Economics
The Open-Access, Open-Assessment E-Journal

Vol. 7, 2013-32 | July 29, 2013 | http://dx.doi.org/10.5018/economics-ejournal.ja.2013-32

Money Creation and Financial Instability: An Agent-Based Credit Network Approach

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Abstract
The authors develop a simple agent-based and stock flow consistent model of a monetary economy. Their model is well suited to explain money creation along the lines of mainstream theory. Additionally it uncovers a potential instability that follows from a maturity mismatch of assets and liabilities. The authors analyze the impact of interbank lending on the stability of the financial sector and find that an interbank market stabilizes the economy during normal times but amplifies systemic instability, contagion and bankruptcy cascades during crises. But even with no interbank market, indirect contagion can lead to bankruptcy cascades. The authors also find that the existence of large banks threatens stability and that regulatory policy should target large banks more strictly than small.

Published in Special Issue Economic Perspectives Challenging Financialization, Inequality and Crises

JEL C63 E42 E51 G01
Keywords Financial instability; agent-based macroeconomics; stock-flow consistency; disequilibrium analysis; Basel II

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Citation Matthias Lengnick, Sebastian Krug, and Hans-Werner Wohltmann (2013). Money Creation and Financial Instability: An Agent-Based Credit Network Approach. *Economics: The Open-Access, Open-Assessment E-Journal*, Vol. 7, 2013-32. http://dx.doi.org/10.5018/economics-ejournal.ja.2013-32

Received November 22, 2012 **Published as Economics Discussion Paper** December 4, 2012
Revised April 2, 2013 **Accepted** July 24, 2013 **Published** July 29, 2013

1 Introduction

The recent crisis has vividly demonstrated that the stability of the banking sector is highly important for the stability of the economy as a whole. A collapse of single banks can have severe and long lasting negative effects on other banks and on the real economy. To shed light on the instability of the banking sector, we develop an agent-based computational economic (ACE) model that covers the monetary side of transactions among households, firms and banks. We are able to show that systemic risk is inevitably interwoven with the creation of money in the credit market and, thus, an intrinsic property of modern economies.

The creation of systemic risk in the banking sector has been subject to numerous research projects in the aftermath of the financial crisis. Battiston et al. (2012) have developed an ACE model of a dynamic credit network. The authors have built on a system of stochastic differential equations and show the existence of a destabilizing financial accelerator. In another related research project Tedeschi et al. (2011) have developed a three sector ACE model that includes the credit sector but also a real sector. The authors have found that credit connections between banks have no impact on GDP but create systemic risk. In line with these findings Lenzu and Tedeschi (2011) have analyzed an interbanking network and have found that the network structure plays an important role for the stability of the system. In a very recent paper, Krause and Giansante (2012) have developed a network based interbanking model and analyzed its stability by letting one bank fail exogenously. They also found that the network structure plays an important role in producing systemic risk and that the probability of observing a cascade is positively correlated with the size of the initially shocked bank.

What is novel in our approach is that individual interactions give endogenously rise to an interconnected banking sector which creates systemic risk and bankruptcy cascades. We show that maturity mismatches (Bank of England 2011, Milne 2013) between different assets and liabilities are a driving force that, first, build up systemic risk and, second, trigger financial crises endogenously. An exogenous depreciation of assets (e.g. burst of bubble) is not needed to trigger a crisis.

In the literature on stock-flow consistent (SFC) modeling it has been argued that the key to understand the recent economic crisis is debt growth. In line with the invocations of Arnold (2009), Bezemer (2010, 2012b) and Caverzasi and Godin

(2013) for an *accounting of economics* we implement SFC as the *accounting part* to our model of the credit sector to investigate the potential contribution of SFC to ACE macroeconomics. Formally, we follow the definition of Patterson and Stephenson (1988) whereupon each flow induces a change of stocks of equal size.[1] In an ACE model SFC simply assures that transactions are consistently accounted for in a double-entry bookkeeping system. A difference to "standard" SFC (Lavoie and Zezza 2012) models is that we compute the balance sheet for every single agent (microscopic level) instead of only consolidated balance sheets for every type of agents (aggregate level). Therefore, we can dispense with the usual (consolidated) matrix notation.

The paper is organized as follows. Section 2 gives a short overview over the current state of ACE macroeconomics. The model is defined in Section 3. A simulation that illustrates the endogenous creation of money is performed in Section 4. Section 5 introduces an interbank market. Simulations of this extended model are presented in Section 6. Section 7 introduces an active central bank that offers standing facilities and analyzes the impact of regulatory policy. Section 8 concludes.

2 The ACE Method

A method that seems well suited for the analysis of endogenous crises is ACE modeling.[2] ACE models can be understood as the simulation of artificial worlds that are populated by autonomous interacting agents. Every agent is equipped with properties describing his internal state and with behavioral rules that guide its interaction with others. Once created, the artificial economy is left alone and agents interact according to the defined rules. Instead of solving a system of equations, the model is simply run. Aggregate statistics like the price index or GDP can then easily be calculated from the resulting individual dynamics.

[1] Consult the definition in Patterson and Stephenson (1988), p. 189. Another, related definition can be found in Taylor (2008).

[2] Axtell (2007), Colander et al. (2008), Keen (2009), Kirman (2010), Delli Gatti et al. (2010).

One strength of the ACE method is that no assumptions about the macro level are necessary. The passage from micro to macro is created by interaction and not by assuming a representative individual or by summing up heterogeneous individual decisions and equilibrating aggregate supply and demand on *the market* for labor, goods, money and so on. All observed regularities of the aggregate variables are, therefore, endogenously emerging from micro assumptions and micro interactions. With our ACE model we can, thus, analyze the banking sector as a large decentralized economic system. We are able to answer how agents, which are not endowed with unrealistically high information processing capacities (Ackerman (2002), Gaffeo et al. (2008), Fair (2009), Kirman (2010)), can coordinate so well through the market mechanism without any central clearing device or auctioneer and, more importantly, why this coordination brakes down from time to time.

The major weakness of ACE models is that the modeler is left with enormous degrees of freedom in choosing the types of agents, their behavioral rules and the structure of markets. Consequently, the few ACE macro models that exist are very different in nature, since they start with very different assumptions and employ very different ways of modeling. Additionally, it is easy to deal with enormous complexity. ACE modelers are, thus, tempted to over-increase the level of complexity in their models (i.g. add too much types of agents, behavioral rules, special cases for a certain interaction, ...). As a result, the available ACE macro models are often so complex that it is unclear which macro pattern is a result of what micro property. Models appear as black boxes where the passage from input to output is not fully clear.[3]

In the present paper we address this criticism by keeping the model as simple as possible. The number of different types of agents and different behavioral rules are kept as small as possible. Following Gode and Sunder (2004), Ussher (2008)

[3] Fagiolo and Roventini (2012) put it as follows: "*The more one tries to inject into the model 'realist' assumptions, the more the system becomes complicate to study and the less clear the causal relations going from assumptions to implications are.*" The authors call this problem *over-parameterization*. They offer a detailed discussion of the pros and cons of ACE and some possible guides to assumption selection that prohibit over-parameterization.
A similar point is made by Farmer et al. (2012) who argue that the fundamental question for ACE economics is how aggregate macro behavior emerges from heterogeneous interacting individuals at the micro level. This question can be addressed with *stylized* ACE models.
Consult also Caverzasi and Godin (2013) who highlight on the didactical use of *simple* SFC models.

and Chen (2012) we assume that our agents are of the zero intelligence type (ZIA). This assumption allows to create a benchmark which isolates the effect of market rules on market outcomes independent of the influence of agent's strategic response to new information.

3 The Model

In this section we present a formal description of our model. Although the following presentation is already very detailed, we have to leave out some minor important aspects that are only intended to make the graphical animation more convenient. The full source code is available upon request. The model description follows the ODD (Overview, Design concepts, Details) protocol.[4]

3.1 Overview

Purpose

Our aim is to build a very simple model that concentrates on the monetary side of transactions. Although simple, our model creates a complex interrelated network of financial claims. This network of claims necessarily produces inherent instability and the threat of deep crises. Since our model has a natural equilibrium benchmark in standard theory, it is well suited to contrast SFC/ACE models with the mainstream approach.

Entities, State Variables and Scales

The artificial environment is populated by three different types of agents: banks (BA), households (HH) and a central bank (CB). HHs in our setting are interpreted as representatives of the complete real sector and, therefore, also have characteristics that are typically ascribed to firms:[5] they buy goods but also produce them,

[4] The ODD protocol has been developed to standardize the presentation of ACE models. The full description can be found in Grimm et al. (2010).

[5] Such *yeoman farmer* assumptions are not unusual as a theoretical approximation, e.g. compare the NOEM approach of Obstfeld and Rogoff (1996).

they save but also take loans. We index BAs by the subscript $b = 1,\dots,B$ and HHs by $h = 1,\dots,H$ where we set $B \ll H$. BAs and HHs are characterized by their positioning on a two dimensional landscape. Space plays a minor role in the model. It is used as a tool to provide random matching and to introduce frictions.

The CB is introduced to close the system from an accounting point of view. For simplicity, we start with assuming that there are no repo operations or standing facilities.

As a result, the CBs' assets are fixed throughout the entire simulation. We denote this exogenously given value by A^{cb} which can be set to any positive value without changing the simulation results and might be interpreted as gold reserves. These assumptions will be relaxed in Section 7.

