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ON THE PAYMENTS EVOLUTION WITHIN THE TWO-CURRENCY MONETARY SYSTEM

1. **Model.** The proposed model was inspired by the methodology of the Agent-based modelling [1].

The paper deals with the evolutionary aspects of trading in a network that uses two different payment systems: (i) traditional US dollar payments and (ii) Cryptocurrency payments. The Cryptocurrency is profitable if compared to the US dollar; however, the dollar payments are more traditional. We focus on the evolutionary aspects of the payments if traders are organised in a fixed free-scale network.

List of parameters and variables	
	Description
V	set of Traders
E	set of prospective trading relations
i	Buyer (Z *EV)*
j	Seller *(j E V)*
κ	Trader in general meaning (Buyer or Seller), *(k EV)*
NW	set of the Ath Trader neighbors
MW°	function assigning No of monetary units of type (.) to Ath trader
s(k)	strategy of trader *k, (s(k) E {USD, Crypto})*
FW	payoff function of Ath trader in one period of time
0	parameter of USD to Crypto exchange rate
П/	number of trades of the /th trader
F{k)	strategy flipping function: random strategy (F = 1), repeat last strategy *(F* = 0)

1.1. Trading Network.

Let $V= \{1, 2,..., v\}$ are the trading partners. Set

E = {{>. j} l*> J Є K there exists relation between z and $j\}$ describes a set of prospective traning relations between the trading partners. Then, $G = [V, E]$ characterizes a trading network. The roles of Buyer / Seller are fully interchangeable during the simulation.

1.2. Trader, trading partners, trading interaction.

To improve the readability of the text, we introduce the following conventions. A Trader is any agent $\kappa \in V$ without considering its trading role. The Trader plays the role of a Buyer denoted by an index z Є Tor a Seller denoted by/ Є V. Each trader $\kappa \in V$ has prospective trading partners in its neighbourhood $N(k)$ S V in network G. Buyer z demands for service by randomly selected trading partner (Supplier) / Є $N(i)$. Both partners have two choices in a one-shot game:

1. US dollar payment;
2. Cryptocurrency payment.

I f there is no concordance between both partners, the trade is cancelled. If they reach a concordance, the trade occurs, and both partners share the added value (payoff) equally. Besides, the traders are endowed with some amount of US dollars $M(k)^{,SD} > 0$ and Cryptos $M(k)^{Cr} > 0$. After the [z,/] trade, Seller z transfers 1 currency unit to the Buyer j, i.e.

M(z)^{0}<- Л/(г)°- 1 and $M(/)^{0}$«- M (/)$^{()}$+1.

and Buyer z decreases and Seller j increases its stock of the currency by 1 monetary unit.

Note: The currency ownership does not bring any payoff to its owner. It just intermediates the payoffs stemming from the trade, and its flow is a necessary condition for the trade. In case a Buyer does not dispose of with the currency it is not involved in any trade and does not receive any payoff.

The trading interaction can be formally described as follows:

1. [z.J] is a pair of trading partners i (Buyer) and/ (Seller) involved into the interaction; (//,// cE);
2. s (z), $s(j) \in$ *{USD, Crypto}* are the strategies of trading partners;
3. The payoff of any trading partner is given as follows:

(/z(z), /z(/) : *{USD, Crypto}* ^{2} -+ {0, 1, *0}* where

$$(\mu(i)=)\mu(j) = \begin{cases} 0 \text{ if } s(i) \neq s(j) \\ 1 \text{ if } s(i) = s(j) = USD \\ \theta \text{ if } s(i) = s(j) = Crypto, \theta > 1. \end{cases}$$

Parameter θ denotes USD to Crypto exchange

1.3. Network dynamics and learning

The dynamics of the network runs in time periods. One period consists of 2(|l^z|-l) one-interaction rounds. In one period of time, Trader z is randomly selected in the role of a Buyer |7V,| times on average. After the selection, the Buyer demands its randomly selected neighbour - a Seller *j* Є *N (i)* for a service. Therefore centrally located traders trade more frequently than the traders with a low degree.

