

### **Simulating the Adoption of a rCBDC**

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### **About FNA**

FNA is a leader in advanced network analytics and simulation.

FNA's software is used to uncover hidden connections and anomalies in large, complex datasets, to predict the impact of stress events, and to optimally configure financial systems and infrastructures.

FNA is trusted by the world's largest central banks, government authorities, commercial banks and financial infrastructures.



Monetary Authority of Singapore



US Department of Defense



Payments Canada



Hong Kong Monetary Authority



The World Bank



CLS Group



RTGS.global



ICE Clear Credit



The Clearing House



Bank for International Settlements



Giesecke + Devrient



UK Finance



Banco de la República-Colombia



Fnality



Bank of England



# **About today**

- Main takeaways
- Why should central banks simulate rCBDC?
- Agent-based simulation of rCBDC adoption
- rCBDC Spanish market adoption
- Further work



# Main Takeaways





# Main takeaways

- Simulating rCBDC adoption can help central banks to iterate design options.
- Without attractive design features or stimulus policies, we found low adoption of rCBDC.
- Reverse waterfall functionality, government payments, and positive remuneration spread can increase rCBDC adoption.
- Balance limits, top-up limits effective to restrain rCBDC adoption.
- In general, rCBDC won't compete with cash but with deposit-related payment instruments—unless the government fosters targeted use of rCBDC

Why should central banks simulate rCBDC?

### **CBDC - Many Stakeholders with Many Interrelated Concerns**

100+ countries are exploring CBDC, of which 26 are in development, and 15 are making pilots\*

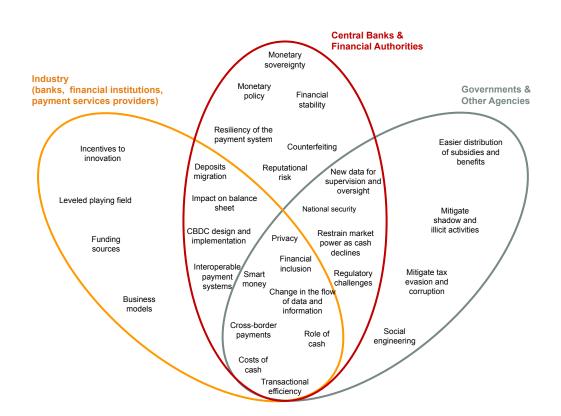
## What model are we looking for?

A model of selected macro-financial effects from deploying a CBDC

A parsimonious and tractable model that enables scenario analysis

A modular, flexible and extendable modelling approach

To add new features and answer new questions opportunely



#### **Our Goals**

Shed light on crucial macro-financial and payments questions

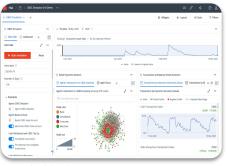
Measure the impact on the economy, financial system and payment ecosystem

Analyse and substantiate the design of CBDCs

Encourage research on CBDC

### **Learning by simulation - rCBDC simulation is the key to modelling the** impact of CBDC introduction on the economy and the payment ecosystem





Learning by doing and simulation with FNA's out-of-box maximum virtual **product** to reduce rCBDC project risk and accelerate the time to value



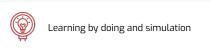
It enables **effective communication** and **shared understanding** among stakeholders by visualising insights through interactive user interfaces



It allows central banks and market participants to **design a safe and efficient CBDC** by testing **multiple policy** inputs and **tailored CBDC** configurations



Design | Validate | Optimize





Is data agnostic - and configurable on publicly available and proprietary data



Substantiates qualitative analysis with quantitative insights



Is technology agnostic - and compatible with any infrastructure underpinning a CBDC



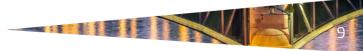
Is modular - and configurable for specific features of each jurisdiction



Provides value beyond the design phase - and crucial for continuous monitoring and stress testing

**Agent-based simulation of rCBDC adoption** 





# **Anything in common?**







Forest fires

Ants

**Retail payments** 

Yes. To understand them, it is better to simulate.











- Large number of individuals (i.e., agents)...
- That interact and adapt or learn...
- With the **emergent (aggregate) behavior** neither explained nor predicted by individual behavior...
- Which commonly show several features, such as
  - Path dependence (i.e., particularly sensitive to changes in initial conditions)
  - **Non-linearity** (i.e., size of input change is unrelated to size of output change)
  - **Self-organization** (i.e., without an authority, the system tends to organize)
  - May display phase transitions (i.e. tipping points)
  - Do not operate under equilibrium

This is why top-down approaches are not very helpful to understand the adoption of an rCBDC—or other type of digital currency.



