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Policy Advice Derived from Simulation Models

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Abstract

When advising policy we face the fundamental problem that economic processes are uncertain. Consequently, policy can err. In this paper we show how the use of simulation models can reduce policy errors by inferring empirically reliable and meaningful statements about economic processes. We suggest that policy is best based on so-called abductive simulation models, which help to better understand how policy measures can influence economic processes. We show that abductive simulation models use a combination of theoretical and empirical analysis based on different data sets. By way of example we show what policy can learn with the help of abductive simulation models, namely how policy measures can influence the emergence of a regional cluster.

Keywords:Policy Advice, Simulation Models, Uncertainty, Methodology

Introduction

1.1 Economic processes are uncertain. So are the outcomes of policy measures. As a consequence policy measures might not meet the goals intended by policy makers. To improve their measures and at the same time meet criticism policy makers increasingly seek advice from scientific experts. However, this does not seem to hinder policy from errors. Unfortunately, we need to accept the fact that there is always a chance that policy measures will produce unintended and undesirable outcomes as uncertainty lies in the very nature of economic processes (Metcalfe 1995). Nevertheless, advice from scientific experts can help reducing the probability of policy errors by identifying the causal structures in economic processes and distinguishing them from chance. The knowledge about the causal structure can be used to influence economic processes by adequate measures, though the outcome remains uncertain (cf. Schwerin and Werker 2003).

1.2 In the following we will concentrate on the question of how abductive simulation models can

be used for policy advice in order to decrease the likelihood of policy errors. We suggest that abductive simulation models are particularly well suited for this, because they belong to models of heterodox economics. These models put (Knightenian) uncertainty centre-stage, thereby mirroring the element of economic processes that makes it impossible to implement policy measures that are successful in any case. The methodology of Critical Realism is core to analysing uncertain economic processes as it helps identifying underlying causal structures —namely by abduction.

1.3 We start providing a methodology for abductive simulation models that use a combination of theoretical and empirical results employing and further developing insights of Critical Realism (Section 2). Based on that we show how abductive simulation models can be used for policy advice (Section 3). By way of example we demonstrate that data and the way it is used are crucial for the quality of policy advice and illustrate how abductive simulation models can be best put to use for policy advice (Section 4). We conclude with a summary of our results and a discussion of their implications (Section 5).

Heterodox Simulation Models Based on Critical Realism

2.1 In order to show which role inference plays in modelling, we first introduce the elements of model building in general and then give a brief overview of principles of inference (2.2). Based on that we show how Critical Realism can provide us with a methodology for abductive simulation models (2.10).

Principles of Inferences in Modelling

2.2 Inference means that we need to discuss the relationship between the two major parts that models contain, i.e. assumptions and implications. Generally spoken, principles of inference help to derive implications from assumptions. 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 distinction is not important for our reasoning, we use the terms "model" and "theory" as synonyms in the following.

2.3 The most important elements of models are premises, hypotheses, as well as data. Every model starts from *premises* that limit the area of application of the model, e.g. limiting the model concerning time, place, and agents involved etc. *Hypotheses* are sentences about causes and effects, i.e. causal relationships. These are often formulated in the form "if … then …" (cf. Machlup 1978, 455f). Hypotheses 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 central to our further discussions as it contains claims about parts of reality, which play a key role in inference. 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 and Foray 2002, p. 540).

2.4 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 some measurement problems might emerge.