The most important state variable that characterizes BAs and HHs is *cash* (C). It is the only medium of exchange, i.e. all transactions have to be payed with cash. We explicitly model every single agent's balance sheet at every point in time.[6] In this balance sheet C is recorded on the *assets*' side. Each agent can also possess claims on the cash of other agents. We denote claims of HHs against BAs with D (for deposits) and claims of BAs against HHs with L (for loans). Obviously, D is recorded as an asset in the HHs balance sheet and as liability in that of BAs, *vice versa* for L. The balance sheet structure is exemplified in Sheets 1 - 3.

Sheet 1: Example HH h

Assets	Liabilities
Cash	Loan Bank
C^h	L^h
Deposits	
D^h	
	Equity
	E^h

Sheet 2: Example BA b

Assets	Liabilities
Cash	HH Deposits
C^b	D^b
Reserve	
R^b	
Credits	
L^b	Equity
	E^b

Sheet 3: Central Bank (CB)

Assets	Liabilities
Gold	Currency
A^{cb}	C^{cb}
	BA Deposits
	R^{cb}
	Equity
	E^{cb}

[6] Compare Cincotti et al. (2010) for a detailed description of the implementation of accounting in a large scale ACE model.

Each BA is required to deposit required reserves at the CB (denoted by R). Required reserves R^b are a claim of b against the CB. We assume that a BA can, immediately and at any height, convert R into C and *vice versa*. This assumption accounts for the fact that transactions between private banks and the central bank are carried out much faster and for smaller time horizons (e.g. overnight) than transactions with the real sector. The *liquidity reserves* of BAs are, therefore, given by $F^b = C^b + R^b$ while those of HHs are given by C^h. We denote the corresponding CB positions $C^{cb} + R^{cb}$ the *monetary base* (M_B).

For simplicity, we assume that every HH can only have claims against one given BA (this BA is denoted $b^{D,h}$) and only one BA (denoted by $b^{L,h}$) can have claims against him. This simplification reflects the fact that most HHs are customers of a very limited subset of BAs and do not lend money from/to the entire set of BAs.[7] As long as more than one BA exists, we assume $b^{D,h} \neq b^{L,h}$, i.e. h places his deposits and takes credits from different BAs. Otherwise, the two positions D and L would partially cancel out against one another. We further assume, for simplicity, that $b^{D,h}$ and $b^{L,h}$ do not change during one simulation.

Following the standard financial reporting rules of the FASB[8], equity positions E^b, E^h and E^{cb} are given by the residual between assets and liabilities (= net worth). All entries – except for equity – have to fulfill a non-negativity constraint. The sum of all individual changes in assets has to equal that of liabilities. We can use this property to check whether all accounting operations have been performed correctly, i.e. we will check that $\sum\limits_h dE^h + \sum\limits_b dE^b + dE^{cb} = 0$ in each time step.

For the ease of exposition, we make use of the common assumption that the interest rate equals zero.[9] We further assume that all BAs equity is initially zero $\left(E^b = 0 \ \ \forall\, b\right)$. E^b will remain unchanged because the interest rate is assumed to be zero.

[7] Battiston et al. (2012) have noted that credit networks are generally incomplete, i.e. not fully connected (p. 2).

[8] "*Equity or net assets is the residual interest in the assets of an entity that remains after deducting its liabilities.*" (Financial Accounting Standards Board, 1985, p. 21).

[9] This assumption is common in most macroeconomic ACE models, e.g.: see Russo et al. (2007) and Gaffeo et al. (2008) for the rate on savings. It could, however, be interesting for future versions of the model to relax this assumption. E.g. the effects of a positive lending rate on distributional effects between different sectors can be studied in a dynamic context.

Process Overview and Scheduling

In our setting, time necessarily comes in discrete steps. To come as close as possible to the ideal of continuous time, we scale down the length of these time steps by so much that the model becomes practically continuous. In each (infinitesimal small) time step, the agents are allowed to make decisions and act.

We assume that agents try to achieve a constant ratio between certain positions of their balance sheet, e.g. keep cash in a given relation to deposits. Whenever this relationship is not matched, they take actions in order to reestablish it. In each time step, we check for the state of every agent and assign one mode to it depending on the relations of its balance sheet positions. The mode in turn determines the actions the agent undertakes.

3.2 Design Concepts

Basic Principles

The basic principle underlying our model is the creation of money. If money is defined as the sum of cash and deposits owned by HHs, it is created both by the central bank (via the monetary base) and by the banking sector (via debt/loan contracts). In equilibrium, the money amount is a multiple of the monetary base. This property of money is well known. But instead of simply deriving the equilibrium outcome, we show that the equilibrium-benchmark is the long run result of a disequilibrium process composed of individual interactions.

Emergence

We will only model interactions among individuals in an explicit way: for every single transaction, we impose a flow of cash from one specific agent to another. This is also true if a loan is granted from a BA to a HH.[10] Each flow is accounted for in the balance sheets by changing the agents' stocks and maybe creating a claim

[10] Implicitly, we assume here that a HH who picks up a loan receives this loan in cash. Alternatively, one could, at first, increase the HH's deposits and then convert them into cash (which is needed to buy goods). For simplicity, we refrain from the latter method since, although it is equivalent to the first method in the end, it requires more transactions. Additionally, it is unnecessary to invoke

of one against the other. We do not assume the existence of a credit market with a given set of properties (like equilibrium or monopolistic competition). We can, however, interpret the sum of all individual credit contracts as *the credit market*. This market is an *endogenous* object growing out of individual transactions. It has endogenous properties founded in micro interactions.

Adaptation

The agents in our model act to achieve a given relation between certain positions in their balance sheet. HHs try to divide their wealth ($C^h + D^h$) into cash and deposits so that they are in a fixed relation to each other. If the wealth of a HH is composed, for example, of a too high share of cash relative to deposits it places further cash in the bank account to match the target relation. BAs are modeled in a similar way. Instead of matching a given C-D-ratio, they have to provide required reserves R^b as a given fraction of deposits D^b.

Objectives

To keep their behavior as simple as possible, we assume that HHs h want to divide their wealth up into C^h and D^h so that

$$C^h = q \cdot D^h \qquad q \in [0,1] \tag{1}$$

holds. Where q is the cash ratio which, for ease of exposition, we assume to be equal among all HHs. BAs, on the other hand, have to obey a reserve requirement according to

$$R^b = r \cdot D^b \qquad r \in [0,1] \tag{2}$$

where r is the reserve ratio set by the CB. Recall that D^b is not the aggregate sum of all HHs' deposits but only of that subset of HHs for whom $b^{D,h} = b$ holds, i.e. sum of all deposits that have been placed at BA b. Since our model is a disequilibrium model, we do *not assume* that (1) and (2) hold. Instead, we will define the agents'

transactions between the BA and CB that would be needed to ensure the reserve requirement (defined below).

behavioral rules such that they strive to arrive at those relationships. It might be possible, however (e.g. after a liquidity shock by the CB), that some agents, temporarily, do not meet (1) or (2), respectively.

Learning

We do not apply a complicate learning procedure for the agents. Instead, we assume, first, that knowledge is generally local, i.e. agents know their own state variables, but not those of others. Second, since the positioning of banks on the landscape is not changing over time, we assume it to be public knowledge. Therefore, HHs do not need to apply a search mechanism to find a BA.

Interaction

Interactions always take place between two agents. Every interaction induces a flow of cash from one agent (say A) to another (B): A's cash entry is reduced by a given amount while B's is increased by the same amount. Some transactions (e.g. buying a good) are directly completed after the flow of cash from A to B. Other types of transactions (e.g. borrowing/lending) consist of the commitment to repay later and, additionally, cause the creation of claims of A against B.

Modeling interactions in such a way assures that all flows between two agents are in line with the change of their stocks (i.e. are SFC[11]). It proves a disciplined way to introduce money into ACE macroeconomics since it obeys a *"fundamental law of macroeconomics analogous to the principle of conservation of energy in physics"*[12].

Stochasticity

Whenever agents are satisfied with their current state, they do not initiate transactions, instead, they take a (stochastic) random walk around the landscape. Regarding interactions, we use pseudo random number generators in two ways. (1) When an agent can choose only one partner to interact with, he decides by picking

[11] A formal definition of SFC can be found in Patterson and Stephenson (1988) or Taylor (2008).
[12] Godley and Cripps (1983), p. 14. Found in Bezemer (2010), p. 682.

randomly. (2) Whenever a BA has excess reserves ($C^b > 0$), it offers loans of the highest possible amount $\Delta L^b = \frac{C^b}{1+r}$. If a HH decides to take a loan from that bank, we determine its demand randomly between the supplied amount $\frac{C^b}{1+r}$ and a small lower bound value close to zero.

Observation

When running the model, we keep track of the balance sheet of every single agent. For all positions that denote a claim of one agent against another, we save the amount of that claim and the two involved agents. Given the set of all individual balance sheets and the way they are interwoven with one another, we can also calculate different monetary aggregates as the respective sum of different individual positions.

3.3 Details

Initialization

At the beginning, all HHs are randomly distributed over the landscape, while BAs are placed evenly (Figure 1). We initialize all balance sheet entries with zero, i.e. there is no money in the economy.

