Macroeconomic Policy in DSGE and Agent-Based Models[*]

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Abstract

The Great Recession seems to be a natural experiment for macroeconomics showing the inadequacy of the predominant theoretical framework — the New Neoclassical Synthesis — grounded on the DSGE model. In this paper, we present a critical discussion of the theoretical, empirical and political-economy pitfalls of the DSGE-based approach to policy analysis. We suggest that a more fruitful research avenue to pursue is to explore alternative theoretical paradigms, which can escape the strong theoretical requirements of neoclassical models (e.g., equilibrium, rationality, representative agent, etc.). We briefly introduce one of the most successful alternative research projects – known in the literature as agent-based computational economics (ACE) – and we present the way it has been applied to policy analysis issues. We then provide a survey of agent-based models addressing macroeconomic policy issues. Finally, we conclude by discussing the methodological status of ACE, as well as the (many) problems it raises.

Keywords: Economic Policy, Monetary and Fiscal Policies, New Neoclassical Synthesis, New Keynesian Models, DSGE Models, Agent-Based Computational Economics, Agent-Based Models, Great Recession, Crisis.

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Tous les événements sont enchaînés dans le meilleur des mondes possibles

Voltaire, Candide

1   Introduction

At the dawn of 2008 a large number of contributions claimed that monetary – and, more generally, economic – policy was finally becoming more of a science (Mishkin, 2007; Galí and Gertler, 2007; Goodfriend, 2007; Taylor, 2007). Almost at the end of the Great Moderation, these authors argued that both the academic world and central banks had finally reached an overall consensus not only on the contingency rules to implement in alternative situations, but also on the fact that "the practice of monetary policy reflects the application of a core set of "scientific principles" (Mishkin, 2007, p.1). These scientific principles, in turn, derived from the so-called New Neoclassical Synthesis (Goodfriend, 2007; Woodford, 2009) grounded upon Dynamic Stochastic General Equilibrium (DSGE) models[1]. What is more, the available toolbox of economic policy rules was deemed to work exceptionally well not only for normative purposes, but also for descriptive ones. For example, Taylor (2007) argued that "while monetary policy rules cannot, of course, explain all of economics, they can explain a great deal" (p.1) and also that "although the theory was originally designed for normative reasons, it has turned out to have positive implications which validate it scientifically" (abstract). Given these Panglossian premises, scientific discussions on economic policy seemed therefore to be ultimately confined to either fine-tuning the "consensus" model, or assessing the extent to which elements of art (appropriable by the policy maker) still existed in the conduct of monetary policy (Mishkin, 2007)[2].

Unfortunately, as it happened with two famous statements made, respectively, by Francis Fukuyama (1992) about an alleged "end of history", and by many physicists in the recent debate on a purported "end of physics" (see, e.g., Lindley, 1994), these positions have been proven to be substantially wrong by subsequent events. The "perfect storm" which followed the bankruptcy of Lehman Brothers on September 15, 2008 brought financial markets on the edge of collapse causing in turn the worst recession developed economies have ever seen since the Great Depression. In 2012, the risks for the world economic system have not finished yet as the crisis is now menacing the sovereign debt of European countries and the very survival of the Euro.

What is worse, mainstream DSGE-based macroeconomics appear to be badly equipped to deal with the big turmoil we are facing. As Krugman (2011) points out, not only orthodox macroeconomists did not forecast the current crisis, but they did not even admit the possibility of such event and, even worse, they did not provide any useful advice to policy makers to put back the economy on a steady growth path (see also Stiglitz, 2011). On the same line, Delong

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[1]For an introduction, see Clarida et al. (1999), Woodford (2003) and Galí and Gertler (2007). Cf. also Colander (2006c) for an historical perspective.

[2]At the opposite, according to Howitt (2011) "macroeconomic theory has fallen behind the practice of central banking" (p. 2). On the same camp, Mankiw (2006) thinks that macroeconomists should not behave as scientist but as engineers trying to solve practical problems. See also Summers (1991) for an extremely pessimistic view on the possibility of taking *any* economic model seriously econometrically. On these points see also Mehrling (2006).

(2011) reports that when the former U.S. secretary Lawrence Summers was recently asked what economics can offer to understand the crisis, he quoted the works of Bagehot, Minsky and Kindleberger, three dead men whose most recent book is 33 years old. This is so because the DSGE approach "has become so mesmerized with its own internal logic that it has begun to confuse the precision it has achieved about its own world with the precision that it has about the real one" (Caballero, 2010, p. 85).

In that respect, the Great Recessions has revealed to be a natural experiment for economic analysis, showing the inadequacy of the predominant theoretical frameworks. Indeed, an increasing number of leading economists claim that the current "economic crisis is a crisis for economic theory" (Kirman, 2010; Colander et al., 2009; Krugman, 2009, 2011; Caballero, 2010; Stiglitz, 2011; Kay, 2011; Dosi, 2011; Delong, 2011). The basic assumptions of mainstream DSGE models, e.g. rational expectations, representative agents, perfect markets etc., prevent the understanding of basic phenomena underlying the current economic crisis[3].

In this paper, we argue that instead of performing Ptolemaic exercises (Stiglitz, 2011; Dosi, 2011; Caballero, 2010) trying to add additional "frictions" to fix the problems of DSGE models, economists should consider the *economy as a complex evolving system*, i.e. as an ecology populated by heterogenous agents whose far-from-equilibrium interactions continuously change the structure of the system (more on that in Kirman, 2010; Dosi, 2011; Rosser, 2011). This is the starting point of agent-based computational economics (ACE, Tesfatsion, 2006a; LeBaron and Tesfatsion, 2008). Bounded rationality, endogenous out-of-equilibrium dynamics, direct interactions, are the tenets of ACE which allow to catch many of the features of the current crisis (e.g. asset bubbles, resilience of interbank network, self-organized criticality, financial accelerator dynamics, etc; see Section 4 for more details).

On the normative side, due to the extreme flexibility of the set of assumptions regarding agent behaviors and interactions, ACE models (often called agent-based models, ABMs) represent an exceptional laboratory to perform policy exercises and policy design. Indeed, as Section 5 shown, an increasing number of macroeconomic policy applications have been already devised and explored concerning fiscal and monetary policies, bank regulation and central bank independence.

Certainly, also in the ACE approach there are still open issues that should be addressed. The most important ones concern empirical validation, over-parametrization, estimation and calibration. Nevertheless, the success of ACE models in delivering policy implications while simultaneously explaining the observed micro and macro stylized facts are encouraging for the development of a new way of doing macroeconomic theory.

The rest of the paper is organized as follows. Section 2 surveys the approach to policy of the New Neoclassical Synthesis. In Section 3 we discuss the main theoretical and empirical difficulties of DSGE models. In Section 4 we instead introduce the ACE paradigm and in Section 5 we briefly review some policy macroeconomic applications in this field. Section 6 concludes by telegraphically accounting for some methodological issues related to policy in ACE models

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[3]More precisely, in Section 3 we argue that the DSGE policy apparatus is plagued by a long list of serious problems concerning theoretical issues (i.e., having to do with formal inconsistencies of the model – given its assumptions), empirical difficulties (i.e., related to empirical validation of DSGE models) and political-economy issues (i.e., concerning the absence of any justification for the often unrealistic and over-simplifying assumptions used to derive policy implications). See also Colander (2006b).

and the ensuing research avenues that these problems open up.

2 Policy in the DSGE Framework

Let us begin by presenting how policy analysis is usually carried out in DSGE models.

The clash between the two competing business cycle theories – the Real Business Cycle (RBC) perspective (see e.g. King and Rebelo, 1999) and the New Keynesian paradigm (cf. Mankiw and Romer, 1991) – ended in the last decade with the development of a New Neoclassical Synthesis (NNS)[4]. In a nutshell, the canonical model employed by the NNS paradigm is basically a RBC dynamic stochastic general equilibrium (DSGE) model with monopolistic competition, nominal imperfections and a monetary policy rule (see Clarida et al., 1999; Woodford, 2003; Galí and Gertler, 2007, for a more detailed exposition of the NNS approach).

In line with the RBC tradition, the starting point of the new vintage models is a stochastic version of the standard neoclassical growth model with variable labor supply: the economy is populated by an infinitely-lived representative household, who maximizes its utility under an intertemporal budget constraint, and by a large number of firms, whose homogenous production technology is hit by exogenous shocks. All agents form their expectations rationally (Muth, 1961). The New Keynesian flavor of the model stems from three ingredients: money, monopolistic competition and sticky prices. Money has usually only the function of unit of account and its short-run non-neutrality is guaranteed by the nominal rigidities introduced by sticky prices. As a consequence, the central bank can influence the real economic activity in the short run by manipulating the interest rate. The RBC scaffold of the model allows one to compute the "natural" level of output and of the real interest rate, that is the equilibrium values of the two variables under perfectly flexible prices. The "natural" output and interest rate constitute a benchmark for monetary policy: the central bank cannot persistently push the output and the interest rate away from their "natural" values without creating inflation or deflation. Note that the assumption of imperfect competition (and of other real rigidities) implies that the "natural" level of output is not socially efficient.

Analytically, the NNS model can be represented by three equations[5]: the expectation-augmented IS equation, the New Keynesian Phillips (NKP) curve, and a monetary policy rule. The expectation-augmented IS equation constitutes the aggregate-demand building block of the NNS model. Assuming perfect capital markets and taking a log-linear approximation around the steady state, one can derive the IS equation from the goods market-clearing condition and the Euler equation of the representative household:

$$\tilde{y}_t = E_t\tilde{y}_{t+1} - \sigma(i_t - E_t\pi_{t+1} - r_t^n), \tag{1}$$

where $\tilde{y}$ is the output gap (i.e., the percentage gap between real output and its "natural" level), σ is the intertemporal elasticity of substitution of consumption, i is the nominal interest rate, π is

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[4]This term was first introduced by Goodfriend and King (1997). Woodford (2003) labeled the approach as "Neo Wicksellian". As stated by Galí and Gertler (2007) the term "New Keynesian" is the most used, even if earlier New Keynesian models were very different from the ones of the New Neoclassical Synthesis.

