Households' Behaviors and Systemic Financial Instability
Experimental Insights and Agent-based Simulations for Macroeconomic Policy Analyses

Paola D'Orazio
Department of Economic-Quantitative and Philosophical-Educational Sciences
University "G. D'Annunzio" Chieti-Pescara, viale Pindaro, 42, 65127 Pescara, Italy

1 OBJECTIVES AND STAGE OF THE RESEARCH

In the last two years my research has focused on macroeconomic financial fragility. In particular, on how to bring different methodologies together to study *endogenous* generated crises[1].
Economics profession is currently engaged in a debate on which are the best methodological tools in order to study the dynamics of the real economy and adequately address important policy issues and social concerns. My research endorse the view according to which traditional economic theories and the models they give rise to (namely, the DSGE models) are ill-equipped to manage serious crises which often emerge in real world economies. In my research project I am trying to address these issues by developing an "experimentally" microfounded Agent-based model (ABM), which will account also for the consistency of stocks and flows[2].
The main research issues concern both the *micro* and the *macro* level, i.e., agents and the environment in which they act and interact. For the *micro level*, I have designed an experiment in order to gain insights into agents' behaviors. For the *macro level*, I plan to build an ABM where agents are *estimated* - rather than calibrated - by using experimental data.[3] I plan to start working on the Agent-based macro structure once finished the micro level analysis, i.e. (a) performing the experiment and data analysis and (b) building the behavioral rules for artificial agents. Once the ABM will be set up, I will perform policy experiments in order to evaluate the effectiveness and "profitability" of different policies.

[1]Endogenous crises are those generated *caeteris paribus* by non-price interactions, localized learning processes, investment practices. For a more comprehensive analysis of financial fragility and its effects on real economy see (Minsky, 1970, 1974, 1992).

[2]This is a relevant aspect of the model that will be built. Detailed explanation and motivations for this requirement are given in 2.3. For an historical and methodological perspective on Stock-Flow consistency nad related models see (Caverzasi and Godin, 2013).

[3]This point is explained in section 4.

2 RESEARCH PROBLEM

The interest in this research originates from the increasingly widespread opinion among scholars who claim for the need of new *tools* to cope with the *complexity* of socio-economic systems. The new tools must be able to allow for the building of *microfoundations* of Macroeconomics by considering also the *feedback* effect the macro system has on individual agents. Analytically solvable pure theoretical macro models are of little help for policy guidance (Velupillai, 2011) because they are based on assumptions that are far from reality and do not consider any interaction among heterogeneous agents (Kirman, 1992). In order to consider the macro economy as a complex *endogenously* organized system, researchers should be able to study both the micro level, i.e., agents, and the macro level, i.e., the environment. Concerning the former, behaviors that guides the decision-making process and the *heterogeneity* of agents' population must be incorporated into the model. Regarding the latter, models have to deal with the complexity and instability of the macro *environment*, which is indeed a central feature of the choices that economic agents face.

2.1 The Micro Level

As Simon argued in 1959, to explain agents' behavior in the face of complexity, the theory must incorporate at least some description of the processes and mechanisms through which the adaptation takes place. Simon claimed that the emergence of new areas of theory and application, in which *complexity* and *change* are central facts, led to the demand for a fuller picture

of economic man (Simon, 1959).
The "behavioral revolution" (Akerlof, 2002; Kahneman, 2003; Camerer et al., 2004), which has unfolded in recent decades following in Simon's footsteps, has contributed to the increase of the explanatory power of Economics by providing it with more realistic psychological foundations and "practical" ways in which behaviors can be incorporated into the models (Kao and Velupillai, 2011).

2.2 The Macro Level

The second problem of the present research is related to the definition of the economy as a *Complex Adaptive System* (Tesfatsion, 2003).

ABMs allow to study the "micro-to-macro mapping" (Epstein, 2007) as well as social complexity. They are indeed flexible, precise and consistent modeling tool, providing the ability to explore *learning* and *adaptation* phenomena and increasing our understanding of economic dynamics (Holland and Miller, 1991). In their "early steps" (LeBaron, 2000), ABMs have been mainly used as a tool to *scale up* to the macro level and to perform counterintuitive hypotheses regarding individual behavior or to gain insights into existing human experiments.

