Is the market really a good teacher ?
Market selection, collective adaptation and financial instability.*

Pascal Seppecher[†], Isabelle Salle[‡], Dany Lang[†]

26th February 2017

Abstract

This paper proposes to model market mechanisms as a collective learning process for firms in a complex adaptive system, namely `Jamel`, an agent-based, stock-flow consistent macroeconomic model. Inspired by Alchian's (1950) "blanketing shotgun process" idea, our learning model is an ever-adapting process that puts a significant weight on exploration *vis-à-vis* exploitation. We show that decentralized market selection allows firms to collectively adapt their overall debt strategies to the changes in the macroeconomic environment so that the system sustains itself, but at the cost of recurrent deep downturns. We conclude that, in complex evolving economies, market processes do not lead to the selection of optimal behaviors, as the characterization of successful behaviors itself constantly evolves as a result of the market conditions that these behaviors contribute to shape. Heterogeneity in behavior remains essential to adaptation. We come to an evolutionary characterization of a crisis, as the point where the evolution of the macroeconomic system becomes faster than the adaptation capabilities of the agents that populate it.

Keywords – Evolutionary economics, Learning, Firms' adaptation, Business cycles.

JEL classification codes – B52, C63, D83, E32.

*Corresponding author: Pascal Seppecher, pascal.seppecher@univ-paris13.fr.

†CEPN (Centre d'Economie de Paris Nord), UMR CNRS 7234, Université Paris 13, Sorbonne Paris Cité, 99 avenue Jean-Baptiste Clément, F – 93430 Villetaneuse, France.

‡Utrecht School of Economics, Utrecht University, NL.

1 Introduction

A market operates on a decentralized ground: it is a place where a collection of heterogeneous agents locally and constantly interact, without seeing the resulting whole picture. This property poses a challenge to the use of a representative agent with rational expectations, and raises the question of how to model agents' behaviors and learning in market economies. This paper proposes a decentralized adaptation model rooted in the functioning of the market itself: the selection mechanism operates through market competition, as firms that use non performing strategies are driven out of the market by bankruptcy.

The idea that market mechanisms determine the *aggregate* behavior of the system, by selecting appropriate behaviors and discarding inappropriate ones, without the need to model any rationality, foresight of adaptive behavior from the *individual* agents is originally due to Alchian (1950). Alchian (1950, p. 219) calls such a process the "blanketing shotgun process" (BSP hereafter): a multitude of agents randomly select strategies, without assuming any intentional decision making at the individual level, and the market selects the best-performing behaviors by excluding the unsuccessful ones. This process requires individual heterogeneity and market interactions, and postulates that the collective adaptation force of the system is superior to the one of the individual agents. This process also puts more emphasis on the *exploration* for potential strategies than on the *exploitation* of already discovered strategies. The BSP therefore appears particularly well-suited to represent adaptation of a population in an *ever-changing* environment. We believe that all these features, rather than referring to the principle of the survival of the fittest as a defense of profit maximization, bring simple but relevant principles that are reconcilable with, and even precursory of both the theory of bounded rationality (Simon 1961) and evolutionary economics (Nelson & Winter 1982), and may be useful for modeling behavior in macro ABMs. Besides, our approach shares affinities with early evolutionary growth models in the way learning and adaptation are modeled (Silverberg & Verspagen 1994*a*,*b*).

In this paper, we introduce investment and capital depreciation in the `Jamel` model[1], along with refinements in the banking sector. Investment dynamics brings instability into the macroeconomic dynamics of the model compared to previous versions, and reinforces market competition. We then apply the principles of the BSP to the determination of firms' leverage strategies. We choose this model as a playground because it is simple enough to get a grip on the emerging dynamics, while allowing for rich monetary and real interactions between agents, and especially between firms, in a fully stock-flow consistent (SFC) framework.[2] We choose the leverage strategies for testing the BSP because this decision is in several ways particularly challenging from the firms' perspective. Leverage decisions amount specifically to solving a "growth-safety trade-off", i.e. a trade-off between a continuous, debt-financed increase in market capacities, and financial safety, that preserves a low debt level, but at the risk of loosing productive capital, if investment is insufficient to renew depreciating capital, and market shares (Crotty 1990, 1992, 1993, Crotty & Goldstein 1992). The debt behaviors of firms in turn collectively contribute to shape the macroeconomic environment, so that the environment constantly changes, and complex dynamics emerge. In such an hostile and selective environment, not even the modeler would be able to identify an "optimal" solution. We therefore let the leverage strategies of a collection of competing firms evolve on a completely random basis, and the only selection pressure comes from bankruptcies.

With the `Jamel` model as a playground, we perform a theoretical exercise that aims to assess to what extent the process of "natural" market selection constitutes a suitable adaptation model for agents in a complex system. This amounts to characterizing the dynamics that emerge from ever-adapting individual behaviors under the sole selection pressure of market conditions, that they in turn contribute to shape: Can the system settle down on an "equilibrium"? Otherwise, what are the emerging dynamics? Admittedly,

[1] `Jamel` stands for Java Agent-based MacroEconomic Laboratory, see Seppecher (2012*b*,*a*), Seppecher & Salle (2015).

[2] Following Cincotti et al. (2010), Kinsella et al. (2011) and Seppecher (2012*a*), a growing literature has emphasized the interest of combining SFC and ABM principles, see Caverzasi & Godin (2015). A non-exhaustive list of SFC-AB models, besides `Jamel` includes Raberto et al. (2012), Caiani et al. (2016), Riccetti et al. (2014), Russo et al. (2016).

the use of evolutionary learning mechanisms to model firms' adaptation under market competition is not new, especially in the AB literature. Our implementation differs, though, along a number of dimensions, that makes our algorithm a very parsimonious and effective way of addressing the so-called "wilderness of bounded rationality", as explained in Section 2. More importantly, the novelty of our paper is a formal and detailed analysis of those evolutionary mechanisms. We shed light on their implications on the micro and the macro dynamics, while those mechanisms have been embedded into ABMs in a mostly implicit way, without being the focus of the analysis.

Our results are as follows. Decentralized market selection allows the firms to collectively adapt the overall leverage level to the changes in the macro environment in a way that the system can sustain itself. However, this regulation comes at the price of wild fluctuations and deep downturns. This emerging macro dynamics are caused by a clear alternating pattern between a sustained rise in indebtedness along the boom phase, that feeds back into the goods demand, and brutal deleveraging movements along the busts, once the financial fragility of firms, combined with increased interest rates and excess production capacities, increases to the point where insolvency and bankruptcies are unavoidable. We conclude that, even if the "natural" market selection process allows for a certain resilience and adaptability of the system, it does not result in collective optimization or convergence towards an "optimal" equilibrium. Our conclusion stands in sharp contrast to the view, dating back to Friedman (1953), that systematically advocates market selection to justify full rationality assumptions and equilibrium reasoning.

We then make the point that heterogeneity of behaviors is essential to the adaptation process of a population in an unstable, and quickly evolving environment. The BSP allows us to make this heterogeneity endogenous and dynamic: it combines converging forces (market selection and imitation) with diverging forces (exploration), so that behaviors co-evolve with the macroeconomic dynamics that they contribute to shape. This property makes the BSP an appealing candidate to model learning and adaptation in complex adaptive systems. We show that, while individual and aggregate behaviors appear to commonly self-reinforce each other, they can suddenly disconnect from each other. This observation leads us to suggest an evolutionary characterization of a *crisis*, as the point where the evolution of the macro system becomes faster than the adaptation capabilities of the agents that populate it.

The rest of the paper is organized as follows. Section 2 discusses the non-trivial problem of modeling individual behaviors in complex systems and details our implementation of the BSP, Section 3 details the `Jamel` model, Section 4 presents the results from the numerical simulations, and Section 5 discusses the results and concludes with the characterization of a crisis in the model.

2 Modeling individual behavior in macro ABMs: learning and adaptation

This section paves the way to the introduction of the adaptation process based on the BSP in the `Jamel` model. We first discuss the challenges posed by the modeling of agents' behavior in macro ABMs. We then define the concepts of adaptation and *learning* and stress their importance in this type of models. We finally contrast individual versus social learning by focusing on evolutionary models and discuss their limitations.

2.1 Particularities and challenges

The "wilderness of bounded rationality" The functioning of ABMs is rooted in a multitude of heterogeneous agents who repeatedly interact in a decentralized way. Those interactions generate *complexity*, in the sense that even the perfect knowledge of individual behavior is not enough to anticipate the resulting macroeconomic outcomes. In such a complex world, uncertainty is both strategic and radical: there is no trivial probabilistic mapping between the entire set of possible actions of an agent and the resulting states of the world and associated pay-off. Neither the agents nor the modeler may be able to define what the fully rational/optimal decision is (Dosi et al. 2003). As a consequence, the use of the standard microeconomic maximization tools is not suited in ABMs, agents' rationality can only be bounded, in the sense of Simon (1955), i.e. *procedural* and *adaptive.* The challenge is how to model this boundedly rational behavior. This is a challenge because the modeler has to cope with the so-called "wilderness of bounded rationality" (Sims 1980): while there is one single way of solving an optimization program, there are many ways of being boundedly rational, and the question is how to discriminate between the multitude of alternative behavioral rules. This is a crucial question as the dynamics of the ABM, and the conclusions drawn from their analysis, are likely to depend on the behavioral rules that have been incorporated into it.

Empirical observations as the main guideline We argue that what we can observe from real-life behavior should be the main ground for modeling agents' behavior in artificial economies (Cohen 1960, Farmer & Foley 2009). The growing amount of experimental evidence from controlled lab environments with human subjects in economics, sociology and psychology, as well as the increasing availability of survey data has fueled our knowledge of how agents actually behave under alternative environments. However, this collection of empirical evidence comes with limitations. People behavior do not always find a clear-cut interpretation, they can be highly heterogeneous and can vary from one period to the next.[3] In other words, real agents' behaviors are *unstable*, and any attempt to summarize agents' reaction by a fixed behavioral rule derived from a sample of empirical observations may pose a problem of realism. Such an attempt could be acceptable if the model is only aimed at the analysis of very short-run dynamics, over which we can consider that agents' behavior is fixed. However, when it comes to the analysis of longer-run dynamics, this modeling strategy introduces an ad-hoc, exogenous stickiness in the model that may distort the conclusions. When it comes to policy analysis and the comparison of different model scenarios, this strategy does not allow to address the so-called Lucas critique: fixing behavioral rules amounts to performing *ceteris paribus* analysis, and ignoring that policy changes are likely to affect in turn micro behavior. This was also the criticism made by Keynes to Tinbergen's macroeconometric models

[3]For instance, Lainé 2016 shows the challenge posed by the heterogeneity of the observed investment behavior of firms if one seeks to derive a model of investment decisions.

(Keuzenkamp 1995). What is more, we argue that this is a gross contradiction with the decentralized and autonomous nature of ABMs (Gaffeo et al. 2008, Delli Gatti et al. 2010).

Modeling adaptation and learning The alternative to the use of a fixed set of behavioral rules is to endow agents with a genuine ability to adapt or, in other words, to *learn* (Farmer & Geanakoplos 2009). Modeling learning shall be understood as designing behaviors that agents constantly and endogenously adapt as a reaction to the feedback that they receive from their environment. Modeling learning can combine heuristics based on empirical observations and adaptation (Delli Gatti et al. 2010). This idea is also at the root of the heterogeneous agent literature in which agents endogenously switch between a fixed (Brock & Hommes 1997) or evolving (Anufriev et al. 2015) set of heuristics according to their relative pay-off performances.

By inducing an intricate co-evolution between the micro and the macro dynamics, learning introduces an *additional layer of complexity* to the model (Winter 1971). On the one hand, agents adapt their behavior as a result of the macro environment, so that the macro level feeds back into the micro level. On the other, there is an interdependence between individual learning behavior. This is precisely what March (1991, p. 81) defines as an "ecology of competition". As a result from this ecology of competition, the environment in which agents interact cannot be considered as exogenous and is, on the contrary, *ever-changing* (Dosi et al. 2003). This idea is a crucial component of *complex adaptive systems* as discussed by Holland (1992). Because the environment is constantly changing, this type of systems cannot be comprehended in terms of fixed point analysis, in which the equilibrium of the system is the fixed point of the mapping between beliefs and realizations, as this is the case for rational expectations macro models. On the contrary, in such a context, learning goes hand-to-hand with adaptation.This point had been made already by Alchian (1950), and this is the reason why this contribution is the starting point of our modeling strategy:

> In a static environment, if one improves his position relative to his former position, then the action taken is better than the former one, and presumably

> one could continue by small increments to advance to a local optimum. ... [in a changing environment] there can be no observable comparison of the result of an action with any other. Comparability of resulting situations is destroyed by the changing environment ... the possibility of an individual's converging to the optimum activity via a trial-and-error process disappears. (Alchian 1950, p. 219)

2.2 Why social learning in ABMs?

Learning can be modeled at the individual level or the social level (Vriend 2000). Individual learning assumes that each agent is endowed with an evolving set of strategies that can be interpreted as his search capacities. Social learning envisions each agent as a single strategy and adaptation intervenes at the population level.