## **Anything in common?**







One good way to model them is Agent Based Models (ABM).

They comply with the four key assumptions of ABM:





 Agents are interdependent: agents are influenced by other agents and by the environment



 Agents are adaptive and backward-looking: agents adapt by learning from their history





### **Agent-Based Models in Money & Banking**



No death, a presentation and of the intending parties is shown it a delign expension of the control of the intending parties is shown it a delign expension of the one of a Popular sign in the control of the control of the one of the parties in the control of th having a characteristic size. A global liquidity market substantially climinishes congestion, requiring only a small fraction of the payment-induced liquidity flow to achieve strong beneficial effects.



This paper lays out and simulates a multi-agent, multi-period model of an RTGS payment system. At the beginning of the day, banks choose how much cestly liquidity to allocate to the settlement process. Then, they use it to execute an exogenous, random stream of payment orders. If a bank's liquidity stock is depleted, payments are quosed until new liquidity antwest from other banks, imposing costs on the delaying benis. The paper studies the equilibrium level of liquidity posted in the system, performing some companies estatics and obtaining; il a liquidity demand curve which links liquidity dotaley costs and il) insights on the efficiency of alternative systems. An agent-based model of payment systems





RANK OF ENGLAND Staff Working Paper No. 619 Macroprudential policy in an agent-based model of the UK housing market Rafa Baptista, J Doyne Farmer, Marc Hinterschweiger Katie Low, Daniel Tang and Arzu Uluc



Working Paper Series Grzegorz Halej Agent-based model of system-wide implications of funding risk

#### BANK OF ENGLAND

Staff Working Paper No. 809 System-wide stress simulation David Aikman, 15 Pavel Chichkanov, 17 Graeme Douglas, 15 Yordan Georgiev, H James Howat F and Benjamin King F

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JEL classification: G18, G21, G22, G23.

2006







2018





Congestion and Cascades in Payment Systems

**FRBNY** 

Walter Beyeler Kimmo Soramäki Robert Glass Morten Bech

An agent-based model of payment systems

> BoE Marco Galbiati Kimmo Soramäki

Exploring ABM for the analysis of payment systems

Bol

Luca Arciero Claudia Biancotti Leandro D'Aurizio Claudio Impenna Macroprudential policy in ABM of the UK housing market

BoE

Rafa Baptista J Doyne Farmer Marc Hinterschweiger Katie Low Daniel Tang Arzu Uluc

ABM of system-wide implications of funding risk

**ECB** 

Grzegorz Hałaj



BoE

David Aikman Pavel Chichkanov Graeme Douglas Yordan Georgiev James Howat Benjamin King

### Agent-Based Models in Money & Banking



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Kry words Systemic risk, stress testing, financial contegion, financial institutions, capital requirement macrogradential policy.



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### Agent-Based Simulation of Central Bank

Digital Currencies\*

Amanah Ramadiah<sup>1</sup>! Marco Galbiati<sup>2</sup>, and Kimmo Soramāki<sup>1</sup>

<sup>1</sup> Pinauciai Network Analysius Liel

<sup>2</sup> Sapp Global

November 9, 2021

### UNIVERSITY OF TWENTE. Adoption and Implications of CBDC: An Agent-Based Modelling.

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Foundations of system-wide financial stress testing with heterogeneous institutions **BoE** 

J Doyne Farmer

Alissa M Kleinnijenhuis Paul Nahai-Williamson Thom Wetzer Macroprudential policy analysis via ABM of the real sector

Bol

Gennaro Catapano Francesco Franceschi Michele Loberto Valentina Michelangeli Agent-Based Simulation of Central Bank Digital Currencies FNA

