European Commission

ECONOMIC COMPLEXITY FOR COMPETITIVENESS AND INNOVATION
A NOVEL BOTTOM-UP STRATEGY LINKING GLOBAL AND REGIONAL CAPACITIES

Economic Complexity is a data driven empirical approach developed to **inform the study of territorial development with quantitative metrics**.

Techniques **inspired by complex systems analysis and network theory** allow measuring the intangible capabilities necessary for a country or region to be competitive, both in overall terms and in specific markets.

We exemplarily analyse the case of **Slovakia's industrial and innovation competitiveness** by looking at the overall potential of the country and focusing on its **Electronics** sector.

1. Current Policy Challenges

The European Union faces several challenges, ranging from shifts in global value chains[1] to the urgent need to address environmental issues. In this respect, the Political Guidelines and the six priorities of the new President of the European Commission[2] constitute a **strategy for growth** where the attention to people's and the planet's needs is combined with the necessary long-term view on European **industrial innovation and competitiveness**. The aim is to boost Europe's competitiveness based on cutting-edge innovation in a broad sense – not only technological innovation, but also social and service innovation, eco-innovation, design and creative industries, new business models and practice-based innovation. Together with this, the new Commission's structure emphasises the need for structural transformation of our economy and the need for crosscutting policy support.

This ambitious vision requires traditional and novel tools to inform policy makers about the complex dynamics linking the various dimensions of the productive and innovation systems. Indeed, to develop effective industrial policies policy makers require an answer to several questions: broadly speaking, they need **a measure of the innovation and production capabilities of countries and regions**, both in general and in specific sectors, products, markets. To do so is the aim of this policy brief.

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[1]https://op.europa.eu/en/publication-detail/-/publication/5f21b462-1a33-11ea-8c1f-01aa75ed71a1
[2]https://ec.europa.eu/commission/sites/beta-political/files/political-guidelines-next-commission_en.pdf

What is Economic Complexity?

Economic Complexity is a framework building on earlier evolutionary and institutional literature (Hirschman, 1958; Cimoli & Dosi, 1995; Teece, et al., 1994) to tackle the complexity of economic systems. It describes the economy as an evolutionary process of globally interconnected ecosystems. The main recent advance with respect to the earlier literature is the use of newly developed *network science* and *complex and dynamical systems* (Hausmann & Klinger, 2006; Hidalgo & Hausmann, 2009; Tacchella, et al., 2012) to separate the random noise from the underlying signal. The Economic Complexity framework shifts the focus of economic analysis from aggregate quantities (*What is the GDP of the country? How many patents are published?*) to their disaggregation (*In which industrial sectors do countries specialize? Which patents are published?*), with the aim to provide information that is complementary to more traditional analysis. This shift creates the opportunity of impacting several cross-cutting themes and answering quantitatively several policy relevant questions that could otherwise only be answered qualitatively, or in specific case studies, or by ad hoc metrics.

