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Empirical Calibration of Simulation Models

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EMPIRICAL CALIBRATION OF SIMULATION MODELS

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Abstract

This paper discusses how the results of simulation models can be made more reliable and the method of simulating therefore more widely applicable. We suggested to calibrate simulation models empirically and developed a methodology based on Critical Realism in order to so. We suggested combining the procedures of two strands of literature: the empirical underpinning of the assumptions (like in microsimulations) and the empirical check of the implications (like in Bayesian inference). Both these strands of literature are mainly concerned with predicting future developments. We, instead, aim to infer statements about causal relations and characteristics of a set of systems or dynamics, such as, e.g., the development of an industry, that have a general validity for this set of systems or dynamics. In other words, instead of deriving probabilistic predictions of the future and statements of the current situation and dynamics of one single system we developed a methodology to gain general statements about the features of systems and dynamics.

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1. Introduction

In economics simulation models are used quite a lot to carry out mathematical experiments. However, the specification of the parameter set with which to run these simulations is, in general, quite an adventure into the unknown. Criticism is easily found with the procedure, as it is difficult to justify why to choose one specification of parameters and not another - especially if the results found in the simulation models are striking. Then, the audience cannot help but think that there has been quite some arbitrary trial and error going on to achieve this. To avoid this impression, we suggest to empirically calibrating simulation models in a way that makes their results more acceptable. However, compared with models of mainstream economics that usually can be solved analytically, simulation models have only recently been opened to empirical data. It is fair to say that also analytically solvable models have quite some problems concerning the integration of empirical data (cf. Kydland/Prescott, 1996). These problems also emerge when working with simulation models.

We will suggest two ways of underpinning the empirical calibration of simulation models methodologically. First, we suggest combining the empirical underpinning of the assumptions with the empirical check of the implications. To this end, we build on two strands of literature in simulation modelling. The one strand is concerned with microsimulations, where empirical knowledge is used to set up the simulation model (cf, e.g., Citro & Hanushek 1991). The other one is the statistical approach under the label of Bayesian inference, where empirical data is used to test the simulation model (cf. Zellner, 1971). Using different two different data sets in this way to confront assumptions as well as implications with reality would also help to improve the way every model deals with empirical data and is not restricted to simulation models.

The second way we suggest underpinning the empirical calibration of simulation models methodologically lies in the very nature of simulation models. In contrast to analytically solvable models simulation models face a severe problem and that is that uncertainty is at their very heart.[1] While most analytically treated models in the economic literature describe deterministic processes, most simulation models deal with stochastic processes. Therefore, the solutions are contingent, i.e. subject to a combination of chance and necessity. How to deal with chance and necessity within simulation models is crucial when modelling both aspects that are of course intertwined. It becomes even more difficult to deal with these two aspects when simulation models have to be empirically calibrated, because historical events take only place once and one has to identify the characteristics a number of historical events have in common and the characteristics that emerge from chance in the data.

We suggest using Critical Realism as methodology, because it helps to categorize empirical events actually taking place and to determine the underlying structural driving forces. We will show that this approach is the most promising way to use simulation models for inferring general knowledge about the features of a set of systems or dynamics. By this simulations become a more interesting and reliable tool for understanding economic processes and developments. To show how empirical data can be used to make simulation models more widely acceptable and applicable, we first look into what one has to take into consideration when modelling the real world by way of simulation models (Section 2.). Then we show particularly how the methodological approaches of Positivism and Critical Realism can be used for economic modelling (Section 3.). Based on this discussion we explore into the question of how Critical Realism can serve to examine the features of economic processes with the help of empirically founded simulation models (Section 4.). We conclude with a brief summary and an overview of additional questions one would like to answer in the context of the empirical calibration of simulation models (Section 5.).

[1] Please note that we do not consider mainstream models that use simulations as a mathematical tool to solve underdetermined equation systems as simulation models here. For a more detailed discussion of the kind of simulation models we consider see Section 3.1.

2. Modelling the Real World

2.1 Elements of Models

To model the real world, theories use different elements and abstract from what is actually going on in the part of reality they want to describe, explain, or prognosticate. Sometimes the term "model" is defined as being a "theory" that is expressed in equations. As this leads to a couple of questions that are not interesting in the context of our analysis,[2] we use the terms "model" and "theory" synonymically here. The most important elements of models are premises, definitions, logical sentences, causal relationships[3] as well as data. Every model starts from *premises* that limit the area of application of the model, e.g. concerning time, place, agents involved etc. Not all premises are made explicitly. One famous premise, that is often not even mentioned, because everybody is expected to know that it applies, is the "ceteris-paribus-clause". *Definitions* are conventions about how to name elements of reality. They are not true or wrong. They simply help to communicate ideas. Not all definitions are formulated explicitly. Usually the exogenous and endogenous variables as well as parameters that are relevant in the theory are defined. However, definitions of terms, with which everybody in the field is familiar, are often not given.

