Avatar-based Macroeconomics
Experimental Insights into Artificial Agents Behavior

Gianfranco Giulioni[1], Edgardo Bucciarelli[1], Marcello Silvestri[2] and Paola D'Orazio[1]
[1]*Department of Philosophical, Pedagogical and Economic-Quantitative Sciences, "G. D'Annunzio" University, Viale Pindaro 42, 65127 Pescara, Italy*
[2]*Research Group for Experimental Microfoundations of Macroeconomics (GEMM), Pescara, Italy*

Keywords: Artificial Intelligence, Experimental Economics, Artificial Economy, Agent-based Computational Economics, Multi-agent Systems.

Abstract: In this paper we present a new methodological approach based on the interplay between Experimental Economics and Agent-based Economics. Advances in the design and implementation of individual autonomous economic agents are presented. The methodology is organized in three steps. The first step focuses on agents. We use an *inductive* rather than a deductive approach: by means of the experimental method we observe agents' behaviors. The second step is the *behavioral rules'* building process that allows us to study how to estimate and structure artificial agents. In the third step, the set of previously induced behavioral rules are used to build artificial agents, i.e. "molded" avatars, which operate in the "archetype" macroeconomic system. The resulting Multi-agent system serves as the macroeconomic environment for our simulations and economic policy analysis.

1 INTRODUCTION

A growing number of economists has been claiming the inadequacy of the Dynamic Stochastic General Equilibrium (DSGE) model which has been considered the standard macroeconomic tool over the past few decades. In order to achieve an internally coherent construction, the DSGE model traditionally relies on the deductive approach through which individual behavior are obtained by sophisticated mathematical models rooted in the axioms of the homo economicus, i.e. the individual maximizing hypothesis, the rational expectations hypothesis, the homogeneity hypothesis. Although the deductive analysis provides an important theoretical benchmark, DSGE models have been questioned because of their microfoundations, i.e. the microeconomic behavior of economic agents. DSGE models *assume* economic agents to solve complex intertemporal optimization problems: the whole model is based on *as if* conjectures rather than empirical evidence. This calls into question the reliability of the predictions of the model which thus need to be *empirically tested* and improved by using different modeling approaches.

According to some economists, the need for analytical tractability that drives the microfoundation process leads to models which are "more simple than possible" (Colander et al., 2008). It is thus clear that a macroeconomic model that is not "more simple than possible" (e.g., a model in which many heterogeneous bounded rational agents interact) loses analytical tractability and requires alternative modeling tools (Velupillai, 2011). The increase in computational power, the development of useful programming languages (such as the object oriented languages) and the striking progress of information and communication technologies has allowed researchers to set up virtual economies and track the results obtained by each artificial agent that operates in the system. These developments have given rise to a new research direction based on a combination of economics and computer science, namely the Agent-based Computational Economics (ACE, Tesfatsion and Judd, 2006).

In this paper we present a research method based on the interplay between Experimental Economics and Agent-based Computational Economics and suggest some advances in the design and implementation of individual autonomous economic agents. The methodology is organized on three levels. On the first level the focus is on agents. We start by following the early steps made by Arthur (1991, 1993) and we try to add possible improvements by adopting the Ex-

Giulioni G., Bucciarelli E., Silvestri M. and D'Orazio P..
Avatar-based Macroeconomics - Experimental Insights into Artificial Agents Behavior.
DOI: 10.5220/0004917902720277
In *Proceedings of the 6th International Conference on Agents and Artificial Intelligence* (ICAART-2014), pages 272-277
ISBN: 978-989-758-016-1

perimental Economics perspective. By means of the experimental method we observe agents' behaviors. In the second level we study how to structure them - the behavioral rules' building process - in order to populate the artificial economy. The goal of the third level is to build a Multi-agent system which serves as the macroeconomic environment for our simulations and economic policy analysis.

2 BEYOND THE DEDUCTIVE APPROACH

Macroeconomists have been working to provide more reliable representations of real economic systems. Hereby we will discuss some points of the wider debate which in turn allow for the assessment of the novelties of our paper.

It is widely agreed that Macroeconomics must be microfounded (Lucas, 1976; Janssen, 2008). This essentially means that:

i) an economist should have a model regulating the behavior of agents that populate the macroeconomic model, and;

ii) the macroeconomic outcome should be obtained by using aggregation techniques that involve (at least) the behavioral rule obtained from the individual model.

There are several ways in which these steps can be undertaken. The choice depends on the requirements the researcher seeks to fulfill.

