AN ADVANCED METHODOLOGY FOR HETERODOX SIMULATION MODELS BASED ON CRITICAL REALISM

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Abstract

In this paper we develop an advanced methodology that makes the results of simulation models in heterodox economics more reliable and acceptable. This methodology copes with the specific characteristics of simulation models in heterodox economics, in particular with inherent uncertainty. We base our advanced methodology on Critical Realism, because it deals with inherent uncertainty by categorizing empirical events into underlying structural driving forces. Data is centre-stage in our advanced methodology, because it is used to infer assumptions and implications. Eventually a combined use of theoretical and empirical analysis based on different data sets helps inferring statements about causal relationships and characteristics of a set of models, such as, e.g., the development of different industries in different countries.

Keywords

Methodology, Heterodox Simulation Models, Critical Realism, Uncertainty

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1. Introduction[1]

In heterodox economics simulation models are used quite a lot to carry out mathematical experiments. However, the specification of the simulation model and 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 the model and its 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 empirically calibrating heterodox simulation models in a way that makes their results more transparent and thereby more acceptable. Data is centre-stage in the advanced methodology we will suggest in the following, because it is used to infer assumptions and implications. To calibrate models empirically is a general problem that models of mainstream economics face as well (cf. Kydland/Prescott, 1996). However, when working with heterodox simulation models we have to deal with additional problems, which stem from their very nature, in particular the inherent (Knightenian) uncertainty involved.

Critical Realism as methodology helps to deal with this inherent uncertainty, because it categorizes empirical events actually taking place and determines the underlying structural driving forces, thereby distinguishing chance and necessity in historical data. We will show that a methodology based on Critical Realism is the most promising way to build simulation models in heterodox economics. By basing heterodox simulation models on Critical Realism they become a more reliable tool for understanding economic processes and developments. To show how empirical data can be used to make the results of simulation models in heterodox economics more widely acceptable and applicable, we first show how elements of models in general and empirical data in particular have been used in models so far (Section 2). Then, we

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look into different methodological approaches that can be used as a basis for modelling. We show the features of the methodological approaches “Positivism” as the standard approach in economics and “Critical Realism” as the one we use (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 in heterodox economics (Section 4.). We conclude with a brief summary and an assessment of our progress (Section 5.).

2. Empirical Data in Models

Empirical data is one important element for the advanced simulation methodology that we develop in the following. In order to show which role empirical data can play, we first introduce the elements of model building in general (Section 2.1) and then give an overview how empirical data has been used in heterodox simulation models in particular (Section 2.2).

2.1 Elements of Models in General

In general, models can be distinguished into two major parts: assumptions and implications. 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. This leads to a couple of questions that are not interesting in the context of our analysis, e.g. is it sufficient that a theory can be potentially expressed in equations to turn it into a model. As these kinds of considerations are not important for our reasoning, we use the terms “model” and “theory” synonymically here.

The most important elements of models are premises, definitions, logical sentences, as well as data. Every model starts from *premises* that limit the area of application of the model, e.g. concerning time, place, and 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 right 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 causes and effects. Causal relationships are also often co-notated as hypotheses and formulated in the form “if … then …” (cf. Machlup, 1978, 455f). Causal relationships can say something about the functioning of the real world in the past as well as in the future, i.e. they can serve to explain past events or to prognosticate future ones.

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 3.1). 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" (Cowan/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 sufficiently be taken into consideration. However, even if researchers collect the data themselves it might be difficult to observe the relevant aspects as there might emerge some measurement problems.

2.2 Empirical Data in Heterodox Simulation Models

The simulation method has been used in heterodox as well as in mainstream economics. In heterodox models the simulation method has been used in order to cope with the specific characteristics of these models. In particular, uncertainty has been subject of heterodox simulation models ever since the seminal work by Nelson and Winter (1982). In the last decade the simulation method has also been used more frequently in mainstream economics. In particular it served purposes such as solving equation systems or analysing rational learning processes. In the following, we will concentrate on heterodox models, where heterogeneous agents decide under inherent (Knightenian) uncertainty in a bounded-rational way. Agents in these models act and interact in complex and open-ended economic systems, which are driven both by emerging novelty and by changes in micro-behaviour. The processes going on in these heterodox models are usually irreversible.

How to deal with inherent uncertainty and the intertwined aspects of chance and necessity within heterodox models is crucial when calibrating these models empirically. Empirical data stems from the observation of historical events. Historical events take only place once and it is difficult to distinguish chance from the characteristics they have in common. In the past heterodox simulation models have used data in three different ways: first by using stylised facts, second by using case studies, and third by comparing a larger set of cases in a systematic way. These different ways of using empirical data also imply different ways of dealing with chance and necessity in economic processes.

