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Which Industries should Prioritization target?

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Economic Impact Modeling of Smart Specialization Policy. Which Industries should Prioritization target?

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Abstract
In this paper we argue that it is necessary to apply economic impact models in smart specialization policy in order to come up with reliable economic impact estimations. Solutions suggested in the smart specialization (S3) literature for economic impact assessments cover the economic effects only partially. To estimate the impacts in the industrial, regional and national dimensions in their entirety the application of specifically designed economic models becomes necessary. We extended the GMR-Hungary policy impact model with additional features to make this model applicable for S3 economic impact estimations. In our policy simulations we illustrate how the application of this model helps policymakers in the prioritization process.

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1. Introduction

Smart specialization (S3) is an innovation-based regional economic development policy (Foray 2015, 2019, McCann and Ortega-Argilés 2015). S3 targets the industrial restructuring of regions based on the support of promising new activities (technologies, inventions) that are rooted in the regions' own knowledge bases. Smart specialization became integrated in the EU Cohesion Policy framework as a pre-requisite for the eligibility of ERDF (European Regional Development Fund) financial supports. Nevertheless, smart specialization is not exclusively a European policy. It has also been initiated and implemented in China as well as in the United States (Radosevic et al., 2017 Anastasopoulos et al., 2017).

Smart specialization policy is a unique mixture of bottom-up and top down elements. Entrepreneurial search as a bottom-up process results in a set of local initiatives by regional stakeholders (like entrepreneurs, public research institutions, universities) that form the basis of those activities that will get eventually selected by the government for support. The selection mechanism – called prioritization – is a key component of smart specialization policy. During the selection process, the proposed new activities (technologies, inventions) are analyzed by the government with respect to different dimensions such as their uniqueness or their likely economic significance.

S3 targets industrial restructuring and growth, therefore it is crucial to understand its economic effects (like its impacts on regional GDP or employment) for policy design and evaluation. Estimation of each suggested activity's economic impacts during prioritization helps policymakers to select from available alternatives. Also, understanding the economic effects by ex-post impact evaluations significantly increases the effectiveness of policy learning. However, despite its key importance, economic impact estimation has not yet become integrated into the framework of smart specialization policy (Varga et al., 2019).

Economic impact estimation is an integral part of large-scale policies and it also has been an essential element of EU Cohesion Policy traditionally. Economic effects of policies are usually estimated by policy impact models which calculate the economic impacts of policy interventions such as investment supports, human capital development or R&D subsidies at the regional, national or supra-national (like EU) levels (Ratto et al. 2009, Brandsma and Kancs 2015, Varga 2017). Economy-wide effects emanate from various linkages that the actors directly supported by the policy have with several other actors in the economy. These impacts are most typically channeled by input-output relations with suppliers and buyers, by income multipliers or by knowledge spillovers. The impacts are usually calculated on several economic variables like the output (GDP), employment, wages, or the price level. Understanding economic effects is important in the policy design phase (ex-ante impact assessment) as well as in the evaluation stage (ex-post impact evaluation).

Experiences in the implementation of smart specialization policy in many European regions suggest that knowledge about the economic effects of S3 would significantly increase policy success both in the policy design and in the policy execution phases. Capello and Kroll (2016) point out that many of the less advanced regions are hardly capable of selecting those priorities that are most compatible with their economic potentials. This observation is further supported by Veugelers (2015) who show that despite the remarkable differences in innovation competences among European regions, the composition of the applied set of policies tend to be much more homogeneous. In this regard, significant differences are observed between regions

located in the North-West segments of Europe, mostly characterized by mature innovation systems, and regions situated in the Southern and Eastern parts of Europe where the innovation and institutional environments tend to be much less developed (Kroll et al. 2016, McCann, Ortega-Argilés 2016, Koschatzky 2017, Hassink, Gong 2019).

A number of remarkable advances have been achieved in the past years in order to broaden the analytical toolbox of S3. Some of them are related to the support of developing smart specialization strategies (Fiore 2016), others address a more successful methodology to search for economic potentials (Reimers 2016) or initiate new approaches for the selection of priorities (Healy 2016). The methodologies suggested by Balland et al. (2018) and Crescenzi et al. (2018) stand the closest to economic impact assessment. However, the paper by Balland et al. focuses on complexity and relatedness and do not cover economic effects and the Crescenzi et al. study estimates firm-level but not economy-level impacts of a smart specialization policy. Within the frame of the GMR-Europe economic impact model, Varga et al. (2019) develop solutions for impact estimation of entrepreneurship and innovation network policies, the two instruments which stand clearly in the center of S3-related interventions.

This paper situates economic impact modelling within the framework of smart specialization policy. The prominent role of economic impact estimation in S3 policy design and evaluation is already emphasized in those scientific papers where the theoretical foundations of smart specialization were laid down (Foray et al. 2011, Foray 2015). Nevertheless, with the methodology suggested there only a limited range of the policy's economic impacts can be taken into consideration. Applying appropriately designed economic impact models opens the possibility to track down the contribution of many factors that influence the success of different S3-related development policies in promoting regional growth. However, before turning to the impact estimation of smart specialization policy with economic models, one needs to resolve several methodological challenges. After outlining these challenges, the paper describes the characteristics of economic impact models suitable for S3 impact estimation. With the application of the latest version of the GMR-Hungary policy impact model we illustrate the capabilities of economic impact estimation in prioritization.

The second section positions economic impact modelling within the structure of smart specialization policy, followed by the third section that outlines the GMR-Hungary policy impact model. This model is applied in the fourth section for impact assessment in the prioritization phase of S3. Summary and conclusions close the paper.

2. Economic impact modeling and smart specialization policy

The approach suggested for S3 economic impact assessment has not experienced significant advancements since this methodology was outlined in Foray et al. (2011). According to this, economic impacts (on trade balance, aggregate employment, professional and skilled workforce) of an industrial sector's expansion are related to 'direct and indirect resource inputs from both the private and public sector suppliers' (Foray et al. 2011, p. 13). This proposal thus identifies economic impacts with the so-called 'backward linkages', which can be computed from regional input-output tables. However, backward linkages cover economic impacts only partially, while leaving out other mechanisms (like forward linkages, production effects and the impacts of changes in demand, interregional trade, migration or productivity) from the picture (Miller and Peter 2009). This lack of a general evaluation of wider economic impacts of discoveries calls for the development of more comprehensive tools which are able to link innovative and economic activities within a region, embedded in a wider economic

environment. This paper argues that with the application of specifically constructed economic impact models the estimation of these wider impacts becomes possible.

What are the most important economic impacts initiated by the support of the introduction of a new activity (a technology or an invention) into production? First, local and interregional intersectoral input-output (backward and forward) linkages are crucial in determining the possible impacts of industry support. Those industries that are heavily embedded in the local economy through their input requirements and sales are expected to put the region in motion more easily in terms of economic growth. Through these direct linkages interconnected industries will be influenced positively, but the positive impact will flow further into the local and national economies through the indirect linkages of other firms influenced by the targeted industry. Additionally, the introduction of a new activity might increase investment demand as a potential pull factor of local production. The resulted additional capital stock has a double function: first, it serves as a factor of production for the selected industry, second it is assumed that the newly created capital stock will be owned by households as a source of income. As an income source it will increase households' consumption budget and savings, generating further (consumption and investment) demand.

As production increases, government tax revenues are also expected to grow, allowing for higher public expenditures which can further boost demand. However, when it comes to the question of total local growth, it has to be emphasized that each demand component can be satisfied by the production of other regions as well (at least to a given extent). If local prices decrease less than in other regions, buyers will substitute local and other products accordingly resulting in another potential source/leakage of economic growth through interregional trade linkages. Apart from national markets, regions are also connected to foreign markets, thus by improving local productivity (decreasing prices) foreign demand might increase as well, which can be another pull factor promoting higher growth. Finally, the mobility of primary inputs (labor and capital) has also a key role in the growth path of each region. As a result of a positive shock, additional net immigration is expected in the long run which further increases the stock of factors of production in the region.