[5]For a formal derivation of the NNS model see Goodfriend and King (1997); Clarida et al. (1999); Woodford (2003); Galí (2008).

inflation, r^n is the "natural" interest rate and E_t stands for the (rational) expectation operator taken at time t. Note that in line with the traditional IS-LM model, the IS equation postulates a negative relation between the output gap and the interest rate gap.

The aggregate-supply building block of the NNS model boils down to a New Keynesian Phillips curve. Starting from the Dixit and Stiglitz (1977) model of monopolistic competition and the Calvo (1983) model of staggered prices (with constant probability of price adjustment), one gets that in any given period firms allowed to adjust prices fix them as a weighted average of the current and expected future nominal marginal cost. The NKP curve can be obtained by combining the log-linear approximation of the optimal price-setting choice, the price index and the labor-market equilibrium:

$$\pi_t = \kappa \tilde{y}_t + \beta E_t \pi_{t+1} + u_t, \tag{2}$$

where β is the subjective discount factor of the representative household and κ depends both on the elasticity of marginal cost with respect to output and on the sensitivity of price adjustment to marginal cost fluctuations (i.e., frequency of price adjustment and real rigidities induced by price complementarities). The term u is usually considered a "cost-push shock": it captures the fact that the natural level of output may not coincide with the socially efficient one for the presence of real imperfections such as monopolistic competition, labor market rigidities, etc. The presence of u implies that inflation does not depend only on the presence of a positive output gap, but also on other factors affecting firms' real marginal costs (the output gap appears in equation 2 because in the underlying model there is a positive relation between $\tilde{y}$ and the log deviation of real marginal cost from its natural level).

The model just sketched leads to a system of two difference equations (cf. eqs. 1 and 2) and three unknowns: the output gap, inflation, and the nominal interest rate. In order to solve the system, one has to append a rule to determine the nominal interest rate. This is the role reserved to monetary policy. The choice of the optimal monetary policy rule is usually carried out adopting a welfare criterion: taking a second-order Taylor series approximation of the utility of the representative household, one can derive a welfare loss function for the central bank that is quadratic in inflation and in deviations of output from its socially efficient level (see Woodford, 2010). The NNS model is often closed with "simple" rules such as the Taylor (1993) rule[6] (see Taylor and Williams, 2010, for a survey; more on that in Section 3.3 below):

$$i_t^\tau = r_t^n + \phi_\pi \pi_t + \phi_y \tilde{y}_t, \tag{3}$$

where i^τ is the interest rate target of the central bank, $\phi_y > 0$ and $\phi_\pi > 1$.

Medium scale DSGE models (see e.g. Christiano et al., 2005; Smets and Wouters, 2003, 2007) are usually expanded to account for investment dynamics. Moreover, given the strong interactions between financial markets and the real economy showed by the Great Financial crisis, a new vintage of DSGE models (see e.g. Curdia and Woodford, 2010, 2011; Christiano et al., 2011; Gertler and Kiyotaki, 2010; Gertler and Karadi, 2011) has tried to embody the credit market into the canonical model.

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[6]Originally, the Taylor rule was just designed for normative purposes, i.e. to provide recommendations on how monetary policy should be carried out (Taylor, 2007). Later the Taylor rule assumed a positive role given its good explanatory and predictive power.

Before performing policy exercises with DSGE models, one should assess their empirical performance and calibrate their parameters. At this stage, different type of shocks (e.g. government spending and private consumption disturbances) are usually added to the model to improve the estimation. Since the assumption of forward-looking agents implies that standard DSGE models are not able to match the econometric evidence on the co-movements of nominal and real variables (e.g., the response of output and inflation as to a monetary policy shock is too fast to match the gradual adjustment showed by the corresponding empirical impulse-response functions), they are usually extended introducing a great deal of "frictions" – often not justified on the theoretical ground – such as predetermined price and spending decisions, indexation of prices and wages to past inflation, sticky wages, habit formation in preferences for consumption, adjustment costs in investment, variable capital utilization, etc..

From an econometric perspective, the equations 1-3 of the DSGE model are naturally represented as a vector auto-regression (VAR) model. The estimation of the resulting econometric model is usually carried out either with a limited information approach or by full-information likelihood-based methods.

Limited information approach. The strategy of the limited information approach to estimate and evaluate DSGE models is usually the following (e.g., Rotemberg and Woodford, 1999; Christiano et al., 2005)[7]:

1. Specify the monetary policy rule and the laws of motion for the shocks.

2. Split the parameters in two sets and calibrate the parameters in the first set providing some theoretical or empirical justifications for the chosen values.

3. Fix the timing of the endogenous variables in order to allow the interest rate to respond to contemporaneous output and inflation, while the latter variables are only affected by lagged interest rate. Under this assumption one can estimate via OLS the coefficients of the monetary policy rule and the impulse-response functions of the three variables to a monetary policy shock.

4. Recover the second set of parameters by minimizing the distance between the model-generated and empirical impulse-response functions.

5. Finally, given the structural parameter values and the VAR, identify the other structural shocks by imposing, if necessary, additional restrictions.

The empirical performance of the model is then measured by comparing the impulse-response functions generated by the model with the empirical ones.

Full information approach. The full information approach was initially discarded to estimate DSGE models because maximum likelihood methods deliver implausible estimates. However, with the introduction of Bayesian techniques, the full information approach regained popularity and it is now commonly employed (see e.g. Smets and Wouters, 2003, 2007). Bayesian estimation is carried out according to the following steps[8]:

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[7]See also Christiano et al. (2010) for a limited information Bayesian approach.

[8]See Schorfheide (2011) for a discussion of recent advances in the econometrics of DSGE models, current challenges, and possible ways of future research.

1. Place if necessary some restrictions on the shocks in order to allow later identification. For instance Smets and Wouters (2003) assume that technology and preference shocks follow an independent first-order autoregressive process with i.i.d. Gaussian error terms, whereas "cost-push" and monetary policy shocks are i.i.d. Normal white noise processes.

2. Employ the Kalman filter to compute the likelihood function of the observed time series.

3. Form the prior distribution of the parameters by choosing their initial values through calibration, preliminary exploratory exercises, and/or to get some desired statistical properties.

4. Combine the likelihood function with the prior distribution of the parameters to obtain the posterior density, which is then used to compute parameter estimates.

One can then assess the empirical performance of the estimated DSGE model comparing its marginal likelihood[9] with the one of standard VAR models (i.e. the Bayes factor) and the model-generated cross-covariances vis-á-vis the empirical ones.

Once one has recovered the parameters of the model by estimation or calibration and has identified the structural shocks, policy-analysis exercises can finally be carried out. More specifically, after having derived the welfare loss function, one can assess the performance of the subset of "simple" policy rules that guarantee the existence of a determinate equilibrium or the more appropriate parametrization within the class of optimal monetary policy rules. This can be done via simulation, by buffeting the DSGE model with different structural shocks and computing the resulting variance of inflation and the output gap and the associated welfare losses of the different monetary policy rules and parameterizations employed (see e.g. Rotemberg and Woodford, 1999; Galí and Gertler, 2007). In practice, assuming that the DSGE model is the "true" data generating process of the available time series, one is evaluating how the economy portrayed by the model would react to the same structural shocks observed in the past if the monetary policy followed by the central bank were different.

3   Policy with DSGE Models: A Safe Exercise?

DSGE models are plagued by at least three classes of problems which could potentially undermine the usefulness of performing policy-analysis exercises in such a framework. More specifically, DSGE models are subject to theoretical, empirical, and political-economy problems that we shall discuss in the next sections.

3.1   Theoretical Issues

From a theoretical perspective, DSGE models are general equilibrium models (GE) rooted in the Arrow-Debreu tradition with some minor non-Walrasian features (e.g., sticky prices). Hence, they share with traditional GE models their same problems and weaknesses. Even if there is a

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[9]Following Smets and Wouters (2003), the marginal likelihood of a model A is: $\int_\theta p(\theta|A)p(Y_T|\theta A)d\theta$, where $p(\theta|A)$ is the prior density for model A and $p(Y_T|\theta A)$ is the likelihood function of the observable time series, Y_T, conditional on model A and the vector of parameter θ.

vast and widely-known literature within the neoclassical paradigm dealing with the theoretical issues affecting GE models (see e.g. Kirman, 1989), we briefly recall what are the major problems at hand.

To begin with, sufficient conditions allowing for the existence of a general equilibrium do not ensure neither its uniqueness nor its stability. In addition, the well-known results obtained by Sonnenschein (1972), Debreu (1974) and Mantel (1974) show that one can never restrict agents' characteristics (e.g., endowments, preferences, etc.) in such a way to attain uniqueness and stability. What is more, Kirman and Koch (1986) show that even if agents are almost identical (i.e., same preferences and almost identical endowments), uniqueness and stability cannot be recovered.