Concerning point *i)*, economics traditionally uses a *deductive approach* to build models that analyze individual behaviors. According to the deductive approach, the axioms of economic behavior are established first; then agents are provided with objective functions that satisfy the axioms. Finally, behaviors are derived by maximizing objective functions given the pertinent constraints. Concerning point *ii)*, the standard way to proceed is to allow the macroeconomic outcome be a function whose sole input arguments are the individual behaviors and the number of agents in the economy (the aggregate outcome is obtained multiplying the representative agent outcome by the number of agents). These methods for handling *i)* and *ii)* are important because they allow researchers to obtain closed form analytic solutions, thus bringing scientific "appeal" similar to that of the hard sciences to the whole sequence.

However, according to some economists the analytic tractability turns to be a straitjacket because it requires over simplified settings. Indeed, difficulties suddenly arise when more realistic elements, i.e., uncertainty and agents' inability to manage large information sets, are included in the microeconomic framework. This in turn implies that in a more realistic setting, agents' behaviors are characterized by bounded rationality and the adoption of norms (Sargent, 1993; Rubinstein, 1998; Akerlof, 2007, among others, maintain that economics needs such elements).

Other difficulties arise in the aforementioned aggregation process. Kirman (1989, 1992) for example maintains that in order to obtain reliable macroeconomic results, the aggregate outcome should be a function of the rules governing (heterogeneous) agents' behaviors and the structure of interactions among them. Obtaining analytic tractability in a system of interacting elements is an hard task.[1]

A growing number of economists acknowledge ACE as the most promising solution for unlacing the mathematical tractability strait-jacket. Artificial economies are indeed a crucial tool in displaying different ways to understand what is going on in a decentralized economy (Vriend, 1994; Arifovic, 2000).

3 AGENT-BASED COMPUTATIONAL ECONOMICS: CRITICISM AND A PROPOSED WAY OUT

More than twenty years after its first implementation, ACE is sometimes described as a promising field of studies. The lack of commonly accepted microfoundations represents the stumbling block of ACE models which have had difficulties in gaining general acceptance among economists.

In terms of microfoundations, the ACE approach allows for modeling a large range of economic behaviors. This potentiality, however, is linked to the "too many degrees of freedom" problem, i.e., the set of implementable individual models increases enormously so that the researcher can easily incur unsuitable choices. The debate over which are the best means to overcome these problems remains one of the key concerns of the ACE community (see Gürcan et al., 2013, for a recent contribution). *Empirical validation*, according to which the output of the model

[1] It can be obtained for example by using statistical mechanics tools (Aoki and Yoshikawa, 2007). However, the application of these tools does not provide a general solution to the problem. Their application to human economic behavior needs an adaptation which should be carefully evaluated because these techniques were originally developed to aggregate the behavior of particles.

should display similarities with real world data, have been used to qualify ACE models since their appearance. One method to proceed consists in changing the assumed microeconomic behaviors until a good fit of empirical data is achieved, thus providing *indirect* microfoundations.[2] Using the mathematical jargon, proceeding in this way yields sufficient conditions: a candidate model generates realistic results, but the existence of other models that could provide a similar or a better fit cannot be excluded. Also, it could be very useful to have necessary conditions; one possibility in this direction could be using the available microeconomic data to set up the individual behavioral model. Although many Agent-based researchers have shown some interest in this direction, this methodology finds significant hurdles in the paucity and availability of historical and micro data (see Klügl, 2008; Werker and Brenner, 2004, among others).

In this paper we maintain that the aforementioned problems can be sidestepped by using Experimental Economics.

In our research we will refer in particular to *nomothetic experiments*[3] which can provide insights into individuals' behaviors. Indeed, information collected from experimental microsystems offer richer insights into the individual and collective dynamics of a model; they are thus different from those obtained from empirical data. According to this, we argue that experimental data could represent a solution to the problem of availability of micro data.

In our opinion, collecting microeconomic data through experimentation opens up the possibility of performing the *estimation* rather than the *calibration*[4] of individual behavioral models to be implemented in simulations. In other words, by means of this approach, both necessary and sufficient conditions are satisfied and the reliability of ACE models would be significantly increased.

4 EXPERIMENTAL ECONOMICS: SOME METHODOLOGICAL NOTES

The experimental method is gaining consent among economists as a valuable and important tool for analyzing and designing economic systems. One of the main strengths of the experimental method is that the experimenter can iteratively add and remove features of the real (i.e., field) environment and thus study the impact of that manipulation on subjects' behaviors.

