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SME efficiency in transforming regional business research and innovation investments into innovative sales output

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ABSTRACT

Based on data provided by the Regional Innovation Scoreboard on 23 capital and 184 non-capital regions in Europe, slacks-based models of data envelopment analysis reveal that the efficiency by which business research and innovation inputs are converted in at regional level aggregated innovative sales output in SMEs was significantly lower in capital regions in the period 2006-2014. In view of efficiency maximization, a majority of the capital regions overinvest in non-R&D innovation activities, are over-specialized in knowledge-intensive industries, and fall behind in converting research and innovation inputs in intermediary intellectual property outcomes.

KEYWORDS capital regions; research and innovation; efficiency; SMEs; slacks-based DEA
JEL O30, R10

INTRODUCTION

This paper follows the idea that the regional context is important for innovation (Asheim and Coenen, 2005), and focuses on the role of capital regions as breeding grounds for innovation in SMEs in Europe. The central research question is, compared to other types of regions in Europe, how well capital regions perform in terms of efficiency in converting their particularly rich research and innovation (from now onwards termed as R&I) investments (Hollanders and Es-Sadki, 2017) into turnover in SMEs. Dynamic slacks-based data envelopment analysis is relied upon to measure the efficiency by which 207 regions in Europe, amongst which 23 capital regions, convert at regional level aggregated R&I investments in aggregated innovation output in SMEs.

In economic terms, efficiency refers to maximization of output produced by a unit of input. A situation is called inefficient when a desired output can be achieved with less means, or when the means employed could give rise to more of the desired outputs (Heyne, 1993). Efficiency is relevant from a policy perspective. On the one hand, R&I expenditures are generally accepted as critical components for regional competitive advantage (Lee et al., 1996), and are one of the four priority areas in European regional policy to reduce regional inequalities (e.g. through the European Regional Development Fund). On the other hand, appropriate interregional performance comparisons in terms of efficiency are a central criterion in evaluating innovation success considering the invested resources (e.g. Han et al., 2016; Broekel et al., 2018). The particular attention to output efficiency also relates to Europe's significant challenge of converting its perceived failure to translate its abundant scientific advances into marketable innovations, and the role of "policies able to increase the innovation capability of an area and to enhance local expertise in knowledge production and use, acting on local specificities and on the characteristics, strengths, and weaknesses of already-established innovation patterns in each region" (Camagni and Capello, 2013, p. 357).

The focus on at regional level aggregated innovation output of SMEs is justified by the fact that SMEs are recognized as generators of employment and economic development (Lukács, 2005). In the EU-28 economy, SMEs represent 99% of all (non-financial) businesses, account for 67% of total employment and generate 57% of gross value added (European Commission, 2019). Regarded as the backbone of regional economies, SMEs are the subject of various policy instruments. The European Commission, complementary to national and regional policies, sustains SMEs through its regional policy to facilitate their creation and operation, as they play an important role in the dynamics of the national and regional economy (Cohendet et al., 2010; Radicic et al., 2016).

Several reasons justify a focus on capital regions. First, capital regions tend to be more urbanized agglomerations, which have proven to be better fits for innovative firms compared to more rural areas (Brouwer et al., 1999; Moseley, 2000; OECD, 2011). These urban agglomerations host key players that have an impact on innovative SMEs, including a variety of small and large firms in various industries, and a critical mass of users and potential customers (Iammarino, 2005). Compared to other urban regions, capital regions (cities) "can be interpreted as the sum of some unique plus some more ubiquitous factors" (Zimmermann, 2010, p. 764). Distinct from most other urban areas, capital regions are characterized by a strong public sector and higher-order (central government related) administrative functions (Porter and Stern, 2001; Zimmermann, 2010). The strong presence of the central government public sector has direct effects on employment creation, presence of lobbying firms, positive spillovers to private activities (e.g. spin-offs from the central government), and has a symbolic function and generates a "special political, cultural and societal environment, which attracts people, enterprises, and other institutions, even if the presence of central government is not essential for their own work" (Zimmermann, 2010, p. 762). Ubiquitous to other urban areas, capital regions have an abundant availability of scientific knowledge related to the presence of universities and broader agglomeration economies related factors (Tödtling and Trippl, 2005; Berkhout et al., 2010). Second, capital regions are crossroads of knowledge and information flows (Doloreux, 2002). Capital regions have a relatively high degree of migration and internationalization (Eurostat, 2021), and the presence of the central government attracts highly educated and innovative young professional (Zimmermann, 2010). Specific knowledge bases of regions could increase their learning capabilities and facilitate knowledge diffusion between the participating players, facilitating regional growth. In most European countries capital regions have a GDP per capita that is superior to the national and EU average (Hollanders and Es-Sadki, 2017), and these large urban areas tend to generate agglomeration economies (Segal, 1976). There's evidence that capital regions occupy a specific position in innovation in a national context (e.g. Annoni and Dijkstra (2019) with regard to competitiveness; Fratesi and Rodriguez-Pose (2016) for job creation; McCann and Acs (2011) for productivity; and Herstad et al. (2011) for innovation). Cooke (2007) points to the attractiveness for innovative SMEs of being located in regions endowed with knowledge capabilities and a solid knowledge base. In this respect, capital regions are found being of particular relevance for (the location of) SMEs in general (Romero and Martínez-Román, 2012), and in highly innovative knowledge-intensive business services and high-tech manufacturing in particular (Doloreux et al., 2010; Teirlinck, 2018). Third, Feldman and Audretsch (1999) found that, given a common knowledge base, the diversity of complementary economic activity which is often prevalent in capital regions promotes innovative output. This idea is expanded on by Frenken et al. (2007) in their discussion on related variety within regions. Fourth, capital regions are characterised by a highly-skilled heterogeneous population (Sassen, 2002). Such qualitatively strong regional research environments are highly conducive to knowledge exchange between innovative actors (Casper, 2013), leading to positive externalities by tapping into knowledge repositories, expertise and skills (Malecki, 2010). These particular characteristics of capital regions enhance regional absorptive capacity which is supposed to contribute to efficiency of knowledge exchange mechanisms (Miguélez and Moreno, 2015), at a level that is hard to reproduce in other regions (Asheim and Isaksen, 2002). Of course, one should not turn a blind eye to potential agglomeration diseconomies such as congestion, crime, commuting costs, land rents, pollution, more intense competition, etc. in densely populated or largely urbanized (capital) regions (e.g. Glaeser, 1998; Cooke, 2007).

This paper adds to the literature in four ways. First, as pointed out by Iammarino et al. (2019), capital regions are in the core of leading (high-income and innovation) regions in Europe, and it can be questioned whether a spatially blind framework focus on efficiency first (in their paper in the form of maximising agglomeration) can be justified. Unfortunately, limited empirical insights exist regarding differences in efficiency in capital regions compared to other regions. Compared to many other studies that focus at (capital) regions in a national context, (e.g. Herstad et al., 2011; Fritsch and Slavtchev, 2011; Broekel et al., 2018), this study investigates the specificities of capital regions by considering a large number of European regions in a broad set of countries. Second, the benchmark between capital regions and non-capital regions, whether or not further classified according to the urban-rural typology, provides original insights in how efficient - at regional level aggregated - SMEs use the (capital) region's particular available resources. Moreover, our approach allows to study the specificities of each region individually (in line with the focus in some studies on how firms use one particular regional innovation system's resources – e.g. Avilés-Sacoto et al., 2020). It also complements earlier work on resilience in the European Union across the urban-rural divide during and in the aftermath of the 2008 economic and financial crisis (Giannakis and Bruggeman, 2020). Third, the longitudinal data covering a time-span of eight years and the slacks-based data envelopment analysis relied upon allow a more sophisticated methodological approach to deal with the topic of efficiency at regional level, including substantial time-lags between inputs and outputs (as recommended e.g. by Broekel et al., 2018). Finally, we enrich the literature on innovation efficiency by looking at output efficiency in terms of sales of innovation in SMEs (the overall innovation efficiency – Chen and Guan, 2012). So far, the variation on the output side for measuring efficiency is relatively small since, due to data availability, patents (referring to the more upstream technological development efficiency – Chen and Guan, 2012) have been the dominant approximation (Broekel et al., 2018).