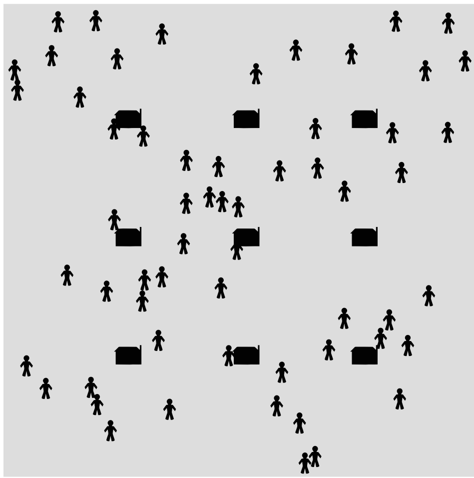
Submodels

A HH's current state of C^h and D^h, straightforwardly, implies three different modes of action:

- HH `mode 0` ($C^h = q \cdot D^h$): desired cash quota holds exactly, no action required.
- HH `mode 1` ($C^h < q \cdot D^h$): not enough Cash, transform D^h into C^h.
- HH `mode 2` ($C^h > q \cdot D^h$): too much Cash, transform C^h into D^h.

If $C^h = q \cdot D^h$ holds for HH h, he enters `mode 0`. In this mode, there is no need for h to initiate any transaction. We illustrate this mode by a random walk around the

Figure 1: Initial distribution of agents in space



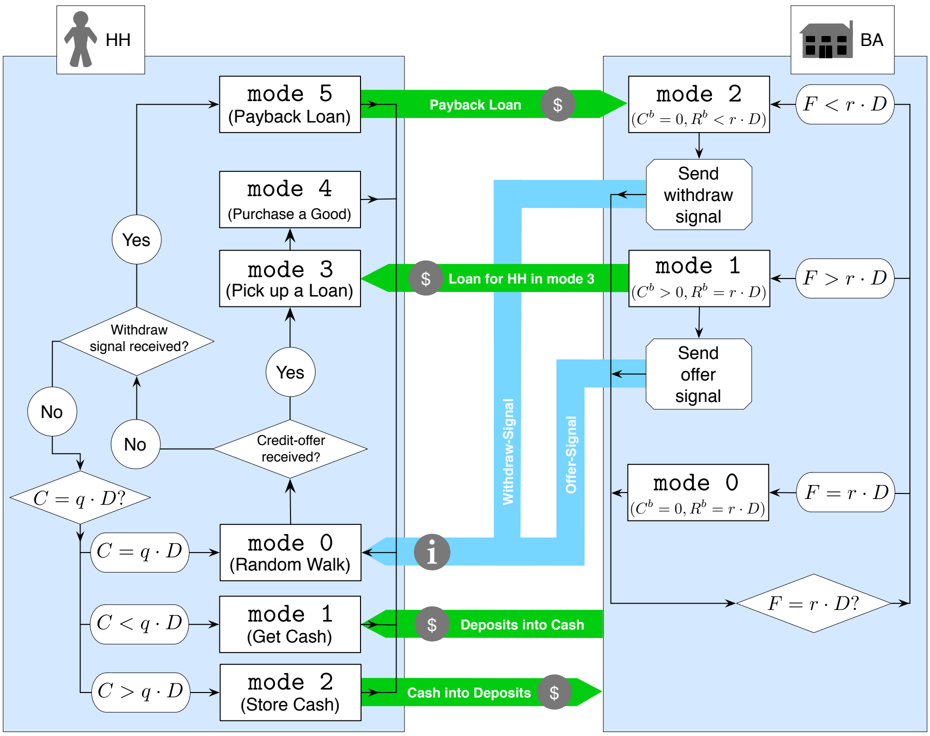
landscape. In the case of $C^h < q \cdot D^h$, he enters `mode 1`. The HH then directly walks to BA $b^{D,h}$ to withdraw deposits until `mode 0` holds. If, *vice versa*, $C^h > q \cdot D^h$ holds (`mode 2`), h directly walks to $b^{D,h}$ to place the excess cash in his bank account, i.e. h converts C^h into D^h until `mode 0` holds. A BA never rejects such receipts of liquidity. Figure 2 illustrates the decisions of all agents in a flow chart.

Similarly, we define 3 modes for BAs. All modes follow directly from the assumption that each BA b has to hold required reserves R^b proportional to the deposits that HHs have placed on bank accounts of b. The different modes are, thus, given by:

- BA `mode 0` ($F^b = r \cdot D^b$): liquidity reserves F^b (given by $F^b = C^b + R^b$) match target value of required reserves $r \cdot D^b$.
- BA `mode 1` ($F^b > r \cdot D^b$): too much liquid funds, grant a credit.
- BA `mode 2` ($F^b < r \cdot D^b$): not enough liquid funds, withdraw a credit.

If b's liquid funds ($F^b = C^b + R^b$) are equal to the reserve requirements, b holds all liquidity reserves at its account with the CB ($C^b = 0$ and $R^b = r \cdot D^b$). If eq. (2)

Figure 2: Simplified decision structure and interaction of households and banks



holds, the bank enters `mode 0`, and no further transactions with other agents are initiated by b. If b's liquid funds are larger than $r \cdot D^b$, the bank holds $R^b = r \cdot D^b$ at its CB account. The remaining excess reserves are hold in the form of cash ($C^b > 0$) and a loan is offered to real sector agents at the amount of $\frac{C^b}{1+r}$.

If $F^b < r \cdot D^b$ holds, the bank, first, transfers all liquid funds into R^b. Second, it withdraws a loan that has been granted to a HH earlier.[13] Practically, this is done

[13] Recall that all transactions have to be payed with cash.

by sending a `withdraw credit`-signal to one of the HHs that b has a claim on and that is currently in `mode 0`[14].

We are aware that, in reality, banks can not simply attain any amount of liquidity in the short-run by withdrawing credits because they are, in general, not legally allowed to do so (due to fixed maturities). Additionally, even if they have this opportunity, the borrower might not have enough liquid funds available (standard maturity transformation problem[15]). Thus, banks can only withdraw credits slowly by refusing to renew old ones that become due. This mechanism is proxied by a simpler one in our model: under normal conditions, a loan runs forever. If a bank intends to bring outstanding loans down, it can withdraw loans from only one agent at a time. Additionally, loans are only repaid partially (about 15%, details below). This simplifies our model a lot, since we do not need to integrate all the thousands of loans with an individual duration. For simplicity, we also assume that BAs are not punished by the CB if they are unable to supply the reserve requirements. This assumption is relaxed in Section 7.

The three modes we have introduced for the HHs above do not yet allow to take and repay a loan. We, therefore, have to add three additional modes to close the credit circle.

- HH `mode 3`: pick up a loan from $b^{L,h}$.
- HH `mode 4`: use loan to buy a good from another HH.
- HH `mode 5`: `withdraw credit`-signal received.

If BA b offers a loan, one HH of those, who are in `mode 0` and for whom $b^{L,h} = b$ holds, gets informed about the loan offer and enters `mode 3`. This HH then moves to $b^{L,h}$ and picks up a loan. We assume that it is offered only to one randomly[16]

[14] Withdrawing only from HHs in `mode 0` is a non-restrictive assumption. First, because most of the time the majority of HHs are in this `mode` anyhow and, second, because a HH in another `mode` will return to `mode 0` quickly so that the BA can withdraw credits from it. This assumption prevents that an active HH is interrupted in its current interaction.

[15] Bank of England (2011)

[16] Technically, we determine the random HH by picking that HH with the highest distance to b. Since HHs take a random walk, picking the one with highest distance to b results in a random choice but assures that a HH that just repaid a credit (and thus stands next to b) is not directly picked again.

determined HH at the same time. The amount of that loan (ΔL^h) is also randomly determined between the supply $\frac{C^b}{1+r}$ and a small lower bound[17].

After taking a loan, the HH h uses the new liquidity to purchase a good (`mode 4`). h randomly walks around the landscape until it meets some other HH (say $\bar{h}$) who is in `mode 0`. h buys a good from $\bar{h}$ and pays with cash. This transaction is accounted for in the balance sheet of h as a decrease of cash by ΔL^h and an increase of cash in the sheet of $\bar{h}$. We are interested in the production and consumption of goods only insofar as it provides a motivation for taking a credit. We, therefore, assume that $\bar{h}$ produces the good directly before the transaction takes place and h consumes it directly thereafter. One can think of this as a service (e.g. hair cut). This simplification allows us to neglect the real sector and to keep the flow of goods out of the balance sheets. It seems odd ,at first, that HHs take loans to buy goods although they still have money left. Households, however, also represent the firm side of the real sector and with this behavioral assumption, we account for firms' leveraging.[18]

If a HH receives a `withdraw credit`-signal, he enters `mode 5` and directly walks to BA $b^{L,h}$. Once reached, he transfers cash to the BA until the loan is repaid or until he has no liquid funds left.

4 The Endogenous Creation of Money

In this section, we are going to analyze how private individuals endogenously create money. We initialize our population as described above with all balance sheet positions set to zero. The parametrization is given by $H = 60$, $B = 9$, $q = 0.15$ and $r = 0.04$. As the initial impulse to the system, we simulate a helicopter drop, i.e. the CB creates 10 units of cash and leaves it to the HHs. For simplicity, we assume that it is completely given to one randomly determined HH. This simplification

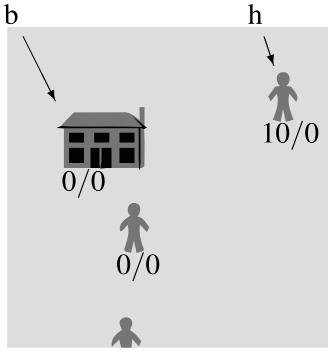
[17] Technically, this lower bound $L_{\min} = \min\left\{0.01, \frac{C^b}{1+r}\right\}$ is required to assure convergence towards a steady state. When a BA reduces its surplus liquidity, its offered loan contracts are also decreasing. The lower bound assures that a falling C^b does not generate loan contracts that are also converging towards zero.