Nevertheless, the complexity of economic systems may prevent experimenters - as well as theorists - from correctly identifying the determinants of a particular decision-making situation or market under scrutiny. According to some economists, the extremely simplified environment recreated in a laboratory questions the realism of experiments: experimenters are indeed forced to make simplifying assumptions about an economic problem in order to derive tractable solutions. Yet, such criticism to the *falsificationist* power of experiments pervades all experimental (and observational) sciences: this is often addressed to as the *Duhem-Quine (D-Q) problem* (as explained in Hertwig and Ortmann, 2001).[5] Further clarification about the experimental method is also needed. Falsification *tout court* is not the main goal of experiments: they are aimed at setting the stage for better theory and a better understanding of the phenomena. When experimental results show that a theory works poorly, experimenters engage in a process of procedures' revision before abandoning the theory because of one or many falsifying observations. They reexamine instructions for lack of clarity, increase the experience level of subjects, try increased payoffs, and explore sources of errors in an attempt to find the limits of the "falsifying process".

Besides the criticism about the way experiments are conducted and more specifically about the philosophy of science that guides the experimental method,

[2] Windrum et al. (2007) refer to this practice as *indirect calibration*.

[3] Nomo-theoretical experiments aim to establish laws of behavior through testing theory.

[4] The seminal paper by Hansen and Heckman (1996) offers an interesting perspective on model calibration and estimation methodologies. It also discusses the related empirical "hidden dangers."

[5] It reminds scientists that testing a theory depends crucially on the methodological decisions researchers make in designing and implementing the test itself and of the impossibility to test a scientific theory in isolation given that every empirical test requires assumptions about auxiliary aspects that cannot be controlled by researchers. According to the skeptics about the use of experimentation in Economics, the D-Q problem makes that a failure of a theory in the laboratory can always be attributed to (unobserved) auxiliary hypotheses and the majority of experiments could not survive such a strong test of external validity. Nevertheless, according to Vernon Smith the D-Q problem "is not a barrier to resolving ambiguity in interpreting test results" (Smith, 2002, p. 106); it is rather a stimulus to improve the confrontation of theory with empirical evidence. He argues that if experimenters have a confounding problem with auxiliary hypotheses, they run new experiments to test them and auxiliary hypotheses that are linked with key issues involving the *state* of the agent (namely, motivation and experience-learning) must be incorporated into the theory, thus making it encompassing real features of agents' behaviors.

there is a voiced criticism of the *internal* validity[6] and *external validity*[7] of experiments. *Ceteris paribus*, the comparative sophistication of subjects inside and outside the laboratory, the adequacy of rewards (i.e., payoffs), the framing of instructions.

Regarding the first point, the large majority of experiments have been undertaken with students; this usually raises criticism about the external validity of results gathered in experiments (see Levitt and List, 2007; Al-Ubaydli and List, 2012, for a broader view and debate on *field vs lab* results' validity). Many experimental works have addressed this issue and found that students generally behave similar to subjects with professional experiences, while demographic and gender effects are statistically significant in the comparison across groups (Guillen and F.Veszteg, 2006). Fréchette (2009) reports an interesting survey of 13 experimental works in which both students and professionals took part in different subject pools. Although there are situations in which focusing on students is too narrow, he found that there is not an overwhelming evidence that conclusions reached by using the standard experimental subject pool cannot generalize to professionals. In a recent paper (Giulioni et al., 2013), we investigate the speculative behavior of entrepreneurs experimentally. We considered three different subject pools, i.e., university students, real life entrepreneurs and high school students and ask them to take part to an experiment on individual decision-making with a special focus on learning to forecast (the experimental setting was the same across subject pools). Our comparative results show that there are not relevant differences in the performances and the learning process of the three subject pools.

Other common reservations are about the salience of reward human subjects receive at the end of experiments, namely the *induced value theory* (Smith, 1976). Being results usually based on experiments with relatively small rewards that are at odds with high-stakes of real world decisions, many are concerned about the conclusions experimenters draw on real world choices or markets. Several researchers have replicated well-known experiments using larger rewards than starting values and found no relevant results in using higher stakes (Smith and Walker, 1993; Bordalo et al., 2012).

Moreover, in order to check for robustness of experimental findings, researchers can replicate the experiment and conduct new analyses (Hunter, 2001; Maniadis et al., 2013). Replication, comparability of results and incremental variations (of setting, instructions, subject pools, etc.) of the experiment are indeed very important to assess the reliability of results (Dewald et al., 1986).