The introduction of a new activity therefore initiates a series of interconnected changes in regional and national economies. To track the complex effects of development policies, economic models have been widely applied tools in impact estimation (such as in the regular evaluations of the EU Cohesion Policy). Thus, economic impact modeling appears to be a suitable methodology for S3 impact estimation as well. However, several technical challenges explain why economic impact modeling has not yet found its place in the framework of smart specialization policy. The first one comes from the fact that S3 is not a sector-neutral innovation policy (Foray 2015). Economic models most frequently applied in Cohesion Policy impact evaluation estimate aggregate effects of sector-neutral policies (e.g., infrastructure investment or R&D support) without considering the industrial aspects (e.g., Ratto et al. 2009). On the contrary, S3 targets the development of specific industrial sectors on the basis of some regional initiatives. Modeling the effects is certainly a challenging task since a very micro-level change (the introduction of a new activity that can be a new technology or other inventions) at the industrial sector level needs to be incorporated in a macro (or regional) impact assessment framework. Consequently, economic models applied in S3 impact estimations should integrate the industrial dimension in their structure.

The second challenge is related to the distinguishing feature of S3 that it is a regional development policy. Therefore, the models need to integrate several geographic dimensions

that significantly determine the economic impacts of smart specialization policy. As such positive and negative agglomeration effects should be part of the model in addition to transport costs and the interregional migration of labor and capital (Krugman 1991). Spatial computable general equilibrium (SCGE) models are one of the options to incorporate these geographic effects (e.g., Brandsma, Kancs 2015).

The third modeling challenge is related to the fact that the macroeconomic (national) dimension also plays a role in the policy and as such this dimension should also be integrated in the model framework. This is because the regional effects of smart specialization policy are also influenced by several changes initiated by the national government such as changes in tax rates or changes in the currency exchange rate. GMR (Geographic Macro and Regional) models developed a solution to integrate the macro and regional dimensions into economic impact estimation (Varga 2017)[1].

The fourth challenge is associated with modelling the impacts of some of the policy interventions that got introduced specifically for smart specialization. Though the estimation of the economic impacts of certain measures (like human capital development, R&D subsidies or investment support) is a routine procedure in impact modeling, the estimation of the effects of S3-specific policy measures, such as regional entrepreneurship policy and interregional network development creates a challenge. Varga et al. (2019) offers a solution for modeling the impacts of entrepreneurship and knowledge network support in the context of smart specialization policy.

Therefore, economic models suitable to estimate the impacts of smart specialization policy need to incorporate *S3-specific instruments* (policies targeting entrepreneurship and interregional knowledge network development) in addition to traditional measures (R&D, human capital, investment support). They also have to integrate the *regional* dimension including agglomeration, interregional trade, technology spillover and labor and capital migration effects additional to the *macroeconomic* dimension. Also, contrary to sector-neutral economic models most frequently applied in Cohesion Policy impact assessment, S3-specific models need to be *multisectoral*. With multi-regional, multi-sectoral models the economic impacts of different development scenarios become comparable at regional and supra-regional levels.

How and to what extent may economic impact models contribute to a more effective smart specialization policy? The models can support policy makers with ex-ante impact assessments (to help governments to come up with more informed decisions in the prioritization process). They can also assist policymaking by evaluating the effects of various interventions (e.g., R&D, entrepreneurship or innovation network policies) that facilitate industrial restructuring based on the introduction of new activities. This evaluation is possible in the monitoring phase (to inform about which policy works and how the policy mix might need to be further adjusted) as well as in the ex-post evaluation phase (to estimate the impacts of the policy at the regional, national and even at the supra-national levels)[2]. The next section introduces the most recent version of

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[1] According to our knowledge the MASST (MAcroeconomic, Sectoral, Social, Territorial model) project is the other currently existing initiative that integrates regional and macroeconomic dimensions (Capello 2007). However, MASST is a forecasting and not a policy impact model.

[2] Most policy impact models like the GMR-Hungary model can trace the impacts on economic variables like the effects on industrial and aggregate regional/national/EU employment, GDP. It is possible to set targets like the change in regional employment or GDP in the planning stage of S3. Even economic models can be of help to estimate ex-ante the likely impacts of policies that support the chosen activity in a certain industry. In the monitoring and ex-post evaluation phase the models can be of help with respect to estimating the effects.

the GMR-Hungary economic impact model. This model bears the features detailed above to make it applicable for S3 economic impact estimation. To demonstrate the model's capabilities in S3 economic impact assessment GMR-Hungary will be applied in illustrative simulations in the context of prioritization in the fourth section.

3. The GMR-Hungary policy impact model[3]

GMR-Hungary is a multi-regional, multi-sectoral economic impact model. GMR stands for Geographic, Macro and Regional modeling. It is regional because the impact of development policies (like investment or R&D support) is modeled at the level of sub-national regions. It is macro because the effect of national level policies (monetary, fiscal policies) is also taken into consideration and it is geographic because the model integrates space into its structure represented by agglomeration effects, interregional trade, labor and capital migration, regional and interregional knowledge spillovers. The GMR approach has been employed to construct economic impact models for Hungary, the European Union and for Turkey. GMR models have been applied to estimate the impacts of various regional development policies such as the effects of Cohesion Policy in Hungary and in European regions or the impacts of EU Framework Policies.

This section shortly describes the GMR modelling approach that we use here to evaluate the economic impacts of S3-related industry support strategies. First, we discuss the general features of the model, then, a brief account of the modelling system's most important building blocks is given, including the specificities of the newly developed multisector spatial computable general equilibrium model block.

3.1. The general features of GMR economic impact models

The GMR modelling framework was designed, and continuously improved in order to support development policy decisions through enabling ex-ante and ex-post scenario analyses. The framework builds on the tradition of standard macroeconomic modelling (ESRI 2002), multisectoral modeling (Eliasson 1985), CGE modelling (Bayar 2007, Atuesta, Hewings, 2013) or the more recently developed DSGE approach (Ratto et al. 2009). On the other hand, it also accounts for the geographic effects of different policy interventions (e.g., agglomeration, migration, interregional trade) allowing for the calculation of both regional and national impacts of these interventions. The inclusion of geography into impact modelling allows us to account for agglomeration externalities, knowledge spillovers, migration of production resources, trade and transportation costs as well as convergence or divergence of spatial units. For more details on this modelling framework, see Varga (2017) or Varga et al. (2019). In this paper, we use the latest version of the GMR models for Hungary, which is a multisector-multiregion model. For an account of previous model specifications and applications see Schalk and Varga (2004) and Varga (2007) (GMR-Hungary), Varga and Baypinar (2016) (GMR-Turkey), Varga (2017) and Varga et al. (2019) (GMR-Europe).

3.2. The structure of the modeling system

From a methodological point of view, the structure of the system is built around three traditions in economics, each one represented by a model block: (1) a productivity (TFP) block, which incorporates relationships described in the field of the geography of innovation (e.g. Anselin et al. 1997, Varga 2000, Sebestyén and Varga 2013); (2) a spatial computable general equilibrium

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[3] More details about the latest version of the GMR-Hungary model is provided in the technical report entitled "The GMR-Hungary multisector-multiregion economic impact model" here:
https://ktk.pte.hu/sites/ktk.pte.hu/files/uploads/rierc/The%20GMR_HU%20multisector-multiregion%20model%20final.pdf

(SCGE) block, rooted in the new economic geography (e.g. Krugman 1991, Fujita et al. 1999); (3) a macroeconomic (MACRO) block building on traditions in macroeconomic analysis. In the following sections, we briefly describe these building blocks.