The next section presents the main insights from the literature regarding specificities of capital regions as breeding places for innovation and innovation efficiency. This is followed by a discussion about the methodological approach and the data. We then turn to the empirical analysis and end-up with discussion and conclusions.

LITERATURE REVIEW

Specificities of capital regions

In line with insights from the literature on regional innovation systems (Cooke et al., 1997; Cooke, 2007), Romero and Martínez-Román (2012) argue that territories with high per capita income offer a fertile context for innovation in SMEs. The OECD (2011) outlines that technological innovations are favoured in more urbanized areas, confirming that innovations differ according to the regional context, with innovations based on the development of new patents in products and services, reflecting a strong R&D knowledge base which is more widely present in urban contexts (Moseley, 2000). Innovation in SMEs located in less urbanized areas focuses more on exploitation in niche markets (OECD, 2014). Less urbanized contexts in which these SMEs are active are characterized by: lower population density, limited local markets, limited access to providers of technological and financial resources, a shortage of knowledge resources and a lower R&D intensity and related absorptive capacity (Reidolf, 2016).

Through the ways capital regions position themselves in the national urban hierarchy as information regions, national information brokers, or transactional regions (Mayer et al., 2016), they offer a particularly fertile context for innovation in SMEs. These regions are characterized by complex relationships between the private sector, the public sector, and government, and often represent national identity (Cochrane, 2006). Capital regions benefit from a strong presence of national and academic research laboratories and technology-mediating organizations as diffusers of knowledge, and knowledge interactions between industry and science actors that are determined by the needs of the public sector (Tödtling and Trippl, 2005). Simmie (2002) highlights that capital regions occupy a particular place in urban hierarchies due to their crossroad function for people and knowledge from other parts of the global economy. Dijkstra et al. (2013) investigate the economic performance of European cities and city regions from the premise that these areas are important for national economic performance (Porter, 1990; Krugman, 1991; Glaeser et al., 1992). They argue that capital regions tend to play a critical role as global regions exhibiting large concentrations of high-level human capital and skills acting as key conduits for inward and outward knowledge flows which are essential for national competitiveness in the global economy, in other words 'magnets' towards which both international and interregional flows of capital and labour gravitate (Sassen, 2002).

More than most other regions, capital regions offer opportunities in terms of interaction between different co-located types of actors (Cooke et al., 1997; Iammarino, 2005), and can be considered as fertile places for a creative class of workers to invent new products or processes which lead to economic growth and wealth (Cohendet et al., 2010; technology, talent and tolerance – Florida, 2002). Firms located in capital regions are believed to benefit from 'being there' (Gertler, 1995) and to enjoy significant innovative capacity advantages compared to firms operating in more isolated environments (Baptista and Swann, 1998). Capital regions are advantaged in terms of productivity (McCann and Acs, 2011), knowledge-driven industrial clusters (Porter, 1990), economies of scale and industry diversity (Jacobs, 1969), and enhanced variety of knowledge exchange limiting repetitive information (Fitjar and Rodriguez-Pose, 2011). The abundance of public R&D and of public innovation support systems help SMEs in applying innovative solutions (Seija, 2007). With regard to the period under consideration in this paper (2006-2014), Fratesi and Rodriguez-Pose (2016) highlight that, compared to country averages, most capital regions have been able to create more (or lose fewer) jobs during the financial and economic crisis starting in 2008.

However, capital regions, as highly urbanized areas, also face potential agglomeration diseconomies in terms of congestion, cost of land, higher competition due to a concentration of economic activity (e.g. Glaeser, 1998; Cooke, 2007), as well as diseconomies due to competition among firms in the labour market (Lee, 2016). The latter may lead to an increase in the average wage in an industry, restraining further agglomeration of the industry. Lee (2016, p. 340) points out that "if the weakened agglomeration is absorbed in other cities, the absorption may provide a basis for medium-sized or smaller cities to maintain vitality or thrive". Moreover, as pointed out by Storper (2010), some economic activities find themselves together in a certain region simply because it has the right factor supply (comparative advantage rather than agglomeration) for that industry (say land, or labour or transport access). In addition, Dijkstra et al. (2013) highlight the advantage in rural and intermediate regions close to cities in terms of quality of life and access to nature, and improved accessibility.

Despite their importance and special characteristics, research on innovation in capital regions is relatively limited (e.g. Campbell, 2000; Mayer et al., 2016). Hollanders and Es-Sadki (2017) have shown that most of the capital regions are high-ranked innovative regions compared to other regions. The reason might be that capital regions have a broader knowledge base since they are an attractive location for creating new products and processes. Romero and Martínez-Román (2012, p. 182), discussing innovation in SMEs, assert that "in highly developed areas with high per capita income, one might expect to find more efficient suppliers of inputs, more and better qualified workers and managers, more public support for self-employment and entrepreneurship or stronger R&D systems (universities, public and private research centres, etc.)." However, based on a comparison of the Oslo capital region with other Norwegian city regions, Herstad et al. (2011) illustrate that capital regions are not necessarily high ranked in terms of product and process innovation. Moreover, Herstad et al. (2011) claim that the characteristics of the local economy influence innovative outputs. Hence the relevance of investigating whether the special characteristics of capital regions in terms of a rich knowledge base for innovation and focus on more explorative innovations go at the detriment of efficiency in the innovation process. This question addresses in an empirical way the theoretical reflection made by Iammarino et al. (2019) whether the level of attention paid to efficiency should be in accordance with spatial specificities.

Innovation sales output efficiency of firm level R&I investments

In recent decades, a shift has occurred in the focus of policy, from the promotion of science to technological innovation emphasizing knowledge with commercial potential. Further enhanced by the economic and financial crisis starting in 2008, together with an increasingly generous policy support to R&I investments in a context of severe public budget restrictions, increasing attention is paid to efficiency of R&I investments (OECD, 2019).

Liik et al. (2014) highlight the variety of studies analysing the efficiency of R&I investments by using different econometric approaches and different kinds of data. Their overview demonstrates that in the relation between R&I investments and economic performance, various factors come into play, and the straightforward relationship between R&I inputs and economic outputs is an oversimplification. Sales from (new-to-firm or new-to-market) product innovation is commonly used as an indicator for measuring innovation performance, and the share of these sales in overall sales provides a measure of the relative importance of product innovations implemented by companies in the region (e.g. Hall et al., 2013; Guan and Chen, 2010).

Although not necessarily following a linear process, a strong relation exists between outputs in terms of sales from product innovation, R&D and broader (non-R&D) innovation investment inputs, and throughputs in terms of intellectual property (IP). In a dynamic framework (see further), a throughput refers to an output of a previous period that serves as an input for the following period. IP in the form of patents, trademarks, and registered designs refers to ownership rights and can have important consequences (both positive and negative) on efficiency (Stiglitz, 2008). Patents are widely recognized as intermediate outputs that further influence broader economic outputs such as exports (Li et al., 2017), productivity, and GDP (Lu et al., 2014). Trademark analysis contributes to capturing relevant aspects of innovation in services and low-tech industries and in SMEs (e.g. Mendonça et al., 2004; Flikkema et al., 2014). Therefore, this form of IP can be seen as a complement to patents as the propensity to patent is lower in SMEs (e.g. Blind et al., 2006). Trademarks and registered designs protect the softer types of innovation, such as marketing and organizational innovation (Flikkema et al., 2014). Flikkema et al. (2014) report that trademarks point to having innovative activities that are close to market introduction. Mendonça et al. (2004) emphasize that innovative firms consistently use more trademarks. Greenhalgh and Rogers (2007) report a positive correlation between trademark registration and product innovation and productivity.