In this framework, the strategy followed by neoclassical economists to get stable and unique equilibria is to introduce a representative agent (RA). If the choices of heterogeneous agents collapse to the ones of a representative individual, one can circumvent all the problems stemming from aggregation and provide GE macroeconomic models with rigorous Walrasian micro-foundations grounded on rationality and constrained optimization. However, the RA assumption is far from being innocent: there are (at least) four reasons for which it cannot be defended (Kirman, 1992)[10]. First, individual rationality does not imply aggregate rationality: one cannot provide any formal justification to support the assumption that at the macro level agents behave as a maximizing individual. Second, even if one forgets the previous point and uses the RA fiction to provide micro-foundations to macroeconomic models, one cannot safely perform policy analyses with such models, because the reactions of the representative agent to shocks or parameter changes may not coincide with the aggregate reactions of the represented agents. Third, even if the first two problems are solved, there may be cases where given two situations a and b, the representative agent prefers a, whereas all the represented individuals prefer b.

Finally, the RA assumption introduces additional difficulties at the empirical level, because whenever one tests a proposition delivered by a RA model, one is also jointly testing the RA hypothesis. Hence, the rejection of the latter hypothesis may show up in the rejection of the model proposition that is being tested. This last point is well corroborated by the works of Forni and Lippi (1997, 1999), who show that basic properties of linear dynamic micro-economic models are not preserved by aggregation if agents are heterogeneous (see also Pesaran and Chudik, 2011). To cite some examples, micro-economic co-integration does not lead to macroeconomic co-integration, Granger-causality may not appear at the micro level, but it may emerge at the macro level, aggregation of static micro-equations may produce dynamic macro-equations. As a consequence, one can safely test the macroeconomic implications of micro-economic theories only if careful and explicit modeling of agents' heterogeneity is carried out.

The fact that solving DSGE models leads to a system of difference equations may potentially add another problem to those discussed above. More specifically, one has to check whether the solution of the system of equilibrium conditions of a DSGE model exists and is determinate. If the exogenous shocks and the fluctuations generated by the monetary policy rule are "small", and the "Taylor principle" holds (i.e., $\phi_\pi > 1$, see eq. 3), one can prove existence and *local* determinacy of the rational expectation equilibrium of the DSGE model presented in Section 2

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[10]A discussion of the limits of the representative assumption in light of the current crisis is contained in Kirman (2010).

(Woodford, 2003)[11]. This result allows one to perform comparative "dynamics" exercises (i.e. to compute impulse-response functions) in presence of "small" shocks or parameter changes and to safely employ log-linear approximations around the steady state. Unfortunately, the existence of a *local* determinate equilibrium does not rule out the possibility of multiple equilibria at the *global* level (see e.g. Schmitt-Grohé and Uribe, 2000; Benhabib et al., 2001; Ascari and Ropele, 2009). This is a serious issue because there is always the possibility, for instance if the laws of motion of the shocks are not properly tuned, that the DSGE model take an explosive path, thus preventing the computation of impulse-response functions and the adoption of the model for policy analysis exercises.

3.2 Empirical Issues

The second stream of problems is related to the empirical validation of DSGE models. As remarked by Canova (2008), estimation and testing of DSGE models are performed assuming that they represent the true data generating process (DGP) of the observed data. This implies that the ensuing inference and policy experiments are valid only if the DSGE model mimics the unknown DGP of the data.

As mentioned in Section 2, DSGE models can be represented as a VAR of the form:

$$A_0(\phi)x_t = H_1(\phi)x_{t-1} + H_2(\phi)E_t, \tag{4}$$

where x are both endogenous and exogenous variables, ϕ is the vector of the parameters of the model and E contains the errors. If the matrix A_0 is invertible, one can obtain a reduced-form VAR representation of the DSGE model.

Following Fukac and Pagan (2006), the econometric performance of DSGE models can be assessed along the identification, estimation and evaluation dimensions. Before going in depth with this type of analysis, two preliminary potential sources of problems must be discussed. First, the number of endogenous variables contemplated by DSGE models is usually larger than the number of structural shocks. This problem may lead to system singularity and it is typically solved by adding measurement errors. Second, H_1 and H_2 are reduced rank matrixes. This problem is circumvented by integrating variables out of the VAR (eq. 4) as long as H_1 and H_2 become invertible. This process leads to a VARMA representation of the DSGE model. This is not an innocent transformation for two reasons: i) if the moving average component is not invertible, the DSGE model cannot have a VAR representation; ii) even if the VAR representation of the DSGE model exists, it may require an infinite number of lags (more on that in Fernandez-Villaverde et al., 2005; Ravenna, 2007; Alessi et al., 2007).

Identification. Given the large number of non-linearities present in the structural parameters (θ), DSGE models are hard to identify (Canova, 2008). This leads to a large number of identification problems, which can affect the parameter space either at the local or at the global level. A taxonomy of the most relevant identification problems can be found in Canova and Sala (2005)[12].

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[11]Of course, also other monetary policy rules different from the Taylor rule (cf. eq. 3) can lead to a local determinate rational-expectation equilibrium.

[12]See also Beyer and Farmer (2004).

To sum them up: i) different DSGE models with different economic and policy implications could be observationally equivalent (i.e., they produce indistinguishable aggregate decision rules); ii) some DSGE models may be plagued by under or partial identification of their parameters (i.e., some parameters are not present in the aggregate decision rules or are present with a peculiar functional form); iii) some DSGE may be exposed to weak identification problems (i.e., the mapping between the coefficients of the aggregate decision rules and the structural parameters may be characterized by little curvature or by asymmetries), which could not even be solved by increasing the sample size.

Identification problems lead to biased and fragile estimates of some structural parameters and do not allow to rightly evaluate the significance of the estimated parameters applying standard asymptotic theories. This opens a ridge between the real and the DSGE DGPs, depriving parameter estimates of any economic meaning and making policy analysis exercises useless (Canova, 2008). For instance, Schorfheide (2008) finds that the parameters of the New Keynesian Phillips curve estimated in 42 DSGE models published in academic journals range from zero to four. In most of the cases, identification problems can only be mitigated by appropriately re-parameterizing the model[13].

Estimation. The identification problems discussed above partly affect the estimation of DGSE models. DSGE models are very hard to estimate by standard maximum likelihood (ML) methods, because ML estimator delivers biased and inconsistent results if the system is not a satisfying representation of the data. This turns out to be the case for DSGE models (see the evaluation section) and it helps to explain why ML estimates usually attain absurd values with no economic meaning and/or they are incompatible with a unique stable solution of the underlying DSGE model.

A strategy commonly employed when the DSGE model is estimated following the limited-information approach (cf. Section 2) consists in calibrating the parameters hard to identify and then estimating the others. Given the identification problems listed above, Canova (2008) argues that this strategy works only if the calibrated parameters are set to their "true" values. If this is not the case, estimation does not deliver correct results that can be used to address economic and policy questions (see also Canova and Sala, 2005).

As we mentioned in Section 2, Bayesian methods are now commonly employed to estimate DSGE models. They apparently solve the problems of estimation (and identification) by adding a (log) prior function to the (log) likelihood function in order to increase the curvature of the latter and obtain a smoother function. However, this choice is not harmless: if the likelihood function is flat – and thus conveys little information about the structural parameters – the shape of the posterior distribution resembles the one of the prior, reducing estimation to a more sophisticated calibration procedure carried out on an interval instead on a point (see Canova, 2008; Fukac and Pagan, 2006). Unfortunately, the likelihood functions produced by most DSGE models are quite flat (see e.g. the exercises performed by Fukac and Pagan, 2006). In this case, informal calibration is a more honest and internally consistent strategy to set up a model for policy analysis experiments (Canova, 2008).

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[13]Fukac and Pagan (2006) also argue that identification problems are usually partly mitigated by arbitrarily assuming serially correlated shocks.

All the estimation problems described above stem also from the fact that DSGE models are not conceived to simplify the estimation of their parameters (Canova, 2008). As a consequence DSGE models put too much stress upon the data, using for instance more unobservable that observable variables (Fukac and Pagan, 2006). This requires strong assumptions about the variances in order to get identification and to employ Kalman filter to obtain the likelihood function. The likelihood functions produced by the Kalman filter are correct only if observations are Gaussian, but macroeconomic time series are typically not normally-distributed (Fagiolo et al., 2008).

Evaluation. Evaluating DSGE models means assessing their capability to reproduce as many empirical stylized facts as possible. For instance, following Fukac and Pagan (2006), one can check: i) whether variables with deterministic trend cotrend; ii) whether I(1) variables co-integrate and the resulting co-integrating vectors are those predicted by the model; iii) the consistency (with respect to data) of the dynamic responses (e.g., autocorrelation, bivariate correlations); iv) the consistency of the covariance matrix of the reduced form errors with the one found in the data; v) the discrepancies between the time series generated by the model and real-world ones. In light of the Great Recession, the last point is particularly important: can DSGE models account for the occurrence of rare large shocks?

Fukac and Pagan (2006) perform such exercises on a popular DSGE model. First, they find that co-trending behaviors cannot be assessed because data are demeaned (a practice commonly followed by DSGE modelers). However, the computation of the technology growth rates compatible with the observed output growth rates shows that the possibility of technical regress is very high. Second, there are no co-integrating vectors, because output is the only I(1) variable. Third, the model is not able to successfully reproduce the mean, standard deviations, autocorrelations, bivariate correlations observed in real data. In addition, the DSGE model predicts the constancy of some "great" ratios (in line with the presence of a steady state of the economy), but this is not confirmed by real data. Fourth, many off-diagonal correlations implied by the covariance matrix of the errors are significantly different from zero, contradicting the DSGE model assumption of uncorrelated shocks. Fifth, the tracking performance of the model depends heavily on the assumed high serial correlation of the shocks.

