UNIVERSITY OF TWENTE.

Adoption and Implications of CBDC: An Agent-Based Modelling Approach

Master Thesis - MSc Industrial Engineering & Management

(Financial Engineering Specialisation)

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September 2021

Abstract

We investigate the adoption and implications of a retail CBDC in the Netherlands among households and firms under the monetary and technical control of the central bank. For this purpose, we have developed a non-spatial agent-based model with network externalities (small-world network) in which households decide among a variety of available payment instruments. In contrast, firms choose to adopt or remove payment instruments. We simulated multiple scenarios, such as deposit-like and cash-like CBDC, which allowed us to measure the crowding-out effect of the CBDC on cash and deposits for several levels of competitiveness. We found that the network effect can either break or make the success of the CBDC, and the competitiveness of the CBDC (relative to other payment instruments) is critical to initiate adoption. The results suggest that a CBDC will likely supplement cash (and deposits depending on specific design choices such as offline capability). The central bank needs to assess both extremes' risks and benefits carefully, not launching CBDC or competitive CBDC with complete crowding-out. Likely, the "golden mean" of CBDC-as-a-complement may not be feasible, at least not within the limits of our model.

Contents

Acknowledgements

First of all, I want to thank my supervisors Reinoud, Abhishta and Erik. I am grateful for the many fruitful discussions we had and the structured feedback they gave which helped me deliver this thesis in its current state. During this research, I was primarily working from home and my partner helped me greatly to stay motivated despite the limited amount of contact I could have with friends, family and colleagues. This thesis does not just mark the end of my studying journey but also the start of my professional career as I will continue working on the CBDC topic at DNB as well as developing the model with the intend to use it for further studies. I have learnt and improved many concepts and skills such as agent-based modelling, programming and artificial intelligence.

Keywords**—** Central Bank Digital Currency, Agent-Based Modelling, Cryptocurrency, Stablecoin, Innovation Adoption

1 Introduction

1.1 Context

Short History of Money It is generally agreed upon that money has three specific functionalities (Graham, 1940):

- Medium of exchange: we live in a world where most people need to purchase goods and services to survive or satisfy the demand for specific desires.
- Store of value: if no goods or services are purchased, the following main functionality is a store of value such that its long-term value is more or less sustained.
- Unit of account: for the above two functionalities to work correctly, money should be used as a unit of account in society; to price different goods and services, record debts, and make calculations using the same units (e.g., in Euro).

The first appearance of money dates back to 770 B.C. The conventional form of money allows people to trade goods indirectly (medium of exchange), store their long-term value (store of value), and price goods in the same unit (unit of account) (Davies, 2003). By definition, the value of money is created by mutual agreement regarding its worth.

Later on, as the complexity of exchange systems evolved, an intermediary was required to account for the trade on behalf of buying and selling parties, namely, a bank. In the past centuries, the traditional role of a bank in deposit acceptance, monetary changing, lending, and fund transferring was combined with the debt issuance function. The influence of the banking industry rapidly expanded, which had its advantages and disadvantages.

In recent years, the concept of Decentralized Finance (DeFi) gained popularity as an alternative for a system with a bank as an intermediary. The ideology behind DeFi denies the idea that a trusted intermediary is required for monetary transactions and is instead based on a permissionless peer-to-peer network of nodes. The applications of DeFi range from virtual money (otherwise known as e-money), i.e., cryptocurrency, to unsecured credit via peer-to-peer lending platforms.

Getting back to the definition of money, it is clear that DeFi products have a monetary value. Furthermore, the advantageous features of virtual means of exchange can outweigh those of conventional money. Many believe that the rise of private initiatives such as DeFi, cryptocurrencies, and stablecoins have led central banks to consider the possibility of a Central Bank Digital Currency (CBDC). The competition among central banks (fear of currency substitution, e.g., dollarisation[1]) and initiatives of tech giants such as Facebook's Diem[2] further increase the necessity to experiment with a retail CBDC.

Social Behavior and Forms of Money We need to make a clear distinction between payment instruments and payment methods. Payment instruments and payment methods have a 1-N relationship in the sense that 1 form of money can have several payment methods; for example, bank deposits can be spent with a debit card, credit card, manual transfer (online banking), or by mandated invoice. It depends on the situation which payment method is preferred by the household or firm and which payment methods are accepted at the point of sale. Before the existence of digital bank accounts, cash was the only form of money widely used. Digital bank accounts introduced another form of payment, namely bank deposits. Before introducing a CBDC, we need to ask ourselves what money really is and what features and functionality it should have if we had the chance to redesign it according to the needs of the present and future society. It gives central banks a unique opportunity to redefine money and the financial market infrastructure as we know it today.

What is a CBDC? First of all, we need to make a distinction between retail and wholesale money. In the traditional banking system, these two forms of money form the basis of the financial system in most parts of the world (Graham, 1940). Wholesale money (e.g., central bank reserves) is used between financial institutions and central banks as a means of settlement. In the European Union, the standard is TARGET2, and it offers TARGET2 account holders real-time gross settlement. The system is maintained by the ECB and allows the ECB to impose monetary policies and ensure proper functioning of the Euro money market.

Retail money, in simple terms, is money used by households, consumers, firms to buy/sell goods and services. It comes in 2 main forms, cash (notes and coins) and digital (commercial bank money); they are readily interchangeable using retail banks' services. There are some other less essential forms of money, such as cheques, e-money, and gift cards.

Digital retail money can only be held with an account at a financial institution with a banking license, while households can keep cash physically in a wallet or elsewhere. Holding an asset such as money for yourself or someone else is often called custody. Using that definition, cash allows owners to be their own custodian while financial institutions are, up till recently, the only possible custodian for digital retail money.

[1]https://www.investopedia.com/terms/d/dollarization.asp
[2]https://www.diem.com/en-us/

CBDCs build upon the concept of these forms of money, with an expanded set of features and characteristics. CBDCs also come in 2 forms, wholesale and retail. This thesis will only focus on the retail version of a CBDC as it can be considered the most disruptive version. Figure 1 gives an excellent overview of how all these forms of money relate (including private forms, such as cryptocurrencies and stablecoins). The figure shows a Venn diagram where four characteristics represent the sets: peer-to-peer, digital, central-bank issued, and wide accessibility. Each one is explained below in detail:

- Peer-to-peer: refers to the characteristic that users can use the money without an intermediary. The money is transferred directly to the counterparty (an optional fee to the validating parties who facilitate the transaction).
- Digital: this feature means that the money is represented only in a digital format either in a shared database (i.e., distributed ledger) or a central database (i.e., account at a retail bank). When digital money is transferred, an account's holding is updated to reflect the new state.
- Central-bank issued: it refers to how money is created. For example, cash is created and distributed by the central bank, whereas a retail bank credits digital money in a bank deposit account.
- Wide accessibility: it refers to how easy it is to acquire, trade and store. Although this depends on the point of view and may differ from country to country (e.g., in a third world country, a bank account could be seen as a privilege, while in most industrialized countries, it is the norm).

So when we talk about a retail-CBDC, we refer to a form of money that possesses all four characteristics. It has a competitive advantage above other forms of retail money. Cash can be used peer-to-peer but is not digital; hence users cannot use it remotely; bank deposits are digital and cannot be used without access to a retail bank or its digital services. The only form of money that CBDC does not implicitly have a competitive advantage over are cryptocurrencies (permissioned and permissionless).

Advantages, disadvantages and risks CBDC is a new and unique form of money that is distinctly different from traditional money. As with anything new, it comes with significant advantages as well as risks and potential disadvantages. Here we state the advantages, risks, and disadvantages that are independent of the (technical) implementation:
We identified the following advantages:

- Expanding financial inclusionFinancial inclusion refers making financial services more accessible.
- Potentially keep an upper hand on "Big Tech" and private initiatives of digital currencies.
- Ensuring access to legal tender in scenarios where cash is unavailable; simultaneously, support to shift to a cashless society.

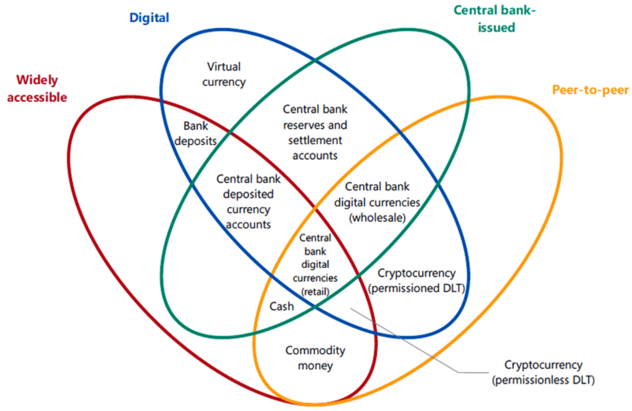

Figure 1: The Money Flower: a taxonomy of money (CPMI, 2018; Boar and Wehrli, 2021)

- Increased efficiency of payment infrastructure.
- Fast settlement for cross-border payments.
- Gives governments a channel to bring subsidies and other fiduciary transactions directly where they belong.

We identified the following disadvantages:

- Central banks could geographically restrict payments while cash is usable anywhere where it is accepted.
- Central banks could become payment service providers and thus compete with existing PSPs.
- May increase competition for retail banks may force banks to change their business model radically.
- May increase the risk of system-wide (digital) bank runs.
- May encourage structural disintermediation.
- Fear of security issues.
- Fear of privacy issues.

1.2 The Netherlands as CBDC Testing Grounds

The Netherlands has one of the highest online banking penetration levels of the EU, 89% compared to the EU average of 60% (Eurostat, 2020). At the same time, cash usage is one of the lowest in the Netherlands, 14% compared to the EU average of 31% (in terms of volume) (De Nederlandsche Bank, 2021). The smartphone penetration was at 79.3% in 2018 in the Netherlands, only topped by the UK at 83%. Also, mobile banking penetration has seen significant growth, which could only fuel the adoption of CBDC even more. Suppose CBDC is assumed to be a substitute for bank deposits but a complement to cash. In that case, it seems natural to predict that the Netherlands is an economy where an introduction of a CBDC will likely have significant effects relative to other countries of the EU.

1.3 CBDC Reference Design

Throughout this thesis, we assume that the CBDC satisfies at least the following criteria:

- Decentralized infrastructure.
- Centralized consensus on transactions.
- Peer-to-peer transactions possible (like cash).
- Offline transactions possible (like cash).
- Transactions are near-instant with low latency.
- All design options and policies are enforceable independent of the technical implementation.

The experiments of the ECB (2020a) have shown that most if not all those criteria can be satisfied. However, it should be noted that these experiments were mostly isolated from each other (i.e. 1 criteria assessed per experiment) and the assessment would likely be different if all criteria need to be satisfied within a single experiment.

2 Literature Review

In this literature review, we wish to to identify key concepts, stakeholders, current challenges and proposed solutions for these challenges. Furthermore, we discuss the knowledge gaps as well as methodologies used to identify challenges and test proposed solutions.

2.1 Search Methodology

The following keywords are of interest: "CBDC", "Central bank digital currency", "Agent based modelling (OR ABM)", "DNN (OR Deep neural network)", "Deep reinforcement learning (OR Deep RL)", "Dynamic stochastic general equilibrium (OR DSGE)", "Distributed ledger technology (OR DLT)", "interest rate", "remuneration", "dynamic stochastic general equilibrium (or DSGE)", "ML or (machine learning)", "design OR policy", "model OR modelling", "optimal". Other searches were performed for other applications of ABM and Deep RF in the same field of interest (finance, econometrics and economy). The results of the search queries can be found in Table 4. The same queries have been entered in Google Scholar, SSRN and Google. Using non-scientific search engines resulted in more corporate backed documents and working papers from central banks and regulators such as BIS and IMF.

