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Towards increased complexity in Russian regions: networks, diversification and growth

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Abstract

Following Hausmann et al. (2011), we apply a network approach to measure the level of economic complexity and diversification opportunities of Russian regions. Using Russian and international export data, we find that the complexity of Russian regional economies varies substantially: relatively high in western and central regions, lower in southern and northern Russia and lowest in eastern regions. While Russian regions, on average, have poor diversification opportunities, regions can still diversify their exports by participating in international value-added chains or cooperating in developing group strategies. Our results are highly consistent with two well-established rankings of Russian regional R&D development based on numerous regional indicators, and imply that our network-based measure of complexity captures important features such as the level of regional R&D.

Keywords: economic complexity, diversification, Russian regions, network analysis, network centrality.
JEL classification codes: O14, O25, R11.

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Introduction

The Ricardian export concentration approach suggests that an economy seeking to grow should focus on those export sectors where it has comparative advantages. Specialization does not, however, imply that an emerging economy should not attempt to diversify its exports. Empirical evidence points at diversification as a growth-maximizing strategy for low-income economies (Imbs and Wacziarg, 2003; Klinger and Lederman, 2006; Cadot et al., 2011). Low-income countries are typically abundant in labour employed in agriculture, so diversification is closely related to traditional industrialization.

In theory, emerging economies sell part of their output internationally, putting them in a position where they can set aside that share of export proceeds above and beyond what they consume. These savings can be used to import industrial capital that allows them to produce and export more sophisticated products. According to this view, an emerging economy's achievement of greater export complexity is a natural consequence of capital accumulation. Unfortunately, this intuition evaporates as soon as we consider the variety of export industries likely available to a country in diversifying its export basket.

Consider, for instance, an emerging economy that specializes in labour-intensive agriculture. Enjoying high international prices for its exports, this country amasses funds that permit it to invest into new production capabilities. For the sake of discussion, it can only choose from two available options: establishing an apparel industry or getting into the business of manufacturing high-speed trains. The train opportunity is doubtless more tempting for ambitious policymakers as it creates a path to production of prestigious high-tech products. On the other hand, it is unclear how farming skills translate into the manufacturing and engineering skills needed to build exportable high-speed trains. The train business requires high-level expertise in such fields as mechanics, metallurgy, electronics, chemistry and marketing that this agriculture-based economy lacks. The more mundane apparels industry, in contrast, is less of a leap. Cheap labour can be allocated from agriculture to industry and retrained. Thus, the apparels industry has better chances in complementing agriculture as a viable export industry in this example.

Both intuition and evidence point to the modest role of capital accumulation in helping economies transition to higher levels of export complexity. We know intuitively that capital is only one of many ingredients collectively responsible for producing complex goods. Moreover, in the above example of the less-developed economy reallocating its labour force from agriculture to an apparels industry, we know the choice of export industry is determined by available ingredients.

Advanced industries such as electronics require sophisticated, capital-intense capabilities (e.g. clean room operations) not likely available in sufficient amounts in an emerging economy. Without an adequate supply of engineering talent, infrastructure, reliable property rights protections, international certification of its products and strong marketing skills, it is unlikely that purchasing state-of-the-art equipment will help an economy become a player in the export of a new category of goods (see e.g. Easterly, 2001).

Apart from irregular exceptions such as technological espionage (Glitz and Meyersson, 2016) or reallocation of entire technological clusters from one economy to another (Hidalgo, 2015), it takes considerable time to acquire these ingredients and accumulate the know-how that make it feasible for the economy become an exporter of sophisticated products.[1] Over the short run, it is more likely that the country has better chances of diversifying into products that bear similarities to what it already exports. The bulk of ingredients are already there, so the economy only needs to add a few capabilities to start exporting a new product. This intuition is supported empirically (see Hausmann and Klinger, 2006, Hausmann and Klinger, 2007, Hausmann et al., 2011). The last paper notes strong *path dependence* in exporting new goods, i.e. countries tend to add products to their production baskets that are closely related to their traditional exports.[2]

Policymakers aware of this dynamic are also likely to shy away from randomly picked new export sectors as they realize a failed export diversification programme can incur huge costs without producing substantial benefits. To minimize risk to their economy (and their political career), the key for the policymaker is effective evaluation of possible export diversification outcomes given the economy's current export structure.