[18] To gain further insight into the rationale of borrowing from a management science perspective, see Jensen (1986), Harris and Raviv (1990) or Stulz (1990).

allows us to focus on one individual agent at the beginning of the simulation since all others remain in `mode 0`. In later simulations, the helicopter money is distributed among all HHs. Our concept of endogeneity is different from that in the Post-Keynesian tradition where the supply of credit is infinitely elastic and hence no exogenous (helicopter) drop is needed.[19] In the paper at hand, the wider monetary aggregates are produced in an interactive process. Money is, therefore, created by behavioral interactions. In this sense it is *endogenous*.

Sheet 4 and 5 illustrate two individual balance sheets immediately after the helicopter drop. The cash entry of one HH h is increased by 10 which also increases h's equity by 10. In the CBs balance sheet the currency position is increased by 10 which induces a fall in equity by 10.[20] Figure 3 illustrates part of the landscape. Each agent in the figure has a subscript showing his two most important assets. These are C^h/D^h for HHs and C^b/R^b for BAs.

Figure 3: Agents at $t = 1$



Sheet 4: Household h ($t = 1$)

Assets	Liabilities
Cash 10	Loan Bank 0
Deposits 0	
	Equity 10
10	10

Sheet 5: Central bank ($t = 1$)

Assets	Liabilities
Gold 15	Currency 10
	BA Deposits 0
	Equity 5
15	15

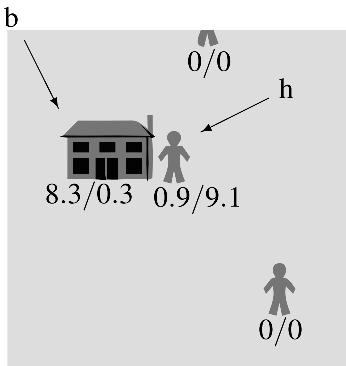
In $t = 1$, all agents are in `mode 0` except for h. Obviously, h's share of cash is too large compared to (1). It, therefore, enters `mode 2` and walks in the direction of BA

[19] A Post-Keynesian version of endogenous money in ACE macroeconomic models can be found in Teglio et al. (2012).

[20] We can quickly perform the consistency check mentioned in Section 3.1: initially, all agents have zero equity. After the shock, only those of HH h and the CB change. The sum of all changes in equity in our model, therefore, equals zero because $10 + (-10) = 0$.

$b^{D,h}$ to place deposits there.[21] After some time steps ($t = 300$ in our simulation), he reaches $b^{D,h}$ and places 8.70 units of cash in his bank account to satisfy condition (1). His balance sheet undergoes a swap of assets: C^h is reduced by 8.70, while D^h is increased by the same amount (Sheet 6). In the balance sheet of bank b, this transaction induces an increase of cash by 8.70. Now, b has a too large amount of liquid funds. It enters `mode 1` and deposits $r \cdot 8.70 = 0.35$ units of cash as reserve requirements at the CB (Sheet 7). The remaining liquidity (8.35) is offered as a loan.

Figure 4: Agents at $t = 300$



Sheet 6: HH h in $t = 300$

Assets	Liabilities
Cash	Loan Bank
1.30	0
Deposits	
8.70	
	Equity
	10
10	10

Sheet 7: Bank b ($t = 300$)

Assets	Liabilities
Cash	HH Deposits
8.35	8.70
Reserve	
0.35	
Credits	
0	Equity
	0
8.70	8.70

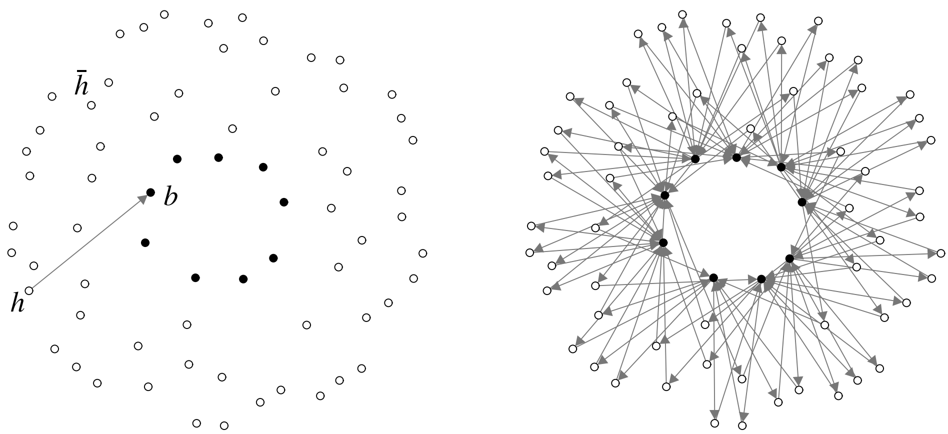
The creation of money through lending is obvious from Sheets 4 - 7. While in $t = 1$ there are 10 units of money among the private agents (the cash of HH h), there are 18.5 units in $t = 300$ (1.3+8.7=10 for HH h plus 8.35 units of cash for BA b).

We have now described one transaction in full detail. After this one, there are of course millions of other transactions following. While the computer program explicitly models all these transactions in full detail, we can step back and focus our attention on the emergence of aggregate properties. First of all, we look at the endogenous generation of a network of claims. Figure 5(a) illustrates BAs as black points and HHs as white circles. The first transaction in $t = 300$ between h and b has created a claim of h against b. We illustrate this claim as a link from h to b.

[21] The helicopter drop applied here is basically in line with the traditional Keynesian theory: surplus liquidity is *not* used to buy goods (e.g. Pigou effect) but financial securities (here: deposits).

Since the other agents have not taken/granted a credit yet, they are not connected. A second connection is established as soon as b uses the excess reserves to grant a loan to another household (e.g. $\bar{h}$), a link from b to $\bar{h}$ is created.

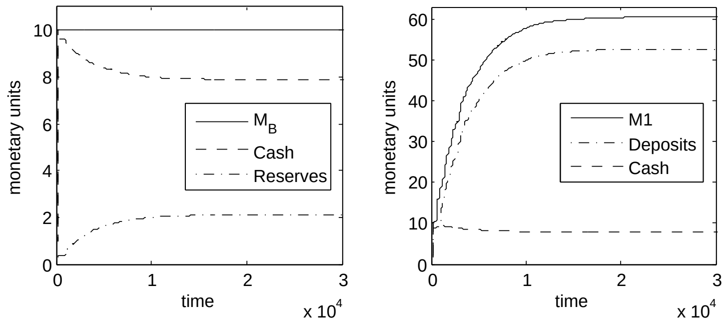
Figure 5: Network of claims (black points denote BAs, circles denote HHs, arrows denote claims)



(a) in $t = 300$ (b) in $t = 20\,000$

As time goes by, more and more individual transactions are carried out. BAs grant more and more loans to HHs, while HHs increase their possession of deposits. By performing these transactions, the agents endogenously weave a network of claims on each other. At the same time, these transactions endogenously produce money. Figure 6 shows the development of the monetary aggregates over time. BAs transform the monetary base from cash into reserve requirements (left panel). At the same time, HHs transform cash into deposits and, thus, allow banks to grant credits. The additional credits strongly increase M_1 (right panel). The process continues until eq. (1) is fulfilled for every HH and (2) for every BA. Such a state results – up to a numerical precision of three digits – around $t = 20\,000$. The monetary aggregates in this situation are given by $M_1 \approx 60.53$ and $L \approx 50.53$. The market is characterized by a highly entangled network of credit claims (Figure 5(b)). In this state, every HH is connected to two BAs ($b^{D,h}$ and $b^{L,h}$).

Figure 6: Development of monetary aggregates



Equilibrium Benchmark

The monetary multipliers μ_1 and μ_L that determine the aggregate amount of M_1 and L in equilibrium are given by[22]

$$M_1^\star = \frac{1+q}{q+r} \cdot M_B = \mu_1 \cdot M_B \qquad \text{with} \quad \mu_1 > 1 \tag{3}$$

and

$$L^\star = \frac{1-r}{q+r} \cdot M_B = \mu_L \cdot M_B \qquad \text{with} \quad \mu_L > 1 \tag{4}$$

For our parametrization, we get $\mu_1 = 6.053$ and $\mu_L = 5.053$. Since the monetary base in our simulation is given by $M_B = 10$, the equilibrium values of M_1 and L are given by $M_1^\star = 60.53$ and $L^\star = 50.53$.

Although it is not assumed, the economy converges against the theoretical equilibrium ($M_1^\star$ and $L^\star$) in the long run. Since the agents in our model are of the ZIA type, this proves that it is the market structure alone (operating in disequilibrium generally) that assures this convergence (compare Section 3.1). We also show that, while the economy moves in the direction of $M_1^\star$ and $L^\star$, it does not only create money but also a strongly interconnected network of claims.

[22] A recent discussion about fractional reserve banking (the cause of the money multiplier) can be found in Mallet (2012).

Now, that we have demonstrated the creation of money and financial interconnections as a product of interaction between HHs and BAs, we can introduce the next dimension of credit markets: interbank lending.