2.2 Results

Disintermediation of the Financial Sector According to Gross and Schiller (2020), CBDCs crowd out commercial bank deposits hence affect the banking sector as they effectively decrease the size of the bank's balance sheet if they cannot acquire alternative funding. This does not need to be a threat for financial stability if the central bank chooses an adequate policy. The chosen methodology in this paper is a New Keynesian DSGE framework with a focus on the effects of interest- and non-interest bearing CBDCs during financial distress and interaction with zero lower bound. Gross and Schiller (2020) also review other literature on modelling CBDCs. Due to the lack of empirical data, only theoretical models have been used.

These models can be divided into DSGE and non-DSGE where DSGE models are of several forms (open/-closed economy, small/medium/large scale etc.) while non-DSGE models are more commonly generic models. Gross and Schiller (2020) model has some key assumptions that differentiate it from others. For example, the amount of bank deposits is determined by households' utility maximization. This gives households a reason to diversify to minimize risk. They also assume a cashless society, which would likely compete with CBDC in terms of households' allocation amongst all monies. There are further simplifications but they are not uncommon for DSGE based models. In the conclusion they describe 2 specific assumptions:

1. Banks always have sufficient assets for collateral if they require central bank funding (which are not actually on their balance sheets)
2. The deposit insurance scheme is left out, which may lower perceived risk on deposits.

The key conclusion from Gross and Schiller (2020) is:

"Even if CBDCs are widely used and indeed crowd out bank deposits, the central bank has sufficient instruments to prevent a structural disintermediation of the banking sector"

They recommend the addition of cash into a model to provide additional insights.

CBDC Control Methods From literature, there several tested methods of control to help the central bank in preventing disintermediation and bank runs. One of these methods is a tiered remuneration policy. This means in simple terms that remuneration policy may be different for certain entities depending on the amount of CBDC on their account (Bindseil, 2019). This is also an example of a purely theoretical non-DSGE analysis on the effects of CBDCs and the effectiveness of the proposed control method. Bindseil (2019) compares conceptual balance sheets of the central bank, a commercial bank and households before and after introduction of CBDC. Another control method is described by Panetta (2018); using account limits (defined as caps) to control the usage of CBDC.

The main takeaway from this analysis is that it provides a simpler and less innovative way to another approach by Kumhof and Noone (2018). Furthermore, Kumhof and Noone (2018) suggests that the central bank may be open to study CBDC in more detail, and in further studies the overall business case and risks to the financial system should be clearly described and quantified. ECB and BIS (2020) describe describe that commercial bank funding does not necessarily decrease and the risk of a system-wide bank run is addressed if the introduction of a CBDC follows a set of core principles. These principles are the following:

1. CBDC pays an adjustable interest rate.
2. CBDC and reserves are distinct, and not convertible into each other.
3. No guaranteed, on-demand convertibility of bank deposits into CBDC at commercial banks.
4. The central bank issues CBDC only against eligible securities (principally government securities).
5. Households and firms can freely trade bank deposits against CBDC in a private market.
6. The private market can freely obtain additional CBDC from the central bank, at the posted CBDC interest rate and against eligible securities.

It appears that this also significantly impairs the functionality and features of a CBDC to such degree that it might not be competitive enough against private stablecoins or cryptocurrencies. Ferrari et al. (2020) use DSGE based models, specifically "model FI" (Financial Institutions), "model EW" (Economy-Wide) and "Model FI+" (FI + CBDC-backed narrow bank access) to obtain the results. The main takeaway from Ferrari et al. (2020) is that if CBDC is introduced in an orderly manner, the size of commercial bank balance sheets may, but do not need to, change significantly. In their conclusion they also mention several starting points for future research. To name some (among others): "What is the substitutability of the bank deposits and CBDC for liquidity purposes?", "How might commercial banks respond to the introduction of CBDC?", "How could CBDC affect the central bank's balance sheet risk?". It should be noted that many of these questions seem to be dependent on the final design choices.

Optimal Design Agur et al. (2019) study the optimal design of a CBDC in an environment where agents have 3 options: cash, CBDC and bank deposits. In this model the preference does not just depend on what gives the agents the highest payoff but also which option offers a certain level of privacy and security. They develop mathematical relations for several different agents in the form of utility maximization problems. The agents in question are households, firms, banks and lastly the central bank. Agur et al. (2019) on page 7 states:

"Overall, in an economy where banks' role is limited, a CBDC is best designed in a manner that is as distinct from existing payment instruments as possible".

In general, there a quite a number of trade-offs to be considered: privacy, security, social welfare, economic welfare, intermediation, payment variety (financial frictions), financial inclusion and others. They conclude that central banks should at least consider the option of an adjustable interest-bearing CBDC but weighing the advantages and disadvantages carefully.

Digital Bank Runs Puyol-Antón (2021) use a Deep Neural Network to model the introduction of a CBDC and its potential impact on commercial bank deposits. The neural net is used to forecast the likelihood of the occurrence of bank runs as a function of system characteristics and intrinsic features of the CBDC. The model assumes a closed economy, with citizens and businesses having direct claims against the central bank when holding CBDC. They also assume that the introduction of CBDC does not eradicate the fractional reserve system, with commercial banks still offering deposits.

Knowledge Gaps Below a non-exhaustive list of knowledge gaps and research recommendations that follow from our literature review:

- Lack of empirical data because no industrialized country has implemented a retail CBDC, as of the moment of writing (Puyol-Antón, 2021).
- Effectiveness of current control methods in the presence of competing solutions (other CBDCs, stablecoins, cryptocurrencies). It might make sense to test current control methods (capping, tiered accounts, remuneration) in an environment where competing solutions exist (stablecoins, cryptocurrencies, other foreign CBDC's).
- Effect on other financial services beyond banks (majority of researchers focus on commercial banks). Other financial services may include payment services providers (such as Mollie, Adyen, and Stripe) and card issuers (such as VISA or Mastercard).
- Effect of other means of payment in the model (e.g. stablecoins, cryptocurrencies).
- Assumption that commercial banks can provide sufficient collateral for central bank funding in case of a bank run (Gross and Schiller, 2020).
- Assumption of a cashless society (Gross and Schiller, 2020).

Other knowledge gaps can be found in Annex A of ECB and BIS (2020), where a number of possible research directions are suggested. Some relevant examples:

- "How can features that enable convenient use of a CBDC (eg open access, offline usage, broad and diverse support from payment system providers) be balanced with security considerations?"
- "What CBDC design can best enable cross-border efficiencies while preventing unintended international spillovers?"
- "What are the best approaches to system design that meets policy goals, enables all key features and supports the desired business model? How should a CBDC system be designed to remain

adaptable over decades in a changing environment?"

3 Project Plan

3.1 Introduction

In the light of the recent surge in cryptocurrencies and digital assets, the idea of a retail Central Bank Digital Currency came to life (abbreviated as CBDC. Especially the increased use of stable coins have put regulators, central bankers and academics alike to think about the future of money. Central Bank Digital Currency can be defined as a third form of base money, next to overnight deposits with the central bank and physical cash (e.g. banknotes). In general, a CBDC could be either retail (households and corporates) and wholesale (supplement or compliment to current central bank money). The major risk of a retail CBDC is the potential disintermediation as an effect of its introduction (ECB and BIS, 2020). Disintermediation refers to the reduction of intermediaries between parties. A clear example of this is the reduction of commercial bank activity (i.e. reduction of their balance sheets) as people convert their deposits into CBDC. But depending on the technical implementation and features, disintermediation could extent much further into the financial services industry (Bindseil, 2019). If risks are so significant, then what is the business case for a CBDC? The following motivations are stated according to the principles and core features of a CBDC as described by ECB and BIS (2020): Core principles:

1. "Do no harm".
2. Coexistence.
3. Innovation and efficiency.

Motivations for CBDC:

1. Increasing resilience: offering a risk-free alternative in an environment with declining cash use.
2. Increased payments diversity.
3. Improving financial inclusion (lower the access boundary to financial services for those who currently have restricted access).
4. Supporting cross-border payments.
5. Improving public privacy.
6. Facilitating fiscal transfers.

Besides the numerous motivations above, there are a few external factors as to why central banks are actively exploring the possibility of a digital Euro. One of these reasons is the growing competition from privately launched initiatives such as the Diem (formerly known as Libra) by Facebook, Inc. or any of the cryptocurrencies available on the market today. Even though the ECB's crypto task force has stated that these do not have a competitive advantage right now (ECB, 2020b), and can not be considered legal tender, they could develop to be competing solutions over the next few years as the underlying technologies develop and mature. That is the reason why we will include this possibility in our analysis and discussion unlike other publications.

From the central bank's point of view it is logical to be prepared for not just competing with the current features offered by cryptocurrencies but also the future promises. At some point there might be such a DLT-based form of money that offers unlimited scalability, transaction finality similar or less than current payment solutions and smart contract capabilities to create decentralized financial services wherever there is demand.

The other factor could be defined as a political issue. Since any central bank is free to launch its CBDC not just for the countries where it is the currency of choice but also offer worldwide acceptability. For example, using the Dollar in the European Union (EU) is generally not accepted, as recipients do not have the means to exchange on demand. A digital Dollar might change this, especially if an instant exchange framework is provided universally. The foreign central bank could in that scenario gain monetary power by simply incentivising European citizens to use the digital Dollar for payments involving American firms and allowing them to open CBDC wallets/deposit accounts. Being the first to launch a CBDC is therefore considered to give a first mover advantage (Chorzempa, 2021) should such global competition for a universally accessible currency become an issue.

These advantages are however dependent on the actual implementation, even if it follows all principles and core features as stated by BIS. We consider the following implementations (Fernández-Villaverde et al., 2021) (excluding additional features and technicalities that will be discussed at a later stage):

1. Deposit-like CBDC: Deposit accounts with the central bank for all households and firms. This would imply scaling the number of deposit accounts to match the number of households and business that are currently excluded. From an innovation point of view it would not be very significant, but technically could still be challenging to implement. Some of these challenges could be outsourced to third parties.
2. Cash-like CBDC: Digital token (crypto-)currency with or without the use Decentralized Ledger Technology (DLT).

Further forms of CBDC can be found in Figure 1. This graph is often referred to as "the Money Flower: taxonomy of money", and as the name suggests it provides a framework to categorize different forms of money. It is based on the following characteristics: universal accessibility, digital, central bank as issuer and peer-to-peer. Also the following are shown: wholesale CBDC and permissionless/permissioned DLT. So why is a fully-fledged

CBDC not yet implemented? There are three key arguments against CBDC. As mentioned before, the first one being the risk of structural disintermediation of the banking sector and wider financial industry. The second argument is the risk of facilitation of digital bank runs and third is the risk of financial instability (ECB and BIS, 2020).

3.2 The Role of the Dutch Central Bank

DNB wants to play a leading role in the development and experimentation with CBDC, that is why this thesis will be performed under supervision of the Dutch central bank. Also, the Dutch economy is a good example of a European country where cash is on decline while consumers are looking for innovative means of payment and financial services (DNB, 2020).