Logical sentences are at the very heart of putting together models, because they combine complex and complicated relationships in a consistent way. Axioms are important logical sentences, which normally can be expressed in mathematical terms. Another important kind of logical sentences are *causal relationships*, which give information about cause and effect. Often researchers formulate causal relationships in the form "if … then …". In case a researcher wishes to explain an economic situation the "then …" part of the causal relationship is known whereas the "if …" part, i.e. the cause is searched for (cf. Machlup, 1978, 455f). In case a researcher wishes to prognosticate a future economic situation it is the other way around, i.e. the

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[2] E.g. one question would be: Is it sufficient that a theory can be potentially expressed in equations to turn it into a model?

[3] Causal relationships are also often co notated as hypotheses.

cause is known and the effect is searched for. Therefore, causal relationships can say something about the functioning of the real world in the past and the future.

Data is particularly important in our further discussions as it contains claims about parts of reality, which play an important role in inference (see Section 2.2.). When discussing how to derive data it is crucial to be aware that "... (e)mpirical analysis in any research field is entwined in theoretical analysis. That is, empirical work depends on theory for concepts, definitions and hypotheses, all of which are used as foundations for empirical investigation" (Coward/Foray, 2002, p. 540). This means, that we do not only use data to build our theories and to check their implications but also that we use theory to produce data from the complex and complicated processes going on in reality. Consequently, a number of problems emerge from data collection. Collecting data requires making a couple of choices and theorizing about how to observe and measure (cf. the following Machlup, 1978, 448-450). When researchers collect the data themselves they can make these choices. Often researchers rely on data collected by others, which means that aspects important for their research questions might not be taken into consideration (sufficiently). However, even if researchers collect the data themselves it might be difficult to observe the relevant aspects. There might emerge some measurement problems. Moreover, data is usually not available for everything within the area of application defined by the premises.[4] This leads to the well-known problem of induction that even if you observe a large part of reality there is no possibility to make all observations – in particular not those in the future. Insofar, it is impossible to verify a model, as there might always be evidence to the contrary.

Data can be obtained through one detailed study, which is open to critical consideration as in such an analysis the problems connected with the production of data become obvious. Usually data found in this way is not covering a wide application area. Therefore, sometimes so-called stylised facts are used following Kaldor's suggestion (Kaldor, 1968, 177f). Stylised facts comprise statements about a wide application area. The problem with stylised facts is that they fall from heaven

[4] For an analysis of measurement of technical advance as well as problems connected with this see Grupp, 1998.

and often remain unmotivated. In order to keep the broad application area but to avoid the pitfalls of stylised facts the concept of structural regularities was developed, which modifies Kaldor's concept. In contrast to Kaldor's original – and still widely used – approach, the concept of structural regularities is based on strict guidelines for the identification of these regularities (Schwerin, 2001, 92-117). Moreover, it explicitly considers chance and necessity elements in economic processes and helps to distinguish the both. The disadvantage of structural regularities as an empirical basis for theories lies in the fact that it requires a lot of work done on the data part (e.g. Schwerin/Werker, 2003).

2.2 Inference in Modelling

In general, models can be distinguished into two major parts: assumptions and implications. Each element of models, e.g. data or premises, can be part of the assumptions and/or of the implications. Where you find them depends on the principle of inference or the combination of principles of inference used. Three different principles of inference can be distinguished: deduction, induction and abduction. *Premises* and *definitions* are usually part of the assumptions as these elements set the boundaries for modelling. However, sometimes definitions and premises can also be part of the implications, especially so if the results of a model indicate that premises and/or definitions have to be revised for further research. *Data* can be used in both parts of models. In assumptions data provides an empirical basis to start from. In implications data is used to corrobate implications stemming from premises, definitions and logical considerations. Logic is of course always at the heart of modelling in all parts and puts all elements of the models together in a consistent way.

In the following, we will show how the three different inference principles work. It is important to notice that modelling usually combine different principles of inference, thereby coming from assumptions to implications. Each principle of inference works in the different way, although meeting the same end, namely inferring implications from assumptions.

Deduction is often summarized as inferring “from general to particular” (cf. Lawson, 1997, 24). From assumptions implications are derived in an analytical and logical way. For example you infer from the general assumption “all ravens are black” the particular implication “that the next raven you observe will be black as well”. Assumptions within deduction already contain all information that there is available. Generally spoken, deduction sustains the information contained already in the assumptions but does not create new one.