To reach this goal, we implement a network approach (Hausmann et al., 2011) that combines natural science methods in network analysis with a social science view of networks. We apply the network approach to measure the level of economic complexity and diversification opportunities of Russian regions. Russia's regional complexity was previously estimated by Farra et al. (2013) and Lyubimov et al. (2017). The former study, however, uses only regional export data. As we show later, this results in biased estimates of economic complexity. The latter paper does not provide a detailed study of export diversification opportunities for Russian regions. Kadochnikov and Fedyunina (2013) use a complementary approach and data on current export structure of Russian regions

[1] See Sabel et al. (2012) for case study of Embraer. See Lederman and Maloney (2007) for discussion of Nokia's story.
[2] Hausmann et al. (2011) do not imply that such diversification strategies result in ever-rising complexity of a country's export basket. If the exports of an economy initially belongs to a cluster with few shared capabilities with other clusters, the economy has low chances for diversification over the long run.

to estimate the level of potential per capita gross regional product. Unlike previous studies, we provide a measure of regional complexity, and an extended discussion of diversification possibilities for the regions of Russia, based on combined Russian regional and BACI CEPII international export data. The combined dataset enables us to provide more precise complexity and diversification estimates. Our results, including the ranking of regional economic complexity and estimates of diversification opportunities for Russian regions, are catalogued in the *Atlas of Economic Complexity: Russian regional pages*.[3]

The paper is organized as follows. Next section explains the method which we use to estimate regional economic complexity and diversification opportunities. Then we introduce our dataset. We continue with a discussion of our main results, including Economic Complexity Index (ECI) for Russian regions and their diversification opportunities. The final section concludes.

Method

The network approach we use in this paper relies on export data in calculating a country-product matrix that can be converted into a *product space*, i.e. a network representation of a collection of exported products, where *nodes* reflect internationally traded products and *links* correspond to technological distances between them.

Products exported in tandem are often considered to be co-located within the product space. Conversely, products rarely co-exported are identified as requiring different skill-sets and capabilities and therefore more distant from each other in the product space. This approach sorts exported products into product groups such that particular locations in the network are reserved for specific product groups.

Network representation helps distinguish among the complexity of various product groups. More complex groups are better connected to other goods (i.e. have more links) than less complex product groups. Assume, for example, that a particular economy can export entire nuclear power plants on a turn-key basis, supplying everything from safety and control systems, generators and containment structure to auxiliary buildings and training. Such capabilities imply the existence of individuals in economy who would also possess the know-how for exporting e.g. computers, monitors, cables, project management and safety solutions, textiles, plastic products and metal fabrication.

[3] URL: https://docs.wixstatic.com/ugd/9db2e8_17a1d03200d646b7860d7826336898bf.pdf. (Russian version).

As an aggregation of skill-sets, the nuclear power plant links to many products, both complex and simple. The knowledge of how to export textiles does not imply knowledge needed to export nuclear power plants or computers. The textile sector is not well connected with other product clusters.

Using academia as a metaphor with regards to its central network position, our nuclear power plant could be compared to a Nobel prize winner. The Nobelist enjoys connections with other academicians, journalists, politicians and businessmen, and possesses a deep understand of his or her field, adjacent fields and a variety of methods. He or she may also be good at communication about relevant skills or popularizing a new research field. With many capabilities shared with other individuals, the Nobelist has many links to peers, specialists and members of the general population. In contrast, a newly minted researcher typically starts out at the edge of the academic community, with skills and knowledge largely relevant to interacting with his or her peers, many of whom are academic newcomers themselves. These entry-level academics must work their way up the ladder to recognition and acceptance through hard work, discipline and novel insights. This metaphor also implicates the homophily hypothesis (McPherson et al., 2001), which assumes that links are primarily formed among individuals sharing common social characteristics such as education or cultural background.

Taking the network representation of exported products, we use a *network centrality approach* to measure the level of centrality of products and economies.

To get a better idea of the network centrality approach, consider node ν linked to a number of neighbouring nodes. This node could, for example, be our above-mentioned Nobelist with many colleagues and friends, or it could be our exemplary nuclear power plant that bundles advanced and simple know-how shared with other complex products.

Unlike other measures of centrality (e.g. degree centrality), *eigenvector centrality* has the specific advantage of allowing us to account for nodes directly and indirectly linked to a particular node. Using our Nobelist example again, when measuring centrality, we can consider both immediate friends and friends of friends. The latter property is important as it is likely that the Nobelist's circle of friends is linked to individuals not directly connected to him or her.

Let x_v denote a centrality measure of node ν, and an element $a_{i,v}$ represent a direct link between ν and other neighbouring nodes. $a_{i,v}$ is binary in the following sense: its entry is equal to 1 in case ν has a direct link with another node, and 0 otherwise. Thus, the measure of centrality of node ν can be calculated as follows:

$$x_v = \frac{1}{\lambda} \sum_i a_{i,v} x_i \ , \tag{1}$$

where λ is a scalar. We can rewrite expression (1) in matrix notation to receive the following equation:

$$Ax = \lambda x \ . \tag{2}$$

Equation (2) corresponds to the definition of eigenvector with λ on its right-hand side representing an eigenvalue. If we apply the Frobenius-Perron theorem to adjacency matrix A, representing the network structure on the left-hand side of equation (2), then the measure of centrality is provided by the eigenvector corresponding to the largest eigenvalue.