Individual learning can be understood as a trial-and-error process. On its own, it is certainly slow, as a time step is necessary to evaluate one strategy (unless the agent makes use of some foregone/"what-if" pay-off functions). By contrast, social learning allows the agents to parallelize the evaluation of the available strategies, so that the larger the population, the quicker the evaluation process.[4] A quick adaptation process is most valuable if the environment is itself ever-changing, as argued above in a complex adaptive system. For this reason, we use social learning, which has to be understood in a broad sense:

> Social learning means all kinds of processes, where agents learn from one another. Examples for social learning are learning by imitation or learning by communication. (Riechmann 2002, p. 46)

Social learning in market economies is derived from the "Darwinian" archetype (Dosi et al. 2003, p. 62). This is also the "as if" interpretation of rational behavior (Friedman 1953): selection between individual strategies operates according to the principle of the

[4] Allen & Carroll (2001) and Palmer (2012) illustrate this difference within the simple framework of the buffer-stock consumption rule; see also Salle & Seppecher (2016).

survival of the fittest, so that the least performing strategies in terms of pay-off are eliminated from the population, and replaced by the best performing ones. Because of this Darwinian analogy, social learning in a decentralized economy is often represented by the means of evolutionary algorithms, such as genetic algorithms (GAs hereafter) – see Arifovic (2000) for a survey of GA in stylized macro models. GA learning dynamics is driven by two main forces: *innovation* that constantly introduces new behaviors in the system, and *selection pressure* that duplicates the best performing ones at the expense of the other.

However, GAs are not exempt of limitations. Their operators do not always find an easy economic interpretation (Chattoe 1998, Salle & Seppecher 2016). Most importantly, because they have been initially developed to find optima in complicated *static* problems (Holland 1975), they have been used in economics as a way for agents to learn how to maximize their profits or utility functions, and the focus has been put on the conditions under which agents end up coordinating on the optimal state of the model under GA learning (Arifovic 1990). In these set-ups, the mapping between strategies and pay-off is supposed to be time-invariant. In face of perpetually evolving environment, GAs perform badly because they assimilate adaptation with convergence on an equilibrium and individual coordination (which implies a progressive loss of diversity in the strategy population). This is even sometimes obtained at the price of ad-hoc mechanisms such as an exogenous decrease in the innovation force of the algorithm (Arifovic et al. 2013).[5] We believe that this is a major flaw of the macroeconomic learning literature: the neoclassical paradigm has contributed to reduce learning to convergence on a fixed optimum. In ABMs however, decentralized learning mechanisms and market selection can be represented without the use of GAs, precisely because ABMs allow to model directly these mechanisms in a simpler and more realistic way.[6] The purpose of this paper is to provide such a proof-of-concept.

[5]Admittedly, several modifications have been proposed to make GA more suited to ever-changing environments (see, e.g., Cobb & Grefenstette (1993)). Classifier systems which combine GA with features taken from other types of expert systems, such as Artificial Neural Networks, are also somehow effective in changing environments. However, those algorithms are often complicated and computationally quite costly. By contrast, the BSP used in this paper is simple, parsimonious, while being flexible in its implementation, finds an intuitive interpretation and involves a low computational burden.

[6]As stressed by Dosi & Winter (2003, p. 396), nor are necessary aggregate/centralized interaction

2.3 The "blanketing shotgun process" (BSP)

We now develop a learning model based on the "blanketing shotgun process" of Alchian (1950, p. 219) because the BSP consists precisely in constantly and randomly covering the space of strategies, instead of modeling learning as an individual converging search. We support the idea that Alchian (1950) can be considered as a major precursor of the evolutionist/post-Schumpeterian school of thought because he provided a precise description of the co-evolution between market selection and behavior adaptation.

Three operators The BSP encompasses three operators, all inspired by the biological, Darwinian metaphor (Alchian 1950). First, profits stand for the natural *selection process*: firms with positive profits are considered successful and survive, while those with losses go bankrupt and disappear. We notice that Alchian stresses that positive, *not maximal* profits, are the success criterion, in tune already with the satisfycing principle *à la* Simon (1955):

> Adaptive, imitative, and trial-and-error behavior in the pursuit of "positive profits" is utilized rather than its sharp contrast, the pursuit of "maximized profits." (Alchian 1950, p. 211).

Second, innovation (or mutation or individual experimentation) intervenes at any time, even in case of positive profits, during a "trial-and-error" process. We follow here Alchian's "extreme" hypothesis by modeling "trial-and-error" as a completely random, blind and unintended model of exploration (Alchian 1950, p. 211). We do not claim that deliberate individual learning plays no role in the real world but, following Alchian, we wish to abstract from it in this paper in order to focus on social learning stemming from regulation by market competition. Therefore, at most, we model individual learning as blind individual experimentation ("random mutations") that is on average ineffective (i.e. the average change in strategies is zero at the population level), see Section 3.2.6 for details. Trial-and-error processes may for instance represent internal organizational changes, whether

models like the replicator dynamics. We could make a similar point for the heuristic switching model à la Brock & Hommes (1997).

voluntary or not. They may happen even if the firm is making profits (Winter 1964). This type of innovations maintains the diversity of the population of strategies. We also refer here to the concept of "persistent search" in Winter (1971):

> By "persistent search" is meant a search process that continues indefinitely, regardless of how satisfactory or unsatisfactory performance may be - although the search may be slow, sporadic, or both. (Winter 1971, p. 247)

Those innovations constantly introduce heterogeneity in the firms' debt strategies, which allows for exploration. This heterogeneity is counteracted by the third operator, *imitation*, that stands for heredity: operating characteristics (or "routines" in the terminology of Nelson & Winter (1982)) of successful firms are copied by non-successful firms, i.e. firms which go bankrupt. The copy of the firm's strategies is not exact though, so that innovation is also introduced at that stage.[7] Imitation provides the endogenous selection process which allows for exploitation.

BSP versus GA Even if, at a first glance, the three operators of the BSP seem to have a lot in common with those of a GA, there are important differences. In a GA, changes in behavior are triggered by exogenously fixed probabilities. By contrast, in our implementation of the BSP, the imitation process is endogenously triggered by *market selection pressure* in the event of a firm's bankruptcy. Indeed, the occurrence of imitation is *endogenous*, because a firm will only imitate another firm's strategy if it goes bankrupt. In the event of bankruptcy, a firm is taken over by a new management team, its operating characteristics (in this paper, its leverage strategy) disappear and are replaced by the ones of a *randomly chosen* firm in the population of surviving firms. Moreover, in GA, the imitated agents are selected in relation to their relative performances, e.g. through a tournament or roulette-wheel selection process. By contrast, under the BSP, a bankrupted firm imitates the strategy of *any* surviving firm, randomly drawn among the population,

[7]This can be because the firm's operating characteristics are not perfectly observable by its competitors, or because the firm's routines cannot exactly transferred to another firm, or because of control error in the implementation of the new routine. Alchian (1950, pp. 218-219) uses the concept of "rough-and-ready imitative rules"

independently from its relative level of profits.

Furthermore, the BSP and GAs differ in the relative weight that they give to exploration versus exploitation. A weak selective pressure favors exploration and allows for the survival of poor-performing strategies. Such systems may end of with "many undeveloped new ideas and too little distinctive competence" (March 1991, p. 1971). Conversely, a strong selection process exposes the system to the risk of a premature loss of diversity and homogenization of the strategies on poor ones. The adaptive process is then potentially self-destructive (March 1991, p. 85). Consequently, the ability of a system to adapt and survive relies heavily on the balance between exploitation and exploration. As GA-based learning algorithms have been primarily designed to coordinate individual behaviors on a fixed optimal strategy, they requires a progressive homogenization of the strategy population, and emphasize *adaptation*, i.e. exploitation over exploration. By contrast, the BSP favors exploration, by keeping a perpetual dispersion of the strategies, and therefore reinforces the *adaptability* of the system. We argue that this feature is most convincing in a dynamic market environment in which firms have to compete without being able to derive an optimal strategy. In Section 4.2.1, we show that this dimension turns out to be crucial in shaping the emerging macroeconomic dynamics. We now apply the BSP learning algorithm in a simple macro ABM – `Jamel` – and raise the question whether "the market is indeed a good teacher" (Day 1967, p. 303).

3 Learning and adaptation in a simple macro ABM

The first innovation of this paper is to model the firms' leverage strategies through the BSP. We therefore introduce capital accumulation and depreciation in the model in the `Jamel` model. The size of the firms evolves endogenously as a result of their investment decisions. We also refine the specification of the banking sector. We intend to provide here a self-contained presentation of `Jamel`, and we pay a specific attention to the description and the explanation of the new features that this paper introduces. We refer the interested reader to Seppecher & Salle (2015) for an exhaustive discussion and justification of the rest of the assumptions of the model. Appendix B provides the pseudo-code of the model that makes the timing of events together with each equation explicit, and defines each variable and each parameter. We refer the reader to this appendix for the detail of the model design. The open source code (in java) as well as an executable demo are available on the corresponding author's website at `http://p.seppecher.free.fr/jamel/`, as we believe that this is a necessary step for the transparency and credibility of the simulation results.

3.1 The main features of `Jamel`

Jamel exhibits two essential features: full decentralization and stock-flow consistency. *Decentralization* ensures that aggregates, such as prices and wages, stem from the local interactions in the markets: there is no planner, no auctioneer and all interactions are direct and individual. The resulting emerging patterns, such as income distribution, are therefore endogenous. *Stock-flow consistency* links all agents' balance sheets together and guarantees that micro behaviors are correctly aggregated (Godley & Lavoie 2007). In Appendix C, we provide the relevant transactions and balance sheet matrices.

The economy is populated by h heterogeneous households (indexed by $i = 1, ..., h$), f heterogeneous firms (indexed by j, $j = 1, ..., f$) and one bank (indexed by b). The firms produce homogeneous goods by using labor, supplied by households, and fixed capital, resulting from their investment decisions. Labor and capital are complementary production factors. Capital depreciates: one unit of fixed capital lasts for an exogenous and stochastic number of periods. In other words, machines break down at some point and become irreversibly unproductive. Both households, for consumption purposes, and firms, for investment purposes, purchase the goods. There is a capital accumulation dynamics through investment, but no technical progress, as the productivity of capital (parameter pr^k hereafter) remains fixed and common to all firms. The bank provides loans to the firms to finance their production (wage bill and capital investment). The firms and the bank are assumed to be owned by households, who then receive dividends. One time step t may be understood as a month.

3.2 The firms

3.2.1 Production process

Each firm j is endowed with an integer $k_{j,t}$ of fixed capital, that can be understood as its number of machines. Each machine can be used in combination with at most one unit of labor (one worker) in every period. One unit of labor increments the production process of the machine by one step in each period. Each machine needs d^p time steps to deliver an output and, after completion, this output represents $d^p \cdot pr^k$ units of goods, and adds to the firm's inventories level, denoted by $in_{j,t}$.

3.2.2 Quantity decisions

We assume that each firm maintains a fraction $1 - \mu_F$ of its inventories $in_{j,t}$ as a buffer to cope with unexpected variations of its demand, and puts in the goods market the fraction μ_F. We also assume that the maximum market capacity of each firm is equal to d^m months of production at full capacity: $d^m \cdot pr^k \cdot k_{j,t}$. Hence, in each period t, each firm j's goods supply is given by: $\max(\mu_F \cdot in_{j,t}, d^m \cdot pr^k \cdot k_{j,t})$

For the sake of parsimony, the maximum market capacity is also the targeted level of inventories of each firm, i.e $in^T_{j,t} = d^m \cdot pr^k \cdot k_{j,t}$. The firms use the changes in their inventories as a proxy for the variations in their goods demand: lower-than-targeted (resp. higher-than-targeted) inventories signal excess demand (resp. lack of demand), and firms are likely to increase (resp. decrease) their production, and hence their labor demand $n^T_{j,t}$. The firms then proceed by small, stochastic adjustments in the corresponding direction.

3.2.3 Price setting

Each firm increases (resp. decreases) its price in case of lower-than-targeted (resp. higher-than-targeted) level of inventories *and* if it was (resp. was not) able to sell all its supply during the last period. Each firm proceeds by *tâtonnement*, and keeps track of a floor price $\underline{P}_{j,t}$ (that can be understood as a a price thought to be lower than the market price), and a ceiling price $\overline{P}_{j,t}$ (a price thought to be higher than the market price). The floor and the ceiling prices constitute the search area for the suitable price $[\underline{P}_{j,t}, \overline{P}_{j,t}]$ in case of price adjustment. This search area is dynamically updated so that it increases when the firm keeps on adjusting its price in the same direction, and decreases when the firm reverts its price trend. Therefore, in a strong inflationary environment (resp. deflationary environment), the firm can quickly increase (resp. decrease) its price, and adapt in order to "catch-up" with the price level in the economy.