3.3 Problem Context

CBDC is a relatively new concept, as there is not yet a single industrialized country that has launched a retail-CBDC. However, there are some examples of central banks whom are actively researching are already running a pilot. One such example is PBoC (People's Bank of China), where a retail-CBDC is currently used in selected regions. A few examples of central banks with a clear plan on launching a CBDC are the Digital Dollar Project (USA), E-Krona (Sweden), Sand Dollar (Bahamas) and Estcoin (Estonia) [3]. Before launching a pilot in the real economy, DNB could trial several potential CBDC designs through modelling and/or simulation. Other central banks have done this through purely analytical analysis and/or (non-)DSGE modelling. In Figure 2, the problem cluster and the relation to the core features of a CBDC and the motivation of the central bank can be found. The problem cluster could be summarized in one dilemma relating the degree of innovation, disintermediation and market dominance (see Figure 3). The figure does not imply that there is necessarily a linear relationship, nor does it imply that there is an optimum level of innovation. The idea is that CBDC control methods could make it possible to offer a highly competitive currency without disrupting the banking sector and financial services industry too much (or at least initially, giving these third parties time to adjust to new circumstances). The problems high lighted in red could be considered as the core problems.

Problem Statement As mentioned in Section 3.1, disintermediation, the reduction of intermediaries in the banking sector and the financial system, is a likely consequence of CBDC. As of now, the ECB has stated that: "a digital Euro should only be launched if the ECB is confident that structural disintermediation of the banking system, and avoidance in systemic crises of a facilitation of aggregate bank runs, have been solved.". The core problem can be stated as: financial instability caused by the introduction of a CBDC (mainly (digital-)bank runs and structural disintermediaton). There are several proposals how to prevent this potential financial instability but it is yet unclear to what degree they can be used and in what circumstances they are most effective. This thesis will attempt to provide additional insight, perhaps additional control methods or optimal combination of methods in order to increase the level of confidence.

[3] https://cbdctracker.org/

4 Research Questions

ECB and BIS (2020) state the following knowledge gap on page 16: "How policy goals, practical issues, and technology intersect requires further research and technological experimentation." The literature review that we conducted had led us to conclude that the most significant challenge of CBDC is the risk of disintermediation, and closely related, the risk of digital bank runs. In other words, the crowding-out effect of CBDC on cash and deposits. The purpose of our research is to use a novel method to explore what factors influence the adoption process of a CBDC and their effects on the crowding out of other payment instruments such as cash and deposits. We gear our research towards one of the open questions mentioned by ECB and BIS (2020) on page 19: "How effective are potential controls against risks to financial stability (e.g. caps, use of interest rates) and what consequences might they have for the functioning of the CBDC system?". Our main research question is stated as follows: How do households allocate their payment portfolio given a set of payment instruments, each with unique characteristics?

To be able to answer the main research question, we defined the following sub-questions:

1. What factors influence a household's personal payment preference?
2. Who are the other stakeholders?
3. What are the current payment preferences of Dutch households, and how do they relate to CBDC characteristics?
4. What types and characteristics of payments are there and which ones are popular among Dutch households?
5. What are the trade-offs to be made when choosing a CBDC design and control policy?
6. What are the possible scenarios for the adoption process of the CBDC?
7. What are the implications of non-optimal introduction and implementation of a CBDC?
8. Is CBDC a complement or substitute to cash and deposits?

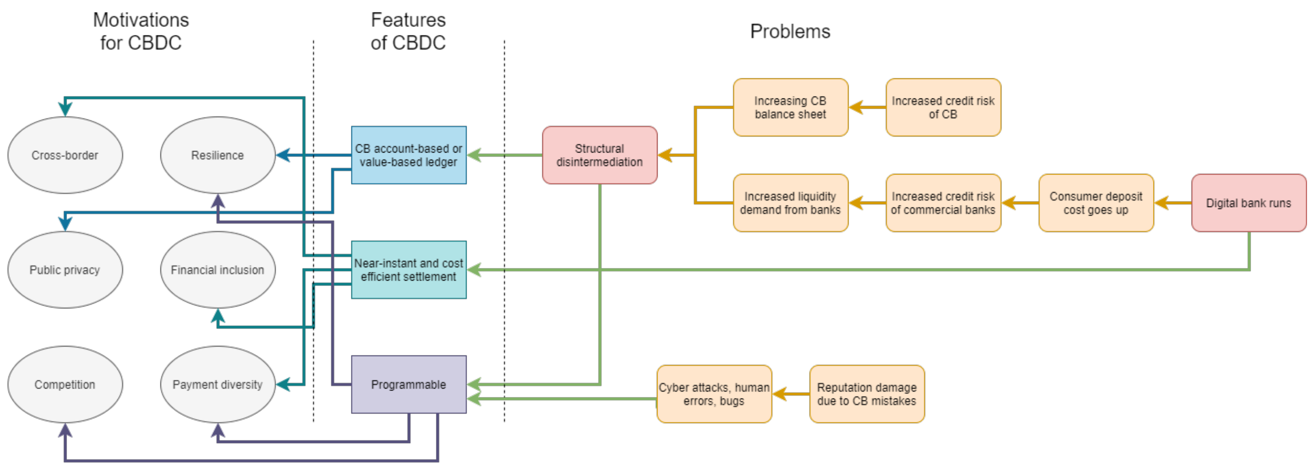

Figure 2: Problem cluster related to CBDC core features and motivations.

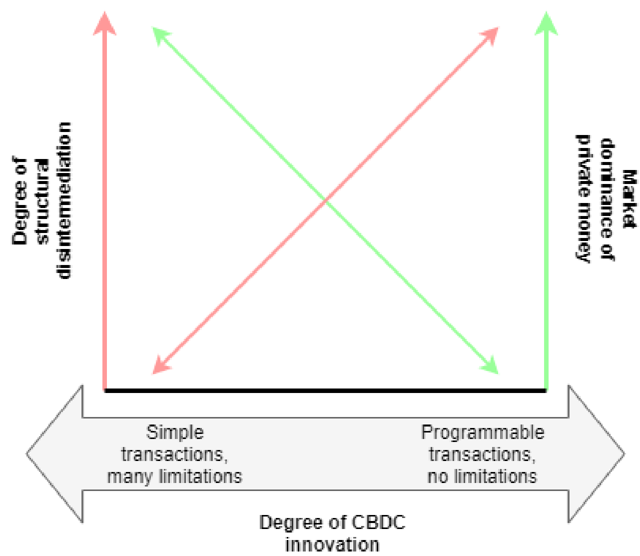

Figure 3: The dilemma relating degree of innovation, structural disintermediation and market dominance of private monies.

4.1 Relevance of this Thesis

Since the first mention of CBDC, the scientific community has shown a still-growing interest in research surrounding the topic (Boar and Wehrli, 2021). It is also the first time in a long time that new forms of money are developing, and the definition and role of money itself are being questioned. It also begs a more fundamental question; How will households, firms, and other entities allocate their spending and savings budgets across an arbitrary number of money forms, each with unique but competing characteristics. We hope to contribute to research on CBDC and in addition to that enrich DNB & the Eurosystem as a whole with new perspectives. There is practically little to no research (as of the moment of writing) on the adoption process and implications of CBDC. There is no large-scale implementation in any industrialized country yet (Mikhalev et al., 2021). We also aim to show that agent-based modelling, specifically agent-based economics, is a promising method for simulating complex behavior.

5 Methodology

We use agent-based modelling, more specifically, agent-based economic modelling. In the sections below, we shortly describe their relevance and advantages compared to traditional economic modelling. We also use unified-modeling language for the agent-based model and publicly available data and libraries for easy replication. Our methodology is similar to a paper by Alexandrova-Kabadjova et al. (2012) in which the adoption process of new payment cards was modelled using Agent-Based Economics. For these types of macroeconomic issues, it is common to use DSGE-based models (either New Keynesian or Real Business Cycle). Agent-based modelling is an emergent trend in the field of finance and economics, whereas in other areas of research, it has already proven its success (Özge Dilaver et al., 2016) (Fagiolo and Roventini, 2016). There is no standardized way to design an ABM as they are usually highly tailored depending on the field of research. However, there are some steps that most papers using ABM as methodology have in common (Crooks et al., 2021). The steps taken to answer the research questions are as follows:

1. Qualitative (and quantitative) description of the problem (i.e., the research question, what real-world process do we want to model?).
2. Designing the model; simplifying real-world processes and agents with assumptions and aggregation.
3. Implementation of the model: using an ABM framework/library for implementing code (we are using Python's MESA framework) or application (e.g., NetLogo).
4. Execution: define global initial condition or per scenario and simulate until a condition is met or a specific number of cycles have finished.
5. Evaluation: report and observe results with figures and data analysis.

5.1 Agent-Based Modelling in Finance and Economics

Agent-based modelling is a general computational technique to simulate dynamic systems with heterogeneous and interactive agents numerically. The use of agent-based modelling in the field of finance and economics is usually referred to as Agent-Based Computational Economics (Meisser, 2015). it is quite different from traditional economic modelling as ABM makes no assumptions about policies or any equilibrium. Instead, it relies on exploring emerging dynamical patterns from which the model may reach an equilibrium. ABM also allows for an internal feedback loop which can amplify small changes of which the aggregate can cause instability, often seen in financial markets, such as herding and panic. Using mathematical terminology, it means that the agent-based models can be non-linear. This feature makes them an interesting alternative to e.g., DSGE-based models, where an equilibrium is assumed, and small changes are cancelled out in the aggregate.

In DSGE models, exogenous shocks are introduced to induce instability, while in ABM, instability can emerge naturally. Usually, agents are created heterogeneously and thus act with some degree of autonomous behaviour. Autonomy does not mean the agents don't care about the actions of each other; they can of course influence each other and also this social behaviour occurs naturally. An example that is often quoted is the flocking behaviour of starlings. The birds seem to operate as a system, but it is an almost instantaneous result of the aggregate of individual decisions. There are a few characteristics of ABMs that are particularly useful for studying economic issues (Kim, 2016). We also shortly highlight the relevance for our research:

- Computational irreducibility: it is challenging to reduce an agent-based model to its analytical form. Similarly, it is challenging to model an economy based on analytical formulas alone.
- Emergent Behaviour: individual actions can lead to undesired or unintended effects in the aggregate. The system as a whole has properties that are not seen on an individual level. For example, even if the system has local stability, overall, it can become unstable. A firm may be able to close its position right at the start of a market crash, but its action among others may drive that same market to become more unstable as a whole. Emergent behaviour is particularly interesting when artificial intelligence drives agents.
- Non-ergodicity: simply said, your action today will not have the same consequence or reward as it did yesterday partly because the environment around the agent is rapidly changing. In other words, the past does not influence the future. Instead, the now influences the future. This is actually the Markov property: the future is independent of the past given the present. In ABM, an agent's current state is a result of past actions. Even if an agent is in precisely the same state tomorrow, it does not guarantee the same set of consequences.
- Radical uncertainty: it refers to not being able to calculate the probability of an event happening because we do not have all information at hand to do so. When studying economic issues, it is helpful because it may prepare policymakers for surprises.

5.2 Drawbacks of ABM

Some of the drawbacks of agent-based modelling are:

- Computationally expensive, especially if some form of reinforcement learning is used. However, this depends on the simulation scale (i.e., how many agents the model simulates) and agents' decision-making process (whether they use simple heuristics or neural networks that need to be updated every step).
- Challenging to calibrate and validate, especially with many free parameters (initial conditions).
- Steep learning curve to design (and build) ABMs.

5.3 Alternative Methods

We have identified the following methods that could possibly be used for the same purpose as agent-based modelling, each with their own advantages and drawbacks. *Swarm Modelling Defining agents and building an environment is perhaps too complex given the time constraints and scope of the research. Another method we may use is swarm modelling, using the SLAPP framework (Python implementation of swarm.org), also a form of ABM but significantly easier to implement. The drawback is that the behaviour of agents is less flexible than in a full fledged ABM.