> Amanah Ramadiah Marco Galbiati Kimmo Soramäki

Adoption and implications of CBDC: an agent-based modelling approach

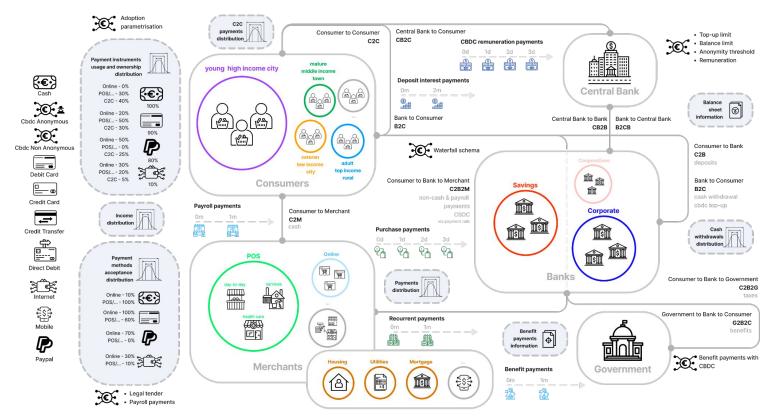
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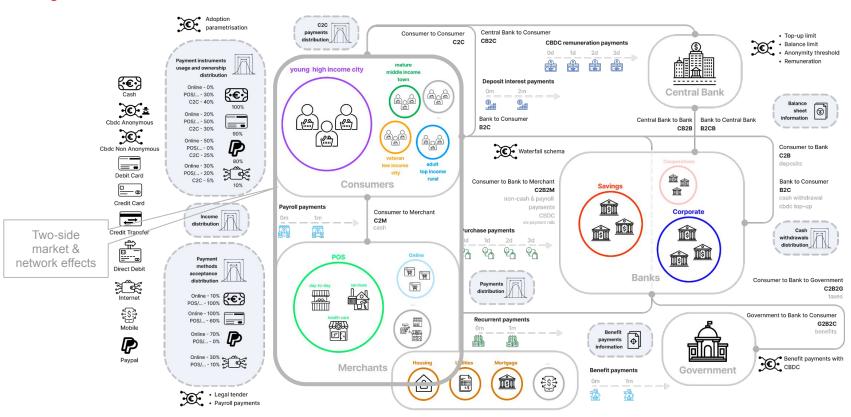
IMF Marco Gross Elisa Letizia Simulating the Adoption of a rCBDC FNA

Carlos León José Morenoi Kimmo Soramäki

# rCBDC ABM: consumer, merchant and bank personas provide heterogeneous decision-making and get us closer to the payment ecosystem



# rCBDC ABM: consumer, merchant and bank personas provide heterogeneous decision-making and get us closer to the payment ecosystem



# **CBDC Simulation Inputs**



### Payments statistics, surveys, diaries

Distribution of number and amount of retail payments



### Payment instruments acceptance

Merchants' acceptance ratio of payment instruments



#### **Income distribution**

Income distribution in your economy, e.g GDP per capita, Gini distribution, household surveys



#### Banks' statistics

Aggregated balance sheet information, assets returns, deposits interest rate



### Payment instruments usage

The proportion of transactions that are settled in different payment instruments



### **Policy instruments**

CBDC top up, balance and anonymity limits, CBDC two-tier interest rate, scenarios configuration

### **CBDC Simulation Inputs - What info do you need?**





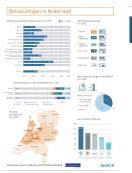












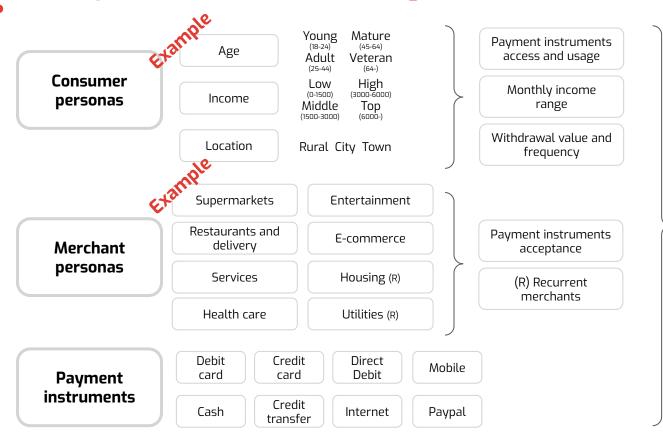






2022年3月 一般社団法人キャッシュレス推進協議会

### Main Inputs – to calibrate and configure



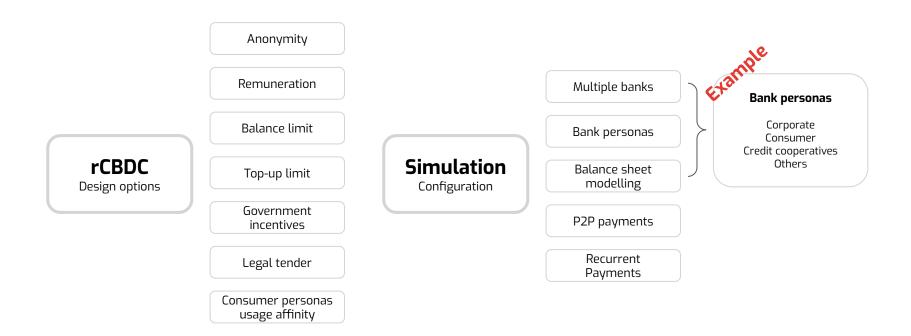
#### Retail payments data

Distribution of payments value per merchant (and consumer) persona

Distribution of payments number per merchant (and consumer) persona

Payment instrument usage weight per consumer (and merchant) persona

### rCBDC design and simulation configuration options



### **CBDC Simulation Scenarios**



### **Merchant adoption scenarios**

Legal tender scenario Two-side market adoption Merchants payments with CBDC?



