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Estimating the economic impacts of knowledge network and entrepreneurship development in smart specialization policy

Attila Varga[a], Tamás Sebestyén[b], Norbert Szabó[c] and László Szerb[d]

ABSTRACT

An undesirable result of the rapid implementation of smart specialization into the framework of European Union Cohesion Policy was that it left several practical issues unanswered. An important unanswered issue is the implementation of economic impact assessment in a smart specialization policy context. Integrating entrepreneurship and interregional network policies into an economic modelling framework is considered among the most prominent challenges. This paper introduces how these two policies are implemented in the GMR-Europe (geographic, macro and regional) model. The simulations highlight that smart specialization policy targeting the development of entrepreneurship and knowledge networks is not equally successful in all regions.

KEYWORDS

smart specialization; GMR modelling; economic impact assessment; Cohesion Policy; innovation networks; entrepreneurship

JEL C54, O00, R11, R58

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INTRODUCTION

Smart specialization policy is a recently introduced innovation-based regional development approach. Industrial specialization of a region is considered 'smart' if it grows out of the regions' own traditions instead of the (typically non-replicable) experiences of well-known successful regions located elsewhere in the world. The main instruments of smart specialization are neither traditionally implemented sector-neutral innovation policy measures (e.g., human capital development or research and development (R&D) support) nor top-down policy tools targeting selected industries. Instead, it is a particular combination of these elements characterized by a government-supported process of 'entrepreneurial discovery'. As a result, smart specialization policy combines the support of entrepreneurs to discover 'new domains of future opportunities' and the promotion of structural changes with non-neutrally designed policy instruments (Foray, 2015).

The theoretical framework of smart specialization policy was developed by the Knowledge for Growth expert group (Foray, David, & Hall, 2009, 2011) and integrated to regional policy context by McCann and Ortega-Argilés (2015). The concept became rapidly popular and became incorporated into the reformed European Union (EU) Cohesion Policy of the 2014–20 planning period. In order to be eligible for Cohesion Policy support, each region is required to develop its Smart Specialisation Strategies (McCann & Ortega-Argilés, 2016). However, as Foray emphasizes, the undesirable result of this rapid implementation was that 'policy run ahead of theory' leaving several implementation issues unanswered (Foray, 2015).

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One of the most important unanswered issues is the implementation of economic impact assessment in a smart specialization policy context. Economic impact assessment targets the estimation of the likely impacts of policy interventions on economic variables such as gross domestic product (GDP) or employment as well as the effect of policies on territorial differences. The purpose of economic impact assessment therefore differs substantially from project-level impact evaluations because it considers direct and indirect aggregate impacts of the projects (including Keynesian demand multiplier effects, supply effects generated by inter-industry linkages or knowledge spillovers). Economic impact assessment is traditionally an essential element of Cohesion Policy and as such it also deserves to play a key role in smart specialization policy in both ex-ante (policy planning phase) and ex-post (final) evaluations.

Specifically designed economic models are commonly applied instruments in economic impact evaluation. Key reasons why economic impact assessment of smart specialization programmes has not been implemented in the Cohesion Policy framework are the challenges in modelling implied by smart specialization. A particular issue in this respect is integrating entrepreneurship and interregional network policies in economic impact models, which are focal points of smart specialization policies. The most recent developments of the GMR-Europe model address the implementation of these two policies. This paper describes the solution we developed in GMR-Europe and illustrates its capabilities with policy impact simulations.

The paper is structured as follows. The next section situates economic impact models in entrepreneurship and knowledge network policy assessment, followed by the description of how the mechanisms of these policies are integrated in the GMR-Europe model in the third section. The fourth section then illustrates the model's capabilities by means of policy simulations. A summary closes the paper.

ENTREPRENEURSHIP, KNOWLEDGE NETWORKS AND SMART SPECIALIZATION POLICY: THE CHALLENGES IN ECONOMIC IMPACT MODELLING

The development of new industries in regions as a result of a bottom-up process is not new; what is novel is the analytical description of the phenomenon and the development of the concept of smart specialization policy (David, Foray, & Hall, 2009; Foray, 2015; Foray et al., 2009, 2011; McCann & Ortega-Argilés, 2015). Smart specialization is the capacity of regions to implement structural changes in their economies through the discovery of new domains of opportunities and the concentration of resources to those fields (Foray, 2015). The key concepts of smart specialization are the 'entrepreneurial discovery process' and 'structural change'. The discovery process includes activities aiming at exploring, experimenting and learning about possible directions of a future economic change within a sector or between different sectors (Foray, 2015). Entrepreneurs who are in good positions to understand a region's economic capabilities take the lead in discovering new domains of opportunities (Hausmann & Rodrik, 2003). Knowledge spillovers from successful initial discoveries then result in a series of imitative firm entries, leading to the concentration of resources in the new domain and a consequent structural change in the region's economy. Structural change may take different forms ranging from diversification and modernization of industries to the appearance of radically new sectors in the region (Foray et al. 2011).

According to the concept of smart specialization no single agent (governments, firms, R&D organizations) has a complete view of the economy. The task of the policy is to coordinate and implement the discovery of new specializations by the agents (Radosevic, 2017). Entrepreneurial discovery is therefore the key concept in smart specialization policy. It is an interactive process in which the entrepreneurs discover and produce information about new activities and government assesses their outcomes and empowers agents most capable of realizing the potential. Smart specialization therefore describes a form of innovation-based regional economic development, which begins with discoveries by entrepreneurs progresses with new firm entries generated by spillovers from successful original discoveries and matures with firms agglomerated in certain industries of the economy. Smart specialization policy stimulates this process in a non-neutral logic favouring selected new activities by means of concentrating resources to those that are anticipated to transform existing economic structures. Proposed policies range from public venture capital and entrepreneurship development programmes to those which support the improvement of human capital conditions, R&D competences and the region's embeddedness in interregional research networks (Foray, 2015).

