Systemic interventions in regional innovation systems: entrepreneurship, knowledge accumulation and regional innovation

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**ABSTRACT**

The paper employs a regional innovation system concept and divides system failures into three categories: institutional infrastructure, organizational landscape and structural connectedness. To analyze the economic effects of systemic interventions, it employs the VISIBLE model, which allows ex-ante policy experiments to be conducted in a virtual simulation environment. First, the findings show that regional learning and knowledge exchange are accompanied by pronounced non-linearities and combined learning strategies generate highest regional returns. Second, systemic interventions, originally designed to stimulate qualitatively different types of entrepreneurial entries, show – against the backdrop of different regional learning regimes – rather ambiguous effects for both the target firms and the incumbent firms. Finally, it can be seen that interventions designed to affect individual linking behaviour of entrepreneurial firms are effective and robust even for different learning regimes.

**KEYWORDS**

system failure; regional innovation policy; agent-based model

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**INTRODUCTION**

The economic consequences of interventions in regional innovation systems (RIS) are far from being fully understood. Knowledge transfer, learning and innovation processes are often affected in unexpected ways by – at least at first glance – well-targeted policy interventions. Martin (2016, p. 167) emphasizes that ‘each new policy instrument will clearly interact with and affect existing policy instruments in a complex and often unpredictable manner’. Accordingly, an in-depth analysis of multifaceted entanglements of institutions, systemic actors and relations is a prerequisite for a more comprehensive understanding of the consequences of policy interventions in complex adaptive socioeconomic systems. We apply RIS (Braczyk, Cooke, & Heidenreich, 1998), draw upon the system failure literature (Dodgson, Hughes, Foster, & Metcalfe, 2011; Klein Woolthuis, Lankhuizen, & Gilsing, 2005) and employ an agent-based modelling (ABM) approach designed for ex-ante policy evaluations (Ahrweiler, Gilbert, & Pyka, 2015). Our overarching research goal is to gain a better understanding of how individual and combined policy interventions affect the exchange, use and transfer of knowledge in RIS and the related economic performance of firms. We draw upon the example of the region Heilbronn-Franken in Germany to show the applicability of our research.

We provide a theoretical framework that allows for identifying potential system failures at the regional level while simultaneously serving as a blueprint for deriving and designing potential policy interventions. We break new ground by applying ABM for ex-ante policy evaluation drawing upon the VISIBLE model (Virtual Simulation Lab for the Analysis of Investments in Learning and Education), which is designed for systematic ex-ante policy evaluations in an in-silicio simulation environment. This approach allows one to gain new insights into the causes and consequences of evolutionary and co-evolutionary dynamics in RIS. We aim to answer the following research question: What are the short- and long-term economic

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consequences – at the firm and system levels – of individual or combined regional innovation policy interventions designed to support (1) the knowledge acquisition and learning of systemic actors, (2) the entries of entrepreneurial firms and (3) their innovation-related cooperation behaviour?

**COMPLEX SYSTEMS, SYSTEM FAILURE AND REGIONAL INNOVATION POLICY ANALYSIS**

General system theory (Bertalanffy, 1968) provides a powerful conceptual and methodological basis on which to study complex adaptive socioeconomic systems (Holland, 2006), including innovation systems (Edquist, 2011). The conceptual link between complex adaptive systems and innovation systems is particularly evident in the neo-Schumpeterian school of thought (Hanusch & Pyka, 2006). In its most fundamental sense, each system can be described by a well-defined population of nodes (or ‘vertices’, ‘agents’) and ties (or ‘edges’, ‘relations’) among them (Barabási & Pósfai, 2016). Formal and informal rules determine the way in which the agents interact. The term ‘complex’ refers to the fact that decision processes are decentralized, structural properties are not further reducible and the magnitude, intensity and direction of interactions cannot be predicted or specified in advance. The term ‘adaptive’ points to the fact that agents and their resource endowments are subject to change over time (e.g., through learning).

**The systemic perspective and the nature of regional innovation systems**

We follow the division proposed by Asheim (1998): (1) territorially embedded RIS; (2) regionally networked innovation systems; and (3) regionalized national innovation systems (Asheim & Coenen, 2005; Cooke, 1998). Asheim and Coenen (2005, p. 1179) argue that the ‘territorial approach’ – also known as ‘grassroots RIS’ (Cooke, 1998) – describes regions in which firms base their innovation activities ‘primarily on localized, interfirm learning processes stimulated by the conjunction of geographical and relational proximity without much direct interaction with knowledge generating organizations (i.e., R&D [research and development] institutes and universities). The ‘regionally networked innovation system’ is characterized by an intentionally strengthened institutional infrastructure (Asheim, 1998). This specification also is referred to as ‘network RIS’ (Cooke, 1998). It can be applied to regions characterized by a more planned and structured way of promoting public–private cooperation (Asheim & Coenen, 2005, p. 1180). Finally, in ‘regionalized IS’, actors typically do not focus on intra-regional activities. Accordingly, actors outside the region, as well as the relationships with these actors, play an important role. Innovation activity takes place primarily via interregional links to actors outside the region (Asheim & Coenen, 2005). Considerable parts of the industry and institutional frameworks within the regionalized IS are functionally integrated into national or international innovation systems (p. 1180).

