the wealth based on a target, $\frac{A}{B} = 1 - \frac{1}{r_A}$, defined previously in Equation (5).

- **Interest rate of asset** We assume $r_A$ to be $\frac{35}{12}$, which is comparable to the Moody’s seasoned AAA corporate bond yield in 2016\(^{15}\).

- **CBDC top-up and cash withdrawal horizon.** The value of $\tau$ and $\tau_c$ are set to be 10. Based on 2017 payment behavior survey (Deutsche Bundesbank, 2019), respondent reported to 42 times in a year withdraw ATM. This would approximately mean to withdraw money every 10 days.

### 4.2 Merchants

We summarize the parameterization for the merchants in Table 2.

- **The number of merchants in the model, $N_m$, is calibrated as follow.** According to Cabinakova et al. (2019), the German retail sector in 2016 encompasses...

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\(^{12}\)https://tradingeconomics.com/germany/retail-sales-annual

\(^{13}\)https://ecommercenews.eu/ecommerce-in-germany-was-worth-e83-3-billion-in-2020/

\(^{14}\)We also assume that, when the consumers sign up for CBDC, they will initially add EUR 100 balance to their wallets.

\(^{15}\)https://fred.stlouisfed.org/series/AAA
<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value</th>
<th>Data Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>$N_m$</td>
<td>Number of merchants</td>
<td>15</td>
<td>Cabinakova et al. (2019)</td>
</tr>
<tr>
<td>$P_B$</td>
<td>The proportion of merchants who accepts card payments</td>
<td>20%</td>
<td>Bagnall et al. (2016)</td>
</tr>
<tr>
<td>$P_K$</td>
<td>The proportion of merchants who initially accepts CBDC</td>
<td>10%</td>
<td>Model assumption</td>
</tr>
<tr>
<td>$h(z_j(t))$</td>
<td>Adoption function, where $z_j(t)$ is the percentage of consumers that visited merchant $j$ and asked to pay via CBDC up to $t$</td>
<td>$h(z) = 0.25z$</td>
<td>Model assumption</td>
</tr>
</tbody>
</table>

Table 2: Model calibration for the merchants.

around 355 thousand stores. Taking into account that the German working-age population in 2016 is about 53 million, this then implies that there is a retailer for approximately each 100 people in the country. We therefore assume a total number of merchant $N_M = 15$ for a total consumer $N_C = 1500$ in the model. An agent in our model, therefore, represents approximately 35,000 consumers or 350 retailers in the German retail market.

- **The proportion of merchants who, at time $t = 0$, accept card and CBDC payments ($P_B$ and $P_K$).** We set the value of $P_B$ to be 20%, which corresponds to $P_B \times N_C = 20\% \times 15 = 3$ merchants in our parameterization. This is stemming from the study of Bagnall et al. (2016) who find that the use of cash is strongly correlated with merchant card acceptance, and that share of cash payment (by volume) reaches more than 80% in the Germany retail market. Meanwhile, we assume that $P_K$ equals to 10%, which corresponds to $P_K \times N_C = 10\% \times 15 = 1$ merchant.

- **CBDC adoption rule.** We assume the function $h(.)$ in Equation (9) to be $h(z) = 0.25z$.

### 4.3 Commercial Bank

Table 3 summarizes the model calibration for the commercial bank. The value of initial deposits, $B(0)$, is computed from the total deposits held by consumers. The initial CBDC borrowing, $K_{bank}(0)$, is set to be EUR 1M. Moreover, by considering a leverage ratio of 20%\textsuperscript{16}, and taking into account the value of $B(0)$ and $K_{bank}(0)$, we then obtain $X(0) = EUR 4.2M$ as the bank’s initial investment in risky assets. Meanwhile, we set