Combining the above insights, we will look at sales of innovations by SMEs as a result of R&D expenditures in the private sector and non-R&D innovation spending by SMEs in the region. As the composition of the industry is an important determinant for explaining (differences) in R&I investments between regions (e.g. European Commission, 2019), account is taken of the structure of the economy by including employment in medium- and high-tech manufacturing and knowledge-intensive services. We consider IP (patents, trademarks, and registered designs) as throughputs between R&I investment inputs and innovation sales. This approach is in line with Lu et al. (2014) and Li et al. (2017), and considers insights from other studies relying on the data envelopment analysis technique (see further). For example, Edquist et al. (2018) select public R&D expenditure, non-R&D innovation expenditure, business R&D expenditure, and venture capital to explain sales of new-to-market and new-to-firm innovations. Li et al. (2017) measure the efficiency of 26 high-tech regions in China from 1998 to 2011. The inputs are R&D expenditure, employment, and fixed-assets' capital stock. The outputs include gross output value and total export value. They also use the number of patents as a throughput. Chen et al. (2018) measure the R&D efficiency of 29 Chinese regions during the period 2006 to 2011. They select R&D expenditure and R&D personnel as inputs; papers in journals listed in the Science Citation Index (world's leading journals of science and technology), domestic granted patents as outputs; and R&D capital stock as throughput.

RESEARCH METHOD

Regions in the Regional Innovation Scoreboard

The basis for the evaluation of output efficiency of business R&I investments are the 220 regions in 22 EU Member States covered in the Regional Innovation Scoreboard 2017 (RIS – Hollanders and Es-Sadki, 2017). We extend this by the information available in the RIS for seven regions in Norway. A large majority of the regions, 200, are defined at NUTS (Nomenclature of Territorial Units for Statistics) 2 level which is the basic regional dimension for the application of EU structural funds and cohesion policies. Because of a lack of data at NUTS 2 level, NUTS 1 level (major socio-economic regions) data are included in the RIS for 27 regions in 5 countries (Belgium – the capital region is the same at NUTS 1 and NUTS 2 level, Bulgaria, France – the capital region is the same at NUTS 1 and NUTS 2 level, Austria, and the UK). Cyprus, Estonia, Latvia, Lithuania, Luxembourg, and Malta are excluded from the analysis because the data for these countries is exclusively available at the national level and the indicators for these countries are calculated based on a country comparison ranking and not on a region-based comparison (Hollanders and Es-Sadki, 2017). As explained before, for policy making reasons our focus is on the NUTS 2 level. This does not disregard that the NUTS levels are not always defined in a homogenous way for capital (and other) regions. For example, some capital regions such as Rome (Lazio - ITI4 - NUTS 2) and Paris (Île de France - FR10 - NUTS2) include their commuting belt, whereas others such as Brussels (Région de Bruxelles-Capitale - BE10 – NUTS2) and Prague (CZ01-NUTS 2) do not (for more insights in these differences, see e.g. Annoni and Dijkstra, 2019).

In the literature review arguments are made in terms of economies of agglomeration, which a simple comparison between capital and non-capital regions might overlook. To address this issue, the OECD and Eurostat classification of urban-rural regions is considered to further refine the group of non-capital regions (Eurostat, 2018). Based on the shares of a region's rural and urban population, the urban-rural typology classifies NUTS3 regions in predominantly urban (rural population counts less than twenty percent of the total population), intermediate (rural population between twenty and fifty percent), and predominantly rural (over fifty percent) regions. By considering the presence of urban centres that can turn regions in a higher (urban) level category (Eurostat, 2018), the urban-regional taxonomy in a creative way can be used at higher NUTS levels that resonate the policy level of the RIS (e.g. by Giannakis and Bruggeman (2020) to investigate linkages between NUTS3 and NUTS2 levels). We follow this approach and identify regions having within ("presence of") a large urban area/city versus others (Capello et al., 2015). So, to define the degree of urbanization at NUTS 2 (and in a limited number of regions NUTS 1) level we start from the classification of the underlying NUTS3 levels and complete this classification by considering the size of the urban centres in the region. A predominantly rural region containing an urban centre of more than two hundred thousand inhabitants making up at least twenty-five percent of the regional population becomes intermediate. An intermediate region which contains an urban centre of more than five hundred thousand inhabitants making up at least twenty-five percent of the regional population becomes predominantly urban.

This approach leads to a group of 23 capital regions, 79 regions (excluding 21 capital regions that were also in this classification) that are "predominantly urban"; 91 "intermediate" regions (excluding 2 capital regions in this class); and 14 "predominantly rural" regions.

Inputs, throughputs and output

The inputs and throughputs are selected from the RIS 2017, the outputs are selected from the RIS 2019 (Table 1). In particular with regard to innovation, the RIS focuses entirely on SMEs, and the IP-related throughputs refer to registration in Europe, which is coherent with the focus on innovation output in SMEs. The RIS ranks the regions' performance based on the average of the indicators in such a way that the higher the average of the indicators, the higher the performance of the region. The resulting data are indexes of each indicator. These indexes are calculated in the RIS by applying a square root to the data since the distribution of the data is not normal and the skewness of the data is more than 1 (Hollanders and Es-Sadki, 2017). Further, the max-min technique (applied on a yearly basis) is used to normalize the data by dividing them by the difference between the maximum and the minimum value of each index. All data required for the empirical analysis is available for 207 regions (out of the target population of 227 regions) in 23 countries.

<Insert Table 1 about here>

Dynamic slacks-based DEA

Given the existence of multiple inputs, through- and outputs, a multiple factors technique called Data Envelopment Analysis (hereinafter DEA) is applied. DEA is a non-parametric technique enabling simultaneous evaluation of the relative efficiency of multiple inputs (resources) and multiple outputs (products) of a group of Decision Making Units (DMUs), here the DMUs are the regions, by applying a linear programming technique (Charnes et al., 1978). DEA allows the efficient regions to form a 'best-practice' or ‘efficient frontier’ as a benchmark for less efficient regions, without guarantee that the efficiency of regions at the frontier is at the optimum level (Cook et al., 2014).

We rely on the slacks-based dynamic DEA model, which is able to consider the lagged effects (called carry-overs, and referring to the IP throughputs in our model) and compute efficiency over a multiple-time period (Tone and Tsutsui, 2010). Dynamic DEA, which measures dynamic efficiencies over multi-periods, is more accurate and proper than traditional DEA models which measure single time period and static performance. Dynamic DEA models have the advantage over standard DEA models that they are unit invariant and stable over changing the input and output slacks (Tone and Tsutsui, 2010).

The dynamic DEA needed for our research is an 'output-oriented' technique since the focus lies on maximizing the production of outputs given fixed inputs, thereby reflecting the logic of maximizing the outputs of restrained R&I budgets. In line with expected increasing returns to scale for R&I investments (Romer, 1990; Scherer, 1982), we focus on the Variable Returns to Scale (VRS) technique, because in this case a proportional change (increase or decrease) in inputs does not lead to the same proportional change (increase or decrease) in outputs (Cooper et al., 2007). If the proportionate variation of outputs would be larger than proportionate changes of inputs, the return to scale is increasing.

The slacks-based DEA model not only determines the efficient regions but also allows for identifying the extent to which each region has allocated inputs above the optimum amount (excess) and produced output below the optimum amount (shortfall). As such, the slacks-based efficiency measure is a scalar measure which allows measuring the excess of inputs and the shortfalls in outputs by region. This technique considers a region as 'efficient' if the efficiency score is equal to one and the region does not encounter any excess and/or shortfall (none of the inputs and outputs can get improved by diminishing the input excess and/or compensating the output shortfalls). Further information on the DEA method and the DEA model relied upon in this paper is outlined in Appendix A.

Figure 1 summarizes the methodological framework. Efficiency is calculated for three sub-periods (2006-2010; 2008-2012; and 2010-2014), referred to as term efficiency, and for the entire period (2006-2014). This approach is largely similar to the one by Chen and Guan (2012) who applied network DEA and considered three time-periods (1995-1999; 1999-2003; and 2003-2007) for studying the efficiency of China's regional innovation systems. Potential endogeneity due to a simultaneous causal relationship between the input and output variables is reduced by including a time-lag between inputs and outputs. With respect to the time-lag between the inputs, throughputs, and the output, different authors allow for three to five years (Wang and Huang, 2007; Lee and Park, 2005; Chen and Guan, 2012). Belderbos et al. (2004) select a two-year time-lag. We have selected a four-year time-lag for the inputs and a two to three-year lag for the throughputs, conditional on the availability of data in the Regional Innovation Scoreboard.