3.2.1 The TFP (productivity) block
Total factor productivity (TFP) is one of the most important variables in the model system, accounting for the overall productivity effects of different innovation-related policy interventions (such as R&D subsidies, entrepreneurship development policies, human capital and interregional knowledge network development programs). This block models the most important factors behind innovation and their interactions in influencing regional productivity levels. The TFP block is based on the knowledge production function literature (Romer, 1990), and describes the production of new knowledge as a function of utilizing knowledge production factors like R&D efforts, labor input (employment), knowledge that already exists both at the regional and national levels. In addition to these standard factors of knowledge production, a novel feature of our approach is to include two other factors of knowledge creation, which are important in smart specialization strategies. The first is the knowledge available through interregional knowledge networks, which we measure by the ENQ index.[4] This knowledge is assumed to enhance the effectiveness of R&D efforts in the region. The second is the role of the entrepreneurial environment in shaping regional productivity levels measured by the REDI index[5] in the model. Entrepreneurial environment is assumed to have strong interaction with the level of human capital in the regions, reflecting the knowledge spillover theory of entrepreneurship (Acs et al. 2009).

The TFP block is the richest component of the GMR-framework in terms of policy intervention tools, as it accounts for the direct impact of policies affecting any of the knowledge factors mentioned above. The block is capable of simulating the region-specific impacts of different policy interventions on regional productivity levels. This change in productivities is then transferred to the SCGE and MACRO blocks, which calculate the economic impacts of these productivity improvements both at the regional and aggregate levels.

Beyond its components, the TFP block is a system of empirically estimated equations describing the relationship between region-level productivity and its key determinants mentioned above. The parameters of the TFP block are estimated, using an econometric model with panel data.[6] Using these estimated parameters, a calibration process is implemented to provide region-specific values of some of the parameters.[7]

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[4] For detailed description see Sebestyén and Varga (2013).

[5] For detailed description see Szerb et al. (2017).

[6] The TFP model block is based on the following two equations (variables are in logarithms):

$$\text{Patent}_{i,t} = \beta_0 + \beta_1 \text{RD}_{i,t-1} + \beta_2 \text{RD}_{i,t-1} * \text{ENQ}_{i,t-1} + \beta_3 \text{PatStock}_{i,t-1} + \beta_4 \text{EMP}_{i,t-1} + \beta_5 \text{SoDum}_{i,t} + \beta_6 \text{SzaDum}_{i,t} + \varepsilon_{i,t}$$

$$\text{TFP}_{i,t} = \beta_0 + \beta_1 \text{HumCap}_{i,t-1} + \beta_2 \text{HumCap}_{i,t-1} * \text{REDI}_{i,t-1} + \beta_3 \text{RegPatStock}_{i,t-1} + \beta_4 \text{BpPeDum}_{i,t} + \beta_5 \text{RegPatStock}_{i,t-1} * \text{BpPeDum}_{i,t-1} + \beta_6 \text{KeDum}_{i,t} + \beta_7 \text{VaDum}_{i,t} + \vartheta_{i,t}$$

where Patent stands for number of new patents per region, RD is regional R&D expenditures, ENQ is regional ENQ-indexes, PatStock is the national patent stock, EMP is regional employment, TFP stands for regional TFP values, HumCap is regional human capital, the REDI index is calculated to each region, RegPatStock is regional patent stock. Dummy variables stand for selected counties. Interaction terms in the equations ensure that the effects of the policy variables (RD, ENQ, HUMCAP, REDI) get region-specific parameter estimates. Therefore, policy shocks invoke regionally different impacts on TFP. Regional specificity of estimated parameters is further enhanced by the calibration process that follows the econometric estimation.

[7] After econometric estimations the next step was to approximate the best accessible goodness-of-fit via calibration which is a more accurate manner of modeling long run regional diversity. The two-equation model was recalibrated

3.2.2 The SCGE block

The TFP block calculates the expected effects of innovation-related policy efforts on regional productivity levels. These impacts serve as primary input for the spatial general equilibrium (SCGE) model block. The SCGE block is designed to simulate the likely impacts of development policies (supports to enhance R&D, human capital, entrepreneurship, knowledge networks, investments and infrastructure developments) on regional economic variables like output, prices, wages, employment, etc. The most important feature of this block is that it takes into account economic interactions across regions such as the trade of goods and services, the inter-industry linkages (input-output connections) and the interregional as well as inter-sectoral mobility of production factors. Furthermore, transportation costs are explicitly accounted for and (positive and negative) agglomeration effects are taken into account in this model block as well. The SCGE model is static. Dynamics is introduced to the model by endogenously determined TFP, labor and capital migration and capital accumulation. The SCGE model operates with perfect competition.

In the SCGE block, we distinguish short- and long-run equilibria. In the short run all markets clear in all regions, given the productivity levels and the stock of production factors in every region, as well as taking into account inter-sectoral linkages, transportation costs and interregional trade. However, this equilibrium does not necessarily mean that the whole interregional system is in equilibrium. In the long run, differences in interregional utility levels (depending on per capita consumption and population density) might trigger interregional migration of production factors, changing the market conditions in the next time period and leading to adjustments in the short run equilibria, further changing utility levels and so on. Interregional utility differences are eliminated through this mechanism, leading to a spatial equilibrium in the long run.

In the following paragraphs, we describe the representation of the main economic actors in the model and the most important assumptions behind them. In the SCGE model block we represent all the important actors in a general equilibrium setting, including productive industries, households, government, investment and foreign actors as well as their interactions.

Starting with production, *firms* (represented by different activities) are characterized by profit maximization and they operate in perfectly competitive markets. Profit is maximized subject to the technology of production, described by a nested production function. Firms satisfy both the aggregate foreign and domestic demand, which is made up of the sum of demands for households' consumption, investments, government purchases and intermediate inputs.

Regional *households* are assumed to maximize their utility. We defined two kinds of utility: 1) utility driving the choice of consumption of different goods and services, 2) interregional utility driving interregional migration. Households' income is composed of wages and capital incomes (we assume that regional capital stock is owned by households). This income is used to pay taxes, save and consume. In the case of interregional migration, households consider the interregional differences of utility levels based on regional real consumption possibilities per capita and the level of housing per capita (as an approximation of negative agglomeration externalities). Migration occurs 'between' discrete time periods, thus in each year regional economies face an exogenous amount of labor supply. As a result of migration, interregional

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until we reached the possible minimum of mean average percentage error between the original and the predicted left-hand-side values. At the end of an optimization process three parameters were calibrated: the constant terms and the parameter β_3. Constants were calibrated for the purpose of catching regional diversity, while the parameter of the regional patent stock variable became the selected one because of goodness-of-fit properties.

utility differences are continuously eliminated in the long run. The capital stock is assumed to be partially mobile between regions and industries with some level of friction. A portion of regional capital stock might be used by other regions' actors since households are motivated to relocate their invested capital to locations where capital is relatively scarce (thus its price is higher).

Investments are modelled in a savings-driven way, so that they are financed by savings of the households, the government and foreign actors (rest of world). Households' saving rate is exogenous, as well as the amount of foreign savings but exogenous government deficit is controlled by the MACRO block in a recursive way (discussed later). All markets clear in equilibrium, thus total saving and investment must be equal. Since savings are determined by exogenous saving rates and foreign and government savings in each discrete time period, investment must adjust to maintain equilibrium. As a result, total investment demand is driven by savings.

Although we account for the most important functions of the *government* in a general equilibrium framework, our approach can be still considered as partial since we do not account for all the connections between central government and the rest of economy. The government collects taxes and use this revenue to make purchases of goods and services. Financing healthcare, education and other government-related activities are accounted for in these channels. Other channels such as unemployment benefits and other social and non-social transfers are not modelled explicitly. We break down taxes into commodity and production taxes (and subsidies), with exogenously fixed ad valorem tax rates. The tax rates are calibrated on the basis of the empirical interregional input-output table. Government saving (deficit) is controlled by the MACRO block.