\textsuperscript{16}Note that, in this paper, we define the leverage ratio as the ratio between the total debts and the equity, while the Basel leverage ratio is defined as the equity divided by the total assets. The value of leverage ratio = 20 in this paper is therefore corresponds to the value of leverage ratio = 4.76% in the Basel definition.
the value of average return on risky assets, Λ, to be $1.2\%_{365}$, which is comparable to the real capital gain in housing (Jorda et al., 2019). Finally, the deposit rate is initially set to be $0.5\%_{365}$. The value is comparable to the deposit rate in Germany in 2016.\footnote{Note that we divide the value by 365, as the model runs daily.}

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value</th>
<th>Data Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>$B(0)$</td>
<td>Initial deposit</td>
<td>≈ EUR 3M</td>
<td>Computed from the model</td>
</tr>
<tr>
<td>$K_{bank}(0)$</td>
<td>Initial CBDC borrowing</td>
<td>EUR 1M</td>
<td>Model assumption</td>
</tr>
<tr>
<td>$X(0)$</td>
<td>Initial investment in risky assets</td>
<td>≈ EUR 4.2M</td>
<td>Computed from the model</td>
</tr>
<tr>
<td>$r_B(0)$</td>
<td>Deposit interest rate</td>
<td>$0.5%_{365}$</td>
<td>World bank’s development indicator</td>
</tr>
<tr>
<td>Λ</td>
<td>Return on risky assets</td>
<td>$1.2%_{365}$</td>
<td>Jorda et al. (2019)</td>
</tr>
<tr>
<td>ξ</td>
<td>Friction in liquidating</td>
<td>0.95</td>
<td>Model assumption</td>
</tr>
<tr>
<td>ϵ</td>
<td>Mark-up on the cost of borrowing</td>
<td>$0.3%_{365}$</td>
<td>Computed from the model</td>
</tr>
<tr>
<td>μ</td>
<td>Adjustment on target balance</td>
<td>1</td>
<td>Model assumption</td>
</tr>
</tbody>
</table>

Table 3: Model calibration for the commercial bank.

### 4.4 Central Bank

All the parameters for the central bank are primarily used to shed light onto the effects of central bank choices, so the central bank variables are left free, to be provided as an exogenous input. We assume a constant policy approach for the central bank where banking maximum leverage $\bar{\Gamma}$, CBDC lending rate $r$ and limit $\beta$ is constant in time, and set to levels which indicatively reflect current conditions. Table 4 summarizes the parameterization for the central bank. The maximum amount of CBDC that a consumer can hold in their wallet is $\beta = EUR 1,000$.\footnote{One can also run the simulation with different values of $\beta$. For example, Bindseil and Panetta (2020) illustrate a case where the CBDC maximum allowed balance equals to EUR 3,000.} Meanwhile, the maximum daily cash withdrawal is set to be fixed at $\beta_c = EUR 300$.\footnote{Note that the definition of $\beta$ for CBDC and $\beta_c$ for cash is slightly different. The former sets the maximum allowed CBDC balance, while the latter corresponds to maximum daily ATM withdrawal.} With regard to the maximum leverage ratio that the commercial bank can take, we set $\bar{\Gamma}$ to be 32.3, which equals to 3% in the Basel terms. Finally, we set the interest rate of CBDC to be $r = 0.2\%_{365}$.
<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value</th>
<th>Data Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta$</td>
<td>Maximum allowed CBDC balance</td>
<td>EUR 1,000</td>
<td>Model assumption</td>
</tr>
<tr>
<td>$\beta_c$</td>
<td>Maximum cash withdrawal</td>
<td>EUR 300</td>
<td>Model assumption</td>
</tr>
<tr>
<td>$\bar{\Gamma}$</td>
<td>Maximum leverage ratio</td>
<td>32.3</td>
<td>Model assumption</td>
</tr>
<tr>
<td>$r$</td>
<td>CBDC borrowing rate</td>
<td>$\frac{0.2%}{365}$</td>
<td>Model assumption</td>
</tr>
</tbody>
</table>

Table 4: Model calibration for the central bank.