2.5 While building a (simulation) model, the modeller has to decide how complex and complicated the model should be and how much data is used to underpin it. There is the well-known debate between the "keep it simple, stupid" (KISS) and the "keep it descriptive, stupid" (KIDS) approaches. Pyka and Deichsel (2009) suggest to rather keep it simple by even accepting unrealistic assumptions—quite in the Friedman tradition. We suggest that there is not necessarily a trade off between the KISS and KIDS approach. In our opinion, most scholars agree that good modelling follows the KISS approach when choosing the research problem and model. In particular modellers do not include more variables and parameters in their models than strictly necessary to answer the research question. Scholars disagree more about how much data should be included in the model. Obviously, the use of data is time- and cost-intensive. Therefore, scholars might refrain from it. In our opinion academic discussion can certainly benefit from models without (broad) use of data. However, we suggest that the model's results as well as its reliability for policy advice increases with the use of data. Therefore, we suggest using the KIDS approach, because policy failure is normally much more expensive than the additional costs for the extensive use of data. Naturally, future developments can include much more severe transition periods than reflected in the data of some relatively stable economic years. However, if policy is interested in transition periods data would have to reflect this.

2.6 For abductive simulation models used to advice policy we suggest —in a first step—to follow the KISS approach and keep the model as simple as possible concerning the research problem and model. In a second step we would rather use data as much as possible. Data can be used in two ways: first, to construct reliable and meaningful assumptions. Second, it can be used to test implications. Usually, data is used in one or the other way. We propose here to utilise both ways at the same time in order to improve theory building.

2.7 Three different principles of inference can be distinguished: deduction, induction and abduction. Each principle of inference works in different ways, although meeting the same goal, namely inferring implications from assumptions.

1. *Deduction* is often summarized as inferring "from general to particular" (cf. Lawson 1997, 24). In deduction assumptions contain all possible elements of models, like e.g. premises or hypotheses. Therefore, it is often claimed that in deduction conclusions stemming from the assumptions have to be true. However, this only holds in the sense that implications inferred that way are logically correct. Here, our aim is to correctly describe, explain and prognosticate reality, though. This can only be achieved if assumptions are supported by appropriate and reliable data.

2. *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. 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. Inductive inference is based on data. Nevertheless, 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, because future observations are by definition not available yet. It is important to note that this uncertainty remains even if we are able to provide policy makers with a reliable and meaningful abductive simulation model describing those economic processes that policy makers want to influence.
3. *Abduction*—sometimes also called retroduction—classifies "particular events into general patterns" (Lawson 1997, 24). Abduction requires much more detailed information to infer implications that are likely to hold when confronted with reality. 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.

A fundamental problem of abduction is that it can produce results that are wrong within its own logical system, because different causes can lead to the same effect and that the same cause can lead to different effects (Downward et al. 2002, 482). Therefore, results of abduction have to be combined with induction or deduction in order to come to substantial and meaningful results (Lipton 2001).

2.9 In the following, we are particularly interested in abduction as the principle of inference that helps us identifying causal relationships that can guide policy decisions. This is notwithstanding that the other two principles of inference have to be employed as well in order to construct a reliable and meaningful abductive simulation model.

Critical Realism as Methodology for Abductive Simulation Models

2.10 Most scholars from heterodox economics still use positivism as methodology to derive their results. This is partly due to the fact that most economic scholars are implicitly trained in Positivism. Moreover, there is a tendency to pretend that methodology is independent from substantive theories and the other way around (cf. Nielsen 2002). As could already be seen from our discussion on principles of inference (see 2.2) this is not the case, though. In the

following, we will argue that Critical Realism is a much better methodological basis for heterodox modelling—in particular so, because these models include uncertainty—and Critical Realism is able to deal with this.

2.11 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).

2.12 Positivism has one problem that is particularly important for our discussion of how to empirically calibrate simulation models, namely how to deal with uncertainty. From inherent uncertainty complex and complicated patterns of economic processes that we want to describe, explain and prognosticate emerge. These patterns cannot be covered by the conditions of closure that positivists use, because they 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).

2.13 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. For the discipline of economics, Downward et al. (2002) showed what Critical Realism means for the use of empirical data and modeling. The aim of Critical Realism is to describe and explain 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.

2.14 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 they aim at identifying these causal relationships. In contrast, the situation is much more difficult when using Critical Realism, because the connection between cause and effect is much more complicated. However, it is this feature of Critical Realism, which helps us modelling inherent uncertainty where cause and effect are usually not connected in a clear-cut way.