### **Consumer adoption scenarios**

Privacy and anonymity
Government or Central bank incentives
Merchant incentives



#### **CBDC** balance sheet scenarios

CBDC waterfall behaviour Merchants CBDC holdings Banks CBDC holdings



#### **Disintermediation scenarios**

CBDC balance and topup limits
CBDC two-tier (or not) remuneration rate



### **CBDC** topup scenarios

Income/salary transfer to CBDC Cash-like CBDC topups



#### **Commercial bank balance sheet scenarios**

Driven by margin
Driven by solvency
Central Bank facilities

# **CBDC Simulation Outputs**



### **Adoption rate**

The pace at which CBDC is acquired and used by the public (financial inclusion effect)



### Composition of consumers' wealth

The amount of asset, cash, CBDC, deposit in consumers' portfolios



### Diffusion of payment instruments

The proportion of transactions that are settled in card, cash, or CBDC



### **Banking disintermediation**

The amount of bank deposits that are migrated to CBDC.



### Banks balance sheet

The composition of asset side (e.g., reserves, cash) and liability side (e.g., deposits)



### Scenario analysis

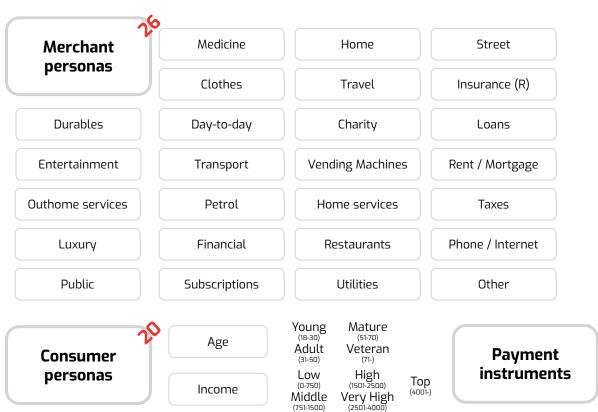
Comparing the impact of different design choices and initial conditions

# rCBDC Spanish market adoption





### **ECB Space Survey Data**



(751-1500)

EUROPEAN CENTRAL BANK Study on the payment attitudes of consumers in the euro area (SPACE) -December 2022

Credit

transfer

Direct

Debit

**CBDC** 

anon.

Cash

Cards

Paypal

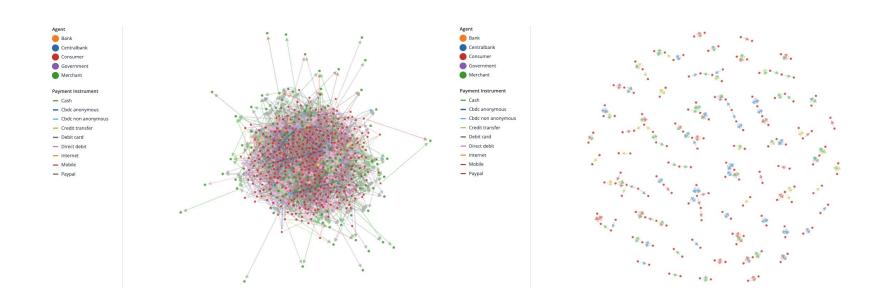
Mobile

Internet

CBDC

non-an.

### **C2M** and **C2C** networks



Extracted from the 180th day of the basic scenario simulation.