4.5 Simulation Software

We have developed a cloud-based simulator with FNA (www.fna.fi) to operationalize the dynamics described above. The simulator is a web application allowing users to define the model parameters, run the model and view the results of the simulation as it progresses, as well as download the simulation results for further analysis.

![Cloud-based agent-based simulator of CBDC created with FNA (www.fna.fi).](https://www.fna.fi)

Fig. 3: A cloud-based agent-based simulator of CBDC created with FNA (www.fna.fi).

5 Results

This section illustrates model’s behaviour, focusing on how a newly introduced CBDC affects the usage of alternative means of payment (and thus brings about “disintermediation”), modifies the composition of households’ wealth, and alters the balance sheets of the banking sector. As mentioned, we parametrize all non-CBDC variables
as described in the above section and run the model for a “burn-in” phase till convergence. Only then, we introduce the CBDC, by letting 10% of merchants accept it. In what follows, $t = 0$ therefore corresponds to the time when the CBDC is introduced. Simulations run from $t = 0$ to $t = 3500$ because by then a new equilibrium has been reached.

5.1 Adoption and Diffusion of Means of Payments

Figure 4 shows the evolution in time of the percentage of consumers (merchants) who have signed up for (accepted) CBDC. The left panel shows the whole simulation run, while the right one zooms into the transition phase, where adoption grows in a non-linear fashion.

![Adoption Rate Graph](image)

(a) Longer period

(b) Shorter period

Fig. 4: The rate of adoption over time. At $t = 0$, 10% of merchants start to accept CBDC, but the number of consumers who have signed-up for CBDC is still 0.

Figure 5 illustrates the process of crowding out of traditional means of payments by the CBDC, showing the total value and the total number of transactions settled in cash, cards and CBDC. Panels (a) and (b) show that, while the relative shares of cash, card and CBDC become stable around $t = 1500$, the CBDC had already been fully adopted some time before (at $t = 75$, as shown in Figure 4). Following our particular calibration, panel (c) shows that, by the time the shares of payments stabilize, both cash and cards have declined by approximately 30%, while CBDC establishes itself as the main means of payment. The decline of card payments by 30% means that card companies would lose $30\% \times \text{EUR 5 billion} = \text{EUR 1.5 billion}$ transaction revenues in the German domestic payments market.\footnote{Recall that, as we consider a total number of 15 merchants, 10% therefore corresponds to 1 merchant in the model calibration.\footnote{According to Germann et al. (2019), the card transactions expected revenues in the German domestic payments market for 2022 is EUR 1.5 billion.}}

\footnote{Recall that, as we consider a total number of 15 merchants, 10% therefore corresponds to 1 merchant in the model calibration.\footnote{According to Germann et al. (2019), the card transactions expected revenues in the German domestic payments market for 2022 is EUR 1.5 billion.}}
Fig. 5: The diffusion of means of payments over time. Panel (a) shows the comparison between the total transaction values that are settled via cash, card and CBDC, while panel (b) shows the corresponding transaction numbers. Panel (c) describe the relative change in the total cash and card transaction values.
5.2 Consumer Wealth Allocation

In the previous section we saw CBDC crowding out deposits and cash as form of payments. Figure 6 below shows that a similar dynamics takes place for consumer’s holdings of cash, deposits and CBDC. Panel (a) in particular illustrates how part of the rise in CBDC happens at the expenses of cash. However, as shown by panel (d), bank deposits and financial assets keep increasing. This happens because we assume that consumers receive an exogenous income that is (slightly) higher than daily purchases\(^{24}\), so that the overall consumer wealth grows. However (this is not shown in the charts but it is suggested later on by Figure 6), the growth in deposits is less than what it would be in the absence of CBDC: cash holdings are impacted to the point of decreasing, deposits are impacted in the sense of increasing at a lower rate.

