Research and development, innovation inputs and productivity; The role of National Innovation Systems

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Abstract

Innovation outcomes are typically linked to measurable resources such as R&D expenses and the number of researchers. However, we show that innovation outcomes are also significantly influenced by the National Innovation System, an aspect often overlooked in the existing literature. The National Innovation System encompasses challenging-to-measure resources such as the amount of staff training, the extent of university-industry or cross-industry collaboration, and the level of intellectual property rights. We demonstrate, using a Data Envelopment Analysis model, that cross-country differences in National Innovation Systems account for a significant share of relative inefficiencies in producing innovation from typical innovation inputs. This finding suggests that countries can support long-term economic growth by simply fostering and advancing a National Innovation System.

Keywords: Data Envelopment Analysis, National Innovation System, country efficiency heterogeneity, patent.

JEL Codes: O32, O47, E22.

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1 Introduction

Almost 90 years ago, Schumpeter (1934) argued that innovation plays a crucial role in economic and social changes. In particular, innovation activities are important for total factor productivity growth. Under the Schumpeterian perspective, Aghion and Howitt (1992) have proposed innovation-based endogenous growth models or innovation-led growth models that clearly show the role of innovation for long term growth and productivity gains. Thus, research and development (R&D) policies and R&D expenses targets are high on the policy agenda. With the exception of the years during and immediately after the financial crisis of 2007, R&D expenses are growing fast in higher education, government as well as in the business sector (OECD, 2022). In the OECD countries, the level of R&D spending rose by 2.7% in real terms during the last decade. Since 1995, R&D intensity (R&D expenses over GDP) grew from 2% to 2.4%. Against this background, a key question is the ability of countries to turn these expenses into innovations.

There is an extensive body of work about the production of knowledge/innovation e.g. Griliches (1990), Griliches (2007), Madsen (2008) or Verba (2022) among many others. In general, these studies link R&D expenses (either in level or as stocks of R&D) and the number of researchers to numbers of patents granted in countries, as a measure of innovation. To maximise innovation output from R&D there is a need to influence both speed and direction of innovation (Hekkert et al., 2007). This requires a well-designed management framework, a National Innovation System. A National Innovation System is the network of institutions in the public and private sectors whose activities and interactions initiate, import, modify, and diffuse new technologies (Freeman, 1987).

This paper investigates whether or not the National Innovation System explains cross-country differences in the production of innovations.

Firstly, we evaluate the impact of the stock of accumulated R&D and the number of researchers on both patents granted and the publication of scientific documents in OECD countries, and additionally Argentina, Russia and Singapore. We use Data Envelopment Analysis (DEA), a popular non-parametric mathematical programming approach for performance assessment and benchmarking, first proposed by Charnes et al. (1978). The aim of this analysis is to gauge to what extent a country turns research and development inputs (R&D and researchers) into innovation outputs (patents and publications) compared to other countries. In a second step, we analyse the factors that explain the differences in country' efficiency in transforming R&D into patents and documents. In particular, we analyse how differences in National Innovation Systems affect the "production" of innovation.

As emphasized by the OECD (1995), National innovation systems act as facilitators for interactions among various actors involved, and in our analysis, we focus on key characteristics that have been acknowledged as important in the literature. These are public-private collaborations, IPR rights, workforce training, and university expenses. According to (Wirkierman et al., 2018), the collaboration between the private and public sectors holds particular significance in enhancing technological capabilities. We first focus on two important type of collaborations: inter-industry collaboration (in the form of cluster development), and industry-university collaboration. On one hand, Inter-industry collaboration in the form of technological clusters stimulates knowledge spillovers, encourages cooperation and stimulate the identification of new technology trends and potential innovation (United Nations Economic Commission for Europe, 2013). On the other hand, industry-university partnerships play a crucial role in facilitating the assimilation and development of new technologies by firms (Veugelers, 2016).

We also investigate if intellectual property protection rights impact inefficiency. This is because it is pointed out that weak intellectual property protection rights might exacerbate free rider behaviour (Shapiro and Willig, 1990) and lower R&D activities. Another important aspect of National Innovation Systems is the absorptive capacity of firms (Kneller and Stevens, 2006). A skilled workforce will increase the ability of firms to implement new technologies (Abramovitz, 1986). Bauernschuster et al. (2008) indicate that continuous training of the work force increases the innovative capacity of firms.

Another element we consider is the share of university gross expenses in R&D in total expenses. As explained by Svarc et al. (2020), this share might be seen as a proxy of the production of more fundamental research, which is the prerequisite for many applied research activities.

This paper is organised as follows: section 2 presents the data used to compute inefficiency and sources of inefficiency. Section 3 summarizes results the estimates of the effect of National Innovation Systems on inefficiency. Section 4 compare Malmquist Total Factor Productivity index with and without innovation inputs and the last section concludes.

2 Data

This document uses a balanced panel dataset of 30 countries including European and OECD countries plus Argentina, Russia and Singapore from 2006 to 2019[2].

We consider four inputs and two R&D outputs. Two inputs are, respectively, the number of researchers in the business sector (mainly working in non-financial corporations) and in the non-business sector (working in university and/or public research departments). Rather than considering R&D expenditures we compute two R&D capital stocks, respectively for the business and the non-business sector. This distinction aims to reflect countries specificities where R&D is mainly public while in other countries R&D is mainly business oriented. It is also justified by the fact that public R&D typically focuses more on fundamental research (generating scientific publications), while business R&D is geared toward business innovations and patenting (Svarc et al., 2020).

The innovation outputs are: produced patents, and academic publications. Data on patents is sourced from the World Intellectual Property Organization. Data on scientific publications come from Scimago, a portal that collects citable scientific documents drawn from over 34,100 titles from more than 5,000 international publishers.

R&D capital stock (KRD_t) are figures computed using the perpetual inventory method and the accumulation of total Gross Domestic Expenditure on R&D (GERD)

[2] Countries included in the panel are: Argentina, Austria, Belgium, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Japan, Latvia, Lithuania, Luxembourg, Netherlands, Norway, Poland, Portugal, Romania, Russia, Singapore, Slovakia, Slovenia, Spain, Sweden, Turkey and the United Kingdom.

in constant 2015 PPPs Prices in USD (I_t) published by the OECD Main Science & Technology Indicators (MSTI).

$$KRD_{t+1} = (1 - \delta)KRD_t + I_t$$

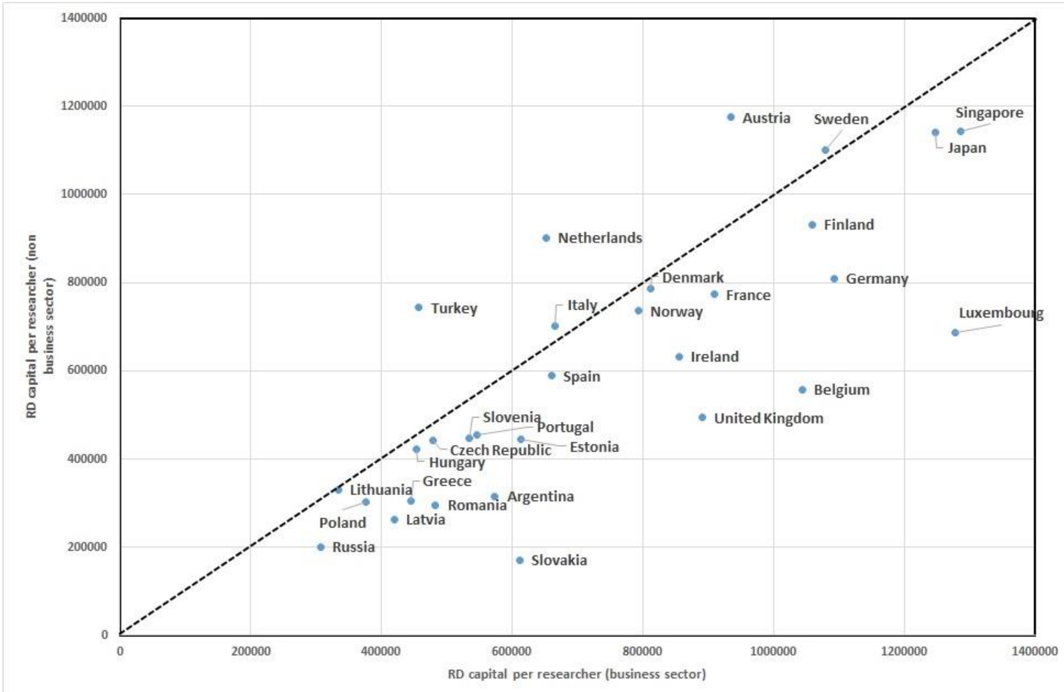
Following the work of Bernstein and Mamuneas (2006), Corrado et al. (2006) and Hall et al. (2010), we use a depreciation rate (δ) of 15 percent, the initial value is based on the average growth rate of GERD (g) for the business sector and the non-business sector. And, as in Hall et al. (2010), the capital stock is computed as,