<Insert Figure 1 about here>

EMPIRICS

Specificities for capital regions

Table 2 first presents the normalized scores for the inputs, throughputs, and the output for each of the 23 capital regions, averaged for the entire period. At the bottom of the table a comparison is made between capital and non-capital regions, and between capital regions and non-capital regions further divided by urban-rural classification. Based on t-tests comparing capital regions with the entire group of non-capital regions we note significant higher inputs in terms of R&D expenditures in the business sector in capital regions, as well as higher employment in medium- and high-tech manufacturing and knowledge-intensive services. Expenditure on non-R&D innovation in SMEs is significantly lower in capital regions. For the throughputs there is a stronger trademark application base in capital regions. No significant differences are found for sales of innovations. If we subdivide the non-capital regions by urban-rural classification, significant differences are found for all inputs, throughputs, and for the output variable. These results are confirmed if we rely on non-parametric rank tests (rank tests are useful since DEA efficiency scores display relative performances for which it is useful to compare ranks, e.g. Chen and Guan, 2012). For the single dimensions of the inputs, throughputs and outputs, despite some differences, we see relatively similar scores between "capital regions" and "predominantly urban regions" (especially in comparison with "intermediate and predominantly rural regions"). This makes sense since both types of regions share some important similarities with regard to agglomeration economies (Zimmermann, 2010). Furthermore, between the capital regions we see a relatively large variation in terms of R&D expenditure in business and in terms of patent applications and design registrations.

<Insert Table 2 about here>

The results of the slacks-based DEA for the sales efficiency for the 23 capital regions are presented in column nine (DEA VRS (M1)) of Table 2. The efficiency scores are based on an analysis including all 207 regions. The difference in efficiency score between capital regions (average score of 0.34) and non-capital regions (0.49) is significant (independent sample t-test). A similar finding of lower efficiency of the capital region at national level was found e.g. by Chen and Guan (2012). The multivariate compare means test also indicates significant differences in efficiency score if we further classify the non-capital regions according to the urban-rural classification. These findings are confirmed by non-parametric rank tests.

The efficiency scores by capital region reveal strong heterogeneity among the capital regions, with two capital regions (London (NUTS 1) and Madrid (NUTS 2)) being fully efficient, and half of the capital regions presenting an efficiency score below 0.20. The Copenhagen (NUTS 2) capital region, with an efficiency score of 0.84, is the third-ranking efficient capital region on the SME innovation sales frontier. An efficiency-based ranking of the regions (not presented here) reveals that six capital regions are in the upper quartile of the rankings, and eight (i.e. more than one out of three) are in the lowest ranked quadrant in terms of innovation sales in SMEs.

These findings confirm specificities of capital regions (even compared to the group of "predominantly urban regions") in terms of attention given to efficiency by which – at regional level aggregated – firm level R&I investments are converted into outputs in terms of at regional level aggregated innovation sales in SMEs.

Before going into more detail in these findings, as indicated before and commonly applied in DEA (e.g. Edquist et al., 2018), we follow a constant returns to scale (CRS) approach as an alternative (robustness check) for the variable returns to scale approach (VRS). The CRS approach reflects the fact that the inputs' proportional change contributes to the same outputs' proportional change (Charnes et al., 1978), while the VRS assumption assumes the inputs' proportional change may not yield the same outputs' proportional change (Banker et al., 1984). The efficiency scores and ranks based on the CRS technique (column "DEA CRS (M1)" in Table 2) confirm the findings using the VRS technique that capital regions present lower output efficiency in terms of innovation sales in SMEs, both in terms of average efficiency score as in terms of ranking. On the SME innovation sales frontier, no efficient capital region is identified. Even though the London (NUTS 1) and Madrid (NUTS 2) capital regions were positioned on the efficient frontier based on the VRS technique, they do not outperform other regions when they are being evaluated based on the CRS technique.

As additional robustness checks to these findings we consider a shorter time-lag between R&D inputs, throughputs, and outputs. In line with Belderbos et al. (2004) we consider a two-year time-lag. First, we test this for the same period and on the same data as for the "DEA VRS (M1)" but by considering the output with a two-year time-lag instead of four years. The results ("DEA VRS (M2)") demonstrate that the differences in efficiency between capital and non-capital regions persist, but they are no longer significant at five percent level. In addition, we consider this same two-year time-lag model for a more recent period of the RIS (shifting all inputs, throughputs, and the outputs with two years compared to the "DEA VRS (M2)" model. The results ("DEA VRS (M3)") are based on the RIS2019 and reveal no significant differences between capital and non-capital regions. The less or non-significant differences found in the models with a two-year time-lag reveal both the importance of the time-lag chosen, and a potential influence of the time period under consideration. However, they still confirm that capital regions are not more efficient than non-capital regions in turning their particularly rich knowledge base into innovation sales in SMEs.

Output efficiency gap in innovation sales in SMEs

The descriptive statistics in Table 2 demonstrated significant differences in terms of firm level R&I inputs, as well as in terms of the sector structure of capital regions. To gain deeper insights in the reasons for lower attention to output efficiency in terms of innovation sales in SMEs in capital regions, Table 3 provides more details on the VRS efficiency scores presented in model 1 ("DEA VRS (M1)") in Table 2. More specifically, 'term' efficiency; i.e. efficiency score in each of the three consecutive periods under consideration is added (t_1: 2006-2010; t_2: 2008-2012; t_3: 2010-2014), as well as insights into excess use of inputs (business R&D expenditure, non-R&D innovation expenditure excess, employment in medium- and high-tech manufacturing and knowledge-intensive services excess), sales of innovations output shortfall, and throughputs' shortfall in terms of patent, trademark, and design applications.

<Insert Table 3 about here>

For example, the overall efficiency of 0.66 for the Brussels-Capital Region (NUTS2) can be traced back to a period efficiency of 0.55 in 2006-2010 (t_1), an efficiency of 0.57 in the second period (2008-2012), and a fully efficient performance in period three (2010-2014). The Brussels-Capital Region (NUTS 2) could have been fully efficient in term one by decreasing (with 0.05 units) R&D expenditures in the business enterprise sector, increasing IP throughput (for all forms of IP considered: patent, trademark, and design applications), and increasing innovation sales (0.09). The lack of full overall efficiency in period two can be explained by a shortfall in sales output of 0.18. Based on the strong increase of business R&D expenditure in this region during the period 2006-2010 (https://stip.oecd.org/stip.html - accessed March 2020) we notice an initial decrease in efficiency, but a gradual shift to full efficiency in terms of innovation sales of SMEs, compared to the benchmark group at the efficient frontier. With regard to the generous policy actions giving clear incentives to enhance IP outputs during the period under consideration (https://stip.oecd.org/stip.html - accessed March 2020), the shortfalls in terms of IP applications disappeared in period two and three. An opposite evolution can be seen for example in the Copenhagen (NUTS2) capital region. In period one and two this region was fully efficient, whereas in period three the region was characterized by excess inputs in business R&D, shortfall in patent and trademark applications, and shortfall in innovation sales output.

If we focus on the use of inputs, an excess in business R&D expenditure occurs in over one out of three capital regions, and an excess in non-R&D innovation expenditure appears in close to half of the regions. The excess in non-R&D innovation expenditure contrasts with the significantly lower overall efforts in this field in capital regions compared to non-capital regions (Table 2). The latter indicates that even the lower endowment with this type of firm level investments in capital regions compared to other regions is not an incentive to focus more on efficiency of amounts invested. Twenty out of the twenty-three capital regions demonstrate an excess input in employment in medium- and high-tech manufacturing or knowledge-intensive services. Most capital regions also present a shortfall in terms of all forms of IP, i.e. these regions generate IP outputs at a lower rate than the regions at the efficient frontier. This finding confirms the assertion that most capital regions allocate the inputs in excess of their efficient amount (in view of IP throughputs).