# Scenarios

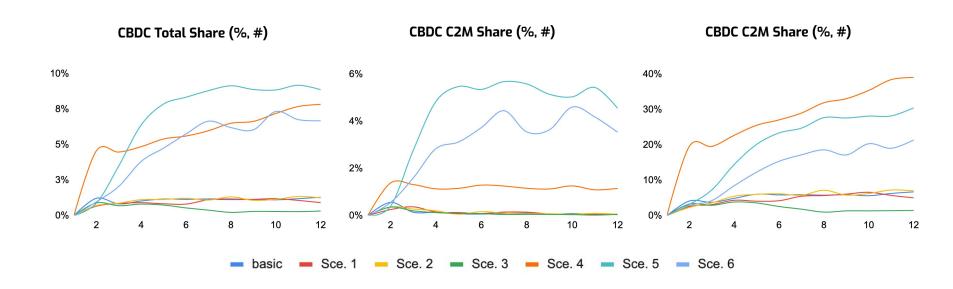
Design options	Baseline	Basic	Sce. 1	Sce. 2	Sce. 3	Sce. 4	Sce. 5	Sce. 6
Legal tender	NA	Yes						
Balance limit	NA	€3,000	€3,000	€3,000	€3,000	€3,000	€3,000	€1,000
Top-up limit	NA	NA	€500	NA	NA	NA	NA	NA
Anonymity threshold	NA	00	∞	€200	∞	∞	∞	∞
Reverse Waterfall	NA	Yes	Yes	Yes	No	Yes	Yes	Yes
Government benefits	NA	NA	NA	NA	NA	Yes	NA	NA
Remuneration spread	NA	NA	NA	NA	NA	NA	Yes	Yes

# Adoption Scenarios Comparison

Scenario	Cash	rCBDC		Cards	Credit transfer	Direct debit	Internet	Mobile	Paypal
		anonymous	non-anon.		transier	uebit			
Baseline	24.77%	0.00%	0.00%	46.93%	5.34%	6.80%	0.03%	13.41%	2.71%
Basic	25.08%	1.29%	0.00%	45.87%	5.19%	6.41%	0.02%	13.73%	2.40%
1	23.34%	0.91%	0.00%	47.06%	5.03%	6.60%	0.01%	14.29%	2.75%
2	25.64%	1.23%	0.02%	46.46%	4.70%	6.68%	0.00%	12.76%	2.51%
3	27.20%	0.32%	0.00%	44.50%	3.91%	6.48%	0.01%	15.08%	2.50%
4	10.93%	7.84%	0.00%	49.06%	5.76%	7.59%	1.14%	13.98%	3.70%
5	29.62%	8.88%	0.00%	39.61%	4.09%	5.48%	0.00%	10.41%	1.92%
6	28.67%	6.68%	0.00%	41.00%	4.27%	5.99%	0.02%	11.41%	1.95%

Payments made during the last month of the simulation, as per cent of the number of payments.

### **Adoption Scenarios Comparison**



# Main takeaways

- Simulating rCBDC adoption can help central banks to iterate design options.
- Without attractive design features or stimulus policies we found low adoption of rCBDC in the Spanish retail payments ecosystem.
- Reverse waterfall functionality, government payments, and positive remuneration spread can increase rCBDC adoption.
- Balance limits, top-up limits effective to restrain rCBDC adoption.
- In general, rCBDC won't compete with cash but with deposit-related payment instruments—unless the government fosters targeted use of rCBDC

# **Future Work**





## **Future work**

- Explore more scenarios with different combinations of design options and stimulus policies.
- Study the adoption of rCBDCs in different jurisdictions.
- Analyze results by consumer and merchant personas.
- Explicitly model commercial banks' balances and make them adaptive decision-makers.
- Enhance the model by calculating confidence intervals, using data about the costs of holding forms of money, and testing other network-generating models.
- Model M2M payments.





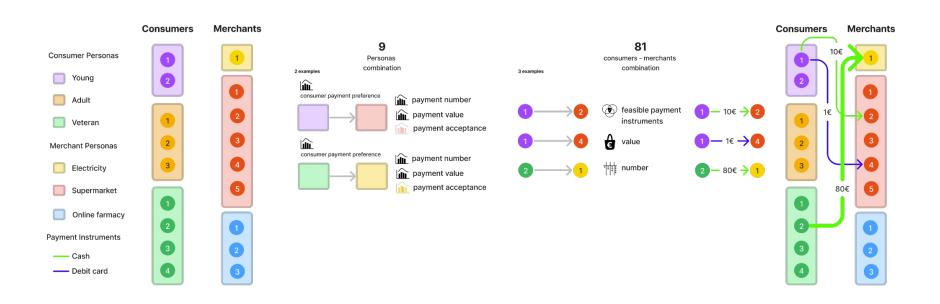


**Agent-based simulation of rCBDC adoption**Details (Appendix)





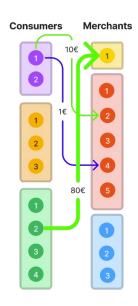
### The consumer and merchant decision making process – C2M network generation