If A = B and B = C, (assumptions)
then A = C. (implication)

In deduction assumptions contain all possible elements of models, like e.g. premises, definitions or causal relationship. Therefore, it is often claimed that inference in deduction is necessary in the sense that the conclusions stemming from the assumptions are correct. In formal sciences like mathematics this holds, because assumptions are often provided in the form of axioms, i.e. they are self-evident and need not be proven. In social sciences like economics such self-evident assumptions do not exist. Implications drawn from premises are in general true but only in the sense that they are logically derived. In social sciences without self-evident premises available it is virtually impossible to derive implications that are true in the sense of correctly describing, explaining and prognosticating reality.

Induction is often summarized as inferring “from particular to general” (cf. Lawson, 1997, 24). Its assumptions describe a part of a larger population and then infer conclusions about the characteristics of this larger population. For example you start from the assumption of the particular observation “that you saw numerous black ravens today” and infer from this the general implication “that all ravens are black nowadays”. As the inductive principle runs “from particular to general” it is often considered as creating information - however doubtful one. The inference in induction says something not contained in the assumptions. If the inference arguments are strong it is probable that the claims made about the conclusions hold. Inductive inference is based on data. However, even if the number of observations in the data set is huge it is in principle impossible to have all observations available, not the least because future events cannot be observed. This means that the implications derived from data are uncertain. In the future, the same will only happen with an unknown probability. This probability is impossible to gain, because future observations can by definition not be made.

Abduction[5] classifies "particular events into general patterns" (Lawson, 1997, 24). You start, e.g., from the particular observation "that there are numerous black ravens" and try to undercover the underlying mechanisms about what is "disposing ravens to be black". You might, e.g., look for other animals that are black and study what they have in common, or look for the differences between ravens and other birds that are not black. It is important to notice that abduction requires data based on substantial and detailed observations. Only then is it possible to find meaningful and sensible underlying mechanisms to infer from the assumptions to the implications. So, e.g., if we observe that ICT firms are usually having staff members below 40 years old and we see a particular person who is less than 40 years old we might conclude that this person is an ICT employee. Obviously, this is quite jumping to conclusions. Abduction requires much more detailed information to infer implications that are likely to hold when confronted with reality. In our example one would wish to know much more about the background of ICT employees, e.g. their education etc. to identify a general pattern. Then, it would be possible to classify a person according to these characteristics and to conclude whether or not s/he is an ICT employee. Whereas an age of less than 40 years is the characteristic of very many people a combination of this characteristic with a degree in informatics would make it much more likely that the person works in the ICT sector. The more relevant details are known about the data the more precisely they can be classified to a general pattern.

Abduction enables us to identify underlying structural elements, which explain observations we make, and to develop a theory of the part of the world we are investigating. This takes us a substantial step further than pure deduction or induction, because abduction helps us to meet theory and data in a creative way. By using the principle of abduction we are able to create new information. According to Peirce (1867, Vol. 5, 145):

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[5] Abduction is often also called retroduction.

"(Induction) never can originate any idea whatever. No more can deduction. All the ideas of science come to it by the way of abduction. Abduction consists in studying the facts and devising a theory to explain them. Its only justification is that if we are ever to understand things at all, it must be in this way."

3. Critical Realism as the Methodology for the Empirical Calibration of Simulation Models

We want to show how simulation models can be empirically calibrated and which methodological principles have to be followed to achieve this in an appropriate and meaningful way. From the methodologies used to develop economic models we will look into Positivism and Critical Realism. To discuss Positivism is important, as it is the mostly used methodological basis for economic modelling. In contrast, Critical Realism is used only rarely. However, we will show that this methodology is best suited to empirically calibrate simulation models. First, the role empirics played in simulation models so far is discussed (Section 3.1). Then, the features of Positivism and Critical Realism are analysed to show that Critical Realism is best suited to meet the requirements of calibrating simulation models (Section 3.2).

3.1 Empirics in Simulation Models

Simulation models in our understanding are tools of heterodox economics and therefore are normally used in contexts where agents are heterogeneous and decide under uncertainty. These features usually lead to underdetermined equation systems so that simulation methods have to be used to find (range of) solutions for the models. However, it is important to note that we do not consider mainstream models that use simulations as a mathematical tool to solve underdetermined equation systems as simulation models here. In these models, assumptions about the behaviour of economic agents, the structure of the economic systems, and the underlying mechanisms are made and the implications calculated. The only difference is that simulating the results allows for more complex models but causes on the other hand more difficulties in analysing the results. Such an approach still faces the problem that in social sciences no self-evident axioms exist. Nevertheless, protagonists of such an approach do as if there are such self-evident axioms, from which necessary implications can be derived.