$$KRD_t = \frac{I_t}{\delta + g}$$

Tables 2 and 3 in appendix provide some descriptive statistics on R&D capital. Eastern European countries and Luxembourg have lower R&D capital and fewer researchers compared to other countries. Clearly there is a size effect, small countries (in terms of population) tend to have less researcher, while countries with lower GDP tend to spent less in R&D. When the amount of R&D capital per researcher is computed, a different picture emerges. Singapore and Luxembourg have the highest ratios of R&D capital per researcher, with 1.29 million USD and 1.28 million USD respectively. It is only 0.31 millions USD in Russia or 0.91 for France. If Luxembourg has a very high ratio for the business sector, the country is close to the sample average regarding the non-business sector with an average value of 0.68 millions of USD. Figure 1 plots average values of R&D capital per researchers in the business and the non-business sector for countries.

One may note that the ratios of capital to researchers in the business and the non-business sector are similar for most countries, as indicated by the proximity of the country points to the dashed line (in Lithuania both ratio have a value of 0.33 millions, in Denmark it is 0.81 and 0.78 millions of USD). In general, researchers in the business sector have slightly more capital than in the non business sector (R&D capital deepening). A notable exception is Luxembourg where the endowment in capital is significantly higher for the business sector.

Figure 1: R&D capital per researcher business versus non-business sector averages 2006-2019 (USD)

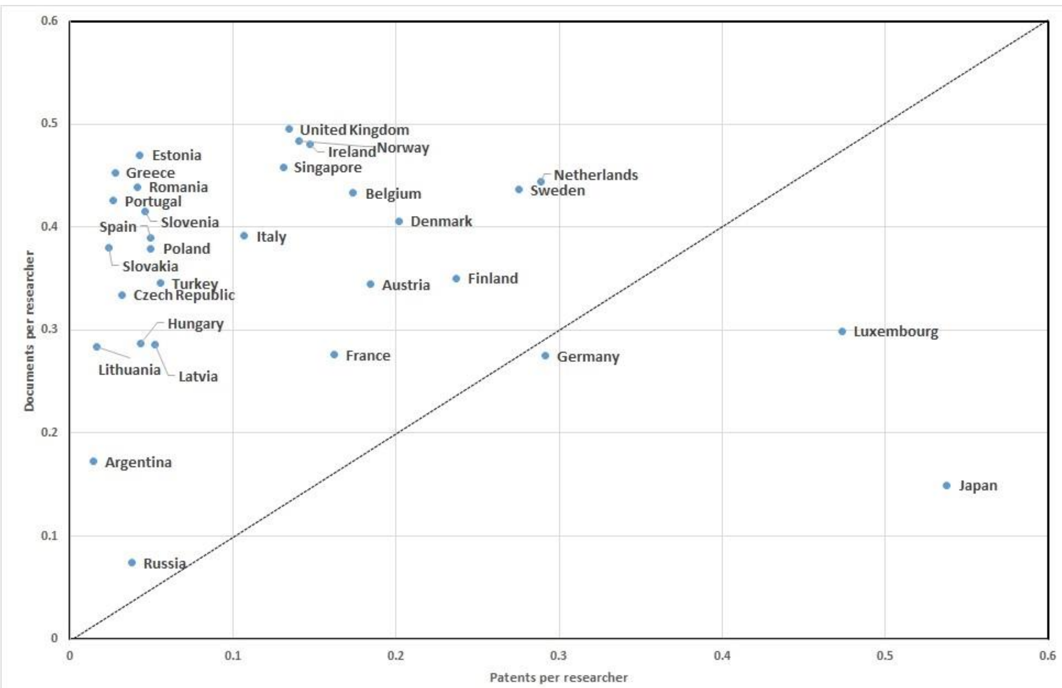


Note: Author computations based on OECD MSTI data.

To proxy innovation outputs we consider two variables. The first one is patent that is often used in studies about the knowledge production function (e.g. Wang, 2007). As explained by Griliches (1990), patents are a good indicator of differences in inventive activity across different firms. Patents can be used as an indicator to signal innovative capabilities (Czarnitzki et al., 2014). However, not all innovation outputs can be patented. For example, scientific theories, mathematical methods, computer programs or procedures for surgical or therapeutic treatment, or diagnosis, to be practised on humans or animals cannot be patented. Thus, all these innovations, in many cases, result from research activities that have been financed by R&D expenditures, but, might generate only academic publications. Thus, citable documents published is our second proxy for innovation output. Few studies have used citable documents to proxy innovation output, with the exception of studies that focus on the productivity of universities (e.g. Courtioux et al., 2022).

Looking at the number of patents and citable documents published, again, eastern countries have the lowest figures (Lithuania, Estonia, Latvia, Slovakia, Slovenia). For patents results are similar. However, when divided by the number of researchers we observe striking differences between countries. Graph 2 shows that countries like Japan or Luxembourg have more patents per researcher than other countries (respectively a ratio of 0.54 and 0.47) compared to 0.04 for Russia, 0.16 for France 0.29 for Germany. This does not come as a surprise, Japan's economic growth has been often attributed to its superior research and development capabilities, but the situation is deteriorating since the 2010s (Nishimura et al., 2022). In general, countries publish more documents than patents. Luxembourg performs well in terms of patent applications but OECD (2008) notes that it might be in part a statistical effect owing to the number of firms head-quartered there.

Figure 2: Citable documents versus patents per researcher - averages 2006-2019



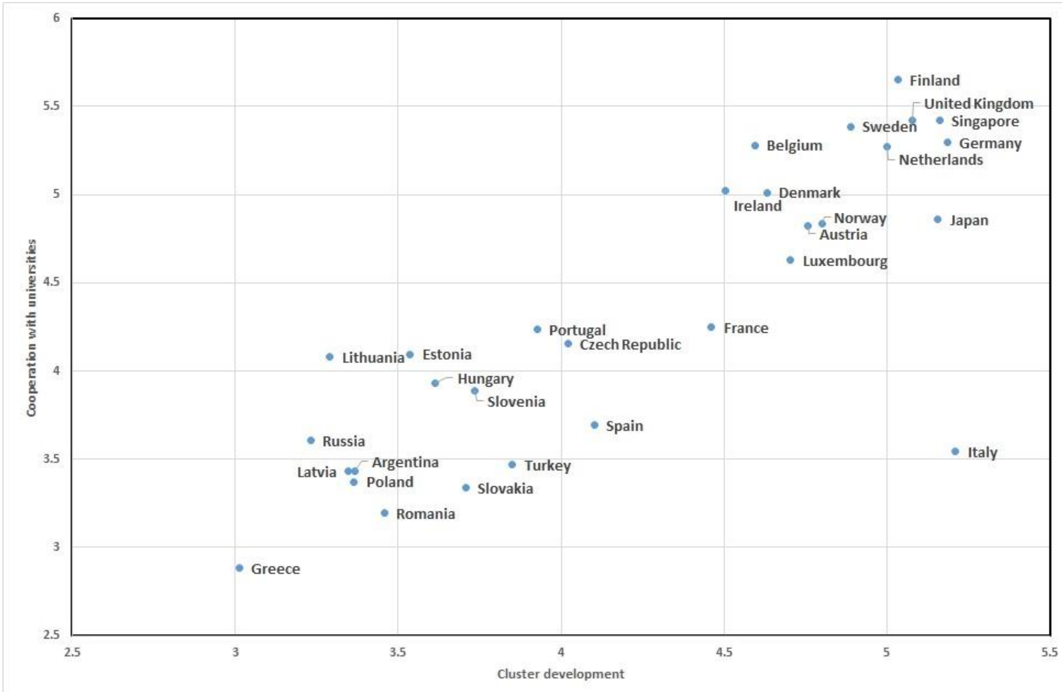
Note: Author computations based on WIPO and Scimago data.

Following Han (2007), we use patent data and citable document to compute two knowledge stocks. The inter-temporal identity used to derive stocks of patents and scientific documents is identical to the one used in deriving capital stocks, with the substitution of R&D by either patents or documents. We will use these stocks as innovation inputs to produce goods and services (GDP) and compute TFP indicators for countries.