In the past, heterodox simulation models have often incorporated data in the form of *stylised facts* in accordance with Kaldor's original idea (Kaldor, 1968, 177f). Stylised facts comprise empirical statements about a wide application area. They mostly rely on common sense and the impression of the scholar using them. The problem with stylised facts is that they fall from heaven and often remain unmotivated (for a detailed critique see Schwerin, 2001, 92-98). As it is usually unclear how stylised facts are derived it is not possible to tell whether or not they comprise only the structural elements of economic processes or whether they partly mirror noise in the form of chance elements. Nevertheless, the use of stylised facts enables modellers who concentrate mostly on theoretical considerations to integrate some empirical reality into their analysis.

Examples of heterodox simulation models, which use stylised facts in their modelling, are Harrison (2004), Fagiolo/Dosi (2003), Werker (2003), Winter et al. (2003) and Windrum/Birchenhall (1998). Harrison (2004) presents a simulation model that can reproduce stylized facts in the form of four different kinds of organizational evolution and firm growth. Fagiolo/Dosi (2003) present an endogenous growth model, which is able to reproduce stylized facts in the form of empirically plausible GDP time-series. Windrum/Birchenhall (1998), Winter et al. (2003) as well as Werker (2003) present models, which are able to account for the stylized facts in the evolution of industry life cycles. Harrison (2004), Fagiolo/Dosi (2003), Werker (2003) and Windrum/Birchenhall (1998) model random effects and perform a sensitivity analysis by running the same specifications at least 100 times. They calculate some statistics and give some qualitative impressions of the results. Winter et al. (2003) concentrate more on the analytical results of their model and limit themselves to only few calculations to test for the sensitivity of their results.

Case studies in the form of history-friendly models are the second way of how empirical data is incorporated in heterodox models. They rely on detailed empirical knowledge about real historical processes and try to find a model that leads to processes with the same characteristics. Although this is usually not mentioned in the final publications, 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 one single case so that generalization is difficult. In the context of our discussion this is particularly problematic because - though usually most of the complicated and complex processes involved are depicted - it is not possible to sufficiently distinguish between chance and necessity. This means that scholars using history-friendly models have difficulties in identifying the underlying structural processes, which could be found back in similar historical circumstances. Usually, they provide some sensitivity analyses of their results, which can be and sometimes are explicitly interpreted as counterfactual histories. This gives some idea how stable the results are and whether they crucially depend on random effects. Generally spoken history-friendly models share the advantage as well as the disadvantage with case studies: they give us deep inside knowledge about real economic processes but lack the possibility to generalize their results in a convincing way.

Recent examples of history-friendly models are Eliasson et al. (2004), Brenner/Murmann (2003), Kim/Lee (2003), Malerba/Orsenigo (2002), Eliasson and Taymaz (2000) and Malerba et al. (1999). Eliasson et al. (2004) show with an empirically calibrated micro-macro model for the Sweden how the new economy affect productivity and growth processes. Brenner/Murmann (2003) simulate the history of the synthetic dye industry from 1856 to 1913 and study by counterfactual analysis why German firms became dominating the industry. Kim/Lee (2003) construct a history-friendly model for the DRAM industry. Malerba/Orsenigo (2002) and Malerba et al. (1999) concentrate on analyzing a history-friendly model of the computer-industry. Only Eliasson and Taymaz (2000) calculate the sensitivity of their results. All other authors run a number of counterfactual histories in order to account for the sensitivity of their results. Thereby, they produce data that can be analyzed statistically. Consequently, these scholars can use more sophisticated methods and can look into the statistical properties of their models in a systematic way. This gives some insights into how counterfactual histories could have run and on how much the results depend on random effects.

The third way to incorporate empirical data in heterodox models is a *systematic comparison of a larger set of cases*. This approach allows for even more detailed and systematic analyses of statistical properties and sensitivities towards random effects. Two approaches with long tradition are worthwhile mentioning, which both have been used mainly for prognosis. The first approach starts from empirically based assumptions about micro-behaviour of agents. These assumptions are used to set up a simulation model and run so-called micro-simulations (surveys and general discussions can be found, e.g., in Merz, 1991, O`Donoghue, 2001, and Creedy/Duncan, 2002). The second approach tests the implications of a set of general models empirically and uses Bayesian inference to infer knowledge about the adequateness of different models (for an introduction to Bayesian inference see, e.g., Citro & Hanushek, 1991 and the original work by Zellner, 1971).