6 CBDC Adoption - A Micro-economic Perspective

6.1 Central Banks

According to Mou et al. (2021), the ECB is in a position to launch a CBDC, or not, and so are all other central banks. They describe two game-theoretical models in which central banks choose to adopt a CBDC or not. Both games result in the central bank adopting the CBDC through a Nash equilibrium. Furthermore, their model suggests that they shouldn't just adopt a CBDC and be a first-mover and gain a competitive edge in the digital economy. Market leaders may lose significant market share if they are not first-mover.

6.2 Households

A recent analysis by Bijlsma et al. (2021) concluded that roughly half of the Dutch population are open to having a CBDC account. Furthermore, the authors state that households may base their decisions primarily on the remuneration policy, privacy, and security of the CBDC design. The expected use of CBDC is highest among households that prefer a high degree of privacy and security and those with low trust in retail banks. This result suggests that payment instruments are chosen mainly based on personal preferences and social influences.

Household Payment Portfolio Model This subsection aims to expand the payment portfolio model as described by Bian et al. (2021). This model is a flexible and generalizable utility function based on the unique characteristics of the different forms of money and an economic agent's individual preferences. However, this model assumes that households will pay with payment instruments in a proportion that maximizes utility. However, this is not accurate as Spaanderman (2020) shows that households generally prefer using one payment instrument with others as backup. For example, in the Netherlands, most people pay their daily expenses with bank deposits via a debit card, keeping only a small amount of cash (Spaanderman, 2020)). Another thing that the authors conveniently left out of the equation is cryptocurrencies and, more specifically, stable coins. According to the ECB, one of the main reasons to launch the CBDC is to compete with private initiatives such as cryptocurrencies. We start by defining the blueprint of the utility function. The function takes the following form:

$$\begin{aligned} &\max_{\{m_1,m_2,\ldots,m_N\}} U = U(p_1,p_2,...,p_K) \\ &\text{subject to} \textstyle\sum_{i=1}^{K} p_i = P \end{aligned} \tag{1}$$

Where $p_1, p_2, ..., p_K$ are the amounts of money for an arbitrary number of unique payment features K and $m_1, m_2, ..., m_N$ is the amount of money for an arbitrary number of unique payment instruments N. The sum of all p_k amounts equals the total demand for payments P. The household wishes to maximize its utility by allocating its payment portfolio using these payment instruments. We consider the following payment instruments: cash, bank deposits, CBDC, and Cryptocurrencies. This model is further generalized by employing a constant elasticity of supply and Cob-Douglas utility function as seen in Equation 2.

$$\begin{aligned} &\max_{\{m_1,m_2,\ldots,m_N\}} U(p_1,p_2,...,p_K) \\ &\quad = (\alpha_1 p_1^{-\gamma} + \alpha_2 p_2^{-\gamma} + ... + \alpha_K p_K^{-\gamma})^{-\frac{1}{\gamma}} \end{aligned} \tag{2}$$

subject to $\alpha_1 + \alpha_2 + ... + \alpha_K \ = 1$ and $\forall \alpha > 0$

Here, parameters $\{\alpha_1, \alpha_2, ..., \alpha_K\}$ are heterogeneous preferences for features $\{1, 2, ..., K\}$ of an economic agent. These preferences should be utility contributing and preferably be affected by monetary and technical CBDC policies. The main idea of this utility function is that households do not have preference or demand for certain payment instruments directly but instead have demands to make payments with certain features, and they will use any payment instruments that can satisfy that demand. The original paper mentions the following features: legal tender, anonymity, interest-bearing, and digitization. We replace some elements of this feature set by the categories used in the Money Flower diagram in Figure 1: wide-accessibility, digital, legal tender, privacy, security, offline, remuneration, and peer-to-peer. We also included privacy, offline, and security as they appear to be important for Dutch households (Bijlsma et al., 2021). All these aspects are non-financial (besides remuneration); they mostly relate to the convenience of the payment instrument.

$p_1, p_2, ..., p_K$ are the number of payment instruments that satisfy the features 1 to k. For example, a feature could legal tender, then $p_{\mathrm{L}} = \mathrm{Cash} + \mathrm{CBDC}$. The main problem in this model is that a payment instrument may have non-binary features such as remuneration or degree of privacy. This may not be a problem in a model where an economic agent can adjust its preference α_k for feature k if feature k is currently favourable or not. This works if there is only one payment instrument that belongs to the set of feature k. When there is more than one payment instrument in the feature set, you could only maximize utility if you can differentiate payment instruments belonging to the same feature; for this purpose, we add another factor representing a relative advantage measure Θ. Essentially this is a matrix of size k x n. In this case the demand for payment instruments with central bank-issued feature becomes $p_{\mathrm{L}} = \theta_{\mathrm{L},Cash}\mathrm{Cash} + \theta_{\mathrm{L},CBDC}\mathrm{CBDC}$. The maximisation problem stated in Equation 2 has a general solution of the following form (credits to Kojic (2015) for the proof):

$$p_k^{*,\mathrm{CES}} = \frac{P}{\sum_{i=1}^{N} \left(\frac{\alpha_k}{\alpha_i}\right)^{-\frac{1}{\gamma+1}}} \tag{3}$$

which in turn equals the following in our case:

$$\frac{P}{\sum_{i=1}^{N}\left(\frac{\alpha_k}{\alpha_i}\right)^{-\frac{1}{\gamma+1}}} = \Theta_k m_k^* \tag{4}$$

Where $M_k^* \subseteq M$ where M is the set of all payment instruments and M_k^* is the amount per payment instrument that satisfies payment demand with feature k. A payment method of an instrument can only be successful if it offers a clear advantage to the end-user, which is expressed as the relative advantage measure per feature. The right-hand side can be written out entirely for all features, resulting in a system of equations that can be solved for each payment instrument expressed in the preferences α and relative advantage measure θ. The relative advantage measure allows us to model the impact of various policies and see how it affects the optimal payment portfolio. We can broadly define the score variable, and it will be different per feature. Using a relative advantage measure seems to be well in line with successes and failures of various payment methods in the past (Gross and Siebenbrunner, 2019).

In the case of remuneration, the score will be simply the interest rate. We could score the payment instrument based on how many of its functionalities can be performed digitally for the feature digital. On the flipside, when two payment instruments both have a feature, their respective relative advantage measure is not equal (i.e. one instrument is better than the other). It is rational for a household, to satisfy the payment demand for feature k using only the best payment instrument for that feature. This reduces the constraint on the information required for solving the maximisation problem, as we don't need to know the relative advantage precisely; we just need to know which is best per feature. The key assumption here is that all payment instruments are riskless. If a household has P_R payment demand for payment instruments with remuneration, the rational household will only use the instrument with the highest remuneration. We assume that this is valid for all features. This observation changes Equation 4 into the following:

$$\frac{P}{\sum_{i=1}^{N}\left(\frac{\alpha_k}{\alpha_i}\right)^{-\frac{1}{\gamma+1}}} = m_{k,n}^*. \tag{5}$$

Where $m_{k,n}^*$ is the amount of payment instrument n that has the maximum relative advantage in feature k. When there are multiple payment methods with maximum relative advantage in that feature, the payment demand for this feature is equally divided. For simplicity, we assume that all payment instruments are unique and thus have a different values for each relative advantage measure. The amount per payment instrument m_n for all $n = 1, 2, ..., N$ that maximize utility by satisfying the payment demand is as follows in Equation 6:

Payment demand (P_k)	Payment instrument (m_n)
Wide-accessibiliy	Cash[4]
Digital	CBDC[5]
Central-bank issued	CBDC[6]
Privacy	Cryptocurrency[7]
Security	CBDC[8]
Remuneration	Deposit[9]
Offline Payments	Cash
Decentralisation	Cryptocurrency[10]

Table 1: Payment demands and potential best payment instrument per demand

$$m_n^{*,CES} = \sum_{m_n \in M_k, \theta_{n,k} = \theta_{\max}} \left(\frac{P}{\sum_{i=1}^{K}\left(\frac{\alpha_k}{\alpha_i}\right)^{-\frac{1}{\gamma+1}}} \right). \tag{6}$$

In Table 1, we summarized an example of how payment instruments relate to the features. We then write out the demand for each payment instrument in terms of the preferences for these features. Before the launch of CBDC in Equation 7 and after the launch in Equation 8.

$$\begin{cases} \text{Cash}^* = P \cdot (\alpha_{\text{WA}} + \alpha_{\text{L}} + \alpha_{\text{O}}) \\ \text{CBDC}^* = 0 \\ \text{Deposits}^* = P \cdot (\alpha_{\text{D}} + \alpha_{\text{R}} + \alpha_{\text{S}}) \\ \text{Cryptocurrency}^* = P \cdot (\alpha_{\text{P}} + \alpha_{\text{P2P}}) \end{cases} \tag{7}$$

After CBDC Launch

$$\begin{cases} \text{Cash}^* = P \cdot (\alpha_{\text{WA}} + \alpha_{\text{O}}) \\ \text{CBDC}^* = P \cdot (\alpha_{\text{D}} + \alpha_{\text{L}}) \\ \text{Deposits}^* = P \cdot (\alpha_{\text{S}} + \alpha_{\text{R}}) \\ \text{Cryptocurrency}^* = P \cdot (\alpha_{\text{P}} + \alpha_{\text{P2P}}) \end{cases} \tag{8}$$

Crowding-out Effect Taking the solution of Bian et al. (2021) as an example. The crowding-out (disintermediating) effect of introducing a CBDC can be defined as follows for cash and deposits, respectively:

$$\frac{\Delta\text{Cash}}{P} = \alpha_L \frac{\alpha_D/\alpha_A}{\alpha_D/\alpha_A + 1} - \alpha_R \frac{1}{\alpha_D/\alpha_R + 1}, \tag{9}$$

$$\frac{\Delta\text{Deposits}}{P} = \alpha_D \frac{\alpha_L/\alpha_R}{\alpha_L/\alpha_R + 1} - \alpha_A \frac{1}{\alpha_L/\alpha_R + 1}. \tag{10}$$

Where ΔCash and ΔDeposits represent the change in the amount of cash and deposits before and after CBDC launch. The use of cash and deposits for point-of-sale payments in the Netherlands is 2.28 and 4.70 in EUR billions, respectively (NFPS, 2020). The total demand is the sum, as per constraint in Equation 1. It follows that $\alpha_L + \alpha_A = 0.327$ and $\alpha_D + \alpha_R = 0.673$. Since we do not know the exact personal preferences for individual features, we could make an assumption for now that they are equivalent for a demonstrative purpose (i.e. $\alpha_L = \alpha_A = 0.1635$ and $\alpha_D = \alpha_R = 0.3365$ such that the constraint in Equation 2 is satisfied). The result is trivial, namely, zero for both. This means that crowding-out of cash and disintermediation of banks starts to occur when the relative preferences change, for example, when legal tender versus remuneration increases above 1, $\alpha_L/\alpha_R > 1$. However, we should note again that the ECB does consider using remuneration as a policy tool for CBDC. So if both deposits and CBDC have remuneration, this model would be invalid. Another case where the model would be invalid is when remuneration negatively affects the household. In that case, we would expect that using the payment instrument causes dis-utility. To use this model without making assumptions on preferences it would be helpful to conduct an empirical study of household preferences for the above-mentioned payment instrument features. In general, there is a lack of research and literature on this topic because it has only become a recent concern with the increase and diversification of (digital) payment instruments and methods for households.