It uses the example of Slovakia to show-case the methodology and its ability to inform policy. The brief starts with a country level analysis, using Economic Complexity to forecast growth trajectories and sectoral export patterns. It then deep-dives into one sector, to give detailed information about specific markets. Finally, it passes to the analysis of the innovation system, giving additional information on market opportunities of the country in question and on a regional level disaggregation.
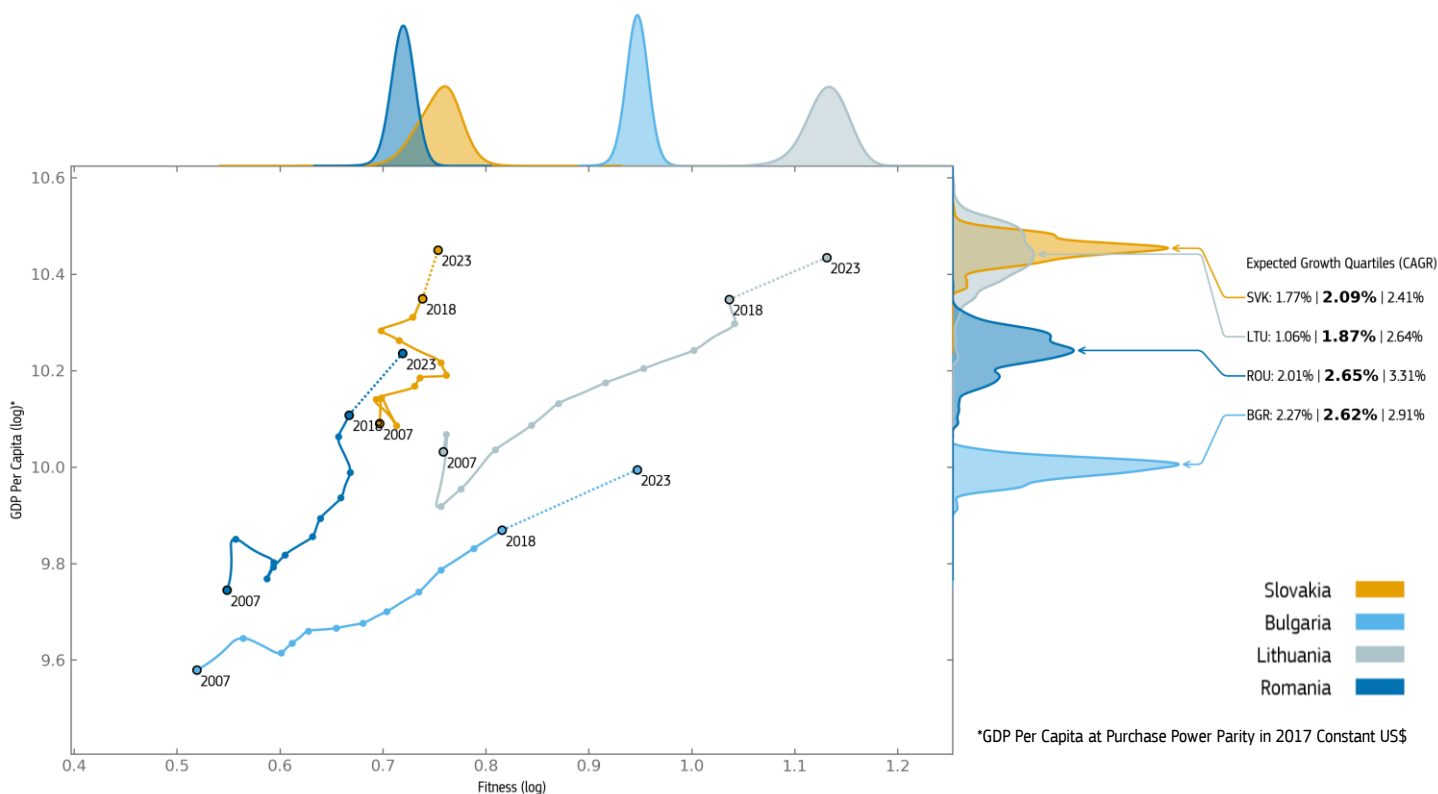
Figure 1 Solid lines: Trajectories in the GDP-Fitness space for Slovakia, Romania, Bulgaria, Estonia and Lithuania from 2007 to 2017. Dashed lines: Forecast 2017-2022. (Axes distributions:) Probability distribution of expected Fitness and GDP$_{pcppp}$ for 2022 obtained as in (Tacchella, et al., 2018). For GDP growth we show first quartile, median and third quartile of expected Compound Annual Growth

This allows having insights on the growth prospects of Slovakia as a whole and on specific markets in specific regions of that country.

2. Development trajectories and GDP Forecast

We start from a country level perspective of Slovakia and a set of comparator countries, by looking at the dynamics of their **Economic Fitness**. The Economic Fitness of a country is a measure of the complexity of the country's productive structure (Hidalgo & Hausmann, 2009; Tacchella, et al., 2012). Complex economies are characterized by their diversification and their ability to compete globally with complex (i.e. non-ubiquitous) industrial products. The Fitness of a country has been shown to be a very effective indicator of competitiveness. It is based on an intensive measure of diversification and therefore carries complementary information with respect to more standard quantifications of economic output, such as the GDP of a country.

The interplay between Fitness and GDP per capita at purchasing power parity (GDP$_{pcppp}$) gives rise to rich dynamics (Cristelli, et al., 2015). A quantitative analysis of the microscopic features of the country

trajectories in the GDP-Fitness plane allows for a rigorous, statistically robust description of macroeconomic dynamics. With techniques inspired by the physics of dynamical systems, it is possible to forecast medium term (5-years) GDP growth up to 25% more precisely than mainstream approaches, such as the IMF (Tacchella, et al., 2018).

The Selective Predictability Scheme (SPS) approach, as discussed in (Tacchella, et al., 2018), provides forecasts that are not relying on specific assumptions, that can be computed for each country through a single model and that provide a robust error estimation.

We have applied the SPS technique to forecast the GDP of Slovakia and three economies moving in the same area of the GDP-Fitness plane: Lithuania, Romania, and Bulgaria. In Figure 1 we show the historical trajectories and the forecasts, in terms of probability distributions projected on the axes, obtained with the SPS methodology.