However, R&D expenditures and the number of researchers are not sufficient to describe the complex process of innovation. The set of distinct institutions which jointly and individually contribute to the development and diffusion of new technologies and which provides the framework within which governments form and implement policies to influence the innovation process (Metcalfe, 1995) also matters. The National Innovation System plays an important role in fostering innovation activities. The OECD (1995) quotes two important features of National Innovation System: Industry alliances and Industry/University interactions. The World Economic Forum provides an assessment made by businessmen to evaluate these elements: State of cluster development and University/Industry collaboration in R&D. These two indicators are based on surveys collecting the views of representative businessmen on these two topics by providing a grade between 1 and 7 (7 indicates the best value) (Schwab, 2019)[3].

[3] These two variables are contextual variables and not inputs as individual businessman cannot change the national value (the perception of others) as well as the central planner (Government). This is in line with the main hypothesis of model of endogeneous growth such as Romer (1986), where, for example, managers can change the stock of knowledge in their firm but cannot change the total stock in the economy that is generating positive externalities. Here, for example, a firm might decide to engage in collaboration with universities but cannot influence other managers on this aspect.

Figure 3: University / Industry cooperation versus industry alliances - averages 2006-2019



Note: Author computations based on World Economic Forum data.

Figure 3 shows that cluster development [4] and Industry/University collaboration are highly positively correlated. Countries with higher levels of industry-university collaborations tend to have a greater presence of clusters. Moreover, the panel can be divided in two groups of countries. A first group of mainly Eastern European countries (Latvia, Poland, Romania, Russia, Slovakia, Lithuania, Estonia, Slovenia and Hungary), and Southern European countries such as Spain and Portugal. These tend to have low cluster development and low collaboration with universities. Portugal, for example, has a lower cluster development than other countries as the regional economic development policies have disregarded the importance of fostering the creation of clusters (Salvador and Chorincas, 2006). At the opposite, we have a group of Nordic countries

[4] clusters are a network of firms which tend to be located in relatively close geographical proximity and whose cross-sectoral linkages generate and renew local competitive advantage (Raines, 2017)

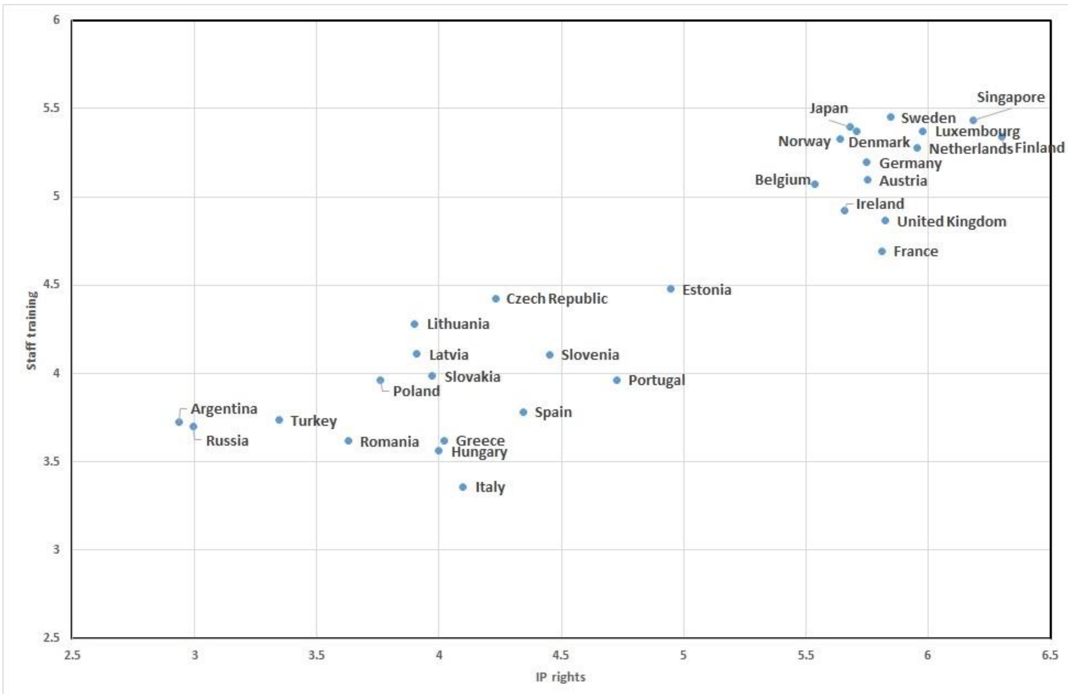
(Finland, Sweden, Norway, Denmark) and Western European countries (Belgium, United Kingdom, Germany, Ireland, Luxembourg) characterized by high cluster development and University / Industry collaboration. For the case of Nordic countries, these high scores translate the successful implementation of a triple helix innovation model in which universities, government authorities, and industrial firms cooperate in order to produce innovation (Solesvik, 2017, Arnkil et al., 2010). An outlier is Italy with high cluster development but low collaboration University / Industry. Interestingly, Abramo and D'Angelo (2009) found that most research projects' results of leading public research scientists and Italian universities do seem to have immediate industrial applicability, but in one third of the cases there are no Italian companies able to exploit the results. Italy registers a low propensity to capitalize on the results of public research (Abramo et al., 2009).

As explained in OECD (1995), a key NIS policy that enhances innovative capacity is staff training. Human capital determines firms' capacity to absorb new technologies (Abramovitz, 1986). Brunello et al. (2007) clearly show that R&D investment and training exhibit a complementary relationship. Bauernschuster et al. (2008) provide (weak) evidence that continuous training improves firm's innovations. For the case of Norway, where staff training is extensive (5.3), Boring (2017) provides evidence that training stimulates new ideas, creativity and increases innovation in firms. From figure 4, one can see that Italy has the lowest score for staff training (3.4). This observation might provide an explanation for the limited ability of companies to capitalize on research outcomes, as highlighted by Abramo and D'Angelo (2009).

The last element that characterize country's innovation systems is the strength of intellectual property protection rights. Intellectual property (IP) protection rights help innovators to temporarily gain monopoly power from successful innovation activities (Greenhalgh and Rogers, 2007). While imperfect appropriability increases the incentives of firms to free-ride on each other's R&D investment (Shapiro and Willig, 1990). Arguably, low assessment of the strength of IP rights might also signal lack of awareness about IP rights as well as low innovative capacities of firms. For example, this is the case of Poland (Clayton et al., 2023). Poland exhibits a property-protection rights score of 3.8 compared to 6.2 for Singapore. The lowest value for IP rights is for Argentina (2.9). Castrillo (2017) indicates that Argentina has a long and poor image as a country that disregards IP rights. Russia is also a country with a low evaluation of IP rights (2.9)

Aleksashenko (2012) attributes it to excess bureaucracy, corruption and absence of independent judicial protection property rights.

Figure 4: Staff training versus strength of IP rights - averages 2006-2019

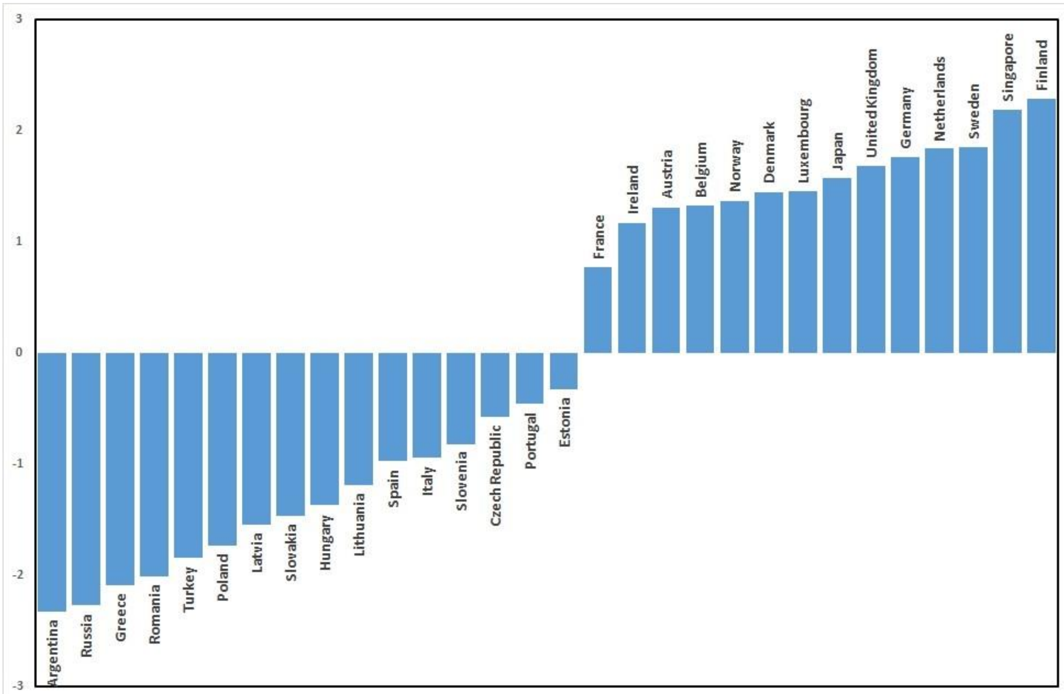


Note: Author computations.