Bayesian inference has become more and more common in econometrics in recent years. Data is used in order to examine the ability of different models to describe observed processes and thereby plays a similar role as in approaches based on stylised facts or case studies. However, the Bayesian simulation approach deviates from the two other approaches described above in two ways. First, data about the economic situation or economic dynamics are used to check the adequateness of various models. For example, Tsionas (2000) uses stock market data to check different models about the stochastic movements of prices. Second, the trial and error process for finding an adequate model is made explicit by using Bayesian inference. This means that all, or many, different parameter sets and model specifications are repeatedly used. Since Bayesian inference deals with stochastic models, for each parameter set and model specification many simulations have to be run because the resulting dynamics vary. Then, for each parameter set and model specification the probability that the real development, which is described by the empirical data used, is obtained in the simulation can be calculated. According to Bayesian inference, this offers some knowledge about the likelihood that each of the parameter specifications is the correct one. The resulting likelihoods can be used in two ways: to make predictions for future developments (see, e.g., Jacobson/Karlsson, 2004 and Jochmann/Leon-Gonzalez, 2004) or for checking the adequateness of different models (see, e.g., Kaufmann, 2000 and Tsionas, 2000).

Heterodox simulation models have used data in three ways, first by using stylised facts, second by using case studies, and third by comparing a larger set of cases in a systematic way. In the following, we will build on quite some of the above approaches in order to develop an advanced methodology, which heavily relies on empirical data (see Sections 3.3 and 4).

3. Critical Realism as Methodology for Heterodox 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, we depict the general principles of inference (Section 3.1). Based on these principles we show the difference of Positivism and Critical Realism (Section 3.2) and why a practical application of Critical Realism is best suited to meet the requirements of heterodox simulation models (Section 3.3).

3.1 Principles of Inference in Modelling

Assumptions and implications are basic elements of inference. From assumptions implications are derived in an analytical and logical way. 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.

Three different principles of inference can be distinguished: deduction, induction and abduction. Each principle of inference works in different ways, although meeting the same end, namely inferring implications from assumptions. *Deduction* is often summarized as inferring “from general to particular” (cf. Lawson, 1997, 24). Let us use as an example throughout this paper the impact of different patent laws in different countries on the development of a certain industry in these countries. Deduction would mean in this context that we have or assume a theory about the development of industries dependent on the national patent law, e.g. that stricter national patent laws protect property rights of innovators better thereby giving more incentives to innovate. From this theory we could deduce that an industry in a country with lax patent laws innovates less compared to the same industry in a country with stricter patent laws. As one can readily see in the example, 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 in deduction conclusions stemming from the assumptions have to be true. In formal sciences like mathematics this holds, because assumptions are usually provided in the form of axioms, i.e. they are self-evident and need not be proven. However, 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. In our example this would mean that we observe the innovative output of a number of industries in a number of different countries with different patent laws. We would then inductively infer general mechanisms, relationships and rules by examining the common characteristics of all observations and might come to the conclusion that industries in countries with stricter patent laws have a larger innovative output. 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 now.

Abduction - sometimes also called retroduction - classifies “particular events into general patterns” (Lawson, 1997, 24). For our example abduction means that we argue that industries vary in their development and are therefore affected by patent laws in different ways. Abduction means that we start by collecting detailed information about the development of different industries in different countries facing different patent laws. Based on this we classify the different developments and derive underlying driving forces, which enable us to describe, explain and predict developments of other industries in other countries with respect to patent laws as well. 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 a number of low-tech industries develop in different countries independent of the actual patent laws, we might conclude that all low-tech industries are not influenced by any change in the patent laws. 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 mechanisms behind the industrial development and the differences between the national patent laws. Especially, it would be important to know what makes an industry’s development independent of patent laws. We could e.g. choose to define classes of industries that show similar developments within one class and different developments between classes, e.g. the famous Pavitt taxonomy (Pavitt, 1984). By going back and forth between theorizing and empirical testing we might come to the conclusion that science-based industries profit more from stricter patent laws than scale intensive industries. This would allow transferring the experience to other industries. 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 (1867/1965, 5, 145f):

> “(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.”

3.2 Positivism and Critical Realism as Methodologies of Inferring Models

Methodologies use principles of inference in order to derive models. From the methodologies used to develop economic models we will look into the approaches of Positivism and of Critical Realism. By and large economic scholars use Positivism as methodological basis for modelling, whereas they use 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. Therefore, models based on Positivism are often considered to be purely deductive. However, in case data is included in the modeling, the implications from deduction are confronted with inductively found results. The aim of such empirically founded models is to objectively measure and quantify observable facts as well as to search for empirical regularities that help to describe, explain and predict reality. Some criticize these kinds of models for implicitly claiming that all knowledge is grounded in experience and deny the existence of an unobservable deep or non-actual level of reality (Lawson, 1997, 19).