Policies that target entrepreneurship development and support regional actors to learn from external knowledge sources play a key role in the process of entrepreneurial discovery. Regions with underdeveloped entrepreneurial ecosystems are hardly capable of acting in the bottom-up discovery process of smart specialization. Even if the region possesses substantial entrepreneurial capabilities the import of knowledge from other regions becomes inevitable if it is not available locally in order to manage the entrepreneurial discovery process.

There are several challenges in integrating entrepreneurship and network policies in models of economic impact assessment. A suitable economic impact model needs to incorporate the accurate spatial and industrial dimensions in its structure. Since the unit of analysis of smart specialization policies is the subnational region, economic models have to address this geographical scale directly. Furthermore, cross-regional interactions in smart specialization (such as knowledge imports from more developed regions or interregional migration induced by policy interventions) necessitate the models to incorporate multiregional aspects as well.

Most economic models applied in Cohesion Policy impact assessment are national, macroeconomic models, such as the QUEST (Ratto, Roeger, & In't Veld, 2009) or the HERMIN (Bradley, 2006) models. However, multiregional spatial computable general equilibrium models are already available for European regions and these models may potentially be integrated in a smart specialization impact assessment framework. The models should also be able to characterize the particular impact mechanisms of smart specialization policy interventions. Some existing models such as RHOMOLO (Brandsma & Kancs, 2015), MASST (Capello, 2007), the dynamic evolutionary simulation model of European regions (Fratesi, 2015) and previous versions of the GMR-Europe model (Varga, 2017) already incorporate features that make them suitable for the impact assessment of regional investment subsidies and policies supporting human capital and R&D.

However, the estimation of the impacts of policies addressing entrepreneurship and knowledge network development is still a challenge. The most recent developments of the GMR-Europe model address this challenge. The following section provides a more detailed account of how GMR-Europe is extended in order to estimate the impacts of entrepreneurship and knowledge network development policies. For the complete technical description of the latest version of the GMR-Europe model including the list of equations, estimation/calibration of parameters as well as data description, see Varga, Sebestyén, Szabó, and Szerb (2018).

KNOWLEDGE NETWORKS AND ENTREPRENEURSHIP IN THE GMR-EUROPE MODEL

The GMR policy impact modelling approach

The GMR (geographic, macro and regional) modelling framework has been established and continuously improved over the past two decades to provide support in economic development policy decisions. As long as models usually applied in Cohesion Policy impact analysis are national models (Bradley, 2006; Ratto et al., 2009), the novel feature of GMR models is that they provide national and (subnational) regional-level impact estimates. The models also incorporate geographic effects (e.g., agglomeration, interregional trade, migration). GMR models provide support in the evaluation of different kinds of policy interventions such as R&D, human capital, private investment or physical infrastructure development subsidies.

The first realization of the GMR approach was the EcoRET model built for the Hungarian government for ex-ante and ex-post evaluations of EU Cohesion Policy (Varga & Schalk, 2004). This was followed by the GMR-Hungary model, which is currently used by the Hungarian government for Cohesion Policy impact analyses (Varga, 2007). GMR-Europe was established in the IAREG FP7 project (Varga, 2017) and further developed in the GRINCOH FP7 (Varga, Járosi, Sebestyén, & Szerb, 2015) and the FIRES H2020 project (Varga et al., 2018). Another version of GMR models is GMR-Turkey (Varga & Baypinar, 2016).

The GMR framework is rooted in different traditions of economics (Varga, 2006). The Romerian endogenous growth theory influences knowledge production modelling (Romer, 1990). Spatial patterns of knowledge flows and the role of agglomeration in knowledge transfers are modelled through insights learned from the geography of innovation. Interregional trade and migration linkages as well as dynamic agglomeration effects are incorporated in the tradition of the new economic geography (Krugman, 1991). Specific macroeconomic theories provide the foundations for modelling national level impacts.

Modelling the impacts of policies targeting extra-regional knowledge network development

During the discovery process different types of knowledge are being integrated. Related diversification of a region's dominant technology is naturally based on the knowledge possessed by the region, but its extension towards new dimensions may require additional knowledge, which is not necessarily available locally. The discovery of new domains of opportunities might therefore require the integration of the local knowledge base with scientific or technological knowledge developed in universities, private research institutes or specialized research groups located in other regions. Identifying those regions that possess the complementary knowledge, selecting the individual partners to cooperate with or establishing the initial connections, are complex and non-trivial tasks, potentially requiring professional assistance as part of the discovery process. As a result, the support of less-developed regions' access to the knowledge that is missing locally but available in more advanced regions is a central tool in smart specialization policy for reinforcing regional entrepreneurial discoveries (Foray, 2015).

With the increasing complexity of knowledge its further development becomes more and more the result of a collective process. Knowledge therefore develops in collaborative networks of different institutions (e.g., universities, public or private research laboratories) and the actors participating in these networks do not necessarily locate in one region. Thus, it is important to emphasize that the external knowledge required for a discovery is not necessarily possessed by one region exclusively, but may be distributed among different regions (Autant-Bernard & Hazir, 2014; Varga & Sebestyén, 2017). The discovery process therefore necessitates connecting regional entrepreneurs into a network of externally located actors. This justifies the need for those specific policy interventions that target the development of a particular region's external knowledge network.

Economic impact models may provide important information for the selection of the directions for external knowledge network development. However, the integration of extra-regional knowledge networks into economic impact models involves at least two challenges. The first is about measuring the knowledge accessible from the network, while the second is about modelling further dynamic changes in the network caused by the region's access to it. The two aspects are interrelated since network dynamics initiated by the region's entry into the network may affect the amount of knowledge the region can access from the network.