5 The Interbank Market

To introduce an interbank market for credits, we augment BAs `mode 1` and `mode 2`. If a BA enters `mode 1`, it does, first, offer a credit to other BAs and, second, to HHs. On the other hand, if a BA enters `mode 2`, it first tries to bridge the shortage in liquidity by taking a credit from another BA. If this is not possible, e.g. because no bank has currently a surplus of liquidity, it withdraws a credit from a HH. To account for interbank credits, we have to extend the balance sheet of banks by I^b_+ (interbank receivables) and I^b_- (interbank liabilities). An example is given in sheet 8.

Sheet 8: Example BA b

Assets		Liabilities	
Cash		HH Deposits	
	C^b		D^b
Reserve		BA Credits	
	R^b		I^b_-
Credits			
HH	L^b	Equity	
BA	I^b_+		E^b

A credit from one bank (say b) to another ($\bar{b}$) is accounted for by a decrease in C^b and an increase in $C^{\bar{b}}$. At the same time, a claim is created by increasing I^b_+ and $I^{\bar{b}}_-$ by the same amount. In contrast to credits from BAs to HHs, we assume that credits between BAs can be carried out immediately and that they have a fixed repay date ($t^{\text{repay}} = t + x$) in the near future. The maturity x is randomly determined between 1000 and 2000.[23] This assumption should account for the fact that interbank credits are, typically, granted quicker and over shorter time horizons than credits to the real sector (Cocco et al. (2009), Demiralp et al. (2006)).

The creation of money in the previous section followed a monotonic path, i.e. from the exogenous increase of cash until an equilibrium was reached, the aggregate M_1 was never decreasing. As a result, no HH and no BA has ever encountered a shortage of liquidity (HH `mode 1` and BA `mode 2`). Interbank lending, however, depends on one BA with a surplus and another with a shortage of liquidity *at the same time*. In the following, we extend HHs behavior in the real sector in order to generate such different liquidity endowments for BAs.

First, we assume that HHs, which are satisfied with their financial position (`mode 0`) do not simply stop their economic actions but interact with one another. To introduce such real market interaction between HHs, we change the above definition of HH's `mode 0` in the following way.

- Extended HH `mode 0` ($C^h = q \cdot D^h$): buy/sell goods.

As before, a HH h, for whom $C^h = q \cdot D^h$ holds, enters `mode 0` and takes a random walk around the landscape. Additionally, he is now looking for transactions with other HHs. As soon as h encounters another HH (say $\bar{h}$), who is also in `mode 0`, one of the two HHs is randomly determined to be the seller of a good and the other one to be the buyer. The price p is also randomly determined between 50% of the buyer's cash and zero. C^h is reduced by p while $C^{\bar{h}}$ is increased by the same amount. As before, we assume (for ease of exposition) that the exchanged good does not enter the balance sheet.

This transaction causes one HH to enter `mode 1` and the other to enter `mode 2`. The first will convert deposits into cash, while the second will transfer cash into deposits. As a result, BA $b^{D,h}$ will end up with a shortage of liquidity and $b^{D,\bar{h}}$ with a surplus. Of course, this (random) behavior is not particularly realistic. But since we are only interested in the impact of real sector transactions on the credit

[23] Recall, HHs have to walk to their BA (which takes some time) before taking a credit. A fixed repay date is also not set.

market, this way of modeling is sufficient for our purpose because it serves as a means for interbank lending.[24]

It is theoretically possible now that a BA b is not able to fulfill its debt obligations if, for example, some HHs demand liquidity from it over a short period of time and no other BA has a surplus of liquidity to grant a credit. Recall that b is never able to withdraw credits *immediately* to obtain liquidity. We, therefore, have to define how agents behave in such a case. For simplicity, we assume that, as soon as a BA b is not able to fulfill an obligation, it becomes public knowledge that it is insolvent. All HHs, who have deposits at it, immediately withdraw as much of them as possible (bank run) and no other BA will grant further credits to it. After a period of insolvency proceedings with randomly determined length up to 2000 time steps, the insolvent BA is removed. All remaining balance sheet positions are depreciated and those HHs for whom $b^{D,h} = b$ holds will pick another solvent BA for placing their deposits.

Now that the interbank market is introduced, we will perform some simulations of the extended model.

6 Endogenous Instability

To analyze the impact of interbank lending on the credit market, we run a new simulation. Initially, all agents' balance sheet positions are again set to zero. We introduce money by an exogenous helicopter drop of 100 cash units that are equally distributed among HHs.

As in Section 4, we find that money is endogenously created over time (see Figure 7). But now, the economy does not smoothly approach an equilibrium and settle down there. Instead, when the market gets close to equilibrium (e.g. $t = 20\,000, \ldots, 32\,000$), we observe small unsystematic fluctuations (see zoom window) that emerge as a result of random trading. During such a period, one often finds a BA that is in `mode 1` and simultaneously another BA in `mode 2`.[25]

[24] Lenzu and Tedeschi (2011) use a similar mechanism and apply exogenous shocks that reduce the liquidity of one BA and at the same time increase that of another (p. 8).
[25] Recall, that this was impossible in the simulation of Section 4 because of the monotonic increase in M_1.

Figure 7: Development of monetary aggregates with interbank market

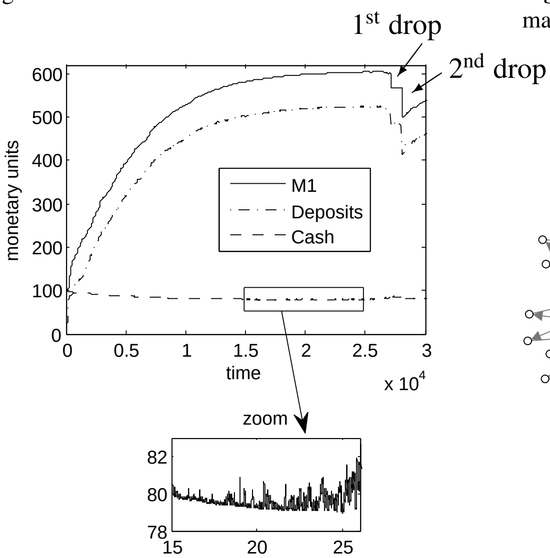
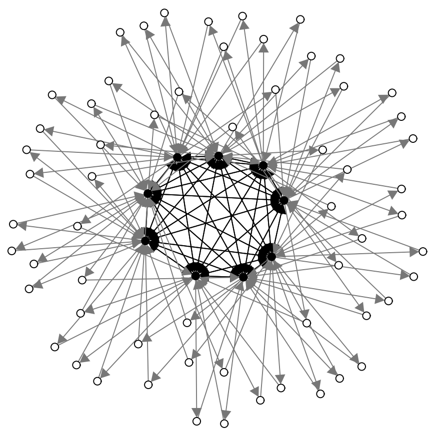


Figure 8: Network of claims with interbank market at $t = 20\,000$

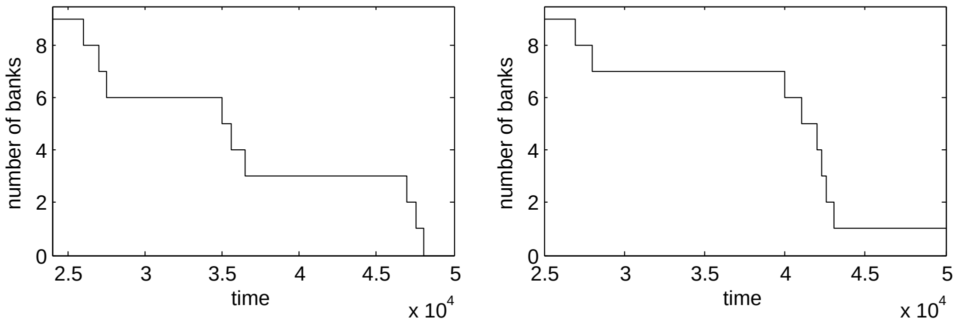


Consequently, there are a lot of interbank credits being granted during such times. Now that BAs lend to each other, they are also directly linked by credit relations (illustrated as black lines in Figure 8). Interconnectedness of the network of claims will, thus, be higher.

Around $t = 33\,000$ one BA becomes insolvent and has to leave the market. As a result, the deposits of some HHs and the interbank credits of some BAs are destroyed which lets the money amount drop. This destruction of money leads to a shortage of liquidity that drives another bank into insolvency shortly thereafter. Again, money is destroyed which is illustrated as a second drop in the monetary aggregates about 500 periods later.

Although, BA failures do occur now, convergence to the close neighborhood of the benchmark equilibrium (3) and (4) is still assured as long as, at least, one BA is present. Only if all BAs fail (no BA survives a bankruptcy cascade), endogenous money creation is not possible anymore. Two situations are possible as absorbing states of the system: (1) all BAs have become bankrupt (Figure 9, left panel, at

Figure 9: Example of the number of operating BAs over time if no BA survives (left) and if one BA survives (right).



period $\approx 4.8 \cdot 10^4$). In this case, higher monetary aggregates cannot be created and the benchmark equilibrium cannot be reached. (2) one BA survives the last bankruptcy chain (Figure 9, right panel, at period $\approx 4.3 \cdot 10^4$). In this case, the benchmark equilibrium will still be reached. Such a state can never break down since a single BA cannot suffer large withdraws of liquidity in our model. Recall that liquidity withdraws are created by random transactions between two HHs that always result in one HH (the seller) with surplus liquidity and one (buyer) with a lack of liquidity. The former will increase its deposits, while the latter will withdraw cash. Since both are necessarily customers of the same BA (because there is only one left), their transactions will cancel out in the BA's balance sheet.

