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Productivity, Smart Specialisation, and Innovation: Empirical findings on EU macro-regions

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Abstract. The paper aims to enrich the discussion on the Research and Innovation Strategies for Smart Specialisation (RIS3) and ongoing development of macro-regions in the European Union (EU). EU macro-regions are defined as geographical related places that are socially, economically, and historically linked and, until now, make a blind spot in the discussion on smart specialisation and regional innovation. While most literature is qualitative, the empirical approach of this paper is to apply a simply pooled OLS-regression with productivity as an independent variable, various exogenous variables on smart specialisation, dummies on EU macro-regions, and time-fixed effects within NUTS2 regions between 2014 and 2019. It can be concluded that smart specialisation has a significant dependency on productivity. The results suggest that regions of a macro-region benefit from each other by co-location. The findings are not perfect for all macro-regions. This raises questions for the development of EU macro-regions, since the EU program policy is targeted towards the European macro-regional level.

JEL classification: O, O47, R11

Key words: productivity, smart specialisation, innovation, European structural and investment funds, macro-regions

1 Introduction

The European Commission has made great efforts to support regions in their social, economic, and institutional growth through Research and Innovation Strategies for Smart Specialisation (RIS3). Smart specialisation represents an innovative policy approach that strives towards positive economic development through the realisation of regional competitive advantages (Gómez Prieto et al. 2019). Its characteristics include a place-based dimension in combination with a bottom-up character through an intensive dialogue between regional stakeholders. Whereas the identification of investment priorities is based on regional evaluation like the so-called Entrepreneurial Discovery Process (EDP). Smart specialisation approach allows for the identification and development of competitive advantages by focusing efforts and resources on regional economic specialisations (priorities), the discovery of knowledge domains, and then focusing regional policies to promote innovation, particularly in these fields of priorities and domains (Gómez Prieto et al. 2019, McCann, Ortega-Argilés 2013). As the saying goes, all that glitters is not gold – but is smart specialisation glitter or gold? And which regions do benefit?

Romão (2020) considers economic specialisations and technology influencing economic growth. This is where the financing of innovation projects in the regions comes in. S3 channels funding and Research and Development (R&D) investment into specific priorities and domains. This prioritisation in S3 should increase the competitiveness of the regions in terms of income and prosperity. Marques Santos et al. (2021) confirmed that R&D and innovation subsidies, such as smart specialisation, resulted in a positive effect on regional productivity, and smart specialisation generated additional regional effects. However, the influence of smart specialisation strongly depends on the type of region (e.g., Prognos, CSIL 2021, D'Adda et al. 2018).

In this context, Pagliacci et al. (2019, 2020) underlined the relevance of interlinking smart specialisation with macro-regional strategies to differentiate geographical areas and regional types. A macro-region is an integrated geographical area which is related to its neighbouring EU and non-EU regions in the same geographical area (European Commission 2021e). Although macro-regions are not a new concept in European regional policy, a gap remains when it comes to the integration of macro-regions into smart specialisation theory and practice. This is even more acute as the European Commission regards macro-regions as "highly relevant in delivering the EU priorities" (European Commission 2020, p. 3), for instance in the context of the Green Deal or the European Digital Strategy. Macro-regions are thus a high priority in EU policy due to neighbourhood policy, common history, historical roots, and path dependency, as well as a connecting geographical element ("Baltic Sea", "Alps") (McMaster, van der Zwet 2016). However, to our knowledge there are no statistical-econometric studies on the effects of macro-regions on the involved territories. In this regard, it is hypothesized that smart specialisation, with its secondary conditions, is positively related to the productivity of a region, as assumed by previous research, and can, as a result, provide an impetus for development. Moreover, it is assumed that macro-regions benefit from each other by co-location, path-dependency, and historical interrelation.

Afterall, gaps in research on smart specialisation remain. These rank from interregional cooperation, particularly on the level of macro-regions, to the analysis of productivity effects of different kinds of specialisation. Derived from this motivation, the authors hope to enrich the ongoing discussion on RIS3 and macro-regions in respect to the following questions: (1) How does smart specialisation contribute to economic development, here productivity, and (2) to what extent is there a connection between the EU's perspective of macro-regions and their actual performance on productivity?

The authors have chosen a quantitative approach to analyse the concept of macro-regions. Since the current analyses of cross-border regions and macro-regions primarily include qualitative research, an empirical approach was more promising to complement the existing literature. The subsequent analysis focuses on the dependence of tested variables and their expected values between smart specialisation operationalised by proxy and control variables such as on research domains and on sectoral specialisation on the one hand and productivity on the other. Using a sample of 212 NUTS2 regions, the article presents a model that studies the relation and the impact of different factors on economic productivity in European NUTS2 regions. A regional macroeconomic view is more specific than an approach from the EU27-states since economic activity, interaction, and the approach of the innovation region can be found in the regions. It is examined how NUTS2 regions have developed in the period between 2014 and 2018 and, ideally, which regional innovation accounts they have pursued. The model supplements data concerning the regional economic accounts and statistics on innovation measures, such as European structural and investment funds. The empirical approach applies a simply pooled OLS-regression with productivity as the independent variable and various exogenous variables on operationalised smart specialisation measures that include time-fixed effects.

The paper is structured in the following way: a brief overview of the literature on smart specialisation and regional development is presented in Section 2. The third section describes the selected variables and explains the methodology of the empirical approach, followed by the results of the applied econometric analysis (Section 4). Section 5 discusses the limitations of the empirical strategy and briefly discusses the results.