Slovakia shows slowly increasing Fitness but has GDP-Growth estimates still high (median Compound Annual Growth Rate (CAGR) 2017-2022: 2.09%) with respect to similar income countries (LTU). Slovakia's
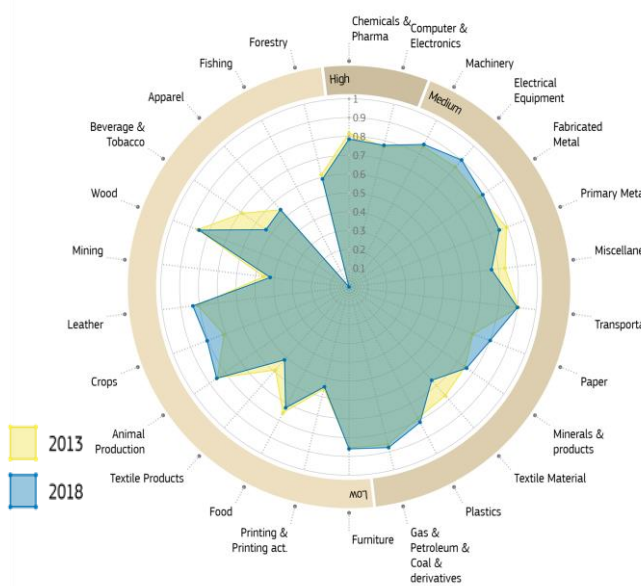
first quartile is especially high, signalling low probability of very slow growth.

Romania and **Bulgaria** show a continuously increasing fitness trend, with GDP-Growth estimates expected to be the strongest within the considered group (median CAGR 2017-2022: 2.65% and 2.62% respectively) due to the high Fitness and lowest GDP_{pc}.

For **Lithuania** SPS indicates slower growth prospects (median CAGR 2017-2022: 1.87%), but a continued trend of rapidly increasing Fitness.

This holistic view of the countries obtained through the Economic Fitness lens can be decomposed into much finer details, down to the sector and product level.

The Fitness metric can be computed also at the sector level, i.e. by considering the diversification and uniqueness of Slovakia's products only within a given industrial sector. In Figure 2 we show the resulting sectoral decomposition of Fitness for Slovakia in 2013 (yellow) and 2018 (blue). The picture for Slovakia is generally static, as expected from the global Fitness trend shown in Figure 1. Slovakia is losing ground in several low-medium complexity sectors, such as Beverage & Tobacco and Textiles, but is slowly improving in some medium-high complexity sectors such as Electrical Equipment, Machinery and Fabricated Metal.

The next sections analyse the future prospects for 2023, for Slovakia and the comparator countries at the sector and product level.
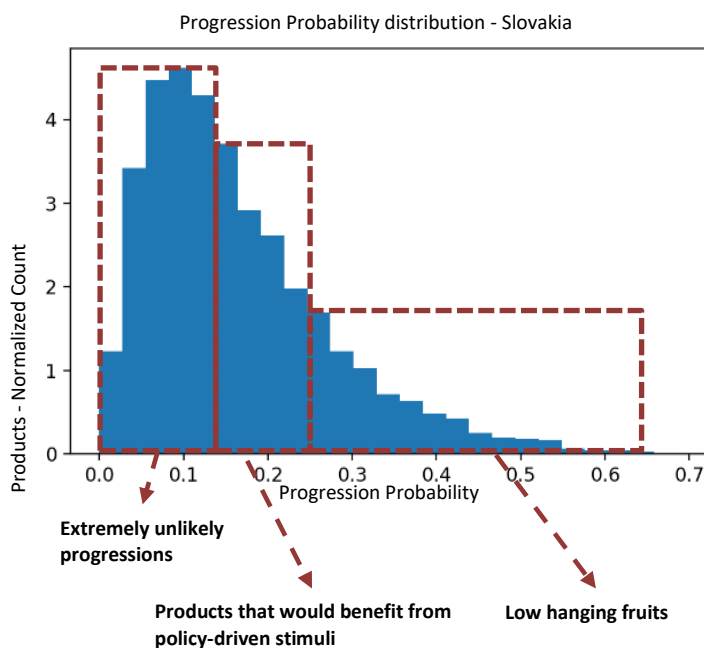
3. Industrial Sectors Forecast

The concept of *Relatedness* is a quantification of how much two economic activities are related in terms of the inputs and contexts typically needed for their development. Since it is easier to move between related activities than towards unrelated ones, empirical approaches to quantify relatedness are currently used to inform policies and industrial strategies in governments, international organizations and firms.