DISCUSSION AND CONCLUSIONS

Differences in output efficiency of business R&I investment cannot be seen independently of regional specificities (Iammarino et al., 2019). The central research question in this paper was whether business R&I investment in capital regions is as efficiently converted into innovation sales of SMEs as in non-capital regions. Capital regions are characterised by geographical concentration and easy access to (high-skilled educated) labour, allowing knowledge to diffuse more rapidly and broadly (Gertler, 1995). They offer specific conditions for innovation in SMEs in terms of factors internal to SMEs, external environment characteristics, and regulation and public support measures (Romero and Martínez-Román, 2012). Capital regions have unique characteristics as crossroads for international talent and in terms of a strong presence of central government (Zimmermann, 2010) and institutions (Mayer et al., 2016). They share strong agglomeration effects with predominantly urban areas (Simmie, 2002).

Based on dynamic slacks-based DEA, a comparison was undertaken between 23 capital and 184 non-capital regions in Europe during the period 2006-2014. The application of a non-parametric technique for evaluating R&I investment output efficiency at the regional level makes it possible to include a set of inputs and throughputs, and to assess the excess or shortfall of each of the variables in their contribution to sales efficiency. The application of the DEA technique to investigate efficiency, whereby firm level inputs are converted into innovation outputs, extends the use of the Regional Innovation Scoreboard which has hitherto been used as a popular source for monitoring and policy purposes (Hollanders and Es-Sadki, 2017).

Our analysis revealed that capital regions in Europe, compared to non-capital regions (whether or not further subdivided by degree of urbanisation), demonstrate significant lower efficiency in converting at region level aggregated firm level investments in R&I into innovation sales of SMEs. The significant lower performance in innovation sales of SMEs in capital regions supports the literature emphasizing particularities and types of regional innovation systems (e.g. Cooke, 2007; Capello and Lenzi, 2013). It indicates that these places that are central to the location of highly innovative knowledge-intensive services (Doloreux et al., 2010; Teirlinck, 2018) or SMEs more generally (Romero and Martínez-Román, 2012), and perceived as places which reflect, shape and change the cultural, social and political characteristics of a country, and as regulators of capital flows which are implemented according to the setting and institutions of these areas (Mayer et al., 2016), innovate with less focus on efficiency.

A detailed analysis of the excess and shortfall contributions of the different R&I inputs and IP throughputs showed that – in view of an efficient conversion of business R&I investment inputs in innovation sales outputs in SMEs – excess in expenditure is more often the case for non-R&D expenditure compared to R&D expenditure. Also, it is rather common for capital regions that at regional level strong business R&I investments are not fully efficiently translated (there is a shortfall) in IP in terms of patents, trademarks and registered designs, from a viewpoint on efficient implementation of innovation sales in SMEs. Moreover, to be fully efficient, a large majority of capital regions overspecialize in medium- and high-tech manufacturing and knowledge-intensive services. Furthermore, marked differences exist between capital regions, implying that capital regions being among the most dynamic in terms of income and employment creation, and forming a rather homogeneous group of high-income leading regions in Europe (Iammarino et al., 2019), are heterogeneous in their focus on efficiency. Our findings also confirm that in terms of efficiency of turning R&I inputs into innovation outputs, capital regions in Europe evolved differently during and in the aftermath of the economic crisis of 2008 (Dijkstra et al., 2015). One of the reasons for this could be that policy decisions influence the output efficiency of firm level investments in R&I, as demonstrated for one of the capital regions, thereby confirming Romero and Martínez-Román (2012).

From the literature, several arguments help explain these results. First, diseconomies of agglomeration (Cooke, 2007; Lee, 2016) could make capital regions less output-efficient in terms of product innovation sales in SMEs. These effects weaken the expected localized agglomeration advantages of these regions in terms of: enhanced knowledge spillovers which may be more prominent in capital regions; concentration of people and economic activities; spatial concentration which helps SMEs find specialized skills and lower transport costs; enhanced knowledge transfers and mutual learning; and culture and creativity (Montalto et al., 2018). However, we would also expect these diseconomies of agglomeration for "predominantly urban regions", whereas the latter regions are the second most efficient type of region in the analysis. This renders the argument of diseconomies of agglomeration to explain the relatively low output efficiency in capital regions less obvious. Therefore, lower efficiency in capital regions could be more due to rather unique characteristics of capital regions in terms of setting and institutions (Zimmermann, 2010; Mayer et al., 2016) giving rise to policy failures (e.g. Edler and Fagerberg, 2017; Grashof, 2021) and/or create abundance of opportunities through an extensive provision of inputs that firms do not need to care so much about efficiency of R&I investments. A second argument for moderate efficiency in capital regions is provided by Zabala-Iturriagagoitia et al. (2007) who state that less wealthy regions (in terms of GDP per capita), which non-capital regions generally are, target to absorb and adopt innovation from other regions which requires lower investment and lower risk. Guan and Chen (2012) arrive at similar conclusions, and point out that regions that invest modestly in innovation still enjoy significant innovation outputs, and therefore reach high output efficiency. This is confirmed at EU country level by Edquist et al. (2018). Furthermore, while the aim of 'leading' innovative regions is radical innovation which brings uncertainty, high-risk and failure, less R&D intensive regions may be more efficient because these regions - relatively more than capital regions - target short term and innovation objectives of a more applied nature. Consequently, they invest fewer inputs and contribute to more marketable output during a short period time-lag which is not enough for leading regions to follow radical innovation (Iammarino et al., 2019).

From a policy making perspective, besides effectiveness of R&I investments, efficiency by which scarce regional level business R&I investment inputs are converted in regional level innovation sales outputs in SMEs increasingly gained attention (Han et al., 2016; Broekel et al., 2018). SMEs are a focal point of regional, national and European policy alike. At European level, the monitoring of innovative SMEs in regions in the Regional Innovation Scoreboard is a way for countries to support all policy levels in their efforts to grow and to hasten the renewal of their economies by stimulating the innovativeness of their SMEs. However, public resources to stimulate private R&I investments are limited and there's increasing "value for money" pressure expressed in a huge range of evaluation studies tackling both effectiveness and efficiency of public support (OECD, 2019). Our finding of lower efficiency in capital regions implies that a blind focus in policy making on efficiency in all types of regions should be avoided (confirming the stream of literature that focuses on classifications of types of regions according to variance in terms of innovation, technology and knowledge - e.g. Camagni and Capello, 2013; Capello and Lenzi, 2013). On the one hand, it may be that innovative ideas generated in capital regions are commercialized outside these regions. If the abundant R&I knowledge base in capital regions in Europe is commercialized elsewhere in Europe (i.e. in non-capital regions), our findings have other policy implications than if it turns out that innovation sales largely take place outside the European Union (“leakage” of the outputs of the R&I knowledge base towards other parts of the world). The latter may be facilitated by the position of capital regions as crossroads of international talent and given their role as places which offer the strategic combination of patents, industrial design, and trademarks that supports technological innovation, in particular in services industries, including SMEs in knowledge-intensive business services (Doloreux et al., 2010). Iammarino et al. (2019) refer to a mechanism of inter-personal and inter-regional compensation acting from spatially concentrated economic growth through the diffusion of knowledge (i.e. spatial knowledge spillovers). Similarly, agglomeration diseconomies affecting the labour market condition of a capital (or highly urbanized) region may affect employment growth in other regions (Lee, 2016). On the other hand, if the moderate output efficiency results from a systematic weakness of at regional level aggregated SME innovation in capital regions, more attention is needed to provide a framework for the conditions for SMEs to innovate in capital regions. As Iammarino et al. (2019) point out; high-income regions are challenged to maintain their specialisation in high-wage activities as in the face of a changing wider landscape of comparative advantages these activities may become progressively more widespread, and because innovative sectors when maturing spread out geographically. The challenge for the richest regions therefore is to maintain prosperity through replacing old activities with new ones on the technological frontier and by continuously pushing the edge of innovation.