2 Literature in brief: Smart specialisation and regional development

Regional prosperity and competitiveness are found to rely on determinants such as productivity and innovation, which need to be addressed to realise sustainable regional growth. This is of particular interest in Europe, which aims towards regional cohesion in terms of income and productivity (Landabaso 1997). Not only the recent economic crisis but also global challenges such as climate change or digitalisation require regions to find new sources of sustainable productivity growth (Tuffs et al. 2020). In this context, R&D as well as innovation-related activities play a role as drivers of regional productivity (Foray et al. 2011). The European policy approach to exploit the opportunities of regional innovation is called smart specialisation. Smart specialisation as a concept was introduced as a response to the increasing productivity gap between Europe and the United States (Barca 2009). Extending from the analysis of an expert group that recommended focusing on regional innovation, smart specialisation was promoted shortly after as an official policy of European structural policy and established as an ex-ante-conditionality for structural funds in the programming period of 2014-2020. This explains the success and coverage that smart specialisation has achieved in Europe and in other parts of the world (Kruse, Wedemeier 2021). Moreover, research on smart specialisation has increased over the last decade (Janik et al. 2020).

The strategy for Europe 2020 and beyond is defined by developing an individual and regional Smart Specialisation Strategy (S3) (Lopes et al. 2018). One of the relevant considerations behind the original S3 approach was that innovation leader regions in a specialisation primarily invest in the invention of a general-purpose technology (GPT), while the moderate innovator regions follow the co-invention aspect of a technology investment. Smart specialisation is therefore not about being specialised in a certain high-tech sector. Addressing the issue of specialisation in the R&D invention and its link to sector activities is particularly crucial for the regions that are not innovation leaders (Foray 2018). For the respective regions, it is more relevant to focus on GPT's potential by the aspect of co-invention of applications. For example, the relevance of R&D for smart specialisation is highlighted by Capello, Lenzi (2013), although empirical analysis shows that different forms of regional innovating should be considered.

Smart specialisation is one of the key instruments of the European Commission to push forward the development of EU regions. The concept of smart specialisation can be summarised as the recognition of the uniqueness of regions and their economic structures. This place-based policy assumes that each region should come up with its own development strategy based on its strengths and characteristics (Di Cataldo et al. 2022). As opposed to traditional cluster policy, smart specialisation not only focuses on already existing strengths but aims towards identifying and facilitating the regional development of sectors with promising technology and market outlook to open new domains of regional competitive advantages. This identification is based on a process of regional stakeholder involvement and entrepreneurial discovery (Foray 2013, Navarro et al. 2014, McCann, Ortega-Argilés 2016, Vezzani et al. 2017, Di Cataldo et al. 2022). Considering the key role of R&D and innovation in developing competitive advantages, the according policy of smart specialisation involves strengthening regional innovative capacities (Foray 2013). By doing so, the specialisation on certain economic domains or sectors makes it possible to benefit from economies of scale, scope, and spill-over effects in knowledge production and application (Foray et al. 2011). While cluster policy implies a focus on a limited number of clusters, smart specialisation aims towards diversification which can be assessed to be successful in the previous European programming period of 2014-2020 (Marques Santos et al. 2021).

Balland et al. (2019) emphasised the problem in the course of the S3 implementation and policy foundation that the quantitative and qualitative monitoring is neglected. More statistical-empirical measurements are required to circumvent the challenges. However, data availability poses a major threat to the analysis as data referring to interregional interaction are scarce. As Eurostat does not provide trade statistics on a regional level, most of the research focuses on patent data and other quantitative measurements (Gianelle et al. 2014, Basile et al. 2016, Mitze, Strotebeck 2018, Ye, Xu 2021, Balland, Boschma 2021). This one-sided approach gives rise to a certain bias in research results as patents refer to research-intensive technological sectors and do not cover basic economic activities. Moreover, patent analyses mostly rely on the same databases such as REGPAT, so that research on interregional cooperation suffers from a limited perspective (Strumsky et al. 2012). It is important to also consider qualitative measures like the innovation biography and entrepreneurial discovery processes for long-term strategies (Hassink, Gong 2019). McCann, Ortega-Argilés (2016) underline the mix of qualitative and quantitative factors in the European approach. They are convinced that a one-sided analysis would be biased. For them, the current European approach can make an important connection between institutions, entrepreneurs, and policymakers.

A challenge that particularly affects the European Union is the homogeneity of the industry. Regions are specialised in the same high-tech industry and therefore, the workforce owns a similar knowledge of capital. For a long time, the innovation strategies were based on a national and not EU-wide level. The actual challenge is to diversify the industry to realise learning effects and innovation (Hassink, Gong 2019). In this context, the relevance of interregional cooperation is increasingly recognised in the literature on smart specialisation (Hassink, Gong 2019, Tuffs et al. 2020, Esparza-Masana 2021). The idea of interregional learning effects that could stimulate the recombination of knowledge and open new development paths was already formulated by Foray et al. (2009) when the smart specialisation concept was created. However, it took years for interregional cooperation to become a focus of attention for the knowledge productivity of regions (De Noni et al. 2017). Balland, Boschma (2021) show empirically in a study on 292 NUTS-2 regions in Europe that an interregional focus has a positive effect on the probability of regions diversifying, particularly in peripheral regions. One explanation is found in regional complementarities of economic domains of specialisation. The authors provide an indicator for partnering strategically in the context of S3. Insofar, the idea of interregional learning effects is statistically derived as solid evidence. However, the number of interregional co-investment projects has remained limited since the introduction of smart specialisation (Larosse et al. 2020). Results from Müller-Using et al. (2020) suggest that strengthening interregional cooperation and establishing support programs can facilitate the innovative ability and competitiveness of SMEs. Based on these findings, the European Commission supports regions on NUTS2 level to cooperate with each other to exchange innovation strategies by S3 platform tools such as the R&I Regional Viewer (European Commission 2021e).