Awareness and Network Effects Network externality is an economics term that describes how a household's demand for specific payment instruments changes depending on the demand of other neighboring households. In other words, the usage patterns of households are influenced by other households. Positive network externalities can aggregate to a network effect. Externalities refer to the situation where a household affects the utility of another household.

$$\theta_{k,n} = \begin{cases} (1 - w_n) \cdot \text{score}_{k,m} + w_n \cdot N_n, & \text{if score} > 0 \\ 0, & \text{otherwise} \end{cases} \tag{11}$$

Where N_n are the network externalities for payment instrument n, $\theta_{k,n}$ and $\text{score}_{k,n}$ are the relative advantage measure and score for feature k and payment instrument m, respectively. Adding network externalities gives the opportunity for a payment instrument to be chosen even if their score is below average.

According to Gross and Siebenbrunner (2019), the network effect can make or break the success of a payment instrument. This means that the eventual implications we would like to analyse, such as disintermediation or bank runs, are highly dependent on the social interactions between agents. If we can manage to capture and replicate stylised facts about social interactions between agents and payment instruments, our model could help policymakers make decisions for their CBDC project. We could also think of the adoption of CBDC as the adoption of technological innovation. Several models try to model the behaviour of agents for the adoption of technology. One such method is the Innovation Diffusion Theory (IST) as mentioned in Section 5, its underlying theory originates from a parabolic partial differential equation known as the diffusion equation (Ismail, 2006).

Central Bank's Dilemma The utility function described in this section shows that households make decisions based on their personal preferences. These personal preferences influence their demands for certain payment features. It is in the central bank's full control to design a CBDC such that it is has a competitive advantage for all features. It has been shown that all features are technically and practically possible given the right implementation (ECB, 2020a). However, DNB (2020) also state, the CBDC should remain a complement to cash and deposits. This suggests that there may be an optimal level of intended usage for a CBDC. Of course, the central bank can design a CBDC such that it is not competitive in terms of all features but only a subset such that its usage is as intended. We believe that the game described by Mou et al. (2021) is not only valid for whether or not to launch a CBDC but also whether or not it should have certain features (especially in terms of competitiveness). Following the same logic suggests that central banks should launch a CBDC that is as competitive as possible, compared to the CBDC of other central banks or digital currencies of private issuers. If the ECB launches a CBDC with features that maximize all relative advantage measures, it could lead to significant changes in the composition of the financial system as disintermediation takes place. A competitive CBDC variant would likely lead to an increased crowding-out effect for all payment instruments.

Effect of Policies and Control Methods on Relative Advantage Measure Most if not all monetary policies and control methods are a result of the question "How can we limit the attractiveness of keeping a significant portion of wealth in CBDC without severely limiting its functionality." If we look at each method case by case, one quickly realizes that most affect how accessible or costly it is to obtain, trade, or hold CBDC. More specifically, tiered remuneration results in a disadvantage for CBDC for that feature all others (as mentioned in 2.2) result in a disadvantage for wide-accessibility.

Payment Types versus Payment Demands As it is pretty challenging to figure out the household's preferences for the payment demands mentioned in Table 1 we propose an alternative perspective on the preferences of households for payment instruments. Examples of payment types are point-of-sale, e-commerce, peer-to-peer. The volumes and number of transactions of such payment types are readily available through official statistical offices (e.g. CBS of the Netherlands). The ECB and DNB regularly conduct various studies as well as monthly or quarterly reports on the payment behaviour of households. To further formalize the differences of payment demands and payment types, payment demands could be seen as characteristics that a certain payment might have (e.g. high security, digital, private, etc.) while payment types relate more to location or the nature of the payment.

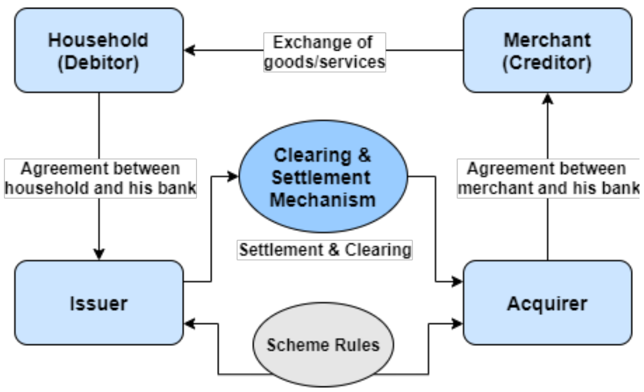

Figure 4: Four corner model of card payments (European Payments Council, 2020).

7 Model Description

Now that we have both qualitative and quantitative descriptions in Sections 3.3 and 6 respectively, we may begin designing our agent-based model. This starts by posing the question: who are all the relevant actors when an agent (a household/consumer) conducts a payment with any given payment instrument? To answer this question we used the "Four Corner Model of Payments" as shown in Figure 4 as a basis. In this model, there are 5 actors directly involved with a monetary transaction (specifically with deposit account payments). This is our starting point, from which we will make further simplifications and assumptions such that the complexity reduces.

7.1 Model Assumptions

Not all the actors mentioned in the previous paragraph are relevant for all payment instruments. For example, cash initially only requires the cash holder to physically give the money to the merchant. Therefore, in our model we will be only looking at the interaction between the cardholder and the merchant, in the rest of the model description, these will be described as the household and the firm (conform with ACE modelling). Any further assumptions and characteristics of the model are listed below.

- The environment is non-spatial, the location of an agent does not influence its state as well as the state of other agents. However, we would still like to see the effect of a social structure which is why we opted for a non-spatial network structure for the households.
- There will be no financial friction for any of the payment instruments. This means, no fees when conducting a transaction and no exchange fees when the household switches between payment instruments. Furthermore, the exchange is instant and there is always sufficient liquidity.
- Any payment method which is settled using the deposit account is considered the same payment instrument (e.g. debit card, credit card, etc.)
- All payment instruments have equal value; all are pegged 1:1 to the domestic currency, in this case the Euro.

7.2 Agents and Environment

Households (i.e. Consumers) Households purchase consumer goods, work at firms and distribute wealth over multiple payment instruments. Households are heterogeneous agents with different personal preferences and social peers. Households aim to maximise the utility function in Equation 2, they do this by choosing the appropriate payment instrument for a given payment demand. As shown in Section 6, households will simply choose the instrument that scores best for a given payment demand. The perception of payment instruments will depend on their personal preferences, social network and effect of network externalities. This makes it possible for one household to select a different payment instrument than other households even if the payment demand is the same. Our intention here is that it contributes to emergent behaviour and the heterogeneous nature of agents in agent-based modelling. More specifically, network effects may be cause for inferior technologies but often standardized to be used in favor of new innovative technologies (David, 1985).

Firms Firms create consumer products using enterprise products, labor, and loans. Firms face only 2 decisions: accepting and removing accepted payment instruments. They do this by evaluating how profitable it is to accept a payment instrument given a certain demand for this instrument. Similarly, if a payment instrument is barely used, it may make sense for a firm to remove it to minimize its running costs. Each firm will have different "thresholds" to use for these decisions. Some firms may accept any payment instrument irrespective of the demand, while others will accept only those that contribute a significant portion of the revenue (i.e. higher than the threshold).

Central Bank The central bank is a monitoring and policy enforcing agent, it learns to apply and optimize policies through some form of learning based on desired social outcomes and previous experience. The central bank may impose the following policies (or a combination thereof) to reach target behaviour:

- (Tiered) Remuneration.
- Absolute account limits.
- Conversion control (limit conversion to CBDC).

We define the following technical control methods:

- Individual transaction limit (x number per person-/entity).
- Overall transaction limit (e.g. x transactions per second).
- Transaction size limits (e.g. x units per transaction).

- Volume limits (e.g. x units per week).

Since it would significantly increase the complexity of the model, we otherwise opt for a model where the central bank directly changes the score of the CBDC instead of deriving each relative advantage score by calculation. We believe this to be a reasonable simplification because in the eyes of the household all of the above measures impact either the availability or convenience of the payment instrument. We think it is unlikely that households' CBDC usage decreases if control measures aim to do so. According to Stavins (2018), it is much more likely that if a CBDC were to be significantly limited in its usage, households will simply stop using it all together. The convenience and availability of the payment instruments are reflected in the instrument scores. We leave it to other researchers to bridge the gap between how payment instruments are perceived by households (instrument scores per payment demand or type) and the actual monetary or technical policies.

7.3 Agent Behaviour

Decision-making is an important part of the agent-based model as it has significant effects on the eventual outcome. Agents must be are a realistic representation of their real-world counterparts or at least a good abstraction where connections to real-life behaviour can be made. Grounded by economic theory and the empirical foundation is key to realize this. Agent decision-making can be described by a function that maps state to action. The function that maps these states can be in various forms such as utility maximisation, social behaviour, probabilistic functions, or deterministic among many others. Lastly, the actions that an agent can take should be clearly defined and reflect real-world decisions.

Social Influence The two main drivers of a household's decision-making in our model come from personal preferences and social influence from their social network. If its decision is based purely on personal preferences, then we refer to it as utility-based decision making. Combining both factors in a decision-making model results in an effective-utility-based decision (Laciana and Rovere, 2011). The weight that should be given to social influence usually depends on the type of choice that has to be made. In our model, the households make a choice on what payment method to use. According to Young (2009), "People adopt [the innovation] once they see enough empirical evidence to convince them that [the innovation] is worth adopting, where the evidence is generated by the outcomes among prior adopters. Individuals may adopt at different times, due to differences in their prior beliefs, amount of information gathered, and idiosyncratic costs".

7.4 The Environment

Forms of Money We are interested in the distribution of usage of different forms of money. The agents are allowed to use the following payment instruments:

- Cash: requires an agent to physically go to the firm to purchase goods but in return offers excellent privacy and anonymity features and never goes offline.
- Deposit account: allows an agent to remotely and physically purchase goods but in return has to pay a fixed fee to a financial service provider to make the settlement. Offers fewer privacy features than cash, can go offline but settles much faster than cash.
- CBDC: allows an agent to remotely and physically purchase goods without paying a fee to a financial service provider. It offers more privacy features than a deposit account but less than cash.
- Private money (e.g., a cryptocurrency): allows remote purchase but a limited degree of acceptance. It requires a small transaction fee but offers the best privacy.

In general, the practical implementation of these different payment instruments will consist of at least the following characteristics: privacy, speed, cost, offline payments, remote payments, intermediaries, and limits. Alternatively, we may use payment types instead of payment demands. The payment types are defined as follows: digital (online) point-of-sale, offline point-of-sale, e-commerce, online peer-to-peer, offline peer-to-peer.

8 Model Implementation

In Table 2 we describe all relevant model and agent-specific parameters that can be set either dynamically during the simulation or used as fixed initial conditions.

8.1 Model Parameters

Social Network Topology Network Effects Households and firms are connected through what is called a "small-world" network, a type of mathematical graph. This network resembles close social contacts with a low node count. We chose this type of graph because even though social media exists, investment and monetary decisions tend to be influenced by close and small social circles (Zaidi, 2012). There are a few parameters that we can adjust to achieve a desired behaviour. Firstly, we can define the average number of neighbors a household has social contact with. The number of neighbors relative to the total number of households describes how well connected the social network is. The rate of adoption is directly influenced by the degree of connectivity of the social network. Secondly, we can define how a household considers opinions from neighbors and what this opinion is. Lastly, we can define how much weight should be given to the opinion relative to the score per payment instrument per payment demand. Each step a household considers the opinion of neighbors by averaging. The opinion itself is implemented as the fraction of volume per instrument of the rolling sum of total transaction volume of the past 30 days.