There are only few simulation models of the heterodox kind that include empirical elements, i.e. history-friendly models (Malerba, Nelson, Orsenigo & Winter 1999 and Malerba & Orsenigo 2002) and microsimulations (Citro & Hanushek 1991). History-friendly models represent case studies and lack the possibility of generalization. They start with some empirical knowledge about real processes – in the one case some stylised facts and in the other case detailed knowledge about one historical realisation – and try to find a model that leads to processes with the same characteristics. Although this is not mentioned in the final publications, this means that different models are tested and rejected by the empirical knowledge until a model is found that is not rejected. It is then argued that the model might describe the mechanisms underlying the known empirical facts. Hence, an inference is made from some, often a few empirical facts to a model describing the whole complex of involved processes. The same holds for many mathematical models in mainstream economics, although this topic is less discussed there. This kind of simulation approach is often criticised because of its lack of completeness, its questionable general validity and its lack of rigour. Nevertheless, such an approach has several advantages in comparison to other approaches. In contrast to mathematical modelling, such an approach can deal with complex mechanisms that include random events. Furthermore, through simulations data can be produced that can then be analysed. This means that a simulation approach can deal with situations where little empirical data is available and that mechanisms and relationships can be studied that cannot be directly observed in reality.

In microsimulations comprehensive empirical knowledge about the changes of a system in the past is used to model future developments. Typically transition probabilities and trends in variables and parameters are empirical estimated. These are, then, used to predict the dynamics in the future. An example is the prediction of the impacts of policy proposals, such as larger benefits for the disabled (e.g., Bagley, Burpee & Jetté 2000). Immigration, emigration and birth rates are estimated on the basis of empirical data about the past whereby trends in these rates are considered. Then a simulation model is developed that includes these empirically estimated rates and processes. Finally, the developed model is used to make prediction about future developments. Microsimulations are, in general, used if comprehensive data is available about the processes on the micro-level. They represent a special case of the method that we propose below.

3.2 Positivism and Critical Realism as Methodologies in Economic Modelling

From the methodologies used to develop economic models we will look into the approaches of Positivism and of Critical Realism. By and large economics uses Positivism as methodological basis for modelling, whereas it uses Critical Realism only rarely. Positivists combine induction and deduction as principles of inference. They start from general assumptions and infer implications for economic processes from them. If positivists include data in their modeling, they confront the implications from deduction with inductively found results. Their aim is to objectively measure and quantify observable facts as well as to search for empirical regularities that help to describe, explain and predict reality. Positivists "… have a notion of causality and connectedness in their theorising, though make closure assumptions. Two forms of closure are central to this perspective. The intrinsic condition of closure - which can be characterised loosely as implying that a cause always produces the same effect ... The extrinsic condition of closure - which loosely can be understood as implying that an effects always has the same cause ..." (Downward/Finch/Ramsey, 2002, 482).

Positivism has two problems that are particularly important for our discussion of how to empirically calibrate simulation models. First of all, it is impossible – like already stated above – to find axioms in social sciences that hold in general. This limits the value deduction has for theoretical work in social sciences in general and in economics in particular. To make statements on such deductively inferred implications is already doubtful. It does only partly improve the model to then extent the analysis by confronting the inferred implication with empirical data in an inductive way. The problem that it is impossible in social sciences to infer theoretically the initial axioms remains. The second problem stems from the fact that we want to develop a methodological basis for simulation models used in the heterodox economics. This means that agents in these models are heterogeneous and decide under uncertainty. These assumptions lead to complex and complicated patterns of the economic processes to be described, explained and prognosticated. These patterns cannot be covered by the aforementioned conditions of closure, which suggest that one cause has one effect and the other way around.

Critical Realism, which we will suggest as the appropriate methodological basis for simulation models used in heterodox economics, uses abduction as principle of inference and uses so-called semi-closure to account for the fact that different reasons can have the same effect and the other way around. Protagonists of this school of thought recognise that the world is structured into different layers (Downward/Finch/Ramsey, 2002). They aim at describing and explaining empirical facts in terms of their underlying structures, i.e. in terms of other layers of reality. This approach uses abduction to infer from empirical facts and observations to the general patterns underlying them, thereby giving a causal explanation on a deeper level. Critical Realists point out that institutions co-evolve with agents own mental models, thereby providing a situation of quasi-closure, i.e. institutions provide stable conditions upon which agents can base their behaviour for a certain period of time (Downward/Finch/Ramsey, 2002, 481f). This means that a specific connection between cause and effect might remain for a while but also changes over time (Downward/Finch/Ramsey, 2002, 495).