**Regional policy interventions, market failures and system failures**

Regional innovation policy has gained in importance over the past decades (Asheim, Smith, & Oughton, 2011a). Against the backdrop of the widening US–European productivity gap in the 1990s, a policy shift in Europe could be observed: knowledge and innovation-related policy concepts – strongly influenced by evolutionary economics and evolutionary economic geography – became important. The most notable policy-related conceptual advancements range from related variety (Frenken, Van Oort, & Verburg, 2007), local path dependencies (Martin & Sunley, 2006), and more holistic approaches, such as creation of regional advantages (Asheim, Boschma, & Cooke, 2011b), to the idea of smart specialization (Foray, 2014). Common to all these theoretical contributions is the recognition that innovation is a systemic phenomenon.

Despite this rethinking, market failures are widely used to justify innovation policies (Dodgson et al., 2011), despite the constant and valid critique that the underlying mainstream economic reasoning fails to address key issues of complex innovation systems (Edquist, 2011). We argue that legitimations of policy interventions based on market failures need to be critically assessed and complemented by a more comprehensive, process-oriented theoretical reasoning that acknowledges the importance of individual and collective learning processes and knowledge-diffusion processes at higher aggregation levels, which is essential for supporting the innovations of actors embedded in the system (Pyka, 2014).

Recognizing the complex and adaptive nature of RIS brings one directly to the concept of system failures. Iammarino (2005, p. 513) argues: ‘Any attempt to analyze why a region is a particularly successful RIS must first, because systems change over time, explain what are the factors underlying such status and their dynamics. Therefore, an evolutionary approach may be the only approach of value.’ By now, there is a broad consensus that systemic imperfections might impede innovation (Dodgson et al., 2011; Klein Woolthuis et al., 2005; Toedtling & Trippl, 2005). One key issue when it comes to the assessment of system failures is that we are unable to specify optimal solutions of reference points in systems of innovation due to their complex nature. The only remaining way is to compare similar existing systems with each other or to compare changes of one particular system over time (Edquist, 2011, p. 1743). Accordingly, both the identification of systemic imperfections as well as the consequences of systemic interventions can only be adequately assessed by an incremental evaluation process where the status quo of a particular system is compared with alternative system configurations. Consequently, our approach does not strive for Walrasian optimality, rather, it follows the notion of a stepwise (evolutionary) identification of improvement potential in typically imperfect and highly complex systems.
Three categories of system failures
Against the backdrop of these considerations, we distinguish three broadly defined categories of system failures: institutional infrastructure, organizational landscape and linking behaviour.\(^1\)

**Category I: Institutional infrastructure**
Edquist (1997) emphasizes the importance of institutions in systems of innovation since they affect the behaviour of economic actors in fundamental ways. We follow the definition of Edquist (1997, p. 2) according to which institutions: ‘constitute constraints and/or incentives for innovation, such as laws, health regulations, cultural norms, social rules, and technical standards’. Institutions fulfill basic functions, that is, the reduction of uncertainty by providing information, coordination, management of conflicts, cooperation and furthermore constituting incentives as well as constraints (Edquist & Johnson, 1997). They either affect all or only various subgroups of actors in a system. Underdeveloped or misspecified (or missing) individual or groups of systemic institutions are accompanied by functional deficits. Similarly, as new institutions need to be integrated into a broader institutional infrastructure, there is always the possibility that new (or modifications of existing) institutions cause substantial frictions.

**Category II: Organizational landscape**
Even economically well-performing regions may suffer from an underdeveloped or incomplete organizational landscape. Toedtling and Trippl (2005, p. 1207) point to this systemic failure: ‘Missing or inappropriate elements have negative effects on the innovation potential of regions.’ Of course, there is a broad range of systemic elements that may be missing, from large and well-established R&D-intensive companies and knowledge-intensive new ventures to other types of organizations such as incubators, universities or local knowledge transfer centres. Each of these organizational entities contributes and represents a unique category of knowledge, abilities and expertise. Thus, instruments designed to stimulate the formation or entry of missing organizational entities in the system are an important lever to counteract restrictions on the functionality of the system.

**Category III: Linking behaviour and structural consequences at the systemic level**
RIS are complex systems composed of actors and institutions interconnected in various ways. Innovation networks constitute one essential structural dimension within these systems. These networks provide the ‘catalyst’ for inter-organizational learning and enable the long-distance transfer of information and knowledge throughout the entire system. Three dimensions of functional deficits can be distinguished here. First, Niosi (2002) argues that inefficiencies and the potential ineffectiveness of innovation systems are typically related to path-dependent processes and lock-in situations. Second, some topologies are more resilient against disruptive forces than others. Similarly, the absence or disappearance of critical ties mirrors a structural deficit at the systemic level seeing as knowledge diffusion and learning processes may be disturbed and hindered. Finally, knowledge access and learning processes may be hampered by an insufficient appropriation and utilization of existing structures.