2.15 However, protagonists of Critical Realism restrict the use of empirical research methods (Downward et al. 2002) 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.

2.16 Critical Realists basically approach empirical data the way scholars carrying out case studies do and therefore face the same kinds of problems: 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.

Abductive Simulation Models Used for Policy Advice

Policy Advice Based on Critical Realism

3.1 Policy advice can be based on different kinds of models (for an categorization of models available for policy advice see Yücel and Van Daalen 2009). The general problem with policy advice based on models—of whatever type—is that these models are not certainly correctly describing and explaining past and future. This means that policy based on such advice might err. However, one needs to consider that this holds anyway (Metcalfe 1995)—despite the fact that policy makers and probably also voters try to pretend that this is otherwise. Although policy can err we can use the nature of economic processes—in particular the distinction between chance and necessity—to design policy measures where the element of error is reduced as far as possible (cf. Schwerin and Werker 2003).

3.2 According to Critical Realism it is possible to model certain behaviours and then to predict a reasonable range of possible outcomes (Lawson 1997). 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 same holds for processes and structures driving social systems (Pinkstone 1999). 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 then 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.

Practical Guideline for Abductive Simulation Models

3.3 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. In the following, we call these models abductive simulation models (for a more detailed discussion see Brenner and Werker 2007). 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 third abductive step.

3.4 Although abduction has been a popular concept since the seminal work by Peirce (1867/1965), until today scholars have remained relatively vague on how to implement abduction 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)

3.5 Abduction helps us to produce classes of models, which combine assumptions and implications based on empirical findings (cf. the following Brenner and Werker 2007). Only those models are included, which are not rejected by confronting either their assumptions or their implications with reality. 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).

3.6 In the following, we use Critical Realism to provide a procedure for building and carrying out abductive simulation models in four steps (cf. a more detailed discussion of the three first steps Brenner and Werker 2007). To do so we follow Pinkstone (1999) by clearly stating what we believe to be realistic causal relationships, which are able to inform policy makers, and to provide as robust evidence as possible for our claim. Naturally, this kind of methodology is much more demanding than that of mainstream modelling but at the same time is potentially much more fruitful as well. It is important to note that depending on the kind of question to be answered the model itself might be rather simple. This means that KISS might be applied in a first step and KIDS in later ones (for a more detailed discussion see 2.2). First, the simulation model has to be set up using the available empirical knowledge about the assumptions of the model. Second, the model is run and the implications are compared to empirical data in order to restrict the parameters ranges further, in fact an inductive step. Third, the most important abductive step is carried out, i.e. the results are used to classify observations in classes. This step is central for Critical Realism, because here empirical observation and theory building meet to identify underlying regularities that hold under specific circumstances (Pinkstone 1999). Fourth, the resulting parameter ranges are used to study the implications of policy measures. Parameter ranges of variables that can be influenced by policy are varied and simulations are run to find out the most promising policy measures by aiming at high effectiveness and efficiency as well as low risk of failure—either by wasting money or by unintended negative side effects. Here, again abduction might play a role.

3.7 In all these steps—depending on availability—we can rely on different sources of empirical data, i.e. employ stylised facts, investigate case studies or compare larger sets of cases in a systematic way. We suggest making use of all these sources if necessary. Like in the Bayesian simulation approach we assume that economic dynamics are based on chance elements as well as causal relationships. Consequently we recommend using larger sets of data to calibrate the model wherever possible, 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 build on reliable empirical data when categorizing empirical events into classes and to distinguish the underlying structural elements of historical processes from chance elements using abduction.