However, as Epstein (2007) points out, "even perfect knowledge of individual decision rules does not always allow us to predict macroscopic structure". The *microspecification* of the ABM is thus crucial: individual behaviors "observed" in the experimental laboratory become the solid foundations of the model. Moreover, information collected from experimental micro-systems differs from that obtained from empirical data (Smith, 1982) in that the former offers richer insights into the individual and collective dynamics of a model. Experimental data could thus represent a solution to the problem of availability of micro data which threatens the research on the microfoundations of macroeconomic models (Carroll, 2012b).

2.3 The Stock-Flow Consistency Requirement

Adding a stock-flow consistency (SFC) requirement to the model helps to overcome the *fallacy of composition* critique[4]. Moreover, it helps in detecting sectoral instability - the household sector in the present research project - by considering agents' balance sheets.

SFC models are specific kinds of macro models that try to coherently integrate all stocks and flows of an economy. The two main components are: (1) the accounting framework, and (2) the behavioral equations. The first of these two components usually relies on a set of matrices reproducing the balance sheets, the transactions, and the capital gains of each of the institutional sectors into which the economy is organized. The second component is a set of behavioral equations modeling all the transactions not directly determined by the accounting structure of the economy.

Their roots lie in the study on "money flows" of Morris A. Copeland (Copeland, 1949, 1962)[5]. Recently, SFC models are drawing new attention by researchers in that they are developing new ways to use the SFC framework as a development of the existing general aggregative models (Kinsella et al., 2011; Seppecher, 2012; Raberto et al., 2012).

Until now SFC models are designed as systems of stock-flow consistent equations describing the laws of motion of the economy at the *aggregate* level. The combination of SFC and Agent-based modeling tools will yield more complete macro models. On one hand, the ABM can display consistency between stocks and flows; the result is a framework that ensures the compatibility of real and financial variables. On the other hand, the ABM provide explicit microfoundations to macroeconomic relations.

3 STATE OF THE ART

Agent-based models have been used to study findings from human subject experiments. In his review, Duffy (2006) calls the attention on the interaction between ABM and Experimental Economics by claiming that they are "natural allies". He points out three main areas in which ABM have been used in this way. The first one is the so-called "*zero-intelligent*" agent approach based on the Gode and Sunder (1991) seminal paper. It consists of models with very low rationality constraints which made evident that self-interested and rational behavior is observed mainly in highly structured and constrained markets. A second line of research focuses on *reinforcerment* and belief-based models of agents' behaviors. Finally, there are *Evolutionary Algorithms* where individual learning is more

[4] It concerns the presumption that what is true of each single part of a whole is necessarily true of the whole as well. Basically, it questions the *aggregation process* used by "standard" macroeconomic models.

[5] The intuition of Copeland was to enlarge the social accounting perspective - which had been used mainly in the study of national income - to the study of money flows. He laid the foundations for an economic approach able to *integrate* real and financial flows of the economy (Copeland (1949), p. 254).

complicated.

Brian Arthur was among the firsts in exploring the idea of calibrating an algorithm to reproduce human behavior (Arthur, 1991, 1993). He called the attention on the need to go beyond the assumption of *rationality*, suggesting some ways to model economic choices. He did not want to design a learning algorithm or automaton that maximizes some criterion. Rather, he aimed at designing an algorithm that can be "*tuned to choose actions in an iterated choice situation the way humans would* "(Arthur, 1991, p.354). To calibrate the algorithm in a way that could be defined as a "good indication" of human behavior, he used the results of an experiment performed in 1952-53 by Robillard at Harvard University. His results - and tests of fitness - showed that the automaton was able to replicate those behaviors also in different choice problems, than those for which it was calibrated.