Further research could pay attention to potential differences between (capital and other) regions in terms of economic evolution and the reasons behind them (Annoni and Dijkstra, 2019; Fratesi and Rodriguez-Pose, 2016; McCann and Acs, 2011), including the influence of the use of EU funds in regions across time (Dijkstra et al., 2013), and institutional quality since institutions play a key role in determining the regional development potential (Iammarino et al., 2019). The analysis presented also allows further comparison between the more fine-grained urban-rural classification and other types or classifications of regions, and extends the RIS as a tool for regional benchmarking analysis for research and innovation efficiency. Another aspect is that the focus on SMEs should not disregard the role of multinational firms in the R&I knowledge base of many regions. Differences in the degree of knowledge spillovers from these firms to SMEs within the region may be an important factor for explaining differences in efficiency by which a region's aggregated firm level investments in R&I are converted in innovation sales in SMEs. In this respect, a more systematic uptake in the RIS of SME and non-SME inputs and throughputs, would be recommended, as for now some of these indicators are measured at the level of the entire business enterprise sectors, whereas others are measured at SME level. Doing so would allow more profound insights in knowledge spillovers between SMEs and other parts of the business enterprise sector, and eventually also of the public sector (Fritsch and Slavtchev, 2011). In addition, even in the limited time-span for which harmonized data are available (2006-2014), our analysis revealed differences in efficiency according to the time-lag considered between inputs and outputs, and to the period under consideration (in line with Fratesi and Perucca (2018) who found heterogeneous influence of the 2008 economic and financial crisis on regions). Availability of indicators that are comparable over a longer time-period would allow more detailed analysis in this respect. Finally, the for-policy reasons used NUTS2 level in this and in many other papers does not fully consider differences in functional diversity in these territorial areas in terms of degree of inclusion of commuter areas (e.g. Annoni and Dijkstra, 2019). This as well is an area for further improvement.

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Figure 1. Methodological framework

Inputs	Throughputs	Output
R&D expenditure in business sector (2006-2008-2010)	EPO patent applications (2007-2009-2011)	Sales of new-to-market & new-to-firm innovations by SMEs (2010-2012-2014)
Non-R&D innovation expenditure SMEs (2006-2008-2010)	Trademark applications (EUIPO) (2008-2010-2012)	
Employment in medium/high-tech manufacturing and knowledge-intensive services (2009*-2009-2011)	Design applications (EUIPO) (2008-2010-2012)	

*No harmonized data available for the year 2007, replaced by data for 2009. As the economic structure changes little in a two-year time-span this can be supposed having little influence on the outcomes of the model.

Table 1. Variable definition

	Indicator	Definition
Inputs	R&D expenditure in business sector	R&D expenditure in the business sector as a percentage of GDP
	Non-R&D innovation expenditure SMEs°	Non-R&D innovation expenditure as a percentage of total turnover for all SMEs
	Employment in medium/ high-tech manufacturing and knowledge-intensive services*	Employment in medium-high and high tech manufacturing and knowledge-intensive services as a percentage of total employment
Throughputs	EPO patent applications	Number of EPO patent applications per billion GDP (in PPS)
	Trademark applications	Number of European trademark applications per billion GDP (in PPS)
	Design applications	Number of individual design applications at the European Union Intellectual Property Office per billion GDP (in PPS)
Output	Sales of new-to-market & new-to-firm innovations SMEs°°	Sales of new-to-market and new-to-firm innovations as a percentage of total turnover of SMEs

Note: in the RIS the variables are classified in "firm level investment", "innovation activities", and "impact" variables (Hollanders and Es-Shadki, 2017). Our "inputs" refer to firm level investments in R&I, the "throughputs" refer to "innovation activities" (with focus on intellectual assets), and the "output" refers to impacts with focus on SMEs. This classification is in line with the one commonly used in the analysis of the RIS ((Hollanders and Es-Shadki, 2017). We apply one difference compared to the RIS classification, i.e. that we control for the sector structure of the economy by including the share of employment in medium- and high-tech manufacturing and in knowledge-intensive services as an input indicator since the sector structure largely determines R&I behaviour (European Commission, 2019). * "Medium-high- and high-tech manufacturing and knowledge-intensive services sectors include Chemicals, Machinery, Office equipment, Electrical equipment, Telecommunications and related equipment, Precision instruments, Automobiles, Aerospace and other transport, Water transport, Air transport, Post and telecommunications, Financial intermediation, Insurance and pension funding, Activities auxiliary to financial intermediation, Real estate activities, Renting of machinery and equipment, Computer and related activities, Research and development, and Other business activities. The share of employment in high-tech manufacturing sectors is an indicator of the manufacturing economy that is based on continual innovation through creative, inventive activity. Knowledge-intensive services can be provided directly to consumers, such as telecommunications, and provide inputs to the innovative activities of other firms in all sectors of the economy. The latter can increase productivity throughout the economy and support the diffusion of a range of innovations, in particular those based on ICT" (Hollanders and Es-Shadki, 2017, p.62). ° "Several of the components of innovation expenditure, such as investment in equipment and machinery and the acquisition of patents and licenses, measure the diffusion of new production technology and ideas" (Hollanders and Es-Shadki, 2017, p.60). °° "This indicator measures the turnover of new or significantly improved products and includes both products which are only new to the firm and products which are also new to the market. The indicator thus captures both the creation of state-of-the-art technologies (new-to-market products) and the diffusion of these technologies (new-to-firm products)" (Hollanders and Es-Shadki, 2017, p.63).

Table 2. Efficiency performance of capital regions – sales from innovation in SMEs - variable returns to scale (VRS) and constant returns to scale (CRS)