A similar, but not identical, approach to measuring the level of nodes centrality can be applied to estimate the complexity of exported products or economies.[4]

We start here with the definition of *revealed comparative advantage* (RCA) introduced by Balassa (see Balassa, 1965):

$$\mathrm{RCA} = \frac{\frac{x_{c,p}}{\sum_p x_{c,p}}}{\frac{\sum_c x_{c,p}}{\sum_p \sum_c x_{c,p}}} \ , \tag{3}$$

where $x_{c,p}$ represents the value of product p exported by country c. The numerator of equation (3) corresponds to the share of product p exported from country c in the total value of products exported by economy c, while its denominator reflects the share of product p in world exports. If the numerator of equation (3) is larger than the denominator, then the share of product p in the export basket of country c is larger than this product's share in world exports. Equation (3) can be interpreted as a ratio between country $c's$ share of world exports of product p and the share of this economy in total world exports. If the country has a larger share in the world exports of product p than in total world exports, i.e. if $RCA \geq 1$, we conclude that the economy has a revealed comparative advantage in exporting product p. RCA defines the country-product matrix M_{cp} with its entry equals to one if country c has a revealed comparative advantage in exporting product p, and 0 otherwise.[5]

[4] We present the basics of eigenvector centrality here mostly for intuition-building purposes. Application of the method of reflections (discussed below) to our export data results in a Markov matrix with an uninformative eigenvector corresponding to the leading eigenvalue. Thus, the standard steps of eigenvector centrality analysis are inapplicable here.
[5] All further mentions of RCA in the text imply $RCA \geq 1$. Thus, the phrase "product exported with RCA" implies "product exported with $RCA \geq 1$".

Let's now consider a hypothetical world with four economies and four exported products. Here, matrix M_{cp} looks as follows:

countries/ products	I	II	III	IV
A	1	1	1	1
B	0	1	0	0
C	1	0	1	0
D	1	0	0	0

Matrix M_{cp} allows us to calculate a series of indicators characterizing complexity of products and economies. The simplest two indicators are *diversity* and *ubiquity*. Diversity is calculated as a summation over exported products for every economy in matrix M_{cp}:

$$k_{c,0} = \sum_p M_{cp} \, . \tag{4}$$

The diversity value equals 4 for economy A, the most diversified country. It is 1 for economies B and D, our least diversified countries in this example.

The ubiquity indicator it is a summation over countries for every product in matrix M_{cp}:

$$\mathrm{k}_{\mathrm{p},0} = \sum_{\mathrm{c}} \mathrm{M}_{\mathrm{cp}} \tag{5}$$

Unlike $k_{c,0}$, which is a column-vector, note that $k_{p,0}$ is a row-vector. Thus, we must find a way to transform it into a column-vector.

In equation (5), product I is the most ubiquitous; it is produced by three out of four countries. This could be an indication that the product is simple, i.e. replicating the know-how necessary for its production is easy. In contrast, product IV is produced only by country A, making it our least ubiquitous product.

Are these two simple indicators adequate for measuring the complexity of economies and products? To answer this question, we revisit the above example of four economies and four products reflected in matrix M_{cp}. Countries B and D look similar with respect to their level of diversification: each exports a single product with RCA. Although these two economies export different products, the diversity indicator ignores this difference. It considers a single dimension (the number of products exported by an economy), making B and D indistinguishable.

Of course, the differences between these economies could be quite important if they export different products. To distinguish between these two economies, we need an additional criterion. Here, we consider the ubiquity of products B and D export. Product I, which is exported with RCA by economy D, is also exported by countries A and C. It is more ubiquitous than product II, which is exported by A and B. The average ubiquity of products exported by economy D equals 3, while the ubiquity of products exported by economy B equals 2.

As the ubiquity of a product could be an indication of simplicity, country B could have a more complex economy than country D. This is just a preliminary inference, however. Product II may be less ubiquitous than product I, but that low ubiquity could have a geographic, rather than technological, basis. Product II, for instance, could be a rare mineral resource such as diamonds, and not a complex product that requires considerable know-how to be exported. Unfortunately, these two cases are indistinguishable in the above example, as countries B and D export only a single product.