The level of knowledge a region can access from a particular network relates both to the region's connections with immediate partners (i.e., the ego network) and to the connectedness of the ego network to more distant parts of the entire knowledge network. To measure the knowledge accessible from a region's position in the network we apply the index of ego network quality (ENQ) developed and introduced by Sebestyén and Varga (2013). The concept of ENQ builds on three intuitions directly influenced by the theory of innovation. First, the level of knowledge in an agent's network is in a positive relationship with the level of knowledge that the (direct and indirect) partners already possess. Second, the structure of connections in the agents' network largely influences the amount and accessibility of new knowledge (e.g., Burt, 1992; Coleman, 1986). Third, partners in the ego network contribute to diversity through connections to different further groups not linked directly to the agent.

The ENQ index measures the knowledge available for a given actor in a network given the knowledge levels of direct and indirect partners and the structure of connections in the network. The set-up of the index emphasizes that this knowledge depends on the knowledge level of the partners and the structure of the network around this knowledge. Technically speaking, we summarize the knowledge of direct and indirect partners but weight this knowledge by the density of network connections within which the partners are embedded and also the distance of the partners in the network. As a result, the ENQ index shows higher values for those actors in the network which are connected (closer) to more knowledgeable partners, on the one hand, and embedded in a dense interaction structure, on the other.

The ENQ index is structured around two concepts, which are then augmented with a related third aspect: (1) knowledge potential (KP), which measures knowledge accumulated in the direct neighbourhood and it is related to the number of partners and the knowledge of individual partners; and (2) local structure (LS), which is associated with the structure of links among partners. LS is important for the dynamics of accessible knowledge. We assume that a network where the actors' collaboration intensity is high results in a higher level of new knowledge production than otherwise. The third concept is global embeddedness (GE), which captures the quality of distant parts of the network (beyond immediate partners). However, this aspect is implemented by applying the concepts of KP and LS for consecutive neighbourhoods of indirect partners in the network.

The ENQ index first calculates the KP for neighbourhoods at different distances from the node in question as the sum of knowledge levels available in that neighbourhood. These KP values are then weighted by the LS value of the respective neighbourhood. Finally, these weighted knowledge levels for the different neighbourhoods are also weighted by a distance-decay factor and summed over neighbourhoods. The ENQ index thus can be divided into a sub-index measuring the knowledge accessible in the direct neighbourhood (ego network) of the node in question and a sub-index called GE, which reflects the knowledge accessible beyond this direct neighbourhood.[1]

As the previous description of the ENQ index shows, this index is sensitive to the knowledge level of the actors in the network as well as the structure of connections among them. Adding connections to or deleting them from the network alters the whole structure, thus it changes the ENQ index to a larger or smaller extent of all actors. This feature of the index can be used when evaluating the impact of network policies. Assuming that these policies are effective in establishing (or redirecting) links at a certain point of the network, the ENQ index is capable of tracing the effect of these changes on the potentially available knowledge for actors in the network, which then can be used in a wider context through its contribution to innovation. Also, given the detailed picture of the network at hand, different policies, affecting different links, can be simulated with the help of the index.

Modelling the impacts of policies targeting regional entrepreneurship development

The general level of regional entrepreneurship may crucially determine the efficiency of smart specialization policies. Experiences already suggest that the effectiveness of programmes addressing smart specialization varies across European regions. In economically and institutionally more developed places the implementation of programmes appears to be more promising than in lagging regions (McCann & Ortega-Argilés, 2016). This difference in the efficacy of smart specialization policy could partly be due to the entrepreneurship level in a region. In a less developed region where entrepreneurship is relatively modest, the variety and richness of discoveries might not be sufficient enough to initiate the expected structural change. In order to create a better environment for smart specialization these regions might therefore be motivated to take steps to reinforce discoveries by way of implementing entrepreneurship development policies (Foray, 2015).

However, entrepreneurship is a complex phenomenon, which emerges in the context of system-wide interactions amongst its different components (Ács, Autio, & Szerb, 2014). Accordingly, to raise the level of entrepreneurship the region may select a particular intervention from the set of different alternative policies or decide to implement a certain combination of them. Alternative entrepreneurship supporting policies could range from improving entrepreneurs' access to financial resources or raising the skills of start-ups to intensifying collaborations among businesses. Due to the systemic nature of entrepreneurship mutually interconnected policies could potentially strengthen or weaken each other. The design of a suitable policy mix to target the intensification of regional entrepreneurial discoveries is therefore an extremely complicated process.

With impact models the economic effects of various regional entrepreneurship policies can be estimated. As such these models can provide important information in the process of policy selection. However, at least two major challenges have to be solved in order to successfully integrate entrepreneurship into an economic impact model. The first is about measuring the level of regional entrepreneurship, whereas the second is about modelling the system-wide impacts of entrepreneurship policies. Similar to what was underlined earlier for the case of knowledge network policies these two challenges are interrelated here as well because at the end entrepreneurship policies change the level of entrepreneurship in the region. To tackle these challenges in economic impact assessment the regional entrepreneurship and development index (REDI) (Szerb et al., 2017) is being integrated into the GMR-Europe policy impact model.

The REDI has been designed to provide a holistic view on the functioning of EU's regional entrepreneurial ecosystems and it should be of particular utility when identifying gaps and bottlenecks that prevent a given region from fully exploiting its entrepreneurial potential. The REDI method builds on the National Systems of Entrepreneurship Theory (Ács et al., 2014) and provides a way to profile regional systems of entrepreneurship. The key idea of this systemic index is therefore that system performance is 'co-produced' by its constituent elements. This means that the different system components are interrelated. Although entrepreneurial actions are undertaken by individuals, they are always embedded in a given institutional context. For example, technology-based new ventures will find it difficult to innovate if the regional job market does not supply workforce with the required special skills. In a regional entrepreneurial ecosystem it is the combination of the different components that ultimately determines whether or not the system will function well (Szerb et al., 2017).