Capital region (NUTS code RIS 2017)	**R&D expenditure business _06_10**	**Non-R&D innovation expenditure _06_10**	**Employment medium- & high- tech _07_11**	**EPO Patent applications _07_11**	**Trademark registrations _08_12**	**Design registrations _08_12**	**Sales of innovation SMEs_10_14**	**DEA VRS (M1) - Efficiency score**	**DEA CRS (M1) - Efficiency score**	**DEA VRS (M2) - Efficiency score**	**DEA VRS (M3) - Efficiency score**
Amsterdam (Noord-Holland - NL32)	0.28	0.30	0.56	0.32	0.46	0.54	0.51	0.45	0.16	0.42	1
Athens (Attiki - EL30)	0.19	0.30	0.52	0.12	0.24	0.20	0.57	0.10	0.06	0.12	0.06
Berlin (DE30)	0.48	0.30	0.70	0.51	0.49	0.48	0.57	0.47	0.13	0.47	1
Bratislava (Bratislavský kraj - SK01)	0.18	0.37	0.73	0.12	0.28	0.31	0.66	0.18	0.09	0.19	0.15
Brussels (Région de Bruxelles-Capitale - BE10)	0.34	0.22	0.54	0.27	0.38	0.44	0.71	0.66	0.18	0.45	1
Bucharest (Bucuresti-Ilfov - RO32)	0.23	0.22	0.52	0.09	0.27	0.19	0.17	0.06	0.04	0.08	0.06
Budapest (Közép-Magyarország - HU10)*	0.35	0.22	0.65	0.23	0.28	0.33	0.29	0.12	0.06	0.12	0.07
Copenhagen (Hovedstaden - DK01)	0.79	0.24	0.68	0.57	0.45	0.74	0.49	0.84	0.19	0.91	1
Dublin (Southern and Eastern - IE02)**	0.37	0.32	0.58	0.25	0.38	0.31	0.46	0.16	0.09	0.18	0.15
Helsinki (Helsinki-Uusimaa - FI1B)	0.70	0.26	0.78	0.42	0.26	0.54	0.50	0.18	0.08	0.17	1
Lisbon (Lisboa - PT17)	0.38	0.24	0.50	0.13	0.30	0.28	0.53	0.09	0.08	0.10	0.07
Ljubljana (Zahodna Slovenija - SI04)	0.42	0.26	0.65	0.30	0.39	0.61	0.42	0.22	0.11	0.24	0.10
London (UKI)	0.21	0.30	0.71	0.22	0.48	0.48	0.88	1	0.14	1	1
Madrid (Comunidad de Madrid - ES30)	0.42	0.12	0.68	0.22	0.44	0.36	0.47	1	0.32	1	0.21
Oslo (Oslo og Akershus - NO01)	0.47	0.34	0.63	0.33	0.26	0.36	0.52	0.38	0.20	0.33	0.09
Paris (Île de France - FR10)	0.56	0.19	0.74	0.45	0.39	0.53	0.49	0.39	0.17	0.69	0.3
Prague (Praha - CZ01)	0.37	0.21	0.70	0.15	0.34	0.50	0.52	0.14	0.09	0.14	0.08
Rome (Lazio - ITI4)	0.27	0.27	0.60	0.19	0.28	0.30	0.59	0.16	0.08	0.15	0.12
Sofia (Yugozapadna i yuzhna tsentralna Bulgaria - BG4)°	0.17	0.18	0.39	0.09	0.34	0.45	0.32	0.13	0.11	0.15	0.12
Stockholm (SE11)	0.69	0.31	0.86	0.60	0.49	0.63	0.45	0.51	0.11	0.41	1
Vienna (Ostösterreich - AT1)	0.52	0.24	0.52	0.40	0.48	0.49	0.52	0.34	0.20	1	0.30
Warsaw (Mazowieckie - PL12)°°	0.21	0.30	0.52	0.12	0.32	0.48	0.16	0.08	0.05	0.14	0.10
Zagreb (Kontinentalna Hrvatska - HR04)	0.25	0.33	0.33	0.11	0.01	0.00	0.40	0.06	0.06	0.06	0.02
Average capital regions (n=23)	0.39 (0.18)	0.26 (0.06)	0.61 (0.12)	0.27 (0.16)	0.35 (0.11)	0.42 (0.16)	0.49 (0.16)	0.34 (0.29)	0.12 (0.07)	0.37 (0.32)	0.39 (0.42)
Average non-capital regions (n=184)	0.30 (0.19)	0.31 (0.08)	0.46 (0.16)	0.30 (0.20)	0.29 (0.11)	0.42 (0.20)	0.49 (0.16)	0.49 (0.36)	0.32 (0.33)	0.49 (0.36)	0.46 (0.39)
Average predominantly urban regions (n = 79)	0.36 (0.18)	0.30 (0.08)	0.51 (0.16)	0.37 (0.19)	0.34 (0.09)	0.50 (0.16)	0.54 (0.17)	0.54 (0.33)	0.29 (0.29)	0.52 (0.33)	0.48 (0.36)
Average intermediate regions (n = 91)	0.25 (0.19)	0.31 (0.08)	0.42 (0.16)	0.26 (0.20)	0.25 (0.11)	0.36 (0.20)	0.45 (0.14)	0.44 (0.36)	0.32 (0.34)	0.45 (0.37)	0.48 (0.42)
Average predominantly rural regions (n = 14)	0.24 (0.17)	0.34 (0.08)	0.39 (0.15)	0.23 (0.15)	0.24 (0.10)	0.36 (0.20)	0.50 (0.09)	0.59 (0.40)	0.42 (0.40)	0.55 (0.42)	0.31 (0.40)
T-test compare means capital vs non-capital	2.12**	-2.94***	4.44***	-0.77	2.47*	-0.13	-0.16	-2.04*	-2.88**	-1.48	-0.82
Kruskal-Wallis rank test (capital vs non-capital)	4.71*	10.06**	19.76***	0.23	6.87**	0.02	0.00	4.87*	10.20**	3.13°	0.55
Multivariate compare means test (Wald chi2)°°°	23.86***	14.77***	46.52***	18.42***	49.97***	24.44***	12.01**	9.70*	50.41***	4.57	3.42
Kruskal-Wallis rank test°°°	25.67***	13.16**	33.04***	19.07***	42.80***	22.45***	6.52°	11.96***	13.15***	8.37*	6.25°

RIS 2019: *HU11 Budapest; ** IE06 Eastern and Midland; °BG41Yugozapaden; °°PL91Warszawski stoleczny. °°°Capital regions and three categories of urban classification.

Table 3. Reasons for inefficiency of innovation sales – fully inefficient capital regions

Capital region - NUTS code RIS 2017	Overall efficiency	Term	Term efficiency	Excess input use			Output shortfall	Throughput shortfall		
				R&D expenditure	Non-R&D innovation expenditure	Employment in medium/ high-tech & knowledge-intensive services	Sales of new-to-market & new-to-firm innovation	Patent applications	Trademark applications	Design applications
Amsterdam - NL32	0.45	t1	0.60			0.16	0.14	0.02		
		t2	0.32		0.05	0.01	0.24	0.06		0.15
		t3	0.50		0.07	0.02	0.04	0.05	0.01	0.12
Athens - EL30	0.10	t1	0.09				0.29	0.16	0.15	0.41
		t2	0.10					0.19	0.17	0.38
		t3	0.11			0.17		0.20	0.21	0.33
Berlin - DE30	0.47	t1	0.48				0.10	0.00	0.01	0.17
		t2	0.45			0.12	0.00	0.03	0.02	0.23
		t3	0.47		0.10	0.27	0.03	0.02		0.22
Bratislava - SK01	0.18	t1	0.21		0.36	0.11	0.07	0.13	0.08	0.15
		t2	0.14			0.36	0.02	0.17	0.14	0.26
		t3	0.21			0.25		0.11	0.08	0.26
Brussels - BE10	0.66	t1	0.55	0.05			0.09	0.02	0.06	0.01
		t2	0.57				0.18			
		t3	1.00							
Bucharest - RO32	0.06	t1	0.05				0.63	0.21	0.18	0.42
		t2	0.06				0.47	0.22	0.19	0.38
		t3	0.08			0.19	0.40	0.19	0.16	0.26
Budapest - HU10	0.12	t1	0.11			0.10	0.37	0.24	0.14	0.40
		t2	0.14			0.17	0.19	0.23	0.16	0.30
		t3	0.11			0.23	0.36	0.20	0.20	0.38
Copenhagen - DK01	0.84	t1	1.00							
		t2	1.00							
		t3	0.64	0.26		0.20	0.11	0.02	0.00	
Dublin - IE02	0.16	t1	0.18			0.17		0.24	0.04	0.33
		t2	0.18		0.19	0.01	0.15	0.22	0.04	0.34
		t3	0.14			0.04	0.27	0.25	0.06	0.43
Helsinki - FI1B	0.18	t1	0.15	0.00		0.17	0.09	0.39	0.22	0.29
		t2	0.18			0.19	0.04	0.42	0.19	0.22
		t3	0.22	0.03	0.03	0.26		0.37	0.20	0.11
Lisbon - PT17	0.09	t1	0.11					0.31	0.04	0.41
		t2	0.08			0.01	0.33	0.39	0.11	0.42
		t3	0.09			0.02		0.42	0.16	0.41
Ljubljana - SI04	0.22	t1	0.24			0.14	0.12	0.27	0.02	0.22
		t2	0.26			0.15	0.06	0.30	0.03	0.15
		t3	0.19			0.16	0.27	0.30	0.11	0.06
Oslo - NO01	0.38	t1	0.30	0.09		0.19	0.48			
		t2	1.00							
		t3	0.28	0.12	0.22	0.19	0.36	0.07	0.04	0.09
Paris - FR10	0.39	t1	0.62	0.08		0.16	0.09		0.02	0.05
		t2	0.37	0.02	0.01	0.10	0.34	0.01	0.03	0.06
		t3	0.29	0.13		0.27	0.36	0.01	0.06	0.04
Prague - CZ01	0.14	t1	0.15			0.25	0.02	0.34	0.13	0.12
		t2	0.12			0.10	0.13	0.38	0.11	0.10
		t3	0.18			0.16	0.02	0.32	0.08	
Rome - ITI4	0.16	t1	0.14		0.002		0.24	0.19	0.14	0.32
		t2	0.16		0.04	0.08	0.25	0.18	0.12	0.26
		t3	0.20			0.16		0.14	0.14	0.25
Sofia - BG4	0.13	t1	0.12			0.03	0.17	0.18	0.07	0.14
		t2	0.13			0.01	0.18	0.18	0.06	0.13
		t3	0.14				0.31	0.18	0.04	
Stockholm - SE11	0.51	t1	0.45	0.00	0.03		0.17	0.05	0.02	0.06
		t2	0.62	0.08		0.28	0.03	0.07		0.07
		t3	0.47	0.06	0.09	0.34	0.12	0.06	0.02	0.11
Vienna - AT1	0.34	t1	0.34	0.03			0.14	0.13	0.01	0.18
		t2	0.36			0.01		0.19		0.19
		t3	0.31	0.01		0.08	0.16	0.16	0.02	0.17
Warsaw - PL12	0.08	t1	0.06				0.74	0.14	0.07	
		t2	0.10		0.16	0.003	0.68	0.11	0.07	0.001
		t3	0.08			0.0004	0.63	0.09	0.09	0.03
Zagreb - HR04	0.06	t1	0.26		0.27		0.12	0.16	0.39	0.48
		t2	0.16		0.25		0.16	0.21	0.44	0.53