Panel (b) of Figure 6 shows the same variables as panel (a), but zooms into the initial transition period and reveals a somehow peculiar behavior in CBDC holdings: these first increase rapidly, then fall, then increase again. This happens because many consumers, on opening a CBDC wallet, top it up by more than they actually need, generating a sudden swell in CBDC accounts\(^{25}\). Later, though, they go over the initial CBDC ‘overhang’, so their aggregate holdings, although subject to small random fluctuations, follow an essentially monotonic path. All this is a not-so-subtle consequence of our exogenous calibration but the point here is that, with appropriate calibration and extensions, this model can generate patterns resembling e.g. the ‘initial / irrational exuberance’ that often accompanies financial innovation.

Another type of analysis that can be carried out within this framework is cross-sectional analysis, to look at how wealth (and its composition) varies in the population of agents. For example, Figure 7 shows the histograms of CBDC balance at different periods: \(t = 44, 125, 1000, 3000\). Note that, as shown previously in Figure 4, the adoption rate grows substantially after \(t = 44\) and reaches 100% rate at \(t = 75\). We see from the figure that, on \(t = 44\), most of the consumers have zero in their balance as they still have not signed up for CBDC. Meanwhile, on \(t = 125\), we find that the number of consumers with zero CBDC balance has declined, and that with EUR 22-40 has substantially increased. We then observe that the shape of the distribution becomes more similar at \(t = 1000\) and \(t = 3000\). In particular, we see that the majority of consumers hold \(\approx\) EUR 50-100 at both periods. Note that, in all figures, there are still consumers with zero CBDC balance, even though the adoption rate is already 100%. This is because some consumers may not enough deposits to top up their CBDC wallets.\(^{26}\)

In a similar vein, Table 5 reports the mean and median of assets holdings, across agents and at four points in time (again \(t = 44, 125, 1000, 3000\)). For example, we see from the table that a consumer holds, initially at \(t\), EUR 88 cash in average. We then see how the cash holding decreases over time and fall to EUR 70 at \(t = 3000\). Moreover, we also see that the CBDC holding grows from EUR 9 at \(t = 44\) to EUR

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\(^{24}\)As per Section 4, the daily exogenous income is 18 EUR and the median (mean) of the daily purchases is 14.21 (21.11).

\(^{25}\)The initial top-up is exogenously set at 100 euros. Subsequent top-ups are determined by individual consumers' average CBDC spending.

\(^{26}\)We assume that the consumers can still sign up and leave the balance to zero.
Fig. 6: The composition of consumer wealth over time (sum over all consumers) allocated between cash, CBDC, deposits and other assets.
Fig. 7: Distribution of CBDC balances across agents (note different scale of y-axes).
71 at $t = 3000$.

<table>
<thead>
<tr>
<th>Wealth</th>
<th>$t = 44$</th>
<th>$t = 125$</th>
<th>$t = 1000$</th>
<th>$t = 3000$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Med</td>
<td>Mean</td>
<td>Med</td>
</tr>
<tr>
<td>Cash</td>
<td>88</td>
<td>88</td>
<td>89</td>
<td>90</td>
</tr>
<tr>
<td>CBDC</td>
<td>9</td>
<td>0</td>
<td>23</td>
<td>22</td>
</tr>
<tr>
<td>Deposit</td>
<td>2265</td>
<td>1281</td>
<td>2292</td>
<td>1316</td>
</tr>
<tr>
<td>Asset</td>
<td>11790</td>
<td>6906</td>
<td>12014</td>
<td>7123</td>
</tr>
</tbody>
</table>

Table 5: Wealth allocation over time (mean and median across agents.