The *rest of world* is represented by imports and exports in the model. Since Hungary is a small and open economy, world prices are assumed to be exogenous. The price of exports and imports measured in the domestic currency is influenced by the endogenous exchange rate, which is assumed to control the balance of payment equation (the difference between the total value of imports and exports, also assumed to be exogenous). In case of imports, we sum up all foreign purchases made by industries, households, investment and the government. If imports or exports are too high/low the exchange rate will adjust accordingly to keep the balance of payment at its exogenous (calibrated) value. Since our model is not designed for international trade issues, more sophisticated aspects of international relations are ignored in the model setup.

The *domestic trade of goods* (and services) across regions is a vital part of the GMR approach, connecting all actors of the economy. Total domestic supply of products and services is assumed to equal total domestic demand in all time periods, however its regional structure can change. Firms are allowed to ship their products to any of the regions and final users and firms can purchase products from all regions. These mechanisms are driven by interregional prices which are influenced by many factors in the model (including productivity, the availability of local inputs, dependency on foreign inputs, etc.), but most importantly by interregional transportation cost, which is assumed to follow the exogenous iceberg logic (Samuelson, 1952). Our approach to interregional demand of goods and services assumes that goods produced in different regions are close but not perfect substitutes for regional actors. As a result, actors make decisions about the regional source (origin) of their purchases on the basis of their preferences and the actual market prices, including transportation costs.

Such a detailed spatial CGE model requires a large amount of statistical data, both at the regional and sectoral levels, which is usually not available in official databases. Particularly, interregional inter-industry transactions are not surveyed by most statistical offices, although crucial in calibrating such models. Our model is based on an estimated interregional input-output table for which we used the combination of standard regionalization methods (e.g. Jackson, 1998), and the available regional and national level data in Hungary (including the national input-output table). The resulted table represents 20 Hungarian NUTS 3 regions (19 counties and the capital Budapest) as well as 37 aggregated NACE rev. 2 industries in 2010. All equations of the SCGE model were calibrated based on our estimated interregional I-O table in a way that in the reference year (also the first year of the simulations, 2010) the model equations replicate the benchmark "database".[8]

3.2.3 The MACRO block

The macroeconomic (MACRO) block of the GMR framework serves as the point, where aggregate relationships and policies can be handled (government debt, fiscal policy, etc.) and where aggregate impacts of different interventions are represented. In the present setup, one of the main roles of the MACRO block is to drive government debt and deficit on the basis of the national debt-to-GDP ratio. It is assumed, that the government will take actions in order to reach an exogenously given target level of the debt-to-GDP ratio in the long-run. More specifically, it adjusts current deficit and purchases in order to keep the debt ratio around its target level. In the present model, the government runs a fixed deficit rate (given in a separate time period) which is changed according to the debt-to-GDP ratio. The adjustment of the deficit is stronger if the growth rate or inflation is low or if the interest payment (after government debt) is relatively high. When the economy grows faster, the debt-to-GDP ratio automatically decreases without cutting back on current deficit. Similar argument can be made in case of inflation. The sensitivity of current deficit to the macroeconomic conditions is calibrated in a way that the long-run debt-to-GDP ratio is sufficiently approximated in the baseline scenario.[9] Furthermore, there is a significant overlap between the macro and the SCGE block since in the latest version of GMR-Hungary we apply a recursive dynamic SCGE model where the dynamic elements (such as capital accumulation, investment decisions, etc.) are accounted for in the SCGE block.

3.2.4. Interactions between the sub-models

Figure 1 shows the interactions of model blocks within the mutually interconnected model system. As mentioned before, the TFP block controls changes in regional productivity levels, which provide the core inputs to the SCGE block. Changes in regional productivity levels then influence the allocation of production factors, production, trade, migration, etc. The SCGE block calculates how regional economic variables respond to these effects, as a result of overall market clearing within and across regions and industries. Economic effects of those policy shocks that enter the model in the SCGE block (i.e., private investment and public infrastructure development subsidies) are also driven by the mutual interactions of the SCGE and TFP model blocks. In addition to changes in several economic variables (like GVA, employment, wages, prices, etc.) induced interregional migration in the next period alters regional employment and as an agglomeration force this affects the level of TFP which then induces further changes in the interconnected model system.

On the other hand, changes in prices, tax revenues, economic growth will have an impact on government spending in the next year calculated by the MACRO block. A change in deficit thus influences current demand of different products through public spending, but on the other

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[8] Further details about the modelling approach, datasets and estimation can be requested from the authors.
[9] This solution represents a fiscal policy rule, targeting a public debt to GDP ratio.

hand the deficit must be financed by domestic or foreign savings. As a result, higher deficit will have a considerable investment loss, which influences long-term growth possibilities. We account for labor migration and capital accumulation between two discrete time periods. In the next time period, changes in employment (as a result of the above effects) are channeled back to the regional TFP block accounting for increased positive agglomeration effects in knowledge production. With higher level of regional employment productivity is further improved *ceteris paribus*, which is then channeled back to the SCGE block and the iteration goes on. As a result of the interactions between each block both supra regional (national) and regional economic impacts are calculated.

As also shown in Figure 1, different policy interventions can be introduced at different levels of the model system. Innovation-related interventions (e.g. R&D support, educational programs, network-development, entrepreneurship programs, etc.) are handled in the TFP block. Region-specific investment support, infrastructural developments are accounted for in the SCGE block, while macro level policies are simulated by the MACRO block (e.g. changes in government spending, tax rates). The direct and indirect effects of all these interventions will flow through the other model blocks and the final economic impacts are determined by the simultaneous interactions between these model components, together with the inner mechanisms of each. As a result, our policy impact simulations are able to track the likely effects of a variety of policy interventions, taking into account complex spatial and inter-industrial interaction mechanisms.
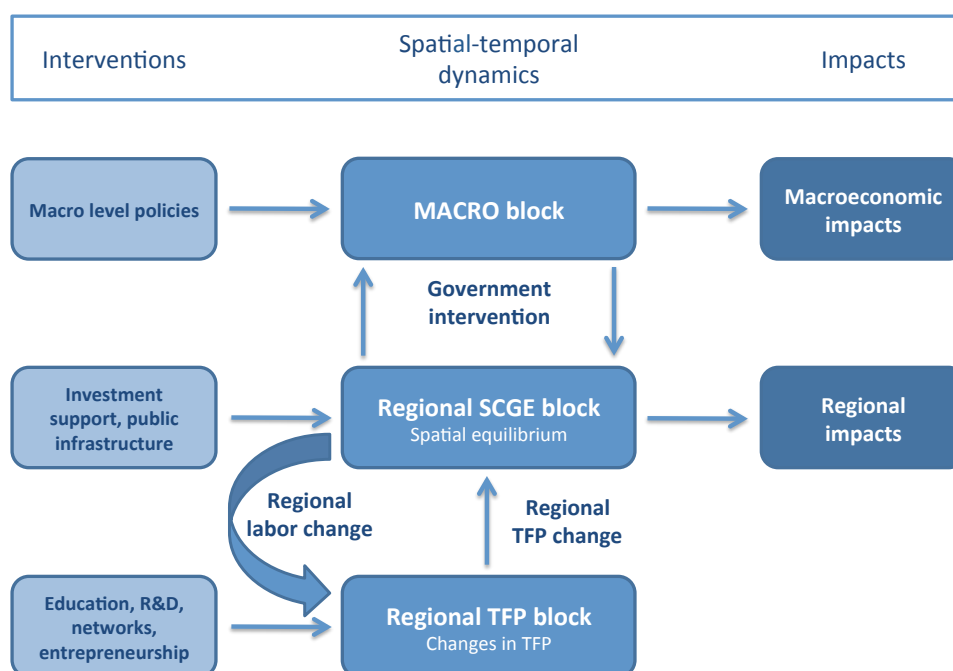