An important field of interregional cooperation is super-regional groups of regions. The idea of cooperation across regional borders is already established in cross-border regions and cross-border regional innovation systems (Lundquist, Trippl 2011, Makkonen et al. 2016, Trippl 2010). The concept of “Euroregions” as a tool of promoting regional integration has been an important cornerstone after a long journey of promoting cross-border cooperation in Europe since the 1960s (Lina, Bedrule-Grigoruta 2009, De Sousa 2012). The analysing literature on cross-border regions, however, is mostly based on case studies and interviews as qualitative rather than quantitative analytical tools (Miörner et al. 2018). An additional perspective is provided by the concept of macro-regions. Here, the focus is broadened to not only cover regions sharing a common border but larger groups of different regions, independent of their respective nation state. Macro-regions are based on the recognition that a bundle challenges are too large for regions to address so that larger groups of like-minded regions are considered when it comes to cooperation in these fields. The concept of macro-regional strategies is still relatively new in Europe, having been developed in the programming period 2007-2013 (Pagliacci et al. 2019). The first implementation dates back to 2009 with the development of the EU Strategy for the Baltic Sea Region (EUSBSR) (Dubois et al. 2009). This transnational strategy was divided into three objectives that represent the key challenges of the Baltic Sea Region (BSR), namely saving the sea, connecting the region, and increasing prosperity (Leino 2020). This challenge-driven innovation has made the BSR macro-regional strategy a role model for the development of further joint (macro-regional and trans-European) strategies

(Uyarra et al. 2014). In combination with the targets of smart specialisation, this scale-up process is expected to help less-developed regions by climbing in value chains and new path-creation based on interregional innovation ecosystems and networks (Mariussen et al. 2016). This will be achieved by exploiting complementarities and synergies among the members of the macro-regions, which gives the concept of interregional cooperation a new stimulus in European policy. Since the macro-regional approach is still relatively new, literature on the topic remains to be scarce, particularly the evaluation and monitoring on macro-regional level related to smart specialisation implementation (Gerlitz et al. 2020).

The productivity effects of smart specialisation and macro-regional strategies are of particular interest at this point as Pagliacci et al. (2019) outlined with a focus on EUSALP. Preliminary studies have been conducted by Pagliacci et al. (2019) who underlined the relevance of interlinking smart specialisation with macro-regional strategies. Regarding the analysis of regional productivity, Romão, Nijkamp (2017) have analysed how regional systems of innovation influence the competitiveness, measured as gross value added (GVA) of tourism destinations in Europe. Thereby, i.e., employment, turnover, or investments have been treated as explanatory variables. A more recent study by Romão (2020) additionally considers economic specialisations and technology-related indicators when analysing the effect on economic growth and employment. Other studies have analysed the relationship between employment growth and relatedness and complexity (Davies, Maré 2019). Marques Santos et al. (2021) confirmed that the implementation of R&D and innovation subsidies, such as smart specialisation, resulted in a positive effect on regional productivity and that smart specialisation generated additional regional effects. A first approach to evaluate the relationship between R&D intensity and specialisation on the labour productivity of a region was conducted by Pisár et al. (2018). The authors found a positive correlation between R&D activities and certain specialisations such as services and manufacturing on labour productivity while specialisations in agriculture, forestry, or fishing are associated with lower regional productivity – as expected from the nature of said activities. Also, the relevance of R&D for smart specialisation is highlighted by Capello, Lenzi (2013).

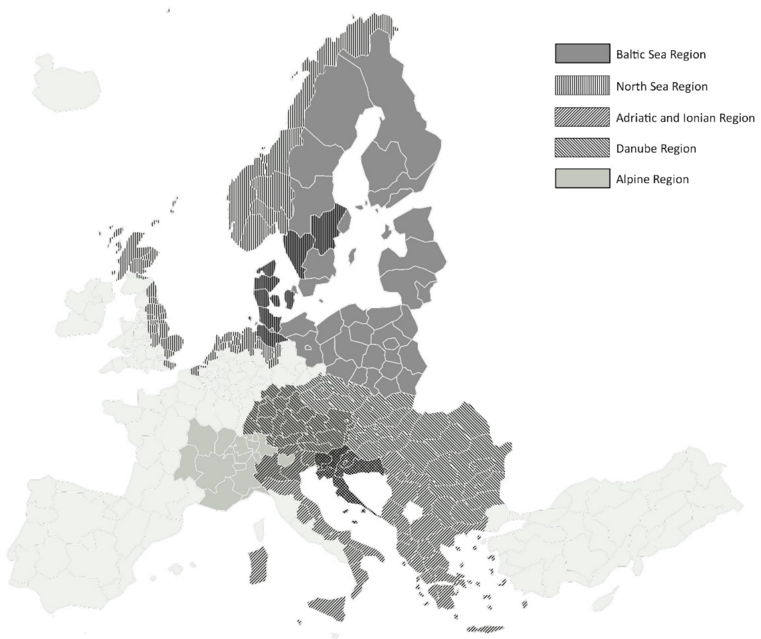
However, several research gaps remain. These rank from interregional cooperation in smart specialisation, particularly on the level of macro-regions, to the analysis of productivity effects of different kinds of specialisation. The lack of appropriate quantification of smart specialisation (Balland et al. 2019) is addressed, while also contributing to the discussion of updating the European smart specialisation concept in the next programming period (2021-27). Marques Santos et al. (2021) analysed NUTS2 regions of Portugal for evaluating the smart specialisation program. In their research, they compared the ex-ante period of the European Union's program (2007 – 2013) with the period after the implementation of S3 (2014 – 2020). Because of the complexity and correlation of influencing factors, the main challenge was to quantify the cause-effect relationship. In their findings, they emphasised the positive effect of Research, Development, and Innovation (RDI) funds on regional productivity and the acceleration of the effect due to other innovation subsidies.