Type	Name	Description
Model parameters	num_households	Number of households in simulation
	num_firms	Number of firms in simulation
	network_effect_weight_max	Maximum weight of network effect
	instrument_scores	Scores per payment demand per payment instrument
	initial_acceptance_rates	Initial acceptance rate per payment instrument
	cash_shortage	Probability of cash shortage
	deposit_outage	Probability of deposits outage
	cbdc_outage	Probability of CBDC outage
	crypto_congestion	Probability of crypto network congestion
	cbdc_seed_rate	Initial acceptance rate upon introduction of CBDC
	month_length	Length of a month (in days)
	payment_instruments	List of available payment instruments
	payment_types	List of payment types (e.g. point-of-sale or ecommerce)
	payment_demands	List of payment demands (e.g. digital, offline, legal tender)
	graph	Network graph used for social structure
	k	Each node in the network is connected to k nodes
	p	Probability of rewiring a node to randomly selected node
Household parameters	salary	Daily wage rate
	neighbors	List of IDs corresponding to other households
	personal_preferences	Preferences for the defined payment demands and payment types
Firm parameters	accepted_instruments	List of accepted instruments

Table 2: Description of the model parameters.

8.2 Decision-making of Agents

Household's Decisions There are 2 sets of decisions that the households perform. 1 set related to planning consumption of goods, this is performed periodically (at the start of each month).

The other set of decisions is more critical for the adoption of CBDC. Every day (each step in the model), the household sets preferred instruments per payment demand. It chooses based on the instrument score for that payment demand and network effect (average opinion of other households). The function is implemented exactly the same as in Equation 11. After setting the payment instrument per payment demand, the household will purchase goods. The household will be randomly assigned a payment demand using the personal preferences as a discrete probability distribution. The household then loops through its list of preferred suppliers. If if it is unable to perform a transaction with a given payment instrument, it will choose randomly from the firm's list of accepted instruments. If for some reason that also fails, it simply goes to the next firm.

Firm's Decisions The firm only faces one critical decision, namely whether or not to accept or remove a payment instrument. Firms make this consideration every day. We implement this as the firm's willingness to accept a payment instrument. The probability of accepting a payment instrument is the volume of failed transactions for a given instrument as a fraction of the total volume of all successful transactions of the past 30 days (rolling sum). The firm also considers removing payment instruments if in the past 30 days a payment instrument's volume is less than a certain threshold (ignoring recently added instruments). To prevent firms from constantly accepting and removing an instrument because its volume is around the threshold we introduced another parameter that tracks the day number a payment instrument is accepted or removed. Firms can only remove a previously accepted instrument (or accept a previously removed instrument) after a certain number of days have passed, in our implementation, this number is 3 months (90 days).

Central Bank's Decisions The central bank can essentially increase or decrease the score given to CBDC at the start of each month. We did not implement this behaviour fully; the score given to CBDC when launched is defined before the simulation starts and is not changed after the launch. However, this model will likely be used further to evaluate monetary or technical policies enforced upon the CBDC and its effect on the adoption process. The central bank could pre-define what measures to take if CBDC is adopted more than desired and translate this by adapting the CBDC score accordingly during the simulation.

8.3 Implementation Process

A significant (if not the majority) of the work performed in terms of both time and effort went into the actual programming of the model. In this section, we aim to document the process of implementing the agent-based model. As mentioned in Section 5, we are using the Python-based ABM framework project MESA along with various other well-known libraries. Project MESA is an open-source framework that allows the programmer to quickly create a working prototype using the built-in classes such as the scheduler, spatial grids, and browser-based interfaces.

Our starting point for modeling was creating a UML class diagram using the knowledge we gathered from literature research on all relevant actors of retail payments. We quickly realised that this was overly complex and in order to continue we had to abstract the list of all relevant actors to something that would be easier to implement given the time constraints of the assignment. We chose to leave out all intermediaries such as payment service providers, commercial banks, card issuers. We were left with only households, firms, and the central bank, who are also the only beneficiaries of the entire list.

Once all relevant actors and their actions were defined we started the implementation process. Over a duration of 3 months, we implemented the agent-based model. We used a top-down approach, starting with a relatively simple environment and agents whose actions were primarily random at best. This environment is provided as an example environment on GitHub under the repository of Project MESA. From this point on-wards, we opted for a Scrum-like process for development so that we could rapidly implement small features and test the model and functionality during every iteration to ensure that the final model would work as expected.

The last part to implement is the user interface, also a default option of Project MESA. The framework allows a user to easily select which data and with which frequency to collect from the model and display this using real-time updated graphs. Since we were not restricted by hardware, we chose to collect all variables every time step and later decide which variables to use for the graphs. Collecting all data also has the benefit that it can be used in further data analysis after the simulation time has passed, allowing the user to set different initial conditions and compare simulations results in combined graphs.

8.4 Functional Validation

In this section, we will try to answer the question: how do we know if each individual component is behaving as expected? In software development, this usually means performing unit tests. Similarly, we performed unit tests on each individual component by “switching off” all other functionalities while altering the unit we intend to validate. Each test case should have a logical outcome that can be readily verified by visually inspecting the graphs and data. The first test case is to validate the transaction logic: if all payment instruments are equally good and the weight of the network effect is 0, the household will choose randomly among the available options using a discrete uniform probability function. The second test case concerns the network effect; if all payment instruments are equally good and the weight of the network effect is non-zero and universally positive, one payment instrument will accumulate all transaction volume. Furthermore, if you repeat this experiment sufficiently many times, the outcome is expected to be a uniform distribution along the number of payment instruments. The third and fourth test cases related to the personal preferences and payment instrument scores respectively. The third test case is to check whether the personal preferences correctly influence the household's choice of payment instrument. All other functions of agents and the environment are tested with Python's Unit Test Framework.

Payment Type	**Volume**	**Fraction**
online POS	€129,360,000,000.00	0.653657
offline POS	€20,000,000,000.00	0.10106
e-commerce	€26,642,000,000.00	0.134622
offline P2P	€8,100,000,000.00	0.040929
online P2P	€13,800,000,000.00	0.069731
Total	€197,902,000,000.00	

Table 3: Payment types and their volumes in EUR

8.5 Calibration Process

Calibrating agent-specific parameters can be rather tricky especially when the to-be-calibrated parameters are multidimensional. Our model is calibrated based on the latest statistics on payment instruments in the Netherlands. Essentially what calibration tries to achieve in our case is a target level of volume and number of transactions per payment instrument. For the sake of simplicity, we set the following target values: 25% cash, 75% deposits, and negligible volume from cryptocurrency transactions. We assume that the scores corresponding to the payment instruments are either 1 or 0 for cash, deposits, and cryptocurrencies. This means that they either satisfy or do not work for a certain payment type or demand. Furthermore, personal preferences for payment types were derived from the facts and figures of 2020 made by the Dutch Payments Association (Betaalvereniging, 2020) and are shown in Table 3. The model was calibrated through an iterative process until the desired target values were reached. The calibrated parameters can be found in Appendix A in Table 5.

General Overview of Implementation In Figure 5 we attempt to give a general overview of the implemented model and the influence that each component may have on other parts of the model. Figures 6 and 7 show what events and actions occur in a single month cycle and the step diagram of our model respectively.

Interface We created two options to use this model; one way is through the graphical user interface which

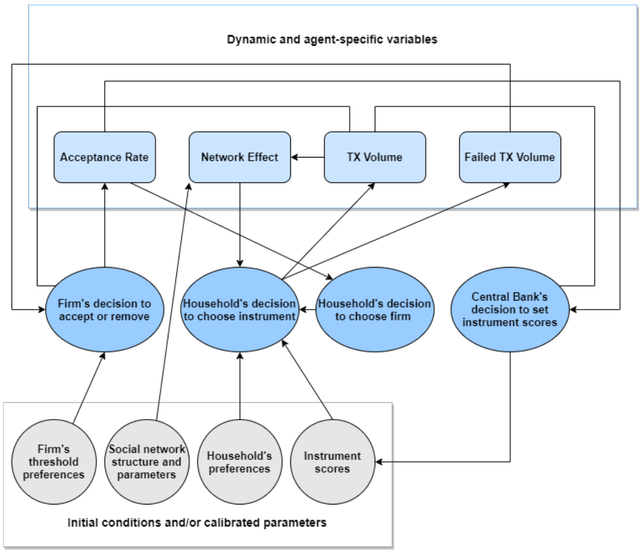

Figure 5: General overview of the model (some variables have been left out to reduce complexity).

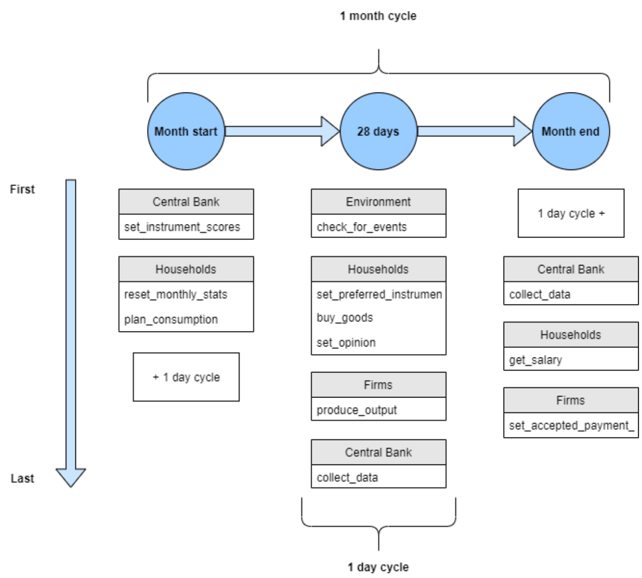

Figure 6: Schedule diagram.

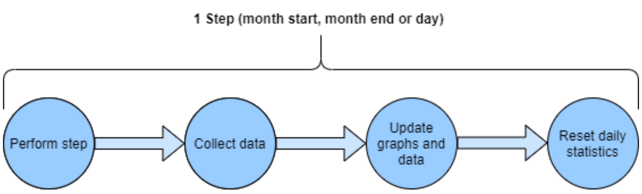

Figure 7: Step diagram.

allows the user to alter a subset of the initial conditions through sliders and observe the results through real-time graphs that are updated every step (see Figure 8). Another way to use our model is through the batch runner, this allows the user to supply a list of possible values per initial condition and the program will automatically create all possible scenarios that follow from these lists. The batch runner collects all the data and plots figures of all simulations which can later be prepossessed and used for further analysis. To obtain our main results and validate the model we used the graphical user interface.

9 Experimental Setting

9.1 Initial Conditions

In our experimental setup, the parameters in Table 5 in Appendix A are kept constant for each scenario we simulate.

Transaction Size and Volume According to the Dutch Payment Association, the number of total transactions in 2019 is 7.03 bn; 4.71 bn debit card transactions, and 2.28 cash transactions (Betaalvereniging, 2020). The total value of those transactions is 117 bn with debit cards and 32.1 bn with cash (we have excluded credit card payments as it would introduce unnecessary complexity given the insignificant volume). This translates to 79% card transactions and 21% cash transactions per day (2019, pre-COVID-19) and 86% card transactions, and 14% cash transactions (2020, post-COVID-19). Where 1 transaction on average is 24.84 and 14.08 Euros respectively for 2019 while the average for 2020 is 26.12 and 15.50 Euros respectively. Because there is a lack of data for cryptocurrency payments in the Netherlands, we assume these to be zero initially.

9.2 Scenarios

The 4 main parameters that we alter for creating scenarios are: CBDC instrument scores, the weight of the network effect, and the initial acceptance rate of CBDC. The length of each simulation is three years (1080 steps), after 1 year the CBDC is introduced as it takes time for the model to initialize to a stable environment. Since there are too many preferences and parameters that we could alter, we chose to create two distinct scenarios instead: cash-like CBDC (offline capability, non-remunerated, decentralized/peer-to-peer) and deposit-like CBDC (no offline use, remunerated, non-decentralized). This can be further subdivided into highly competitive (score above average) and non-competitive (score equal to average). Both scenarios can be further split into competitive (score < 1) and non-competitive (score $>= 1$).