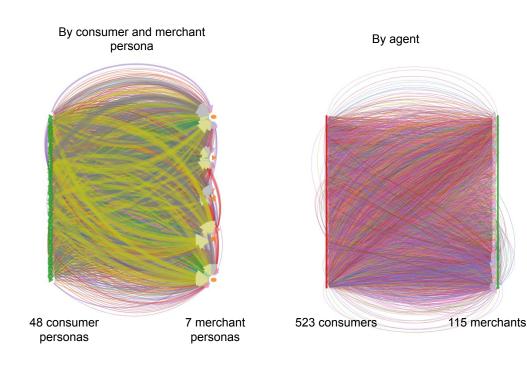


### The consumer and merchant decision making process - C2M network generation

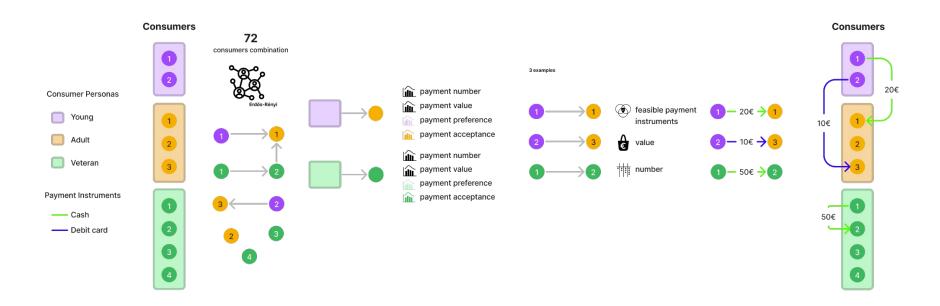
Example

**CBDC Simulation Actual Result** 

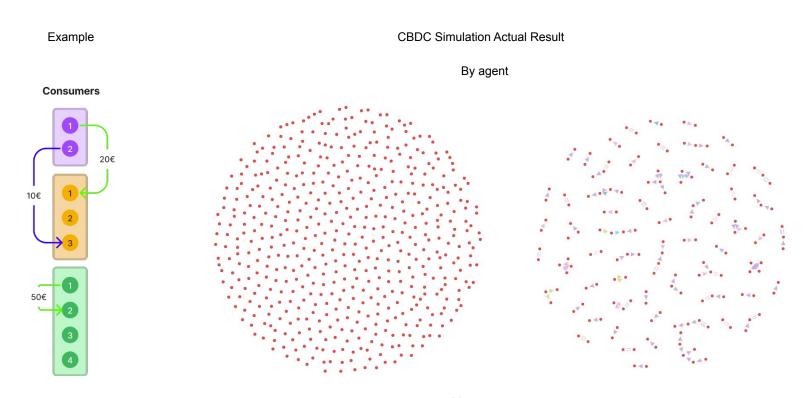




### The consumer and consumer decision making process – C2C network generation



### The consumer and merchant decision making process - C2C network generation



523 consumers 159 connected consumers

### **Consumers initialisation**









Income  $\rightarrow$  4350€ Cash  $\rightarrow$  25€ Benefits  $\rightarrow$  43.5€ Salary  $\rightarrow$  4306.5€



# **Monthly payments**

Consumer recurrent, merchant payroll, and banks deposit interest payments

### **Initialisation Info**







By recurrent merchant persona

min median mean max 1 2 2 5 number per month **Benefits** → 43.5€ **Salary** → 4306.5€

#### Mechanics

Payroll Payer → POS merchant 3 × Recurrent payments\*

→ day: 2, value: 300€, merchant: utilities 1→ day: 3, value: 100€, merchant: utilities 3

→ day: 1, value: 1500€, merchant: housing 1

TOTAL: 1900€













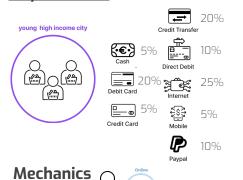


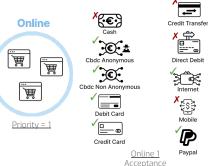


<sup>\*</sup> Prioritised payments. No default allowed. It means consumers always pay and save money for making these payments.