Finally, DSGE models are not able to account for the occurrence of rare economic crises (see Section 3.3 below for a theoretical explanation). This is not surprising since macroeconomic time series distributions are well approximated by fat tail densities (Fagiolo et al., 2008) and DSGE models typically assume Gaussian distributed shocks[14]. Moreover, Ascari et al. (2012) find that even assuming fat-tailed Laplace shocks, the distributions of the time series generated by DSGE models have much thinner tails than those observed in real data.

The results just described seem to support Favero (2007) in claiming that modern DSGE models are exposed to the same criticisms advanced against the old-fashioned macroeconometric models belonging to the Cowles Commission tradition: they pay too much attention to the identification of the structural model (with all the problems described above) without testing the potential misspecification of the underlying statistical model (see also Johansen, 2006; Juselius

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[14]An exception is Curdia et al. (2011) where shocks are drawn from a Student-t distribution.

and Franchi, 2007)[15]. In DSGE models, "restrictions are made fuzzy by imposing a distribution on them and then the relevant question becomes what is the amount of uncertainty that we have to add to model based restrictions in order to make them compatible not with the data but with a model-derived unrestricted VAR representation of the data" (Favero, 2007, p. 29). There are many signals of the potential misspecification of the statistical model delivered by DSGE models: the presence of many persistent shocks, the fact that theory-free VAR models of monetary policy need to include additional variables such as commodity price index to match the data, the absurd estimates produced by standard maximum likelihood estimation, etc. (Fukac and Pagan, 2006; Favero, 2007). If the statistical model is misspecified, policy analysis exercises loose significance, because they are carried out in a "virtual" world whose DGP is different from the one underlying observed time-series data.

3.3   Political-Economy Issues

Given the theoretical problems and the puny empirical performance of DSGE models, one cannot accept the principles of the positive economics approach summarized by the "as if" argument of Milton Friedman (1953). The assumptions of DSGE models can no longer be defended invoking arguments such as parsimonious modeling or matching the data. This opens a Pandora's box, forcing us to consider how policy-analysis exercises performed with DSGE models are influenced and constrained by the legion of underlying assumptions.

DSGE models presume a very peculiar and un-realistic framework, where agents endowed with rational expectations (RE) take rational decisions by solving dynamic programming problems. This implies that: i) agents perfectly know the model of the economy; ii) agents are able to understand and solve every problem they face without making any mistakes; iii) agents know that all other agents behave according to the first two points. In practice, agents are endowed with a sort of "olympic" rationality and have free access to the whole information set. Note, however, that while rational expectations is a property of the economic system as a whole, individual rationality is not a sufficient condition for letting the system converge to the RE fixed-point equilibrium (Howitt, 2011). It is also unreasonable to assume that agents possess all the information required to attain the equilibrium of the whole economy (Caballero, 2010), especially in periods of strong structural transformation, like the the Great Recession, that require policies never tried before (Stiglitz, 2011). In presence of structural breaks, the learning process of agents introduce further non-stationarity into the system preventing the economy to reach an equilibrium state (Hendry and Minzon, 2010). No surprise that empirical tests usually reject the full-information, rational expectation hypothesis (see e.g. Guzman, 2009; Coibion and Gorodnichenko, 2011). Assuming agents behaving according to what suggested by the psychological and sociological evidence allow to build models which better account for macroeconomic phenomena (Akerlof, 2002) including the current crisis (Akerlof and Shiller, 2009).

The representative-agent (RA) assumption prevent DSGE models to address distributional

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[15]On the contrary, the LSE-Copenhagen school follows a macroeconometric modeling philosophy orthogonal to the one followed by DSGE modelers. Scholars of the LSE-Copenhagen approach have concentrated their efforts on improving the statistical model in order to structure data with an identified co-integrated VAR that could then be used to produce stylized facts for theoretical models (Johansen and Juselius, 2006; Juselius and Franchi, 2007).

issues, which are one of the major cause of the Great Recession and they are fundamental for studying the effects of policies. Indeed, increasing income inequalities induced households to indebt more and more over time paving the way the subprime mortgage crisis (Fitoussi and Saraceno, 2010; Stiglitz, 2011). In this framework, redistribution matters and different policies have a different impact on the economy according to the groups of people they are designed for (e.g. unemployed benefits have large multipliers than tax cuts for high-income individuals, see Stiglitz, 2011). Moreover, the RA assumption coupled with the implicit presence of a Walrasian auctioneer, which sets prices before exchanges take place rule out almost by definition the possibility of interactions carried out by heterogeneous individuals.

Besides being responsible for the problems analyzed in Sections 3.1 and 3.2, the RE and RA assumptions strongly reduce the realism of DSGE models. This is not a minor issue when one has to perform policy analyses (on this point cf. also Colander, 2006a, p. 5).

As a consequence of the "as if" methodology, the macroeconomics of DSGE models does not appear to be truly grounded on microeconomics (Stiglitz, 2011). For instance, DSGE models do not take into account the micro and macro implications of imperfect information. Moreover, the behavior of agents is often described with arbitrary specification of the functional forms. The common employed (Dixit and Stiglitz, 1977) utility function provides a bad description of agents' behavior toward risk. Similarly, the Cobb-Douglas production function is not suited for studying income distribution issues.

More generally, within the Neoclassical-DSGE paradigm there is a sort of internal contradiction. On the one hand, strong assumptions such as rational expectations, perfect information, complete financial markets are introduced *ex-ante* to provide a rigorous and formal mathematical treatment of the problems and to allow for policy recommendations. On the other hand, many imperfections (e.g., sticky prices, rule-of-thumb consumers) are introduced *ex-post* without any theoretical justification only to allow DSGE model to match the data[16]. This process is far from being innocuous, for instance Chari et al. (2009) point out that the high level of arbitrariness of DSGE models in the specifications of structural shocks may leave them exposed to the Lucas critiques, preventing them to be usefully employed for policy analysis. Adopting less stringent – but in tune with the microeconomic statistical evidence – assumptions may contribute to jointly solve many empirical puzzles without introducing an army of ad-hoc imperfections.

There are a couple of other internal inconsistencies which could potentially undermine the reliability of the policy prescriptions developed following the DSGE approach. The first one is related to the marginal role (in the best case) that DSGE models reserve to money and banks. This bizarre situation in which models designed for monetary policy analyses do not include money stems from the simplifying assumption that the representative agent behaves respecting the transversality (or No Ponzi Game) condition, i.e. she is perfectly creditworthy and never default (Goodhart, 2009). As a consequence, agents face the same interest rate (no risk premia) and all transactions can be undertaken in capital markets without the need of banks. Moreover, since agents can swap IOUs without facing any credit risk, money has only the function of unit of account and it can be ruled out from DSGE models[17]. The abstraction from default risks

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[16]Citing a very provocative sentence of a famous evolutionary economist, this way of theorizing is like claiming that biology stems from thermodynamics equilibrium with some imperfections.

[17]When money is present in the utility function of consumers, the transactions requiring money are assumed

does not allow DSGE models to contemplate the conflict between price and financial stability that Central Banks always face (Howitt, 2011)[18]: they just care about the nth-order distortions caused by price misallignments which can eventually result in inflation without considering the huge costs of financial crisis (Stiglitz, 2011). No surprise that DSGE models work fine in normal time but they are unequipped not only to forecast but also to explain the current crisis (Goodhart, 2009; Krugman, 2011).

The second potential inconsistency concerns how business cycles arise in the DSGE framework. DSGE models can be employed to assess the impact of different monetary policies because they are genuine business cycle models. However, the theory of business cycles embedded in DSGE models is exogenous: the economy rests in the steady state unless it is hit by a stream of exogenous stochastic shocks. As a consequence, DSGE models do not explain business cycles, preferring instead to generate them with a sort of deus-ex-machina mechanism. This could explain why even in normal times DSGE models are not able to match many business cycle stylized facts or have to assume serially correlated shocks to produce fluctuations resembling the ones observed in reality (cf. Zarnowitz, 1985, 1997; Cogley and Nason, 1993; Fukac and Pagan, 2006)[19]. Even worse, the subprime mortgage crisis Great Recession clearly shows how bubbles and, more generally, endogenously generated shocks are far more important for understanding economic fluctuations (Stiglitz, 2011). How policymakers can assess the impact of policies in models not explaining business cycles is an open issue. For instance, the Great Recession revealed that the FED's doctrine about cleaning up afterward asset bubbles bursts was patently wrong.

Moving to the normative side, one supposed advantage of the DSGE approach is the possibility to derive optimal policy rules. However, policymakers adopting optimal policy rules face certain costs – the strict assumptions at the root of DSGE models – but uncertain benefits. As argued by Galí (2008), optimal monetary policy rules cannot be used in practice, because they require the knowledge of the "true" model of the economy, the exact value of every parameter, and the real time value of every shocks. Moreover, when the "true" model of the economy and the appropriate loss function are not know, rule-of-thumb policy rules may perform better than optimal policy rules (Brock et al., 2007; Orphanides and Williams, 2008).

3.4 Any Ways Out?

Given the theoretical and empirical problems of DSGE models discussed above, the positive economics approach advocated by Milton Friedman would suggest to remove or change the plethora of underlying assumptions in order to improve the performance of the model.

This recommendation is reinforced by two related observations. First, the assumptions

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to be sufficiently unimportant, so for "reasonable" calibrations, money-augmented DSGE models deliver almost the same results of the standard ones (Woodford, 2003, chapter 2). Of course, the unimportance of transactions requiring money, the calibration reasonability and the quantitative discrepancies between standard and money-augmented DSGE models is debatable and subject to the judgement of policymakers.

[18]As Howitt (2011) puts it, financial accelerator dynamics have recently been introduced in some DSGE models (see Gertler and Kiyotaki, 2010; Brunnermeier et al., 2011, for a survey) just to analyze how shocks can be amplified by financial considerations without any reference to the price-stability trade-off.