To mitigate multicollinearity (due to the high correlation among contextual variables, as shown in table 4 in appendix), and maintain a manageable number of parameters to be estimated, we substitute contextual variables with a composite indicator variable obtained through principal component analysis (see Joliffe and Cadima (2016) for a presentation of the method).

The weights to aggregate the variables are computed on average values of each contextual variable and these weights are used to compute yearly aggregates. In other words the weights are constant across year. The first component explains 90 percent of total variance and is highly positively correlated with the four variables (Cluster Development, 0.89, Industry / University cooperation, 0.96, Staff development, 0.94, IP rights, 0.98).

Figure 5: National Innovation System composite index - averages 2006-2019

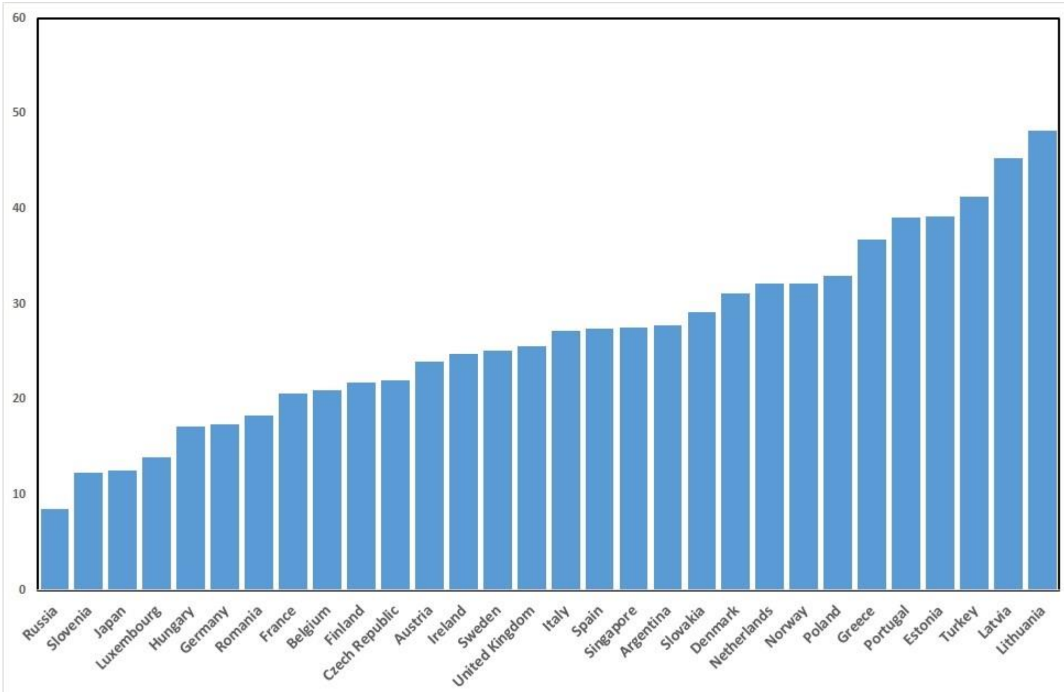


Note: Author computations based on World Economic Forum data.

One may argue that these variables are subjective and might not reflect the objective reality of National Innovation Systems. We quote Okun (1960) about the use of confidence surveys, that are also subjective assessments, to describe and predict the economic evolution of countries: "the population can sense the presence of a viruses in the atmosphere and still be totally unable to predict who will be stricken". Interestingly, the ranking implied by our composite index echoes the taxonomy of National Innovation Systems proposed by Wirkierman et al. (2018) based on the Community Innovation Survey firm level data. Wirkierman et al. (2018) classifies Austria, Belgium and Norway as "Top-notch NIS" countries. Our composite indicator also ranks these same countries highly in terms of all collaborations (see figure 3). Netherlands and Sweden rank high (labelled as the linear R&D-based NIS) . (these countries rank above average for all indicators used to compute our composite index.) On the bottom of the ranking, we have countries that are labelled Coping-NIS, Spoiled under-performing NIS and embryonic NIS following the taxonomy of Wirkierman et al. (2018). Finland ranks first for our indicator as, for most indicators, this country exhibits among the highest values. The high score of Finland on our indicator is not surprising, considering that innovation policy is regarded as one of the most vital public policies in the country. But also successful university reforms to improve research careers, research infrastructures and sectoral research. On the contrary, countries like Greece rank low, primarily due to their limited absorptive capacity of firms, as previously highlighted in OECD (2008).

Last, as explained by Veugelers (2016), Universities play three important roles: their teaching, universities disseminate knowledge and improve the quality of human capital employed in society; through the research they perform, universities extend the horizons of knowledge; and by their third-mission activities, they transfer their knowledge to society. Garca-Vega and scar Vicente Chirivella (2020) provide evidence that technology transfers from universities foster firm innovativeness. Thus, we look at the share of universities' R&D expenses in total expenses. This variable is not included in the computation of the composite indicator since the indicator is composed of variables that capture perceptions rather than expenses.

Figure 6: Share of R&D university expenses in total R&D expenses - averages 2006-2019



Note: Author computations based on OECD MSTI data.

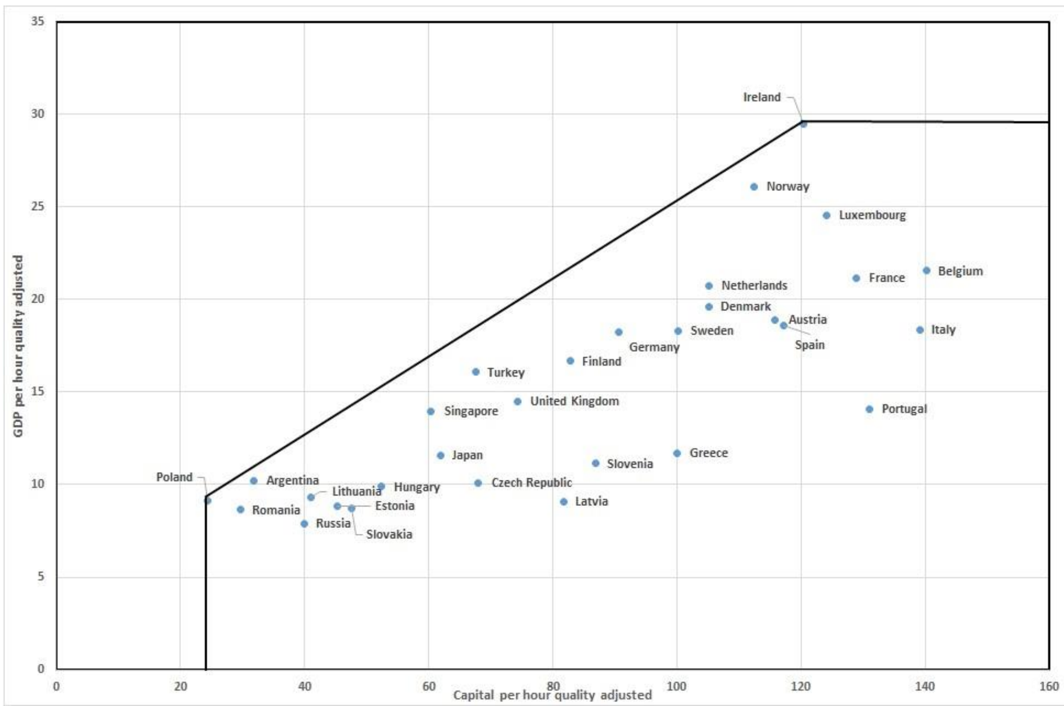
In the first step, we will use data on R&D capital and the number of researchers to assess the efficiency of countries in converting inputs into innovation outputs, such as patents and citable documents. In the second step, we will seek to explain the variations in efficiency of this conversion process by considering contextual NIS variables.

