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POLICY ADVICE DERIVED FROM SIMULATION MODELS

Thomas Brenner and Claudia Werker*

Abstract

When advising policy we face the fundamental problem that economic processes are connected with uncertainty and thus policy can err. In this paper we show how the use of simulation models can reduce policy errors. 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. This helps inferring empirically reliable and meaningful statements about how policy measures influence economic processes. By way of example we show how research subsidies by the government influence the likelihood that a regional cluster emerges.

Keywords

Policy Advice, Simulation Models, Uncertainty, Methodology

JEL Classification

B41, B52, C63, H89

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1. Introduction

Economic processes are uncertain. Thus, the outcomes of policy measures are uncertain as well. 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 (Metcalf, 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 then be used to influence economic processes by adequate measures, though the outcome remains uncertain (cf. Schwerin/Werker, 2003).

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. For this abductive simulation models are particularly well suited, because they belong to models of heterodox economics. These models put (Knightian) uncertainty centre-stage, thereby mirroring the element of economic processes that makes it impossible to implement policy measures that are successful in any instance. Critical Realism is core to analysing uncertain economic processes as it helps to identify underlying causal structures – namely by abduction.

We start providing a methodology for abductive simulation models that use a combination of theoretical and empirical results employing 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.).

2. Heterodox Simulation Models Based on Critical Realism

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 (Section 2.1). Based on that we show how Critical Realism can provide us with a methodology for abductive simulation models (Section 2.2).

2.1 Principles of Inferences in Modelling

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” synonymically in the following.

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. 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/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 some measurement problems might emerge.

In models implications are inferred from assumptions. Data can be used in two ways: first of all, to construct reliable and meaningful assumptions. Second, it can be used to test implications. Obviously, the quality and use of data determines and quality of the resulting model and its reliability for testing policy measures.

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). 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. Therefore, the approach of abductive simulation models is based on the principle to include as much data as possible in assumptions.

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. 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. 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.

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.”

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.

2.2 Critical Realism as Methodology for Abductive Simulation Models

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 Section 2.1) 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.

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 one problem that is particularly important for our discussion of how to empirically calibrate simulation models, namely that heterodox models imply inherent uncertainty. Therefore, we aim at developing 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. 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.

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: 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. Abductive Simulation Models Used for Policy Advice

3.1 Policy Advice Based on Critical Realism

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 (Metcalf, 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/Werker, 2003).

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.

3.2 Practical Guideline for Abductive 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. In the following, we call these models abductive simulation models (for a more detailed discussion see Brenner/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.

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 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)

Abduction helps us to produce classes of models, which combine assumptions and implications based on empirical findings (cf. the following Brenner/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).

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/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. First, the simulation model has to be set up using the available empirical knowledge about the assumptions of the model. Critical Realism does not rule out deduction as long as the assumptions from which implications are derived are realistic (Pinkstone, 1999). 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.

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 to make 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.

4. An Example of Policy Advice Based on an Abductive Simulation Model

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 described in Section 3.2 we first discuss the set-up of the model (see Section 4.1), to then restrict the parameters by empirical data on the economic processes the model describes (Section 4.2). In a third step, we classify our results according to classes of industries (Section 4.3) and finally show what effect public research organizations have on local cluster building (Section 4.4).

4.1 Setting up the Model: Simulating spatial industrial dynamics

If we want 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. This model explicitly models the start and liquidation of firms, their growth and the innovations they generate. The innovation process is modelled to be dependent on spillovers from other firms and

public research and on qualified labour. The dynamics of the available labour in each region is modelled by taking education within and outside of firms into account. The impact of local policy and attitudes in the population are included as well as interdependencies between neighbouring regions. Hence, the model includes the processes that are assumed in the literature to be most important for the existence of local clusters and is able to describe the dynamics of cluster formation (Brenner 2004, Ch. 4).

As a consequence of the high complexity of the model, it 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 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.

In line with the arguments above, a simulation model is obtained that 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.

4.2 Restricting Parameters: Comparison with Empirical Observations

The second step is to 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.

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 cluster in Brenner/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.

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 run¹. After the simulation is run, we check whether a local cluster has emerged. Local clusters are defined in line with the literature (Sternberg/Litzenberger 2004) as regions with a location coefficient of above 3 for the studied industry – 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

¹ 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).

analysis because the parameter set does not lead to dynamics that are in line with what we observe in reality.