t3	0.03	0.03	0.01	0.09	0.20	0.48	0.51

Note: The London and Madrid regions are fully efficient and therefore not presented in the table.

Appendix A: Slacks-based DEA

The DEA technique has several advantages in evaluating the relative efficiency compared to parametric techniques. First, DEA can measure the relative efficiency when each DMU (region) utilises multiple resources to generate multiple outputs. Each DMU is simultaneously evaluated by its allocation of inputs and generation of outputs, and is evaluated against other DMUs in order to create an efficient frontier. Second, DEA does not assume a specific R&D production describing the interrelationships between the research inputs and outputs (Wang and Huang, 2007). Thus, DEA is an apt technique to measure the efficiency of the regions as there is no information on how the regions operate to create knowledge and innovation, meaning that the regions allocate various resources in order to generate different kinds of innovation outputs. Third, DEA can be an effective tool where the weights (importance) of the inputs and outputs are not specified by each DMU. DEA allows each DMU to choose the inputs' and outputs' weights that maximize the ratio of weighted output to weighted input, subject to constraints that the weights obtained by the DMU under evaluation should not let any other DMU obtain a ratio of weighted output to weighted input exceeding one.

Even though the DEA approach has some advantages, it also is associated with some drawbacks. Standard DEA models only consider inputs and outputs for performance evaluation and do not take into consideration the internal DMUs' operation. In other words, standard DEA models overlook the interconnecting activities in a production process meaning that they are unable to investigate the black-box process of R&D activities of each DMU (Lu et al., 2014). Also, standard DEA models can measure the efficiency of the DMUs using multiple inputs and outputs for a single period of time (Cooper et al., 2000), which means the performance of the DMUs is evaluated, based upon historical records of merely one specific previous period. Therefore, one of the main caveats of the standard DEA models is that they are independent across a multiple-period time horizon (static) and ignore lagged productive effects that happen when the inputs contribute to the current evaluation period and to the future period (Chen and van Dalen, 2010), in our case lagged effects of accumulated knowledge inherent in R&I activities between two or multiple consecutive time periods.

The dynamic slacks-based DEA as proposed by Tone and Tsutsui (2010) is applied as the production of accumulated R&I investments have lagged effects on outputs. The dynamic slacks-based DEA model allows assessing the time change effect of the DMUs during a planning horizon with multiple time periods. This model includes desirable and undesirable carry-over variables (Tone and Tsutsui, 2010). Desirable carry-overs are considered as outputs and are carried to the next period. Undesirable carry-overs are taken as inputs which cause inefficiency if they comparatively excess. In the first stage of our analysis, we measure the efficiency using a model in terms of allocating R&D expenditure in the business sector, non-R&D innovation expenditure in SMEs, and employment in medium- and high-tech manufacturing and knowledge-intensive services to produce EPO patent applications, trademark applications, design applications and sales of new-to-market and new-to-firm innovations by SMEs. We define "EPO patent applications", "Trademark applications" and "Design applications" as desirable (good) carryovers and "non R&D innovation expenditure SMEs" as undesirable (bad) carryover, or in other words, a source of inefficiency. These three carryovers play the role of connecting activity from one period to the next period.

The output-oriented dynamic slacks-based DEA model under Variable Returns to Scale (VRS) is outlined as follows (Tone and Tsutsui, 2010): Suppose that n DMUs are observed in the dynamic production process over T terms where each DMU utilizes m inputs and s outputs. Let $x_{ijt}(i = 1, \dots, m; j = 1, \dots, n; t = 1, \dots, T)$, $y_{ijt}(i = 1, \dots, s; j = 1, \dots, n; t = 1, \dots, T)$ denote the observed input and output values of DMU j at term t, respectively. The throughputs in terms of (desired or good because considered as positive output) IP are symbolized as $z_{ijt}^{good}(i = 1, \dots, ngood; j = 1, \dots, n; t = 1, \dots, T)$. The output-oriented overall efficiency τ_o^* is given as the following linear program:

$$\frac{1}{\tau_o^*} = max\frac{1}{T}\sum_{t=1}^{T} w^t \left[1 + \frac{1}{s + ngood}\left(\sum_{i=1}^{s}\frac{w_i^+ s_{it}^+}{y_{iot}} + \sum_{i=1}^{ngood}\frac{s_{it}^{good}}{z_{iot}^{good}}\right)\right] \quad (1)$$

Subject to:

$$x_{iot} = \sum_{j=1}^{n} x_{ijt}\,\lambda_j^t + s_{it}^- \qquad (i = 1, \dots, m; t = 1, \dots, T) \quad (2)$$

$$y_{iot} = \sum_{j=1}^{n} y_{ijt}\,\lambda_j^t - s_{it}^+ \qquad (i = 1, \dots, s; t = 1, \dots, T) \quad (3)$$

$$z_{iot}^{good} = \sum_{j=1}^{n} z_{ijt}^{good}\,\lambda_j^t - s_{it}^{good} \qquad (i = 1, \dots, ngood; t = 1, \dots, T) \quad (4)$$

$$\sum_{j=1}^{n} z_{ijt}^{\alpha}\,\lambda_j^t = \sum_{j=1}^{n} z_{ijt}^{\alpha}\,\lambda_j^{t+1} \qquad (\forall i; t = 1, \dots, T - 1) \quad (5)$$

$$z_{io0}^{good} = \sum_{j=1}^{n} z_{ij0}^{good}\,\lambda_j^1 - s_{i0}^{good} \qquad (i = 1, \dots, ngood) \quad (6)$$

$$\sum_{j=1}^{n} \lambda_j^t = 1 \qquad (i = 1, \dots, T) \quad (7)$$

$$\lambda_j^t \geq 0, s_{it}^- \geq 0, s_{it}^+ \geq 0, s_{it}^{good} \geq 0 \quad (8)$$

Where $s_{it}^-, s_{it}^+, s_{it}^{good}$ are slack variables denoting input excess, output shortfall and throughput shortfall. The slacks express the required output increase and input decrease that an inefficient DMU needs to become efficient.

If the optimal solution (1) subject to (2)-(8) will be $(\{\lambda_o^{t*}\}, \{s_{ot}^{-*}\}, \{s_{ot}^{+*}\}, \{s_{ot}^{good*}\})$, the output-oriented term efficiency for the term t would be obtained by:

$$\tau_{ot}^* = \frac{1}{1 + \frac{1}{s + ngood}\left(\sum_{i=1}^{s} \frac{w_i^+ s_{iot}^{+*}}{y_{iot}} + \sum_{i=1}^{ngood} \frac{s_{iot}^{good*}}{z_{iot}^{good}}\right)}, \quad (t = 1, \ldots, T) \tag{9}$$

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