Positivism has two problems that are particularly important for our discussion of how to empirically calibrate simulation models: the first one is that general axioms do not exist in social sciences; the second one is that heterodox models imply inherent uncertainty. The impossibility to find axioms in social sciences that hold in general (see also Section 3.1) stems from the fact that these sciences always analyze situations where human beings are involved who do not necessarily behave similarly under similar circumstances, as their mood and preferences change. 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. Even if the model's inferred implications is confronted 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 heterodox economics that imply inherent uncertainty. This inherent uncertainty leads to complex and complicated patterns of the economic processes to be described, explained and prognosticated. These patterns cannot be covered by the conditions of closure used by positivists, which suggest that one cause has one effect and the other way around. 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 et al., 2002, 482).

In contrast to Positivism, Critical Realism acknowledges that different causes can lead to the same effect and that the same cause can lead to different effects. Critical Realism, which we will suggest as an appropriate methodological basis for heterodox simulation models, uses abduction as one major 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 et al., 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 and distinguishing chance from structural elements.

The way Critical Realists look at the world does by no means suggest that virtually everything is possible. Quite the contrary, there are stabilizing features available. Critical Realists point out, for example 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 et al., 2002, 481f). This means that a specific connection between cause and effect might remain for a while but also changes over time (Downward et al., 2002, 495). The goal of modelling can thus not be to detect insights into the real world that hold forever but to detect structural elements of historical processes, which hold for a while but than evolve further. To detect these more fundamental periods of transitions of systems and the conditions for them is another goal of heterodox simulation models based on Critical Realism.

This different view on how causes and effects are connected has severe implications for how to deal with data. For Positivism dealing with data is rather clear-cut, because according to its protagonists one cause is always connected with one effect and one has only to identify these straightforward causal relationships. On the contrary, the situation is much more difficult when using Critical Realism, because such a straightforward connection between cause and effect is missing. However, it is this feature of Critical Realism, which helps us to cover models with inherent uncertainty, as in the context of uncertainty cause and effect are never connected in such a clear-cut way.

It is, though, not completely clear which implications Critical Realism has for empirical research methods (Downward et al., 2002), as in general protagonists of Critical Realists restrain themselves in using empirical data to

"… (t)he measuring and recording of states of affairs, the collection, tabulation, transformation and graphing of statistics about the economy, … detailed case studies, oral reporting, including interviews, biographies, and so on." (Lawson, 1997, 221).

Lawson approves of all kinds of ways to collect data but restricts its use to a local and specific analysis (Brown et al., 2002, 782). The reason for this is that he and other Critical Realists do not approve of using statistics and mathematics in order to compare larger sets of cases in a systematic way or in order to test deductively inferred models empirically. They believe that the use of statistics and mathematics only serves to detect intrinsic and extrinsic conditions of closure, i.e. that one cause has one effect and the other way around. However, this is quite jumping to conclusions: As Reiss (2004) shows in a very convincing way the use of statistics and mathematical modelling does by no means imply that these strict conditions of closure are used. In particular, there are some mainstream modellers who employ statistics and mathematics in such a way that they account for the historical context, i.e. that their specific data only hold in the context of a particular time and place.

Critical Realists basically approach empirical data the way scholars carrying out case studies do and therefore face the same kinds of problems (see Section 2.): Data collected and analysed lack the potential to generalize results. To overcome this problem one has to compare larger sets of cases in a systematic way and to identify what they have in common independent of their specific historical circumstances. In a first attempt to do so Brown et al. (2002) suggested combining Critical Realism with "systematic abstraction" as a means to achieve a historical level of generality and to identify the inner connection of social phenomena. However, they do not provide a guideline how to put their suggestion into practice. We will in the following employ and further develop these insights in order to provide a methodological basis for the empirical calibration of simulation models and to put it to practical use.

3.3 An Advanced Methodology of Heterodox Simulation Models

In line with Critical Realism, we argue that what we observe in reality is the result of processes on a deeper level, which might be (partly) observable but is not the level on which we observe the phenomenon that is to be studied, explained or predicted. Therefore, it is not sufficient to describe the relationships on the observation level – the level where the phenomenon that is to be studied occurs. We need to understand these relationships on the basis of the processes of the underlying level. Critical Realism asks for empirical data to be used but does not provide a clear practical guideline. We will provide such a practical guideline in the following. Our suggestion to calibrate simulation models relies on abduction as the major inference principle. However, 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 in the first two steps to prepare the final abductive step.