Figure 1: The interconnection of the main blocks, policy variables and impacts in the GMR-Hungary model

4. An illustrative policy impact assessment: Which activity to support from potential alternatives in prioritization?

Establishing a strict assessment procedure in the prioritization process is crucial to minimize the costs of making mistakes (Foray 2015). New activities (inventions, technologies) are assessed along three main dimensions in the course of prioritization: the activity's individual features, its regional spillover capacity and the new activity's economic significance. The first

dimension incorporates individual characteristics of the activity such as its degree of novelty, the extent to which it targets the discovery of new opportunities for the region, the existence of global demand, identification of main competitors and regional availability of key supply factors (Foray 2015). A new activity may be highly valued according to the first dimension, but it might not be rich enough in spillover potentials to generate firm concentration. The second dimension of assessment therefore reflects the capacity of the activity to initiate the process of firm agglomeration by means of imitative entries. Even if a discovery has excellent spillover potentials the project might be too narrow in terms of its regional economic significance. As a consequence, firm concentration induced by the new activity would not result in significant impacts on regional jobs or GDP (Foray 2015). The third dimension of discovery evaluation thus targets its likely impact on the region's economy.

To operationalize the multi-dimensional principles of assessment in prioritization outlined in the previous paragraph we develop an empirical modeling framework. This framework will be applied in concrete prioritization exercises in the second part of this section. Out of the three criteria above only the second and third conditions (spillover capacity and economic effects) become legitimate for economic analysis as evaluation along the first criteria (the activity's individual features) is best carried out by experts of innovation in the given field. Spillover capacity reflects the strength of an activity to initiate the concentration of firms producing competing or related products. This practically means that firm entry initiated by learning from the original activity increase the diversification of the activity's industry. On the other hand, economic impacts reflect the effects which emerge when the activity gets introduced in production.

According to the assessment principles of prioritization, those activities are the suitable recipients of government support that potentially generate significant firm concentration and at the same time provide the basis of meaningful regional economic impacts. The difficulty arises when one wants to empirically measure spillover capacity and economic impacts. In the S3 literature spillover capacity is associated with the size of the industrial sector of the activity and the connectedness of the sector with other industries. (Foray et al. 2009, David et al. 2009, McCann, Ortega-Argilés 2015). The larger the size and connectedness of the sector the higher the probability of learning from the original activity by others in the region.

We model potential spillovers from a given activity on the basis of the position the activity fulfills in the knowledge network of industrial sectors in the region. This network is proxied by regional input-output connections. Our choice for the input-output network is supported by the finding of innovation surveys that buyers and suppliers are the leading sources of information for innovation.[10] The position of an industrial sector within the network measures the extent to which new knowledge in a sector's activity could potentially spill over to other industries in the region. To measure position, we apply the eigenvector centrality index. Eigenvector centrality of a sector is high if that sector is strongly connected to many other industries which are also strongly connected to further industries etc. Since the strength of connections in the input-output network reflect the size of the transactions between sectors, eigenvector centrality is able to measure both the connectedness and the size of the industries as suggested by previous studies mentioned before.

With respect to economic impact estimation we apply the GMR-Hungary model. We assume that the introduction of the activity to the production structure requires certain government

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[10] For a good example consult the corresponding results in the Community Innovation Surveys: https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=inn_cis10_sou&lang=en

supported investments in the activity's industry. Policy support of an activity is expected to result in future concentration of firms and the economic impacts (on GDP or employment) after the activity gets introduced in the production of the sector. However, the impacts in those two dimensions will most probably vary by industries. With the application of this methodology we are able to select those industries where S3 support appears promising. In the selected sectors, both economic impact and spillover capacity stand above regional average.

4.1 Measuring the spillover capacity of industrial sectors
Motivating centrality – spillovers
When it comes to knowledge spillovers, there is an increasing recognition that the structure of the network within which actors are embedded and through the links of which information and knowledge flows are important. These knowledge networks are shown to be important for innovation and diffusion (see e.g. Stuck et al. 2015, Grabher 2006, Glückler 2007). Some studies also emphasize that different actors can have different access to knowledge due to their differing embeddedness in these networks (Giuliani and Bell 2005, Boschma and ter Wal 2007, Sebestyén and Varga 2013). One of the most prominent aspects of this embeddedness is how central actors are within these networks (Stuck et al. 2015). There is also a wide literature emphasizing that different aspects of network position, the most prominent of which is network centrality, significantly contributes to the innovative performance of actors (see e.g. Zaheer and Bell (2005), Powell et al. 1999, or Tsai 2001).

Eigenvector centrality
There are several ways to express how central nodes are in the network and the literature argues that different measures highlight different aspects of network position (Meng et al. 2017, Oldham et al. 2019, Schoch and Brandes 2016). In this paper we use eigenvector centrality, a commonly used measure to capture centrality within the whole network structure (see e.g. Bonacich, 2007). Eigenvector centrality builds on a recursive definition: a given node is assumed to be more central if its partners are more central as well. Formally, we can define

$$c_i = \frac{1}{\lambda} \sum_{j=1}^{n} a_{ij} c_j$$

(1)

where c_i measures centrality of node i, a_{ij} is the general element of the adjacency matrix of the network, reflecting the existence or the strength of connection between nodes i and j, while λ is a constant. When written for all nodes i, the expression in (1) can be rendered in the following matrix form:

$$\lambda \mathbf{c} = \mathbf{A}\mathbf{c}$$

(2)

where $\mathbf{c}$ is the vector of centralities and $\mathbf{A}$ is the adjacency matrix of the network. Equation (2) is an eigenvalue problem and it can be shown that the eigenvector corresponding to the dominant eigenvalue of $\mathbf{A}$ provides the adequate centrality measures as defined above. The merit of this measure of centrality is that it takes into account the whole network and the embeddedness of nodes in it while also controlling for the weights of the connections, which indirectly reflect the size of industries and the extent to which they are connected to other sizeable industries. Eigenvector centrality is classified as a centrality measure reflecting influence in a network (Jackson, 2010). This means that the centrality measures obtained with this method reflect the extent to which a disturbance at a given node in the network affects other nodes in the system. In our context this means that eigenvector centrality is a suitable way to

capture spillover potential as it is able to show how the changes in a given industry is able to affect the innovation system of the region through knowledge spilling over supplier and buyer connections as primary channels of knowledge flows.[11]

Eigenvector centrality in our regional context
In order to calculate eigenvector centralities as reflections of regional spillover capacities, we focus on the regions separately and evaluate the embeddedness of sectors within the regional economies. We use the network of observed input-output linkages between sectors as two of the most important channels of knowledge spillovers namely buyers and suppliers.

Let's denote the matrix of input and output linkages by $\mathbf{R}$, where the general element $r_{pi,qj}$ represents the transaction volume between sector j in region q as the buyer and sector i in region p as the supplier. Note that this network of transactions is directed. First we render the network undirected by simply adding the two-way transaction volumes: $\bar{r}_{pi,qj} = \bar{r}_{qj,pi} = r_{pi,qj} + r_{qj,pi}$. These values are stored in matrix $\bar{\mathbf{R}}$, which is now reflecting both supplier and buyer relationships between two sectors as a general proxy for potential knowledge flows between them.

Then, centralities are calculated using intra-region linkages only. This means that we separate diagonal blocks of matrix $\bar{\mathbf{R}}$, corresponding to regions. Technically, the intra-regional network of region r is considered as $\bar{\mathbf{R}}^r$, where the general element is $\bar{r}_{ij}^r = \bar{r}_{ri,rj}$. After setting up these undirected, intra-regional transaction matrices, the centrality measures of the sectors in region r are obtained as the elements of the eigenvector corresponding to the dominant eigenvalue of $\bar{\mathbf{R}}^r$ (see equations (1) and (2) for details).