The REDI organizes the various factors that determine the level of entrepreneurship in a region in a systemic manner. The index is composed of three sub-indices. The entrepreneurial attitude (ATT) sub-index aims to identify the attitude of the people in a region towards entrepreneurship. In REDI, the attitude is characterized by the level of opportunity recognition and start-up skills within the population, the extent to which the fear of failure of starting a business is present in the region, the strengths of personal networks and the sufficiency of cultural support of successful entrepreneurs.

The entrepreneurial abilities (ABT) sub-index is principally concerned with measuring certain important characteristics of both entrepreneurs and start-ups with high growth potential. Abilities are related to the extent to which new opportunities motivate business start-ups, the share of technology intensive and creative sectors in the region, the education levels of entrepreneurs and employees, and the extent of competition in the business sector.

The entrepreneurial aspiration (ASP) sub-index refers to the distinctive, qualitative, strategy-related nature of entrepreneurial start-up activity. Aspiration level is associated with the degree of innovativeness – both product and technology – and the extent to which high growth, internationalization and good access to finance characterize entrepreneurial businesses.

All three sub-indices contain four or five pillars, which can be interpreted as quasi-independent building blocks of this entrepreneurship index. Each pillar reflects the characteristics of individual entrepreneurs and the regional institutional context. The idea behind this approach is that entrepreneurship is considered as a systemic phenomenon and as such it is the result of both individual and contextual factors. Technically, each of the 14 pillars is therefore the result of the multiplication of an individual variable and an associated institutional variable.

The second challenge is modelling the system-wide impacts of entrepreneurship policies. The REDI deviates from traditional 'one-size-fits-all' policy approaches and acknowledges that entrepreneurship policy should be case-based (tailor-made) (Ács et al., 2014). Moreover, REDI benchmarks the optimal configuration of the 14 pillars as being balanced (have the same level). The presence of a bottleneck indicates imbalance and consequently a lower efficiency in the system. A bottleneck is the worst performing element or binding constraint and is defined as a shortage or the lowest level of a particular entrepreneurial pillar as compared with the other 13 pillars.

According to the penalty for bottleneck (PFB) principle, the REDI is constructed in such a way that the value of each pillar is penalized by linking it to the score of the pillar with the weakest performance in the region. This simulates the notion of a bottleneck, and if the weakest pillar were raised, it would have a multiplicative effect to improve the other pillars and therefore the whole REDI would show a significant improvement. Raising a non-bottleneck pillar would have only a minor effect on that particular pillar; hence, it can be viewed as an inefficient policy step.

The optimum allocation of all entrepreneurial resources is attained when all the bottlenecks are alleviated. Therefore, decreasing the retraction influence of the bottleneck pillar(s) drives the selection among the potential policies. The notion of this policy is based on the classical public policy view about the correction of market failures, that is, intervening only where the private market system has weaknesses. This approach is present in regional development and innovation policies. Here, the aim of entrepreneurship policy is to correct system failures (Autio & Levie, 2015). The resulting change in the REDI enters the GMR-Europe model where economic impacts of the policies are estimated.

The PFB method calculation implies that the greatest improvement in system performance can be achieved by alleviating the weakest performing pillar: the bottleneck pillar. In policy simulations, each bottleneck pillar is alleviated to a point where it seizes to be a bottleneck. At this point, any further resources is allocated to the second-most binding constraint within the system, again up to a point where this constraint is no longer the most binding constraint within the system. By successively alleviating most binding constraints, the simulation therefore provides an idea of how policy effort should be allocated to achieve an 'optimal' outcome, defined as the largest possible increase in the REDI score.

Assessment of smart specialization policies: productivity effects

The third dimension in prioritization targets the assessment of discoveries' economic impacts. Part of this relates to the evaluation of discovery-specific policy interventions: the assessment of public venture capital investment support, human capital, R&D, interregional network and entrepreneurship policies. The current section outlines how GMR-Europe models the productivity impacts of policies whereas the subsequent section focuses on the estimation of their economic impact.

Regional total factor productivity (TFP) – the overall productivity of production factors – is one of the most crucial variables in GMR-Europe.[2] It represents the main point through which different aspects of smart specialization policy interventions interact with other parts of the model. The TFP block of the GMR system serves as the point where 'soft' and 'hard' factors behind innovation are modelled. Then, in line with the traditions in economic modelling, all these factors are implemented in the rest of the model through the TFP variable. An increase in TFP (*ceteris paribus*) results in higher regional GDP, which may be associated with lower production costs or with the introduction of new products on the market.

Figure 1 illustrates the set-up of the TFP block in GMR-Europe.[3] It consists of two equations: one is the knowledge production function, which links new knowledge (measured by regional patent applications) to knowledge inputs. The second is the TFP equation, which links, among others, regional knowledge to TFP. The two equations are first estimated econometrically then based on these estimations some of the individual regional parameters are calibrated.

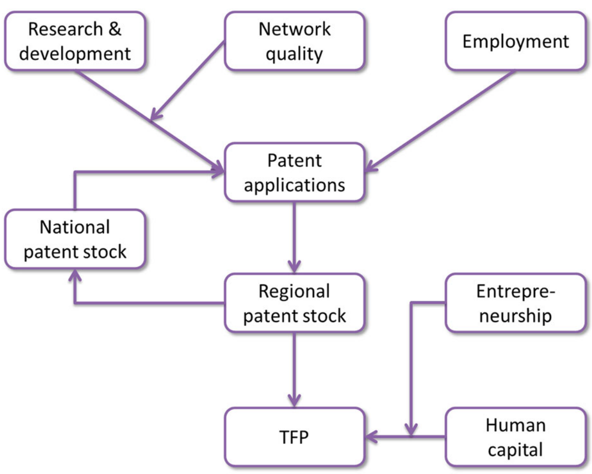

Figure 1. Structure of the total factor productivity (TFP) block.