In all three steps of our methodology we will heavily rely on empirical data, thereby building on all three approaches, in which heterodox simulation models have used data. These three approaches have been using stylised facts, investigating case studies or comparing a larger set of cases in a systematic way (see Section 2.2). We suggest to use all approaches if necessary but will in particular use insights of Bayesian simulation approach which assumes, as we do in the following, that economic dynamics are based on chance elements as well as causal relationships. This means that wherever possible we recommend using larger sets of data to calibrate the model, thereby giving a broader empirical basis to the models. Where no larger sets of data are available we suggest relying on either stylised facts or case studies in order to give some empirical underpinning. By proceeding like this it is possible to cope with uncertainty, because empirical data is used to reduce the degrees of freedom of the complex systems modeled, thereby identifying the structural elements, which drive systems. This specific way of dealing with data in calibrating simulation models is one element of the advanced methodology presented here. It helps to categorize empirical events into classes and to distinguish the underlying structural elements of historical processes from chance elements using abduction (see Section 4.).

Although abduction has been a popular concept since the seminal work by Peirce (1867), until today scholars have remained relatively vague on how to implement abduction (sometimes also called retroduction) in practical terms:

"Not much can be said about this process of retroduction independent of context other than it is likely to operate under a logic of analogy or metaphor and to draw heavily on the investigator's perspective, beliefs and experience." (Lawson, 1997, 212)

In the following we will show how – in quite practical terms - abduction helps us to produce classes of models, which combine assumptions and implications based on empirical findings (Section 4.3). Only those models are included, which are not rejected by confronting either their assumptions or their implications with reality (Sections 4.1 and 4.2). Note 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. This means that only a subset of all model specifications is considered that is not in contrast with empirical findings. Second, we can study the correctness of these specifications with the help of empirical data on implications (see below).

4. A Practical Guide to an Advanced Methodology for Heterodox Simulation Models

In the following we will show how the methodology of Critical Realism can be used to calibrate simulation models in practical terms. 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 assumptions. Based on that, implications are inferred by deduction and induction (Section 4.2). Here, empirical data is confronted with implications inferred from the dynamics of the described economic system. The two kinds of data that are used have to be different, because different levels of the whole system are concerned. Moreover, this safeguards the models from being self-evident. In a third and final step, abduction is used to combine empirical findings and to derive causal relationships. This results in theoretical knowledge about the part of the world we want to explain (Section 4.3).

4.1 Inferring Assumptions by Deduction and Induction

We start with setting the assumptions of the model and defining the system that the simulation model is intended to describe. In order to do so we combine deduction and induction. The relevant 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 relationships and especially the choice of parameters should be fixed using a broad empirical basis. This is rarely done in the field of computational and evolutionary economics (for the use of empirical data in these models see Section 2.2). We argue that more can be achieved by using simulations in combination with empirical data, especially with respect to the reliability of the results and the clearness of the method. The first step towards this end is based on the statement that the assumptions on which the model is built 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 as many central assumptions of the model as possible on empirical knowledge, because there are no self-evident axioms in social sciences and logic is not sufficient to come to a full set of assumptions.

Since the method that is proposed here is based on a practical application of Critical Realism, we need to clarify a number of terms that will be used in the following (see Table 1).

Term	*Definition*
Bundle of assumptions	All assumptions on which one specific simulation model is based
Set of simulation models	All simulation models that are considered. They differ in their assumptions about the relationships between variables as well as in the parameter specifications
Model specification	One specific simulation model with given relationships between the variables and specified parameters
Theoretical implication	The implications of one model specification
Set of theoretical implications	Set of all potential implications of all simulation models that are included in the study
Empirical realization	Dynamics observed in reality
Specific system	One specific part of the real world, such as a specific industry in a specific country
Class of systems	A certain group of specific systems that share some characteristics

Table 1: Definition of terms used

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. This implies, for example, that many parameters cannot be fixed but can only be restricted to certain ranges. 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. 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.

In our example of the industrial development dependent on the existing patent laws this means that the simulation model has to describe the mechanisms by which the patent laws influences firm’s strategies, innovative success and growth. For each impact of patent laws on firms’ activity the available data and empirical evidence should be examined and stated and the assumptions should be inferred from this evidence. The available knowledge and data will not allow for the restriction to one simulation model with a clear specification of all parameters. Instead, it is likely that some variants of the model have to be included in the analysis and that most parameters can only be restricted to certain ranges.