**ANALYTICAL DESIGN AND MODEL DESCRIPTION**

Bridging the gap between system failures and ex-ante policy evaluation
Analyzing the consequences of interventions in complex adaptive systems is challenging. ABM provides a powerful tool to account for the causes and consequences related to system dynamics, to analyze and compare system characteristics with a prespecified benchmark, and to point to potential systemic misspecifications (Pyka & Fagiolo, 2007). To bridge the gap between system failure categories (see the second section) and ex-ante policy evaluation (see the fourth section), we proceed as follows: the reference to system failure categories represents the starting point of every ex-ante policy analysis. The categories are broadly defined on purpose, so as to capture the full set of potential failures. Within each of the categories, we specify potential system failures and corresponding policy interventions. Next, we introduce three simulation experiments designed to analyze the effects of the respective policy interventions.\(^2\) We then present the results of our simulation. In a final step, we interpret the simulation result against the backdrop of each system failure category.

For our research approach, we use data and background information from a real case: the region Heilbronn-Franken. It is important to note that our VISIBLE model does not aim at mirroring the RIS in this region in full detail. Instead, it provides a simulation that accounts for the most salient features of RIS: firms located in a region that innovate within a competitive market environment. Well aware of the possibilities and limitations of calibrated and validated simulation models (Windrum, Fagiolo, & Moneta, 2007), we follow a two-stage approach to enhance the applicability of our research approach. We first specify the model in a theoretically informed but abstract version. Second, to account for regional peculiarities and to increase the realism of the simulations we employ – whenever possible – empirical data to specify the theoretically legitimized assumptions and elements. This includes, for example, initial parameter settings, such as for the number of firms and the average number of cooperation for a given point in time.\(^3\) Additionally, we use detailed background information on the region to identify and specify appropriate research scenarios (e.g., knowledge channels, learning regimes, start-up types or linking strategies). However, due to the abstract nature of the knowledge representation in the model, some conceptual elements of our simulation model do not correspond to empirical counterparts (e.g., the parameter settings defining the range of capabilities, abilities and expertise levels). A common way to tackle this issue is to identify and specify key processes behind
these unobservable parameters based on theoretical analysis and experience. This is followed by a stepwise elimination of extreme and unrealistic parameter settings to constitute a plausible parameter space. Building on this, a detailed sensitivity analysis of the remaining parameter space yields a comprehensive understanding of the simulation behaviour and the robustness of simulation results against different parameter settings.

**Methodological and conceptual background of the VISIBLE model**

ABM (cf. Gilbert & Troitzsch, 2005) offers both a new scientific method and a new perspective on the complex interplay between actors within socioeconomic systems. ABM provides an in-silico representation of real-world innovation systems allowing for ex-ante analyses of interdependent policy interventions (Ahrweiler et al., 2015).

The VISIBLE model represents a simulation environment that allows for a systematic exploration of knowledge exchange and learning that translates into the creation of innovations at the regional level and how these complex processes are affected by various types of systemic interventions. For this purpose, an economic actor in an innovation system is most appropriately represented by its knowledge stock and its ability to (ex)change knowledge. We draw upon the concept according to which economic actors can be represented by a finite number of units of knowledge. Each unit of knowledge $K_i$ is described as a triple of a firm’s capability $C$, an ability $A$ and the expertise level $E$.

\[
K_i = \left( \begin{array}{c} C_1 \\ A_1 \\ E_1 \\ \vdots \\ C_n \\ A_n \\ E_n \end{array} \right)
\]  
(1)

The knowledge $K_i$ of a firm $i$ can thus be written as follows:

\[
K_i = \left( \begin{array}{c} C_1 \\ A_1 \\ E_1 \\ \vdots \\ C_n \\ A_n \\ E_n \end{array} \right)
\]  
(2)

The respective capability refers to the general technological or business domain (e.g., biochemistry) and its ability is the indicator for the application in this field (e.g., a synthesis procedure or filtering technique in the field of biochemistry). Finally, the expertise level yields information about the expertise, that is, the particular level of competences and skills of this firm in a particular field. Equation (3) provides an example of a firm’s knowledge stock representation:

\[
K_i = \left( \begin{array}{c} 1 \\ 4 \\ 2 \\ 14 \\ 47 \\ 8 \\ 7 \\ 9 \\ 33 \\ 2 \\ 1 \end{array} \right)
\]  
(3)

**Innovation processes**

A firm’s innovativeness is determined by its ability to accumulate and use new knowledge via learning or other available knowledge channels (Foray, 2004). Knowledge endowments are assumed to be highly dynamic since firms can gain new knowledge units to extend their knowledge base and use it to generate innovations. The model distinguishes three different channels for firms to acquire new knowledge units. For all three channels, we assume crucial differences in terms of the novelty of new knowledge (on both a regional and a firm level). The difficulties encountered when integrating external knowledge into the existing body of knowledge is expressed through the expertise level ($E_n$) exhibited by this respective knowledge unit at the time a firm receives this knowledge unit.