The main role of the TFP block is to provide a sophisticated background for determining TFP and implement innovation-oriented policy interventions for each region in the model. The TFP block is based on the knowledge production function approach. New knowledge (represented by patent applications) is produced using knowledge production factors, namely R&D expenditures as well as the already existing knowledge represented by national patent stock. The size of the region (measured by the level of employment) also assumed to have a positive impact on new knowledge, implementing an agglomeration externality in the model. In addition to this standard approach, knowledge available through interregional research networks (measured by the ENQ_index) is also assumed to affect the productivity of R&D in knowledge creation. In GMR-Europe we measure research collaboration by EU Framework Program network participation. The specification follows the assumption that a better interregional network position leads to higher knowledge output for the same amount of R&D inputs. Therefore, increased access to extra-regional knowledge sources increases the efficiency of R&D in knowledge production (Varga & Sebestyén, 2017). New knowledge, that is, patent applications at the regional level, then feed back into knowledge creation in a dynamic way by building up national patent stock.

TFP is primarily linked to the regional knowledge level (measured by the patent stock) in the model, but two additional factors are added directly and a third indirectly. First, the level of human capital in the region is supposed to affect productivity, and second, a focal element of this set-up of the GMR model, we added the entrepreneurial environment (measured by the REDI) in the model which is also assumed to have a positive influence on productivity, via enhancing the contribution of human capital to TFP. Our formulation is influenced by the knowledge spillover theory of entrepreneurship (Acs, Audretsch, Braunerhjelm, & Carlsson, 2009). Entrepreneurs transfer knowledge to economic applications, therefore a better entrepreneurial climate in a region intensifies new firm formation. A higher level of entrepreneurship in a region helps better exploit the knowledge embodied in human capital, which eventually leads to increasing total factor productivity.

Assessment of smart specialization policies: the economic impacts

GMR models reflect the challenges of incorporating regional, geographical and macroeconomic dimensions in development policy impact modelling by structuring the system around the mutual interactions of three sub-models, which are (1) the total factor productivity (TFP), (2) the spatial computable general equilibrium (SCGE) and (3) the macroeconomic (MACRO) model blocks. The mutually interconnected model-block system is depicted in Figure 2.

Economic effects of policy interventions at the regional level are calculated in the SCGE block. SCGE models add the spatial dimension to the (usually a-spatial) computable

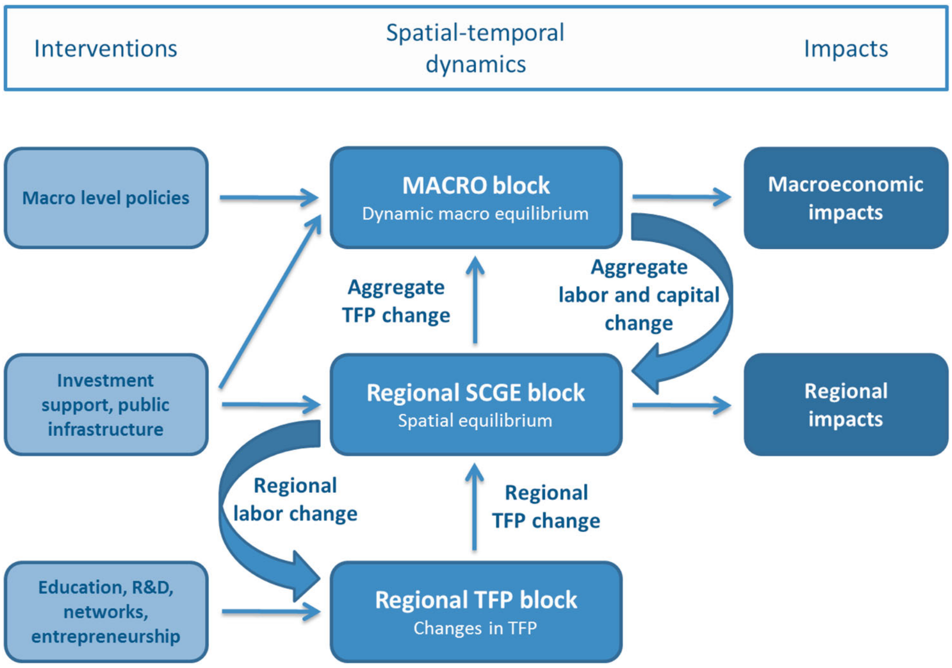

Figure 2. Regional and macroeconomic impacts of the main policy variables in the GMR-Europe model.
Note: R&D, research and development; SCGE, spatial computable general equilibrium; TFP, total factor productivity.

general equilibrium (CGE) models. Economic units are regions, which are interconnected by trade linkages and migration. Transportation costs, positive and negative agglomeration effects are also parts of the model structure. The model distinguishes between short- and long-run equilibria. In the short-run markets are in equilibrium within and across all regions. However, this does not necessarily mean that the whole regional system has reached a balanced situation. In the long run, differences in utility levels across regions induce labour migration (followed by the migration of capital) leading to a long-run spatial equilibrium where interregional utility differences are eliminated.

The macroeconomic block is a standard, large-scale dynamic, stochastic, general equilibrium (DSGE) model. The role of this block is to model dynamic economic effects and to provide a framework for the static SCGE block by determining the dynamics of given macroeconomic variables. We apply the QUEST III model developed by the European Commission for the Euro area, and re-estimated it for the purpose of our model with data on additional Central European countries. The description of the original model can be found in Ratto et al. (2009); the re-estimated version is described in Varga et al. (2018).

The macroeconomic block of GMR-Europe calculates policy impacts at the EU and national levels while the 181-region NUTS-2-level TFP and SCGE blocks provide results at the regional level. The model calculates the policy impacts on various economic variables such as GDP, GDP growth rate or employment at the regional, national and aggregate European levels.