Simulation models in our understanding (see Section 3.1) are tools of heterodox economics and therefore are normally used in contexts where agents are heterogeneous and decide under uncertainty. This means that they face a much more complex and complicated environment in which they nevertheless have to take decisions and act. One could jump to the conclusion that under such circumstances it is impossible to develop any models based on empirical data. However, this is not so. Protagonists of Critical Realism have started to develop a methodology that is providing a way to deal with these issues and we will use and further develop their insights in order to provide a methodological basis for the empirical calibration of simulation models.

3.3 Critical Realism in Simulation Models

In line with Critical Realism, we argue that what we observe in reality is the result of processes on a deeper level. Therefore, it is not sufficient to describe the relationships on the observed level. We need to understand these relationships on the basis of the processes of the underlying level. In the following we will show how the methodology of Critical Realism can be used to calibrate simulation models in practical terms.

Although our suggestion contains as the major inference principle to put together theory and empirics abduction this does not mean that the other principles of inference, i.e. induction and deduction, are not used. In fact, they are used quite substantially to prepare the final abductive step. First, we will show how the set of assumptions is put together by induction and deduction (Section 4.1). We suggest including empirical data available on the assumptions. Based on that, implications are inferred by deduction and induction (Section 4.2). Here, empirical data about implications inferred from the dynamics of the described economic system is used. The two kinds of data that are used have to be different, because they concern different levels of the whole system.

In a third and final step, abduction helps us to produce classes of models, which combine assumptions and implications based on empirical findings, i.e. only those models are included which are not rejected by confronting either their assumptions or their implications with reality (Section 4.3). Notice that we do not aim to find one simulation model that describes reality. We believe that this is impossible. As in statistics, all that can be done with the help of empirical data are two things. First, we can reject some models meaning that we restrict the parameters of the general model to certain ranges, so that only a certain subset of all model specifications is considered. Second, in a later step we will study the correctness of these specifications with the help of empirical data on implications (see below).

4. Inference in Empirically Calibrating Simulation Models

4.1 Induction and Deduction of the Set of Assumptions

The first step, as usual, is setting the assumptions by defining the system that the simulation model is intended to describe. This means that the relevant factors and variables have to be chosen and their interaction has to be built into the structure of the simulation model. This is usually done according to theoretical consideration and common knowledge. However, we argue here that the details of the model, the specification of relations and especially the choice of parameters should be fixed according to empirical data, i.e. inductively. This is rarely done in the field of computational and evolutionary economics (some exceptions can be found in Eliasson & Taymaz 2000, Richards 2002, Brenner and Murmann 2003 and Brenner 2004, Ch. 4). We argue that more can be reached by using simulations. To this end, the premises on which the model is build should be induced from empirical data whenever this is possible. Of course, the conceptualisation of variables and parameters can never be theory-free. However, it is important to base all central assumptions of the model on empirical knowledge.

Whenever no sufficient data is available or whenever the model should capture different kinds of systems, the model should be defined as general as necessary. In such a case ranges should be defined for the respective parameters of the model. If the data does not allow for determining between different forms of relationships between the variables of the model, all of them should be included in the model with the help of additional parameters. The ranges of parameters have to be chosen such that the modeller is sure that the real values lie within these ranges. Logical sentences and premises that restrict the area of application of the model can be used to reduce the ranges of the parameters. However, it has to be made clear how this reduction is reached.

Hence, we argue that parameters should not be fixed to one value, except if the empirical data allows for such a fixing. This means that we do not aim for developing one specific simulation model that reflects one bundle of assumptions. Instead, we go for a set of simulation models of which each represents one bundles of assumptions.

Each specific simulation model – in the following we use for simplicity the term `model specification´ -- represent one specific choice of parameters and premises (see Figure 1).