Relatedness is typically represented through network topologies in which related activities are connected with a strength that is proportional to their relatedness. The most prominent example of these ideas in the literature is the so-called Product Space (Teece, et al., 1994; Hidalgo, et al., 2007).

There are several techniques for inferring such topologies but most of them revolve around the idea of considering binary co-occurrences of activities in locations: the more often a pair of activities is found in the same location, the stronger is their inferred relatedness.

In real-world applications the problem of deriving Relatedness from co-occurrences results to be quite difficult and the estimations are often unreliable.

Figure 2 Radar Chart of the Sector Fitness scores for Slovakia in 2013 (Yellow) and 2018 (Blue). Sectors are arranged by average complexity increasing counter-clockwise

Figure 3 Distribution of progression probability across all products in which Slovakia was not competitive in 2017.

To overcome these problems we employed a Machine Learning approach that is able to infer a highly effective representation of the Relatedness Space. The output of this methodology is a score, the Product Progression Probability (PPP), that represents the probability that a country will become (or remain) a globally competitive exporter of a given product within a five years horizon. In Figure 3 we show the distribution of the PPP scores for Slovakia in 2018, forecasting competitiveness for 2023, across all products for which the country did not show a revealed comparative advantage. The bulk of the distribution is represented by products that have a very low relatedness (<0.15) with Slovakia's current exports and are therefore unlikely to kick off in the near future. The set of products between 0.15-0.35
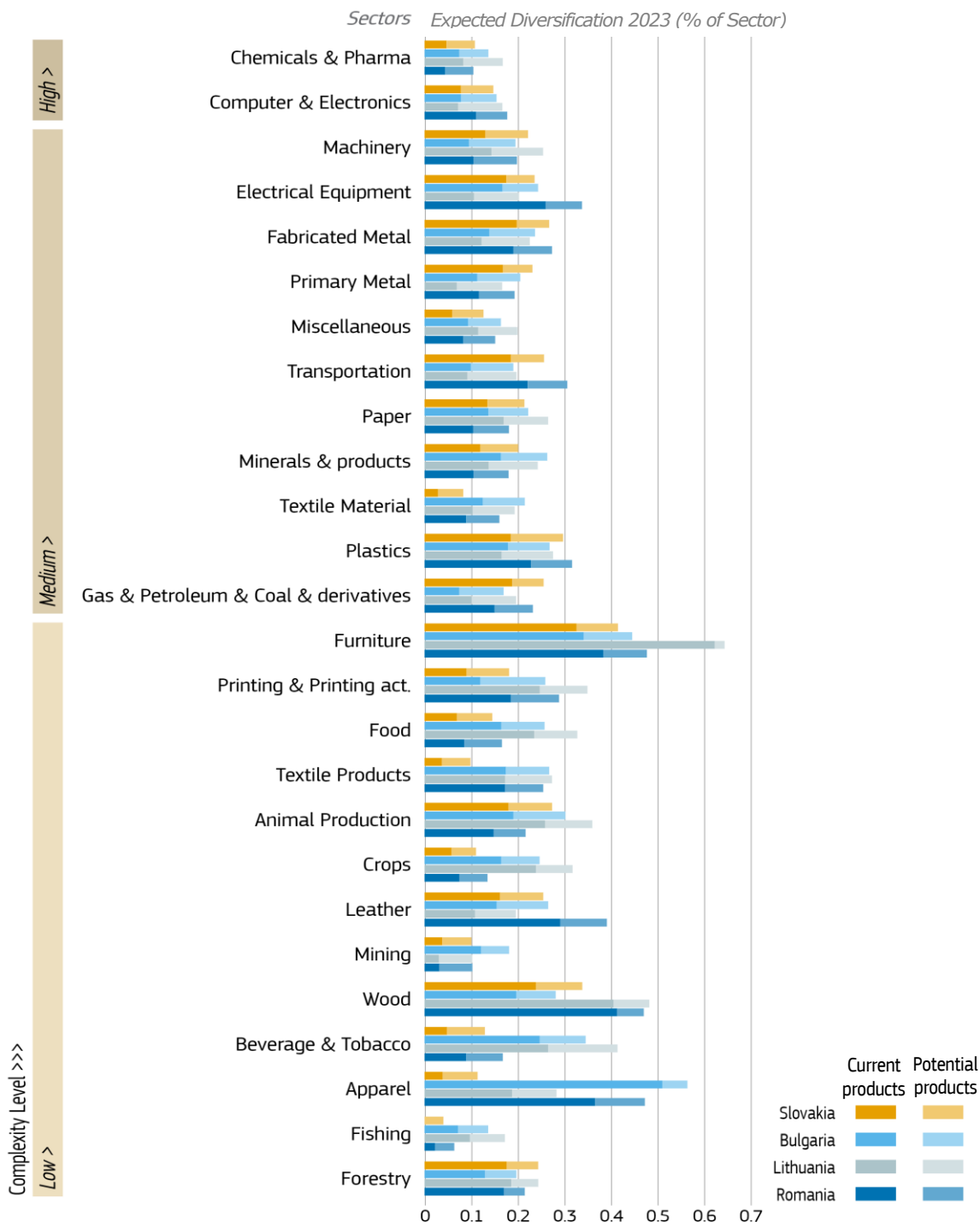
Figure 4 Expected diversification as a fraction of the sector size, for Slovakia and the comparator countries. Darker shade of the bars represents expected diversification in currently competitive products, lighter shade represents addition of new products. Slovakia is generally lagging behind in terms of expected diversification, with the exception of a few sectors such as machinery, transportation and plastics.