From Arthur on, *Genetic Algorithm* (GA) has been extensively used in Economics; simulations' results show GAs successfully replicate experimental behaviors in different environments (see Arifovic, 1996, 2000; Dawid, 1996, for a comprehensive survey). However, in the ABM literature artificial agents have usually been considered as "equally smart" (Chen and Yu, 2011) and they are built by relying on available theories on individual decision-making (see Raberto et al., 2012; Dosi et al., 2010, 2013, among others). The exploration and *induction* of agents' behaviors by means of the experimental method is thus a more recent strand of research.

4 METHODOLOGY

Households' financial behaviors (in particular, their "debt love"/debt aversion) will be put under the "magnifying glass" by means of the experimental method in order to detect flaws in traditional theories of intertemporal consumption/saving decisions. The experimental method will allow also to explore actual decision-making processes and heterogeneity across agents. Data collected from experiments will be used to analyze the aggregate implications of households' behaviors and to eventually *estimate* the behaviors of artificial agents that will interact in the artificial environment. As showed in Giulioni et al. (2013), the use of experimental data allows to go beyond the standard parameters' *calibration* procedure.

The household sector will be included in a broader project, i.e. a macroeconomic ABM, in which the firm sector and the banking sector will be also considered. The "integrated" experimental-ABM methodology will allow studying both how the macro dynamics evolve and the eventual *endogenously* generated crises.

4.1 Experimental Insights on Intertemporal Decision-making

Experimental Economics complements computational, theoretical and empirical works (Davis and Holt, 1993; Binmore, 1999; Samuelson, 2005) in that it helps identifying behavioral rules agents use in economic decision-making (Kahneman, 2003). Indeed, the experimentation process is not a "simple" additional element of the modeling process; rather it interacts at a deeper level with the limited cognitive abilities of economic agents.

Several studies have been highlighting that individual preferences - and macro feedbacks - are observable and controllable in the laboratory such that economic modeling becomes richer and more realistic (Smith, 1982, 2002). In this sense, the experimental approach follows both the warnings of the well-known *Lucas' critique* (Lucas, 1986) and the *Lucas' invitation*[6]. In his "invitation", Lucas stresses the relevance of experiments in shedding light on humans decision making processes, and therefore on the economic analysis as a whole.

In my research, *experiments* are used to closely investigate human behaviors in an attempt to contribute to the research stream concerned with the building of *new microfoundations* for macroeconomic models. This method also allows for "detecting" agents heterogeneity and how they interact with each other.

4.1.1 The Experimental Design: Some Theoretical and Methodological Considerations

The designed experiment will address two issues in intertemporal consumption models. On one side, the experimental approach will allow to investigate the ability of subjects to solve the task of *intertemporal optimization* and the extent to which subjects behave according to standard optimization rules (Carroll, 1996, 2012b). In this way, the experiment will take the theoretical predictions seriously and *test* if consumers are able to carry out a dynamic intertemporal (utility) optimization problem. On the other side, the experimental method will be used to study the *pervasiveness* of debt in the liabilities side of households' portfolios. The model will thus account

[6] As described in the Experimental Economics entry in the New Palgrave Dictionary of Economics (Duffy, 2008).

also for the role financial innovations have been gaining in capitalistic economies in the last decades.

The experimental design is grounded on methods and results of the early experiments performed on intertemporal consumption. The first attempt of testing how closely the predictions of the optimality theory fit the actual behavior of subjects in an experimental setting is the paper by Hey and Dardanoni (1987). My experiment is closely related to the more recent experiment performed by Ballinger et al. (2003) (although I do not focus on intergenerational learning) and it is designed in the footprints of the "learning to optimize" experiments (LtOEs) where subjects are asked to directly make economic decisions (to consume, invest, trade, produce, etc.) [7].

4.1.2 The Experimental Design: The Model

The starting point is the building of a benchmark intertemporal consumption model which is used to compute the optimal (theoretical) solution that will be compared to our experimental data in order to assess if there is a deviation from the optimal behavior. The major *innovation* introduced concerns the relaxation of the standard budget constraint by allowing borrowing, hence debt.