5 EXPERIMENTALLY MICROFOUNDED AGENT-BASED MACROECONOMICS

There is a large literature that has focused on parallel experiments with real (human) and computational agents (see, among others, Arifovic (1996); Duffy (2001); Miller (2008) and Chen (2012) for a broader comparative perspective on the design of agents in Agent Based Models). We believe, however, that combining experimental and computational economics will open new and interesting opportunities for research in macroeconomic issues. One of the first economists who called attention to the *complementarity* of experimental economics and ACE has been John Duffy, who argued that bottom-up, bounded rational, inductive models of behavior provide a better fit for experimental and field data (Duffy, 2006).

Figure 1 will help in describing our proposed methodology.

The first phase is identified by the block labeled experimental level, which consists of gathering data through laboratory experiments. In the following microfoundation level phase, a deep data mining process is performed in order to identify the rules used by experimental agents. Neural networks, evolutionary algorithms, heuristics and global optimization techniques are used to identify recurrent patterns of experimental data gathered from each subject. By examining these patterns, the researcher can formulate dynamic behavioral rules that also take into account the existing theoretical insights concerning the decision at hand. Finally, the parameters of the identified behavioral rules are set by using standard or innovative computationally-intensive techniques. In the final stage, the *induced* rules are implemented in the code of artificial agents (see the artificial agents box in figure 1). The *heterogeneous molded avatars* created in this way are used to build an agent-based

[6] It defines the extent to which the environment that generated the data corresponds to the model being tested.

[7] It defines the ability of the causal relation observed in the experiment to generalize over subjects and environments. As noted by Frechette "..[e]xternal validity does not have to be about generalizing from the subjects or environment in the experiment to subjects and environment outside the laboratory. It can also be about variations in subjects and environments within the experiment (for instance, does the result apply to both men and women in the experiment?)" (Fréchette, 2009).

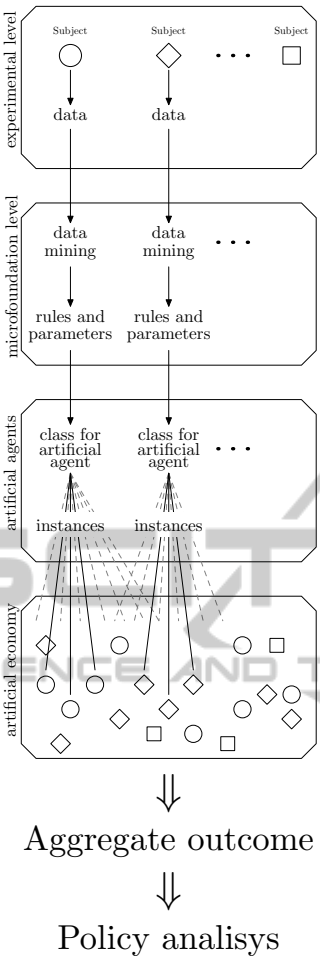

Figure 1: Graphical representation of the proposed approach.

model, which consequently allows the experimenter to increase the number of agents to a level that makes comparisons with real macroeconomic data acceptable. This final step is represented in the artificial economy box of figure 1.

Our ongoing research on the macroeconomic effects of entrepreneurs financial behavior shows that the proposed methodology is effective.

6 CONCLUSIONS

In the proposed approach, *experimental* and *computational economics* cooperate with and complement each other. In particular, we argue that macroeconomic analyses will benefit from the synergy between the two approaches. Moreover, by adopting the presented methodology, computational modeling techniques (e.g., data mining and statistical techniques) will improve their function in economic analysis. Indeed, the novelty of our approach resides in the extremely accurate and demanding work at the microscopic level. As highlighted above, microeconomic data are often missing or yield ambiguous results, which causes difficulties in modeling agents' behaviors. Although the proposed approach is highly demanding, we claim it provides appropriate guidelines for *molding heterogeneous agents* in that it allows the construction of software agents which represent human experimental subjects (i.e. avatars). The outcome of an experimentally-microfounded macroeconomic agent-based model is meant to undergo both the micro and the macro empirical validation process, which will ask the researcher to return to the laboratory to repeat the microfoundation phase in case of ambiguous validation results. This process makes the resulting model particularly reliable. In this sense, we maintain that the combined use of experiments, data mining and Agent-based techniques is particularly useful for economic policies analyses.

REFERENCES

Akerlof, G. A. (2007). The Missing Motivation in Macroeconomics. *American Economic Review*, 97(1):5–36.

Al-Ubaydli, O. and List, J. A. (2012). On the generalizability of experimental results in economics. Working Paper 17957, National Bureau of Economic Research.

Aoki, M. and Yoshikawa, H. (2007). *Reconstructing Macroeconomics: A Perspective from Statistical Physics and Combinatorial Stochastic Processes*. Cambridge University Press, Cambridge.