The distinction between a rare natural resource and a complex product requires employing higher step indicators, but here we provide only an intuitive example. If a less ubiquitous good is exported in tandem with simple (ubiquitous) products, it is likely to be a simple product such as a natural resource. If it shares the same export basket with complex products, there is a high likelihood that that the product is also complex.

The above intuition illustrates an algebraic process known as the *Method of Reflections* (see Hidalgo and Hausmann, 2009; Hausmann and Hidalgo, 2011). This process can be described by the following two equations:

$$k_{c,N} = \frac{1}{k_{c,0}} \circ M_{cp} k_{p,N-1}^{T} \tag{6}$$

$$\mathrm{k}_{\mathrm{p,N}}^{\mathrm{T}} = \frac{1}{k_{p,0}^{T}} \circ M_{cp}^{T} k_{c,N-1} \,, \tag{7}$$

where ° denotes the element-wise multiplication and conventional matrix product is assumed whenever ° is not mentioned.

To see the Method of Reflections at work, we return to the above example with four economies and four products. We first check if our conclusion is correct that country B exports more ubiquitous products than country D. From equation (5) it follows that the indicator of ubiquity is $\mathrm{k}_{1,0} = 3$ for product I and $\mathrm{k}_{2,0} = 2$ for product II. The entire ubiquity vector which is defined in equation (5) is $\mathrm{k}_{\mathrm{p},0} = (3,2,2,1)$. We pre-multiply its transpose $\mathrm{k}^{\mathrm{T}}_{p,0}$ by the country-product matrix M_{cp} to find the total ubiquity of products that are exported by economies A, B, C and D.

In order to average these ubiquities to make meaningful comparisons, we divide every total ubiquity corresponding to a particular economy over the respective level of diversification calculated in equation (4) and equal to $\mathrm{k}^{T}_{\mathrm{c},0} = (4,1,2,1)$. For instance, the total ubiquity of economy A is 3 + 2 + 2 + 1 = 8, and for economy C is 3 + 0 + 2 + 0 = 5. Country A exports all four products, while C sells only two of them internationally. Their average ubiquities equal 2 and 2.5, respectively. A's exports are less ubiquitous than C's, even though this was not clear from comparing total ubiquities of these two economies. Country A has the less ubiquitous export basket; it exports product IV, which no one else is able to export with RCA. Note that the average ubiquities of countries B and D are 2 and 3, respectively, i.e. exactly the same values obtained in our simple calculations.

The Method of Reflections corresponds to a series of substitutions of a lagged version of equation (7) into equation (6) when economic complexity is calculated (or vice versa if product complexity is evaluated). Rephrasing, we can say that the Method of Reflections uses an indicator of product complexity to estimate economic complexity, and a measure of economic complexity to evaluate product complexity.

This series of substitutions can be summarized in the following expression:

$$\mathrm{k}_{\mathrm{c,N}} = \frac{1}{k_{c,0}} \circ M_{cp} \frac{1}{k^{T}_{p,0}} \circ M^{T}_{cp} k_{c,N-2}\ . \tag{8}$$

It is important to consider matrix $W = \frac{1}{k_{c,0}} \circ M_{cp} \frac{1}{k^{T}_{p,0}} \circ M^{T}_{cp}$ on the right-hand side of equation (8) in more detail. This matrix is a key part of equation (8) as it represents the structure of network, in much the same manner matrix A from the left-hand side of equation (2) represented the network structure of links between the Nobelist and his friends and colleagues.

Each element of the transpose of the country-product matrix M_{cp} is weighted by the transpose of the ubiquity measure $k_{p,0}$ defined in equation (5), therefore transforming elements of this matrix, albeit imperfectly, into a complexity measure of each product exported by every economy. Pre-multiplication by the country-product matrix transforms its weighted transpose into an adjacency matrix, whereby each element reflects the level of proximity between two random economies. This level of proximity can be alternatively interpreted as a path length between two economies. In terms of export similarity, a less developed and a more developed economies are likely to be less similar to each other than a pair of more developed economies. In other words, a less developed economy has a longer way to go become similar to the more developed economy.

Another part of W is $\frac{1}{k_{c,0}}$, which makes W asymmetric and can be considered as a normalizer indicating the side (less developed or more developed economy) from which the path from one economy to the other starts.

We conclude that W is an asymmetric adjacency matrix that represents the structure of a network linking various economies by means of similarities in their export structures. Economies with more diversified and complex export baskets might be considered our "export Nobelists." They have considerable export capabilities, including know-how, well-protected property rights, a developed banking industry, infrastructure, internationally certified production processes and strong marketing skills. Given these capabilities, they can produce and export both complex and non-ubiquitous products, as well as simple and ubiquitous product. Complex economies are similar to each other as they have many capabilities in common. As a consequence, they are not only better linked to each other but also to less developed economies as the less complex capabilities are more likely to be used universally. At the same time, less diversified and less complex economies have less in common with highly developed economies (and in many cases, with each other). For instance, the export structure of Saudi Arabia differs from that of Vietnam or India.[6]

A similar logic applies to products, so the method of reflection also lets us derive a product version of matrix W. Without replicating it here, the intuition behind the product adjacency matrix will be laid out in the discussion below when we consider the definition of proximity.