3.2.4 Wage setting

The wage setting procedure encompasses two routines, so as to account for both an adjustment component to labor market tightness and an "institutional" component, that undoubtedly plays an essential role in the determination of wage levels. Large firms tend to be wage makers, and follow the first routine, which is essentially the same mechanism as the price updating process just described. They adjust their wage offer according to their observed level of vacancies compared to their targeted one, and their past wage levels.

However, the vacancy level is indicative only if the firm's size is large enough, but is of little informational content for a small firm. For instance, in case of a single employee, this information is binary: either 0 or 100% of vacancies. Moreover, such a routine is easy to implement in the case of prices, as firms interact with consumers and/or investors in the goods market in every period. However, firms go to the labor market only in periods when they need to renew a contract or increase their workforce, so that the information that they collect by interacting with households is fragmented, and may be insufficient to set wages that are compatible with market conditions. We therefore introduce a second wage setting routine that is akin to a convention or a norm: small firms tend to be wage takers, and simply use the wage levels prevailing in larger firms of their sector. Copying another firm's wage offer can be easily justified as every machine, and hence every worker, has exactly the same productivity.

The duration of an offered contract is set to a maximum of $d^w > 1$ periods, and the wage remains fixed for this whole period.

We shall stress that these pricing rules imply flexible and independently-fixed prices and wages. The only rigidity stems from the dependence on the previous price and wage levels. For the purpose of this paper, it appears to us important not to impose exogenous constraints such as menu costs, or fixed pricing rules, such as a mark-up procedure, on the firms, in order to let the market exert the only pressure on the firms.

3.2.5 Financial decisions and investment

Payment of dividends At the beginning of each period, the firm distributes to its owners a share of its equities $E_{j,t}$ as dividend.

Borrowing The firm may have to obtain loans from the bank. There are four types of loans. Short-run (non-amortized) loans allow the firm to finance wages if its available cash-on-hand is not enough to fully cover its expected wage bill. Short-run (amortized) loans partly finance its investment (see below), and investment is primary financed with (amortized) long-run loans. The bank also grants short-run loans as overdraft facility in the case where a firm does not have enough cash-on-hand to cover its monthly repayments (see Sub-Section 3.3.2 how the loans are granted).

Investment decisions Each firm has a targeted level of equity $E^T_{j,t} \equiv (1 - \ell^T_{j,t})A_{j,t}$, where $A_{j,t}$ denotes the total assets of the firm j in time t, and $\ell^T_{j,t} \in [0, 1]$ its target debt ratio. Its equity target is the amount of its assets that the firm is not willing to finance by debt. Each firm compares its equity target to its actual level $E_{j,t}$. Only if $E_{j,t} > E^T_{j,t}$ will the firm consider to invest.[8] If so, the firm computes the size of its investment by applying an expansion factor, or "*greediness*" factor $\beta > 1$, to its average past sales (in quantities). Note that this investment objective includes *de facto* both the renewing of obsolete, aging machines and the purchase of new ones.

[8] See e.g. Kalecki (2010), who stresses that the amount of the entrepreneurial equity is the main limitation to the expansion of a firm.

The firms willing to invest buy and transform the homogeneous goods into machines. Firms need v^k goods to deliver a machine. Once purchased, we assume that those goods are transformed into machines immediately and at no cost.[9] We assume that each firm uses the net present value (NPV) analysis to choose the number of machines to purchase.[10] The firm randomly samples g sellers in the goods market to estimate the price of the investment. The discount factor is taken to be equal to the risk-free interest rate of the bank (see below) discounted by average past inflation, the expected cash-flow of the project is computed using the firm's current price and wage, within the limit of its maximum market capacity.[11] The firms reviews the possible investment projects by starting from $m = 0$ (i.e. buying 0 machine), then $m = 1$, etc. until the NPV of the project $m+1$ is less than the NPV of the project m previously considered. The firm then chooses the project m, and buys m machines.

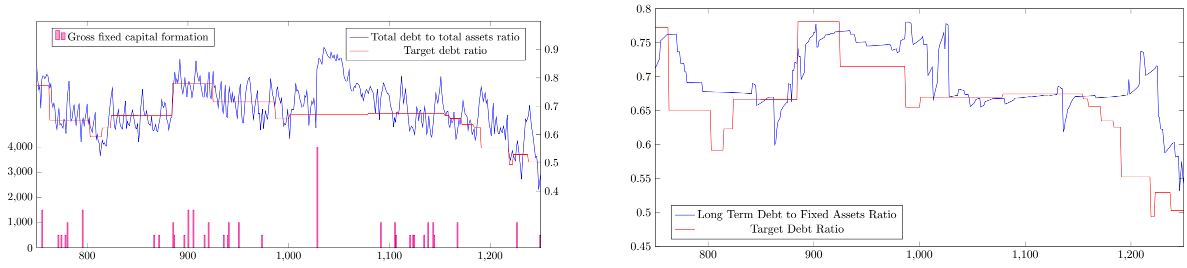
As an illustration, Figure 1a shows the pace of investment decisions for an arbitrary chosen firm in the baseline simulation: only when the effective level of debt lies below its target can investment be performed, but this is not a sufficient condition though. The NPV also integrates expected demand, real interest rates and profitability considerations.

Once the firm decides to purchase m new machines, it computes the share $\ell^T_{j,t}$ of the total price of the investment I_m that is to be financed using a long-run, *amortized* loan. For simplification, we assume that the length of a long-run loan equals the average expected lifetime of the machines d^k. If the firm's cash-on-hand is not enough to cover the share $1-\ell^T_{j,t}$ of the investment, the firm uses an *amortized short-run* loan. This procedure ensures that the firm is never constrained by insufficient cash-on-hand whenever it has decided to invest. The firm's debt may temporary exceed its debt objective due to the additional short-run loan, but the gap progressively closes, as illustrated in Figure 1b for the same, arbitrary chosen firm in the baseline simulation.

[9] This simplifying assumption avoids complicating the model by introducing a second industrial sector. An upcoming version of the model does encompass a capital good sector.

[10] This is a quite standard procedure in corporate finance. However, other types of investment functions could be easily envisioned, and will be considered in further developments of the model.

[11] The price and wage could be computed in a more complicated way, such as a trend projection of past values over the next *window* periods. However, this would complicated the decision making of firms, without adding much to the qualitative simulation results.



(a) Investment and debt ratios

(b) Fixed assets financing

Figure 1: An individual example of a firm's investment and financing behaviors from the baseline simulation: periods 750–1250

Each new machine adds to the firm's assets $A_{j,t}$ at its purchasing price and is uniformly depreciated by a fraction $\frac{1}{d^k}$ of its initial value in every period, unless it breaks down before d^k periods, and its value then falls to zero. The fixed capital depreciation on the asset side of the balance sheet, together with the long run loan amortization on the liability side, allow the firms to roughly maintain the ratio between long run loans and fixed assets in line with their debt objective throughout the life of the machines (see Figure 1b).

3.2.6 Firms' adaptation through the BSP

Firms adapt their indebtedness strategy $\ell^T_{j,t}$ through the BSP, because it summarizes the "growth-safety trade-off" in our model: the higher the debt target, the more likely the investment to be realized and the quicker the market expansion, because the firm needs less of its own equity to finance it; but the higher the risk of insolvency and bankruptcy.

Innovations The permanent trial-and-error innovation process is completely random, blind and unintended: in each period, with a given probability $proba_{BSP}$, firms perturb their debt objective $\ell^T_{j,t}$ by a Gaussian noise, with the same standard deviation σ_{BSP} as the one applied during the imitation process (see hereafter).

Bankruptcy and imitation Firms can go out of business in two ways: bankruptcy by insolvency (when negative profits exhaust their equity, i.e. when their liabilities exceed their assets), and the loss of productive capacities (in the case where they do not succeed in investing to renew their aging machines). We simplify here the entry-exit process of firms and assume that the failed firm does not disappear. The firm is bailed out by the bank, its ownership is changed, its management team is fired, and replaced by another team coming from a more successful firm. Concretely, its debt objective $\ell^T_{j,t}$ is copied on a randomly chosen surviving firm. The copy is not exact though, as a (small) Gaussian noise is introduced (with the same standard deviation σ_{BSP}).

3.3 The rest of the model

3.3.1 The households

In the labor market, each household i is endowed with a constant one-unit labor supply and a reservation wage. If employed, his reservation wage is his current wage. If unemployed, his reservation wage is adjusted downward as a function of his unemployment duration.

Regarding consumption decisions, the households follow a buffer-stock rule *à la* Allen & Carroll (2001) to smooth their consumption in face of unanticipated income variations by building precautionary savings as deposits at the bank. Households cannot borrow and consumption is budget-constrained in every period.

3.3.2 The bank

The functioning of the banking system is very stylized. The bank hosts firms and households deposits at a zero-interest rate, and grants to firms short-run and long-run credits for exogenously fixed duration, common across firms. For simplification, we assume that the interest rate is the same for the two types of loans and is equivalent to the risk-free interest rate. The risk-free interest rate is set by a central bank according to a most simplified Taylor rule that aims to stabilize inflation and takes into account the zero-lower bound.

At a first step, the bank is fully accommodating, and satisfies all the credit demands. However, when a firm is not able to pay off a loan in due terms, the firm receives an overdraft facility at a higher interest rate $i_t + rp$. Parameter $rp > 0$ translates a risk premium and is assumed to be the same for all firms. If a firm j becomes insolvent, it goes bankrupt and the bank starts a foreclosure procedure. The bank first recapitalizes the failed firm : it computes the targeted value of the failed firm, $E^T_{j,t} = \kappa_s A_{j,t}$ and then erases the corresponding amount of debt: $L_{j,t} - A_{j,t} + E^T_{j,t}$, absorbing this loss through its own resources. Then the bank attempts to resell the restructured firm at its new book value $E_{j,t}{=}E^T_{j,t}$, by soliciting households that hold more than a threshold fraction of the restructured firm value in cash-on-hand, and progressively decreasing this threshold if not enough funds can be raised. In the case where the capital of the bank is not enough to recapitalize the bankrupted firm, the bank goes bankrupt and the simulation breaks off.[12]

The bank also distributes dividends to its owners. We assume that it simply distributes its excess net worth, if any, compared to its targeted one.

3.3.3 Markets and aggregation

The markets operate through decentralized interactions based on a standard tournament selection procedure. In the labor market, each firm posts its job offers, and each unemployed household consults g job offers, and selects the one with the highest wage, provided that this wage is at least as high as its reservation wage. Otherwise, it stays unemployed.

In the goods market, each firm j posts $s^T_{j,t}$ goods at a price $P_{j,t}$, each household i enters with its desired level of consumption expenditures, and each investing firm enters with an investment budget. Firms first meet investor-firms, and then interact with households.[13] Each household selects a subset of g firms, and chooses to buy to the cheapest one. These processes are repeated until one side of the markets is exhausted.

As usual in ABMs, aggregate variables are computed as a straightforward summation of individual ones.

[12] We document the frequency of this event in the simulations in Section 4, see Footnote 17. This is due to the very simplistic design of the banking sector in `Jamel`, a feature that is intended to be abandoned in future versions of the model.

[13] This matching order ensures that the biggest purchasers first enter the market, which appears as reasonable. However, this order does not matter as all simulations show that households' rationing in the goods market remains a rare and negligible event, which would not be realistic otherwise.

3.4 Simulation protocol

We use a baseline scenario of the model derived from the empirical validation exercise performed in Seppecher & Salle (2015), but we do not attempt to statistically match empirical micro- or macroeconomic regularities in this paper.[14] We use the model as a virtual macroeconomic playground to test the simple idea of adaptation through the BSP learning model. This playground is nevertheless qualitatively realistic in the following important dimensions for the purpose of our study: it is a complex, monetary and stock-flow consistent market economy. Regarding the new parameters that have been introduced, the lifetime d^k of the machines is a random draw in $\mathcal{N}(120, 15)$, and we set $v^k = 500$, where v^k represents the real cost of an investment/a machine. This positive cost of capital shall be counter-balanced by a moderate length of production of a machine, to maintain a similar profit share; see Seppecher (2014) for further discussion. We then set $d^p = 4$. We set the firms' greediness at $\beta = 1.2$, which translates into a intended 20% increase in productive capacities. This could appear ambitious at a first glance, but it is actually rather conservative: recall that this investment objective includes both the renewing of aging machines and the purchase of new ones. Highest values of this parameter only slightly accentuate the cycles, which is quite expected given the importance of the investment multiplier in our model. We fix the individual experimentation parameters of the BSP to small values ($proba_{BSP} = \sigma_{BSP} = 0.05$), as usual in the learning literature discussed in Section 2. We set the parameters of the Taylor rule to standard values ($\phi_\pi = 2$ and $\pi^T = 2\%$). We set $\delta^P = 0.04$ and $\delta^W = 0.02$, which implies more flexible prices than wages. This relative wage rigidity is necessary to dampen, and even interrupt deflationary dynamics along the bust dynamics, so that the single bank does not go bankrupt (see Seppecher & Salle (2015) for more detail).[15] The risk premium rp on doubtful debt is set to 4% (monthly) and the recapitalization rate in case of bankruptcy is $\kappa_s = 20\%$. The number of wage

[14] However, we do have checked that our model is able to reproduce the empirical macro regularities of Seppecher & Salle (2015). This is indeed the case, along with few more stylized facts that we can seek to reproduce now that our model incorporates investment, e.g. more volatile investment than GDP, and strong positive correlation between firms' debt.