PPP score are products that are moderately feasible for Slovakia and are likely to benefit from policy driven stimuli. Finally, the tail of the distribution contains 'low-hanging fruits', i.e. products that are highly related to Slovakia's current exports, and that can therefore turn into competitive exports even without policy intervention.

In Figure 4 we show the sectorial expected diversification in 2023 (i.e. the sum of the probability scores across the products of the sector) for Slovakia, Lithuania, Romania and Bulgaria, expressed as a fraction of the number of products in the sector. The darker shade is the expected diversification coming from already competitive products, while the lighter shade represents additional products, not yet competitive in 2018.

From this analysis emerges that Expected diversification is heterogeneous across sectors. Slovakia appears to be lagging behind its comparators in most low-complexity sectors with few exceptions (e.g. Forestry). The gap is much smaller in medium complexity sectors, with Slovakia often ranked first or second among the comparators (e.g. Primary Metal, Transportation). All the four countries

are expected to be poorly diversified in high complexity sectors.

The Transportation sector emerges as one of the most promising medium-high complexity sectors for Slovakia and the list of top 15 products in the sector ranked by progression probabilities for the country is reported in Table 1.

The focus of the analysis will now shift to analyse Slovakia's innovation system, at the national as well as at the regional level. In Section 4 there will be an analysis of the general technological capabilities of the country and its regions, while Section 5 will focus on the technological fields driving competitiveness in a specific export market. This last exercise will analyse the Transportation sector, which was identified as particularly interesting by the sector level analysis of this Section.

4. Regional Innovation System

In Pugliese & Tübke (2019) the Regional Technological Fitness was introduced, a measure of the technological capabilities of a region based on patent data linking each region to the technological fields in which the region is specialized. The measure is complementary to the analysis done in the previous sections in two respects. First, it helps to characterize the economic capabilities of a country by looking at its technological potential and not its present exporting activities. This is particularly relevant for advanced sectors. Second, since patent data are easily geo-localized at different granularity, it allows performing analysis at a sub-national level, closer to the geographical dimension at which economic activities are performed: industrial clusters and cities. The results of that analysis are reported in Figure 5.