We have to note two things. First, the obtained centrality scores are invariant up to a scaling constant – they reflect the relative differences of the centralities of the sectors. And second, they are not directly comparable across regions as they result from separate eigenvector calculations. In order to provide a type of comparability, we calculate the average centrality scores in every region and use these values as normalizing constants for the raw centralities:

$$\hat{c}_i^r = \frac{c_i^r}{\bar{c}^r}$$

(3)

where c_i^r is the raw centrality score of sector i in region r, $\bar{c}^r$ is the average of these scores in region r while $\hat{c}_i^r$ are the normalized centrality values, which reflect the percentage deviation of the centrality of sector i in region r from the regional average.

4.2 Estimating the economic impacts of the support of industrial sectors
Centrality is helpful in the prioritization stage to indicate spillover capacities. On the other hand, we need the application of a comprehensive economic impact assessment model in order to estimate the economic effects of the support of new activities that are expected to diversify certain industrial sectors. In our scenarios, we examine the effects of an identical, but separate

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[11] As Aldasoro and Angeloni (2015) point it out, eigenvector centrality can be defined as a limiting case of the Rasmussen-Hirschmann indices which are the row-sums of the Leontief inverse used in input-output analysis and are commonly used to express the extent to which given sectors are able to affect or prone to be affected by other sectors in the economic system.

investment support to every industry in a region. We set the size of the industry-specific intervention equal to 1% of the total regional capital stock. Then we distribute this investment support over 9 years between 2014 and 2023 based on the expected trend of the distribution of EU funds (illustrated by Figure 2) which is based on past Hungarian experiences. Economic impacts are measured as the average annual change of total regional value added between 2014 and 2029. Therefore, in this experiment the interest lies in total regional effects of industry support policies.
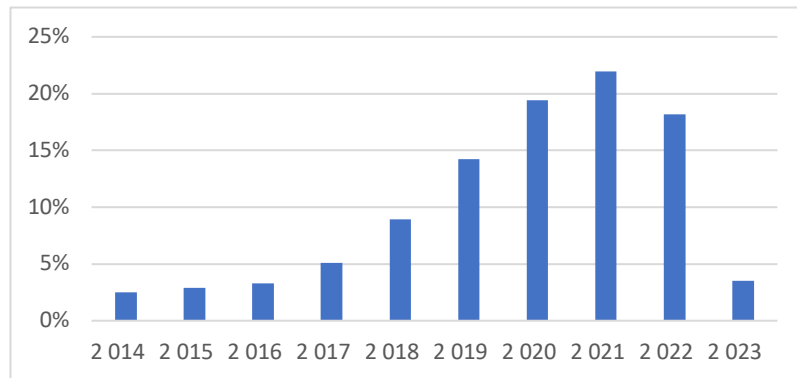

Figure 2: The distribution of investment support over time

4.3 Industry selection for S3 support: Regional cases
In this section we apply our framework to identify those sectors where S3 support of new activities is expected to result in comparatively high spillovers and economic impacts. The aim of these simulations is to illustrate the capabilities of our modeling framework, so we restrict the analysis to a limited set of regions. The sample simulations are carried out for three Hungarian NUTS 3 regions with significantly different economic potentials but still representing typical Hungarian counties: Budapest, Győr-Moson-Sopron and Baranya county. Budapest is the most developed region of Hungary, whereas Győr-Moson-Sopron is a traditional industrial region and Baranya is a rural county. For presentation purposes both measures (economic impact and centrality) are compared to each of their regional averages in the diagrams.

In our illustrative simulations we highlight the basic drivers of regional economic growth in case of an identical industry specific investment support. The economic effects are the result of complex interactions of different mechanisms in the impact assessment model. In what follow we elaborate the most important determinants of potential regional growth. First, we found that capital (and labor) intensity of industries is highly important in the determination of potential regional growth. Since labor intensive activities rely heavily on labor, supporting these activities can improve regional attractiveness in terms of labor migration. However in the capital of the country due to negative agglomeration externalities these effects are reduced. As a result labor intensive activities perform better in the countryside, and capital intensive activities operates better in the capital. Second, apart from capital intensity local inter-industry linkages also influence how industries may impact regional growth. Industries with strong backward and forward linkages are better capable of promoting higher growth due to local multiplier effect. Third, if industries are connected to highly productive sectors (via I-O relations) economic effects can be further enhanced. Forth, foreign demand can be another source of local growth however industries that are highly dependent on foreign inputs have less capabilities to positively affect regional production since import expenditures weaken the local multiplier effect. Finally, additional income created as the interplay of all the above-mentioned

effects can further increase the production of some sectors that satisfy different groups of final demand groups (consumption, investment, government).

In Figure 3 we highlighted the value of the location quotients calculated in case of each regional industry based on industrial value added. For presentation purposes we narrowed down the scope of analyses to industries that show regional specialization (LQ>1). Budapest the most developed region of the country concentrates many service sectors (publishing, telecommunication, informatics, financial services, scientific activities, R&D, etc.), some knowledge intensive manufacturing is also located in the region (e.g. pharmaceuticals, coke production) and government services.
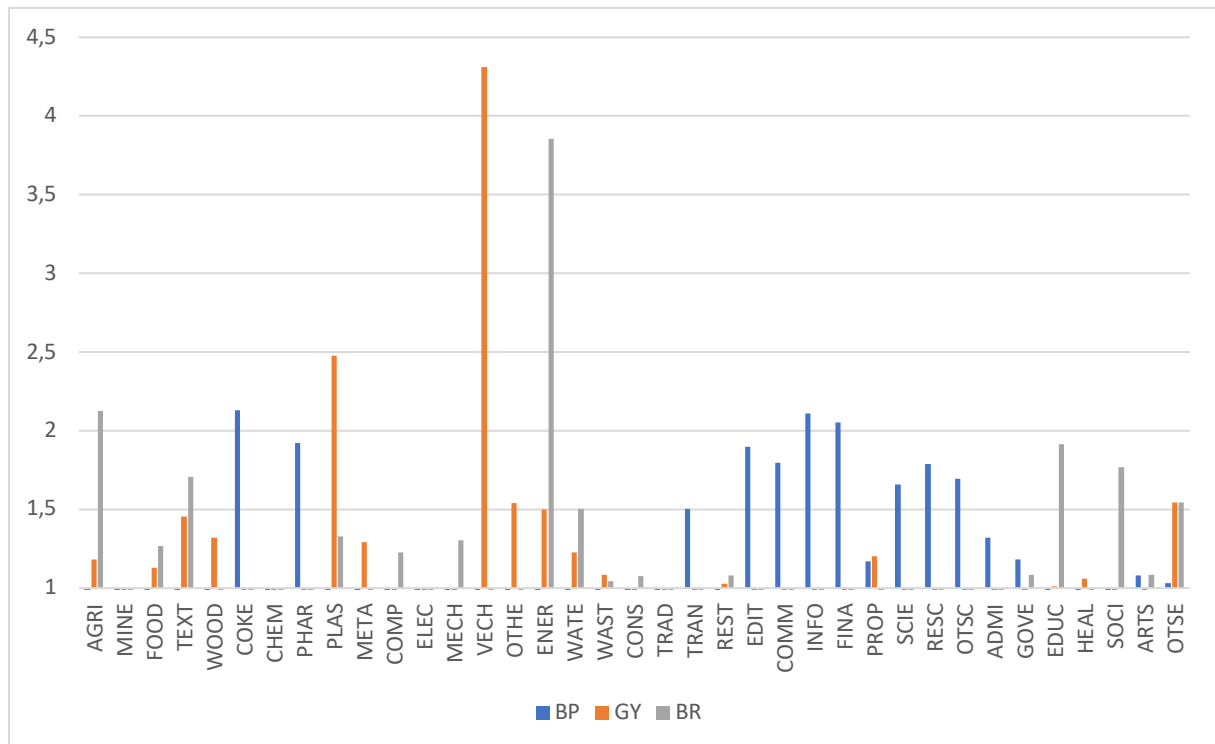

Figure 3: Location quotient of industries in the three selected regions

Győr-Moson-Sopron county is considered as a developed, industrialized region in Hungary with strong linkages to the German automobile industry. However GDP per capita is more than half of the value in Budapest (approx. 16000 EUR in Győr and 28000 EUR in Budapest). The specialization of Győr-Moson-Sopron county shows a clearly different picture. We can identify most of the manufacturing activities as specialization (especially motorvehicles /due to the local plant of a German car manufacturing company/, plastic, metallic products, textiles, paper production, other manufacturing).