Armed with the clear understanding of matrix W, we continue by rewriting equation (8) to obtain:

$$k_N = \mathrm{W} k_{N-2} \,. \tag{9}$$

It can be shown empirically that as N increases, k_N converges to a finite limit (see Hidalgo and Hausmann, 2009). The intuition behind convergence is simple. While the Method of Reflections can be considered as a process of collecting more information about products and economies, less information is extracted with each iteration, i.e. each iteration extracts so much information that

[6] Saudi Arabia's exporting industries are dominated by petroleum (67% of total export value), so the country is likely to share similarities with to other major petroleum exporters such as Kuwait (84% share of petroleum exports). On the other hand, Indian largest export industries are diamonds (9%) and refined petroleum products (10%). Some 30% of Vietnamese exports consist of complex equipment (see https://atlas.media.mit.edu/en/).

only a small portion of information remains undiscovered. Because of convergence, we can rewrite equation (9) as a definition of eigenvector with an eigenvalue equal to 1:

$$\mathrm{k} = \mathrm{Wk}\ . \tag{10}$$

As W has only positive entries, our natural inclination is to apply the Perron-Frobenius theorem to find the eigenvector corresponding to the largest eigenvalue in order to rank economies according to centrality. This step of the analysis is not standard, however.

On the one hand, we can clearly apply the Perron-Frobenius theorem here, as W is irreducible (all entries are positive). Stated differently, all countries are interlinked as they share at least one set of common capabilities. Even though two countries might differ, they still export with RCA a smaller or larger subset of similar products such as farm produce or textiles. As a real-world example, the Israeli economy is more complex than the Moroccan economy, but both countries export oranges and thus possess the same skill-sets with respect to citrus exporting.

On the other hand, using the eigenvector corresponding to the largest absolute eigenvalue as a measure of centrality is inapplicable here. The eigenvector corresponding to the largest absolute eigenvalue (1) has equal entries and is therefore uninformative. To illustrate this problem, we replicate the proof from Kemp-Benedict (2014).

We introduce a vector with each of its c elements taking the value of one, i.e. $n_c = 1$ for all c. If n_c is pre-multiplied by the transpose of the country-product matrix M_{cp}^T, then the resulting vector is clearly the transpose of $k_{p,0}$ which is defined in equation (5). Keeping this result in mind, we pre-multiply n_c by W, and then go through the following short series of derivations:

$$Wn_c = \frac{1}{k_{c,0}} \circ M_{cp} \frac{1}{k_{p,0}^T} \circ M_{cp}^T n_c =$$

$$= \frac{1}{k_{c,0}} \circ M_{cp} \frac{1}{k_{p,0}^T} \circ k_{p,0}^T =$$
$$= \frac{1}{k_{c,0}} \circ M_{cp} n_p =$$
$$= \frac{1}{k_{c,0}} \circ k_{c,0} =$$
$$= n_c$$

From the Perron-Frobenius theorem it follows that any positive eigenvector of W has entries taking the same value. This same value is one.

As we cannot use the eigenvector corresponding to the largest eigenvalue to rank economies, we take the second-largest eigenvalue and its corresponding eigenvector. The second-largest eigenvalue is smaller than 1 as the largest eigenvalue is equal to 1 (W is row-stochastic).[7] A simple intuition allows us to conclude that the second-largest eigenvalue is relevant. If countries have many capabilities in common, implying they are similar, these common capabilities are captured by the eigenvectors corresponding to the largest eigenvalues. As the largest eigenvalue is one, and the corresponding eigenvector has the same entries and therefore uninformative, we take the eigenvector corresponding to the second-largest eigenvalue.

After we calculate the eigenvector corresponding to the second-largest eigenvalue, we standardize this eigenvector to get the following:

$$\mathrm{ECI} = \frac{\vec{\mathrm{K}} - <\vec{\mathrm{K}}>}{\mathrm{stdev}(\vec{\mathrm{K}})}, \tag{11}$$

where $\vec{\mathrm{K}}$ is the eigenvector of W corresponding to the second-largest eigenvalue, $< \vec{\mathrm{K}} >$ denotes its average value, and $\mathrm{stdev}(\vec{\mathrm{K}})$ correponds to its standard deviation. Expression (11) defines our Economic Complexity Index or ECI.