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

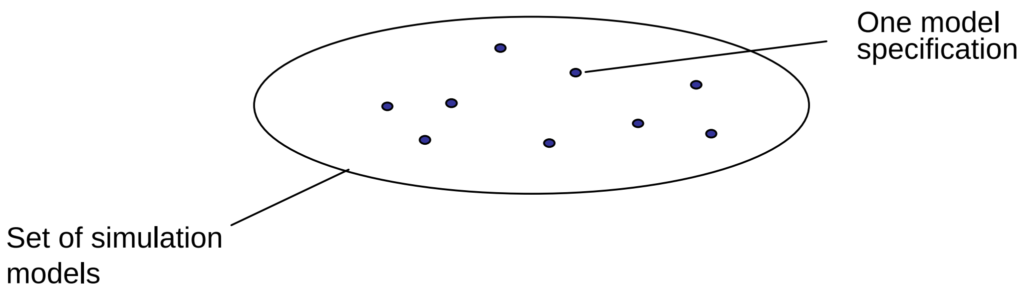

Figure 1: Set of model specifications

4.2 Inferring Implications by Deduction and Induction

When inferring implications by deduction and induction semi-closure, i.e. the fact that the same cause can have different effects and vice versa, has to be translated into practical terms. In order to do so, we run each model specification many times so that we can distinguish random effects from necessity. It is likely that different effects emerge from the same model specification. In order to obtain knowledge about the various possible model specifications, we use the Monte-Carlo method and we pick some of the infinite number of possible model specifications randomly.

Each model specification is 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 the theoretical implication of the assumptions on which the model specification is based. Rerunning the simulation for the same model specification might lead to exactly the same theoretical implication. However, because of the stochastic processes that are included in the model, it is more likely that the outcome is a different theoretical implication. If one model specification is simulated many times, a set of theoretical implications is the result. For each model specification we can determine such a set of theoretical implications. It should be noticed here that this means that we do not obtain a unique matching between assumptions and implications, as it is assumed in Positivism. In the terminology of Critical Realism this means that each bundle of assumptions can lead to different effects.

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, if available according to an ex-ante probability distribution 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.

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). In the terminology of Critical Realism we thereby have a situation where different causes can have the same effect.

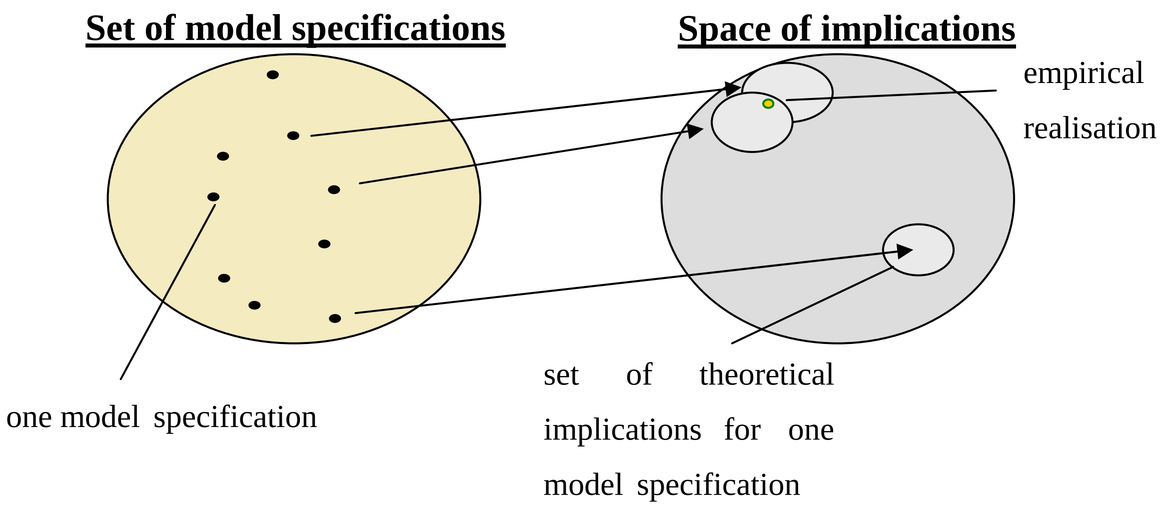

Figure 2: Set of model specifications and sets of implications

Now a second data set is used to test the theoretical implications against empirical realisations. 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. Concerning our example, we would consider one industry and its development in a specific country as a specific system. The simulation model that is set up to describe this development can be expected to be applicable to other industries and other countries as well. 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. Of course, many different variables can be observed that describe the dynamics of the specific system. The more variables are recorded and used for the test of the theoretical implications, the more selective this part of our method becomes with respect to the model specifications and the more robust become the final results of the method. Hence, a huge amount of data is preferable but not always available.