[19]The highly persistency of the estimated shock processes and the fact that their path is very akin to the path of one of the observable raises concerns about whether shocks capture aggregate uncertainty or misspecification (Schorfheide, 2011).

underlying DSGE models become a sort of strait jacket that preclude the model to be flexible enough to allow for generalizations and extensions. Second, the un-realism of these assumptions prevent policymakers to fully trust the policy prescriptions developed with DSGE models.

It is far from clear why within the mainstream DSGE paradigm there is a widespread conservative attitude with no significative attempts to substitute the "Holy Trinity" assumptions of rationality, greed and equilibrium (Colander, 2005) with more realistic ones. For instance, Akerlof (2007) argues that a broader definition of agents' preferences which take into account the presence of realistic norms can violate many neutrality results of neoclassical economics without recurring to imperfections. Moreover, introducing heterogeneous agents or substituting the rationality assumption with insights coming from behavioral economics could substantially change the working of DSGE models, "making monetary policy more of a science" (Mishkin, 2007).

In any case, if neoclassical economists truly enlist themselves among those advocating an instrumentalist approach to scientific research, they should agree that when models display estimation and validation (descriptive) problems such as those exhibited by DSGE ones, the only way out would be to modify the models' assumptions. *A fortiori*, this should be the recommendation that an instrumentalist researcher would provide if, in addition, the model, as happens in the DSGE case, would also display problems on the normative side.

This is exactly the research avenue that a growing number of scholars have been pursuing in the last two decades. Dissatisfied with standard macroeconomic, micro-founded, general-equilibrium-based neoclassical models like those discussed above, they have begun to devise an entirely new paradigm labeled as "Agent-Based Computational Economics" (ACE)[20]. The basic exercise ACE tries to perform is building models based on more realistic assumptions as far as agent behaviors and interactions are concerned, where *more realistic* here means rooted in empirical and experimental micro-economic evidence. For example, following the body of evidence provided by cognitive psychologists (see for example, among a vast literature, Kahneman and Tversky, 2000), the assumptions of perfect rationality and foresight are replaced with those of bounded rationality and adaptive behavior. More generally, ACE scholars share the view that agents in the model should have "the same information as do the economists modeling the economy" (Colander, 2006a, p. 11). Similarly, insights from network theory (e.g., Albert and Barabasi, 2002) and social interactions (e.g., Brock and Durlauf, 2001) suggest to move away from the unrealistic and oversimplifying assumptions concerning agents interactions typically employed in neoclassical models and allow for direct, non-trivial interaction patterns. Finally, the widespread evidence on persistent heterogeneity and turbulence characterizing markets and economies indicate to abandon crazy simplifications such as the representative agent assumption, as well as the presumption that economic systems are (and must be observed) in equilibrium, and to focus instead on out-of-equilibrium dynamics endogenously fueled by the interactions among heterogenous agents.

In other words, ACE can be defined as the computational study of economies thought as

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[20]The philosophical underpinnings of ACE largely overlap with those of similar, complementary, approaches known in the literature as "Post Walrasian Macroeconomics" (Colander, 2006b) and "Evolutionary Economics" (Nelson and Winter, 1982; Dosi and Nelson, 1994). The overlap is often so strong that one might safely speak of an emerging "heterodox synthesis". Historically, the first attempt to develop agent-based economics can be traced back to Marshall (Leijonhufvud, 2006).

complex evolving systems (Tesfatsion, 2006a). Notice that neoclassical economics, on the contrary, typically deals with economies conceived as simple, linear, homogeneous and stationary worlds. It should not come as a surprise that the class of models used by ACE to explore the properties of markets, industries and economies (called agent-based models, ABMs) are far more complicated – and harder to analyze – objects than their neoclassical counterparts. In the following Section we will therefore begin by outlying the basic building blocks of ABMs. Next, we will address the question how ABMs can be employed to deliver normative implications. Then, we will briefly review some examples of policy exercises in ABMs. Some final remarks about pro and cons of using ABMs for policy analysis will be left for the concluding section.

4 Agent-Based Models and Economic Policy

4.1 Building Blocks of ABMs

The last two decades have seen a rapid growth of agent-based modeling in economics. An exhaustive survey of this vast literature is of course beyond the scope of this work[21]. However, before proceeding, it is useful to introduce the main ten ingredients that tend to characterize economic AB models.

1. *A bottom-up perspective.* A satisfactory account of a decentralized economy is to be addressed using a bottom-up perspective. In other words, aggregate properties must be obtained as the macro outcome of a possibly unconstrained micro dynamics going on at the level basic entities (agents). This contrasts with the top-down nature of traditional neoclassical models, where the bottom level typically comprises a representative individual and is constrained by strong consistency requirements associated with equilibrium and hyper-rationality.

2. *Heterogeneity.* Agents are (or might be) heterogeneous in almost all their characteristics.

3. *The evolving complex system (ECS) approach.* Agents live in complex systems that evolve through time. Therefore, aggregate properties are thought to emerge out of repeated interactions among simple entities, rather than from the consistency requirements of rationality and equilibrium imposed by the modeler.

4. *Non-linearity.* The interactions that occur in AB models are inherently non-linear. Additionally, non-linear feedback loops exist between micro and macro levels.

5. *Direct (endogenous) interactions.* Agents interact directly. The decisions undertaken today by an agent directly depend, through adaptive expectations, on the past choices made by other agents in the population.

6. *Bounded rationality.* The environment in which real-world economic agents live is too complex for hyper-rationality to be a viable simplifying assumption. It is suggested that

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[21]This and the following subsections heavily draw from Pyka and Fagiolo (2007) and Fagiolo et al. (2007b). For further details see, among others, Dosi and Egidi (1991), Dosi et al. (2005), Lane (1993), Tesfatsion and Judd (2006), Colander (2006a) and Tesfatsion (2006b).

one can, at most, impute to agents some local and partial (both in time and space) principles of rationality (e.g., myopic optimization rules). More generally, agents are assumed to behave as boundedly rational entities with adaptive expectations.

7. *The nature of learning.* Agents in AB models engage in the open-ended search of dynamically changing environments. This is due to both the ongoing introduction of novelty and the generation of new patterns of behavior; but also on the complexity of the interactions between heterogeneous agents (see point 5 above).

8. *"True" dynamics.* Partly as a consequence of adaptive expectations (i.e., agents observe the past and form expectations about the future on the basis of the past), AB models are characterized by true, non-reversible, dynamics: the state of the system evolves in a path-dependent manner[22].

9. *Endogenous and persistent novelty.* Socio-economic systems are inherently non-stationary. There is the ongoing introduction of novelty in economic systems and the generation of new patterns of behavior, which are themselves a force for learning and adaptation. Hence, agents face "true (Knightian) uncertainty" (Knight, 1921) and are only able to partially form expectations on, for instance, technological outcomes.

10. *Selection-based market mechanisms.* Agents typically undergo a selection mechanism. For example, the goods and services produced by competing firms are selected by consumers. The selection criteria that are used may themselves be complex and span a number of dimensions.

4.2 The Basic Structure of ABMs

Models based on (all or a subset of) the ten main ingredients discussed above typically possess the following structure. There is a population – or a set of populations – of agents (e.g., consumers, firms, etc.), possibly hierarchically organized, whose size may change or not in time. The evolution of the system is observed in discrete time steps, $t = 1, 2, \ldots$. Time steps may be days, quarters, years, etc.. At each t, every agent i is characterized by a finite number of micro-economic variables $\underline{x}_{i,t}$ (which may change across time) and by a vector of micro-economic parameters $\underline{\theta}_i$ (that are fixed in the time horizon under study). In turn, the economy may be characterized by some macroeconomic (fixed) parameters Θ.

Given some initial conditions $\underline{x}_{i,0}$ and a choice for micro and macro parameters, at each time step $t > 0$, one or more agents are chosen to update their micro-economic variables. This may happen randomly or can be triggered by the state of the system itself. Agents selected to perform the updating stage collect their available information about the current and past state (i.e., micro-economic variables) of a subset of other agents, typically those they directly interact with. They plug their knowledge about their local environment, as well as the (limited) information they can gather about the state of the whole economy, into heuristics, routines, and other algorithmic, not necessarily optimizing, behavioral rules. These rules, as well as interaction

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[22]This has to be contrasted with the neoclassical approach, where agents hold rational expectations and, as Mehrling (2006, p. 76) puts it, "the future, or rather our ideas about the future, determines the present".

patterns, are designed so as to mimic empirical and experimental knowledge that the researcher may have collected from his/her preliminary studies.

After the updating round has taken place, a new set of micro-economic variables is fed into the economy for the next-step iteration: aggregate variables $\underline{X}_t$ are computed by simply summing up or averaging individual characteristics. Once again, the definitions of aggregate variables closely follow those of statistical aggregates (i.e., GDP, unemployment, etc.).

The stochastic components possibly present in decision rules, expectations, and interactions will in turn imply that the dynamics of micro and macro variables can be described by some (Markovian) stochastic processes parameterized by micro- and macro-parameters. Hoverer, non-linearities which are typically present in decision rules and interactions make it hard to analytically derive laws of motion, kernel distributions, time-t probability distributions, etc. for the stochastic processes governing the evolution of micro and macro variables.

This suggests that the researcher must often resort to computer simulations in order to analyze the behavior of the ABM at hand. Notice that in some simple cases such systems allow for analytical solutions of some kind. Needless to say, the more one injects into the model assumptions sharing the philosophy of the building blocks discussed above (cf. Section 4.1), the less tractable turns out to be the model, and the more one needs to resort to computer simulations. Simulations must be intended here in a truly constructive way, e.g. to build and "grow" a society "from the bottom up", in the spirit of object-oriented programming.