Running an MC experiment, we found that the model ends up in the first state with a probability of 73.7% and in the second with a probability of 26.3%. The impression might arise that the banking sector in our model is extreamly fragile because of these high probabilities. Therefore we want to stress that the above probabilities are a natural result in our setting. If the probability of single BA failure in each period is small but postive and the entry of new BAs is not allowed, the number of BAs is neccessarily decreasing over time until an absorbing state is reached. The probability of reaching either state 1 or 2 in the very long run therefore has to be 100%. Since these very long run absorbing states are of minor economic importance we neglect them in the remainder of this paper and focus on short-run stabilization.

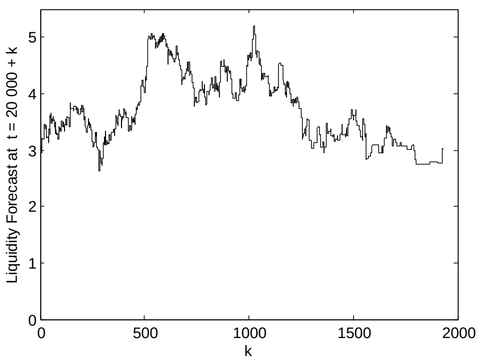
The Cause of Bankruptcies

To explain the chain of events that drives BAs into bankruptcy, we have to leave the macro level of aggregates and markets and enter the micro level of single agents and interactions. For illustration purpose, we pick one BA (say b) at $t = 20\,000$ and look at its balance sheet (Sheet 9). At this point in time, b has liquid funds equal to $C^b + R^b = 3.01$. As stated above, interbank credits have a fixed repay date. We can, therefore, create a liquidity forecast for b based on the current liquidity and its future change by due credits. Figure 10 shows such a forecast for the subsequent 2000 periods. For the current time step ($k = 0$) it starts at 3.01. For $k = 1, \ldots, 2000$ it decreases if b has to repay credits and increases if b receives credit repayments from other BAs. Since interbank credits on the assets and liabilities side are almost equal ($25.82 \approx 25.83$), the cash forecast ends up where it started (near 3).[26]

Sheet 9: Bank b, $t = 20\,000$

Assets		Liabilities
Cash		HH Deposits
	0.01	75.01
Reserve		BA Credits
	3.00	25.83
Credits		
HH	72.01	Equity
BA	25.82	0.00
	100.84	100.84

Figure 10: Liquidity forecast for b, $t = 20\,000 \ldots 22\,000$



Bank b has a very robust financial position. Comparing with another bank (say $\bar{b}$) at the same point in time, we find a very different picture. Sheet 10 and Figure 11 illustrate the situation of $\bar{b}$. The liquidity forecast starts at $C^{\bar{b}} + R^{\bar{b}} = 2.17$. It follows a downward trend because the bank has taken much more credits from other BAs than it has granted ($35.26 > 28.15$). Around $k = 600$, the liquidity forecast

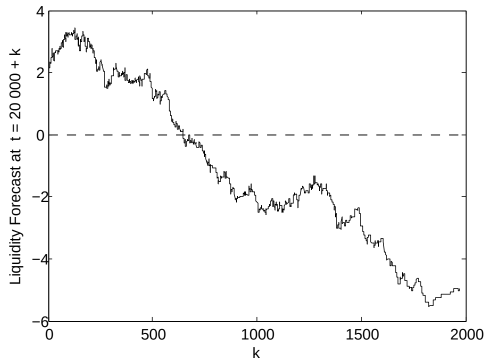
[26] Liquidity of 3.01 plus repayments *from* other BAs of 25.82 minus repayments *to* other BAs of 25.83 result in 3.00.

falls below zero. In this situation, $\bar{b}$ will not be able to fulfill its debt obligations. Note, however, that this insolvency is not a result of too low equity. The value of equity is zero from the beginning on since nothing is added or removed from it. It results simply because cash in- and outflows are asynchronous.

Sheet 10: Bank $\bar{b}$, $t = 20\,000$

Assets		Liabilities
Cash		HH Deposits
	0.1	52.2
Reserve		BA Credits
	2.07	35.26
Credits		
HH	57.14	Equity
BA	28.15	0
	87.46	87.46

Figure 11: Liquidity forecast for $\bar{b}$, $t = 20\,000 \ldots 22\,000$

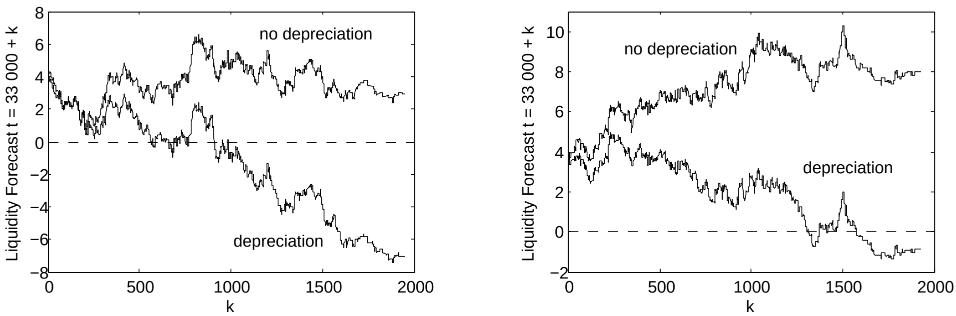


Recall that the described situation is just a snapshot in $t = 20\,000$. What will happen as time goes by? BA $\bar{b}$ will repay credits and its liquid funds will decrease. Therefore, it will enter `mode 2` and try to attain new liquidity (e.g. new credits from other BAs or withdraw loans from HHs). If $\bar{b}$ is successful (e.g. in raising new credits) until $t = 20\,600$, it does not become insolvent but, instead, rolls it's debt position over. The process can continue and $\bar{b}$ can stay in the market. At some future point in time ($t = 33\,000$), it might happen that, first, no other BA has the necessary surplus in liquidity and, second, the HHs, who borrowed from $\bar{b}$, are not able to repay as quick[27] as $\bar{b}$ needs cash. Therefore, $\bar{b}$ is unable to roll over the debt position and becomes insolvent. Other agents withdraw as much credits and deposits from $\bar{b}$ as possible which makes the endogenously produced money amount fall (Figure 7). After the randomly determined length of the insolvency proceedings, $\bar{b}$ is removed and all claims against it become worthless. Other BAs, which are also in a weak financial position or who have lent to $\bar{b}$ and depend

[27] Recall, that we have assumed in Section 3 that withdrawing credits from the real sector can not be done immediately but takes time.

on repayment, will also be in trouble now and eventually become insolvent. A bankruptcy cascade might follow.

Figure 12: Liquidity forecasts of two lenders of $\bar{b}$ with and without the depreciation of credits to $\bar{b}$



We can illustrate the spillover of this cascade by looking at two lenders of $\bar{b}$ (Figure 12). Both have a robust financial position: the liquidity forecast of the first one is almost a horizontal line, while that of the second has a slight upward trend (*no depreciation* case). If $\bar{b}$ becomes insolvent, it is not able to pay all of its credits back. Consequently, the two lenders will not receive all of the granted credits back. The *depreciation* line shows the same liquidity forecasts but with all credits to $\bar{b}$ depreciated, i.e. the development of liquid funds if no credit from $\bar{b}$ is repaid. The insolvency of $\bar{b}$ moves liquidity forecasts downward. Both BAs will, therefore, also be financially less robust. They withdraw credits and grant less to other BAs which can drive further BAs into insolvency and so on.

In our simulation, the crisis is spread by the non-performance of interbank debt. But the argument is general enough to be extended to any depreciation of bad debt. Regarding the current developments in southern Europe, for example, it is intuitively clear that a depreciation of bad government bonds has exactly the same effect on banks' liquidity position and can, therefore, also trigger a bankruptcy cascade among BAs.

We can identify instability as an *emerging property* of the aggregate that stems from asynchronous in- and outflows of liquidity created by individual transactions. The liquidity requirements of a failing BA, in turn, creates the risk of contagion. This result casts serious doubt on the value of general equilibrium modeling, since all interesting behavior is observed outside of equilibrium. For example, the question under what conditions a banking sector brakes down or what the government or CB can do to stop a bankruptcy cascade cannot be answered if we restrict ourselves to equilibrium.

To evaluate the threat of systemic risk, we perform a Monte Carlo experiment with 2000 runs of the model. Results are shown in table 1. The *start*-column gives the probability that, conditional on the amount of interbank credits in a period t, a first bank will fail in the near future (i.e. until $t+800$). The other columns give the conditional probability that, if a failure has been observed in t, a further bank will fail until $t+800$. In other words, the *start*-column contains the probability that a crisis starts and the other columns those that it spreads to a further BA.