**Organizational learning processes** play a key role in all organizations (Levitt & March, 1988). We focus on a particular type of organizational learning, that is, internal R&D, which is defined as an experimental process on a systematic basis comprising creative work undertaken to increase the existing stock of knowledge, and use it to devise new applications (Organisation for Economic Co-operation and Development (OECD), 2015, p. 44). Knowledge created through internal R&D processes is always related to existing knowledge of the firm and affected by its experience. This type of organizational learning is implemented by allowing agents to create new knowledge units internally (cf. the third section), while assuming that the capability value ($C_n$) for each newly created knowledge unit ($K_{n}$) falls into a prespecified range of the capability value of an existing knowledge unit while the ability value ($A_n$) is chosen randomly.

**Intra-regional networks** provide the second knowledge channel. These types of linkages play a key role in ‘regionally networked RIS’ (Asheim, 1998). The cooperation activity and network embeddedness are crucial for the firms’ abilities to exchange knowledge and mutual learning. Keeble and Wilkinson (1999, p. 299) emphasize the importance of the spatial dimension concerning the access to implicit knowledge and argue that the geographical location ‘increases its internal circulation but impedes its external accessibility’. The regional dimension implies repeated face-to-face interactions, thereby building trust among actors (Keeble & Wilkinson, 1999), which is a prerequisite for inter-organizational learning (Lui, 2009). We assume that agents are embedded in a temporarily static network topology. Learning via intra-regional networks is reflected by copying one randomly selected knowledge unit of a cooperation partner, that is, its capability ($C_n$) and ability value ($A_n$).

**Interregional networks** provide a complementary knowledge channel. Building trust over large distances is often a cumbersome process and access to tacit knowledge is only
limited. Yet, if that process should prove successful, the accessed knowledge would prove very valuable for the firm. External knowledge — new to the firm and new to the region — differs fundamentally from previously used knowledge. It brings in new and fresh ideas and complements a firm’s existing knowledge stock. This enables firms to generate radically new products and services. However, it is also extremely difficult to integrate new knowledge elements. This comes closest to what is described by Asheim (1998) as ‘regionalized IS’. We implement this by assuming that firms can acquire a new knowledge unit with random capability ($C_n$) and ability values ($A_e$) which is not bound to the existing knowledge of firms within the region.

Finally, for ‘learning by doing’ and ‘forgetting by not doing’ processes, we assume that firms gain experience by using their knowledge, that is, producing and selling a product for which that particular unit of knowledge is required. For each knowledge unit used in the production of a product the expertise levels in the respective knowledge units are increased by one with a chance of 50%. Simultaneously, firms lose expertise for knowledge not used in production. The expertise levels in these knowledge units are decreased by one with a chance of 50%. If the expertise level becomes zero, the firm forgets the knowledge unit and it is removed from its kene.

For the creation of new products, we follow Schumpeter (1911) and consider innovation as the (re)-combinations of existing knowledge. To implement this idea, we conceptualize products as so-called innovation hypotheses ($IH_i$), a unique and actor-specific combination of two knowledge units of firm $i$ (Ahrweiler et al., 2011). Firms have a 30% chance per simulation step to form a new innovation hypothesis, that is, a 30% chance to recombine their knowledge in new ways. For instance, one possible product is displayed in equation (4), which is simply a combination of firm $i$’s knowledge units two and four (see equation 3):

$$IH_i = \begin{pmatrix} 47 \\ 8 \\ 9 \\ 1 \end{pmatrix}, \begin{pmatrix} 14 \\ 9 \\ 1 \end{pmatrix}$$ (4)

**Market environment**

The creation of new products is conceptualized as ‘trial and error’. We assume that each agent has a constant chance per time step to combine existing knowledge units to invent new IHs. New IHs are only included in an actor’s time step to combine existing knowledge units to invent a new product. It is operationalized as the product of two random values for the respective knowledge units, drawn from an exponential distribution with a mean of 10. Furthermore, we assume the existence of a number of factors limiting a firm’s capability to exploit fully the potential demand: the expertise ($E_{x_{ni}}$) gained so far, the competition in the market ($C_{ni}$) and a factor representing the product lifecycle over time ($D_{ni}$). Each of these factors can take values between 0 and 1.