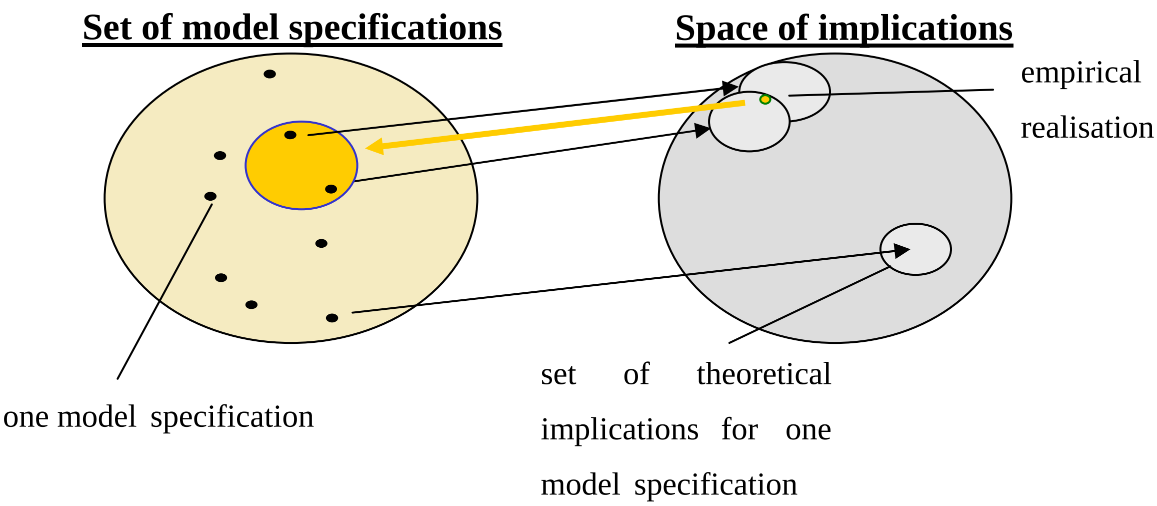

Figure 3: Explaining an empirical realisation

The method proposed here allows for dealing with any amount of available data. Naturally, as in econometrics in general, more data leads to more significant results; something that is usually not considered in simulation approaches in heterodox economics. Usually it will be possible to gather data about several empirical realisations. Nevertheless, let us first consider the treatment of one empirical realisation. We can examine for each model specification whether the observed realisation falls into the range of theoretical implications that this model specification predicts (see Figure 3). According to the above statements, there is not necessarily 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 (for a detailed discussion of this approach see Section 2.2). However, we extend the usual simulation approach that is based on Bayesian inference in two ways: First, we use empirical data extensively also for the development of the set of models that are tested. Second, we are not only interested in checking models but also we aim to obtain more knowledge about the underlying causes for the observed dynamics. Hence, the Bayesian approach is used here to check different assumptions about the relationships and parameters of the model and to structure the described systems according to their characteristics (see next paragraph). Though we here show our modeling methodology for description and explanation it is also possible to use it for predictions, which it is usually used for in Bayesian simulations.

4.3 Inferring Underlying Relationships by Abduction

In this last step we identify the underlying mechanisms driving the part of the world we want to describe and explain. In some studies the method might lead to a full theory, in others it might only provide some causal relationships that do not form a complete theory. In the latter case the results would imply additional questions and additional necessity for research.

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). In our example this would mean that we would have identified all model specifications that might explain the observed developments in one specific industry in one specific country. This procedure allows us to obtain a subset of model specifications for each empirical realisation. For each empirical realisation observed the subset of model specifications, which cannot be rejected, can be determined. Now these subsets can be used to find out the characteristics of the system. Generally spoken, 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 coloured ellipses in Figure 4). If we have a number of empirical realisations, a number of subsets of model specifications will be identified.