First of all, we find that the amount of interbank credits monotonically increases the probability to fail. This effect is obviously a result of a stronger entangled web of claims. If a BA has taken more credits from others, it becomes more likely that these credits can not be payed back. Or, vice versa, the more credits a BA has granted, the more assets it has to depreciate if its borrowers fail. As a consequence, debt growth is a central factor that originates financial instability.[28]

Table 1: Conditional probabilities to become insolvent

		Recent BA failures					
IB Credits	start	1	2	3	4	5	>5
0-200	0	0.04	0	0	0	0	0
200-400	0.02	0.22	0.21	0.11	0.09	0.05	0.12
400-600	0.17	0.62	0.73	0.51	0.52	0.42	0.35
600-800	0.56	0.93	0.93	0.84	0.77	0.72	0.61
>800	0.88	0.99	0.99	0.94	0.84	0.77	0.75

We also find that the probability to observe a bankruptcy is much higher if there have been bankruptcies before. E.g. assume the system is in a state where interbank

[28] This point is also in line with Minsky's *Financial Instability Hypothesis*. Compare Minsky (1977), Minsky (1978) as well as Godley and Lavoie (2007) or Bezemer (2012a).

credits are between 400 and 600. In this state, the probability that an initial BA will fail is 0.17. But if one BA has already failed before, this probability increases to 0.62. If two BAs have failed before, it increases to 0.73. We can, therefore, identify a clear contagion effect of bankruptcies. This effect, however, *is non-monotonic*, i.e. probabilities are first increasing the more BAs have failed, but decreasing later on. In the case of IB credits > 800, it even falls below the probability that a crisis is started. The economic rationale for this non-monotonicity is the following: as soon as the first BAs are removed from the market, there are some HHs who have withdrawn as much deposits as possible from those BAs and consequently hold their wealth in cash only. Those households will pick another solvent BA for depositing part of their cash. Thus, they will provide further liquidity to the liquid BAs which will help to stabilize those. This behavior will bifurcate the economy. Money is withdrawn from the insolvent BAs and given to the solvent ones. The downside is that the latter will be in excess of liquidity but will not provide it to the former. The upside is, that such behavior protects the healthy BAs by reducing their probability to fail and, thus, helps to stop a cascade.[29]

Table 2: Conditional probabilities to become insolvent

		Recent BA Breakdowns					
IB Market	start	1	2	3	4	5	> 5
Off	0.04	0.14	0.23	0.22	0.09	0	0
On	0.02	0.78	0.9	0.8	0.72	0.59	0.4

We can now analyze the effect of an interbank market on the emergence of systemic risk. We perform another Monte Carlo simulation with the interbank market turned off, so that the model equals the baseline version of the previous sections again. Table 2 compares the probabilities to fail, conditional on the existence of an interbank market. Firstly, we find that the probability of a first bank to fail is very small in both scenarios. The banking sector is, therefore, very stable under normal conditions. With no interbank market, the probability is only 0.04. If an interbank market exists, it even decreases to 0.02. The existence of an

[29] A similar idea of bifurcation can be found in Leijonhufvud (2012).

interbank market, therefore, stabilizes the banking sector because of the improved possibilities for BAs to refinance.

Secondly, we find that the probabilities of contagion are much higher if an interbank market exists (e.g. $0.78 \gg 0.14$). The impact of an interbank market is, therefore, twofold. It stabilizes the banking sector under normal conditions but strongly increases systemic risk.[30] Interestingly, the probabilities of contagion do not become zero if the interbank market is turned off. Therefore, the interbank market amplifies but does not create systemic risk. If one BA becomes bankrupt, it starts withdrawing as much credits from HHs as possible. These HHs, in turn, withdraw deposits from other BAs. These other BAs might, thus, also be driven into liquidity problems and might ultimately become insolvent. Bankruptcy cascades can, thus, also be transmitted by HHs if BAs are not directly connected by an interbank market.

The probability of observing a total breakdown of the banking sector where all BAs fail in one single cascade is positive and results from multiplying all probabilities in one row. In the case of an interbank market this probability becomes $0.02 \cdot 0.78 \cdot \ldots \approx 0.00011$, without an interbank market it becomes zero.

One strength of ACE modeling is that parameter heterogeneity can be directly introduced. We can, therefore, easily check whether our results are robust against assumption of parameter heterogeneity among agents. Instead of setting $q = 0.15$ for all HHs, we draw the individual q^h from a uniform distribution with support $[0.1,\ 0.2]$, i.e. $q^h \sim \mathrm{U}(0.1,\ 0.2)$. Since the reserve requirement is set by the CB, we do not assume heterogeneity among the parameter r. Repeating the Monte Carlo exercise shows that the above results are stable against parameter heterogeneity (results are not shown).

In another experiment, we analyze the role of large (systemically important) banks. We perform 500 independent simulations with different underlying random seeds. To calculate the impact of bank concentration on stability, we calculate (for each simulation i) the number of BAs that survive 40000 ticks Y_i as a proxy of stability and different concentration measures X_i in the time step before the first BA becomes bankrupt. The size of each BA is proxied by its balance sheet size. In

[30] This result is in line with Farmer et al. (2012), p. 14: "*[...] interbank lending [...] can provide security in normal times but may amplify the extend of a crash in bad times.*"

five regressions of the form

$$Y_i = \beta_0 + \beta_1 \cdot X_i, \tag{5}$$

our stability proxy Y_i is regressed on one concentration measure X_i. Since regression results are going to depend on the way concentration is measured, we directly check the robustness of our estimation by using five different measures: size of the largest BA, standard deviation of BA size, Herfindahl index, Theil's index and Gini coefficient. Estimation results for β_1 and the corresponding p-values are shown in table 3. All estimates suggest that the influence of concentration (i.e. the existence of large BAs) on stability is *negative*. This effect is robust over all applied concentration measures. Since X_i is located on a very different interval depending on the underlying index, we are not able to compare the different estimates of β_1 directly. To be able to compare the estimates quantitatively, we calculate the percentage change in stability $\frac{\Delta Y}{Y}$ that is induced by a one percent change in the stability measure X in an economy with average concentration $\overline{X} = \frac{1}{500}\sum_i X_i$ (last row of table 3). Our calculations show that a 1% increase in concentration is roughly followed by a stability decrease between 0.11% and 0.99%.

Table 3: The effect of concentration on stability

X_i	Largest	Std	HHI	Theil	Gini
$\hat{\beta}_1$	-0.016	-0.039	-26.9	-0.5	-3.9
p-value	*0.000*	*0.000*	*0.012*	*0.004*	*0.014*
$\frac{\Delta Y}{Y}\ if\ \frac{\Delta X}{X} = 1\%$	-0.88%	-0.51%	-0.99%	-0.11%	-0.22%

To check the robustness of our findings against different measures of stability, we perform an estimation of a binary choice probit. As explaining variable, we use the same five concentration measures as before while the endogenous (binary) event $Y_i = 1$ is now given by the occurrence of a total breakdown of our economy.[31] All qualitative results still hold under the changed specifications: estimators and marginal effects are positive (table 4). Since it is again difficult to compare the

[31] We define a total breakdown as a situation in which only one or less BAs survive because in such a situation no further bank failures are possible.

obtained marginal effects in a quantitative way, we calculate the implied change in probability for a total breakdown to occur given a 1% change in concentration. Our results (last row of table 4) show that an increase in BA concentration by 1% is followed by an increase in the probability of a total breakdown between 0.06% and 0.61%.

Table 4: The effect of concentration on total breakdowns

X_i	Largest	Std	HHI	Theil	Gini
$\hat{\beta}_1$	0.0078	0.0199	16.92	0.294	2.38
p-value	*0.000*	*0.000*	*0.014*	*0.007*	*0.021*
marginal effects	0.0022	0.0056	4.87	0.084	0.686
$\Delta Prob(Y=1)\ \ if\ \ \frac{\Delta X}{X}=1\%$	0.41%	0.25%	0.61%	0.06%	0.13%

From this section, we can robustly conclude that a financial sector composed of equally sized BAs is more stable than one composed of BAs with strongly differing size. In Section 7, we come back to this result and show that regulatory policy should regulate large BAs over-proportionately strong to counteract on the instability they create.

An Aggregate Perspective

The strength of ACE modeling is that it allows for a completely disaggregated view on the economy. This advantage can be pointed out by asking ourselves how the previous simulations of this section would have looked like if one does not have access to individual information in the simulation but only to aggregates. For example, if we would only have the sum of all individual HHs as *the household sector* that is "representing" all its constituting individuals and only the sum of all BAs as *the banking sector*.

Sheets 11, 12 and 13 show the situation of the above simulation at $t = 20\,000$ from an accounting perspective. First of all, the three balance sheets look qualitatively identical to the ones before. But there is an important difference in the balance sheet of the banking sector. Since every interbank credit appears on the assets side of one bank and the liabilities' side of another, it cancels out in the

Sheet 11: Household sector

Assets	Liabilities
Cash 79.99	Loan Bank 492.65
Deposits 512.66	
	Equity 100
592.65	592.65

Sheet 12: Banking sector

Assets	Liabilities
Cash 0.00	HH Deposits 512.66
Reserve 20.01	BA Credits 0
Credits	
HH 492.65	Equity
BA 0	0
512.66	512.66

Sheet 13: Central bank

Assets	Liabilities
Gold 150	Currency 79.99
	BA Deposits 20.01
	Equity 50
150	150

aggregate ($I_+ = I_- = 0$). Interbank lending, therefore, simply disappears on the aggregate level (Sheet 12). This becomes evident by looking at the cash forecast of the banking sector (Figure 13). Since all committed repayments of interbank loans induce a positive flow for one bank and a negative flow for another, they also cancel out on the aggregate and the cash forecast becomes a horizontal line. Since this horizontal line can impossibly intersect with the horizontal-axis, we are not able to see the event of insolvency as a result of maturity mismatch. At the same time, we are unable to picture the credit market as an endogenous network but only as the relation between two aggregate representatives in isolation (Figure 14). An event, like agent A withdrawing credits from B which forces B to withdraw from C and so on (i.e. a bankruptcy cascade through the web transmitted by the individual need for liquidity), is simply impossible when dealing with aggregates.