The solution for the intertemporal consumption problem is found by backward induction, following the method for microeconomic dynamic stochastic optimization problems. Among others, we considered the methods developed by Carroll (2012a) and Stachurski (2009). Given that an explicit solution to the problem does not exist (it is implicitly characterised by an Euler equation), *numerical methods* are needed in order to find an optimal policy function (for saving and borrowing tasks) to be compared to subjects' decisions in the lab. This methodological choice is of particular importance because in the experiment we should be able to control for all possible confounding factors and focus on few variables of interest.

For the standard intertemporal consumption model set up, I compute the policy function for a consumption/saving task which in turn will be used as a benchmark for experimental data.

In order to have a simple and tractable model I do not consider the *discount factor*; a separate experiment is necessary in order to elicit - thus estimate - the discount parameter of subjects in the lab. I indeed decided to leave this investigation for another experiment (Cubitt and Read, 2007; Coller and Williams, 1999; Harrison et al., 1995).

The intertemporal settings that will be analyzed will be basically two. The *perfect certainty* model (*deterministic*) which would be the "candidate" framework to test the predictions of the model built on the rational expectations assumptions, and a *stochastic* version in which there is *uncertainty* about the future income stream. The latter will be useful to assess which kind of expectations (adaptive, etc) arise among experimental subjects.

Th experimental subject pool will be composed by students and workers[8] in an attempt to address the usual criticism about the *external validity* of experimental data and results.

4.2 The Economy as a *Complex Adaptive System*

Agent-based modeling is of particual interest for my research since it allows for taking into account the possibility of endogenous *co-evolution* of micro-behaviors and institutions (namely, the macro structure), the heterogeneity and interactions among economic agents that can lead the system to breakdown without external interference, i.e., shocks. In this, ABMs are a versatile tool: observed dynamics are open-ended (not closed form) and they allow for an *ergodic state* of the system, i.e., an equilibrium, which is an emergent and optional outcome (Delli Gatti et al., 2008). While DSGE models are based on the centralized information processing structure, ABM takes a bottom-up approach that starts modelling realistic microfoundations and ends up analyzing the resulting aggregate behaviour. The dynamics of aggregate variables are the result of complex, continuously and endogenously changing micro-structure. This yields substantial advantages in modelling macroeconomic policies (LeBaron and Tesfatsion, 2008).

However, there are some methodological problems related to ABM. *Caeteris paribus*, the empirical model validation[9] and robustness checks of results. Indeed, the large flexibility of the setup (starting values) of agent-based models and the number of selected parameters give many "degrees of freedom" to the researcher. This in turn poses serious challenges to the use of ACE models for the *evaluation* and design of *economic policy* measures. This problem could be (partially) overcome by using the ex-

[7] LtOEs differ from "learning-to-forecast" experiments (LtFEs) in that LtFEs aim at elicitating subjects' forecasts of the relevant endogenous variables such as the market price, interest rate or wages. See, Arifovic (1996) and Smith et al. (1988).

[8] They have been recruited throught the ORSEE software (Greiner, 2004).

[9] For a broader discussion on this issue see (Fagiolo et al., 2007a,b).

perimental method to build (i.e., estimate) agents that populate the artificial environment.

4.3 Genetic Algorithm "Revisited"

The application and development of the methodology presented and discussed in this paper benefits mainly from theoretical and "practical" insights of Brock and Hommes (1997) seminal paper. It is also inspired from the improvements of "heuristics switching models", in which agents have a set of imple forecasting heuristics (adaptive, trend extrapolating and so on) and choose those that had a better past performance.

However, in order to account for a "complete" agents' heteroegeneity and give the model better microfoundations, the researcher needs tools that allow to consider the whole set of behavioral rules finded in experimental data. In the last decades, many schoars have been engaged in this line of research so that heterogenous, interacting agents in ABM are designed in many different ways (for a comprehensive survey see Chen (2012)).