By means of trial and error, we adjust the parameters until we come across situations that create crowding-out effects for cash and deposits. Furthermore, we tried

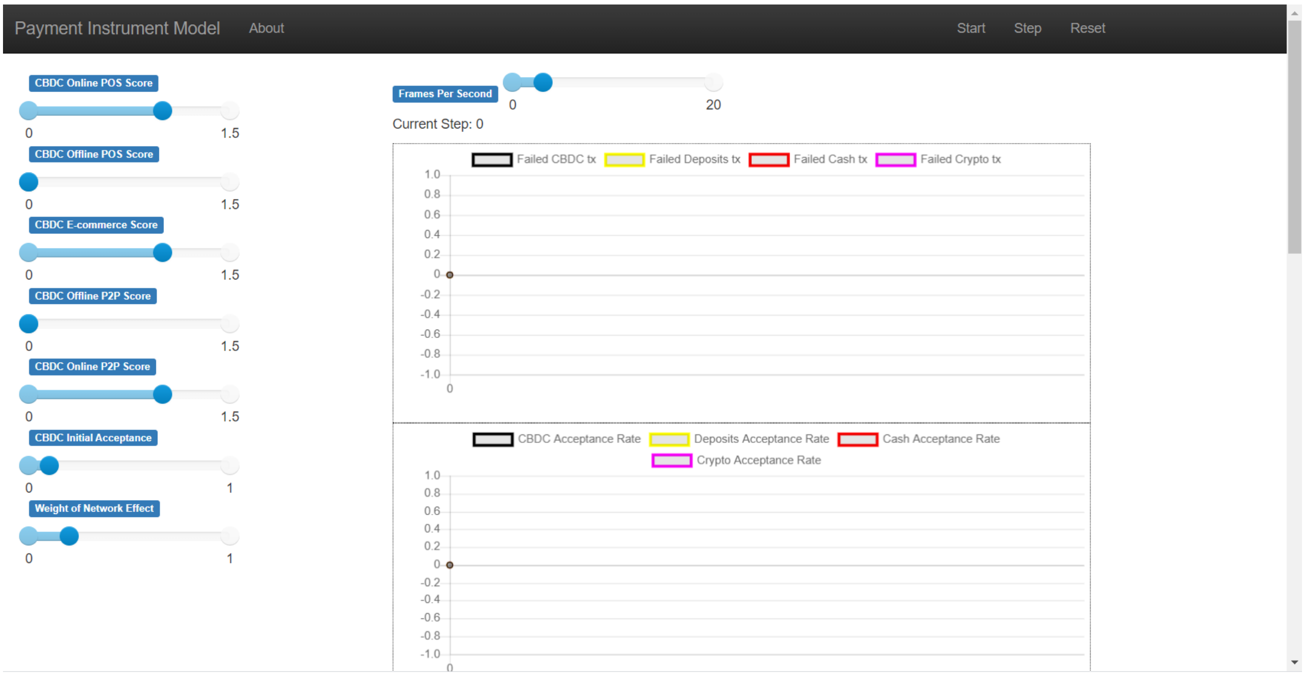

Figure 8: The graphical user interface of the agent-based model.

to adjust parameters such that it creates a scenario where CBDC is not adopted at all, partly adopted, and fully adopted. The first one is trivial, to create a CBDC that is not adopted at all, it simply needs to score equal or lower than all payment instruments for all payment types. This would be different if we allow for a negative network effect; where households may reduce the overall relative advantage of an instrument which would allow a non-competitive CBDC to still be used as an alternative and gain a positive network effect. The scenario in which a CBDC is fully adopted in both acceptance rate and transaction volume is also trivial, with the instrument score sufficiently higher than 1 to also overcome any positive network effect of other instruments. In other words, when the CBDC is so competitive relative to other payment instruments, it will readily be chosen as the preferred payment instrument.

This begs the question: is it possible to design a CBDC such that it is only partly adopted? As mentioned in Section 3.3, the goal is not to replace cash or deposits but to simply complement and offer a larger variety of payment instruments or households and firms. This might be logical, but it is exceptionally hard to create a complement to something if both allow for the same functionality, namely the characteristics of money described in Section 3.1. A follow-up question might be: How stable is the scenario of a party adopted CBDC? What kind of events would drive it to the extremes of no adoption or full adoption?

For this purpose we introduced the idea of events (e.g. a shortage of cash or an outage of debit card payments), which enables us to see if such events would allow a marginally competitive CBDC to still be fully adopted if such an event were to take place. This could of course also work against the adoption of CBDC. For example the event of the central bank enforcing policies upon CBDC usage. Such functionality we have not implemented but this would be a logical next step if DNB were to continue developing this model.

10 Results

In this section, we present the main results (the simulations of which the scenarios were most compelling). In general, our results seem to coincide with research on the adoption process of any innovative technology, namely the S-curve. We see similar emergent behaviour that we did not intentionally build into the model. his is due to the positive feedback loop that the network effect creates. This is most evident in the network effect graph as seen in Figure 9.

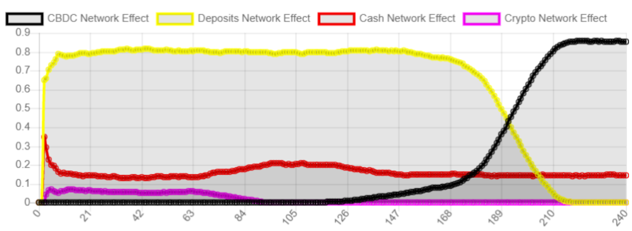

Figure 9: Network effects of a competitive deposit-like CBDC.

In total there are 2000 scenarios we simulated using the batch runner, however, we would like to highlight only 5 scenarios specifically using the graphical user interface. The main result of all simulations is that it is indeed very difficult to obtain the "golden mean" of CBDC design, that is, a design functionally the same as or better than cash, and at the same time a complement to cash. The extremes (full adoption or no adoption) are relatively trivial to achieve. The exact quantitative values of initial conditions bound to these scenarios are not so meaningful without knowing more about how the scores are calculated, how the score is actually perceived by households, and to what degree households depend on the network effect for their decision-making. To illustrate our results we chose to display two charts: the adoption by firms (acceptance rate) and the adoption of households (transaction volume per payment instrument).

The default is the scenario with no CBDC, one could consider this the model validation scenario to see whether the simulation runs stably and the desired volumes and acceptance rates for existing payment instruments are achieved. Figure 10 shows the volumes of cash and deposit stabilize after initialization to the desired values of 25% and 75% respectively. It is important to mention that this is not really emergent behaviour as it is based on the calibrated initial conditions shown in Table 5.

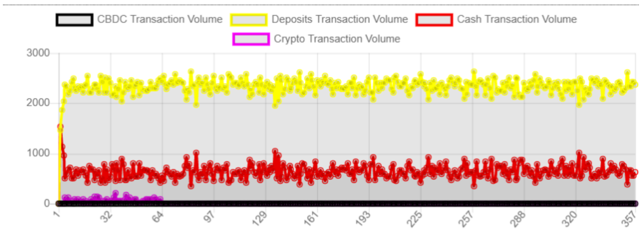

Figure 10: Transaction volumes of cash and deposits in the scenario of no CBDC.

10.1 Competitive Deposit-like

The first scenario is the competitive deposit-like CBDC. This is a CBDC with no offline point-of-sale or peer-to-peer capabilities which suggests that its impact on cash should be insignificant. Figures 11 and 12 show the adoption process of the competitive deposit-like CBDC. An interesting behaviour to notice is a temporal increase of cash usage when the volume and acceptance of deposits is dropping significantly. This happens when the acceptance rate of deposits drops, some use cash as an alternative in case they are not sufficiently aware of CBDC yet (the local network effect for CBDC is low or the weight bound to the network effect is high relative to the rest of the small-world network).

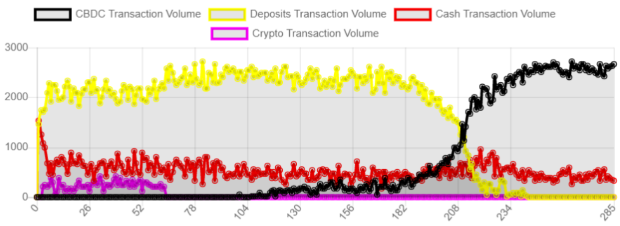

Figure 11: Transaction volumes of competitive deposit-like CBDC.

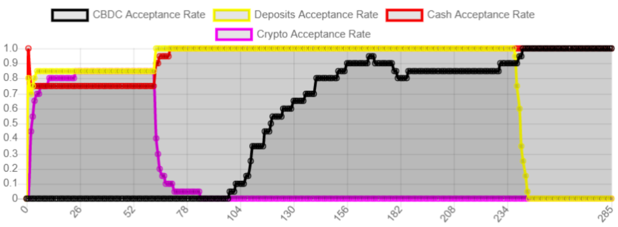

Figure 12: Firm acceptance of competitive deposit-like CBDC.

10.2 Competitive Cash-like

The competitive cash-like CBDC does not only capture all volume of cash transactions but also all deposit transactions it is also competitive for deposit-like features (online). This suggests that a cash-like CBDC is a substitute for both cash and deposits. This does not need to be the case when the cash-like CBDC is only competitive in terms of its offline point-of-sale and offline peer-to-peer capabilities (see Figures 13 and 14)

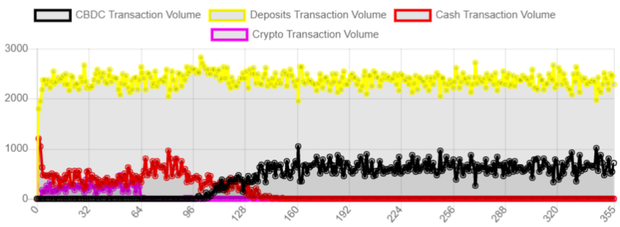

Figure 13: Transaction volumes of competitive cash-like CBDC.

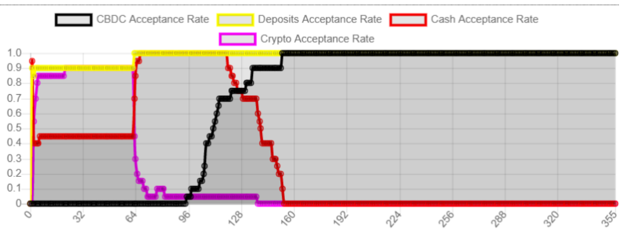

Figure 14: Firm acceptance of competitive cash-like CBDC.

10.3 CBDC-as-Complement Scenario

The third scenario is a partly adopted CBDC (in terms of both the acceptance rate and the transaction volume). This scenario emerges when the demand is too low for all firms to accept it (in the model this is tracked through the volume of attempted payments i.e. failed transactions) but too high for some firms to remove it. This emergent behaviour is the oscillation of the acceptance rate around a seemingly stable value (see Figure 15). We believe this is due to firms having different criteria that they consider when making decisions on accepting and/or removing payment instruments. Firms are in that sense heterogeneous and have different preferences. Of course, in reality, they may have different heuristics to determine to remove or accept payment instruments.

In our model, firms simply consider (by assigning a probability) how significant the fraction of potential revenue is if they were to accept that payment instrument. The partly adopted CBDC is the scenario that the ECB seems to be trying to achieve through means of clever design choices and/or enforcing monetary policy. We found that this scenario is relatively unstable, and the slightest change that puts CBDC in favour over cash will cause full adoption in terms of both acceptance rate and transaction volume. A growing body of research suggests that this scenario is in reality unobtainable, which now also includes the result of this model.