### Daily purchase payments Selected payment instrument

### Payment Info







→ value: 20€, merchant: online 1 → value: 40€, merchant: online 5

### Feasible Payment Instruments\*









### **Budget check**

→ 20€ ≤ 2450€ (budget) ✓

### Payment instrument\*

→ 20€ ≤ 4325€ (deposits) ✓





value per transaction min median mean

number per day

max

median mean

40€ 50€

max

2000€

#### consumer\*\* persona **Assets** → 4350€

- → Deposits: 4325€
- → Cash: 25€

**Recurrent payments** → 1900€ **Budget** → 2450€

#### **Transaction**

- → from: consumer Y-HI-C 1
- → to: merchant online 1
- → value: 20€
- → payment instrument: internet
- → status: completed
- → type: purchase

Assets C → 4330€ Assets M → +20€

- → Deposits: 4305€ → Deposits: +20€
- → Cash: 25€ → Cash: N€







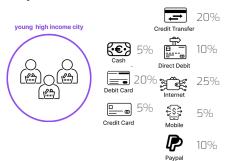


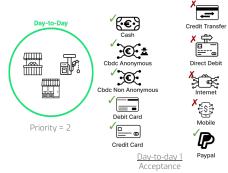


### Daily purchase payments

Multiple payment instruments transfer

### **Payment Info**







median mean max 40€ 50€ 200€ value per transaction

min median max mean 6 By merchant persona number per day

#### Assets → 50€

p.e. Online

- → Deposits: 25€
- → Cash: 25€

**Recurrent payments** → paid **Budget** → 50€

### merchant persona **Payments**

Mechanics\*

per consumer and

→ value: 40€, merchant: day-to-day 2 → value: 2€, merchant: day-to-day 5

#### Feasible Payment Instruments (1)











→ 40€ ≤ 50€ (budget) ✓

### **Payment instrument**

→ 40€ ≤ 25€ (deposits) **X** 



#### Transaction 1

- → from: consumer Y-HI-C 1
- → to: merchant day-to-day 2
- → value: 25€
- → payment instrument: debit card
- → status: completed
- → type: purchase

#### Transaction 2

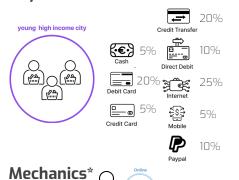
- → from: consumer Y-HI-C 1
- → to: merchant day-to-day 2
- → value: 15€
- → payment instrument: **cash**
- → status: completed
- → type: purchase

#### **Assets C** → 10€ Assets M $\rightarrow$ +4 $\cap$ €

- → Deposits: O€
- → Cash: 10€
- → Deposits: +25€
- → Cash: +15€

### Daily purchase payments Money transfer

### **Payment Info**







median mean max 2000€ 40€ 50€ value per transaction

min median max mean number per day

**Assets** → 350€

p.e. Online

→ Deposits: 325€

→ Cash: 25€

**Recurrent payments** → paid **Budget** → 350€

#### **Payments**

per consumer and merchant persona

> → value: 350€, merchant: online 1 → value: 100€, merchant: online 5 X

### Feasible Payment Instruments (1)











#### Transaction 1

- → from: consumer Y-HI-C 1
- → to: consumer Y-HI-C 1
- → value: 25€.
- → payment instrument: cash

→ Deposits: O€

- → status: completed
- → type: deposit top-up

→ Cash: O€

#### Transaction 2

- → from: consumer Y-HI-C 1
- → to: merchant online 1
- → value: 350€
- → payment instrument: debit card
- → status: completed
- → type: purchase

Assets C → N€ **Assets M** → +350€

- → Deposits: +350€
- → Cash: O€



→ 350€ ≤ 350€ (budget) ✓

### **Payment instrument**

→ 350€ ≤ 325€ (deposits) X



### **C2C Network**



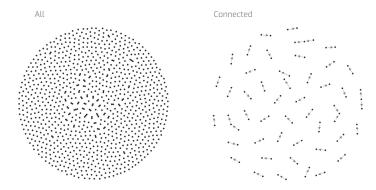


### Erdős-Rényi network model

#### for consumer in consumers:

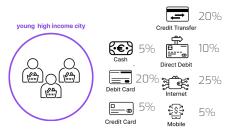
- → if consumer ≠ Y-HI-C 1:
  - → if random.uniform(0, 1) ≤ **network density**:
    - → add consumer to my c2c network