 An Example of Policy Advice Based on an Abductive Simulation Model

4.1 In the following we show by way of example, based on an existing simulation model (Brenner 2003), how the procedure proposed above can be used. In addition to the original simulation studies (Brenner 2001, 2003 and 2004), we conduct some new analysis in line with the procedure proposed above. In particular, we address the question of whether the support of private innovation activities and start-up activities—e.g. by financing a related public research organization—in an industry in a specific region for a limited period of time increases the chances that a local cluster emerges and sustains in this industry and region. In line with the procedure of four steps described in 3.3 we first discuss the set-up of the

model (see 4.2), to then restrict the parameters by empirical data on the economic processes the model describes (4.6). In a third step, we classify our results according to classes of industries (4.10) and finally show what effect public research organizations have on local cluster building (4.14).

Setting up the Model: Simulating spatial industrial dynamics

4.2 In a first step the abductive simulation model is set-up by using deduction and induction. Critical Realism does not rule out deduction as long as the assumptions from which implications are derived are realistic (Pinkstone 1999). Moreover, it is important that this knowledge, concepts and theories are realistic, meaning that they are well-supported by empirical observations (Pinkstone 1999).

4.3 In order to study the emergence of local clusters we have to build a simulation model that describes the development of an industry in space. This is done in the simulation model by Brenner (2001). A variant of this simulation model (described in detail in Brenner 2003 and 2004) is used here. It explicitly models the start and liquidation of firms, their growth and the innovations they generate. The innovation process itself depends on spillovers from other firms and public research and on qualified labour. The dynamics of the available labour is in each region is modelled by taking education within and outside the firms into account. Moreover, the impact of local policy and attitudes in the population as well as interdependencies between neighbouring regions are included. This means that the model includes the processes, which are most important for the existence and formation of local clusters (cf. a literature overview Brenner 2004, Ch. 4).

4.4 The research problem modelled is rather complex and therefore the model contains many parameters that determine the interaction between the variables, such as, e.g., two parameters that determine how strongly innovation performance depends on firm size and whether this dependence is linear or quadratic in form. Brenner (2001 and 2004) uses empirical studies of various kinds to find empirically estimated ranges in which the parameters fall. Sources of information are studies on firms' growth processes, on the dependence of innovation rates on firm size and co-located other firms and public research, on the spatial distribution of spillovers, on the impact of innovations on sales, on the strength of economies of scale, on demand reactions on prices and product specificity, on start-up activities and its dependence on local factors, on the shares of qualified workers in firms, on the mobility of workers, and on the dependence of wages on the supply and demand for labour. All these works provide empirical estimates for parameters that are needed in the simulation model (see Brenner 2001 and 2004 for details and sources). If possible, the parameter ranges are fixed in the simulation approach according to these empirical estimates. In a few cases logical arguments (such as that worker can remain in the workforce for a maximum of 50 years) are used to generate ranges, which are, therefore, sometimes quite large.

4.5 In line with the methodological reasoning in Sections 2 and 3, the simulation model used here is very general, because it includes a lot of different processes and mechanisms and which parameters are only restricted according to empirical knowledge and some carefully used logical arguments. The model emerges from deduction and induction. Deduction is used by

building on already existing knowledge, concepts and theories, induction by employing extensive empirical information.

Restricting Parameters: Comparison with Empirical Observations

4.6 In the second step we use empirical data or knowledge about the implications of the model to restrict the parameter ranges further. In our case the implication of the simulation model is the spatial dynamics of the industrial development that results from the parameters chosen. The initial conditions with which the simulations are started are also very important. We consider them part of the parameters. Furthermore, the simulation model is stochastic, so that the same parameter set can result in many different dynamics of the industry. This implies that we can conclude that a parameter set is unrealistic only if repeatedly running the simulation model with this parameter set never leads to the empirically observed dynamics.

4.7 In our case the only empirical observation that we will use to restrict the parameters further is the fact that the literature identifies for all manufacturing industries, at least, one local cluster somewhere (see the meta-study of clusters in Brenner and Mühlig 2007 which includes case studies of local clusters in all kinds of manufacturing industries). Hence, we conclude that each considered parameter set has to allow our simulation to generate local clusters. Otherwise, we can conclude that the parameter set is unrealistic. This is our example of a second step according to the procedure proposed in 3.3. It is deliberately chosen very simple here for demonstration. Much more empirical knowledge could be used for this inductive step.