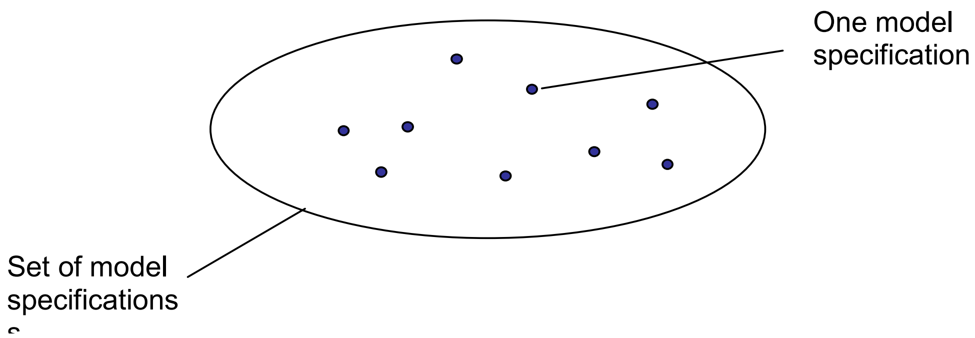

Figure 1: Set of model specifications

4.2 Deduction and Induction of Implications

Each model specification can be run separately. This is the usual approach in the literature, where mainly one specification (with respect to the parameters) of the simulation model is run and its characteristics are studied. Due to the existence of stochastic processes in the models, many runs are necessary to obtain a complete picture of all possible implications of each model specification. Whenever a simulation is run for one model specification, a certain development of the artificial system results. We call this a theoretical realisation. Rerunning the simulation for the same model specification might lead to exactly the same theoretical realisation. However, because of the stochastic processes that are included in the model, it is more likely that a different theoretical realisation results. If one model specification is simulated many times, a set of theoretical realisations results. For each model specification we can determine such a set of theoretical realisations.

There are an infinite number of model specifications. Therefore, not every model specification can be studied. A Monte-Carlo approach is chosen. This means that many model specifications have to be randomly picked and the set of theoretical realisations (depicted as an ellipse in Figure 2) for each of the picked model specifications have to be studied by deduction. The more model specifications are examined the higher is the validity of the obtained results. Therefore, a high number of simulation runs is required for the procedure that is proposed here. However, with increasing computer power this will become less of a problem in the future.

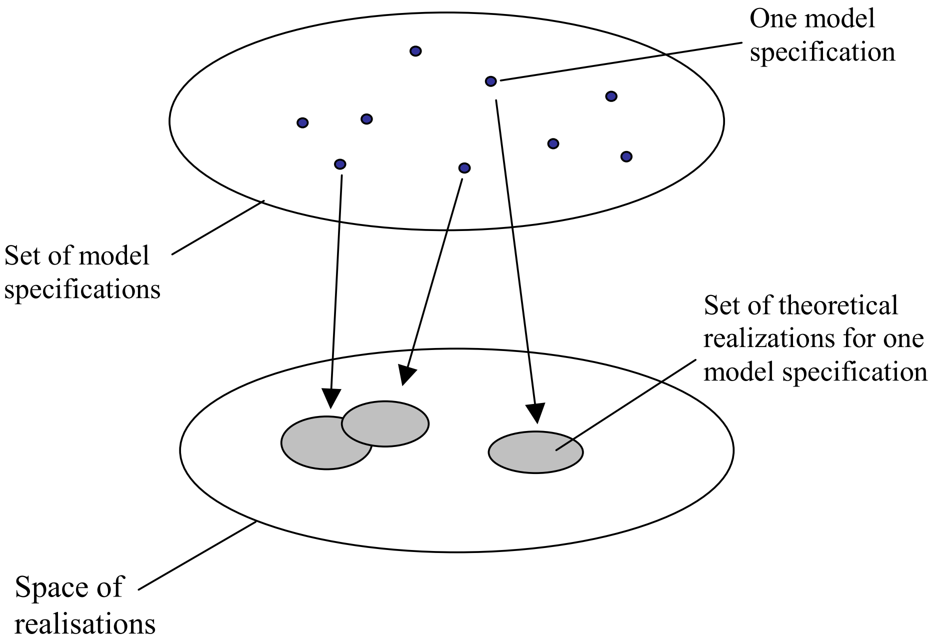

Figure 2: Set of model specifications and sets of realisations

Notice that the random choice of model specifications has nothing to do with the chance elements that are included in the models. Examining only a (high) number of randomly picked model specification is simply a device to deal with the problem that simulations cannot be run for an infinite number of model specifications. This is the only disadvantage of this method compared to a mathematical analysis of models. This disadvantage becomes the smaller the larger the number of analysed model specifications.

The stochastic elements in the models are responsible for the fact that one model specification can cause different theoretical realisations. As a consequence, two different model specifications might cause the same theoretical realisation (see the overlapping ellipses in Figure 2). This is what critical realists mean when they state that different causes can have the same effect.

Now the second kind of empirical data is used, those about empirical realisations of the dynamics of the whole system that is modelled. The simulation models that are considered here describe the dynamics of a system that is part of the whole economy. Usually it will not describe only one specific system but a number of systems that share common features (e.g. the same processes in different countries or industries). Whenever one such system and its dynamics are observed, we call this one empirical realisation of the class of systems that our models aim to represent. Usually it will be possible to gather data about the characteristics of several empirical realisations.