5.3 Banking Disintermediation and Balance Sheet

In the following, we study the impact of the introduction of a CBDC on the banking disintermediation. The disintermediation process, in general, involves removing the middleman (commercial bank) that sits between two parties (consumers and merchants) in a transaction. Disintermediation can be investigated, first, by looking at the total value of CBDC in circulation compared to that of bank deposits. This is illustrated by Figure 8 - panel (a) that shows the ratio of the former to the latter is 2.8%. To put this number into perspective, the impact of 2.8% to the total bank deposits in Germany would corresponds to EUR 75.04 billion.\(^{27}\)

Another aspect of disintermediation will be a negative impact on bank deposits. In this regard, Figure 8 - panel (b) shows that deposits keep growing after introduction of the CBDC\(^ {28} \), but at a slower pace than before.\(^ {29} \) In more detail, the growth rate in deposits falls by approximately three quarters (from $0.75 - 1\%$ to $0 - 0.25\%$). To put this into perspective, for the German banking market the fall would correspond to approx EUR 20 billion in 20 days. In the short run, we also see a fall in deposits by approximately $0.75\%$ in the period through $t = 75$ (by which time the CBDC is fully adopted by all consumers and merchants), related to the synchronous initial CBDC top-ups that discussed when commenting Figure 6.

\(^{27}\)As described in https://fred.stlouisfed.org/series/DDOI02DEA156NWDB, the total bank deposits in Germany for 2017 is EUR 2.68 trillion. The impact of 2.8% will therefore correspond to $2.8\% \times \text{EUR 2.68 trillion} = \text{EUR 75.04 billion.}$

\(^{28}\)This is mainly due to our assumption that consumers’ (exogenous) income is above their spending

\(^{29}\)The growth rate depicted in the figure is $\frac{B(t) - B(t-20)}{B(t-20)}$, i.e. is the average growth over 20 days. Daily rates are much more volatile.
Fig. 8: Banking sector disintermediation. Panel (a) describes the ratio of the total value of CBDC to deposits. Panel (b) shows the growth rate of bank deposits over the previous 20 days. The CBDC is introduced to the system at $t = 0$ and is fully adopted by all consumers and merchants at $t = 75$.

6 Discussion

We proposed an agent-based simulation model to study the economic impact of introducing a retail central bank digital currency (CBDC): a general purpose and non-interest-bearing central bank liability, which competes with cash and card as a means of payments. Our model features 4 classes of agents, namely consumers, merchants, a commercial bank and a central bank, who interact in time according to defined rules. We used data on the German economy to calibrate the model.

Firstly, we looked at the adoption rate of CBDC and the change in the diffusion of means of payments. We showed a non-linearity in the adoption function such that the rate would grow substantially following the adoption by a small proportion of consumers and merchants in the system. As CBDC is being adopted, we found that both cash and card payments would decline by approximately 30%. The latter indicates that card companies would lose EUR 1.5 billion transaction revenues in the German domestic payments market. Secondly, we studied the composition of consumer wealth that is allocated between cash, CBDC, deposits and other assets. Over time, we found that consumers would allocate their wealth for a higher value of CBDC and a lower value of cash. We also saw a slower growth rate of deposits and other asset following the CBDC adoption. Thirdly, we discussed the banking disintermediation and balance sheet. We found that the total value of CBDC in circulation is 2.8% of the total deposits, which corresponds to EUR 75.04 billion of the total deposits in the German banking system. We also found that the growth rate of the bank deposits would decline by 0.75% in 20 days, which corresponds to the fall of approximately EUR 20 billion for the German banking market.

The model presented in this paper is still a prototype, ready for refinements and
extensions. First the parameters shown here, meant to approximately represent the German retail market, could be pinned down more precisely, and/or be tailored to gauge the effects of a CBDC on other economies. Second, a variety of policy experiments could be carried out, to assess the impact of different CBDC ‘configurations’ or design. Third, in the current version of the model, the CBDC does not bear interests, so consumers’ demand is determined only by retail payment needs. Small changes to the model could allow for an interest-bearing CBDC competing with deposits and other assets as a store of value; and similarly, for other payment instruments such as electronic money and stable coins. Finally, by adding a richer variety of consumers and more articulated bank behaviour, the model could be extended to explore issues related to financial inclusion and financial stability.
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Electronic copy available at: https://ssrn.com/abstract=3959759