4.3 Descriptive Analysis of ABMs

When studying the outcomes of ABMs, the researcher often faces the problem that the economy he/she is modeling is by definition out-of-equilibrium. The focus is seldom on static equilibria or steady-state paths. Rather, the researcher must more often look for long-run statistical equilibria and/or emergent properties of aggregate dynamics (that is, transient statistical features that last suffficiently long to be observed and considered stable as compared to the time horizon of the model; see Lane, 1993, for an introduction). Such an exploration is by definition very complicated and it is made even more difficult by the fact that the researcher does not even know in advance whether the stochastic process described by its ABM is ergodic or not and, if it somehow converges, how much time will take for the behavior to become sufficiently stable.

Suppose for a moment that the modeler knows (e.g., from a preliminary simulation study or from some ex-ante knowledge coming from the particular structure of the ABM under study) that the dynamic behavior of the system becomes sufficiently stable after some time horizon T^* for (almost all) points of the parameter space. Then a possible procedure that can be implemented to study the output of the ABM runs as the one synthetically depicted in Figure 1.

Given some choice for initial conditions, micro and macro parameters, assume to run our system until it relaxes to some stable behavior (i.e., for at least $T > T^*$ time steps). Suppose we are interested in a set $S = \{s_1, s_2, \dots\}$ of statistics to be computed on micro and macro simulated variables. For any given run the program will output a value for each statistic. Given the stochastic nature of the process, each run will output a different value for the statistics. Therefore, after having produced M independent runs, one has a distribution for each statistic
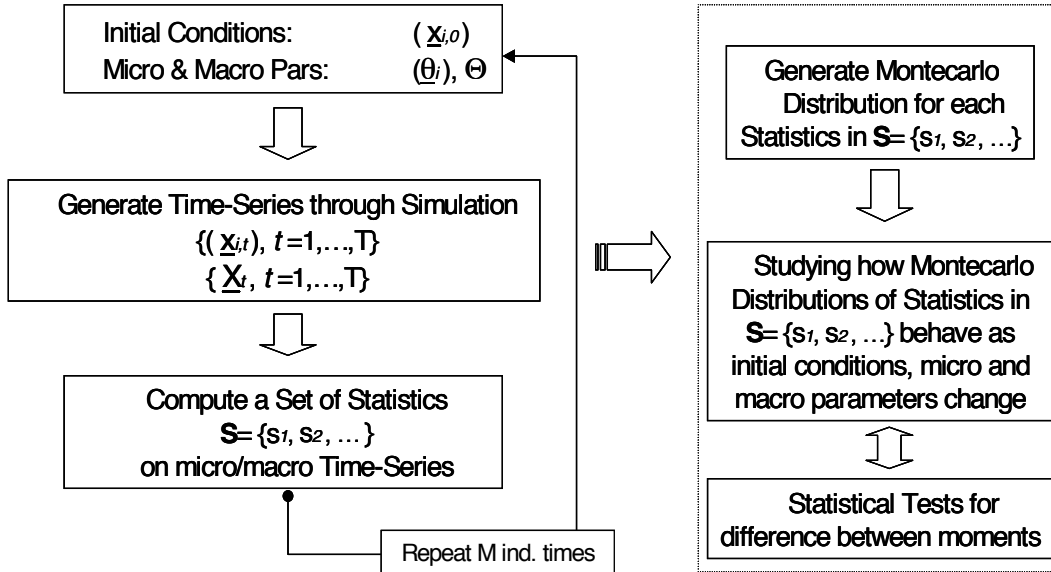
Figure 1: A schematic procedure for studying the output of an AB model

containing M observations, which can be summarized by computing its moments.

Recall, however, that moments will depend on the choice made for initial conditions and parameters. By exploring a sufficiently large number of points in the space where initial conditions and parameters are allowed to vary, computing the moments of the statistics of interest at each point, and by assessing how moments do depend on parameters, one might get a quite deep *descriptive* knowledge of the behavior of the system (see Figure 1).

4.4 Model Selection and Empirical Validation

From the foregoing discussion it clearly emerges that in agent-based modeling (as in many other modeling endeavors) one often faces a trade-off between descriptive accuracy and explanatory power of the model. The more one tries to inject into the model "realist" assumptions, the more the system becomes complicated to study and the less clear the causal relations going from assumptions to implications are. ABM researchers are well aware of this problem and have been trying to develop strategies to guide the process of assumption selection. For example, one can try to solve the trade-off between descriptive capability and explanatory power either by beginning with the most simple model and complicate it step-by-step (i.e., the so-called KISS strategy, an acronym standing for "Keep It Simple, Stupid!") or by starting with the most descriptive model and simplify it as much as possible (i.e., the so-called KIDS strategy, "Keep It Descriptive, Stupid!"). A third, alternative strategy prescribes instead to start with an existing model and successively complicate it with incremental additions (this strategy might be labeled TAPAS, which stands for "Take A Previous model and Add Something").

In all these procedures, the extent to which the ABM is able to empirically replicate existing reality should play a crucial role in discriminating the point at which any procedure should

stop[23].

Notice that the very structure of ABMs naturally allows one to take the model to the data and validate it against observed real-world observations. Indeed, an ABM can be thought to provide a DGP, which we think real-world observations being a realization of. More precisely, let us suppose that we believe that observed data are generated by an unknown (to us) colossal DGP, with an almost infinite number of parameters, which we can label as real-world DGP (rwDGP). Suppose further that such rwDGP can be broken in reasonable smaller weakly-exogenous components, each one with a reasonable number of parameters, and each one describing a small set of variables that we are interested in, on the basis of a small set of other variables. Building an ABM means attempting to approximate one of those small rwDGPs. Due to its stochastic structure, an ABM actually mimics the small rwDGP we are studying by a theoretical DGP that generates the same variables each time we run the model. Of course, we only have one observation generated by the rwDGP, and this makes any inference very difficult (but this has to do with another story, which philosophers call the problem of induction...).

Many approaches to empirical validation (and selection) of ABMs can be in principle taken, and the debate is very open here[24]. For example, one might select among ABMs (and within different parameter setups of the same ABM) with respect to the number of stylized facts each of them is able jointly to replicate. A typical procedure to be followed starts with asking whether a particular model can simultaneously reproduce some set of stylized facts for a given parametrization (a sort of "exercise in plausibility"); then explore what happens when the parameter setup changes; finally, investigate if some meaningful causal explanation can be derived out of that step-by-step analysis. Alternatively, one can first select among parameters by calibrating the model (e.g., by directly estimate parameters, when possible, with micro or macro data) and then judge to which extent the calibrated model is able to reproduce the stylized facts of interest. A recent stream of literature tries to recover the parameters of ABMs by indirect estimation (see e.g. Gilli and Winker, 2003; Alfarano et al., 2005; Winker et al., 2007). Notice that, unlike economists supporting the NNS approach — who hold strong theoretical priors rooted in the DSGE model — ACE scholars are more interested in developing plausible theories, which however are not dogmatically deemed to be the "correct" ones (on this point, see also Colander, 2006a).

No matter the empirical validation procedure actually employed, its basic goal is often to restrict the size of the set of free parameters. In fact, over-parameterized models are difficult to interpret and analyze, because no one knows whether the same conclusions could have been obtained in a simpler, less parameterized model. Even if empirical validation allows one to restrict the set of free parameters to a reasonably-sized one, many methodological problems still remain when the model is used to perform policy experiments. If any parametrization represents an alternative world, which one should be employed to assess policy performance? What is the role of initial conditions? We shall briefly come back to these issues in the concluding remarks.

For the moment it is important to notice that the methodological debate within the agent-

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[23]For a more in-depth discussion of empirical validation in ABMs, we refer the reader to Fagiolo et al. (2007a), Pyka and Werker (2009) and papers therein.

[24]Cf. the special issues edited by Fagiolo et al. (2007a) in Computational Economics and by Pyka and Werker (2009) in the Journal of Artificial Socities and Social Simulations.

based community is very lively. Among many interesting lines of methodological research, one of the most crucial ones concerns the issue of realism of the assumptions in economic models (for a more general appraisal, see Schlefer, 2012). Indeed, whereas many ABM scholars argue that their approach allows for more realism in the way individual behaviors and interactions are accounted for in theoretical models (as opposed to neoclassical ones), others have maintained that ABM must as well trade off between successful model building and empirical accuracy of assumptions (Deichsel and Pyka, 2009). Therefore, in order to provide ABMs that deliver meaningful statistical implications, agent-based researchers must often employ assumptions that are not the most descriptively accurate ones.

4.5 Policy Experiments in ABMs: Some Considerations

ABMs configure themselves as a very powerful device to address policy questions in more realistic, flexible and modular frameworks. Indeed, as far as economic policy is concerned, ABMs have many advantages as compared to neoclassical tools as the DSGE model, which we organize in what follows into two classes: theory and empirics.

Theory. ABMs, contrary to neoclassical ones, do not impose any strong theoretical consistency requirements (e.g., equilibrium, representative individual assumptions, rational expectations). This is because they are not required ex-ante to be analytically solvable. Such no-strait-jacket condition allows for an extremely higher flexibility in model building. If this is coupled with a serious empirical-validation requirement (see below), we are in presence of a semi-instrumentalist approach, where bad (but empirically-plausible) assumptions can be replaced with better (and empirically-plausible) ones if the model does not perform as expected. Notice also that in absence of strong consistency conditions, assumptions can be replaced in a modular way, without impairing the analysis of the model. Indeed, in standard neoclassical models one cannot simply replace the optimization assumption with another one just because the model does not behave well, as that would possibly destroy its analytical solvability. This is not so in ABMs: assumptions – or simply small elements of them – can be taken out of the shelf and easily implemented in the model thanks to the flexibility of computer programming languages.