Learning is based on the following assumptions valid for each trader:

1. Trader *κ* selects its strategy *s(k)* in the start of the time period while keeping it constant until its end;
2. Each trader takes into account its liquidity, i.e. pays with the disposable currency;
3. Trader *κ* remembers its previous-period strategy *s(k)*-\.
4. Trader *κ* disposes with information on the previous-period average payoffs of its neighbours E *I* fy]-ifor / Є *N (κ)* and n_t be a number of interactions performed by the /th trader. It also remembers its previous-round average payment, i.e. E I^й *W I* tt/cl-i. If its payoff is not strictly the worst, if comparing with other neighbours in the neighbourhood, it repeats its previous strategy, i.e. its strategy flipping function F(/c) sets zero value. Otherwise, it takes value 1. More formally

$$F(k) \begin{cases} = 0 \text{ if } \left[\frac{\sum \mu(k)}{n_k}\right]_{-1} \geq \min_{l \in N(k)} \left(\left[\frac{\sum \mu(l)}{n_l}\right]_{-1}\right) \\ = 1 \text{ if } \left[\frac{\sum \mu(k)}{n_k}\right]_{-1} < \min_{l \in N(k)} \left(\left[\frac{\sum \mu(l)}{n_l}\right]_{-1}\right) \end{cases}$$

where E ft *(κ)IИκ]-i* and E f^L(0/^ni]-i are the average payoffs (payoffs per interaction) of an trader in the previous round.

In the trading process, the following rules are applied:

1. Payment strategy of Buyer *i*

- If $M(i)^{\prime\prime SD} = 0$ and $M(i)^{Cr} = 0$ then the trade is cancelled (//(/) = *p(j)* = 0);

- if $M(i)^{USD} > 0$ and $M(i)^{Cr} = 0$ then s(z)«- USD;
- If $M(i)^{USD} = 0$ and $M(i)^{Cr} > 0$ then $s(i)$ «— Crypto;
- 1 f $M(i)^{USD} > 0$ and $M(if' > 0$ and F(Z) = 0 then $s\{i)$ <- $s(i)_{4;}$

If $M(i)^{1iSD} > 0$ and $M(i)^{<r} > 0$ and $F(i) = 1$ then choose currency strategy .$■(/) randomly.

2. Payment strategy of Seller *j*

1 f $F(j) = 0$ then $s(f)$ «— .s(/) $i_{;}$

If $F(j) = 1$ then choose currency strategy $s(j)$ randomly.

2. Simulation Results

The simulation analysis consists of two cases. First, we run the simulation with exclusive USD currency to get the reference data to compare with the twocurrency economy. Second, we run the simulation, where the Crypto and USD liquidity is distributed equally among the agents.

The simulation results are introduced in Fig. 1 and Table 2. During the process of the simulation, the differences among the agents' wealth grow. The final wealth distribution is represented in Fig. lb, where the diameters of the circles represent the agents' wealth. On the other side, the average payoffs stay at the same level during the whole simulation. The wealth redistribution among the agents depicts Fig. 2 and Table 2. However, the normalized Herfindahl-I lirschman index achieved 0.012 that is considerably low. On the other side, the average payments stay at the same level during the whole simulation.

(a) Initial situation. (b) Final situation.

Fig. 1. Simulation results of one-curreney USD economy.

Table 1.

Setting of the simulation parameters and selected results.

Parameter / Result	value
Num. of Agents	50
Initial USD	400
Initial Crypto	0
initial HHI	4.8469e-7
final HHI	0.012
Initial avg. payoff	3.92
Final avg. payoff	3.92

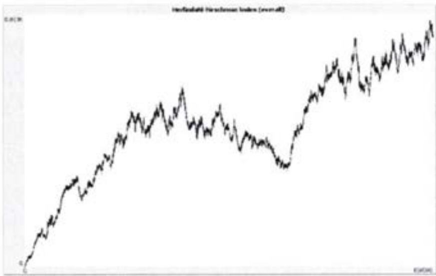

Fig. 2. Evolution of the Herfindahl-Hirschman index in the course of the simulation.

3. Conclusion

The presented research offers a simulation analysis of the payment system using two currencies. The higher profitability of the Cryptocurrency payments is assumed. The agents organized in a scale-free network seek for the most economical strategies to achieve high payoffs. We show that as far as there is no coordination of the system, the network is prone to its desynchronization leading to the problem of the traders' insolvency and low economic activity.

References

1. Farmer J. D. and Foley D. (2009). The economy needs agent-based modelling. Nature, 460 (7256):685.