Figure 13: Liquidity forecast for banking sector, $t = 20\,000 \ldots 22\,000$

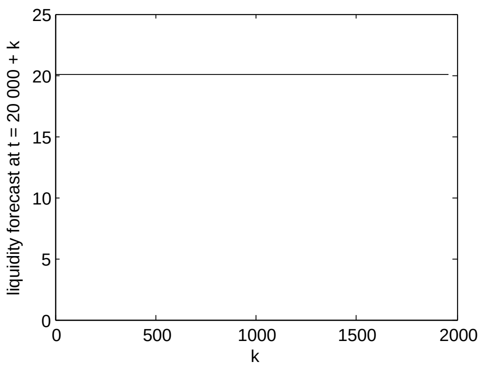


Figure 14: Network of claims on aggregate level, $t = 20\,000$

These considerations make clear why it is problematic to deal with aggregates directly, even if they are sums of heterogeneous individuals or SFC. Financial instability is neither deducible from the behavior of a single individual in isolation nor from the aggregate of all (maybe heterogeneous) individuals. These considerations illustrate why it is *not* sufficient to replace the rational representative agent by a non-rational one,[32] or to introduce heterogeneity among some kinds of agents, sum them up and confront the resulting sums of supply and demand with the other side of the market. How maturity mismatches create systemic financial risk can only be understood in an individual and interaction based analysis with a consistent accounting structure.

7 Standing Facilities, Reserve Requirements and Regulatory Policy

In this section, we extend our framework by allowing BAs to receive liquidity from the CB via standing facilities. We assume that BAs can, by its own initiative, place a secure asset (e.g. AAA bonds) at the CB to obtain liquidity. Technically, the CB and each BA are given a new position on its assets' side S (compare Sheets 14

[32] As done, for example, in the literature on learning. Compare Evans and Honkapohja (2001) or Adam (2005) among others.

and 15) that denotes the amount of such assets they possess. If a BA makes use of standing facilities, we add a positive value to its account at the CB R^b, subtract the same value from its bonds S^b, add it to the CB's bonds S^{cb} and create a liability for the CB against the BA by increasing R^{cb}.

Sheet 14: BA b with secure assets

Assets	Liabilities
Cash	HH Deposits
C^b	D^b
Reserve	BA Credits
R^b	I^b_-
Credits	
HH L^b	
BA I^b_+	
AAA Bonds	Equity
S^b	E^b

Sheet 15: CB with secure assets

Assets	Liabilities
AAA Bonds	Currency
S^{cb}	C^{cb}
	BA Deposits
	R^{cb}
	Equity
	E^{cb}

For simplicity, we control the initial endowment of save assets exogenously. Since all balance sheet entries are initially zero, the equity position of banks becomes equal to their initial endowment of assets. Additionally, we assume that each BA is now *forced* by the CB to hold R^b at the amount given by (2). Similar to all other non-fulfilled obligations, we declare a BA bankrupt as soon as it fails to provide the required reserves.[33]

Microprudential Bank Regulation

The Bank of International Settlements has published new regulatory rules for commercial banks in December 2010 (known as Basel III) with the aim of increasing

[33] In previous examples BAs where able to buffer shortages of liquidity by bringing down reserves at the CB without ever being punished. Introducing standing facilities, would strongly increase stability, because BAs are just given an additional liquidity buffer (reserve requirements + AAA bonds). E.g. increasing AAA bonds from 0 to 8 would result in an increase in stability Y_i (compare p. 31) from 3.6 to 4.8. By assuming that reserve requirements are mandatory, we replace the previously used reserves-buffer by a AAA-bonds-buffer.

the stability of the financial sector. Among others, the new guide lines strengthen the capital requirements as they increase the core capital quota (CCQ), which is defined as the minimum ratio of core equity capital that a bank has to hold in relation to its risk weighted assets, from 2% to 7%.[34] In this subsection, we use our model to analyze the implications of Basel III CCQ requirements on aggregate stability. For simplicity, we assume L^b to be the part of BA assets that the regulator has defined to be risky. The CCQ is, thus, given by:

$$CCQ_b = \frac{E^b}{L^b} \tag{6}$$

To determine the impact different CCQ regulatory settings have on stability, we perform the following experiment:[35]

1. Perform one simulation for a given endowment of secure assets $S^1, S^2, \ldots S^B$ with random trading turned off to obtain a steady state benchmark.
2. Perform the same simulation with random trading turned on for 1000 different realizations of the random number generator.
3. Repeat step 1 and 2 for different endowments with save assets.

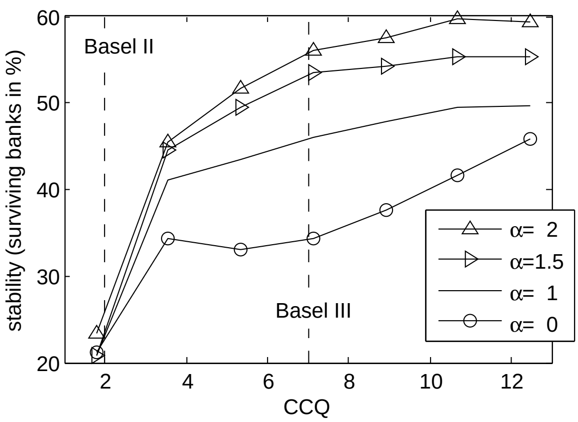
The endowment with save assets is controlled in two ways. First, we vary the sum $S^{Aggr} = \sum_b S^b$ of all BAs to control for the impact of larger capital requirements in general. Second, we control for the initial distribution of S^b among BAs according to their size. A similar aspect can be found in Basel III where higher CCQs are set for banks that are declared as *systemically relevant*.[36] Let save assets of b be given by

$$S_b = S^{Aggr} \frac{size_b^{\alpha}}{\sum_{i=1}^{B} size_i^{\alpha}} \tag{7}$$

[34] We neglect here that there is also a cyclical component in the CCQ requirement that allow banks to fall below 7% for some time to buffer the credit contraction that appears typically during recessions.
[35] Computationally, these steps are already (despite the model's simplicity) very involved. We have run the simulations from this section in parallel on a high-performance Linux-Cluster. Running them on a standard desktop computer would have taken about one week.
[36] Compare BCBS (2011).

where the size of a BA ($size_b$) is now given by the amount of loans to HHs (obtained from the benchmark simulation). By defining $size_b$ this way, the baseline case ($\alpha = 1$) results in a distribution of assets that is proportional to BA's loans and, hence, CCQs that are equal among banks. In case $\alpha = 0$, the absolute endowment of S^b is equal among banks. In this case, small BAs face larger CCQs than large ones. The opposite holds for $\alpha > 1$, where CCQs will be larger for big BAs.

Figure 15: Impact of different CCQ regulations on stability



To illustrate the influence of banks' capital basis on systemic risk, we plot the average steady state CCQ obtained from step 1 against the average relative number of BAs that survive the first 40000 periods in step 2 (Figure 15). The results are in line with Hannoun (2010), Allen et al. (2012) and also Arnold et al. (2012) who state that banks' capital basis were too low in the pre-crisis period, i.e. we show that a larger capital basis (larger CCQ) has a positive effect on stability. The intention of Basel III to increase stability by forcing banks to increase their CCQ from 2% to 7% is, thus, confirmed.

Additionally, we find that a higher value of α results in a more stable banking sector. Comparing, for example, the Basel III setting of 7% CCQ for different values of α shows that higher values of α result in a more stable financial sector, e.g. stability increases from 35 to 56 if α is increased from 0 to 2. Regulating large banks more strictly than small ones (as Basel III already does, see BCBS (2011)) has a positive effect on stability, although the average CCQ has not changed.

8 Conclusion

We present an ACE model of the credit and interbank market. The only two different kinds of agents it consists of are household/firms and banks, both of which follow very simple behavioral rules. We show how money is produced in the banking sector (as a multiple of the monetary base) through individual interactions in a disequilibrium process. Our model is a generalization of standard theory since it contains the common equilibrium result as a limiting case.

We also show that the creation of money inevitably produces instability. When applying a perspective that is strictly individual based and SFC, it is impossible to make sense of endogenous money without a web of claims between agents. This web, however, produces the threat of systemic risk. Instability is, therefore, systematically produced in monetary economies and can not be put aside as an *exogenous shock* or a *friction*.

Additionally, we show that the banking sector is more stable if it is composed of equally sized banks. The existence of large banks creates endogenous instability. As a consequence, regulatory policy should be more restrictive for such large banks compared to small ones.

The model can also be used to answer further policy relevant questions. For instance, the capital and liquidity requirements proposed by the Basel Committee on Banking Supervision aims to mitigate the subsequent destabilizing effects of a spreading/growing credit network on the economy since they have been identified as key drivers of financial instability. Hence, it would be worthwhile to analyze in what way the implementation of the complete spectrum of the Basel III regulatory framework (apart from just CCQ) would affect the outcome of the model in terms of bank defaults. Furthermore, the effects of single and simultaneous requirements as well as the impact of pure micro- or macroprudential instruments could be compared.

Acknowledgements: We would like to thank Marco Raberto, Dirk Bezemer, Alan Kirman, Michael Roos, Paul Ormerod, David Colander, Giorgio Fagioli, Thomas Lux, Joanna Bryson, Sven Offick, Ulrich Stolzenburg, Stephen Sacht, two anonymous referees and participants of the *International Symposium: Crisis in Macroeconomics?* (Bochum, 2012), the *Latsis Symposium (Zurich, 2012)* and the *MAFIN* (Genoa, 2012) for a lot of fruitful comments.

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