[15] This firstly comes from our very stylized banking system and the absence of government intervention besides the Taylor rule that is ineffective in deflationary downturns.

observations is set to $g' = 3$. However, the qualitative dynamics of the simulation does not seem sensitive to these three specific values. Appendix A lists all parameter values used in the sequel, and the initialization of the model is described in Appendix B.

4 Numerical results

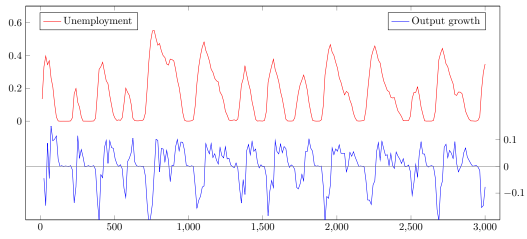
We now give a broad description of the cyclical dynamics that comes out as a robust pattern of the simulations, and then zoom on one cycle to highlight the mechanisms at play.

4.1 Overview of the macroeconomic dynamics

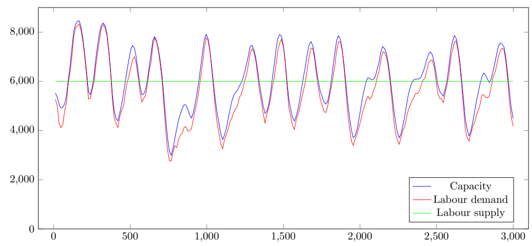
Figure 2 reports typical time series of one run of the baseline scenario: demand and supply in the goods and the labor markets, the corresponding (downward sloping) Phillips and Beveridge curves, nominal and real interest rates, firms' debt, the number of firms' bankruptcies as well as financial fragility.[16] We measure financial fragility by the ratio between the aggregate debt level and the aggregate net profits (i.e. the firms' profits minus the interests). It is clear from the dynamics of all aggregate variables displayed that the macroeconomic dynamics of the model is characterized by a *cyclical pattern*, with alternating periods of booms and busts. Figure 2g already reveals the engine of those cycles: a *pro-cyclical leverage*. We stress that this is an endogenous product of the adaptation process, not an ingredient of the model. This explains why financial fragility and potential output (as measured by the total amount of goods that can be produced by all the machines in the economy) interact along a strongly circular dynamics (Figure 2h). Along a business cycle, the simulations show that the economy follows an anti-clockwise motion in the output/fragility diagram, which indicates that output peaks before financial fragility; see Stockhammer & Michell (2014) for a detailed discussion. Moreover, Figure 2i proves that the building up and the collapse of *assets* of non-financial businesses (firms) is the main force driving the adaptation of the system as a whole: debt ratios of firms are

[16]The contribution of each figure to our argumentation will be presented throughout the whole section.

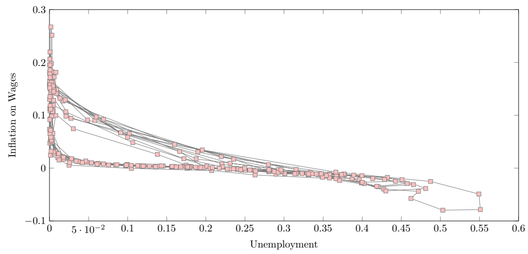
leading GDP, high debt ratios in the past are associated with high present GDP. In the sequel, we discuss those dynamics in details.



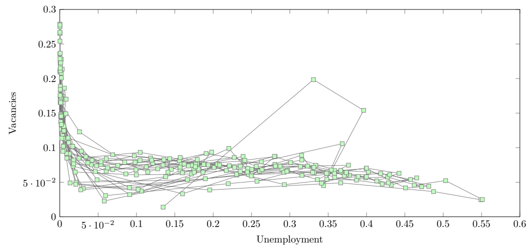
(a) GDP growth and unemployment



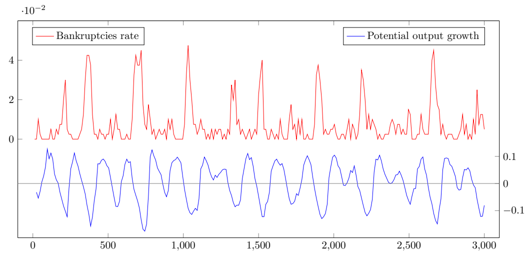
(b) Labor market



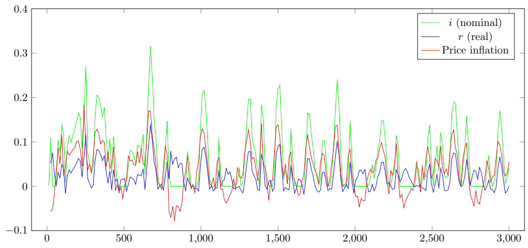
(c) Phillips curve



(d) Beveridge curve

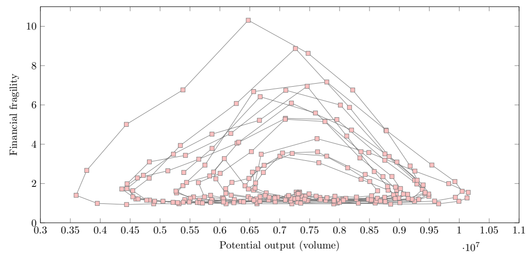


(e) Bankruptcies

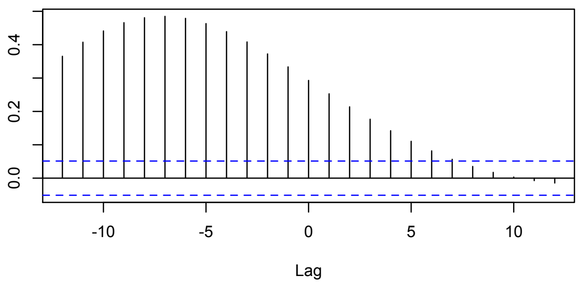


(f) Inflation and interest rates

(g) Firms' debt ratios



(h) Financial fragility



(i) Cross-correlation between debt ratios of firms in $t+k$, $k = -12, ..., 0, ...12$ and GDP in t (detrended series)

Figure 2: Baseline simulation

Giving a closer look at the emerging cycles, we notice that the boom and the bust phases differ in terms of both length and magnitude throughout the same simulations. For instance, in Figure 2, the recession around period 800 is the deepest in this simulation, while fluctuations between periods 1400 and 1800 are the most dampened. This reflects the complex nature of the ABM. The timing as well as the size of the downturns are an *endogenous* product of the model, and result from the intricate relations between the collective adaptive behavior of firms and market selection. In the following section, we unpack the underlying mechanisms.

Before we do so, we shall stress that the observed cycles are a *robust feature* of our model, that we observed in all simulations that we have run, albeit irregular and of various amplitudes.[17] In order to show so, Table 1 presents descriptive statistics of the model outcomes over 30 replications of the baseline scenario with different seeds of the RNG. The similarity between the replications of the baseline scenario is clear from the low values of the standard deviations *between runs*, for all macroeconomic indicators that we report (see all numbers in brackets). As for the cyclical pattern, it is reflected by the particularly high values of the standard deviation of these indicators compared to their average values. For instance, on average between all runs, the GDP growth rate is 0.2%[18], but with a standard deviation of 0.065. This clearly depicts a strong macroeconomic volatility.

The main conclusion that we can draw from our observations is that there seems to be *no such thing as equilibrium or collective optimization.* Nevertheless, the system exhibits some regularities and is sustainable. There is no explosive dynamics. The macroeconomic system survives and reproduces itself but at the price of a strong volatility. Market pressure does work as a selection device between a multitude of randomly generated firms' behaviors, but the market discipline is "brutal", not stabilizing, as reflected by the pace of bankruptcies (Figure 2e).

[17] Because the model is randomly initialized and the single bank bears alone all the costs of firms' losses (see Appendix B), the required adjustments may be too drastic for the single bank to absorb firms' losses, and the simulation may break off at the beginning. We observe that this is the case in roughly 15% of the simulations. We do not report those runs in Table 1. However, once the economy survives this take-off period, we have always observed the same cyclical aggregate pattern.

[18] Recall that the model does not encompass any technological progress nor population changes. An average growth rate close to zero is therefore an expected outcome.

	mean	std. dev.	maximum	minimum
GDP growth rate	0.00226 (0.00092)	0.06493 (0.0028)	0.12335 (0.01408)	-0.21521 (0.01502)
Inflation rate	0.03852 (0.00547)	0.04709 (0.00283)	0.15261 (0.01128)	-0.06213 (0.0143)
Bankruptcy rate	0.0075 (0.00065)	0.01054 (0.00122)	0.0628 (0.01057)	0 (0)
Financial fragility	2.18919 (0.05951)	1.74851 (0.26648)	12.53134 (3.26673)	0.96359 (0.01974)
Firms' leverage	0.5976 (0.00621)	0.0551 (0.00334)	0.73687 (0.00969)	0.49978 (0.01391)
Investment growth rate	0.11017 (0.01198)	0.47834 (0.05258)	2.99064 (0.81132)	-0.60634 (0.06073)

Table 1: Average (and standard deviation between brackets) computed over all periods (discarding the first 500 periods) over 30 replications of the baseline scenario.

4.2 Analysis of a typical cycle

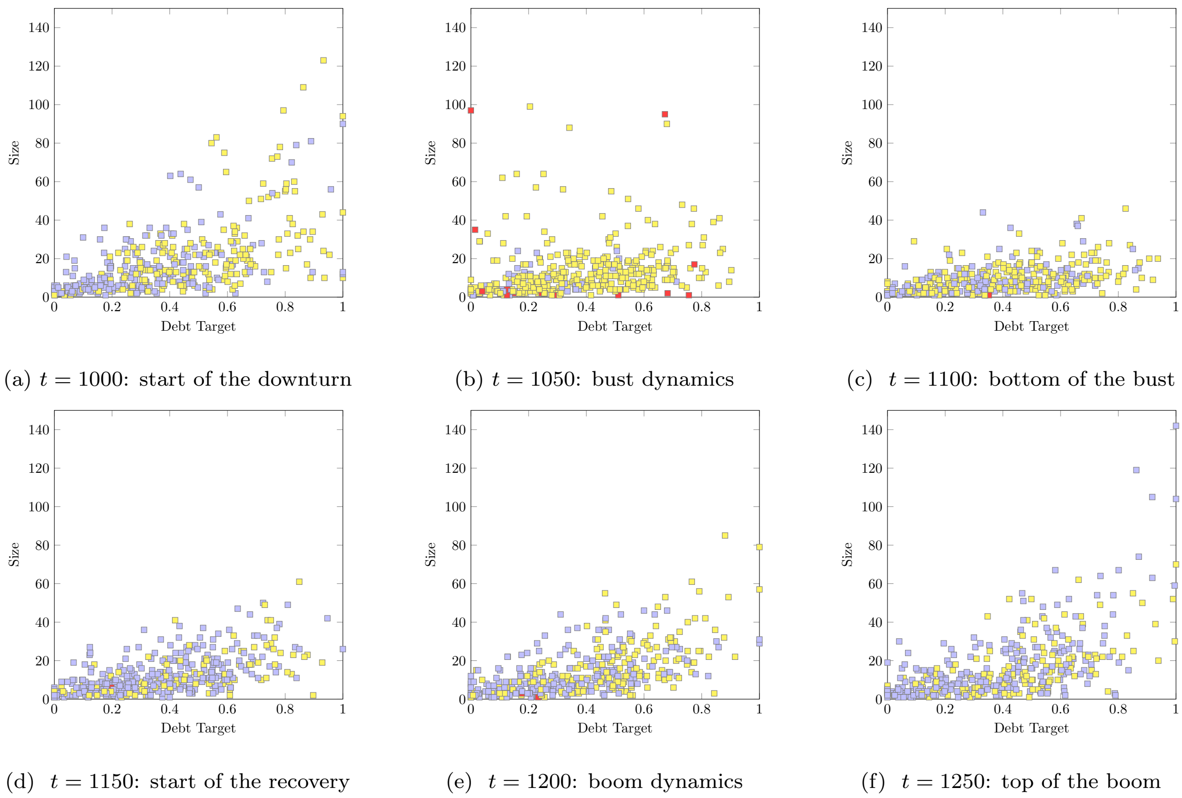
In this section, we zoom on a typical cycle (between periods 750 and 1250) of the baseline simulation displayed in Figure 2.