4.8 We repeatedly run the simulation and record the resulting dynamics. Each time a different parameter set is used (Monte Carlo approach). This means that all initial variables and all parameters are randomly chosen from their ranges for each simulation run. All parameter ranges are taken from Brenner (2004). The initial values, such as firm numbers and firm size are set to zero as in Brenner (2004), except for the initially available human capital which is randomly chosen for each region from the range [0,50]. The simulation is run for 20 year with the market dynamics as described in Brenner (2004).

4.9 After the simulation is run, we check whether a local cluster has emerged. Local clusters are defined in line with the literature on the basis of the location quotient (see Isaksen 1996, Braunerhjelm and Carlsson 1999 and Sternberg and Litzenberger 2004), assuming that this quotient has to be above 3 for an industry in a region to qualify as cluster—meaning that the share of the region's employees who work in the studied industry is three times as high as average share of employees working in this industry in the whole country. If local clusters emerge, the recorded dynamics are used for the further analysis. Otherwise, the results are ignored and the parameter set is not used in the analysis because the parameter set does not lead to dynamics that are in line with what we observe in reality.

Group Classification: Types of Industries

4.10 The simulation model that is used here describes the spatial dynamics of an industry. It is evident that different industries show different developments (Malerba 2004). Hence, different parameter sets are adequate for different industries.

4.11 Empirical evidence on the parameter values is not available for industries separately, at least not for all parameters. Nevertheless, we might distinguish types of industries according to some parameters. In the following, we argue that public research institutes play a stronger role in industries, in which the innovation process is based on an extensive use of external knowledge. In the simulation model the number of innovations per employee in the firm is given by the parameter m_L. The effect of spillovers from other research activity in the region on the innovation performance of a firm is given by the parameter s (see Brenner 2003). Hence, industries with a high ratio s/m_L are industries, in which the firms rely in their innovation activities strongly on external sources, while industries with a low ratio s/m_L contain firms that build their innovation activities mainly on internal sources.

4.12 In a more elaborate study we could use a taxonomy, such as the Pavitt taxonomy (Pavitt 1984), and determine all parameters separately for a number of industry classes. Alternatively, we could use separate empirical estimations of parameters for different industries if available. However, our only purpose it to illustrate the procedure by an example here. Therefore, we simply define two classes of industries that we analyse separately below. One contains those industries, in which firms rely strongly on internal sources for innovations (with a ratio $s/m_L > 1.5$). The other contains those industries, in which firms rely more on external sources in their innovation activities (with a ratio $s/m_L < 0.667$). This distinction separates the total number of studied parameter sets into three groups of approximately similar size. We expect that the intensity of local knowledge flows has an impact on the effect of the studied policy measure on the emergence of local clusters and on the effect of the studied policy measure.

4.13 This procedure falls somewhat short of the potential that the third abductive step of our approach has. In 3.3 we argue that theoretical knowledge on the modelling level should be used, as done here, as well as the simulation results. This would mean that we classify the parameter sets according to the simulation outcomes, for example using a cluster analysis. The resulting classification could then be compared to a theoretical classification in order to understand the meaning of the various classed in the context of the study. For simplicity we restrict the demonstrative analysis in the next subsection to the above classification.

Estimation of Policy Impact: Effect of Innovation Support

4.14 To calculate the impact of policy measures we have to deal with two sources of impreciseness in the results that we obtain. First, real processes are random and different outcomes might result from a policy measure. Therefore, simulations have to be repeatedly run to estimate the distribution of implications of policy measures. Second, additional impreciseness in the results stems from our inability to fully understand the mechanisms that govern the real dynamics. This problem might be reduced by further research. However, at any given point in time we only have an incomplete understanding of the relevant mechanisms. Consequently, we suggest that abductive simulation models rely on parameter ranges instead of estimated parameter values to calculate the impact of policy measures. Estimated parameters are estimates and, hence, might be wrong. The results are more reliable if we use parameter ranges. This implies that the impact of policy measures has to be calculated by simulating different parameter sets. This means that we have to run many simulations—for the same and for different parameter sets—to obtain information about the distribution of the resulting

dynamics.