This paper focusses on the production of innovation, many studies highlight the importance of innovation for economic growth (Ibrahim, 2023). Thus, in a last step, we compute Malmquist total factor productivity (TFP) index using as inputs: physical capital and qualified labour plus innovation inputs (knowledge stocks based on patents and citable documents) and as outputs goods and services produced (Gross Domestic Product, GDP)[5]. To contrast our results we will compute

[5] In this study, economic inputs and GDP are sourced from the Penn World Tables (Feenstra and Timmer (2015) present the data). Physical capital correspond to equipment and are measured

Malmquist total factor productivity indicators without innovation inputs. Figure 7 indicates that, on average, countries with higher capital deepening (capital stocks divided by hours quality adjusted) have higher GDP per hours quality adjusted. Countries are more or less efficient in turning inputs into outputs, for example Portugal and France have relatively similar capital deepening (respectively 131 and 129 thousands of USD) but very different GDP per hours (respectively 14 and 21 thousands of USD).

Figure 7: GDP versus capital per hours quality adjusted - averages 2006-2019



Note: Author computations based on Penn World Data.

in USD in constant 2015 prices while labour is hours adjusted for quality. As explained in Feenstra and Timmer (2015) hours worked are adjusted by an index of human capital that takes into account the average years of schooling, linearly interpolated from Barro and Lee (2013), and an assumed rate of return for primary, secondary, and tertiary education, as in Caselli (2005).

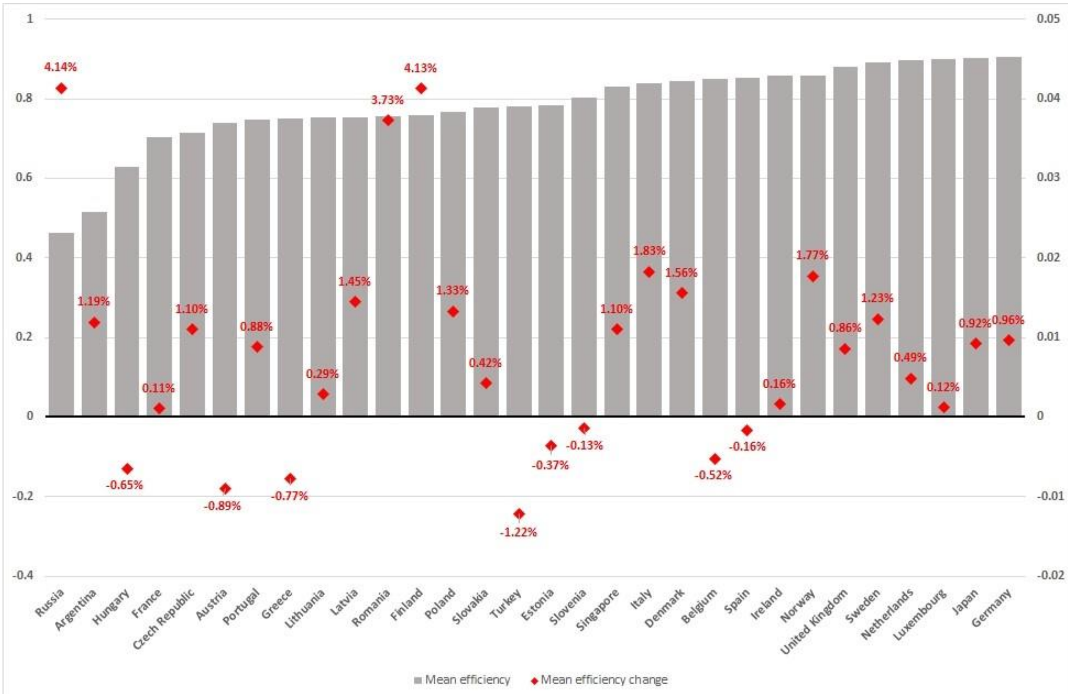
3 National Innovation Systems and efficiency

This section presents result on innovation efficiency and the role of National Innovation systems in explaining inefficiency differences (ineffiency is one minus efficiency) differences across countries. We now present the country efficiency scores in transforming research inputs, namely R&D capital and the number of researchers, into innovation outputs. In Figure 8, the grey bars depict the efficiency levels for the 30 countries under investigation. These scores range empirically from 0.5 to 0.9, with higher scores indicating higher efficiency.

Our results indicate that the least efficient country in producing innovation outputs is Russia (figure 8). several authors have noted the low performance of the Russian National Innovation System (Gianella and Tompson (2008) speak of a Russian innovation paradox). Many explanations have been proposed for this result: insufficient evaluation of public R&D spending (Graham and Dezhina, 2008), degradation of human capital (Gaddy and Ickes, 2013), lack of alignment of regional innovation efforts as explained by Crescenzi and Jaax (2017). The second worst performance is Argentina. Bank et al. (2021) explain the Argentinian poor performance by low absorptive capacities (figure 4 shows that staff training is far below sample average with a score of 3.7 compared to an average of 4.5) and weak cooperation between firms and universities (figure 3 confirms this explanation, the sample average is 4.3 and the score for this country is 3.4).

Germany is on average more efficient than France. Robin and Schubert (2013) in their study suggest that differences in science policy, in particular less coordination and integration than what characterises French policies, reduce cooperation, thus generating less innovation output. In figure 3 one can see that both indicators have a lower score for France compared to Germany, for collaboration with universities 4.2 for France and 5.3 for Germany and for cluster development it is 4.5 to be compared to 5.2).

Figure 8: Efficiency (left axis) and efficiency change (right axis) for innovation activities - averages 2006-2019



Note: Author computations.

We now explain the differences in inefficiency scores (one minus efficiency scores computed) with the quality of NIS, as represented by our composite indicator, and with the share of university R&D expenses. We regress, using the bootstrap algorithm of Simar and Wilson (2007), inefficiencies on the National Innovation System indicator and the percentage of university R&D expenses in total expenses. A negative value indicates improvement in efficiency, a reduction of inefficiency. Marginal effects indicate that both variables reduce inefficiencies. However, the impact of an improved National Innovation System has a stronger effect in reducing inefficiency than University expenditures. On average, the impact of National Innovation System is to reduce inefficiency by 14 percent (the year 2014 is excluded as non-significant) while the percentage of university R&D expenditure decreases inefficiency by about 2 percent.

Table 1: Marginal effects on inefficiency

Variable	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Innovation System	-0.09	-0.09	-0.14	-0.07	-0.04	-0.22	-0.24	-0.26	-0.46	-0.26	-0.2	-0.14	-0.09	-0.09
p. val.	0.00	0.00	0.00	0.17	0.26	0.04	0.02	0.03	0.28	0.07	0.02	0.00	0.00	0.00
University R&D	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03	-0.04	-0.02	-0.01	-0.01	-0.01	-0.01
p. val.	0.00	0.00	0.00	0.00	0.00	0.11	0.03	0.03	0.23	0.04	0.08	0.00	0.00	0.00

Note: Author computations.

4 Malmquist TFP and innovation inputs

So far we have focused on the production of innovation as there is a general consensus that innovation is an important driver of economic growth as exemplified in the model of Aghion and Howitt (1992). The last step in our analysis is computing malmquist TFP indexes using GDP as an output and two different sets of inputs. The first set only includes labour (hours adjusted for quality) and physical capital, TFP_{ref} while the second set includes labour, physical capital and knowledge stocks based on patents and citable documents (innovation inputs) TFP_{ino}. We then compute sources of changes in Malmquist between the alternative specifications with different inputs set. As explained in Sickles and Zelenyuk (2019), TFP change can be decomposed as the product of efficiency change (EFF) and technical change (TECH).