3 Methodology: Measuring the impact of technological activities and innovation on smart specialisation

Derived from this motivation, the authors strive to contribute to the ongoing discussion on RIS3 and macro-regions with following research questions:

(1) How does smart specialisation contribute to economic development, here productivity, and (2) to what extent is there a connection between the EU's perspective of macro-regions and their actual performance on productivity?

Therefore, the authors proceed as follows: First, the geographical scope is defined, and the single NUTS2 regions of Europe are assigned to the macro-regional areas. The procedure is described in Section 3.1. The data is then discussed in more detail in Section 3.2. The variables are selected by following the logic of developing Smart Specialisation Strategies (S3). Section 3.3 then describes the empirical strategy.



Source: own elaboration

Figure 1: European macro-regions

3.1 Geographical scope

A macro-region is defined as an integrated geographical area that is related to its EU and beyond regions in the same geographical area (European Commission 2021e). The first implementation of a macro-region dates back to 2009 with the development of the EU Strategy for the Baltic Sea Region (EUSBSR). Since then, three more macro regional strategies have been established in the EU: the Danube region (EUSDR, in 2011), the Adriatic and Ionian Sea (EUSAIR, in 2014), and the Alpine region (EUSALP, in 2016). The four macro-regions involve 21 EU (Austria, Belgium, Bulgaria, Croatia, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Italy, Latvia, Lithuania, the Netherlands, Poland, Romania, Slovenia, Slovakia, Sweden) as well as 8 non-EU countries (Albania, Montenegro, North Macedonia, Norway, Russia, Serbia, Switzerland, the United Kingdom) and show some degree of regional overlaps (European Commission 2020, Pagliacci et al. 2019, Tursie 2015, Gänzle 2016, Gänzle et al. 2018). This limitation must be considered when reviewing the results, there may be distortions in the analysis and interpretation of the data sets. In the following analysis, we complemented the official list by countries of the North Sea Region (NSR), which lacks the formal status of an EU macro-region but still constitutes an institutionalised geographical entity with its own INTERREG program and organisations such as the North Sea Commission. A map of macro-regions in the EU that are addressed in the scope of this paper is presented in Figure 1.

To conduct the analysis at the level of European macro-regions, dummy variables for the macro-regions of the Baltic Sea Region, North Sea Region, Alpine Region, Adriatic-Ionian Sea Region, and the Danube Region were assigned to the NUTS2 regions. We fitted the regression with the European macro-regions with a categorical variable to analyse whether, on average, productivity is associated with the European macro-regions.

3.2 Data

Several proxy and control variables are occupied to empirically investigate the impact of smart specialisation. While the paper attempts to analyse the smart specialisation policy framework in terms of its impact on regional productivity, measuring it empirically is challenging. For this purpose, the individual quantitative components for determining an S3 are recorded to evaluate the regional smart specialisations. (Balland et al. 2019, Kruse, Wedemeier 2021): sectoral specialisation (i), research and innovation (ii), economic openness (e.g., trade export) (iii), and funding (iv). The variables for determining the regression can be selected based on these components. However, there were no control variables for regional openness due to data availability (e.g., trade, FDI) on the NUTS2 level. In addition, the location quotients (LQ) can only record the degree of specialization of the regions and thus reflect their concentration or, vice versa, their diversification. The regional employment concentrations are reflected in nine sectors and approximate the prioritisation within the region. This will provide the technical link to the S3 policy of the regions; the prioritisation is one of the components for developing a S3. In the end, the measurement is only an approximation. For a more detailed approach, see Varga et al. (2020), albeit with the paper's research question of examing industry concentration, knowledge spillover, and impact modelling of smart specialisation. Similarly, the use of the innovation variables reflects a broad approach in our model to measuring regions' innovative capacities and does not reflect their underlying dynamics.

However, unless otherwise stated, primarily Eurostat data were applied in the empirical analysis (in that case, data from the European Structural and Investment Funds (ESIF) were used). The Eurostat and ESIF data ensure a high data quality and replicability of the analysis. The data were collected for EU and non-EU countries by Eurostat; the database for the subsidies is also harmonised data. The authors have used a wide range of data in the period (of the EU-program) 2014-2019. This timeframe was selected since the EU strategy program S3 was implemented in 2014. For reasons of data harmonisation, the research ends in 2019 since more recent data were not available for all data points.

1. The first step in the data set compilation was to determine the location quotients of the employment data in order to provide information on the sectoral specialisation of the regions (variable *lqagr*, ..., *lqart*). The location quotients were calculated by applying the following formula:

   $$LQ_{j,t} = \frac{e_{j,t}/E_{j,t}}{E_{j,t}/E_t}$$

   where $LQ_{j,t}$ is the vector of location quotients for sector j in the regional economy in year t, $e_{j,t}$ is the employment in sector j in the regional economy, e is defined as the total employment in the local region, $E_{j,t}$ as the employment in sector j in the national economy and respective year, with E being the total employment in the national region. If the location quotient takes on values above 1.0, employment in a particular industry is represented above average. In contrast, a value below 1.0 indicates below-average specialisation. Values of more than 1.5 indicate that a region is highly specialised in a particular industry (Varga et al. 2020).