4.15 Abductive simulation models have some similarities to scenario analysis. Both approaches study a number of different developments, so that the exact developments remain uncertain. However, in our approach this uncertainty is not only due to stochastic elements in the model but also owing to a lack of precise knowledge about the parameters (as well as about the model itself). As a consequence, abductive simulation models are very modest with respect to predictions. They rather detect general features and predict structural characteristics of developments instead of predicting exact outcomes.

4.16 The calculation of the impact of a policy measure works straightforward for each simulation. We conduct one simulation run for a region and industry with a parameter set taken from the parameter ranges. Then, we conduct another simulation with the same parameter set but change the parameters that describe the policy measure. By way of example we study one specific policy measure, namely financing a public research organization in a specific region. We assume that this policy measure influences the number of start-ups and the innovation activities of the firms in the region. To measure the impact of public research institutes we increase the number of start-ups (ten times the original value) and the basic innovation activities of firms (ten times the original value). With respect to the number of start-ups please note that we only consider the influence on the number of start-ups not resulting from spin-offs from existing firms. Concerning the basic innovation activities please note that innovation activities are the sum of two parts: a constant part that is caused by sheer existence of a firm and location factors and a size-dependence part that increases if the firm becomes larger. We assume that only the constant part of innovation activities is increased by the policy measure. Hence, mainly small firms are influenced. Correctly stated, we do not study the effect of a public research institute, but the effect of a policy measure that changes start-up rates and innovation probabilities in the above defined manner. To capture the effects of publicly financing a research organization in a specific region more research on the exact effects of public research institutes would be necessary.

4.17 The measure is assumed to be applied industry-specifically to one region for the duration of five years, at either the beginning of the industrial life cycle, after five years, i.e. during the expansion phase, after ten years, i.e. when the industry has just become mature, or after fifteen years, i.e. during the mature phase of the industry life cycle.

Table 1: Probability of the emergence of a local cluster in a certain region with or without specific policy measures (*/**=significant difference to the case without policy measure on a significance level of 0.1/0.05)

	no policy support	***policy measure implemented in the first five years***	***years 5-10***	***years 10-15***	***years 15-20***
all industries (all	8.8%	**13.1%****	11.3%	**12.5%***	10.4%

parameter sets)					
internal sources dominate ($s/m_L<2/3$)	8.2%	13.0%	12.3%	11.7%	9.9%
external sources dominate ($s/m_L>1.5$)	6.7%	**15.3%****	11.5%	**15.3%****	10.2%

4.18 What we want to know is whether the studied policy measure makes the emergence of a local cluster in the supported region more likely. Therefore, we look at the probability that a local cluster emerges in a region (a local cluster is still defined by a location quotient above three) without any policy measure. We compare this probability with the one with the policy measure implemented in each of the four time periods mentioned in Table 1. In total we run simulations for 600 different parameter sets of which we excluded 99 from the further analysis, because they failed to produce dynamics with a local cluster emerging. Empirical evidence suggests that one local cluster exists in each industry (see 4.6). So, we use this empirical fact for checking the realism of each parameter set. Of the 501 different parameter sets analysed, 171 show feature of an industry, in which internal sources dominate the innovation processes, and 164 features of an industry, in which external sources dominate the innovation processes.

4.19 The results in Table 1 show that the policy measure increases the likelihood of the emergence of a local cluster. The impact is especially given for measures that are applied at the beginning of the industry life cycle or when the industry becomes mature. This means that a policy measure that is conducted outside of these windows of opportunity, namely in the industry life cycle, is unlikely to have any significant effect on the emergence of a local cluster. This result is in line with earlier findings that suggest that the increase in the start-up activities has a significant impact if it is caused very early in the industry life cycle and that the increase in the innovation activities has a significant impact if it occurs when the industry becomes mature (Brenner 2003).