At the present stage of my research I am considering retaking Brian Arthur's main arguments and results (as discussed in section 3) and go *beyond the calibration process* by estimating the behavioral rules for artificial agents. Indeed, the main point of the present research project is that by means of the experimental method it is possible to gain insights into human behavior and collect information on heterogeneity of the population. Experimental data can thus be used to *estimate*, rather than "merely" calibrate, the behavioral rules that guide artificial agents' actions[10].

In order to fit the ABM using experimental data, I am considering the implementation of a Genetic Algorithm, Classifier Systems or a combination of both. GA is a flexible optimization procedure which has been extensively used in Economics (Arifovic, 2000, 1996). Classifier systems is a machine learning system that learns syntactically simple string rules, called classifiers (Booker et al., 1989; Birchenhall, 1995). The decision will come after a comparison and careful analysis of the pros and cons - ad the related *effectiveness* - of the application of the two techniques to the problem under scrutiny.

In the evaluation of which evolutionary method and technique will best fit for my project, I am also concerned about the economic soundness of this tools. I am indeed considering both the concerns and the warning of Waltman et al. (2011); Dawid and Dermietzel (2006) about the economic interpretation of evolutionary algorithms based on binary encoding and other techniques adopted from computer science without any modification.

[10] Hansen and Heckman (1996) offer an interesting perspective on model calibration and estimation methodologies. It also discusses the related empirical "hidden dangers".

5 TIMING AND EXPECTED OUTCOME

The research presented in this paper represents a doctoral research project which is still in progress. It benefits from the integration of different methodologies and modeling techniques. The last 2 years have been devoted to the study of both the experimental and the agent-based methods and to figure how they can benefit from each other in order to build a macro model. The experimental phase is ready to be implemented; once performed I will use experimental data to build the behavioral rules for artificial agents and thus populate the artificial economy, i.e., the ABM. The expected outcome of the present research is indeed the development of an "integrated" methodology of research which is based on the interaction of Agent-based modeling tools and Experimental Economics method, with the "additional" requirement of SFC.

The combined use of Experimental Economics method and Agent-based Computational Economics, enriched by the "informed intuition" of stock-flow consistency, will allow to develop more real-like macro models and more practical tools to guide policymakers. The ABM will be then used to perform some policy experiments, i.e., analyses on the effects and effectiveness of different fiscal and/or monetary policies. The problem of availability of micro data (Carroll, 2012b) for a "proper" estimation of agents' behavioral rules will be overcome by relying on data collected from experiments. Finally, the present research is also aiming at contributing to the improvement of the ABMs' calibration/estimation techniques.

REFERENCES

Akerlof, G. A. (2002). Behavioral macroeconomics and macroeconomic behavior. *American Economic Review*, 92(3):411–433.

Arifovic, J. (1996). The behavior of the exchange rate in the genetic algorithm and experimental economies. *Journal of Political Economy*, 104(3):510–41.

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

Arthur, W. B. (1991). Designing Economic Agents that Act like Human Agents: A Behavioral Approach to

Bounded Rationality. *American Economic Review Papers and Proceedings*, 81(2):353–359.

Arthur, W. B. (1993). On designing economic agents that behave like human agents. *Journal of Ecolutionary Economics*, 3:1–22.

Ballinger, T. P., Palumbo, M. G., and Wilcox, N. T. (2003). Precautionary saving and social learning across generations: an experiment. *Economic Journal*, 113(490):920–947.

Binmore, K. (1999). Why Experiment in Economics? *Economic Journal*, 109(453):16–24.

Birchenhall, C. R. (1995). Genetic algorithms, classifier systems and genetic programming and their use in the models of adaptive behaviour and learning. *The Economic Journal*, 105(430):788–795.

Booker, L. B., Goldberg, D. E., and Holland, J. H. (1989). Classifier systems and genetic algorithms. *Artificial Intelligence*, 40(1-3):235–282.

Brock, W. A. and Hommes, C. H. (1997). A rational route to randomness. *Econometrica*, 65(5):1059–1096.

Camerer, C. F., Loewenstein, G., and Rabin, M. (2004). *Advances in Behavioral Economics*. Princeton University Press, Princeton.