   A short look at the descriptive statistics shows that sectoral specialisation within the NUTS2 regions is characterised by large differences in the minimum and maximum values. When observing the average specialisation, these differences are harmonised by the amount of data, so that the values indicate an above-average specialisation of the regions in the selected employment areas.

2. The data of the Regional Innovation Scoreboard were considered (variable *innovationscore*) to measure approximatively the research and innovation domains of NUTS2 regions. This annually collected data assesses the innovation performance of European regions based on selected indicators that consider topics such as human resources, digitization, finance, ICT, willingness to cooperate, innovation activity, and environmental awareness (European and Regional Innovation Scoreboards 2021).

3. To include political investments in the macro-regions of Europe, a variable on European Structural and Investment Funds (ESIF) was added to the data set (variable *investment*). The ESIF fund structure has five areas: research and innovation (i), digital technologies (ii), supporting low-carbon economy (iii), and transformation (iv) such as supporting small businesses (v). The funds consist of the

European Regional Development Fund (ERDF), the European Social Funds (ESF), the Cohesion Fund (CF), the European Agricultural Fund to Rural Development (EARFRD), and the European Maritime and Fisheries Fund (EMFF) (European Commission 2021b).

4. Further controls for size (variable *density*) are used. The variable controls for specific geographical differences in size, for example for urbanization and periphery.

NUTS 2 regions were ranked and split into three groups. According to this GDP per inhabitant subdivision, the amount of the allocations is made via the European Structural and Investment Funds. The lower the GDP per inhabitant, the higher the allocation of funds. They follow this subdivision (European Commission 2021d):

- less-developed regions (where GDP per inhabitant was less than 75% of the EU average)
- transition regions (where GDP per inhabitant was between 75% and 90% of the EU average)
- more-developed regions (where GDP per inhabitant was more than 90% of the EU average)

The variables were included in the data set to control for the level of GDP and its development status of NUTS2 regions. The categorical variables can take values between 1 to 3 (variable *dev*).

The number of observations consists of 1,696 NUTS2 regions in Europe. As can be seen in Table 2, the number of 1,484 NUTS2 regions can be assigned to European macro-regions. This corresponds to a share of 87.5%. As shown in Table 2, both the variables were used to assign NUTS2 regions to European macro-regions (variables *EUBSR*, *NS*, *EUSALP*, *EUSAIR*, *EUSDR*). Likewise, missing values for individual indicators and time series were not added. We will now show how the use of descriptive statistical characteristics creates an overview of the data set used in the rest of the study. It should be mentioned that the created data set consists of both categorical and numerical variables (see Table 1).

The ratios and frequencies of the variables used in the entire data set serve as suitable statistical ratios. The mean, minimum, and maximum values of the numerical variables are presented in Table 2.

3.3 Empirical strategy

The authors conducted a simple ordinary least squares regression (OLS) with gross value added as independent variables to motivate the research question and eventually, present a more elaborate multiple ordinary least squares regression model that controls for other factors.

The empirical strategy is to consider a stepwise regression of modelling fitting to motivate the research question. The strategy is to build a model process for proofing model uncertainty and to correct for reflections. First, the relationship between productivity and gross value added is calculated:

$$lnprod_{i,t} = a + b_1 lngva_{i,t} + \epsilon_{i,t} \tag{1}$$

Productivity in region i and year t is thereby explained by the respective region's gross value added and an unobserved error term $\epsilon_{i,t}$ by region and year. The hypothesis is that productivity might be driven by other factors which are correlated with gross value added. First, this postulates that regional productivity can be further explained by the region's innovation level. To this end, a model describing the relationship between the innovation index and regional productivity is estimated. In the following, a simple linear regression function is assumed:

$$lnprod_{i,t} = a + b_1 lngva_{i,t} + b_2 innovationscore_{i,t} + \epsilon_{i,t} \tag{2}$$

Table 1: Overview of variables, by data type

Numerical Variables

- Gross value added at basic prices (*gva*)
- Total employment (*totalempl*)
- Employment, agriculture, forestry, fisheries (*agri*)
- Employment, industry excluding construction (*ind*)
- Employment, construction, and building (*constr*)
- Employment, trade, maintenance, transport, hotels, and restaurants (*trade*)
- Employment, information, and communication (*info*)
- Employment, provision of financial and insurance services (*finance*)
- Employment, real estate, and housing (*realest*)
- Employment, professional, scientific, and technical activities, other business activities (*sciencetech*)
- Employment, public administration, defense, education, health, and social services (*admin*)
- Employment, arts, entertainment and recreation, other service activities, private households, extraterritorial organisations, and bodies (*art*)
- Regional Innovation Scoreboard (*innovationscore*)
- GPD per capita (*gdppc*)
- Yearly actual investment on the ground from EU structural and investment funds (*investment*)
- Population density (*density*)

Categorical variables

- Baltic Sea Region (*EUBSR*)
- North Sea Region (*NS*)
- Alpine Region (*EUSALP*)
- Adriatic-Ionian Sea Region (*EUSAIR*)
- Danube Region (*EUSDR*)
- Development of regions (*dev*)
- Time dummies (*yearid*)

Source: Eurostat (2021a,b,c,d,e,f,g), European Commission (2021a,c,d), European and Regional Innovation Scoreboards (2021)

Productivity might be driven by additional factors that are potentially correlated with gross value added and a region's innovation score. Introducing location quotients for each sector, region, and year accounts for this. The LQ measures the regional specialisation of employment and is therefore an integral part of an S3 analysis. The next specification is based on the following regression formula:

$$lnprod_{i,t} = a + b_1 lngva_{i,t} + b_2 innovationscore_{i,t} + \boldsymbol{b}_3 \boldsymbol{lq}_{i,t} + \epsilon_{i,t} \quad (3)$$

Here, $\boldsymbol{lq}_{i,t}$ represents the vector of location quotients for each region and year, with $\boldsymbol{b}_3$ being the vector of corresponding coefficients.