$$TFP = EFF \times TECH$$

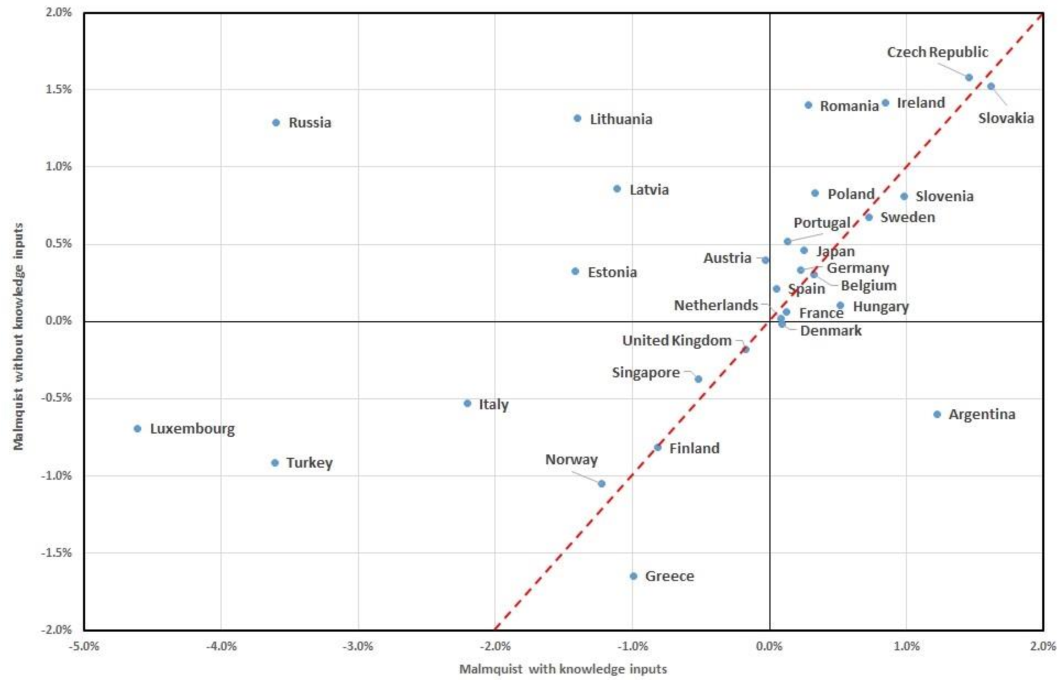
Taking logs one has an estimate of the growth rate of TFP change that decomposes into the sum of log efficiency change and log technical change (contributions to TFP growth) and we take the difference between the two decomposition. Basically,

$$\log(TFP_{ino})-\log(TFP_{ref}) = [\log(EFF_{ino})-\log(EFF_{ref})]+ [\log(TECH_{ino})-\log(TECH_{ref})] \quad (1)$$

Figure 9 presents a comparison of TFP indices obtained with the standard set of inputs with the TFP indices obtained with the augmented input set, which includes knowledge/innovation inputs. This depiction allows us to visually compare results and as such to “gauge” the relevance of the knowledge inputs set for those economies. For some countries, using different input sets marginally change the value of TFP, for example, Finland, Denmark, Spain, Belgium, Japan or Sweden. For only three countries TFP using innovation inputs have a significantly increased productivity growth (Argentina, Greece and Hungary). For a small set of countries TFP growth dramatically decreased: Luxembourg and Russia are two extreme examples (see figure 9). For Luxembourg we believe that large losses in technical changes indicate a possible statistical artefact. That is, many patents allocated to Luxembourg might not be the results of activities carried out in Luxembourg. Instead, they might be registered by a multinational whose headquarters is located in Luxembourg. As a result, they might not have any real economic impact on the local economy. In this case, there is an over estimation of innovation inputs given the level of GDP. We note, in particular, that during the financial crisis the growth rate of TFP is -7 percent and -5 percent in 2007 and 2008, and, when adding knowledge inputs, the decrease is -19 and -17 percent!

For the case of Russia we propose a slightly different explanation but still linked with the idea of an over-estimation of inputs. Several studies, e.g. Ito (2012), indicate that the evolution of the Russian GDP is highly correlated with TFP evolution, and is correlated with the price of oil. Thus, knowledge inputs are likely to play a minor role to increase GDP.

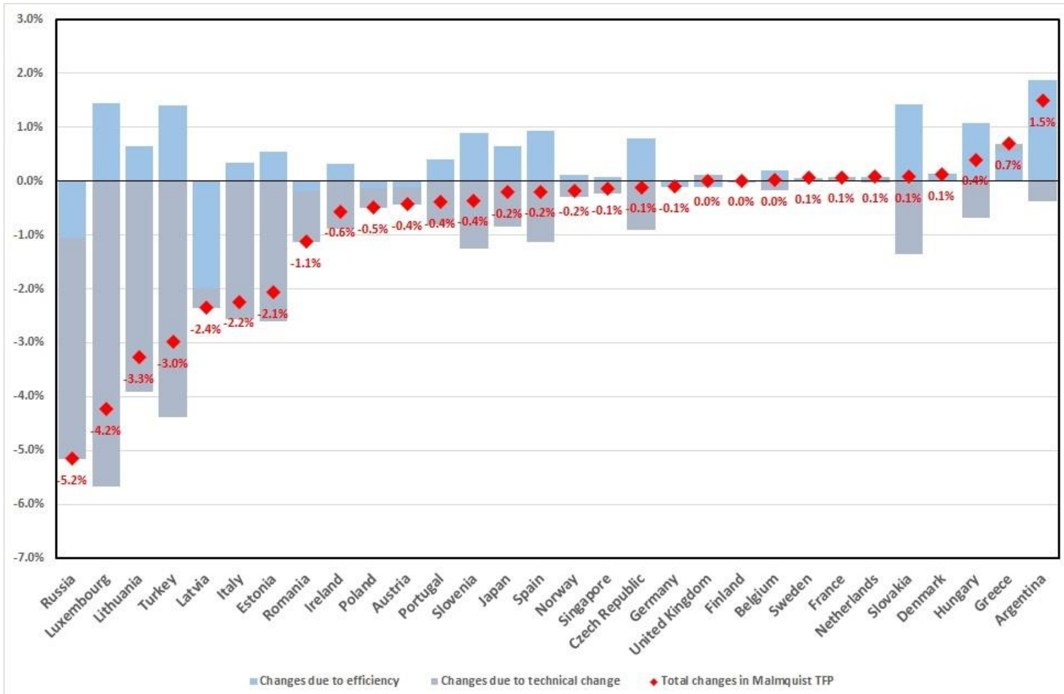
Figure 9: Malmquist TFP indicators - averages 2006-2019



Note: Author computations. The dotted line indicates equality between the two Malmquist TFP indexes.

The decomposition presented in equation (1) allows us to track changes due to the introduction of innovation inputs in the computation of Malmquist TFP. It is interesting to note that changes are mainly due to losses in technical changes (figure 10). For example, technical change is of about 4 percentage points lower in Russia when innovation inputs are considered. TFP is the non-explained growth of output that is not due to an increased use of inputs. In our comparison we add more inputs, innovation inputs that can be seen as reflecting technical progress. As a consequence, we reduce the unobservable part that is otherwise attributable to technical progress.

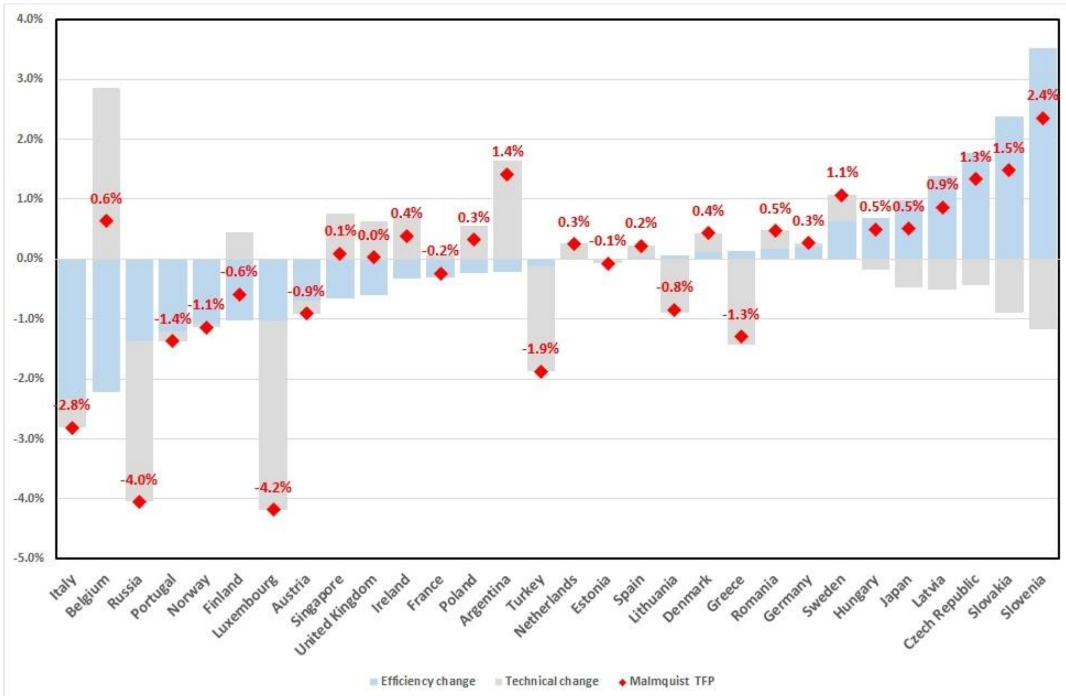
Figure 10: Sources of Malmquist TFP changes - averages 2006-2019



Note: Author computations.