Some of the policy interventions are modelled in the macroeconomic block (such as changes in international trade, in tax regulations or in income subsidies) via policy shocks affecting specific macroeconomic equations. However, smart specialization policies are modelled at the regional level, stimulating the regional base of economic growth such as public venture capital investment support, human capital development, R&D subsidies, promotion of (intra- and interregional) knowledge flows and entrepreneurship. These interventions are modelled in the two regional-level model blocks and they also interact with the macroeconomic part.

Without interventions TFP follows a steady-state growth rate in each region. The impacts of interventions run through the system according to the following steps.

1. Interventions related to R&D, human capital, interregional knowledge networks and entrepreneurship first affect regional TFP levels through the TFP block.
2. Changing TFP levels induce changes in regional output, prices and factors of production in the short run. In the long-run migration of production factors implies further changes in the level of TFP not only in the region where the interventions are applied but also in regions that are connected by trade or factor migration.
3. Public venture capital investment support expands regional private capital, which implies further changes in regional production. This impact also affects the macro-model as well via increased private capital.
4. For each year, changes in regional TFPs are aggregated to the national level where the aggregated changes enter the macroeconomic block as time specific shocks. The macroeconomic block calculates the changes in all affected variables at the national level.
5. Changes in aggregate employment and investment calculated in the macroeconomic block are distributed

to the regions following the spatial pattern of TFP impacts.

6. The SCGE block runs again with the new employment and capital values to calculate short- and long-run equilibrium values of the affected variables.
7. The process described in steps 5 and 6 run until aggregate values of regional variables calculated in the SCGE block converge to their corresponding values calculated in the MACRO-block.

With GMR-Europe various ex-ante and ex-post impact analyses can be carried out for different policy interventions (Figure 2). In this paper our interest is in entrepreneurship and knowledge network policies. Various factors affect the resulting economic impacts of these policies in GMR-Europe. A policy affecting entrepreneurship first changes the level of entrepreneurship via changing the value of the REDI. Analogously a network policy first influences the ENQ index, which represents the region's access to knowledge from the entire network. Regional and macro-level economic impacts of entrepreneurship and knowledge network development policies are determined by a number of important factors in GMR-Europe:

- The initial levels of REDI and ENQ are crucial in terms of economic growth since a relative increase in REDI and ENQ implies a higher economic change when initial values are also higher.
- The level of human capital in a region plays a crucial role in the determination of how effectively entrepreneurship can influence productivity and the level of R&D plays a similar role in the case of a network policy.
- Temporal trends in human capital development enhance the efficiency of entrepreneurship whereas trends of R&D augment the effects of network policies in the long run.
- The interaction of dynamic changes in employment and capital also play a crucial role in generating economic impacts.
- Changes in economic growth will influence migration, which in some regions can be a further source of growth while for other areas it can be a leakage of resources.
- Changes in interregional trade play a further significant role in the development of regional economies. The relative size, and direction of all those forces will eventually determine the economic growth of regions and nations.

HOW ARE REGIONS WITH DIFFERENT EXPERIENCES IN SMART SPECIALIZATION POLICY IMPLEMENTATION AFFECTED BY ENTREPRENEURSHIP AND NETWORK POLICIES?

This section presents some illustrative simulations to demonstrate the capabilities of GMR-Europe. The recent literature has already collected some cases with varying experiences in smart specialization policy. The analysis contains a sample of six European regions. Karlsruhe region in Baden-Württemberg (DE12) is a highly developed industrialized region, where the implementation of the smart specialization concept has not generated significant changes in regional innovation policy (Kroll, Muller, Schnabl, & Zenker, 2014). Dresden in Saxony (DED2) is a post-socialist German region with well-developed innovation system where the basics of Smart Specialisation Strategy were successfully implemented even before the elaboration of the concept of smart specialization (Baier, Kroll, & Zenker, 2013; Koschatzky, Kroll, Schnabl, & Stahlecker, 2017). Pomerania (PL63) is a less developed region but the only one in Poland where the emergence of smart specialization was implemented as a bottom-up process through competition (Kamrowska-Zaluska & Soltys, 2016). Lithuania (LT00) is characterized by a high dependence on EU funds and a weakly performing innovation system that has not gone through major changes as a result of Smart Specialisation Strategy (Reimeris, 2016). Northeast Romania (RO21) is one of the least developed EU regions where regional strategy planning and its implementation are strongly constrained by the lack of local capacities (Healy, 2016). Southern Transdanubia (HU23) is a Central European region in Hungary with low innovation capacities, a low level of industrialization and no history in the implementation of S3 principles (Hungarian National Innovation Office, 2014).

In terms of the development of their entrepreneurial ecosystems both German regions perform very well, especially Baden-Württemberg, while all the regions in the East have a significant lag, especially Northeast Romania and Southern Transdanubia. Entrepreneurship in Lithuania and Pomerania can be considered as mediocre (Figure 3).

Since ENQ measures the regional availability of external knowledge and the network of FP projects among regions is highly interconnected we can experience less variance in the initial level of the ENQ index (Figure 3). If a region has many connections, it can gain access to a bigger pool of knowledge but it does not mean necessarily that the region's ENQ will rise. On the other side, if a region has few connections but those partners are highly embedded and have large amount of available knowledge, the region's ENQ can rise significantly. Karlsruhe (DE12), Dresden (DED2) and Lithuania (LT00) perform above average in this case.

In our entrepreneurship policy simulations we gradually increase the resources devoted to entrepreneurship with 10 units between 2014 and 2020. The 10 units of additional efforts are distributed among the 14 pillars of entrepreneurship based on the PFB principle, in order to achieve the largest possible improvement in the REDI. The resulting distribution of the additional efforts over the pillars is shown in Figure 4 where only those pillars are displayed that actually gained more effort from the optimization.