Empirics. As discussed above, ABMs can be thought as generators of alternative worlds, i.e. theoretical DGPs that approximate the unknown one. Contrary to neoclassical models, the structure of ABMs allows to take them to the data more easily. This can be done in two ways. First, one can validate the inputs of ABMs, i.e. fine-tune modeling assumptions about individual behaviors and interactions to make them more similar to the observed ones. Second, one can validate the model on the output side, by e.g. restricting the space of parameters, individual behaviors and interactions, and initial conditions to those that allow the model to replicate the stylized facts of interest. This allows for a degree of realism that is much higher than that exhibited by e.g. DSGE models. Furthermore, thanks to the theoretical flexibility discussed above, the set of stylized facts that one can target can include more than one piece of evidence, as instead happens in neoclassical models. In other words, each neoclassical model is typically built – in order to retain analytical solvability – to explain one or two single stylized facts (see

the discussion in Aoki, 2006, for more details). On the contrary, each ABM can easily explain a great deal of pieces of empirical evidence at the same time.

But how can one actually conduct policy experiments in ABMs? In a very natural way, indeed. Take again the procedure for ABM descriptive analysis outlined in Figure 1. Recall that micro and macro parameters can be designed in such a way to mimic real-world key policy variables like tax rates, subsidies, interest rates, money, etc. and other key behavioral measures affecting individual incentives in growth, innovation or technologically-related policies. Moreover, initial conditions might play the role of initial endowments and therefore describe different distributional setups. In addition, interaction and behavioral rules employed by economic agents can be easily devised so as to represent alternative institutional, market or industry setup. Since all these elements can be freely interchanged, one can investigate a huge number of alternative policy experiments and rules, the consequences of which can be assessed either qualitatively or quantitatively (e.g., by running standard statistical tests on the distributions of the statistics in S). For example, one might statistically test whether the effect on the moments of the individual consumption distribution (average, etc.) will be changed (and if so by how much) by a percentage change in any given consumption tax rate. Most importantly, all this might be done while preserving the ability of the model to replicate existing macroeconomic stylized facts (e.g. some time-series properties of observed aggregate variables such as persistence of output growth-rate fluctuations, relative standard deviations, cross-correlations, etc.), as well as microeconomic empirical regularities (e.g. firm size distributions, firm productivty dynamics, firm investment patterns, etc.).

5   Macroeconomic Policy in ABMs: A Survey

Thanks to their flexibility, the number of agent-based models dealing with policy issues is increasing fast over time[25]. This success is partly due to the fact that policy makers appear to be more and more willing to believe in results stemming from detailed simulation models (such as ABMs), where the underlying economic structure can be observed[26], rather than in general insights produced by quite abstract mathematical models such as DSGE ones.

The number of ABMs addressing policy issues is becoming so large, that a survey of the whole literature would be beyond the scope of this paper. ABMs have indeed been employed in many different policy arenas such as economic growth, industrial dynamics, market design, environmental regulation, traffic management, etc. We then decide to restrict our attention to ABMs evaluating the impact of macroeconomic policies in order to assess what the agent-based literature can say on the current Great Recession and to provide a straightforward comparison with DSGE models. More specifically, in what follows we classify agent-based models in four macroeconomic policy areas, namely fiscal policy, monetary policy, bank regulation, and central bank independence.

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[25]See for example the papers contained in the special issue "Agent-Based Models for Economic Policy Design" edited by Dawid and Fagiolo (2008).

[26]Moss (2002) discusses the importance of involving the actual decision makers in the process of the generation of agent-based models for policy evaluation.

Fiscal policy. The Great Recession has rewaked interest for employing fiscal policies to tackle economic downturns. An advantage of agent-based models vis-á-vis mainstream ones is the possibility to jointly study the short- and long-run impact of fiscal policies. Dosi et al. (2010) try to do so developing an ABM, bridging Keynesian theories of demand-generation and Schumpeterian theories of technology-fueled economic growth (the K+S model). The model is populated by capital-good firms, consumption good-firms, consumers/workers and a public sector. Capital-good firms perform R&D and sell heterogeneous machine tools to consumption-good firms. Consumers supply labor to firms and fully consume the income they receive. The government levies taxes and it provides unemployment benefits. The model is able to endogenously generate growth and business cycles and to replicate an ensemble of stylized facts concerning both macroeconomic dynamics (e.g. cross-correlations, relative volatilities, output distributions) and microeconomic ones (firm size distributions, firm productivity dynamics, firm investment patterns). After having been empirically validated according to the output generated, the K+S model is employed to study the impact of fiscal policies (i.e. tax rate and unemployment benefits)) on average GDP growth rate, output volatility and unemployment rate. The authors find that Keynesian fiscal policies are a necessary condition for economic growth and they can be successfully employed to dampen economic fluctuations[27]. Moreover, Dosi et al. (2012) find a strong interaction between income distribution and fiscal policies: the more income distribution is skewed toward profits, the greater the effects of fiscal policies.

The assessment of alternative uses (demand vs. supply policies) of resources collected through taxation is explored in Russo et al. (2007), who develop an ABM where a population of heterogenous, boundedly-rational firms and consumers/workers interact according to random matching protocols. The model delivers sustained growth characterized by fluctuations and reproduce micro and macro regularities such as Beveridge, Phillips and Okun curves, firm growth-rate distributions, etc. On the policy side, they find that average output growth rate is non-monotonically linked to the tax rate levied on corporate profits if revenues are employed to finance R&D investment, whereas growth is negatively affected if the money raised through taxes is employed to provide unemployment benefits.

Finally, the interactions between different expectation-formation mechanisms and fiscal and monetary policies is studied in the ABM developed by Haber (2008). The model is characterized by the presence of households, firms, banks, a government and a central bank, and it is calibrated in order to produce "reasonable" time series for GDP, consumption, unemployment and the inflation rate. The presence of positive fiscal (lower tax rate) and monetary shocks (higher money target) increases GDP growth and inflation and reduce unemployment. The introduction of more sophisticated assumptions about expectations reduce the effects of fiscal policy, whereas it increases the impact of monetary policy.

Monetary policy. DSGE models mostly deal with monetary policy, searching for the best monetary rule. At the same time the current Great Recession has showed that monetary policy alone is not sufficient to put economies back on their steady growth path. Agent-based models can be employed to assess the effects and the limits of monetary policy and to compare the ensuing

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[27]More generally, the model of Dosi et al. (2010) highlights a strong complementarity between Keynesian policies affecting demand and Schumpeterian policies affecting innovation.

results with policy prescriptions suggested by DSGE models.

Dosi et al. (2012) extend the K+S model introduced above by adding a bank which collects the deposits of firms and provides (costly) loans to financially constrained firms on a pecking-order basis. The model is then employed to assess the effects of monetary policy through changes in the interest rate and the impact of different bank regulatory frameworks (see the section below) preserving its capability to reproduce macro and micro empirical regularities. Simulation results show that higher economic inequalities increase the volatility of output, the unemployment rate and the likelihood of a severe crises, supporting the conjecture advanced by Fitoussi and Saraceno (2010) and Stiglitz (2011) that increasing level of economic inequalities are at the root of the Great Recession. The characteristics of the income distribution also affect the effectiveness of monetary policy. Monetary policy is very effective when inequality is low and interest rates can have significant impact both on output volatility and long-run growth. When income inequality is high, however, the economy is stuck into a liquidity trap where monetary policy is totally ineffective. Similarly, Lengnick (2011) employ a short-run ABM to assess the short- and long-run neutrality of money. More specifically, after checking the capability of the model to reproduce some statistical regularities (e.g. Phillips and Beveridge curves), a series of policy experiments are run by stochastically increasing the money stock. The model shows that money is neutral in the long-run but it affects output in the short-run.

A growing set of agent-based models (Delli Gatti et al., 2005; Oeffner, 2008; Raberto et al., 2008; Mandel et al., 2010) employ Taylor rules to explore the effects of monetary policy on the economy. In this respect, such policy analyses exercises are similar to the ones conducted with DSGE models, but the complexity-rooted approach of ABM can bring new insights. Delli Gatti et al. (2005) build an artificial economy populated by firms, workers and a central bank. The latter performs monetary policy employing either a commitment strategy (i.e. fixed parameter Taylor rule) or an adaptive, discretionary strategy (i.e. the parameter of the Taylor rule change according to a genetic algorithm, mimicking a learning process). Pervasive capital market imperfections imply that monetary policy affects the economy through the credit channel and that money is not neutral in the long-run. Simulation results show that the Taylor principle does not hold and that the adaptive rule outperforms the commitment one according to the standard loss function criterium. Similarly, Raberto et al. (2008) compare the effectiveness of a random monetary policy rule vis-á-vis an output gap targeting one, finding that the latter rule can improve social welfare and it outperforms the first one in stabilizing inflation. Oeffner (2008) engages in an accurate input-output empirical validation procedure to study the properties of a monetary ABM which embeds both Keynesian and Wicksellian features (i.e. Taylor rule). He finds that monetary policy has real effect also in the medium-run unless the economy is not stuck in a liquidity trap endogenously generated by the model. Mandel et al. (2010) develop a multi-sector, heterogenous-agent model, initialized according to input-output tables, and they show that monetary policy performed according to Taylor rule may lead to higher instability in the economy.