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.

Bordalo, P., Gennaioli, N., and Shleifer, A. (2012). Salience in experimental tests of the endowment effect. Working Paper 17761, National Bureau of Economic Research.

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.

Colander, D., Howitt, P., Kirman, A., Leijonhufvud, A., and Mehrling, P. (2008). Beyond DSGE Models: To-

ward an Empirically Based Macroeconomics. *American Economic Review*, 98(2):236–40.

Dewald, W. G., Thursby, J. G., and Anderson, R. G. (1986). Replication in empirical economics: The journal of money, credit and banking project. *American Economic Review*, 76(4):587–603.

Duffy, J. (2001). Learning to speculate: Experiments with artificial and real agents. *Journal of Economic Dynamics and Control*, 25(3-4):295–319.

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.

Fréchette, G. R. (2009). Laboratory experiments: Professionals versus students. *The Methods of Modern Experimental Economics. Oxford University Press, forthcoming*.

Giulioni, G., Bucciarelli, E., Silvestri, M., and D'Orazio, P. (2013). The educational relevance of experimental economics: a web application for learning entrepreneurs hip in high schools, universities and workplaces. In *International Journal of Technology Enhanced Learning*, volume forthcoming. Springer-Verlag.

Guillen, P. and F.Veszteg, R. (2006). Subject pool bias in economics experiments. ThE Papers 06/03, Department of Economic Theory and Economic History of the University of Granada.

Gürcan, O., Dikenelli, O., and Bernon, C. (2013). A generic testing framework for agent-based simulation models. *Journal of Simulation*, pages 1–19.

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

Hertwig, R. and Ortmann, A. (2001). Experimental practices in economics: A methodological challenge for psychologists? *Behavioral and Brain Sciences*, 24:383–403.

Hunter, J. E. (2001). The desperate need for replications. *Journal of Consumer Research*, 28(1):149–58.

Janssen, M. C. (2008). Microfoundations. In Durlauf, S. N. and Blume, L. E., editors, *The New Palgrave Dictionary of Economics*. Palgrave Macmillan, Basingstoke.

Kirman, A. (1989). The Intrinsic Limits of Modern Economic Theory: The Empereur has No Clothes. *The Economic Journal*, 99(395):126–139.

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

Klügl, F. (2008). A validation methodology for agent-based simulations. In *Proceedings of the 2008 ACM symposium on Applied computing*, SAC '08, pages 39–43, New York, NY, USA. ACM.

Levitt, S. and List, J. (2007). What do laboratory experiments tell us about the real world? *Journal of Economic Perspectives*, 21(2):153–174.

Lucas, R. J. (1976). Econometric policy evaluation: A critique. *Carnegie-Rochester Conference Series on Public Policy*, 1(1):19–46.

Maniadis, Z., Tufano, F., and List, J. A. (2013). One swallow doesnt make a summer: New evidence on anchoring effects. Discussion Papers 2013-07, The Centre for Decision Research and Experimental Economics, School of Economics, University of Nottingham.

Miller, R. M. (2008). Don't let your robots grow up to be traders: Artificial intelligence, human intelligence, and asset-market bubbles. *Journal of Economic Behavior & Organization*, 68(1):153–166.

Rubinstein, A. (1998). *Modeling Bounded Rationality*. MIT Press, Cambridge and London.

Sargent, T. J. (1993). *Bounded Rationality in Macroeconomics*. Clarendon Press, Oxford.

Smith, V. L. (1976). Experimental Economics: Induced Value Theory. *American Economic Review*, 66(2):274–79.

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

Smith, V. L. and Walker, J. M. (1993). Monetary rewards and decision cost in experimental economics. *Economic Inquiry*, 31(2):245–261.

Tesfatsion, L. and Judd, K. L., editors (2006). *Agent-Based Computational Economics*, volume 2 of *Handbook of Computational Economics*. Elsevier/North-Holland (Handbooks in Economics series).

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

Vriend, N. (1994). Artificial intelligence and economic theory. *Many-agent Simulation and Artificial Life (Frontiers in Artificial Intelligence & Applications)*, pages 31–47.

Werker, C. and Brenner, T. (2004). Empirical Calibration of Simulation Models. Technical Report 04.12, Eindhoven Centre for Innovation Studies, The Netherlands.

Windrum, P., Fagiolo, G., and Moneta, A. (2007). Empirical validation of agent-based models: Alternatives and prospects. *Journal of Artificial Societies and Social Simulation*, 10(2).