The same steps apply to the derivation of our Product Complexity Index (PCI), defined as follows:

$$\mathrm{PCI} = \frac{\vec{\mathrm{Q}} - <\vec{\mathrm{Q}}>}{\mathrm{stdev}(\vec{\mathrm{Q}})}, \tag{12}$$

where $\vec{\mathrm{Q}}$ is the eigenvector corresponding to the second-largest eigenvalue of the respective adjacency matrix, with its entries reflecting weighted and normalized co-export of different pairs of products, $< \vec{\mathrm{Q}} >$ denotes the average value of $\vec{\mathrm{Q}}$ and $\mathrm{stdev}(\vec{\mathrm{Q}})$ is its standard deviation. We do not consider the respective matrix here, but a nearly identical matrix is discussed a few lines below.

Our last expression defines proximity between two products. Algebraically, it is defined as follows:

$$Proximity = \frac{m_{cp'}^{T}\ m_{cp}}{\max(k_{p,0}, k_{p',0})} \tag{13}$$

[7] A stochastic matrix (Markov matrix) is a square matrix in which entries reflect the transition probabilities of a Markov chain. Each entry of matrix W can be interpreted in terms of the conditional probability of one economy reaching the same level of complexity as another economy given the first economy's export structure (see Kemp-Benedict, 2014).

To calculate the numerator of the right-hand side of equation (13), we pick up a particular pair of products, p and $p\,'$ and then, by multiplying the respective row $m^T_{cp\,'}$ from matrix M^T_{cp} by the respective column m_{cp} of its transpose, we find how many times these two products are exported in tandem by all the economies. We normalize the resulting value over the maximum of two products ubiquities to make meaningful comparisons between the levels of similarity of various pairs of products.

This measure is somewhat similar to the typical entry of the adjacency matrix reflecting links among products. In the adjacency matrix, each entry is a weighted and normalized frequency of a pair of products to be co-exported. However, unlike adjacency matrix entries, the proximity measure defined in equation (13) is not a result of iteration process. In contrast to a typical entry of W, $Proximity$ is not normalized over $k_{c,0}$, it is instead normalized over $\max(k_{p,0}, k_{p',0})$, which makes the matrix of proximities symmetric.

Normalization lets us compare proximities between different pairs of products. To see this, consider a hypothetical world with 100 countries and four products. Let product I be exported by all 100 economies, while only 50 countries export product II. Therefore, both products are co-exported 50 times. Let product III be exported by 30 economies, and product IV can be found in export baskets of 25 countries. Assume for simplicity that every economy exporting product IV also exports product III. The latter implies that products III and IV are co-exported by 25 economies. If we compare only absolute values, i.e. 50 and 25, then we can mistakenly conclude that two products in the first pair have a higher level of proximity than two products belonging to the second pair. To avoid such misleading inferences, we normalize the number of intersections over the maximum of two products' ubiquities. Using this normalization, the number of intersections within the second pair of products, i.e. 25, is normalized over 30, which is clearly larger than the normalized number of intersections within the first pair, which equals ½.

In our analysis, we use ECI, PCI and Proximity defined in equations (11)–(13) to analyze the complexity, structure and diversification potential of regional export baskets in Russia. In the following section, we discuss the data – the most problematic building block of our discussion.

Data

Data availability is the main limitation in applying this approach to Russian regions. We overcome this drawback by distinguishing among limitations related to data availability.

Some limitations are common for any dataset used in this method. For instance, the lack of data prevents decomposition of values of products into value-added chains. Such decomposition has been applied to aggregated product groups (see Timmer et al., 2014), but not to data corresponding to a deep disaggregation based on 4-digit SITC product groups. In other words, given current data it is impossible to determine where a car was designed, what share of its value should be attributed to designers, where the engine and transmission were produced, or how much of its final value should be attributed to the engine and transmission manufacturers. Thus, it would be impossible to specify how much of a Lada car's value is produced in Russia and how much of it is produced abroad. The same limitation applies to regional data as well. As a result it is impossible to estimate how much of the Lada car's value should be attributed to the Samara region and how much of it to manufacturing activity in other Russian regions.

Another common data limitation is the lack of data on internationally traded services. Obviously, money earned on exportable services is no less valuable for an economy than money earned from exportable products. For instance, tourism, the largest export service sector in Spain (Coscia et al., 2016), generates much more value than car manufacturing, Spain's largest exporting industrial sector. However, as disaggregated data on services export are unavailable, services are ignored when economic complexity is estimated. This data limitation biases complexity estimates. The more services-oriented the economy, the larger the bias.