4.20 We also find significant differences between the kinds of industries that we studied. Without policy measures the likelihood to find a local cluster in a region is higher if the innovation processes are mainly based on internal sources. This is caused by the fact that for such industries co-location is less important, so that they are less concentrated in space. As a consequence, more regions contain a local cluster. However, the effect of our policy measure is much more pronounced in the case of industries with a stronger importance of external sources. Due to the stronger relevance of co-location and spillovers public research institutes seem to have a much larger impact on the emergence of local clusters. Consequently, policy makers should focus their measures of financing public research organizations on specific industries as they have most impact there. These industries are in the early stage of their life cycle and innovation activities of their firms rely strongly on external sources.

4.21 The reliability of results of studies, such as the one conducted here; depend on the availability and quality of the empirical data we use. The empirical studies used to determine the parameter ranges and the validity of the model in 4.2 and 4.6 are almost all conducted for

manufacturing industries in Western Europe or in the U.S. Hence, this study indicates how policy measures financing public research organizations would affect manufacturing industries in Western industrialized countries. However, it is much less reliable for other sectors and countries. Furthermore, empirical knowledge provided on human capital accumulation, on interaction between local firms and policy makers as well as on the population's attitudes is very weak. We tried to keep the ranges for the respective parameters very large (see Brenner 2001 and 2004), but this might make the finding here less strong than they could be given better empirical data.

Conclusions

5.1 The purpose of our exercise was to show how simulation models could help to improve policy advice. To do so we started from methodological considerations. In particular, we discussed the question how models are designed and how empirical data is used to set-up models and to infer results. We suggest that simulation models can serve as basis for policy advice depending on the availability and quality of data that is used to infer results. Here, we provide a methodology for abductive simulation models that is based on Critical Realism (Section 2). We show that data can be used in much more elaborated and detailed ways than suggested by most protagonists of Critical Realism. These insights help us to develop a methodologically sound and at the same time practical guideline for abductive simulation models (Section 3) Generally spoken, a combined use of theoretical and empirical analysis based on different data sets in so-called abductive simulation models helps best to infer statements about causal relationships and characteristics of a set of models. This is the reason why we consider abductive simulation models being a good tool for policy advice.

5.2 By way of example we study the impact of a policy measure that finances public research organizations on cluster formation (Section 4). To do so we use a simulation model that describes the emergence of local clusters in space. We find that such a policy measure is most effective if it is applied to industries with two specific features, i.e. industries where innovation processes are heavily based on external sources and industries which are in early phases of their industry life cycle.

5.3 Obviously, compared with other approaches abductive simulation models are rather time-consuming, because they require detailed research for available data and a lot of simulation runs. Nevertheless, 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 and are able to provide valuable advice for policy. At the end of the day we need to compare the costs of such a time- and resource consuming abductive simulation model with the costs of a failure of policy measures wrongly implemented that could have be avoided by using an abductive simulation model. Thus, not only the availability of data and possibility to build a meaningful and reliable simulation model but also the budget and impact of the planned policy measure determines whether abductive simulation models can be put to good use. We suggest that it is a smart and practical approach to start with research problems and models by following the "keep it simple, stupid" (KISS) strategy. However, we believe that in order to deduce well-founded policy advice we need to follow the "keep it descriptive, stupid" (KIDS) strategy.

References

BRAUNERHJELM, P. & Carlsson, B. (1999). Industry Clusters in Ohio and Sweden, 1975-1995. *Small Business Economics*, 12, 297-293.

BRENNER, T. (2001). Simulating the Evolution of Localised Industrial Clusters—An Identification of the Basic Mechanisms, *Journal of Artificial Societies and Social Simulation*, 4 (3), 4. http://www.soc.surrey.ac.uk/JASSS/4/3/4.html

BRENNER, T. (2003). Policy Measures to Create Localised Industrial Clusters, in T. Brenner and D. Fornahl (eds.): *Cooperation, Networks, and Institutions on Regional Innovation Systems,* Cheltenham: Edward Elgar, 325-349.