Last we present the average value of Malmquist TFP when considering innovation inputs and its decomposition into efficiency change and technical change. Some countries exhibit technical regress (Figure 11). This means that for a given level of inputs countries are not able to produce the optimal level of GDP that was observed in the past. Technical regress has been observed in many studies e.g. Deliktas and Balcilar (2005) or Chen and Yu (2014) and in most cases they provide no explanations why. We propose several possible explanations: as mentioned for the case of Luxembourg it might be the case that inputs are over-estimated in particular patents, we do not consider labour hoarding as well as capacity utilisation rate. We leave this issue for further investigations.

Figure 11: TFP and TFP decomposition with innovation inputs - averages 2006-2019



Note: Author computations.

5 Conclusions

This document provides evidence that National Innovation Systems matter to the efficient production of innovation in countries. As a consequence, a country might improve its efficiency to produce innovation by easing inter-firms cooperation, as well as enhancing collaboration between universities and firms or improving the credibility and effectiveness of intellectual property rights. Another efficiency leverage is staff training that increases the absorptive capacity of firms. We also show that fundamental research is an important aspect of innovation as it is the basement of many applied research.

However, this work suffers from several drawbacks. As stated by OECD (2008), at least for the case of Luxembourg, the number of patents might be a statistical artefact due to the large number of headquarters of multinational firms located in the country. Another data issue, while it might not be the most frequent case, some patents and citable documents might result from people who are not researchers, but are workers-employees and not funded by R&D expenses. In this case we fail to measure accurately the set of inputs. For example, Walsh and Nagaoka (2009) show that about 40 percent of patents granted to US small firms result from the activity of people who do not have a R&D functional affiliation in the firm, they are not researchers. Moreover, a firm might chose secrecy rather than patenting and/or the publication of scientific documents, therefore some innovations are not captured by our innovation outputs (Fedorenko et al. (2023) provide a nice survey on secrecy).

A possible methodological extension could be to consider the production of innovation and goods and services (GDP) in the framework of a cooperating network. In a first stage is the production of innovation outputs that are used in a second stage as inputs to produce goods and services. But the two sectors coordinate in order to maximise the positive outcome for the economy: innovation outputs and the creation of goods and services (see Li et al. (2012) for a presentation of network DEA). We conclude with a final remark. As in almost all studies about innovation, we implicitly assume that patents and scientific publications correlate with the technological sophistication of production process in economies. If a country is producing less innovation outputs, it is still possible to incorporate the newest technologies through investment in tangible or intangible capital goods/assets. But we still believe that countries that innovate the most are more able than others to use more efficiently inputs to produce outputs.

6 Appendix

Table 2: Variable averages 2006-2019

country	KRD business	KRD non-business	Researcher business	Researcher non-business	Patents	Documents	Capital K	Qualified hours	GDP
Argentina	5901.20	265720.08	10290.50	60119.07	977.42	12139.28	2987306.91	93834.16	957471.76
Austria	42929.94	332511.81	45932.20	20211.79	12198.28	22793.92	2668975.23	23044.61	434944.30
Belgium	42626.14	230102.12	40833.95	29452.45	12212.78	30460.21	3169319.76	22609.87	487212.90
Czech Republic	15567.91	174118.52	32505.99	28179.13	1931.07	20288.14	2302551.30	33894.58	342047.41
Denmark	29161.23	233253.44	35940.18	21179.66	11522.78	23183.71	1485411.75	14124.63	277032.19
Estonia	1203.83	22883.85	1960.30	3668.00	241.07	2645.85	190070.16	4193.26	37131.07
Finland	32319.74	296376.20	30500.97	22723.24	12616.92	18640.78	1156442.79	13970.53	232756.36
France	222147.43	1824665.91	244461.29	168589.23	66840.57	114013.50	16694949.35	129509.18	2738076.51
Germany	411818.38	2523210.42	376742.50	222533.36	174593.57	165001.57	19580037.71	215971.84	3933015.67
Greece	4570.10	133269.06	10257.60	31262.83	1138.64	18805.35	2674053.83	26743.19	312687.74
Hungary	8791.55	100728.41	19396.07	17062.50	1578.64	10475.64	1279869.46	24408.87	241184.44
Ireland	13237.62	101628.86	15477.50	11477.76	3971.00	12946.21	1329291.02	11049.10	325729.56
Italy	91543.50	1181225.99	137581.82	120023.17	27527.07	100913.57	18478932.57	132812.95	2440462.60
Japan	755851.00	4442097.82	606078.57	278334.92	475891.57	132083.28	25823922.14	417607.84	4830374.92
Latvia	471.96	16949.09	1124.50	4600.42	297.21	1636.78	443520.64	5427.04	49389.15
Lithuania	876.11	41861.43	2627.42	9025.27	187.28	3313.64	336907.95	8201.05	76384.26
Luxembourg	4158.17	17420.99	3252.17	1814.43	2400.14	1516.57	240501.59	1939.32	47609.55
Netherlands	52281.87	553980.63	80183.04	43846.42	35813.64	55139.14	4427440.41	42105.93	873802.57
Norway	15877.63	201289.83	20022.65	19544.35	5542.64	19154.14	1484992.11	13211.05	344988.75
Poland	14228.17	277440.84	37886.27	65261.34	5113.64	39141.71	2558497.77	105078.49	958873.57
Portugal	9366.43	197059.43	17150.32	30864.74	1270.28	20430.85	2848049.55	21744.46	306001.43
Romania	5355.11	80667.06	11100.64	19456.85	1257.85	13416.78	1490426.02	50224.42	433463.58
Russia	132798.69	1122022.36	433402.78	397625.57	31191.28	61622.35	18793813.28	471028.00	3716915.78
Singapore	26983.86	303658.37	20987.55	18963.08	5219.50	18303.85	1666800.43	27610.43	385777.95
Slovakia	2514.35	32426.32	4112.32	13530.32	421.35	6698.85	701942.66	14756.16	128944.10
Slovenia	4556.50	33265.33	8519.57	5298.57	633.00	5738.57	481082.45	5542.10	61675.44
Spain	60882.76	980044.91	92225.73	118888.48	10402.42	82262.85	10955028.28	93487.06	1738360.54
Sweden	63478.73	369726.07	58835.35	24011.92	22819.00	36184.42	2568480.57	25649.30	468914.66
Turkey	26247.75	543529.73	57371.28	52233.88	6033.28	37857.21	7172627.35	106121.36	1705807.57
United Kingdom	166339.46	1384532.69	186686.67	200368.95	51904.57	191564.00	14054866.85	189016.66	2737716.85

Note: Author computations. Variable in million USD exception made of hours in thousands, documents and publications are counts.

Table 3: Variable averages 2006-2019

country	University collaboration	Cluster	Staff training	IP rights
Argentina	3.430574494	3.36633581	3.727458234	2.935126416
Austria	4.820844277	4.757798441	5.095469491	5.751528957
Belgium	5.280290015	4.595760291	5.073180176	5.535703475
Czech Republic	4.155096707	4.022513539	4.424857634	4.229904806
Denmark	5.011370158	4.632838285	5.37106268	5.707708939
Estonia	4.094651887	3.53731321	4.477174264	4.946167888
Finland	5.64963417	5.035234774	5.337644322	6.299398637
France	4.24852789	4.460711598	4.694936243	5.809781545
Germany	5.296398469	5.185913367	5.196981479	5.749549029
Greece	2.883074697	3.013333301	3.621279813	4.021495538
Hungary	3.929542264	3.612826309	3.562676714	3.9975066
Ireland	5.019250711	4.50302009	4.919836081	5.660186473
Italy	3.54386931	5.209231153	3.359580862	4.098088034
Japan	4.86050463	5.154116082	5.395293655	5.682229036
Latvia	3.430089824	3.345606888	4.11271805	3.909898218
Lithuania	4.080650384	3.289538737	4.282673482	3.900148137
Luxembourg	4.629821925	4.703902487	5.373840037	5.979305957
Netherlands	5.274641038	4.999817997	5.275077368	5.953729959
Norway	4.837863342	4.801764375	5.329510283	5.639493452
Poland	3.372662587	3.364518451	3.961174227	3.760758088
Portugal	4.234796457	3.928184039	3.965090209	4.725888516
Romania	3.196018415	3.457370975	3.617179861	3.628427984
Russia	3.604921143	3.23098662	3.698479042	2.994620323
Singapore	5.421204565	5.161804863	5.436628507	6.185388238
Slovakia	3.339260877	3.707068416	3.986017065	3.972770228
Slovenia	3.88851726	3.734212672	4.107921758	4.451726496
Spain	3.693999935	4.10354853	3.783427496	4.343399606
Sweden	5.386423187	4.890519281	5.450892172	5.845216662
Turkey	3.46970182	3.850886271	3.735151682	3.346893023
United Kingdom	5.41832159	5.076938154	4.865645893	5.824236861

Note: Author computations. Scores are between 1 (worst) and 7 (best).