4.2.1 Firms' adaptation

We show that the very core mechanism at play in generating the cycles is the *alternating of two phenomena*: a sustained increase trend in firms' indebtedness, followed by a brutal correction through a chain of bankruptcies. This is particularly clear from the evolution of the targeted debt ratio of firms weighted by their assets (blue curve in Figure 2g). To provide further insights into firms' behavior over a business cycle, Figure 3 reports the debt objectives ℓ^T versus the sizes of the firms (in number of machines) at six different phases of a cycle, in the following order: the start of the downturn, the bust, the bottom of the bust, the beginning of the recovery, the boom and the top of the boom.

Figure 3 sheds light on the growth-safety trade-off that the firms face: the higher the financial risk (the further on the right side on the scatterplots of Figure 3), the quicker the expansion of the firms (the further up on these same graphs). As a consequence, in the boom dynamics (Figures 3e-3f), we observe a *dispersion* towards the top-right corner of the scatterplots (heavy debt and big size). This evolution is progressive, as a result of the small random but perpetual innovations in the adaptation process that determines the investment behavior of the firms. The “skittish” behaviors, that correspond to low debt strategies, run the risk of being eliminated if they are not enough to even renew the aging and obsolete machines, which would then drive the productive capacities to zero (i.e. towards the origin on the scatterplots). In this case, the firms go bankrupt and imitate another surviving firm. However, the top right corners of those plots are not densely populated because this area is competitive and represents risky behaviors: only a few firms will end up cornering the market, but they all run the risk of unsold production, which would lead to a drop in profits and a risk of insolvency. The riskiness of this behavior is clear from the proportion of speculative, and even Ponzi firms in the top right corner of the figures. This risk is also illustrated by the evolution of firms' positions on the scatterplots throughout the cycles. Once the downturn starts, we observe a clear contraction of the firms towards the bottom of the scatterplot (see Figures 3a-3c). This tightening phenomenon is the result of a twofold motion: the bankruptcies of the most indebted firms that massively and brutally drive out non-cautious high debt strategies (movements towards the left of the plot); and the decrease in capital due to the non-renewal of depreciating productive capacities (movement towards the bottom). As it is clear by comparing Figures 3f and 3c, economic crises endogenously produce an homogenization of firms' behavior because they first affect the few, but biggest firms which grew by heavily indebtedness (see how the population of speculative firms starts growing among the biggest firms first in Figure 3a). In the wake of the bust, the speculative, and even Ponzi-types of financing seem to affect every firm, not only the biggest ones (Figure 3b). Once the recovery starts (Figure 3d), indebtedness starts increasing again, and few firms start growing and cornering the market again (Figure 3e). This process repeats itself along each cycle (to see this, notice the striking similarity between Figures 3a and 3e).

Importantly, the market selection through bankruptcies along the bust dynamics is brutal (movements towards the bottom left of the scatterplots), and much quicker than



(a) $t = 1000$: start of the downturn (b) $t = 1050$: bust dynamics (c) $t = 1100$: bottom of the bust

(d) $t = 1150$: start of the recovery (e) $t = 1200$: boom dynamics (f) $t = 1250$: top of the boom

Figure 3: Firms' size distribution against debt behavior in six phases of a business cycle. Scatterplots report, $\forall j$, ℓ_j^T (debt target, x-axis) versus k_j (size as the number of machines, y-axis). Colors denote income-debt relations, according to the classification and terminology of Minsky (1986): blue for hedge, yellow for speculative, red for Ponzi-financing firms.

the pace of the small-step innovations that progressively drive the system towards an increasing financial fragility along the boom dynamics (i.e. movements towards the top right). This difference explains why recoveries are slow and crises are severe. Deep crises as a brutal disciplining device have been part of the evolutionary economics ideas for a long time:

> Severe depression eliminates large numbers of firms from the economy, but behavior patterns that would be viable under more normal conditions may be disproportionately represented in the casualty list. At the same time, behavior patterns that were in the process of disappearing under more normal conditions may suddenly prove viable... (Winter 1964, p. 266)

Our ABM allows for a detailed and formal analysis of this mechanism in a micro-founded macro model.

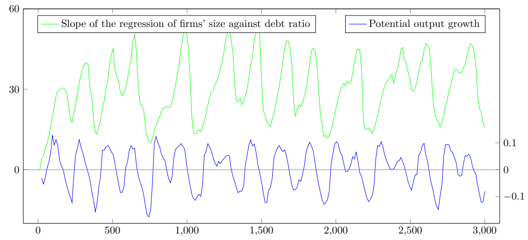


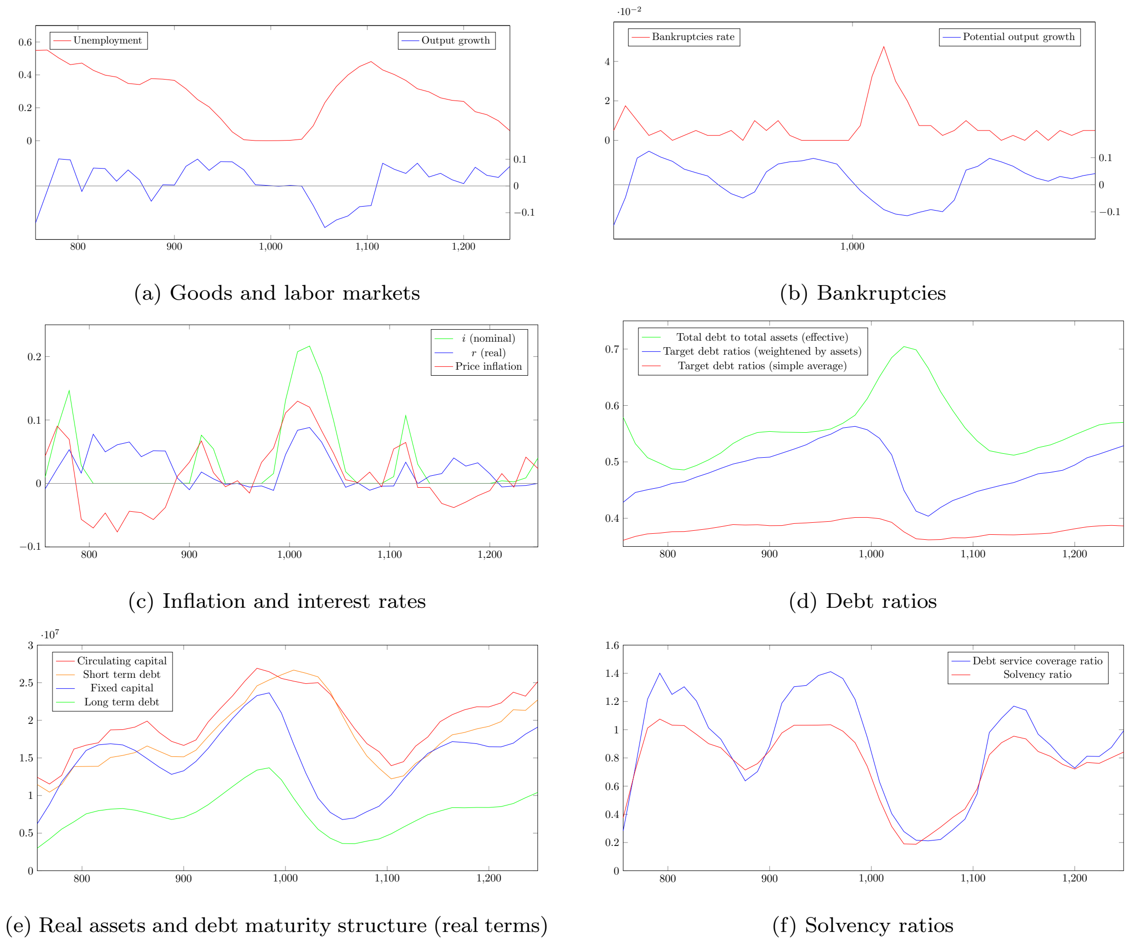
Figure 4: Robustness check of the pattern in Figure 3 along different cycles

As a final exercise on the firms' side, we verify the robustness of those observations across different cycles of the baseline simulation. We use the slope of the regression line in the scatterplots of Figure 3 (sizes *vis-à-vis* debt targets) and its dynamics over the cycles as a synthetic indicator.[19] Figure 4 indicates a strongly pro-cyclical and coincident pattern: the slope is high at the top of the bubbles, then decreasing during the bust and finally increasing up to the top of the boom.

From these observations, we draw the following conclusions. The adaptive model provided by the BSP collectively solves the growth-safety trade-off faced by the firms by eliminating the investment behaviors that are incompatible with current market conditions. The BSP ever creates heterogeneity in behaviors, with a strong emphasis on exploration. This heterogeneity is not random but is characterized by a salient emerging and recurring structure. This structure is endogenous, relatively stable from one cycle to the next, but importantly, *dynamic*: market conditions evolve along the cycle, and behaviors that were judged virtuous in a given phase of the cycle (audacious behavior in the boom) turn out to be vicious in another (during a bust). This heterogeneity provides to the system as a whole its ability to react and adapt. This simple simulation exercise shows that there is no such thing as an efficient or optimal behavior in this complex adaptive system, but the characterization of successful behaviors itself constantly evolves as a result of the market conditions *that these behaviors contribute to shape.*[20] We now focus on those aggregate market conditions.

[19]We are grateful to an anonymous referee for suggesting this exercise.

[20]Brock & Hommes (1998) make a similar point by showing that "non-rational", trend-chasing traders are not driven out by fundamental ones in a financial market model; but their relative share co-evolve in a non-linear way with the dynamics of the market that can display, as a result, very complicated, and even chaotic dynamics. See also Hommes (2006) for a related discussion.



(a) Goods and labor markets

(b) Bankruptcies

(c) Inflation and interest rates

(d) Debt ratios

(e) Real assets and debt maturity structure (real terms)

(f) Solvency ratios

Figure 5: Zoom on one cycle of the baseline simulation: periods 750–1250

4.2.2 Macroeconomic dynamics

Figure 5 zooms on the cycle between period 750 and 1250 of the baseline simulation.On Figure 5d, the blue curve that depicts the average debt ratio weighted by assets moves faster than the red one, that reports the simple arithmetic average over firms. This reflects the fact that during a boom, the aggregate amount of debt grows mostly as a result of few, big firms with high leverage strategies. We now explain how this financial instability interacts with the goods demand, and provokes the boom and bust cycles.

Along the boom phase of the cycle, investment feeds the demand for goods, which calls in turn for more expansion in market capacities (Figure 5a). This optimistic outlook of firms is self-reinforcing because it is followed by the bank, which is fully accommodating in our model. However, the balance sheet of the firms also becomes more fragile

(Figure 5d), and the lending interest rates rise in the boom phase[21] (Figure 5c). This rise generates a negative feedback between firms' financial fragility, investment and goods demand that puts an end to this boom dynamics. Larger and larger shares of firms' cash-flow are absorbed by debt services, especially for the biggest, and therefore more indebted, firms. At some point, this mechanism leads to a drop in profits and investment (see the evolution of potential output on Figure 5b), a rise in bankruptcies (Figure 5b) and a rise in unemployment results (Figure 5a). A series of bankruptcies accelerates the imitation process through the BSP, bankrupted firms imitate the debt strategies of surviving firms. Those strategies correspond to more cautious debt behavior, as explained in Section 4.2.1. However, a phenomenon akin to a Fischerian debt-deflation sets in: we observe a sharp increase in indebtedness precisely when firms choose to deleverage (Figure 5d).[22]

We can also look at the building up and collapse of assets and the interaction with the goods demand through the balance sheets of the agents. Along the bust phase, firms' fixed capital drops, which reflects the drop in productive capacities stemming from the non-renewal of depreciated capital (Figure 5e). However, firms' circulating capital (which consists of the sum of finished and unfinished goods, and therefore measures firms' inventories) only drops with a lag and less dramatically than fixed capital, which indicates excess inventories. Figure 5e also illustrates the liabilities side of firms' balance sheets along the bust dynamics: the dramatic increase in inventories translates into firms' financial difficulties, and a strong rise in overdraft facilities/short-run loans (even above the amount of circulating capital). Figure 5f synthesizes the categorization of firms into the three Minskian financing types (hedge, speculative and Ponzi, see the blue curve that represents the ratio of revenues over debt services), and indicates the degradation of firms' solvency at the macroeconomic level.

Tables 2 and 3 allow for a similar reading. Those tables report the balance sheet

[21]In our model, this raise stems from the Taylor rule that increases nominal rates along the boom. Another explanation is the increase in the bank's risk premium in an attempt to control for the increasing borrowers' financial fragility (Stockhammer & Michell 2014). For simplicity, we abstract here from modeling endogenous risk premiums.

[22]As explained in Seppecher & Salle (2015), the relative wage rigidity that we assume, see Section 3.4, is the driving force that brings back the system on an increasing trend.