To promote network collaborations we gradually increase the number of cooperative projects with the 10 leading partners of all the six regions separately: we add

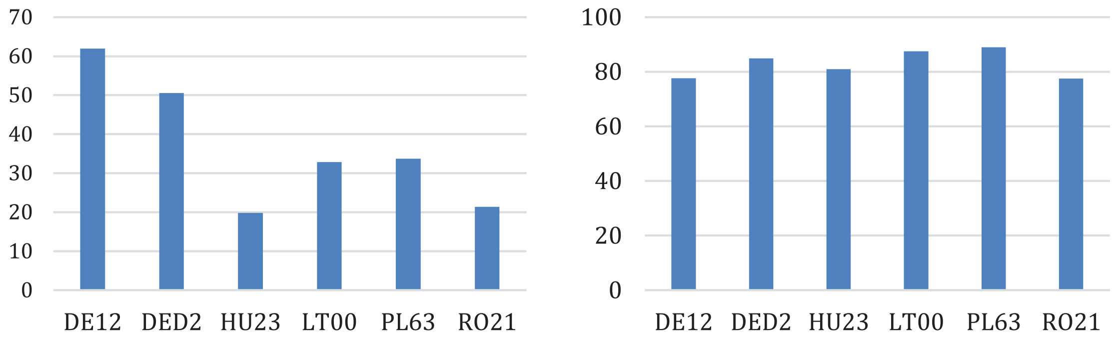

Figure 3. Initial level of the regional entrepreneurship and development index (REDI) (left-hand panel, on a 100-point scale) and ego network quality (ENQ) (right-hand panel, on a 100-point scale) in the selected regions.

10 new cooperations annually between 2014 and 2020. Given that even the less developed regions in our sample introduce around 50–200 new FP or H2020 projects annually, this magnitude of our policy shock does not seem unrealistic even for their cases. The resulting impacts on REDI and ENQ are shown in Figure 5.

The economic impacts of entrepreneurship development are shown in Figure 6. Regions with well-developed entrepreneurial ecosystems (DE12, DED2, LT00) follow similar paths with some variation mostly in the long run. Almost all the factors of successful economic progress are available in these regions: a developed ecosystem, high level of human capital and the effective elimination of bottlenecks. Due to prosperous local conditions presumably these regions can implement the S3 concept without great difficulties. Lagging regions in terms of entrepreneurship grow on a different scale. Pomerania is not able to efficiently eliminate bottlenecks to improve the state of its entrepreneurial ecosystem, which can indicate future challenges for S3 strategy implementations (Figure 5). Partially this effect can be compensated by the presence of a relatively large stock of human capital but the region in general is not able to reach significant improvements. Ecosystem development in Southern Transdanubia and Northeast Romania is even less successful than in Pomerania, however in Romania the low level of skilled human capital weakened the effectiveness of the policy. Therefore, the implementation of Smart Specialisation Strategies can be efficient in those locations only if policy makers take additional actions in favour of local human capital accumulation.

The long-run impact mechanism of network policy is depicted on the right-hand-side panel of Figure 6. Imported knowledge fosters local research initiatives, which eventually results in more patents and larger knowledge stocks both in the region and in the nation. These stocks will carry on a long-term boost for new knowledge creation in the region, which indirectly influences productivity. As a result the network policy impacts do not deplete immediately after 2020. Economic growth slows down only in the long run due to the gradual depreciation of patent stocks.

All the lagging regions (HU23, PL63, RO21) gain notably more knowledge since their position in the network is less central, thus there is more room for further improvements. Interestingly, although Southern Transdanubia accesses the most knowledge from the network (Figure 5) this improvement is not transformed into economic growth due to a low level of local R&D activity. However, Pomerania and Northeast Romania gain less additional knowledge but still experience meaningful economic improvement through their better R&D conditions. On the other hand, developed regions gain only a modest

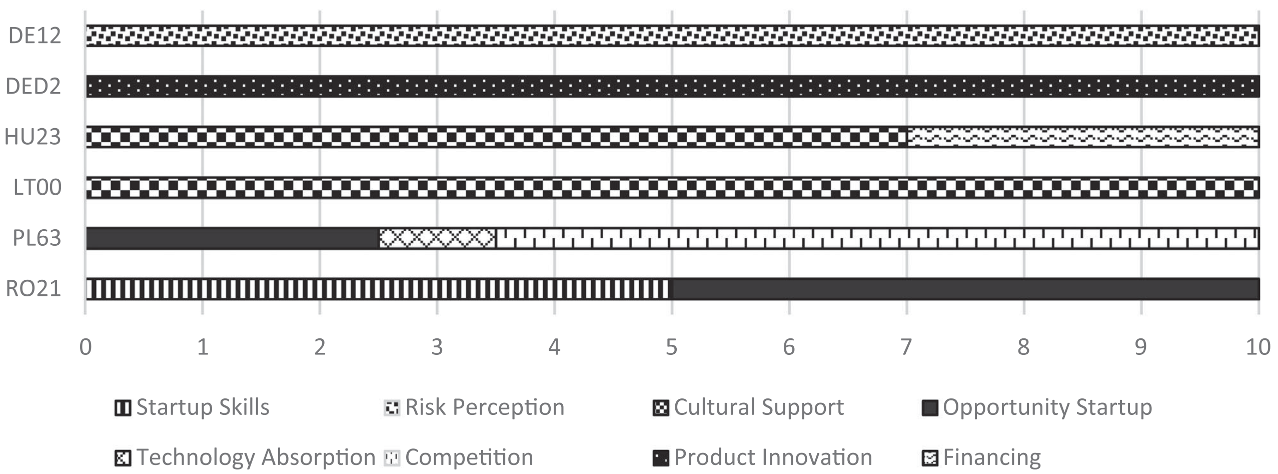

Figure 4. Regional distributions of 10 additional units of efforts among regional entrepreneurship and development index (REDI) pillars.