Carroll, C. (2012a). Lecture notes on solution methods for microeconomicdynamic stochastic optimization problems. *Lecture Notes - John Hopkins University*.

Carroll, C. D. (1996). Buffer-stock saving and the life cycle/permanent income hypothesis. NBER Working Papers 5788, National Bureau of Economic Research, Inc.

Carroll, C. D. (2012b). Representing consumption and saving without a representative consumer. In *Measuring Economic Sustainability and Progress*, NBER Chapters. National Bureau of Economic Research, Inc.

Caverzasi, E. and Godin, A. (2013). Stock-flow consistent modeling through the ages. Economics working paper archive, Levy Economics Institute, The.

Chen, S.-H. (2012). Varieties of agents in agent-based computational economics: A historical and an interdisciplinary perspective. *Journal of Economic Dynamics and Control*, 36(1):1–25.

Chen, S.-H. and Yu, T. (2011). Agents learned, but do we? knowledge discovery using the agent-based double auction markets. In *Frontiers of Electrical and Electronic Engineering in China*, pages 159–170. Springer.

Coller, M. and Williams, M. (1999). Eliciting individual discount rates. *Experimental Economics*, 2(2):107–127.

Copeland, M. A. (1949). Social accounting for moneyflows. *The Accounting Review*, page 254264.

Copeland, M. A. (1962). Some illustrative analytical uses of flow-of-funds data. In *The Flow-of Funds Approach to Social Accounting*, pages 195–238. National Bureau of Economic Research, Inc.

Cubitt, R. and Read, D. (2007). Can intertemporal choice experiments elicit time preferences for consumption? *Experimental Economics*, 10:369–89.

Davis, D. D. and Holt, C. A. (1993). Experimental economics: Methods, problems and promise. *Estudios Economicos*, 8(2):179–212.

Dawid, H. (1996). *Adaptive Learning by Genetic Algorithms: Analytical Results and Applications to Economic Models*. Springer Verlag New York, Inc.

Dawid, H. and Dermietzel, J. (2006). How robust is the equal split norm? responsive strategies, selection mechanisms and the need for economic interpretation of simulation parameters. *Computational Economics*, 28(4).

Delli Gatti, D., Gaffeo, E., Gallegati, M., Giulioni, G., and Palestrini, A. (2008). *Emergent Macroeconomics*. Springer Verlag, Berlin.

Dosi, G., Fagiolo, G., Napoletano, M., and Roventini, A. (2013). Income distribution, credit and fiscal policies in an agent-based keynesian model. *Journal of Economic Dynamics and Control*, 37(8):1598–1625.

Dosi, G., Fagiolo, G., and Roventini, A. (2010). Schumpeter meeting keynes: A policy-friendly model of endogenous growth and business cycles. *Journal of Economic Dynamics and Control*, 34(9):1748–1767.

Duffy, J. (2006). Agent-based models and human subject experiments. In Tesfatsion, L. and Judd, K. L., editors, *Handbook of Computational Economics*, volume 2 of *Handbook of Computational Economics*, chapter 19, pages 949–1011. Elsevier.

Duffy, J. (2008). experimental macroeconomics. In Durlauf, S. N. and Blume, L. E., editors, *The New Palgrave Dictionary of Economics*, volume 3. Palgrave Macmillan, Basingstoke, second edition.

Epstein, J. M. (2007). Agent-based computational models and generative social science. In *Generative Social Science Studies in Agent-Based Computational Modeling*, Introductory Chapters. Princeton University Press.

Fagiolo, G., Birchenhall, C., and Windrum, P. (2007a). Empirical Validation in Agent-based Models: Introduction to the Special Issue. *Computational Economics*, 30(3):189–194.

Fagiolo, G., Moneta, A., and Windrum, P. (2007b). A critical guide to empirical validation of agent-based models in economics: Methodologies, procedures, and open problems. *Computational Economics*, 30(3):195–226.

Giulioni, G., Bucciarelli, E., Silvestri, M., and D'Orazio, P. (2013). Agent-based computational economics and experimental economics: a bridge to progress macroeconomics. manuscript submitted.