To understand the impact of EU payments to the regions, the model is extended by estimating a multiple linear regression of the following form:

$$\begin{aligned} lnprod_{i,t} \quad = \quad & a + b_1 lngva_{i,t} + b_2 innovationscore_{i,t} + \boldsymbol{b}_3 \boldsymbol{lq}_{i,t} \\ & + b_4 investment_{i,t} + b_5 investment_{i,t} dev_{i,t} + \epsilon_{i,t} \end{aligned} \quad (4)$$

$investment_{i,t}$ does not represent the sum that was paid out of different funds to the region in a certain year, but rather the sum of money that has been estimated to have been invested by the regions on-the-ground based on a large simulation. This allows for a comparison of the effectiveness of EU structural fund payments across regions without having to consider any inefficiencies that might occur in the process of using the granted sums for on-the-ground investments. It is also considered to be interesting how EU payments affect less developed regions, so the effect of the actual investment on the ground in the regions each year in interaction with an economic development dummy is

Table 2: Descriptive analysis of variables

Variable	n	Mean	Min.	Max.	Year
nuts2	1,696	106.5	1	212	2014-2019
gva	1,199	48,523	1,125	659,678	2014-2019
lqagri	1,355	1.283	0.0206	9.921	2014-2019
lqind	1,445	0.992	0.175	2.307	2014-2019
lqconstr	1,447	1.027	0.309	2.197	2014-2019
lqtrade	1,463	1.015	0.641	2.280	2014-2019
lqinfo	1,308	0.905	0	3.262	2014-2019
lqfinance	1,351	0.896	0.168	3.372	2014-2019
lqrealest	838	1.375	0.199	5.220	2014-2019
lqsciencetech	1,455	0.917	0.184	2.061	2014-2019
lqadmin	1,463	1.043	0.411	2.335	2014-2019
lqart	1,449	0.927	0.269	2.237	2014-2019
innovationscore	1,696	91.95	0	191.6	2014-2019
investment	1,045	1.778e+08	1.087e+06	2.434e+09	2014-2019
density	1,242	308.8	3.400	6,513	2014-2019
eusbsr	1,484	0.208	0	1	2014-2019
ns	1,484	0.113	0	1	2014-2019
eusalp	1,484	0.137	0	1	2014-2019
eusair	1,484	0.175	0	1	2014-2019
eusdr	1,484	0.241	0	1	2014-2019
gdppc	1,187	0.0271	0.00354	0.0906	2014-2019
dev	1,187	1.776	1	3	2014-2019
year	1,696	2,018	2,014	2,021	2014-2019
yearid	1,696	4.500	1	8	2014-2019

estimated in the next step. This accounts for the effect of on-the-ground investments in less economically developed European regions.

Additionally, a population density variable for each region and year to control for urbanization and agglomeration effects is introduced. Moreover, the vector $macroregion_i$ contains five dummy variables accounting for the different European macro-regions, with $\boldsymbol{b}_6$ being the vector of corresponding coefficients. Due to missing data, the number of observations drops from roughly 1,200 in the first specification to only about 500 in the last. This is caused by missing employment data for certain sectors and regions. Lastly, an ID *yearid* for each year is introduced to account for variation over time. The final model specification is given by:

$$\begin{aligned} lnprod_{i,t} \quad = \quad & a + b_1 lngva_{i,t} + b_2 innovationscore_{i,t} + \boldsymbol{b_3 lq}_{i,t} \\ & + b_4 investment_{i,t} + b_5 investment_{i,t} dev_{i,t} + b_6 density_{i,t} \\ & + \boldsymbol{b_7 macroregion}_{i,t} + b_8 yearid + \epsilon_{i,t} \end{aligned} \tag{5}$$

Even though the data is constructed as a panel, a pooled OLS regression has been chosen for several reasons. Firstly, the Hausman test indicates that a fixed effects model should be used. However, it is also interesting how belonging to a specific macro-region influences the productivity of a certain NUTS2 region. Macro-region dummies do not have any variation over time, so they would have dropped from the model. More importantly, it is not possible to group all NUTS2 regions according to their membership in a macro-region, as some regions belong to as many as three macro-regions. Moreover, the analysis also aims to explore the effect of the interaction between economic development and structural investments, which can be easily done in an OLS model and interpreted. The application of an interaction term and its positive significance indicates that the effect of one predictor variable is of different values. There is no singular effect of investments, but it depends on the interaction with the development status of the region.

Moreover, a central issue is that the specified model has heteroskedastic standard errors. Transformations have been conducted on some of the variables to ensure the linear specification is correct. However, the Breusch-Pagan test for heteroskedasticity still yields a statistically significant result, motivating the choice to employ robust standard errors to account for this issue.

Multicollinearity could also be a concern due to the relatively large number of variables included in the final model specification. For example, it is plausible that the innovation score is highly correlated with the location quotients. To this end, pairwise correlations between the variables have been checked to ensure that correlations between the independent variables are less than 0.5 and additionally to make sure the model is not overly complicated or overfitted. For instance, the business demographics variable was dropped because it was highly correlated with gross value added. After additionally calculating variance inflation factors (VIF) for the independent variables, the location quotient for the industry sector had to be dropped since this variable has a variance inflation factor of over 20 across all specifications.