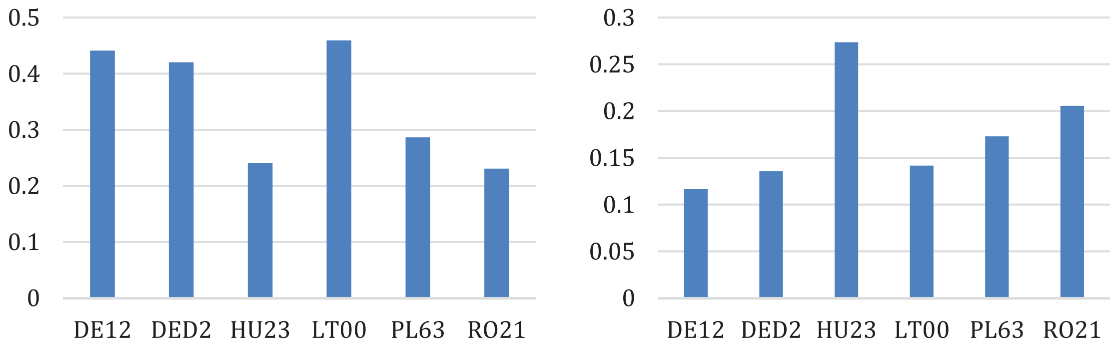

Figure 5. Annual absolute change of regional entrepreneurship and development index (REDI) (left-hand panel) and ego network quality (ENQ) (right-hand panel) in the selected regions.

amount of knowledge since they are already well embedded in the network but the substantial level of local R&D support of networking enhances those gains. As a consequence, we cannot identify significantly different regional development paths.

The dimensions of economic impacts in case of the two policies are different. The comparison of the impacts of the two policy strategies would be complete if we would know the exact costs of the policies targeting entrepreneurship and network developments. However, the monetary costs of adding one additional unit of resources to regional entrepreneurship and increasing the number of regional FP projects by a unit is unfortunately not yet clarified precisely. This will be a future challenge in REDI and ENQ developments.

Our findings suggest that in regions where entrepreneurial development is hindered by many obstacles network policy might contribute to entrepreneurship policy by improving access to external knowledge. Combinations of the two policies could therefore potentially create improved entrepreneurial conditions for the discovery process in smart specialization.

SUMMARY AND CONCLUSIONS

Smart specialization is a recently developed framework to foster regional economic development based on the bottom-up principle of entrepreneurial discovery supported by specifically designed government policies. Although the theoretical concept is quite advanced, there are several challenges in the economic impact analysis of the policies targeting smart specialization. The most important challenges are capturing entrepreneurship and knowledge networks, on the one hand, and embedding their complex interrelationship with wider economic mechanisms, on the other, together shaping the impact of smart specialization policies.

This paper provided a brief review of the GMR-Europe policy impact modelling framework, the latest developments of which renders it suitable for the evaluation of smart specialization policies. We showed the specific ways knowledge networks (the ENQ index) and entrepreneurship (the REDI) are integrated in the model and described the basic mechanisms through which the model is able to capture regional and supra-regional economic effects. With the help of this model framework we made some illustrative simulations of impact assessments of possible smart specialization policies.

Our simulations confirm that targeting regional entrepreneurship and external knowledge development in a smart specialization policy is not equally successful in all regions. The impact of policies depends on several interrelated factors including the level of entrepreneurship in the region, the embeddedness of the region in interregional knowledge networks, the magnitude of policy shocks, the size of R&D and human capital together with further dynamic effects generated by the policy shocks such as changes in (migration of) regional production resources (labour and capital). In less developed regions a single entrepreneurship or network policy remains unsuccessful in supporting the entrepreneurial discovery process unless

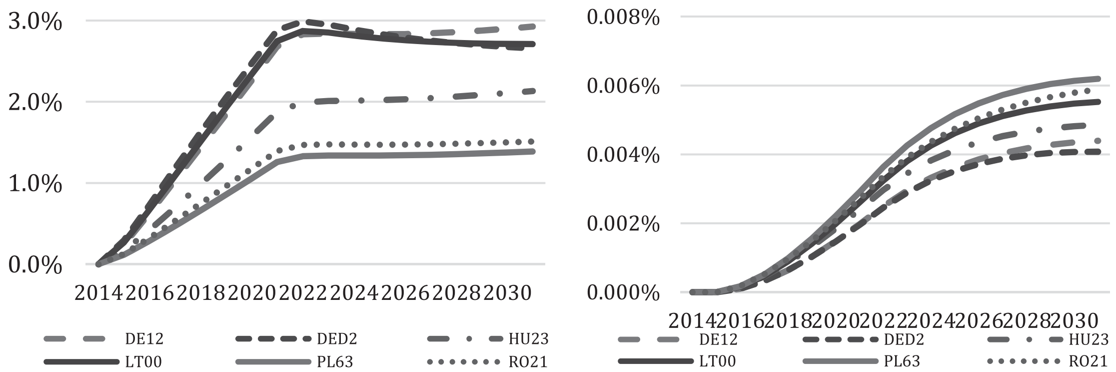

Figure 6. Relative gross value added (GVA) impacts of entrepreneurship (left-hand panel) and network (right-hand panel) policies.

they are combined with a mix of human capital development and targeted R&D promotion policies as part of a carefully designed regional Smart Specialisation Strategy. Economic impact models could helpfully contribute to the design of such a strategy.

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NOTES

1. See Sebestyén and Varga (2013) for a more detailed discussion of the ENQ index.
2. TFP as the residual of the aggregate production function is frequently used in economic analyses to explain the factors in aggregate productivity changes, despite its well-known shortcomings (such as the potential noise in measuring productivity). The application of TFP in recent papers studying the impact of entrepreneurship on aggregate productivity is also common (e.g., Acs, Estrin, Mickiewicz, & Szerb, 2017; Acs, Lafuente, Sanders, & Szerb, 2018; Prieger, Bampoky, Blanco, & Liu, 2016).
3. According to the principles of the GMR system mentioned above, the unit of analysis is the subnational region. The model includes 181 EU NUTS-2 regions in the Eurozone and Central Eastern Europe.

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