Gode, D. and Sunder, S. (1991). Allocative efficiency of markets with zero intelligence (z1) traders: Market as a partial substitute for individual rationality. Gsia working papers, Carnegie Mellon University, Tepper School of Business.

Greiner, B. (2004). An online recruitment system for economic experiments. Forschung und wissenschaftliches rechnen 2003, GWDG Bericht.

Hansen, L. P. and Heckman, J. J. (1996). The empirical foundations of calibration. *Journal of Economic Perspectives*, 10(1):87–104.

Harrison, G. W., Harstad, R. M., and Rutstrm, E. E. (1995). Experimental methods and elicitation of values. Discussion paper serie b, University of Bonn, Germany.

Hey, J. D. and Dardanoni, V. (1987). Optimal consumption under uncertainty: An experimental investigation. *Economic Journal*, 98(390):105–16.

Holland, J. H. and Miller, J. H. (1991). Artificial adaptive agents in economic theory. *The American Economic Review*, 81:365–370.

Kahneman, D. (2003). Maps of bounded rationality: Psychology for behavioral economics. *American Economic Review*, 93(5):1449–1475.

Kao, S. Y. F. and Velupillai, K. V. (2011). Behavioural economics: Classical and modern. Technical report.

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

Kirman, A. P. (1992). Whom or What Does The Representative Individual Represent. *Journal of Economic Perspective*, 6:117–36.

LeBaron, B. (2000). Agent-based computational finance: Suggested readings and early research. *Journal of Economic Dynamics and Control*, 24(5-7):679–702.

LeBaron, B. and Tesfatsion, L. (2008). Modeling macroeconomies as open-ended dynamic systems of interacting agents. *American Economic Review*, 98(2):246–50.

Lucas, R. E. (1986). Adaptive behavior and economic theory. *Journal of Business*, 59:S401–S426.

Minsky, H. P. (1970). *Financial instability revisited: the economics of disaster*. Board of Governors of the Federal Reserve System, Washington.

Minsky, H. P. (1974). The modeling of financial instability: an introduction. In *Modelling and Simulation. Proceedings of the 5th Annual Pittsburg Conference*, pages 267–272.

Minsky, H. P. (1992). The Financial Instability Hypothesis. Working Paper 74, The Jerome Levy Economics Institute of Bard College.

Raberto, M., Teglio, A., and Cincotti, S. (2012). Debt, deleveraging and business cycles: An agent-based perspective. *Economics - The Open-Access, Open-Assessment E-Journal*, 6(27):1–49.

Samuelson, L. (2005). Economic theory and experimental economics. *Journal of Economic Literature*, 43(1):65–107.

Seppecher, P. (2012). Flexibility of wages and macroeconomic instability in an agent-based computational model with endogenous money. *Macroeconomic Dynamics*, 16(S2):284–297.

Simon, H. A. (1959). Theories of Decision-Making in Economics and Behavioral Science. *The American Economic Review*, 49(3):253–283.

Smith, V. L. (1982). Microeconomic Systems as an Experimental Science. *American Economic Review*, 72(5):923–55.

Smith, V. L. (2002). Method in Experiment: Rhetoric and Reality. *Experimental Economics*, 5:91–110.

Smith, V. L., Suchanek, G. L., and Williams, A. W. (1988). Bubbles, crashes, and endogenous expectations in experimental spot asset markets. *Econometrica*, 56(5):1119–51.

Stachurski, J. (2009). *Economic Dynamics. Theory and Computation*. MIT Press.

Tesfatsion, L. (2003). Agent-based computational economics: Modeling economies as complex adaptive systems. *Information Sciences*, 149:263–269.

Velupillai, K. V. (2011). Towards an algorithmic revolution in economic theory. *Journal of Economic Surveys*, 25(3):401–430.

Waltman, L., Eck, N., Dekker, R., and Kaymak, U. (2011). Economic modeling using evolutionary algorithms: the effect of a binary encoding of strategies. *Journal of Evolutionary Economics*, 21(5):737–756.