4 Results

The regression results will now be presented and discussed. The chosen explanatory variables predict as much as 88.9% of the outcomes in log productivity, indicating that our model as outlined in equation (5) fits the data well.

In the first specification, a 1% increase in a region's gross value added leads to a modest average increase of 0.33% in productivity. As more variables are included in the model, the increase drops to 0.11% in the final specification. A region's innovative capability significantly increases log productivity across all specifications – more concretely, the increase of one point in a region's innovation score translates to an average statistically significant increase in its productivity by approximately 0.41% in the full model compared to 0.96% in the second specification. While this seems like a small effect, it is worth looking at an example. In 2014, the region of Yugozapaden in Bulgaria had an innovation score of 37.75. The same region managed to increase its innovation score to 52.64 by 2020, which is an increase of about 15 points. According to the model, productivity in Yugozapaden has increased by 6.15% within only six years due to higher innovation in a general sense when all else is equal. The Innovation Score has also been applied, in a descriptive way, by Pagliacci et al. (2019) in the context of smart specialisation in macro-regions.

Specialisation can also have a positive impact on productivity. For instance, a 0.1 increase in the location quotient for the information and communication sector of any given region leads to an approximate increase in productivity by 7.4%. Likewise, a 0.1 increase in the location quotient for the public administration, defence, education, health, and social services sector increases productivity by approximately 52.6% on average. Interestingly, a 0.1 increase in the location quotient for the arts, entertainment and recreation, other service activities, private households, extraterritorial organisations, and bodies sector leads to an increase in productivity of about 15.1%.

The results regarding the effect of investments from EU funds are not as straightforward though. When looking at the interaction between on-the-ground investments and economic development, it can be observed that being classified as a less-developed region leads to a virtually non-existent effect of investment on productivity. This is also the case for transition regions. Even though the coefficient is not statistically significant, since the different types of EU structural and investment funds (ESIF) are either targeted at improving infrastructure in underdeveloped and transition areas (CF), at promoting human capital and employment (ESF), and at supporting rural regions (EAFRD) as well as a balanced economic development of the EU overall (ERDF). For this reason, transition and less-developed regions are usually allocated a higher share of EU payments. Therefore, not only would it be expected that the payments in general have a positive impact on productivity, since there is more room for improvement in these regions in comparison to more developed ones, but also a disproportionately large effect of investments on productivity. One probable reason for this result is found in the applied data. When looking at the investments made in only less-developed regions and plotting them against log productivity, a large range of investments becomes apparent. While the mean is at around €229 million in each region, there are outlier regions with investments as high as nearly €2 billion that have roughly the same productivity, driving the respective coefficient nearly to zero. Additionally, investments have a lagged effect on productivity that goes beyond the short run. Running the regression (model 5) with a lagged investment variable (one year as well as two years) does not change the effect substantially. Productivity in year t is also not substantially more highly correlated with investments made in $t-1$ (-0.0939) or $t-2$ (-0.1114) than with investments made in t (-0.0827).

Population density also has a negligible effect on productivity. There is great heterogeneity in the density levels of regions with similar productivity levels. Some of the most productive regions are not very dense, such as regions in Northern Europe.

Belonging to a specific macro-region translates to higher average productivity. When all else is equal, being a part of the Adriatic-Ionian Sea Region on average increases productivity by approximately 11.7%. Interestingly, being a member of the Baltic Sea Region or the Danube Region on average decreases productivity by approximately -19.6% and -13.9%, respectively. While these results could be driven by the similarity or heterogeneity of the NUTS2 regions that make up a macro-region in the data set as well as the fact that the number of observations varies from one macro-region to the next (which range from 168 observations for the North Sea Region to 357 observations for the Danube Region). Further analyses are required to be able to statistically explain these differences between macro-regions (see Section 5). The regression results from the previously outlined specifications are in Table 3.

5 Conclusion

To empirically analyse the role of smart specialisation, various proxy and control variables are included in the model by the authors. There are components involved in evaluating a regional intelligent specialisation: sectoral priorities (i), research and innovation domains (ii), economic openness (e.g., trade export, FDI) (iii), and funding (iv). Eurostat data in the period (of the EU-program) 2014-2019 were used to create a panel to ensure high data quality and replicability of the analysis.

In relation to the hypothesis, it can be concluded that smart specialisation - here operationalised by the components of a S3 by the sectoral prioritisation of employment concentrations, Regional Innovation Scoreboard indicators, and funds on structural transformation and innovation (ESIF) such as further regional conditions as population density – has a statistically significant impact on the productivity of a region and can thus provide impetus for further development. This is in line with previous studies on productivity effects, for instance by Marques Santos et al. (2021) who analysed Portuguese regions in that regard. By analysing regions in Slovakia and the Czech Republic, Pisár et al. (2018) found that both an appropriate infrastructure and research-related factors have a positive impact on regional productivity.