By integrating PATSTAT data using the *Geocoding of worldwide patent data* from (de Rassenfosse, et al., 2019), it is possible to recover geographic coordinates
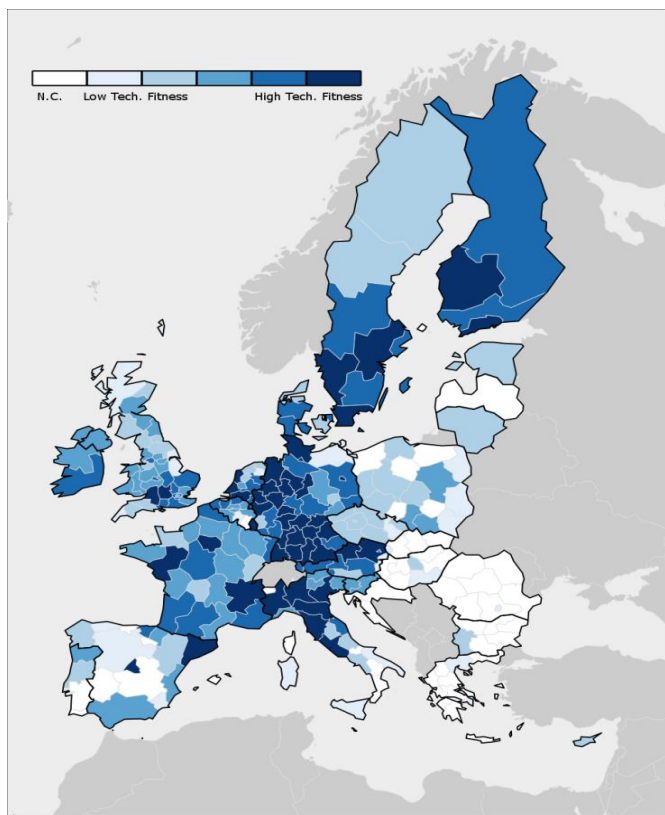
Figure 5 Technological Fitness of European NUTS 2 regions in 2015 from Pugliese & Tübke **(2019)**. Technological Fitness is a measure of technological diversification weighted with the complexity of the fields on which the region has specialized. Not Classified (NC) regions are regions for which there are not enough patents in the database. The
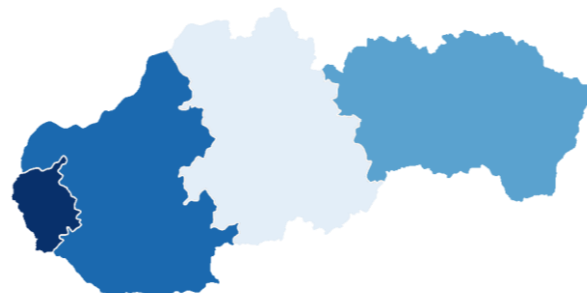
Figure 6 Regional Technological Fitness of Slovakian regions. The darker the colour, the higher the relative technological capabilities of the region.

for inventor and applicant location in 18.8 million patent documents, from all major patent offices. This gives a higher coverage of peripheral regions. We can therefore repeat the same analysis for Slovakian regions, as reported in Figure 6.

The analysis shows – as expected – the crucial role of Bratislava for the national innovation system. This analysis can give unique information to guide policy, since, as in the previous exercises, it is not dependent on traditional quantitative measures (like the number of patents in the region) but on qualitative measures (which patents and in which technological fields the region is specialized in) from which a quantitative measure is recovered as an emergent property.

5. Export market specific analysis of the regional innovation system

The analysis will now focus on the Transportation sector that was highlighted in section 3. This analysis is done in two steps. First, the technological fields that are relevant for the export of a specific product will be identified by looking at the multi-layer network connecting countries with the products they export and the technologies they patent. Later, the regions showing capabilities in those fields are identified, using a methodology similar to the one employed in the previous section. This allows building a measure for each EU regions' technological capability in each product.