BRENNER, T. (2004). *Local Industrial Clusters: Existence, Emergence, and Evolution*. London: Routledge.

BRENNER, T. and A. Mühlig (2007). Factors and Mechanisms Causing the Emergence of Local Industrial Clusters—A Meta-Study of 159 Cases, mimeo, Max Planck Institute of Economics, Jena.

BRENNER, T. and C. Werker (2007). A Taxonomy of Inference in Simulation Models. *Journal of Computational Economics*, 30, 227-244. .

BROWN, A., Slater, G. and Spencer, D.A. (2002). Driven to abstraction? Critical realism and the search for the 'inner connection' of social phenomena. *Cambridge Journal of Economics*, 26, 773-788-

COWAN, R. and Foray, D. (2002). Evolutionary economics and the counterfactual threat: on the nature and role of counterfactual history as an empirical tool in economics. *Journal of Evolutionary Economics*, 12, 5, 539-562.

DOWNWARD, P.J., Finch, H. and Ramsay, J. (2002). Critical realism, empirical methods and inference: a critical discussion. *Cambridge Journal of Economics*, 26, 481-500.

ISAKSEN, A. (1996). Towards increased Regional Specialization? The Quantitative Importance of New Industrial Spaces in Norway, 1970-1990. *Norsk Geografisk Tidsskrift*, 50, 113-123.

LAWSON, T. (1997). *Economics and Reality.* London, New York: Routledge.

LIPTON, Peter. (2001). *Inference to the Best Explanation*. London, New York: Routledge.

MACHLUP, F. (1978). *Methodology of Economics and other Social Sciences.* New York, San Francisco, London: Academic Press.

MALERBA, F. (2004). *Sectoral Systems of Innovation*, Cambridge: Cambridge University Press.

METCALFE, J.S. (1995). The Economic Foundations of Technology Policy: Equilibrium and Evolutionary Perspectives, in: Stoneman, P. (ed.) *Handbook of the economics of innovation and technological change*, Oxford, Cambridge MA (Blackwell), 409-512

NIELSEN, P. (2002). Reflections on critical realism in political economy, in: *Cambridge Journal*

of Economics, 26, 727-738.

PAVITT, K. (1984) Sectoral Patterns of Technical Change: Towards a Taxonomy and a Theory. *Research Policy*, 13, 343-373.

PEIRCE, C.S. (1867/1965). *Collected papers of Charles Sanders Peirce.* Edited by Hartshorne C and P Weiss, 1-6, Cambridge (MA) US: Harvard University Press.

PINKSTONE, B. (1999). Underlabouring Postkeynesian Economics, in: *The Journal of Postkeynesian Economics*, 22 (1), 45-48.

PYKA, A. and S. Deichsel (2009) A Pragmatic Reading of Friedman's Methodological Essay and What It Tells Us for the Discussion of ABMs. *Journal of Artificial Societies and Social Simulation* 12(4)6 http://jasss.soc.surrey.ac.uk/12/4/6.html.

REISS, J. (2004) Roundtable: Tony Lawson's Reorienting Economics. *Journal of Economic Methodology*, 11, 3, 321-327.

SCHWERIN J. and C. Werker (2003). Learning Innovation Policy Based on Historical Experience, in: *Structural Change and Economic Dynamics*, 14 (4), 385-404.

STERNBERG, R. and Litzenberger, T. (2004) Regional Clusters in Germany: Their Geography and their Relevance for Entrepreneurial Activities, in: *European Planning Studies*, 12, 767-792.

YÜCEL, G and C. E. Van Daalen (2009) An Objective-Based Perspective on Assessment of Model-Supported Policy Processes'. *Journal of Artificial Societies and Social Simulation* 12(4)3 http://jasss.soc.surrey.ac.uk/12/4/3.html.