We denote by $E_{x_{ni}}$ the average expertise levels within the respective knowledge units used by firm $i$ for the production of a product $n$ (Ahrweiler et al., 2011). We assume that with an increasing average expertise level, a firm benefits from learning-by-doing processes and thus increases its ability to exploit the potential demand more efficiently. This non-linear relationship between $E_{x_{ni}}$ and the factor $E_{x_{ni}}$ is defined by equation (6):

$$E_{x_{ni}} = 1 - e^{-\frac{E_{x_{ni}}}{4}}$$ (6)

Next, we consider $C_{ni}$, which represents the amount of competition among firms in a region offering the same product. Competition is defined by equation (7):

$$C_{ni} = \frac{1}{\text{number of competing firms}}$$ (7)

Finally, we consider that the profitability of a product is determined by its product lifecycle stage (Rogers, 1983). The factor $D_n$ describes the position of a particular product for a given firm within the product lifecycle (equation 8). Accordingly, early- and mature-stage products are accompanied by a low factor $D_n$:

$$D_n = 2\times\frac{-(\text{age} - 15)}{e^{5} + \left(\frac{-(\text{age} - 15)}{5e^{5}}\right)^{2}}$$ (8)

**Population dynamics**

Within each simulation step, new firms (‘newcomers’) enter the population at a constant rate. At the same time, we assume that firms can also leave the region by implementing two qualitatively different exit procedures for incumbents and newcomers. For incumbents (i.e., firms created during the initialization), we assume that each firm has a constant chance of 5% of leaving the region for every 100 simulation steps. Newcomers are assumed to be much more dependent on their recent innovation activities than established firms with a broad, diversified and well-established product portfolio. A second selection process is implemented according to which a newcomer leaves the market if the average profits over the last five periods is below 10.
INNOVATION POLICY EVALUATION IN RIS: SCENARIOS, RESULTS AND DISCUSSION

Scenario specification

Scenario 1: ‘Learning regimes’

With our first scenario, we focus on interventions targeting potential category 1 system failures. The given set of norms and rules in an RIS determines the knowledge transfer, learning and subsequent innovation performance of all actors involved. One example for a category 1 system failure are misspecified knowledge-exchange regulations in publicly funded R&D projects. Organizations participating in these projects have to agree to a number of regulations designed to organize mutual knowledge exchange within the project consortium (Broekel & Graf, 2011, p. 6). By changing these regulations, funding authorities have access to an instrument that affects the behaviour not only of project members but also of all other actors within the system. Consequently, it is reasonable to assume that new rules lead to a shift in the use of the different knowledge channels available to firms in a region.

To analyze the relationship between the use of different knowledge channels and firms’ innovativeness, we specify different learning regimes. Each regime represents a particular distribution of firm engagements in the three knowledge channels (explained in the third section) and thus different probabilities of receiving knowledge through each channel:

- **No intervention**: organizational learning 3.0%, intra-regional learning 3.0% and interregional learning 3.0%.
- **Internal focus**: organizational learning 14%, intra-regional learning 3.0% and interregional learning 3.0%.
- **Regional focus**: organizational learning 3.0%, intra-regional learning 14% and interregional learning 3.0%.
- **External focus**: organizational learning 3.0%, intra-regional learning 3.0% and interregional learning 14%.
- **Diversified**: organizational learning 6.66%, intra-regional learning 6.66% and interregional learning 6.66%.

The first regime (‘no intervention’) represents a baseline setting. It reflects a situation where all firms in the region barely engage in the use of knowledge channels and instead focus on a go-it-alone strategy by increasing their expertise levels in the existing knowledge stock. The following four regimes represent scenarios reflecting the situation after potential policy interventions designed to mitigate the systemic failure in category 1 by fostering learning activities of firms with a particular focus on different knowledge channels. The regimes ‘internal focus’, ‘regional focus’ and ‘external focus’ represent interventions that foster the use of knowledge channels of firms through organizational, intra-regional or interregional learning respectively. Finally, the regime ‘diversified’ represents a more differentiated and balanced strategy that fosters all knowledge channels simultaneously, albeit at a lower level.

Scenario 2: ‘Entries of entrepreneurial firms’

Next, we focus on system failures, that is, situations with a misspecified (or incomplete) organizational landscape at the regional level. One example for a specific category 2 system failure are situations in which we face an underrepresentation of entrepreneurial activities in RIS. Policy-makers are confronted with a situation in which several different instruments are at hand to incentivize the entry of entrepreneurial firms including, for example, venture capital, financial support, tailored training etc. However, we assume that each instrument triggers different types of entrepreneurial activities within a region.

To analyze the economic effect of different types of firm entries into a region, we implement four types of start-ups that differ in terms of the number of initial knowledge units and the relatedness of their knowledge stock to existing firms. The first type (‘low-tech spin-offs’) are operationalized as firms that copy a small subset of the knowledge stock of an existing firm (three knowledge units). The second type (‘high-tech spin-offs’) differs from the previous group solely in the scope of their initial knowledge endowment (five knowledge units). Similarly, ‘low-tech de-novo entrants’ and ‘high-tech de-novo entrants’ differ in the scope of their knowledge endowments but do not have a knowledge imprint from a parent organization.

Scenario 3: ‘Attachment logics’

Insights from network science (cf. Barabási & Pósfai, 2016) show that a system’s overall topology affects not only systemic properties such as resilience against disruption, diffusion efficiency etc., but also individual knowledge-exchange processes, learning modes and innovation outcomes of the actors involved. One concrete example for a category 3 system failure is a situation in which an RIS is characterized by a misspecification of links between incumbents and entrepreneurial firms. Policy-makers may follow qualitatively different policy paradigms to mitigate these types of systemic irregularities. For instance, a ‘picking-the-winner’ approach aims at supporting the strongest actors, while ‘egalitarian’ counter-concepts emphasize the need to support all actors. Policy may intervene along these lines with qualitatively different instruments to mitigate cooperation-related system failures through incentivizing particular forms of cooperation.