**Consumers number** → 1000 **Network density** → 0.00005



### **Daily C2C payments**

### **Payment Info**











min median mean max  $10 {\in} 40 {\in} 50 {\in} 2000 {\in}$  value per transaction

min median mean max 1 2 2 5 number per day

**Assets →** 4350€

→ Deposits: 4325€

→ Cash: 25€

**Recurrent payments** → 1900 $\in$  **Budget** → 2450 $\in$ 

### **Mechanics**\*

per consumer bounded by her c2c network



#### **Payments**

→ value: 10€, consumer: A-TI-R 2 → value: 25€, consumer: Y-HI-C 5

### Feasible Payment Instruments\*











10%

### Budget check

→ 10€ ≤ 2450€ (budget) ✓

### Payment instrument\*

→ 10€ ≤ 4325€ (deposits) ✓



#### **Transaction**

- → from: consumer Y-HI-C 1
- → to: consumer A-TI-R 2
- → value: 10€
- → payment instrument: paypal
- → status: completed
- → *type:* purchase

**Assets Y-HI-C 1** → 4340€ **Assets A-TI-R 2** → +10€

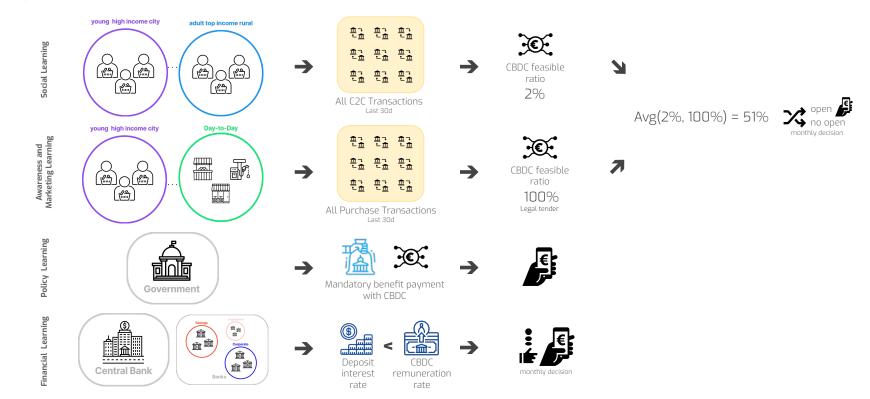
- → Deposits: 4315€
- → Deposits: +10€

→ Cash: 25€

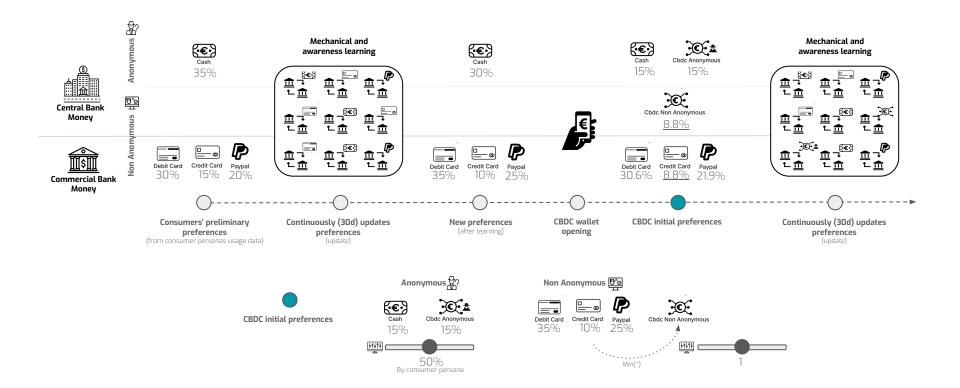
→ Cash: +0€



### **Consumers opening a CBDC wallet**



### **Payment instruments preferences and CBDC adoption**



### CBDC details

### First top-up\*

**Assets** → 4350€

→ Deposits: 4325€ → Cash: 25€

**CBDC** → 555.43€

→ Deposits: 4325€ × **12.55%** = 542.93€

→ Cash: 25€ × **50%** = 12.5€

Cbdc Anonymous Of anonymous payment Cbdc Non Anonymous instruments

8.8%

→ 12.55% Of non anonymous payment instruments

### Top-ups\*

**Frequency** → As cash withdrawal

- → Daily
- → Weekly
- → Consumer persona







Completed with

CBDC value

(last frequency transactions)

#### First attempt with CBDC failed value

(last frequency transactions

### **Anonymity**

Threshold → O€

→ completely non anonymous

Threshold → ∞€

→ completely anonymous

#### Threshold → 200€

- → if transaction value > 200€ → Code Non Anonymous

→ if transaction value ≤ 200€ → Chide Anonymous



### Top-up limit

**Balance limit** 

\*Limits

- → max top-up value
- → subject to balance limit

→ max CBDC account balance value

→ waterfall behaviour (e.g. salary > limit)

### Remuneration

Daily remuneration to avoid default in the negative remuneration scenario























remuneration

decision scenario