	Households	Firms	Banks	Σ
Work In Process		$828,809.29$		$828,809.29$
Inventories		$766,196.57$		$766,196.57$
Fixed Capital		$1,526,549.43$		$1,526,549.43$
Deposits	$1,413,349.64$	$855,523.67$	-2,268,873.31	0
Short Term Loans		-1,672,184.92	$1,672,184.92$	0
Long Term Loans		-875,731.31	$875,731.31$	0
Equities	$1,708,205.65$	-1,429,162.72	-279,042.92	0
Σ	$3,121,555.28$	0	0	$3,121,555.28$

Table 2: Balance sheet matrix, period 1000 (in real terms)

matrix just before (in period $t = 1000$) and right after ($t = 1050$) the downturn (see Appendix C how these matrices are constructed). Within these 50 periods, the overall value of the net worth (i.e. the sum of deposits and equities held by households) has lost 30% of its real value. This loss stems from the collapse in investment which implies that depreciated capital is not replaced: the firms' capital represent almost half of the overall net worth before the downturn, and but only account for a quarter 50 periods later. By contrast, on the asset side of the firms, inventories represent 25% of the overall net worth in $t = 1000$, and more than 40% in $t = 1050$, which reflects the drop in goods demand and firms' sales. On the liabilities side of the firms, the drop in investment shows up in the drop of long-run loans (i.e. the loans that are only intended to finance investment), from 28 to 14% of the overall net worth. On the contrary, the share of the short-run loans increases from 54 to more than 70%, which translates the firms' liquidity problems as a result of the drop in their sales. This simple exercise stresses the usefulness of *stock-flow consistency* for macroeconomic modeling. SFC modeling provides both a disciplinary device in the design of the financial behaviors and accounting relations between sectors, and an analysis tool to dissect dynamics emerging from the simulations.

We conclude that, in our ABM, the process of collective adaptation through the market selection pressure yields cyclical macroeconomic dynamics that look more in line with the "financial instability" hypothesis (Minsky 1986) than with the "as-if" hypothesis (Friedman 1953), which predicts a stabilization of the system around a socially desirable steady state

	Households	Firms	Banks	Σ
Work In Process		700,091.60		700,091.60
Inventories		878,428.60		878,428.60
Fixed Capital		586,028.52		586,028.52
Deposits	1,039,460.42	603,749.48	-1,643,209.89	0
Short Term Loans		-1,529,421.24	1,529,421.24	0
Long Term Loans		-312,271.74	312,271.74	0
Equities	1,125,088.31	-926,605.22	-198,483.09	0
Σ	2,164,548.73	0	0	2,164,548.73

Table 3: Balance sheet matrix, period 1050 (in real terms)

by driving out inefficient behaviors.

5 Conclusions

Our model touches upon two, somehow distinct, research areas – learning and agent-based modeling. This section first makes the point that these areas should be more closely linked together in order to improve macroeconomic modeling and our understanding of macroeconomic dynamics.

Our exercise shows the interest of modeling learning, not as a process intended to converge towards a particular steady state, but as an *ever-changing, ever-adapting process*. In an adaptive complex environment, like the simple macroeconomy modeled in Section 3, and probably like the real world, there is no such thing as an "optimal" or efficient behavior. On the contrary, the characterization of successful behaviors itself constantly evolves as a result of the market conditions that these behaviors contribute to shape. To put our results in parallel with a quote from March (1991, p. 73), in our model, there is not a single efficient way for the firms of addressing the growth-safety trade-off:

- "What is good in the long run is not always good in the short run": a cautious financial strategy (limiting the indebtedness of the firm) is desirable in a long-run perspective because these firms are more resilient to severe downturns, but impeding in the short-run, because it restrains their expansion and make them loose market shares in favor of more audacious firms.

- "What is good at a particular historical moment is not always good at another time": high leverage strategies allow a virtuous expansion circle to set in in periods of output growth, while they turn into a vicious circle in downturns, when firms unsuccessfully try to deleverage.[23]

- "What is good for one part of an organization is not always good for another part": while the fast growth of capital is desirable from the production division viewpoint, it puts the financial department at risk by deteriorating the capital ratio of the firm.

- "What is good for an organization is not always good for a larger social system of which it is a part.": in the wake of a downturn, bankrupted firms tend to imitate deleveraging strategies, hence downsizing their investment to improve their financial situation and avoid insolvency, but this behavior has in turn dramatic effects on the macroeconomic system as a whole because it amplifies and deepens the recession.

We conclude our formal and detailed analysis of learning and adaptation mechanisms with a conceptual definition of an economic crisis. Our model shows how an economic downturn or *crisis* endogenously stems from the adaptation *and* the failure of adaptation of the agents in the system.[24] As shown by our model, a crisis corresponds to the sudden moment when behaviors that were judged by the market successful and compatible with the environment suddenly appear unsuited and unsustainable from the firms' financial perspective, and for the financial system as a whole. In other words, a crisis is the moment when individual behaviors suddenly turn out to be incompatible with the macroeconomic environment, while the two had been reinforcing each other previously. Stated differently, a crisis arises as a sudden, brutal event, when the pace of change of the economic context becomes faster than the adaptation capacities of the agents that populate it.

The occurrence of a crisis results therefore from the combination of the bounded rationality hypothesis and an ever-changing complex environment. Bounded rationality

[23] On the deleveraging crisis and debt-deflation phenomenon, see notably Eggertsson & Krugman (2012). See Seppecher & Salle (2015) for an analysis within a simpler version of the `Jamel` model.

[24] On the phenomenon of economic crises as coordination failures, see also Clower (1965), Cooper & John (1988), Howitt (2001), Gaffeo et al. (2008), Delli Gatti et al. (2008, 2010).

implies that adaptation of behaviors is gradual and inertial (Winter 1964). If the environment evolves only slowly, or has even a constant structure, agents are likely to be able to adapt, and crises are not likely to be an inherent, *endogenous* feature of the system. On the other extreme, if agents are fully rational and fully informed, so that they are able to be infinitely far-sighted, they can adapt *instantaneously* to any new condition, and crises could only result from exogenous shocks.

The interpretation of crises as brutal disconnections between individual behaviors and aggregate outcomes and reversal between what used to appear virtuous and what used to be considered as vicious have recently found some revival interests, in the wake of the Great Recession (Eggertsson & Krugman 2012, Blanchard 2014, Battiston et al. 2016). Modeling such a transition is a challenge though, and our paper shows how ABM can provide a micro-founded, fully decentralized, stock-flow consistent and endogenous approach to this question. The general interdependence of agents' balance-sheets and the interconnection between the financial and the real sectors provided by the stock-flow consistency constitute an essential channel through which imbalances can propagate and crises can emerge as contagion phenomena. Genuine behavioral heterogeneity, together with full decentralization, produces the resulting co-evolution between micro behaviors and macro outcomes, and the endogenous emergence of this type of crises.

Finally, we conclude this paper by pointing towards an interesting extension of our work. In our model, the BSP mechanism only operates on the demand side of the credit market. Banks are actually subject to the same type of trade-off as the firms: a too prudent strategy can lead the bank to lose customers and profit opportunities along the boom, whereas a too aggressive strategy may expose the bank to undue risks. In a version of `Jamel` where the banking sector is disaggregated, credit supply strategies could also evolve under a BSP mechanism. The concomitant selection processes operating on the demand and supply side of the credit market may reinforce the boom and bust dynamics explained in this paper, but they might also dampen it. This is a promising research question that we leave for future work.

References

Alchian, A. A. (1950), 'Uncertainty, evolution, and economic theory', *The Journal of Political Economy* pp. 211–221.

Allen, T. W. & Carroll, C. (2001), 'Individual Learning about Consumption', *Macroeconomic Dynamics* **5**, 255–271.

Anufriev, M., Hommes, C. & Makarewicz, T. (2015), Learning to Forecast with Genetic Algorithms. CeNDEF, University of Amsterdam, mimeo.

Arifovic, J. (1990), Learning by genetic algorithms in economic environments. SFI Working Paper: 1990–001.

Arifovic, J. (2000), 'Evolutionary algorithms in macroeconomic models', *Macroeconomic Dynamics* **4**(03), 373–414.

Arifovic, J., Bullard, J. & Kostyshyna, O. (2013), 'Social Learning and Monetary Policy Rules', *Economic Journal* **123**(567), 38–76.

Battiston, S., Farmer, D., Flache, A., Garlaschelli, D., . Haldane, A., Heesterbeek, H., Hommes, C., Jaeger, C., May, R. & Scheffer, M. (2016), 'Complexity theory and financial regulation', *Science* **351**(6275), 818–819.

Blanchard, O. (2014), 'Where danger lurks', *Finance & Development* **51**(3), 28–31.

Brock, W. A. & Hommes, C. H. (1997), 'A Rational Route to Randomness', *Econometrica* **65**(5), 1059–1096.

Brock, W. & Hommes, C. (1998), 'Heterogeneous beliefs and routes to chaos in a simple asset pricing model', *Journal of Economic Dynamics and Control* **22**(8-9), 1235–1274.

Caiani, A., Godin, A., Caverzasi, E., Gallegati, M., Kinsella, S. & Stiglitz, J. E. (2016), 'Agent based-stock flow consistent macroeconomics: Towards a benchmark model', *Journal of Economic Dynamics and Control* **69**, 375 – 408.

Caverzasi, E. & Godin, A. (2015), 'Post-keynesian stock-flow-consistent modelling: a survey', *Cambridge Journal of Economics* **39**(01), 157–187.

Chattoe, E. (1998), 'Just how (un)realistic are evolutionary algorithms as representations of social processes ?', *Journal of Artificial Societies and Social Simulation* **1**(3).

Cincotti, S., Raberto, M. & Teglio, A. (2010), 'Credit money and macroeconomic instability in the agent-based model and simulator eurace', *Economics: The Open-Access, Open-Assessment E-Journal* **4**(26).

Clower, R. W. (1965), The keynesian counterrevolution : A theoretical appraisal, *in* D. Walker, ed., 'Money and Markets', Cambridge University Press, pp. 34–58.

Cobb, H. G. & Grefenstette, J. J. (1993), Genetic algorithms for tracking changing environments., Technical report, DTIC Document.

Cohen, K. J. (1960), 'Simulation of the firm', *The American Economic Review* **50**(2), 534–540.

Cooper, R. & John, A. (1988), 'Coordinating coordination failures in keynesian models', *The Quarterly Journal of Economics* pp. 441–463.

Crotty, J. & Goldstein, J. (1992), 'The investment decision of the post-Keynesian firm: A suggested microfoundation for Minsky's investment instability thesis'.

Crotty, J. R. (1990), 'Owner–manager conflict and financial theories of investment instability: a critical assessment of Keynes, Tobin, and Minsky', *Journal of Post Keynesian Economics* **12**(4), 519–542.

Crotty, J. R. (1992), 'Neoclassical and Keynesian approaches to the theory of investment', *Journal of Post Keynesian Economics* **14**(4), 483–496.

Crotty, J. R. (1993), 'Rethinking Marxian investment theory: Keynes-Minsky instability, competitive regime shifts and coerced investment', *Review of Radical Political Economics* **25**(1), 1–26.

Day, R. H. (1967), 'Profits, learning and the convergence of satisficing to marginalism', *The Quarterly Journal of Economics* **81**(2), 302–311.

Delli Gatti, D., Gaffeo, E. & Gallegati, M. (2010), 'Complex agent-based macroeconomics: a manifesto for a new paradigm', *Journal of Economic Interaction and Coordination* **5**(2), 111–135.

Delli Gatti, D., Gaffeo, E., Gallegati, M., Giulioni, G. & Palestrini, A. (2008), *Emergent macroeconomics: an Agent-Based Approach to Business Fluctuations*, Springer, Milan.

Dosi, G., Marengo, L. & Fagiolo, G. (2003), Learning in evolutionary environments. LEM Working Paper Series.

Dosi, G. & Winter, S. G. (2003), 'Interprétation évolutionniste du changement économique', *Revue Economique* **54**(2), 385–406.

Eggertsson, G. B. & Krugman, P. (2012), 'Debt, Deleveraging, and the Liquidity Trap: A Fisher-Minsky-Koo approach', *The Quarterly Journal of Economics* **127**(3), 1469–1513.

Farmer, J. D. & Foley, D. (2009), 'The economy needs agent-based modelling', *Nature* **460**(August 6), 685–686.

Farmer, J. D. & Geanakoplos, J. (2009), 'The virtues and vices of equilibrium and the future of financial economics', *Complexity* **14**(3), 11–38.

Friedman, M. (1953), *Essays in Positive Economics*, University of Chicago Press.

Gaffeo, E., Gatti, D. D., Desiderio, S. & Gallegati, M. (2008), 'Adaptive microfoundations for emergent macroeconomics', *Eastern Economic Journal* **34**(4), 441–463.