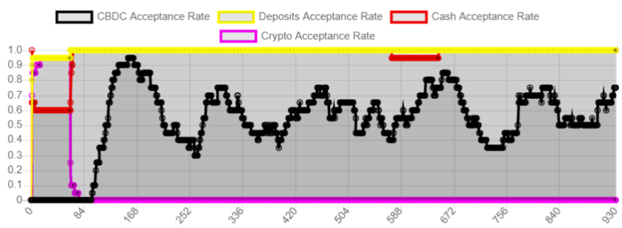

Figure 15: Oscillating CBDC acceptance rate when marginally competitive.

Lastly, we found that a plausible scenario is a deposit-like CBDC with inconvenient (low score, i.e. less than 1) offline capabilities. In this scenario, the CBDC may still gain enough network effects to overcome the inconvenience of its offline capabilities and yet be able to replace cash. Furthermore, the deposit-like CBDC behaves as a substitute rather than a complement, especially if it is a sufficiently better alternative compared to deposits. Figures 16 and 17 show the adoption process of the competitive deposit like CBDC.

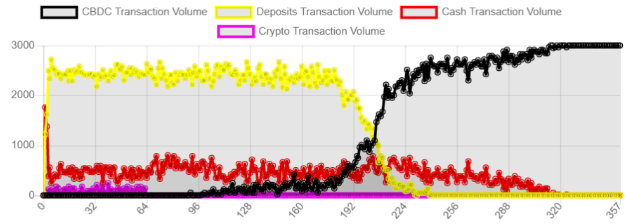

Figure 16: Transaction volume of competitive deposit-like CBDC with some offline capabilities.

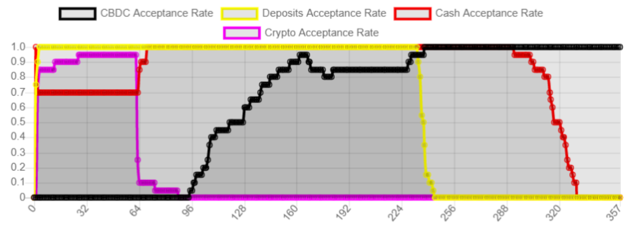

Figure 17: Firm acceptance of competitive deposit-like CBDC with some offline capabilities.

11 Discussion

11.1 Personal Preferences and Payment Types

We recognised that the payment characteristics, implemented as described previously, may not be sufficient to describe all payment demands or combinations thereof. For example, it could be that a household has an intention to combine several characteristics to form a new payment demand; for example, the household may want to make digital transactions but also wants them to be as secure as possible, in case the payment is of significant amount. In general, it seems logical that any of these combinations may exist, which would make it rather difficult to define all possible combinations and personal preferences for them. What we could instead do is define payment types such as: point-of-sale, e-commerce, person-to-person, business-to-business, etc.

There are also significantly more data found on the volumes and payment instruments used for each payment type than there is for each payment characteristic. Although this would not change the model significantly, as we would simply have to rename the characteristics to payment types and score payment instruments based on how they perform for a payment type, we decided to continue using payment characteristics as a basis for this model.

11.2 Hoarding of Cash

Cash is currently not evenly distributed among the Dutch population and also the function of cash also depends on the value it has. For example, someone hoarding notes of 200 and 500 units probably does not use them for their daily groceries (medium of exchange) but instead as savings or for larger and more infrequent payments (store of value).

11.3 Existing Infrastructure and Acceptance Rate

Even though we initially assumed no specific technical implementation, instead we assume that each functionality is technically possible irrelevant to the actual technologies used.

However, the system infrastructure is an example of an aspect that would have a significant effect on the potential acceptance among firms. The CBDC could either require new infrastructure such as payment terminals and gateways or could leverage existing payment terminals as well as the underlying systems. This design choice would heavily influence the potential initial acceptance rate of the CBDC. If all firms that can accept debit or credit cards can also accept CBDC without extensive work it would most likely speed up the adoption process. The acceptance rate plays a significant role in the convenience of the payment instrument.

The initial acceptance rate is set as an initial condition and directly influences the number of failed transactions. We decided it might be worthwhile to perform an additional scenario where CBDC is accepted at all firms that also accept deposit payments (acceptance rate of 87%). We found that full adoption with a high initial acceptance rate (crowding out both cash and deposits) takes 30 steps less than with a low initial acceptance rate. One could say that if there is enough demand for CBDC transactions, the only constraint for firms adopting the technology is the availability and time it takes to set up the CBDC payment terminal.

11.4 Role of DLT

Lastly, we want to discuss the role of DLT for a CBDC. It is very likely that the invention and success of Bitcoin, blockchain and DLT in general have led to CBDC and without DLT we would likely not have considered the possibility of a digital euro in its envisioned form. Initially, blockchain was thought of as enabling technology for a retail-CBDC. This idea has been mostly dropped by almost all central banks (Mikhalev et al., 2021). Blockchain could potentially allow for a form of money that fulfills all criteria of a retail-CBDC. Next to that, it could also be permissionless, open for all and trustless. However, it is these qualities that make a DLT-based digital euro undesirable for central banks because it is unclear how monetary policy and control methods discussed in this thesis could be enforced in such a system. But perhaps, nobody being able to control a currency is not necessarily a bad thing. This is an idea that central banks could consider, and it is at least worth experimenting if a Bitcoin- or Ethereum-like CBDC offers any benefits. Central banks could verify if those potential benefits could outweigh the disadvantage of not being able to control the currency and its value.

12 Conclusion

We have developed an agent-based model that allows us to understand the interactions between different agents and the potential impact and adoption process of a CBDC. The initial conditions were chosen to fit the Dutch economy and match the payment preferences of Dutch households. The results of the simulation have given us great insight into the complex nature of the problem that is the adoption of a new payment instrument and its potential effects on the use of cash and deposits. We have learned that households will choose a CBDC over cash and deposits, not marginally but fully, when the CBDC design is competitive. The crowding-out effect of a competitive CBDC is significant for both cash and deposits with a cash-like CBDC and significant for deposits but almost no effect on cash with a deposit-like CBDC.

The central bank has a clear incentive to make the CBDC competitive as described in Section 3.1. At the same time, the central bank wants to minimize the crowding-out effect on cash but specifically on deposits because of the risk of digital bank runs and further financial instability. We found that the "golden mean" is rather complicated to achieve, if not impossible, simply because CBDC is a substitute and not a complement to cash and deposits if it fulfills the same payment needs.

The proposed control methods may be sufficient but the central bank should question whether it affects the functionality such that it would not get adopted at all. At the same time, other central banks or even private forms of money may not care that much about the crowding-out effect and may be as competitive as their technology allows. Keeping all these factors in mind, it seems inevitable that there will be some form of payment instrument competition as described in Section 3.1. Moreover, the impact on cash and deposits is likely unavoidable and therefore the central bank should question the business models and roles of commercial banks, payment providers, and practically all other parties involved in the process of cash and deposit transactions.

It is often the case with agent-based models that the results may be obvious, this is sometimes referred to as the hindsight bias. It is not necessarily a bad thing because the model served its purpose as a tool for understanding the problem better. Most researchers look for a surprising element, emergent behaviour that is not expected initially or "programmed in". Even though we may not have been surprised by the results, we still believe we succeeded in building a model that helps us better understand the potential impact a CBDC may have on the economy. In that sense, our initial concerns with the crowding-out of cash and deposits are validated by the model.

12.1 Limitations

The use of agent-based modelling for this research also comes with drawbacks that may put the results in jeopardy. Selecting the right number of features, functions, and parameters is challenging. On one side one would like the model to accurately represent the real world as possible (e.g. EURACE model by Deissenberg et al. (2008)) but on the other side keep it practically and theoretically manageable to implement. This is often represented as the curse of dimensionality. A very accurate representation of a real-world process may not have much theoretical value. Furthermore, a model with as few parameters as possible could be statistically more significant because it is able to run with a higher number of agents (in case access to sufficient hardware is a constraint). In our case, the model implementation is kept relatively simple to fit the time constraints of the research.

The most significant drawback of the model is the lack of quantitative data for calibration and data validation. We used only the latest available statistics of the Dutch economy to set the initial conditions of the model but preferably the model should be calibrated and validated with a series of data. It is also very likely that the payment preferences of households change over time, and may change based on the introduction of a CBDC. The same could be said about the other parameters, whether or not it is realistic to keep them fixed as initial conditions require more research. For many initial conditions, we had to make an educated guess as to what they could be and adjust on a trial and error basis to achieve the desired behaviour. One example of this is the network effect; the parameters such as the number of peers and weight of network effect on decision-making influence the results in a variety of ways. In order to make the model more realistic one would need to know how monetary decisions in Dutch households are made and how opinions of neighbors (i.e. friends, family, and others) are considered.

12.2 Further Research

We propose the following ideas for further research listed below. We would also like to continue building and improving the model. Originally we planned to implement deep reinforcement learning as a way for the central bank agent to modify the policies such that it may achieve a target usage and adoption level.

- Research on the relation between substitutability and the design options, technical limitations, and monetary policies of a CBDC.
- Social behaviour study on payment instrument preferences of households.
- Use of deep reinforcement learning for policy optimization.
- Applying different methods to model the adoption process and impact of CBDC.
- More research on the technical feasibility of CBDC functionality on a larger scale.
- Use of quantitative data to calibrate the model, the ECB could learn a lot from other countries implementing CBDC by collecting data about the adoption process.
- Game theoretical analysis on the wider scale currency competition in the world.

Acknowledgments

Glossary

ABM Agent-Based Modelling. 3

ACE Agent-Based Economics. 7

CBDC Central Bank Digital Currency. 5

Deep RF Deep Reinforcement Learning. 3

DLT Decentralized Ledger Technology. 5

DNN Deep Neural Network. 4

DSGE Dynamic Stochastic General Equilibrium. 7, 8

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A Tables

Query	Results (pre-filter)
(central bank digital currency) OR CBDC	291
“” AND (AI OR (Artificial intelligence))	1
“” AND (DLT OR (decentralized ledger technology))	8
“” AND blockchain	32
“” AND (DNN OR (Deep neural network))	3
“” AND (Deep RF OR (deep reinforcement learning))	1
“” AND (ABM OR (agent based modelling))	0
“” AND (DSGE OR (dynamic stochastic general equilibrium))	1
“” AND (ML OR (machine learning))	3
“” AND (design OR policy)	90
“” AND (model OR modelling)	46
“” AND (optimal)	8
“” AND (interest rate)	9
“” AND (financial stability)	0
“” AND (remuneration)	1
others	88
(ABM OR (agent based modelling)) AND (finance OR econometrics OR economics)	2632
(Deep RF OR (Deep reinforcement learning)) AND (finance OR econometrics OR economics)	103

Table 4: Scopus search results

Type	**Name**	**Calibrated value**
Model parameters	num_households	1000
	num_firms	100
	network_effect _weight_max	0.2
	instrument_scores	1, 0, 0, 1, (online POS) 0, 1, 0, 0, (offline POS) 1, 0, 0, 1, (e-commerce) 0, 1, 0, 0, (offline P2P) 0, 1, 0, 1 (online P2P) (deposits, cash, cbdc, crypto)
	initial_ acceptance_rates	[0.87, 0.97, 0, 0] (deposits, cash, cbdc, crypto)
	month˙length	30
	graph	Watts Strogatz graph (small-world network)
	k	2
	p	0.2
Household parameters	salary (daily)	70
	neighbors	average of 2
	personal_preferences	[0.654, 0.101, 0.135, 0.041 ,0.070]
Firm parameters	accepted_instruments	Initially the same as initial_acceptance_rate

Table 5: values of calibrated model parameters