Let us consider the treatment of one empirical realisation. We can examine for each model specification whether the observed realisation falls into the range of theoretical realisations that this model specification predicts. According to the above statements, there is not only one model specification that is able to predict the empirical realisation. However, we can reject a number of model specifications on the basis of the empirical observations. Hence, for each model specification we can statistically state whether or not it is rejected by the empirical data about one specific realisation of the system's dynamics. A subset of model specifications that are not rejected remains.

Furthermore, for all model specifications that are not rejected by the empirical data the likelihood for their validity can be given. A Bayesian approach can be used to do this (see Zellner 1971 and Ghosh & Ramamoorthi 2003). Hence, a probability distribution over the set of model specifications is obtained for each realisation that is empirically observed.

In the literature such an approach is taken in statistics under the name of Bayesian inference (see Zellner 1971). There a set of models is defined and for each model the likelihood of its adequateness is empirically estimated. Each model is then weighted by its likelihood and predictions are made on the basis of the weighted sum of the predictions of each model. This can also been done in the approach taken here. The major difference is that the method proposed here uses empirical data extensively also for the development of the set of models that are tested. Furthermore, we propose two further steps in the analysis that are discussed in the next section.

4.3 Abduction of a Set of Models

Above we have determined all model specifications that are in line with the observation of one empirical realisation of the dynamics of the system (ellipse in set of assumptions in Figure 3), such as, for example, the development of an industry in one country. Hence, the above procedure allows for obtaining a subset of model specifications for each empirical realisation. If a number of realisations are observed, for each of them the subset of model specifications that cannot be rejected can be determined. Now these subsets can be used to determine the characteristics of the system. This is done in two steps, which are explained in the following.

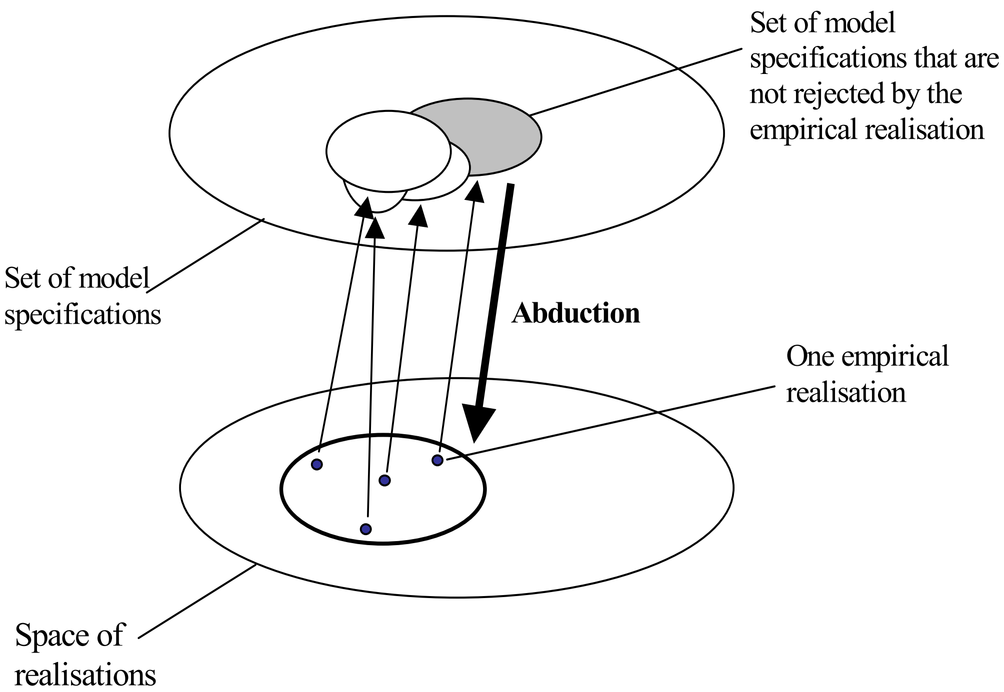

Figure 3: Abduction Between Set of model specifications and Set of realisations

Usually not only one realisation is observed. In general we look for models that can explain a number of similar systems (e.g. the developments in different industries or in different countries). For each single empirical realisation the above method leads to a subset of model specifications that are in line with this realisation (see the shade ellipse in Figure 3). If we have a number of empirical realisations, a number of subsets of model specifications result.