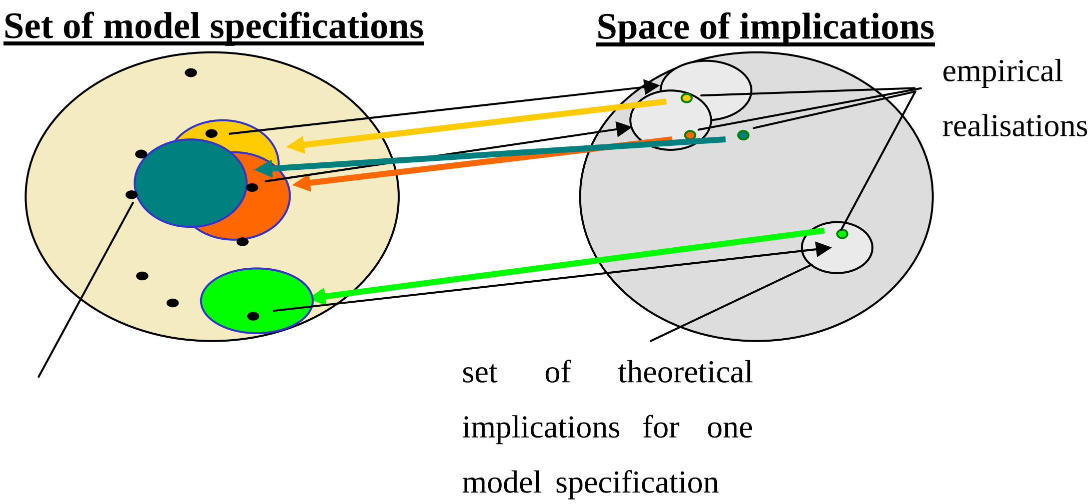

Figure 4: Abduction Between Set of Model Specifications and Set of Realisations

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 obtained subsets of model specifications (e.g. if the resulting subsets of model specifications show obvious differences for different empirical realisations as depicted in Figure 4). This means that we define kinds of systems, for which we are interested in their common features. This is the major aim of abduction: to classify events, facts or processes and to analyse the characteristics of each class. Here, it means that we want to define a class of systems and study the characteristics that all systems in this class have in common. This is done on the basis of model specifications. A class of systems is defined by the set of model specifications, which includes all model specifications that might explain at least one of the developments of the systems that are included in this class. Hence, defining the set of model specifications for a class of systems has two consequences at the same time. First, it offers a definition of the class of system because it can be tested for each new empirical observation whether this observation might be predicted by one of the model specifications in the defined set. Second, it defines the common characteristics of the class of systems, which can be inferred from the set of model specifications with the help of simulations. This is the step of abduction, which is central to Critical Realism.

Concerning our example, this means that we define a set of parameter specifications (e.g. by defining ranges for the parameters) of the simulation model. For each industry and country it is possible to collect data about the developments of this industry and country. The data can be used to check whether the observed developments can be explained by the set of model specifications that has been chosen. If this is the case the system of this specific industry and country belongs to the defined class of systems. This means that we can examine which systems belong to the defined class. At the same time, we can examine our original question: how do patent laws in a country influence the development of an industry there. To this end, we simulate all model specifications that belong to the defined class of systems. If we obtain the same influence of the patent laws for all these simulations, we can state that this influence holds in general for the defined class of systems.

Simulating various model specifications of a class of systems allows studying any characteristic of these systems. This also includes relationships between variables and processes involved. What kind of characteristics 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. In contrast to the common approaches, however, 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 model specifications 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. 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. Although we will not know the characteristics of the real systems in this case, we will therefore obtain knowledge about which factors cause different characteristics.

5. Conclusions

The purpose of our exercise was to make the results of simulation models in heterodox economics more reliable and acceptable. In order to do so we stepped into a methodological discussion, i.e. into the question how Critical Realism can serve as a methodological basis for heterodox simulation models. 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 that they can deduce a priori and then test by confronting them with data. Despite the way economists following Positivism organize their papers it is correct to say that when working on their analysis they do not really deduce all abstract concepts a priori in a first step. Instead they also use empirical insights, mostly emerging from stylized facts in the form of a few observations interpreted by common sense. Based on this a theory is developed and then tested. What we argue in this paper is that these steps should be made more explicit. Models should be based in a well-described way on empirical data. Assumptions that are not based on empirical knowledge should be avoided if possible or made at least explicit. Preferably models should rely on more sophisticated ways to incorporate empirical data like suggested here.

In order to calibrate heterodox simulation models we developed a methodology based on Critical Realism, which enables us to deal with the uncertainty inherent in these models. We do this by categorizing empirical events into underlying structural driving forces. Data is centre-stage in our advanced methodology, because it is used to infer assumptions and implications. So far heterodox simulation models have used data in the three different ways: first by using stylised facts, second by using case studies, and third by comparing a larger set of cases in a systematic way (Section 2). We propose to use as much detailed data as possible and to only refer to less detailed data, e.g. in the form of stylised facts, if other data is unavailable. Generally spoken, a combined use of theoretical and empirical analysis based on different data sets helps us to infer statements about causal relationships and characteristics of a set of models, such as, e.g., the development of different industries in different countries. We did not only provide methodological considerations on Positivism as the usual methodology in economics and Critical Realism as the one we propose to use (Section 3) but also a practical guide for creating simulation models (Section 4). We suggest first putting together the set of assumptions by induction and deduction and by including empirical data available. In a second step, implications are inferred by deduction and induction using again empirical data – naturally stemming from another data set. In a third and final step, we look for a theory about the part of the world we want to describe and explain by deriving causal relationships from them.

We have argued that the results of this proceeding in three steps can be used to create knowledge about classes of systems, where the classes can be chosen according to different considerations. Compared with other methodologies this advanced methodology is rather time-consuming, because it requires detailed research for available data and a lot of simulation runs. However, this methodology leads us beyond the common use of simulation model, as we are able to infer 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. It is crucial to realize that in line with Critical Realism these results hold only temporarily, because either the underlying mechanism might change in time or because more detailed information might be available later on so that the underlying causal relationships can be studied in more detail.

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