Table 4: Variable correlations 2006-2019

variable	University collaboration	Cluster	Staff training	IP rights
University collaboration	1	0.824	0.905	0.897
Cluster		1	0.747	0.832
Staff training			1	0.909
IP rights				1

Note: Author computations.

1. Efficiency measurement and regression procedure

DEA (Data Envelopment Analysis) and SFA (Stochastic Frontier Analysis) are the main methods commonly used to estimate efficiency of a Decision Making Unit DMU (countries, industries, firms,...). Each method allows to handle the case of multiple inputs and multiple outputs. For example, Löthgren (1997) or Kumbhakar and Lai (2021) propose a stochastic frontier model that allows for multiple outputs. However, in practice, DEA is easier to use in the case of multiple outputs as it is the case in our study.

Let $X = (x_1, \dots, x_N) \in R_+^N$ be the set of inputs. For the production of innovation outputs, we consider four inputs: R&D capital and researchers in the business sector and the non-business sector. For the production of goods and services we also consider four inputs: qualified hours of work, physical capital, patents and citable documents. The two last inputs are outputs in the first set of efficiency estimates. Let $Y = (y_1, \dots, y_M) \in R_+^M$ be the set of outputs. In the first model there are two outputs: Patents and citable documents, in the second model there is only one output GDP. The production is characterised by the production set $T = \{(Y, X) \mid X \text{ can produce } Y\}$. At this stage one should make an assumption on returns to scale: Constant, variable or increasing. In this document we assume variable returns to scale for the production of innovation outputs and constant returns to scale for GDP[6] . Assuming constant returns to scale for GDP generation allows us to compute Malmquist total factor

[6] Bogetoft and Otto (2011) present a statistical test to select returns to scale, in our case the assumption of variable and constant returns to scale cannot be rejected.

productivity (TFP) indexes that correctly assess TFP changes (see Bjurek (1996)). The second assumption to be made is to use an input or an output oriented DEA models. In an input orientation, DEA minimizes input for a given level of output; in other words, it indicates how much a country can decrease its input for a given level of output. In an output orientation, DEA maximizes output for a given level of input; in other words, it indicates how much a country can increase its output for a given level of input. In the case of constant returns to scale efficiency scores of countries are mathematically similar. However, policy implications are different. For this study we opt for an output orientation. We assume that countries are not willing to reduce R&D or to produce less citable documents and patents. The model to gauge efficiency is the following linear program,

$$\begin{aligned}
\text{Max} \quad & \vec{D}(x_{io}, y_{ro}) = \beta \\
\text{s.t.} \quad & \sum_{c=1}^{C} \mu_c x_{ic} \leq x_{io}, \qquad i = 1, \dots, N \\
& \sum_{c=1}^{C} \mu_c y_{rc} \geq \beta y_{ro}, \quad r = 1, \dots, M \\
& \mu_c \geq 0, \qquad\qquad\quad c = 1, \dots, C
\end{aligned}$$

If a country is able to provide the maximum output technically feasible given its use of inputs the country will be said efficient and will receive an efficiency score of 1 . Any deviation from 1 will indicate inefficiency. Sickles and Zelenyuk (2019) provide a nice introduction to DEA models.

A key question in this document is: does the National Innovation Systems explain why some countries are more efficient in producing citable documents and patents? A naive approach would have been to regress efficiency scores on a set of $Z = (z_1, \dots, z_K)$ contextual variables. Simar and Wilson (2007) explain that treating efficiency scores computed using model (1) as independent observations will lead to invalid inference on estimated parameters in the model. Thus, they suggest a double bootstrap procedure. The regression model is:

$$\beta_c = z_c \alpha + \epsilon_c$$

where α is a vector of parameters to be estimated. The error term ϵ is truncated normally distributed with zero mean, constant variance σ and left truncation at $1 - z_c\alpha$. The bootstrap algorithm is the following:

1. Compute efficiency scores $\hat{\beta}_c$ for all countries $c = 1, \ldots$, C using DEA.

2. Use those $C^*(C^* < C)$ countries, for which $\beta_c > 1$ holds (inefficient countries), in a truncated regression (left-truncation at 1) of $\beta_c > 1$ on z_c to obtain coefficient estimates $\hat{\alpha}$ and an estimate for variance parameter $\hat{\sigma}$ by maximum likelihood.

3. Loop over the following steps 3.1 - 3.4 B times, in order to obtain a set of B bootstrap estimates $\hat{\beta}_c^b$ for each country $\mathrm{c} = 1, \ldots$, C, with $\mathrm{b} = 1, \ldots$, B.

3.1 For each country $\mathrm{c} = 1, \ldots$, C, draw an artificial error $\tilde{\epsilon_c}$ from the truncated $N(0, \hat{\sigma})$ distribution with left-truncation at $1 - z_c\alpha$. 3.2 Calculate artificial efficiency scores $\tilde{\beta}_c$ as $z_c\hat{\alpha} + \tilde{\epsilon}_c$ for each country $\mathrm{c} = 1, \ldots$, C.

3.3 Generate $\mathrm{c} = 1, \ldots$, C artificial countries with input quantities $\tilde{x}_c = x_c$ and output quantities $\tilde{y}_c = \left(\hat{\beta}_c / \tilde{\beta}_c\right) y_c$.

3.4 Use the N artificial countries, generated in step 3.3, as reference set in a DEA that yields $\hat{\beta}_c^b$ for each original country $\mathrm{c} = 1, \ldots$, C.

4. For each country $\mathrm{c} = 1, \ldots$, C, calculate a bias corrected efficiency score $\hat{\beta}_c^{bc}$ as $\hat{\beta}_c - \left(\frac{1}{B} \sum_{b=1}^{B} \hat{\beta}_c^b - \hat{\beta}_c\right)$.

5. Run a truncated regression (left-truncation at 1) of $\hat{\beta}_c^{bc}$ on z_c to obtain coefficient estimates $\hat{\hat{\alpha}}$ and an estimate for variance parameter $\hat{\hat{\sigma}}$ by maximum likelihood.

6. Loop over the following steps $6.1 - 6.3 B^*$ times, in order to obtain a set of B^* bootstrap estimates $\left(\hat{\hat{\alpha}}^b, \hat{\hat{\sigma}}^b\right)$, with $\mathrm{b} = 1, .., B^*$.

6.1 For each country $\mathrm{c} = 1, \ldots$, C, draw an artificial error $\tilde{\tilde{\epsilon}}_c$ from the truncated $N(0, \hat{\hat{\sigma}})$ distribution with left-truncation at $1 - z_c\hat{\hat{\beta}}$.

6.2 Calculate artificial efficiency scores $\tilde{\tilde{\beta}}_c$ as $z_c\hat{\hat{\alpha}} + \tilde{\tilde{\epsilon}}_c$ for each country $\mathrm{c} = 1, \ldots$, C.

6.3 Run a truncated regression (left-truncation at 1) of $\tilde{\tilde{\beta}}_c$ on z_c to obtain bootstrap estimates $\hat{\hat{\beta}}^b$ and $\hat{\sigma}^b$ by maximum likelihood.

7. Calculate confidence intervals and standard errors for $\hat{\hat{\beta}}$ and $\hat{\hat{\sigma}}$ from the bootstrap distribution of $\hat{\hat{\beta}}^b$ and $\hat{\hat{\sigma}}^b$.

This bootstrap algorithm insures that coefficients and their p values are reliable. Note that we have panel data and the procedure is designed for cross-section, then we compute regression coefficients for each separate years.

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