Godley, W. & Lavoie, M. (2007), *Monetary Economics, An Integrated Approach to Credit, Money, Income, Production and Wealth*, Palgrave Macmillan, Basingstoke.

Holland, J. H. (1975), *Adaptation in Natural and Artificial Systems*, University of Michigan Press, Ann Arbor.

Holland, J. H. (1992), 'Complex adaptive systems', *Daedalus* **121**(1).

Hommes, C. (2006), Heterogeneous Agent Models in Economics and Finance, *in* L. Tesfatsion & K. L. Judd, eds, 'Handbook of Computational Economics', Vol. 2 of *Handbook of Computational Economics*, Elsevier, chapter 23, pp. 1109–1186.

Howitt, P. (2001), Coordination failures, *in* 'An Encyclopaedia of Macroeconomics', Citeseer.

Kalecki, M. (2010), *Theory of Economic Dynamics*, Routledge.

Keuzenkamp, H. A. (1995), Keynes and the logic of econometric method, Technical Report 113, CentER Discussion Paper, Tilburg University, NL.

Kinsella, S., Greiff, M. & Nell, E. J. (2011), 'Income distribution in a stock-flow consistent model with education and technological change', *Eastern Economic Journal* **37**(1), 134–149.

Lainé, M. (2016), 'The heterogeneity of animal spirits: a first taxonomy of entrepreneurs with regard to investment expectations', *Cambridge Journal of Economics* .

March, J. G. (1991), 'Exploration and exploitation in organizational learning', *Organization Science* **2**(1), 71–87.

Minsky, H. P. (1986), *Stabilizing an Unstable Economy*, McGraw-Hill, New York.

Nelson, R. & Winter, S. (1982), *An Evolutionary Theory of Economic Change*, Belknap Press.

Palmer, N. (2012), Learning to Consume: Individual versus Social Learning. George Mason University.

Raberto, M., Teglio, A. & Cincotti, S. (2012), 'Debt, deleveraging and business cycles: An agent-based perspective', *Economics: The Open-Access, Open-Assessment E-Journal* **6**.

Riccetti, L., Russo, A., & Gallegati, M. (2014), 'An agent-based decentralized matching macroeconomic model', *Journal of Economic Interaction and Coordination* **10**(2), 305–332.

Riechmann, T. (2002), Genetic algorithm learning and economic evolution, *in* 'Evolutionary Computation in Economics and Finance', Shu-Heng Chen, pp. 45–60.

Russo, A., Riccetti, L. & Gallegati, M. (2016), 'Increasing inequality, consumer credit and financial fragility in an agent based macroeconomic model', *Journal of Evolutionary Economics* **26**(1), 25–47.

Salle, I. & Seppecher, P. (2016), 'Social learning about consumption', *Macroeconomic Dynamics* **20**(7), 1795–1825.

Seppecher, P. (2012*a*), 'Flexibility of wages and macroeconomic instability in an agent-based computational model with endogenous money', *Macroeconomic Dynamics* **16**(s2), 284–297.

Seppecher, P. (2012*b*), Jamel, a java agent-based macroeconomic laboratory. GREDEG, Université de Nice Sophia Antipolis.

Seppecher, P. (2014), 'Pour une macroéconomie monétaire dynamique et complexe', *Revue de la Régulation* **16**(2eme semestre/Autumn).

Seppecher, P. & Salle, I. (2015), 'Deleveraging crises and deep recessions: a behavioural approach', *Applied Economics* **47**(34-35), 3771–3790.

Silverberg, G. & Verspagen, B. (1994*a*), 'Collective learning, innovation and growth in a boundedly rational, evolutionary world', *Journal of Evolutionary Economics* **4**(3), 207–226.

Silverberg, G. & Verspagen, B. (1994*b*), 'Learning, innovation and economic growth: a long-run model of industrial dynamics', *Industrial and Corporate Change* **3**(1), 199–223.

Simon, H. A. (1955), 'A behavioral model of rational choice', *The Quaterly Journal of Economics* **69**(1), 99–118.

Simon, H. A. (1961), *Administrative Behavior*, The free press, New York.

Sims, C. (1980), 'Macroeconomics and Reality', *Econometrica* **48**(1), 1–48.

Stockhammer, E. & Michell, J. (2014), Pseudo-Goodwin cycles in a Minsky model, Working Papers PKWP1405, Post Keynesian Economics Study Group (PKSG).

Vriend, N. J. (2000), 'An illustration of the essential difference between individual and social learning, and its consequences for computational analyses', *Journal of Economic Dynamics and Control* **24**, 1–19.

Winter, S. G. (1964), 'Economic "natural selection" and the theory of the firm', *Yale Economics Essays* **4**(1).

Winter, S. G. (1971), 'Satisficing, selection, and the innovating remnant', *The Quarterly Journal of Economics* pp. 237–261.

A Parameter values

Parameter	Description	Baseline value
Households		
h	number	6,000
d^r	wage resistance	12 (months)
g	size of the market selection (same for firms)	10
$window$	memory (same for firms)	12 (months)
η_H	wage adjustment parameter	0.05
κ_S	targeted savings rate	0.2 (share)
μ_H	rate of consumption of excess savings	0.5
Firms		
f	number	400
d^k	lifetime of the machines	$\mathcal{N}(120, 15)$ (months)
d^l	short-run credit length	12 (months)
d^L	long-run credit length (= average machine lifetime)	120 (months)
d^m	market capacity, also targeted proportion of inventories	2 (months of production)
d^p	length of the production process	4 (months)
d^w	length of employment contracts	$\mathcal{U}[6, 36]$ (months)
g'	number of wage observations	3
pr^k	productivity of the machines	100 (units)
v^k	value of a new machine in real terms (number of goods to produce a machine)	500 (units)
β	greediness in investment	1.2
δ^P	price flexibility parameter	0.04
δ^W	wage flexibility parameter	0.02
ρ^T	targeted level of vacancies	0.03
μ_F	proportion of goods to be sold	0.5
κ_d	maximum share of equity to be distribute as dividends	0.2
ν_F	production flexibility parameter	0.1
σ_{BSP}	size of individual innovations	0.05
$proba_{BSP}$	probability of individual innovations	0.05
Bank		
κ_b^T	capital adequacy ratio target	0.1
rp	risk premium on doubtful debt	0.04 (monthly)
κ_s	recapitalization rate (for insolvent firms)	0.2
ϕ_π	reaction to inflation (Taylor rule)	2
π^T	inflation target	0.02/12 (monthly)
Model		
d^S	length of the simulations	3,000 (months)

Table 4: `Baseline` scenario. Random draws are performed at each period and for each agent.

B Pseudo-code of Jamel

Initialization :

Variable	Description	Initial value ($t=0$)
Household i		
$C_{i,t}$	actual level of consumption expenditures	0
$C^T_{i,t}$	desired level of consumption expenditures (consumption budget)	0
$d^u_{i,t}$	unemployment duration	0
$FD_{i,t}$	dividends received	0
$M_{i,t}$	cash on hand (bank deposit held)	0
$W_{i,t}$	wage received	0
$W^r_{i,t}$	reservation wage	0
$Y_{i,t}$	monetary income ($=W_{i,t}+FD_{i,t}$)	0
Firm j		
$A_{j,t}$	total assets (inventories, fixed capital and money)	0
$E_{j,t}$	shareholder's equity ($=A_{j,t}-L_{j,t}$)	0
$E^T_{j,t}$	target equity ($=(1-\ell^T_{j,t})A_{j,t}$)	0
$F_{j,t}$	net profits ($=E_{j,t}-E_{j,t-1}+FD_{j,t}$)	0
$FD_{j,t}$	dividends paid to the owners	0
$i_{j,t}$	new fixed capital goods (investment) in number of machines	0
$I_{j,t}$	new fixed capital goods (investment) in nominal terms	0
$in_{j,t}$	inventories (finished goods) in real terms	0
$in^T_{j,t}$	inventories target in real terms $=d^m\cdot pr^k\cdot k_{j,t}$	0
$k_{j,t}$	number of machines, maximum number of jobs	15
$L_{j,t}$	total liabilities (bank loans)	0
$\ell^T_{j,t}$	target debt ratio	$\hookrightarrow\mathcal{U}(0,0.9)$
$M_{j,t}$	cash on hand (money deposit held)	0
$n_{j,t}$	actual workforce, actual number of employees	0
$n^T_{j,t}$	demand for labour, workforce target	12
$P_{j,t}$	unit price of goods supplied	0
$s_{j,t}$	actual sales in real terms	0
$s^e_{j,t}$	sales expansion objective in real terms	0
$s^T_{j,t}$	goods supply (targeted sales) in real terms $=\max(\mu_F\cdot in_{j,t}, d^m\cdot pr^k\cdot k_{j,t})$	0
$W_{j,t}$	the wage offered in nominal terms	50
Bank		
$A_{b,t}$	total assets (= total outstanding loans to the firms)	0
$E_{b,t}$	shareholder's equity ($=A_{b,t}-L_{b,t}$)	0
$E^T_{b,t}$	capital requirement $=\kappa^T_b A_{b,t}$	0
$FD_{b,t}$	dividends paid to the owners of the bank	0
$L_{b,t}$	total liabilities (= sum of deposits held by households and firms)	0
i_t	rate of interest on bank loans (nominal) $=\max\big(\phi_\pi(\pi_t-\pi^T),0\big)$	0
r_t	discount rate (real rate of interest on bank loans) $=i_t-\pi_t$	0
Equities ($E_{j,0}$) of each firm and of the bank are divided in ten equal shares, and given to randomly drawn households.		
Macroeconomic public data		
π_t	price inflation rate	0

Execution In each period t, $t = 1, ..., d^S$:

1. **(Interest rate adjustment:)**

$$i_t = \max\left(\phi_\pi(\pi_t - \pi^T), 0\right) \tag{1}$$

where π_t is the price inflation computed over past *window* periods, ϕ_π and π^T are parameters.

2. **(Fixed capital stock depreciation:)** Each machine m of each firm j is depreciated by $\frac{I_{j,m}}{d^k}$ where $I_{j,m,}$ is the initial value of the machine paid by j and d^k the expected life time of the machine (in months, straight-line depreciation method).

3. **(Payment of dividends:)**

   Each firm j i) computes $\tilde{F}_{j,t}$, its average past net profits F_j over *window* periods, ii) computes the share of net profits to be distributed as $\frac{E_{j,t}}{E^T_{j,t}}$, and iii) distributes to its owners the amount $FD_{j,t} = \min\left(\frac{E_{j,t}}{E^T_{j,t}}\tilde{F}_{j,t}, \kappa_d E_{j,t}\right)$, in proportion to their relative share holding.

   The bank distributes $FD_{B,t} = \max(E_{B,t} - E^T_{B,t}, 0)$

   Updating of the firms' and the bank's balance sheets.

4. **(Price:)**

$$\begin{array}{ll}
\text{if } (s_{j,t-1} = s^T_{j,t-1} \text{ and } in_{j,t} < in^T_{j,t}) & \begin{cases} \overline{P}_{j,t} = \overline{P}_{j,t-1}(1+\delta^P) \\ \underline{P}_{j,t} = P_{j,t-1} \\ P_{j,t} \hookrightarrow \mathcal{U}(\underline{P}_{j,t}, \overline{P}_{j,t}) \end{cases} \\
\text{else if } (s_{j,t-1} < s^T_{j,t-1} \text{ and } in_{j,t} > in^T_{j,t}) & \begin{cases} \overline{P}_{j,t} = P_{j,t-1} \\ \underline{P}_{j,t} = \underline{P}_{j,t-1}(1-\delta^P) \\ P_{j,t} \hookrightarrow \mathcal{U}(\underline{P}_{j,t}, \overline{P}_{j,t}) \end{cases} \\
\text{else} & \begin{cases} \overline{P}_{j,t} = \overline{P}_{j,t-1}(1+\delta^P) \\ \underline{P}_{j,t} = \underline{P}_{j,t-1}(1-\delta^P) \\ P_{t,j} = P_{j,t-1} \end{cases}
\end{array} \tag{2}$$

   with :

   - $\overline{P}_{j,t}$, the ceiling price,
   - $\underline{P}_{j,t}$, the floor price.

5. **(Wage offer:)** Each firm j observes a random sample of g' other firms. If the observed sample contains a firm k such that $k_{k,t} > k_{j,t}$, then:

$$\begin{cases} W_{j,t} = W_{k,t} \\ \overline{W}_{j,t} = W_{j,t}(1+\delta^W) \\ \underline{W}_{j,t} = W_{j,t}(1-\delta^W) \end{cases} \tag{3}$$

else:

$$\text{if } (\rho_{j,t-1} > \rho^T) \quad \begin{cases} \overline{W}_{j,t} = \overline{W}_{j,t-1}(1+\delta^W) \\ \underline{W}_{j,t} = W_{j,t-1} \end{cases}$$

$$\text{else} \quad \begin{cases} \overline{W}_{j,t} = W_{j,t-1} \\ \underline{W}_{j,t} = \underline{W}_{j,t-1}(1-\delta^W) \end{cases} \tag{4}$$

$$\text{and then} \quad W_{j,t} \hookrightarrow \mathcal{U}(\underline{W}_{j,t}, \overline{W}_{j,t})$$

with:

- $\rho_{j,t-1} = \frac{n^T_{j,t-1} - n_{i,t-1}}{n^T_{j,t-1}}$, the vacancy rate previously observed by the firm,
- $\overline{W}_{j,t}$, the ceiling wage,
- $\underline{W}_{j,t}$, the floor wage.