Accordingly, we implement a benchmark that is frequently assumed to reproduce real-world cooperation behaviour (Barabási & Albert, 1999; Powell, White, & Owen-Smith, 2005). Thus, our baseline scenario is based on a ‘preferential attachment’ process, that is, firms entering the market link to two out of the 10% of most connected firms. Next, we implement two policy intervention scenarios. The ‘egalitarian’ approach is represented by a scenario in which newcomers randomly choose two partners. The second strategy involves a ‘preferential profit’ process, that is, firms link to two out of the 10% of most successful firms (i.e., in terms of current profits).
**Selected simulation results**

This section shows the results for each of the three scenarios presented above. If not stated otherwise, we employ the parameter setting listed in Appendix C in the supplemental data online. To eliminate random effects, the reported simulation results are the average over 2000 simulation runs with the same parameter setting.

**Scenario 1: ‘Learning regimes’**

First, we explore the economic consequences of distinct policy interventions designed to stimulate qualitatively different learning regimes. To evaluate the performance of each regime, we measure the average profits made by firms in the region over 300 simulation steps for each regime (Figure 1(a)). The reference scenario ‘no intervention’ exhibits only low profits made by firms. For all other regimes (‘internal’, ‘regional’, ‘external’ and ‘diversified’), we see that firm profits are considerably higher. Although for these scenarios the total amount of knowledge gained over time is the same, the results for the four different interventions indicate substantial differences. While in the very short run \( t < 140 \) interventions aim at fostering learning via intra-regional networks are advantageous, for \( t > 140 \) the diversified regime outperforms all other interventions.

However, the question is whether a diversified knowledge acquisition strategy also represents a preferable alternative from an individual firm perspective. For this purpose, we divide the population of firms into four homogeneous subgroups, each characterized by firms following one of the four learning regimes (‘internal focus’, ‘regional focus’, ‘external focus’ and ‘diversified’). Figure 1(b) shows the average profits for each group of firms in the region and we see that the group of firms focusing on learning via intra-regional networks performs better than other firms.

**Scenario 2: ‘Entries of entrepreneurial firms’**

Next, we explore the economic effects of policy interventions targeting entries of qualitatively different entrepreneurial firms into the RIS. Figure 2(a) shows the number of firms within the region over time for the four archetypal entrepreneurial firm entries into the RIS. The assumption behind our first simulation setting is that firms enter the region against the backdrop of a given learning setting, that is, the ‘no intervention’ regime. We see that the marginal survival rates of ‘low-tech spin-offs’ and ‘low-tech de novo’ entrants barely compensate for the drop-out of incumbent firms, and the most successful type of newcomers are high-tech spin-offs. While high-tech firms generally have higher survival rates than low-tech newcomers, we do not see a clear picture comparing de novo and spin-off firms: although high-tech spin-offs have higher survival rates than high-tech de novo firms, low-tech de novo firms have higher survival rates than low-tech spin-offs. Similar to the results in Figure 2(a), we see in Figure 2(b) that the aggregated profits of the region in the long run increase the most if policy interventions aim at high-tech spin-offs.

However, we have to consider that the entry of new firms has an impact on an individual level, that is, the profits made by incumbents and profits of start-ups after 300 simulation steps (Figure 2(c, d)). Although high-tech spin-offs have the highest chance of survival and contribute most to regional profits, they are nonetheless not the most successful start-ups when considering profits at the individual firm level. Instead, high-tech de novo entrants turned out to have the highest profits, especially in a ‘regional focus’ regime.

The explanation for this surprising result can be found by focusing more on the fundamental differences between the different types of start-ups. Both types, that is, high-tech spin-offs and high-tech de novo entrants, have access to a large knowledge base. The main difference is that the knowledge tapped by high-tech spin-offs is rooted in the region and has already been successfully applied by incumbents for creating novel products. In contrast, high-tech de novo firms are most likely endowed with knowledge radically new to the region. At first, this leads to low survival rates of de novo firms; yet, if successful, these firms can occupy new and highly profitable niches.

Another insight becomes obvious when comparing the average profits of incumbents and newcomers for two different learning regimes (Figure 2(c, d)). Incumbent firms in particular are positively affected when policy instruments fostering entrepreneurial activities are combined with a ‘regional focus’ learning regime. As Figure 2(d) shows, profit differences between incumbents and newcomers vanish for under ‘regional focus’ learning regimes and, in the case of low-tech spin-offs, incumbents’ profits even outperform the profits of newcomers.