4.3 Group Classification: Types of Industries

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.

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. We might, for example, argue that we expect 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.

One might go into details here and might use a taxonomy, such as the Pavitt taxonomy (Pavitt, 1984), and determine all parameters separately for a number of industry classes. One might also use separate empirical estimations of parameters for different industries if available. To keep things simple and because we only want to illustrate the procedure by an example, we restrict the approach here such that we only 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 firm 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 emergence of local clusters and on the effect of the studied policy measure.

4.4 Estimation of Policy Impact: Effect of Innovation Support

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.

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 except changing the parameters that describe the policy measure. As an example we want to study here the policy measure of financing a public research organization in a region, which we assume to have an impact on the number of start-ups in the region and on the innovation activities of the firms there. There is no empirical evidence available that would allow us to make exact predictions of the impact of public research institute. We assume here two effects, an increase of the number of start-ups (ten times the original value) and of the basic innovation activities of firms (ten time the original value). Notice that we assume only an influence on start-ups that do not result from spin-offs from existing firms. Furthermore, notice that

the simulation model assumes an innovation activity that is 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. Only the constant innovation activity is assumed to be 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. More research on the exact effects of public research institutes would be necessary to go beyond this.

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

	<i>no policy support</i>	<i>policy measure in the</i>			
		<i>first five years</i>	<i>years 5-10</i>	<i>years 10-15</i>	<i>years 15-20</i>
<i>all industries (all parameter sets)</i>	8.8%	13.1%**	11.3%	12.5%*	10.4%
<i>internal sources dominate ($s/m_L < 2/3$)</i>	8.2%	13.0%	12.3%	11.7%	9.9%
<i>external sources dominate ($s/m_L > 1.5$)</i>	6.7%	15.3%**	11.5%	15.3%**	10.2%

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)*

What we want to know is whether the studied policy measure makes the emergence of a local cluster in the supported region more likely. To this end, we compare the probability that a local cluster emerges there (a local cluster is still defined by a location coefficient above three) without any policy measure and the same probability with the policy measure active in one of the four time periods (see 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 in which local clusters

emerged (see Section 4.2). Thus, 501 different parameter sets are analysed, 171 of which can be assigned to an industry in which internal sources dominate the innovation processes and 164 of which can be assigned to an industry in which external sources dominate the innovation processes.

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, for example later in the industry life cycle, is unlikely to have a significant effect on the emergence of a local cluster. A comparison with the results obtained by Brenner (2003) suggests 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. Nevertheless, independent of the measures taken the likelihood for the emergence of a local cluster remains to be far below one.

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. This implies that policy makers should focus policy measures that increase start-ups and innovation rates on industries that are at the beginning of their life cycle or just becoming mature, respectively, and in which firms rely strongly on external sources in their innovation activities.

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 fix the parameter ranges and to determine the validity of the model in Sections 4.1 and 4.2 are almost all conducted for Western Europe or the U.S. and for manufacturing

industries. Hence, this study provides a good indication of what is going on in Western industrialized countries but a lesser indication for Asian countries or developing countries. Moreover, we still know little about the way the service industries function. However, this is a rather general problem, mostly stemming from a lack of research done in this field. Furthermore, the empirical knowledge in the literature on human capital accumulation and the interaction between local firms and policy makers and 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.

5. Conclusions

The purpose of our exercise was to show how simulation models could help to improve policy advice. In order to do so we stepped into a methodological discussion, i.e. into the question how models are designed and how empirical data is used to build models and to infer results. We suggest that simulation models can serve as basis for policy advice to different degrees depending on the kind of data used and the way it is used in inferring results. Here, we provide a methodology for abductive simulation models that is based on Critical Realism (Section 2.) to then show how a practical guideline for abductive simulation models would look like (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. By way of example we use a simulation model that describes the emergence of local clusters in space and study the impact of a specific policy measure that increases start-up and innovation rates on the probability that a local cluster emerges in a specific region (Section 4.). We find that such a policy measure is most effective if it is applied to industries in which innovation processes are heavily based on external sources and to industries that are in early phases of their industry life cycle.

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 one needs 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 been 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.

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