Some data limitations are idiosyncratic, that is, specific to Russian regional data. Two of these limitations deserve mention.

First, even though their main production facilities are not located in the city or the Moscow region, many Russian manufacturers maintain their head offices in Moscow. Companies headquarters are in Moscow because they need to stay close to federal authorities. For example, Moscow has no oil fields or production, yet Russian customs data show Moscow as an oil exporter. The somewhat imperfect solution to clarifying such data is to complement customs datasets with data that identify the production sites of Russian companies.

The second limitation is more intractable. There are no data on inter-regional trade in Russia, so this method is arguably inapplicable to estimations of the economic complexity of Russian regions. While correct from statistical point of view, however, its economic grounds are weaker.

Considering the statistical part of this problem, using Russian customs data on internationally traded products alone likely results in incorrect estimates of complexity.[8] These data are not representative and thus could lead to bias. For instance, the complexity of fruits can be overestimated. Home-grown fruits are rare products in Russia. If a regional producer of fruits exports a complex local product, then the fruit may also be identified by the method as a complex product.

To avoid this confusion, we need additional data on specific products and economies. Complementing Russian customs data with the BACI CEPII data for the year 2015 on international trade helps us correctly estimate the complexity of regional economies. It increases our total number of observations from 63878 region-product entries to 234,479 region/country-product observations, all corresponding to 4-digit SITC codes. The international data tell us that fruits are produced by many economies exporting ubiquitous products, so the method now correctly identifies fruit as a simple product.

Appendix II shows the differences in estimates of complexity between Russian customs data alone and with the combined datasets. Another result supporting this approach to data is provided in the next section.

Intuitively, combining Russian customs data and BACI CEPII data into a single adjacency matrix helps us answer two questions. How similar are Russian regions to each other regarding their export structures? How similar are the economies of Russian regions, such as Moscow or Rostovskaya oblast, to the economies of countries, such as Czech Republic or Australia, regarding their export structures? Overall, a larger dataset improves the precision of estimates.

There is an economic argument against considering regions as autonomous economies such that their exports to other regions is considered at par with their international exports. The weakness of the latter viewpoint stems from ignoring the important difference between externally and internally traded products. If products are sold internationally, this might be an indication of higher quality, while a national market might be less selective about the quality of goods. The view of a less-discriminating domestic market implies more low-quality products among internally traded products than among externally exported goods. This difference between export and domestic quality may not be important in, say, a study that estimates industrial rather than export complexity of a particular economy. In such case, the researcher needs to collect data on inter-regional trade, as otherwise such a study would be incomplete (see Gao and Zhou, 2017, for an example of a solution

[8] Several studies use these data to estimate regional economic complexity. See e.g. Farra et al. (2013).

to the inter-regional data problem). However, if the goal of the study is to estimate regional export complexity, as here, then the need to add in inter-regional trade data is no longer pressing.

Results

We use our Economic Complexity Index (ECI) results to rank regional economies according to their levels of economic complexity. We visualize these rankings on a map of Russian regions.[9] The more complex regional economies are located in the western and central parts of Russia, while the level of economic complexity is clearly lower in the eastern and northern parts of the country. The Moscow region, Moscow, Sverdlovsk Region, Nizhny Novgorod Region, St. Petersburg and Smolensk Region top our ECI-based rankings. The Amur Region, Trans-Baikal Territory, Republic of Altai, Jewish Autonomous Region, Murmansk Region oblast and Primorye Territory are at the bottom, representing the least complex regional economies (see Appendix I) [10].

As this ranking is the result of combining Russian customs and BACI CEPII export datasets, the meaningfulness of such an approach to such dataset construction deserves scrutiny. To show this approach improves the quality of estimates, we compare simple Product Complexity Index (PCI) values that are based only on Russian customs data, with a second version that uses combined data. From Appendix II it becomes clear that the second PCI gives a much higher level of precision than the first. When only Russian customs data are used, we find many not-so-complex products, e.g. bread, tables, mattress supports, at the very top of the ranking. At the same time, some complex products are placed at the bottom of the ranking. These results indicate that using customs data alone results in a large bias. Adding BACI CEPII data to Russian customs data improves the precision of estimates substantially. The top part of the ranking and its bottom part become, respectively, much more homogenously complex and simple.

[9] For examples of country analysis see Hausmann, Klinger (2010), Hausmann, Hidalgo (2013), Farra et al. (2015).
[10] The Republic of Crimea was accessed by Russia in 2014.