**Scenario 3: ‘Attachment logics’**

Lastly, we explore the effects of policy interventions designed to induce a certain type of linking behaviour among previously introduced types of start-ups. Figure 3 displays the average profits of entrepreneurial firms for different types of start-ups and linking strategies after 300 simulation steps for two different learning regimes. We here distinguish between three linking strategies, that is, when entering the market, start-ups link to: (1) other well-connected firms in the market (‘baseline’); (2) randomly chosen partners (‘egalitarian’ approach); and (3) firms with the highest profits (‘picking-the-winner’ approach).

Again, we analyze the economic consequences for different learning regimes. For a ‘no intervention’ learning regime, we observe only marginal differences in the average profits of entrepreneurial firms following a random strategy compared with firms following a ‘preferential attachment’ logic. Interestingly, entrepreneurial firms, following a ‘preferential profit’ linking strategy perform best in terms of average profits. In other words, both policy interventions are effective while the ‘picking-the-winner’ scenario outperforms the ‘egalitarian’ scenario. The introduction of the ‘regional focus’ learning regime reveals some notable additional aspects. Again, for each of the four types of entrepreneurial firms, the ‘preferential profit’ linking
Figure 1. (a) Average profits of firms over 300 simulation steps for different learning regimes; and (b) average profits of firms with different learning strategies over 300 simulation steps (direct comparison).

Figure 2. (a) Number of firms in the region over 300 simulation steps for different entrepreneurial firms; (b) regional profits over 300 simulation steps for different entrepreneurial firms; (c) average profits made by start-ups and incumbents after 300 simulation steps against the backdrop of a ‘no intervention’ learning regime; and (d) average profits made by start-ups and incumbents after 300 simulation steps against the backdrop of a ‘regional focus’ learning regime.
strategy clearly outperforms other strategies. Comparing a ‘random linking’ and ‘preferential linking’ confirms our initial result and shows at the same time that ‘random linking’ clearly dominates. We also see that low-tech entrepreneurial firms especially benefit from the ‘regional focus’ learning regime, ultimately leading them to catch up with their high-tech counterparts. Finally, low-tech de novo firms, following a ‘preferential profit’ linking strategy, even outperform high-tech spin-offs with the same linking strategy in terms of average profits.

**DISCUSSION OF KEY FINDINGS AND LIMITATIONS**

Our simulation demonstrates how ABM can be used to reveal the consequences of policy interventions in complex adaptive socioeconomic systems such as RIS. However, there is always a trade-off between simplicity and realism when modelling policy interventions in a systemic context. The VISIBLE model and the three illustrated scenarios – each representing a system failure and related policy interventions – need to be viewed as artificially created test environments representing only an approximation of the full complexity of reality.

Consequently, the focus of our study is not on making quantitative predictions or providing point estimates but on revealing qualitative differences and potential co-evolutionary processes related to systemic interventions. More precisely, we aim both at highlighting generic effects that need to be accounted for when designing policy interventions and at demonstrating that a deep understanding of general systemic issues and a differentiated analysis of each individual RIS is needed before initiating a new policy intervention.

Starting with the situation where firms barely engage in the use of knowledge channels, we see that, especially in the long run, a well-balanced strategy mix of different knowledge channels is best at fostering innovation and knowledge creation at the regional level. In other words, it is not only about gaining more knowledge but also about providing the optimal conditions for firms to get the right knowledge and, thereby, enabling them to exploit existing knowledge bases and explore novel ideas (cf. March, 1991; Schlaile, Zeman, & Mueller, 2018; Vermeulen & Pyka, 2018). At the same time, we face a situation where some actors may profit from a free-rider position by deviating from the collectively superior diversification strategy in order to focus only on regional network activities. From a policy perspective, this implies that norms and rules are needed that facilitate a well-balanced use of the different knowledge channels, considering both the individual and collective incentive structures.

The aim of our second scenario is to analyze how different types of entrepreneurship contribute to the economic performance at the firm and regional level. As early as 1911, Schumpeter (1911) proclaimed the idea that the creative power of exceptional individuals is one of the main driving forces of economic growth and prosperity. However, empirical research shows that a well-specified relationship between firm foundations, regional innovativeness and growth does not exist (Fritsch, 2007). With our second scenario, we contribute to this debate in several ways. First, we see that policy interventions indeed have ambiguous effects when considering the survival rates of entrepreneurs, the individual performance of incumbents and entrepreneurs, and the regional profits within a RIS. Second, we see that these effects strongly depend on other systemic interventions, for example, policy interventions aiming at fostering regional learning. Our results show that the initialization of a second policy intervention changes the rules of the game in the sense that policy interventions targeting one particular group of firms also affect other (indirectly involved) actors in the system. This implies that policy-makers need to consider carefully the institutional set-up as well as other regional characteristics before designing and implementing a new
entrepreneurship policy intervention. In line with previous research (Foray, 2014), our findings underline the importance of entrepreneurial activities and customized instruments for the innovativeness of regions.