It is now possible to classify the empirical realisations in groups, either according to empirical characteristics (e.g. high-tech and low-tech industries) or according to the similarity of the subsets of model specifications, which are not rejected through the above procedure. This means that we define kinds of systems for which we are interested in their common features. This is the major aim of abduction: a classification of events, facts or processes and a determination of the characteristics of each class. Here, it means that we want to define a class of systems or dynamics and study the characteristics that all systems or dynamics in this class have in common. Two steps are necessary. First, the class of systems or dynamics that is to be studied has to be defined, all empirical data, meaning all observations of such systems or dynamics, has to be gathered and the above method has to be used to identify the respective set of model specifications (depicted by the arrows leading upwards in Figure 3). Second, the common characteristics of all realisations that can be obtained by any model specification in this set have to be studied (depicted by the arrow leading downwards in Figure 3). Let us assume that a group of empirical realisations is defined that belongs to the class of systems that is to be studied. The choice of empirical realisations defines a set of model specifications that consists of those model specifications that are not rejected by all empirical realisations in the group that is considered. All these model specifications have to be considered because the aim is to identify the characteristics that are common to all systems in the chosen group. Notice that in this case it is impossible to assign a probability to each model. The empirical realisations represent just a few examples of the dynamics that might be caused by the studied kind of system. It is in no way clear how we should weight the induced knowledge of each empirical realisation. This would only be possible if we have a very large number of observations. Hence, we refer from calculating probabilities for model specifications and only determine a subset of model specifications that is in line with the observed realisations (all the area within any of the ellipses in the upper part of Figure 3).

To understand the characteristics of a class of systems, now all model specifications that belong to this subset can be simulated. For each model the theoretical realisations that it might imply can be studied. What kind of characteristics of these realisations is studied depends on the research question. Everything is possible that is also done in the common simulation approaches that are based on theoretical models. For example, it is possible to study causal relations or the outcomes of the modelled processes. In the contrast to the common approaches the model specifications that are used here are based on an extensive use of empirical data that causes a high validity of the obtained results. All implications that the whole group of models share are characteristics of the studied class of systems.

This means that, instead of arguing that there is one model that explains all systems within a certain class, we argue that a subset of model specifications can be obtained by abduction. This subset of model specifications contains all possible bundles of assumptions that cannot be rejected by the empirical data about the systems that are to be studied. If the model specifications in this subset share characteristics, these characteristics can be expected to hold also for the real systems (given the development of the model has not included any crucial and false premise). Hence, we obtain robust knowledge about the characteristics of a certain kind of systems.

If the characteristics within a group of model specifications differ, the causes of these differences can be studied. It can be examined which factors in the models are responsible for the differences. Hence, although we will not know the characteristics of the real systems in this case, we will obtain knowledge about which factors cause different characteristics.

5. Conclusions

To underpin simulation models by empirical data means that one has to step into methodological discussion, in particular into the question how deduction, induction and abduction are related to each other. Most economists are educated in the tradition of Positivism. As a consequence heterodox as well as mainstream economists pretend - at least in their papers - that there are theoretical concepts they can deduce a priori and then test them by confronting them with data. Despite the way economists organize their papers it is correct to say that they also do not really deduce all abstract concepts a priori in a first step but that they use empirical insights, mostly emerging from a few observations interpreted by common sense in order to come to a theory and then test this theory. What we argue in this paper is that these steps should be made clear. Models should be based in a well-described way on empirical data. Additional assumptions that are not based on empirical knowledge should be avoided if possible or made at least explicit.

In order to calibrate simulation models we developed a methodology based on Critical Realism. In order to do so we suggested using different sets of empirical data in two ways by building on two strands of literature, which have already started to deal with this problem. Firstly, in the literature on microsimulations empirical data is extensively used for setting up the simulation model (see, e.g., Citro & Hanushek 1991). Secondly, in statistics Bayesian inference has been proposed to use empirical data in order to detect the adequate models within a set of models (see Zellner 1971). Both these strands of literature are mainly concerned with predicting future developments. We, instead, aimed to infer statements about causal relations and characteristics of a set of systems or dynamics, such as, e.g., the development of an industry, that have a general validity for this set of systems or dynamics. In other words, we aimed for general statement about the features of systems and dynamics instead of probabilistic predictions about their future and for statement about a set of systems or dynamics instead of an analysis of one single system. To this end, we combine the procedures of microsimulations and Bayesian inference.

We have argued that the result of such a twofold use of empirics can be used in an abductive way to create knowledge about classes of systems, where the classes can be chosen according to different considerations. This leads us beyond the common use of simulation model. We are able to infer from empirical data characteristics of classes of systems that have a general validity. The examined characteristics might include causal relationships as well as predictions of future developments. Hence, we are also able to add to the understanding of economic processes. However, it is important to realize that according to Critical Realism these results hold only temporarily, because either the underlying mechanism might change in time or because better underlying causal relationships are identified at a later stage.

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