Finally, the effects of unconventional monetary policy are explored in Cincotti et al. (2010). They develop and ABM based on the EURACE platform to assess the effects of quantitative-easing monetary policy, i.e. central bank finance government deficit buying treasury bonds. The

EURACE[28] is a large-scale ABM aiming at capturing the main characteristics of the European economy and addressing European policy analyses (Deissenberg et al., 2008; Dawid et al., 2011). Simulation results show that the performance of the economy improves when expansionary fiscal policy and quantitative-easing monetary policy are implemented. However, such expansionary policies raise inflation and lead to higher output volatility in the long-run.

Bank regulation. The flexibility of agent-based models is extremely useful when policy maker want to test the impact of different regulation frameworks on banks' behavior. For instance, one can assess how different regulations affect the liquidity of the interbank payment system or how alternative micro-prudential rules impact on macroeconomic stability. The latter policy question is addressed by Ashraf et al. (2011) with an ABM where heterogenous firms interact with banks providing them credit. Banks are subject to various regulations, such as capital-adequacy ratio and limits to loan-to-value ratios. Simulations of the model, calibrated to U.S data, show that the economy can be hit by "rare disasters", where the behavior of banks strongly affect macroeconomic performance. Banks indeed can be an important "financial stabilizers" of the economy, easing the entry of new firms and avoiding the incumbents to go bankrupt. As a consequence, less strict micro-prudential bank regulation (i.e. higher loan-to-value ratios and lower capital-adequacy ratios) allow the economy to recover faster from a crisis. Somewhat similarly, Dosi et al. (2012) find that in the bank-augmented K+S model, higher loan-to-value ratios positively affect macroeconomic growth when firms can rely less on internal funds. Finally, employing the EURACE model, Raberto et al. (2011) find that lower capital-adequacy ratios can spur growth in the short-run, but the higher stock of private debt can lead to higher firm bankruptcies, credit rationing and more serious economic downturns in the long-run.

The modeling of the network structure of an economy has never been embedded in DSGE models. This lack of consideration has prevented these models to explain the emergence, the depth and the diffusion of the current crisis, where the topological properties of the credit market network have a fundamental role. On the contrary, ABMs have started to study the links between alternative network setups and macroeconomic performance. Delli Gatti et al. (2010) develop an ABM populated by banks, financially constrained downstream and upstream firms to study the properties of network-based financial accelerator. The topology of the network is continuously evolving because firms can switch their partner trying to finding better credit conditions (i.e. lower interest rates). Simulation results show that the interactions of financially constrained agents, occurring through the evolving credit network, give rise to business cycles and to financial crises. Hence, policy makers can try to design a structure for the credit network in order to reduce the magnifying effect of the financial accelerator.

The resilience of the banking system to liquidity shocks is studied by Gai et al. (2011) developing an agent-based model of the interbank lending network where heterogenous banks are randomly connected together though unsecured claims and repo activity. The impact of idiosyncratic liquidity shocks are then analized for different network configurations, degrees of connectivity between banks, haircut assumptions, and balance sheet characteristics of financial institutions. The model shows that greater degree of complexity and concentration in the bank

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[28]More information are available on http://www.wiwi.uni-bielefeld.de/vpl1/projects/eurace.html. See also http://www.wiwi.uni-bielefeld.de/vpl1/research/eurace-unibi.html for the current Eurace@Unibi model.

network augment the fragility of system, increasing the probability of contagion phenomena and liquidity crises similar to the ones experienced in the Great Recession. Policy experiments show possible ways (e.g. tougher micro-prudential liquidity regulation, countercyclical liquidity requirements) to reduce the network externalities responsible for the emergence of systemic crisis. Similarly, Galbiati and Soramaki (2011) studied the efficiency of the interbank payment system under alternative system configurations. Their model shows that the efficiency of the payment system increases if the number of banks is small and if they are encouraged to provide more liquidity. Moreover, there are strong economies of scale in payment activity (higher volumes reduce total payment costs) calling for higher level of coordination and regulation.

Central bank independence. Agent-based models can be employed to study political economy issues related to the evolution of the institutional role of central banks and to the way monetary policy is announced to the public. Rapaport et al. (2009) study why during the nineties many governments decided to delegate authority to their central banks, employing an ABM where heterogenous countries decide whether introducing central bank independence taking into account the behavior of their neighbors. Simulation results, conducted under a Monte Carlo exploration of the parameter space, show that the emergence and the rate of adoption of central bank independence is positively related to the size of the zone of influence of the other countries.

The time-inconsistency problem face by central banks is analyzed in a more general framework by Arifovic et al. (2010) using an ABM where the interaction between a boundedly-rational, evolutionary learning policy maker and a population of heterogenous agents determines the actual inflation rate. The agents can either believe the inflation rate announced by the central bank or employ an adaptive learning scheme to forecast future inflation. The simulations of the calibrated model show that the central bank learns to sustain an equilibrium with a positive, but fluctuating fraction of "believers" and that this outcome is Pareto superior to the equilibrium determined by standard models.

6   Concluding Remarks

The subprime mortgage crisis and the ensuing Great Recession has prompted a debate about the state of macroeconomic theory. Certainly, we stand in the camp of those arguing that macroeconomics have entered in a Dark Age (Krugman, 2011). Indeed, as discussed in Section 3, DSGE-based models suffer from a series of dramatic problems and difficulties concerning their inner logic consistency, the way they are taken to the data, the extent to which they are able to replicate existing reality, and the realism of their assumptions. These problems are so deep that impede DSGE models even to conceive the possibility of the current crisis and to propose possible solutions to policymakers. We think that such difficulties are so hard to solve within the neoclassical paradigm that a different research avenue, which attempts to replace the basic pillars of neoclassical economics (rationality, equilibrium, etc.), would be more fruitful.

This alternative paradigm does actually exist and it is called agent-based computational economics (ACE). Section 4 has been devoted to a (necessarily) brief discussion of its philosophical underpinnings, building blocks and policy applications. As our synthetic survey shows (cf. Section 5), the number of areas where ACE policy experiments have been already applied

with success is rather vast and rapidly increasing. The discussion of Section 4 has also outlined the most prominent values added deriving from performing policy experiments within an ACE approach. These include ACE's extreme modeling flexibility; the friendly relation of agent-based models with empirical data; the easiness of carrying out empirical-validation exercises; the almost infinite possibility of experimentation; and, last but not least, the positive impact that a more realistic and algorithmically-structured model can have on political decision makers – as compared to obscure and un-intuitive mathematical neoclassical models.

Of course, as happens for the New Neoclassical Synthesis, many issues are still far from being settled and the debate is very open. Here, by a way of conclusion, we recall just three of them.

The first issue – which we can label as the problem of over-parametrization – has to do with the role played by micro and macro parameters in ABMs. As mentioned, ABMs are often over-parameterized, for one typically injects in the specification of agents' behavioral rules and interaction patterns many ingredients in order to meet as much as possible what he/she observes in reality. Suppose for simplicity that initial conditions do not matter. Even if empirical validation can provide a way to reduce free parameters, the researchers are almost always left with an ABM whose behavior depends on many free parameters. Many questions naturally arise. How can one interpret these different parameterizations? Which one should be used if one employs the model to deliver policy implications? Should one perfectly calibrate (if possible) the model using the data so that no free parameters are left? Should policy implications be robust to alternative parameterizations instead? Notice that this issue is closely related to a common critique that ABMs usually face: if an ABM contains many free parameters and it is able to reproduce a given set of stylized facts, how can one be sure that it represents the minimal mechanisms capable of reproducing the same set of stylized facts? This point reminds the "unconditional objects" critique in Brock (1999) and it is certainly true for "oversized" ABMs. In practice, however, ACE researchers are well aware of the problem and always try to simplify as much as possible their model by using empirical validation techniques and a KISS or TAPAS approach. Even if it is very difficult to show that a given ABM is the minimal model describing a set of stylized facts, the more stylized facts a model can reproduce, the more one is able to restrict the class of theoretical mechanisms that can do the job.

The second issue concerns the role played by initial conditions. Recall that (if random ingredients are present in the model) any ABM can be considered as an artificial (stochastic) data generation process ($mDGP$) with which we try to approximate the one that generated the data that we observe (i.e., the $rwDGP$). The question is: is the $rwDGP$ ergodic or not? If the underlying real-world $rwDGP$ is thought to be non-ergodic (as well as the theoretical $mDGP$ described in the AB model), then initial conditions matter. This raises a whole host of problems for the modeler. The modeler needs to identify the "true" set of initial conditions in the empirical data, generated by the $rwDGP$, in order to correctly set the initial parameters of the model. Even if *the* "perfect database" would exist, this is a very difficult task. How far in the past does one need to go in order to identify the correct set of initial values for the relevant micro and macro variables? There is a possibility of infinite regress. If this is the case, then one may need data stretching back a very long time, possibly before data started to be collected.

This issue is closely related to a third (and final) one, regarding the relation between simu-

lated and real-world data. While in principle we could generate as many theoretical observations as we like, in practice we may only have a few of such empirical realizations (possibly only one!). If we believe that the empirical observations come from an underlying DGP that could have been "played twice" (i.e., could have generated alternative observations, other than the one we have) the problem of comparing simulated with empirical data becomes very complicated.

It must be said that all three issues above are the subject of never-ending debates among philosophers of science, since they raise fundamental questions related to probability, modeling, inference, etc. (see, e.g., Fagiolo et al., 2007b). As such, they might (and do) affect any stochastic, dynamic (economic) model, DSGE-based ones included. Nevertheless, the large majority of those advocating the New Neoclassical Synthesis approach seems not to care about them. In our view, the fact that they instead occupy center stage in the current ACE debate is another signal of the vitality of this young but promising paradigm.

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