Finally, results from scenario 3 clearly indicate that policy interventions designed to affect linking decisions matter for the economic performance of the actors involved. Building on the literature on network formation (e.g., Barabási & Albert, 1999; Barabási & Pósfai, 2016), it is reasonable to assume that linking to most connected firms in the region reflects cooperation behaviour in a realistic way. We argue that cooperation decisions of entrepreneurial firms are influenced by policy instruments designed against the backdrop of the ‘picking-the-winner’/egalitarian’ policy paradigms. Our results show that a rather undifferentiated ‘one-size-fits-all’ approach (i.e., ‘egalitarian’ approach) has a positive but marginal effect on the target firms within a ‘no intervention’ learning regime. The prevalence of a ‘regional focus’ learning regime enhances the positive effects for all types of entrepreneurial firms. Finally, a well-specified policy intervention approach – explicitly accounting for structural effects as well as firm attributes (i.e., ‘picking the winner’) – generates highest returns. This result remains robust, irrespective of the assumed learning regime.

CONCLUSIONS AND FURTHER RESEARCH

From a theoretical point of view, the present study contributes to the contemporary debate on regional innovation policy by emphasizing the need for a more holistic approach allowing for the identification of factors impeding the prevailing level of innovation and the economic performance of RIS. By drawing upon the innovation system literature and system failure concepts, we disclose potential systemic deficits and derive a set of policy interventions. It is important to note that the system failure categories, introduced in the second section are very broadly conceived. Consequently, a sophisticated differentiation and specification of a systemic weakness must constitute the beginning of every simulation analysis. Therefore, the results reported here provide insights on specific sets of systemic irregularities. To sum up, it can be affirmed that the applied perspective allows one to address systemic issues that go beyond the scope of the market-oriented legitimization of policy interventions. Knowledge exchange and learning processes are consequently placed at the centre of the debate, even though the operationalization of some knowledge-related conceptual elements remains a demanding task. From a methodological point of view, we contribute to the literature by applying a novel analytical tool. ABM allows one to replicate real-world RIS in an in-silicio policy laboratory and to study the consequences of policy interventions under controlled conditions. Against the backdrop of systemic failures within a regional setting, our simulation results reveal important (co-)evolutionary processes and self-enforcing dynamics that typically remain hidden when applying empirically ex-post evaluation approaches. The conceptualization and implementation of economic actors as unique, heterogeneous and strategically oriented agents provides a more differentiated picture and avoids over-simplifications. Overall, we are convinced that the intersection between the system failure literature and agent-based modelling techniques provides a fruitful ground for ex-ante policy evaluations.

Despite the above-reported advances, several possible extensions are left for future research. First, the conceptual basis for the presented model is the kene concept. Despite its strengths, it also has its limitations. As it relates to applying this modelling approach for the purpose of ex-ante policy simulations in particular, some of the conceptual elements have the potential for further improvements. Second, our analytical exercise represents only a small selection of interventions into RIS. Additional experiments are required to provide a more comprehensive picture of how policy interventions affect each other. In particular, the translation of a real-world policy instrument into a set of systemic interventions within an in-silicio simulation environment is a demanding task that requires close coordination between researchers and policy-makers. Third, the model specification and the results presented above are closely tied to the empirical observations for one illustratively chosen region, namely the Heilbronn-Franken region. However, the comparison with other regions would prove highly insightful and enable one to check and reassess the findings critically. This would be all the more important as optimality criteria are hard to define in complex-adaptive systems. Finally, we see great potential in combining our approach with other analytical tools. On the one hand, further empirical research is needed to test the predictions, patterns and effects revealed by our simulation. On the other hand, the integration of further insights from behavioural economics and socio-psychological experiments on knowledge exchange and learning would enrich the VISIBLE model significantly.

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NOTES

1. There is no general rule that allows for specifying imperfections within these categories in the sense that particular rules, or certain types of organization and cooperation, are missing. Instead, systemic characteristics are conceived to be imperfect based on systematic comparisons with benchmark systems.

2. Appendix D in the supplemental data online provides examples for potential system failures, corresponding policy interventions and related simulation scenarios.
3. Appendix C in the supplemental data online provides an overview of data sources and parameter settings.
4. For a discussion of the scientific value of ABM, the kene approach, calibration, validation and the usability of ABM for the ex-ante analysis of policy interventions, see the editorial.
5. The simulation is implemented in NetLogo (https://ccl.northwestern.edu/netlogo/).
6. For a detailed explanation, see Ahrweiler et al. (2011).
7. For the simulation results presented in the fourth section, it is assumed that: $[C_n \in N \mid 0 \leq C_n \leq 50]$; $[A_n \in N \mid 0 \leq A_n \leq 20]$; and $[E_n \in N \mid 0 \leq E_n \leq 20]$.
8. See Appendix A in the supplemental data online for a flowchart of the model procedures.
9. Numerically, for organizational learning we use 7, for intra-regional learning we use 5 and for interregional learning we use 3 to express the increasing difficulties of learning, first outside the firm and second outside the region.
10. See Appendix B in the supplemental data online.
11. We assume one new entrant to the region at each simulation tick, while each of these newcomers automatically establishes a link to two randomly chosen incumbent firms.
12. The standard error for all presented results is lower than 10.

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