In addition, it was questioned whether there is a connection between the EU's macro-regions and their actual performance on productivity. In linkage to this question is the assumption that regions of a macro-region benefit from each other by co-location, path dependency, and common historical interrelationship. More important, however, is that a considerable part of the EU program policy is targeted towards the European macro-regional level and the monetary transfers take place within this framework. In this respect, the categorisation into macro-regions is relevant, even if the spatial effects of co-location should be specified within a spatial model (see also Section 2). The correlation between productivity and macro-regions differs in result. Being a member of the Adriatic-Ionian Sea Region on average increases productivity, whereas the results for the Baltic Sea Region or the Danube Region lead in the analysis to a decrease of productivity. The diversity of structural patterns on NUTS2 level in the different macro-regions was described by Pagliacci et al. (2019) who categorised regions in clusters. The categorisation followed the indicators of income level, population density, and economic specialisation and revealed that macro-regions, although being characterised by shared challenges, show a certain

Table 3: Regression results

	(1)	(2)	(3)	(4)	(5)
lngva	0.331***	0.0676***	0.119***	0.121***	0.112***
	(19.77)	(4.64)	(7.88)	(8.22)	(6.65)
innovationscore		0.00958***	0.00520***	0.00308***	0.00413***
		(39.75)	(12.04)	(6.40)	(8.72)
lqagri			-0.0277	-0.0155	0.00729
			(-1.80)	(-0.88)	(0.39)
lqconstr			-0.0574	-0.0636	0.0831
			(-1.23)	(-1.26)	(1.75)
lqtrade			0.0104	0.00427	0.0423
			(0.17)	(0.07)	(0.68)
lqinfo			-0.130***	-0.0170	0.0740*
			(-4.09)	(-0.55)	(2.08)
lqfinance			0.100**	0.00173	-0.0393
			(2.92)	(0.05)	(-1.14)
lqrealest			-0.0261	-0.0482*	0.0120
			(-1.40)	(-2.57)	(0.64)
lqsciencetech			0.248***	0.109	0.0537
			(4.32)	(1.75)	(0.90)
lqadmin			0.711***	0.612***	0.526***
			(12.81)	(11.38)	(10.29)
lqart			0.328***	0.217***	0.151***
			(11.49)	(5.99)	(3.86)
2.dev#c.investment				9.95e-11	2.28e-10
				(0.78)	(1.73)
3.dev#c.investment				2.90e-11	9.67e-11
				(0.46)	(1.63)
density					-0.0000698*
					(-2.01)
eusbsr					-0.196***
					(-6.48)
ns					0.0457
					(1.87)
eusalp					0.0338
					(0.97)
eusair					0.117***
					(4.14)
eusdr					-0.139**
					(-2.96)
yearid					-0.00291
					(-0.51)
const	7.362***	9.226***	7.928***	8.592***	8.537***
	(40.97)	(64.07)	(40.70)	(44.61)	(40.44)
Observations	1199	1199	654	530	530
R-squared	0.357	0.668	0.831	0.861	0.880
F-statistic	390.9	1233.4	441.4	.	.

Notes: dependent variable: lnprod, t statistics in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

level of internal differences when it comes to income or specialisation patterns as well as differences between the macro-regions. Areas in Southern and Eastern Europe are particularly expected to have serious difficulties when it comes to identifying their specific smart specialisation, which also represents a challenge for the macro-regions (Pagliacci et al. 2019, Varga et al. 2020). Explanations could be provided by the different state and private institutions, in the sense of the varieties of capitalism and institutions. Moreover, the political and economic integration of macro-regions took place over different periods of time. Although the countries of the eastern EU member states joined the EU in the years 2004 and 2007, the EU-integration process is still ongoing. In addition, the macro-regions of the eastern EU member states are also part of the European neighbourhood of non-EU countries, which increases the heterogeneity between the countries and their regions within the macro-regions. A limitation is that the study did not observe the role of these institutional (and political) capabilities. Weak institutions could negatively impact innovation (Rodríguez-Pose, Di Cataldo 2015). The Iron Curtain still lies as a cutting edge from the past, covering various European regions, including directly through some of the macro-regions. Germany, for example, is still divided when it comes to entrepreneurship and knowledge domains (Fritsch 2004, Fritsch, Storey 2014). The same can be assumed for many overlapping areas of macro-regions. Future focused case studies of individual EU macro-regions could be helpful to try to understand the synergies (or not) between the S3 specialisation within and between the overlapping macro-regions.

A limitation is that a certain endogeneity problem exists. According to the macro accounting, there is a certain degree of dependence between productivity and GVA. They are not fully independent. In order to control for this effect, we regarded a certain structure of a panel and added time and regional variables. Lagging independent variables, e. g. a period, were not added due to the specific structure of the data set. Further limitations include that the potential of smart specialisation is approximately solved by operationalising different heterogenous variables. Third, the number of observations is limited to the observed program period 2014-2019. Last, but not least, further research should include variables for regional openness, which need to be integrated to fulfil all components of a Smart Specialisation Strategy (S3). Due to data availability, it was not feasible to control for regional openness, using for instance regional trade data on the NUTS2 level. Moreover, the components of a S3 applied in the here used model do not fully reflect the nature of a S3 in practice. For example, the regional employment concentrations in nine sectors do not reflect the prioritisation decisions within a regional strategy. This approach has to be chosen due to the availability of data. Far more variables would have reduced the degree of freedom with simultaneously limited regional observations. However, the research method chosen is an approach to the question of the connection between productivity, smart specialisation, and innovation. At the same time, this paper points to the need for further research on the empirical findings on EU macro-regions and their limitations.

The result shows that smart specialization is more than glitter to give regions a growth boost, but it is not the sole 'golden' solution of regional development. To conclude, the analysis shows that additional research into the definition and meaning of European macro-regions and their spatial functionality is needed. The importance of interlinking smart specialisation with macro-regional strategies is given: The European Commission considers macro-regions as highly relevant to fulfil the EU priorities within the new programme period and beyond. The Smart Specialisation Strategies (S3) of the EU-member (and non-EU member states) are the instruments to achieve the ambitions aims of the Green Deal and further EU policy goals. Macro-regions provide the territorial and programming framework for this. In this respect, smart specialisation is a cornerstone of European structural and innovation policy. In the end, the European macro-regions are above all a political order, a framework for project planning with a budget, but it is also the design of a neighbourhood policy.

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