6. **(Labor demand:)** $n^T_{j,t}$ (within the lower bound 0 and the upper bound $k_{j,t}$):

$$n^T_{j,t} = (1+\delta^h_{j,t})n^T_{j,t-1} \tag{5}$$

where $n^T_{j,t-1}$ is the labor demand of the firm in period $t-1$, and $\delta_{j,t}$ is the size of the adjustment, computed as:

$$\delta^h_{j,t} = \begin{cases} \alpha_{j,t}\nu_F & \text{if } 0 \leq \alpha_{j,t}\beta_{j,t} < \frac{in^T_{j,t} - in_{j,t}}{in^T_{j,t}}, \\ -\alpha_{j,t}\nu_F & \text{if } 0 \leq \alpha_{j,t}\beta_{j,t} < \frac{in_{j,t} - in^T_{j,t}}{in^T_{j,t}}, \\ 0 & \text{else.} \end{cases} \tag{6}$$

with $\alpha_{j,t}$, $\beta_{j,t} \hookrightarrow \mathcal{U}(0,1)$ and $\nu_F > 0$.

$$\begin{cases} \text{if } n_{j,t} > n^T_{j,t} & \text{fires } n_{j,t} - n^T_{j,t} \text{ (on a last-hired-first-fired basis)} \\ \text{else} & \text{posts } n^T_{j,t} - n_{j,t} \text{ job offers.} \end{cases} \tag{7}$$

7. **(Financing of current assets):** according to the existing job contracts, the workforce target $n^T_{j,t}$, and the new wage rate offered on the labor market $W_{j,t}$:
   - computes the anticipated wage bill $WB^T_{j,t}$;
   - borrows $\max(WB^T_{j,t} - M_{j,t}, 0)$ (non-amortized short-term loan).
   - Updating of the firms' and the bank's balance sheets.

8. **(Reservation wages:)**
   Each household i updates his reservation wage $W^r_{i,t}$.
   - If i is unemployed:
   $$W^r_{i,t} = W^r_{i,t-1}(1-\delta^w_{i,t}) \tag{8}$$
   where $\delta^w_{i,t} \geq 0$ is the size of the downward adjustment, and is computed as:
   $$\delta^w_{i,t} = \begin{cases} \beta_{i,t} \cdot \eta_H & \text{if } \alpha_{i,t} < \frac{d^u_{i,t}}{d^r} \\ 0 & \text{else.} \end{cases} \tag{9}$$

where $\alpha_{i,t}$, $\beta_{i,t}$ are $\mathcal{U}(0,1)$, and $\eta_H > 0$ and $d^w \geq 1$ are parameters.

- Else:

$$W^r_{i,t} = W_{i,t-1} \tag{10}$$

where $W_{i,t-1}$ is the wage earned by household i at the previous period $t-1$.

9. **(Labor market :)**

   Each unemployed household i) consults a random sample of g job offers; ii) selects the job offer with the highest offered wage, denoted by $W_{j,t}$; iii) if $W_{j,t} >= W^r_{i,t}$, accepts the job for a duration of d^w months; else, remains unemployed for the period t.

10. **(Production):** Each firm distributes uniformly the hired workers on its machines (one per machine). Once a production process of a machine is completed (after d^piterations by a worker), it adds pr^kgoods to the firm's inventories $in_{j,t}$, whose value is then incremented by the production costs of pr^kgoods.

    This process updates i) firms' wage bills and vacancy rates, ii) production levels, and iii) households' cash-on-hand $M_{i,t} = W_{i,t} + FD_{i,t} + M_{i,t-1}$ (where $W_{i,t} + FD_{i,t}$ represents its income flow, made of $FD_{i,t}$, the dividends that household i may receive if it owns shares in the bank or a firm, see Step 1., and $W_{i,t}$ its labor income, and $M_{i,t-1}$ is its cash-on-hand transferred from $t-1$).

11. **(Goods supply:)** Each firm j puts $s^T_{j,t}$ goods in the goods market:

$$s^T_{j,t} = \max(\mu_F \cdot in_{j,t}, d^m \cdot pr^k \cdot k_{j,t}) \tag{11}$$

12. **(Individual experimentation :)** With a probability $proba_{BSP}$, for each firm j, $\ell_{j,t+1} \hookrightarrow \mathcal{N}(0, \sigma_{BSP})$, else $\ell_{j,t,+1} = \ell_{j,t}$.

13. **(Investment decision):**

    (a) selects a random sample of g suppliers (other firms);

    (b) if ($k_{j,t} = 0$) buys $m = 1$ new machine, for a value $I_{j,t}$;

    (c) else if ($E^T_{j,t} > E_{j,t}$):

    i. computes the vector of the prices of each investment project I_m (m the number of new machines to be bought), with $m = 0, 1, 2, ...$;

    ii. computes $\tilde{s}_{j,t}$, average of the sales s_j over the past *window* periods;

    iii. computes $s^e_{j,t} = \beta \cdot \tilde{s}_{j,t}$, its sales expansion objective;

    iv. given its sales expansion objective $s^e_{j,t}$, the expected life time of a machine d^k, the current price $P_{j,t}$, the current wage $W_{j,t}$, the discount factor $r_= i_t - \tilde{\pi}_t$ ($\tilde{\pi}_t$ is the average past inflation computed over the *window* last periods), and the price I_m of each investment project m, computes the net present value NPV_m of each investment project m:

$$NPV_m \equiv \frac{CF_m}{r_t}\left(1 - \frac{1}{r_t(1+r_t)^{d^k}}\right) - I_m$$

where CF_m is the expected cash-flow of the project:

$$CF_m = \min(s^e_{j,t}, m \cdot pr^k) \cdot P_{j,t} - m \cdot W_{j,t}$$

where the min term ensures that the future sales cannot exceed the maximum market capacity of the firms.

v. chooses the project m for which $NPV_{m+1} < NPV_m$, for a value $I_{j,t}$.

vi. adds $\frac{I_m}{m}$ per new machine to its assets.

14. **(Financing of fixed assets):**

    (a) borrows (amortized long-run loan) the amount: $\ell^T_{j,t} I_{j,t}$;

    (b) borrows (amortized short-run loan) the amount: $\max((1 - \ell^T_{j,t})I_{j,t} - M_{j,t}, 0)$;

15. **(Saving/consumption plan:)** Each household computes

    (a) his average monthly income flow over the last *window* periods, denoted by $\tilde{Y}_{i,t}$;

    (b) his cash-on-hand target $M^T_{i,t} = \kappa_S \cdot \tilde{Y}_{i,t}$;

    (c) is targeted consumption expenditures as:

$$C^T_{i,t} = \begin{cases} (1 - \kappa_S)\tilde{Y}_{i,t} & \text{if } M_{i,t} \leq M^T_{i,t} \\ \tilde{Y}_{i,t} + \mu_H(M_{i,t} - M^T_{i,t}) & \text{else.} \end{cases} \tag{12}$$

    where $\mu_H \geq 0$ is a parameter. The budget constraint always gives $C_{i,t} \leq \min(C^T_{i,t}, M_{i,t})$.

16. **(Goods market :)**:

    (a) matches first the firms' demand, then the households' demand with the firms' supply;

    (b) goods bought by firms are transformed in new machines, while goods bought by households are consumed;

    (c) updates the firms' inventories $in_{j,t}$, number of machines $k_{j,t}$, assets $A_{j,t}$ and equities $E_{j,t}$, and the households' remaining cash-on-hand $s_{i,t}$.

17. **(Loans :)** The firms pay back part of their loans and the interests to the bank. Interest is due at each period. For an amortized loan, principal is repaid by equal fractions at each period, while for a non-amortized loan, the total principal is due a the term. If the cash-on-hand $M_{j,t}$ of a firm j cannot fully cover the debt repayments, it benefits of an overdraft facility, ie a new short term loan at an higher rate including the risk premium of the bank $(i_t + rp)$.

18. **(Foreclosure :)** If a firm has become insolvent $(A_{j,t} < L_{j,t})$, the bank starts the foreclosure procedure, a new $\ell^T_{j,t}$ is copied from a surviving firm $(+\mathcal{N}(0, \sigma_{BSP}))$, the firm is recapitalized up to $E_{j,t} = \kappa_s A_{j,t}$, and new households become owners as follows: all households that have at least 20% of $E_{j,t}$ as cash-on-hand are solicited for at most 50% of their wealth, and the firm's shares are distributed in proportion

to their contribution. If the collected cash-on-hand is lower than $E_{j,t}$, the selection threshold is decreased to 10% of $E_{j,t}$. If the cash-on-hand on the solicited households is still not enough, the threshold is decreased to 4%, and then 2%. If this is still not enough to buy all the shares of the firm, the price of the shares is decreased by 10% until enough cash-on-hand can be collected. In case of more than 10 decreases, the simulation would stop.

19. This process starts all over again for a given length of d^S periods.

C Stock- flow consistency

E	Value of equities held by households
E_b	Value of equities issued by banks
E_f	Value of equities issued by firms
IN	Inventories of finished goods, at production cost
K	Value of fixed capital stock
L	Loans supplied by banks
L_f	Loans to firms
M	Money deposits supplied by banks
M_f	Money deposits held by firms
M_h	Money deposits held by households
NW	Net worth of households
WIP	Work in process, at production cost

Table 5: Stocks

	Households	**Firms**	**Banks**	$\boldsymbol{\Sigma}$
Work In Process		WIP		WIP
Inventories		IN		IN
Fixed Capital		K		K
Deposits	M_h	M_f	$-M$	0
Loans		$-L_f$	L	0
Equities	E	$-E_f$	$-E_b$	0
Balance	$-NW$	0	0	$-NW$
Σ	0	0	0	0

Table 6: Balance sheet matrix

AF	Amortization funds
C	Consumption goods sold by firms to households
CAP	Recapitalizations
F_b	Bank profits
F_f	Entrepreneurial profits
FD_b	Dividends of banks
FD_f	Dividends of firms
I	New fixed capital goods
INT	Interest payments paid by firms
L^{back}	Repaid loans
L^{new}	New loans
L^{np}	Non performing loans
$PROD$	New finished goods valued at cost
S	Value of sales, at historic costs
WB	Wages paid to households

Table 7: Flows

	Households	Firms		Banks		Σ
		Current	Capital	Current	Capital	
Consumption	$-C$	$+C$				0
Fixed investment		$+I$	$-I$			0
Δ Work In Process		$+WB-PROD$	$-WB+PROD$			0
Δ Inventories		$+PROD-S$	$-PROD+S$			0
Depreciation allowance		$-AF$	$+AF$			0
Wages	$+WB$	$-WB$				0
Dividends	$+FD_f+FD_b$		$-FD_f$		$-FD_b$	0
Recapitalization	$-CAP$		$+CAP$			0
Entrepreneurial profits		$-F_f$	$+F_f$			0
Bank profits				$-F_b$	$+F_b$	0
Interest on loans		$-INT$		$+INT$		0
Loan defaults			$+L^{np}$		$-L^{np}$	0
Δ Deposits	$-\Delta M_h$		$-\Delta M_f$		$+\Delta M$	0
Δ Loans			$+\Delta L$		$-\Delta L$	0
Σ	0	0	0	0	0	0

Table 8: Transaction-flows matrix

Change in the stock of	**Households**	**Firms**	**Banks**	**Σ**
Work In Process		$+WB\ -PROD$		$+WB\ -PROD$
Inventories		$+PROD\ -S$		$+PROD\ -S$
Fixed Capital		$+I\ -AF$		$+I\ -AF$
Deposits	$+WB\ -C\ +FD_f$ $+FD_b\ -CAP$	$+L^{new}\ -L^{back}$ $-WB+C\ -INT$ $-FD_f\ +CAP$	$-L^{new}\ +L^{back}$ $+INT-FD_b$	0
Loans		$-L^{new}\ +L^{back}\ +L^{np}$	$+L^{new}\ -L^{back}\ -L^{np}$	0
Equities	$-S\ +CAP\ +I\ -AF$ $+C\ -FD_f\ -FD_b$	$+S\ +INT\ -L^{np}\ -I$ $+AF\ -CAP\ -C$ $+FD_f$	$-INT\ +L^{np}\ +FD_b$	0
Σ (Δ Net worth)	$+WB\ -S\ +I\ -AF$	0	0	$+WB\ -S\ +I\ -AF$

Table 9: Full-integration matrix