These results can inform policy in two ways. First, it is possible to **focus on one specific market** and look
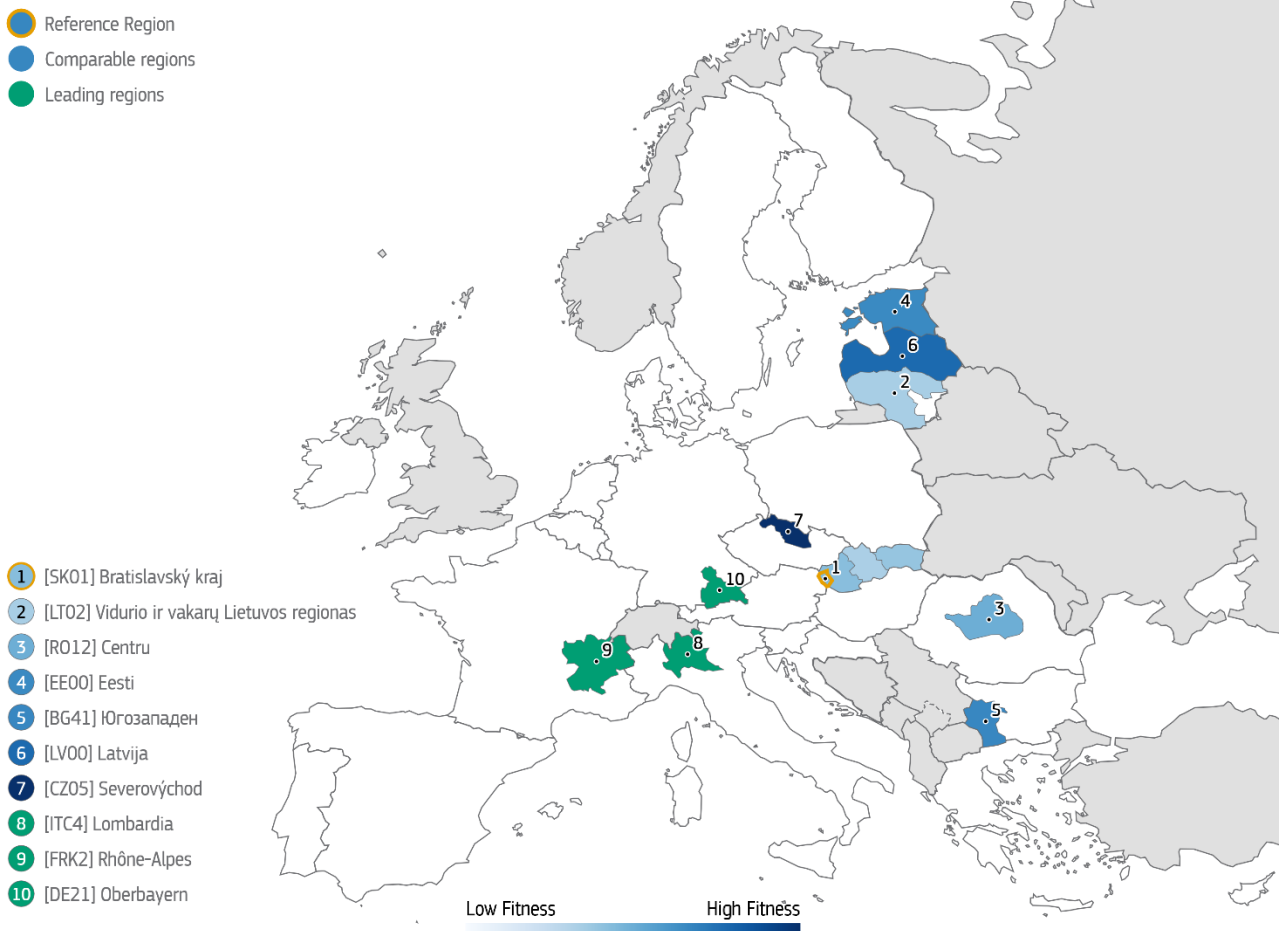

Figure 7 Technological fields that are early signals for the export of "Railway Cars, closed & covered". The black line represents the 'noise' level, therefore the analysis defines as significantly linked those fields in which the gray area crosses the black line;

at which Slovakian regions have an advantageous position in it, and compare them with main European competitor regions. As an example it is possible to look at the export of **"**Railway Cars, closed & covered", since this was identified as a possible emerging opportunity for Slovakia from the analysis in section 3 (see Table 1). In Figure 7 are highlighted the technological fields that are relevant for the export of that product.

RANK	PRODUCT PROGRESSION PROBABILITY	TOP 12 TRANSPORTATION PRODUCTS BY PRODUCT PROGRESSION PROBABILITY - SLOVAKIA	SLOVAKIAN NUTS2 REGION WITH HIGHEST PRODUCT SPECIFIC TECHNOLOGICAL CAPABILITIES
1	0.64	Trailers, semi-trailers (not else specified)	[SK04] Východné Slovensko
2	0.51	Rail locomotives, non-electric	[SK02] Západné Slovensko
3	0.37	Railway cars, closed & covered	[SK01] Bratislavský kraj
4	0.33	Diesel powered buses	[SK04] Východné Slovensko
5	0.32	Parts of electrical ignition equipment	[SK04] Východné Slovensko
6	0.32	Railway cars, self-discharging	[SK01] Bratislavský kraj
7	0.30	Tanker trailers and semi-trailers	[SK03] Stredné Slovensko
8	0.29	Buses, non diesel	[SK02] Západné Slovensko
9	0.28	Engines, spark-ignition, 250-1000cc	[SK04] Východné Slovensko
10	0.28	Rubber tubes, metal reinforced, with fittings	[SK02] Západné Slovensko
11	0.27	Special purpose motor vehicles (not else specified)	[SK04] Východné Slovensko
12	0.27	Railway maintenance vehicles	[SK02] Západné Slovensko

Table 1 Top 12 products out of 127 products in Transportation currently not exported by Slovakia, ordered according to their probability of being exported by Slovakia, based on current Slovakian exports of related products. On the right column it is highlighted the Slovakian region with the highest technological advantage in that product.

Figure 8 Regional Technological Capabilities of Slovakian regions for the technological fields that emerge as relevant for the export of "Railway Cars closed & covered", compared with immediate competitors and – highlighting in green – the market leaders.