Baranya is one of the poorest, under-industrialized regions in Hungary. Its GDP per capita measure is only one third of the value of the capital (around 9000 EUR). In case of Baranya, specialization is concentrated only to a small number of industries. These industries consist of traditional sectors (e.g. agriculture, the manufacture of food and textile), the energy sector (thanks to a local power plant), some of manufacturing to a given extent (due to some smaller representatives of global companies) and education since Pécs (the capital of the region) is characterized as a university town.
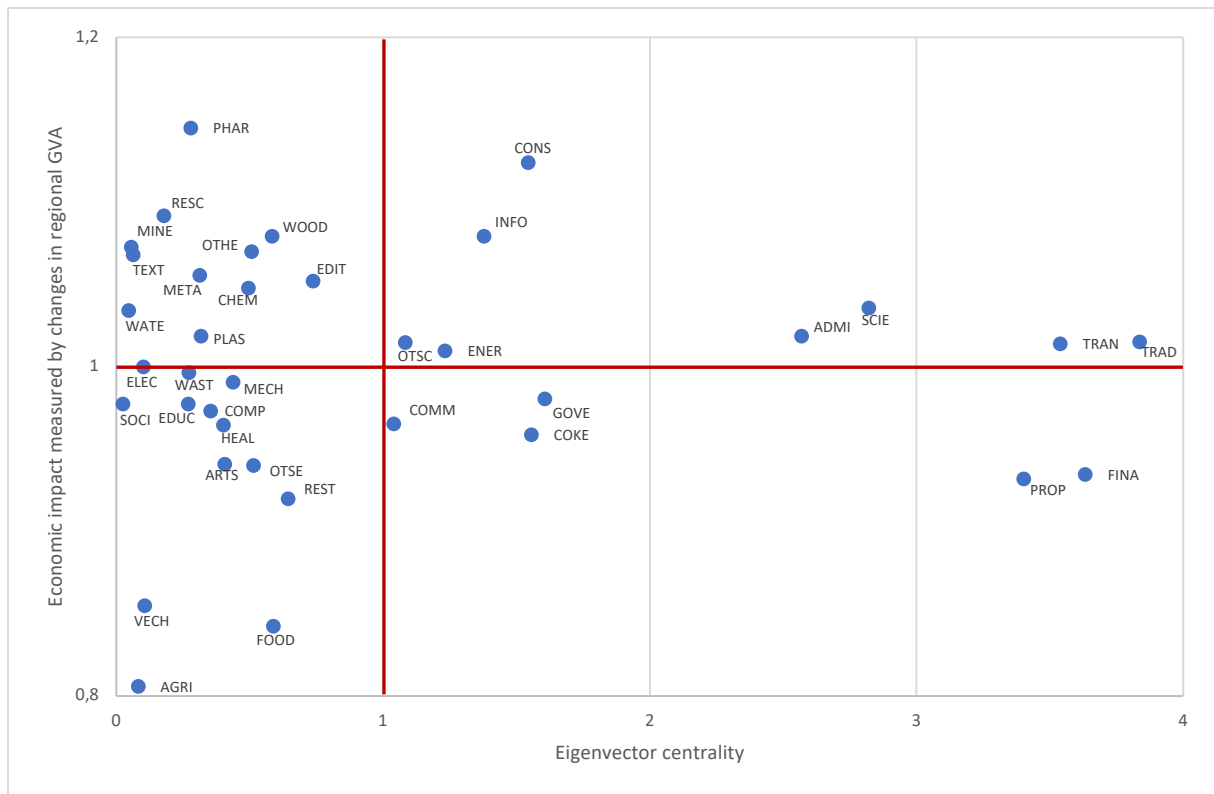
Figure 4: Economic impacts and centrality in Budapest[12]

Our first county of observation is *Budapest*, the capital city of Hungary. Figure 4 shows the calculated centrality/embeddedness values (horizontal axis) and economic impacts (vertical axis) on the basis of the methodology presented in sections 4.1 and 4.2. The figure thus reflects the development potential of the individual economic sectors with respect to the two dimensions under question (spillover capacity and economic impact): the most promising areas would be those showing both high spillover capacity and economic impact. However, it is not granted that all regions have at least one sector like this.

Budapest has a particular economic structure since it concentrates many high value-added, knowledge intensive sectors, typically business services, ICT, R&D and other services. As expected, most of these activities are highly embedded in localized knowledge flows (except pharmaceutical products and publishing-editing services since they have less local inter-industry linkages) and their economic impacts are above-average such as informatics, administrative and support services and other scientific services. The construction sector is also among the embedded and high economic impact industries. However, despite their high levels of centrality, some of the service sectors generate below-average economic impacts such as financial services (FINA). We can also see that government services, which are heavily concentrated in Budapest, are very central in the region but their economic significance is less than average. On the other hand, some sectors (energy, trade and transportation, real estate) are central by nature but do not represent significant input-output relations. These activities are highly embedded since their primary function is to connect all actors of the economy through sales and purchases (inside and outside of the region) but their centrality most probably do not

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[12] For detailed description of industries see the Appendix
Note: Red lines in the Figure indicate the level of average industrial centrality and the average growth rate of region at hand as a result of industry support intervention.

reflect high levels of spillover capacities. The rest of the sectors are less central and less potent in terms of economic impacts and spillover capacity.
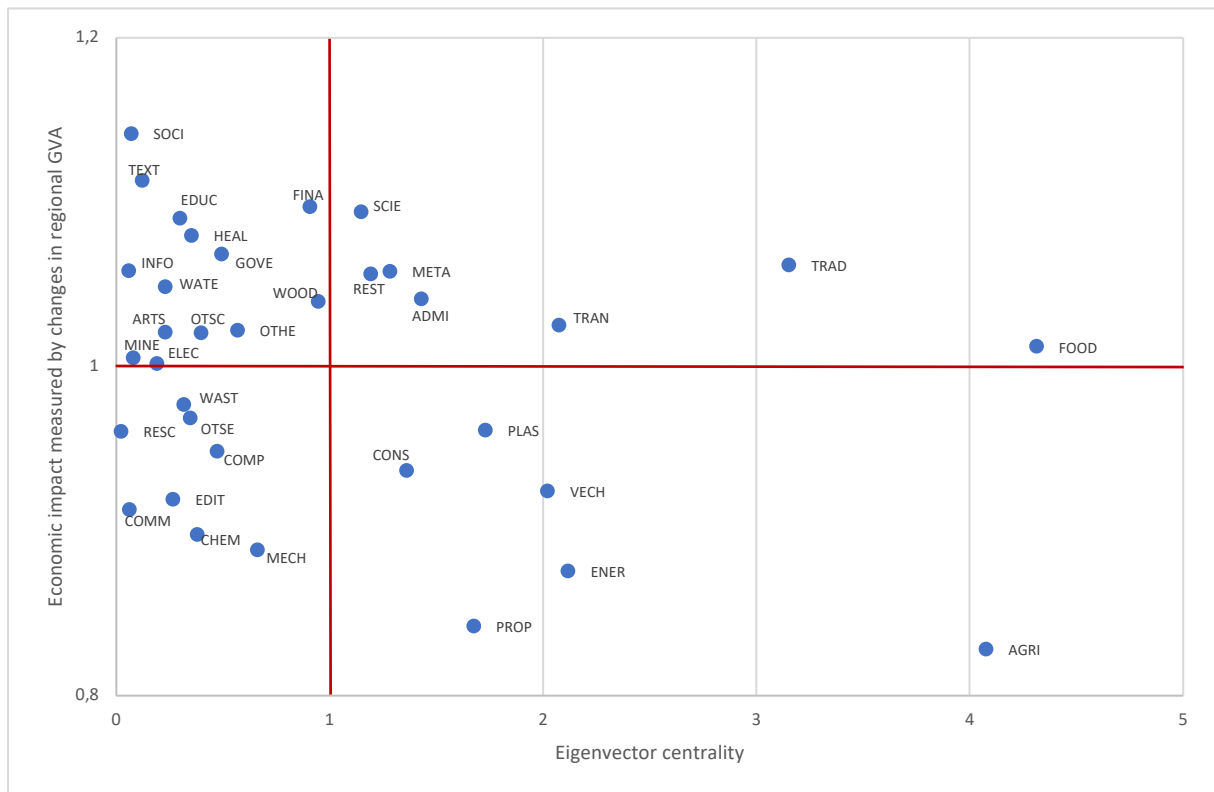

Figure 5: Economic impacts and centrality in Győr-Moson-Sopron county

Győr-Moson-Sopron county is one of the most industrialized regions in Hungary. It is characterized by significant involvement in the manufacture of automobiles and related products. Although motor vehicle production is one of the most dynamic sectors in the economy, the majority of the activity consists of assembly. Most of the components is imported and the majority of the output is exported to foreign countries. However, there are a few significant local suppliers as well. As a result, this sector performs under average in terms of boosting the local economy. On the other hand, some of its related sectors perform better (especially the manufacture of metallic products). Apart from industrial production, the region is specialized in the agro-industry. It seems that food production, which still relies heavily on labor, has better capabilities in stimulating the local economic environment, while agriculture is less potent but still very central. Apart from the relatively industrialized nature of Győr-Moson-Sopron, the rest of the industries does not show a significantly different picture. Based on our centrality and economic impact measures (Figure 5) we identify two clusters of industries with above-average spillover capacity and economic impact: 1) the manufacture of food and beverages, and accommodation and food service activities, 2) automobile manufacturing related industries (metallic products) and business services.

Figure 6: Economic impacts and centrality in Baranya county

In contrast to the capital's more balanced economic structure, less developed regions experience larger variation in terms of centrality. There are some highly central activities and the rest of the sectors are characterized by relatively low centralities. On this line, we can find the lowest number of relatively central industries in *Baranya*. The manufacture of food, beverages and agriculture are highly central, which is in line with our expectations since this region has long traditions in these activities. Again, we experience that the food industry performs better than agriculture. Since Baranya is considered as an under-industrialized region in Hungary, we are less capable of identifying key dominant sectors in contrast to Győr or Budapest. Baranya lacks the productive manufacturing industrial base which could efficiently promote regional growth. Nevertheless, other competitive areas might be identified in Baranya as well since it is rich in gastronomical, cultural traditions. There could be a role of developing tourism since hotel and restaurant services are embedded in the region and they have a high economic significance.

The three analyzed regions show different potentials in terms of industries that show good potentials for smart specialization policy. Therefore new activities that diversify dominantly the knowledge intensive service sectors in Budapest, the tourism and automobile manufacturing related sectors in Győr-Moson-Sopron and the tourism industry in Baranya seem to be the ones that have the best potentials in generating future firm concentrations and sensible economic impacts.

5. Summary and conclusions

Smart specialization policy targets industrial restructuring and economic growth, therefore understanding the economic effects of S3 is crucial for policy design and evaluation. Despite its key importance, economic impact estimation is not yet part of smart specialization policy (Varga et al., 2019). We developed a framework for economic impact estimation of smart specialization policy that can be applied in the prioritization stage (ex-ante impact assessment),

in monitoring and in ex-post impact evaluation. The recently developed GMR-Hungary model bears the features that make the model capable of carrying out S3 economic impact estimations.

In our illustrative policy simulations, we applied the two-dimensional framework suggested by Foray (2015) for prioritization: spillover potential and economic significance. The spillover potential is proxied by the centrality of industrial sectors in the region. Centrality is considered as an important factor of long-term regional restructuring since highly central sectors have intensive connections within the regional economy through which knowledge spillovers can get enhanced. Economic significance is estimated with the latest version of the GMR-Hungary policy impact model.

Our illustrative simulations suggest that developed regions (such as Budapest) have plenty of potential for S3-based economic development since many high value added and knowledge intensive services are both embedded and economically significant. On the other hand, industrial regions (such as Győr-Moson-Sopron) are dominated by a handful of manufacturing industries and not all of the centrally situated industries are capable of generating high regional growth. Finally, lagging regions (such as Baranya) are primarily dominated by agriculture and there is limited potential in developing highly embedded economically significant industries. These findings are in line with previous studies in smart specialization (Balland et al., 2018).

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Appendix

The list of industries

AGRI	Agriculture (A)
MINE	Mining and quarrying (B)
FOOD	Manufacture of food products, beverages and tobacco products (C 10, 11, 12)
TEXT	Manufacture of textiles, wearing apparel and leather products (C 13, 14, 15)
WOOD	Manufacture of wood and of products of wood, except furniture, paper and paper product and printing and reproduction of recorded media (C 16, 17, 18)
COKE	Manufacture of coke and refined petroleum products (C 19)
CHEM	Manufacture of chemicals and chemical products (C 20)
PHAR	Manufacture of basic pharmaceutical products and pharmaceutical preparations (C 21)

PLAS	Manufacture of rubber and plastic products and other non-metallic mineral products (C 22, 23)
META	Manufacture of basic metals and fabricated metal products (C 24, 25)
COMP	Manufacture of computer, electronic and optical products (C 26)
ELEC	Manufacture of electrical equipment (C 27)
MECH	Manufacture of machinery and equipment n.e.c. (C 28)
VEHI	Manufacture of motorvehicles and other transport equipments (C 29, 30)
OTHE	Other manufacturing, repair and installation of machinery and equipment (C 31, 32, 33)
ENER	Electricity, gas, steam and air conditioning supply (D)
WATE	Water collection, treatment and supply (E 36)
WAST	Sewerage; waste collection, treatment and disposal activities; materials recovery; remediation activities and other waste management services (E 37, 38, 39)
CONS	Construction (F)
TRAD	Wholesale and retail trade; repair of motor vehicles and motorcycles (G)
TRAN	Transportation and storage (H)
REST	Accommodation and food service activities (I)
EDIT	Publishing activities, motion picture, video and television programme production, sound recording and music publishing activities; programming and broadcasting activities (J 58, 59, 60)
COMM	Telecommunications (J 61)
INFO	Computer programming, consultancy and related activities; information service activities (J 62, 63)
FINA	Financial and insurance activities (K)
PROP	Real estate activities (L)
SCIE	Legal and accounting activities; activities of head offices; management consultancy activities and architectural and engineering activities; technical testing and analysis (M 69, 70, 71)
RESC	Scientific research and development (M 72)
OTSC	Advertising and market research and other professional, scientific activities (M 73, 74, 75)
ADMI	Administrative and support service activities (N)
GOVE	Public administration and defense; compulsory social security (O)
EDUC	Education (P)
HEAL	Human health activities (Q 86)
SOCI	Social work activities (Q 87,88)
ARTS	Arts, entertainment and recreation (R)

OTSE   Other services activities (S)