In Figure 8 this result is used to identify which Slovakian regions have higher technological capabilities in relationship to this specific export market, to compare them with the most relevant comparator regions outside the country, and to identify the technological leaders. Notice that, while for Slovakia this market is an opportunity – i.e. a product that it is not exported competitively by Slovakia today but that it is identified as a potential market in the future – the regional competitors identified are already important players in the market.

The same approach can be extended. It is possible to look **at all different products suggested by Product Progression to Slovakia in Transportation**. For each product, we look at which Slovakian region has an advantage with respect to its overall level of capabilities. This allows providing an operational starting point to identify untapped opportunities for each region, informing for example Smart Specialization Strategies. The resulting ordered list of products is summarized in Table 1.

6. Conclusions

The Economic Complexity framework provides a novel analysis with the potential to inform the industrial policy of the European Commission. It takes into account the complex dynamics relating the various dimensions of the productive and innovation systems. In particular, our framework is able to provide forecasts of countries' structural growth that are grounded on data. Using techniques developed in network science and machine learning we can provide not only information on country-level capabilities, but also deep dive into sectoral and regional level of analysis. By mixing export and innovation data we can extract a detailed map of the whole economic system.

Through the lenses of Economic Complexity, we see that Slovakian growth prospects in general are higher than in other EU countries with similar income but the complexity of their economy is decreasing. In particular, Slovakia is losing ground in low complexity sectors (Textiles and Agrifood) but it has a better outlook in medium-high complexity sectors

(Transportation, Electrical Equipment). Even more in detail, we provide information on specific products that Slovakia is not currently exporting competitively but that could be easily accessible in view of its capabilities. By looking at the patenting activities of Slovakian regions, we can localize new market opportunities for Slovakia and inform industrial policy.

This policy brief serves as a showcase for the techniques. Indeed, similar analysis are systematically provided for different countries and sectors and can thus help to strengthen the foresight capacity of the EU Commission

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Data Source and Methodology

The general workflow in Economic Complexity is to start from micro-data at the level of industrial agents to build a network binary structure connecting countries and regions to the activities in which firms excel that are localized there. This network – connecting technological, scientific or production activities to a geographical location – is the basic element of analysis. This map is used to infer information on the hidden layer of unobservable capabilities that were behind its dynamical evolution.

In this work two data sources are used: patent data – localized through their applicant at the country and region level – extracted from OECD REGPAT (Maraut, et al., 2008) and from *Geocoding of worldwide patent data* (de Rassenfosse, et al., 2019), and trade data at the country level from UN COMTRADE.

The analysis in Section 2 is based on (Tacchella, et al., 2018).

The analysis in Section 3 is based on the Random Forest algorithm. The basic idea behind is to increase the number of available data points (a method known as Data Augmentation in machine learning) and then learn complex non-linear relations between products. This allows to go beyond the simple binary co-occurrences and to relate patterns of presence and absence of many products at the same time. This approach vastly outperforms standard Product-Space techniques in its ability to provide reliable forecasts of diversification patterns.

The methodology in Section 4 adapts the methodology recently developed for export products called Exogenous Fitness (Operti, et al., 2018) to technologies. The idea of Exogenous Fitness is to run the Fitness-Complexity algorithm in one setting in which there is abundance of information (all world countries) to extract the complexity of products, and then use those complexities to infer the Fitness of geographical entities in a different setting where there is not as much information (subnational regions). The idea of adapting techniques developed for products to be used with patents and technological classes is not new (Breschi, et al., 2003; Balland, et al., 2018), as there are many similarities in the data structure. Since the measure in (Pugliese & Tübke, 2019) was computed on REGPAT data, a database connecting patents from the European Patent Office (EPO) to regions, the measure did not cover adequately peripheral EU regions, as EPO patents are costly patents not commonly filed by smaller firms. This is visible in Figure 4, where regions without enough patents for computing their Regional Technological Fitness are reported in white. In Slovakia, only the Bratislava region would have enough data to be analysed. In this exercise we employed therefore additional data from *Geocoding of worldwide patent data* (de Rassenfosse, et al., 2019), geolocalizing data from 18.8 million patents from every patent office. This allow us to carry out a regional analysis for all Slovakian regions.

The analysis in Section 5 is based on previous academic work (Pugliese, et al., 2019), and the interested reader is pointed to such work for more information. The methodology introduced in that article allows identifying whether the activity in specific technological fields in a country are early signals of the potential capabilities to export a specific (advanced) product in the future. The connection between this and the regional analysis performed in Section 5 is introduced in (Pugliese & Tübke, 2019). While it is founded on well-tested scientific work, at this point it is just a prototype that needs to be further validated.

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