Figure 1a ECI index

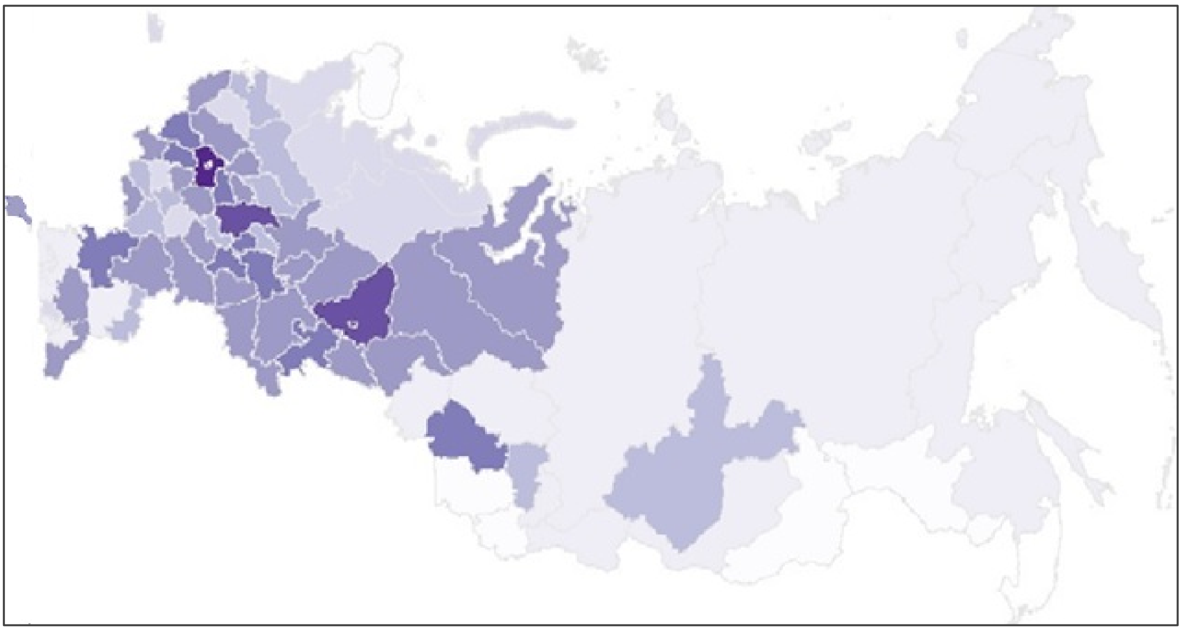


Figure 1b HSE index

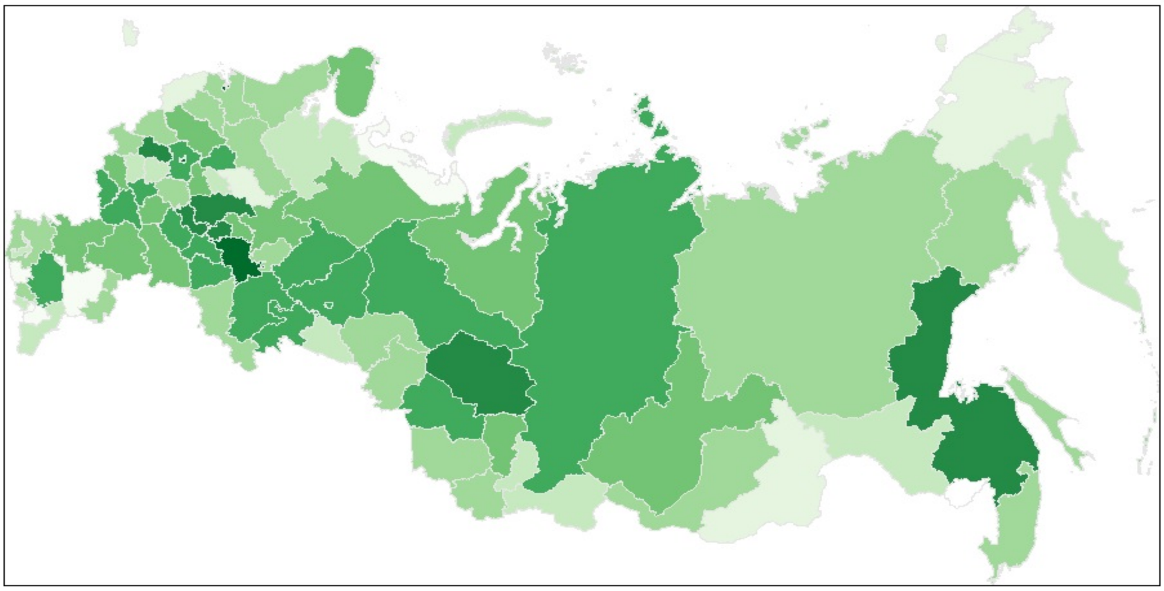
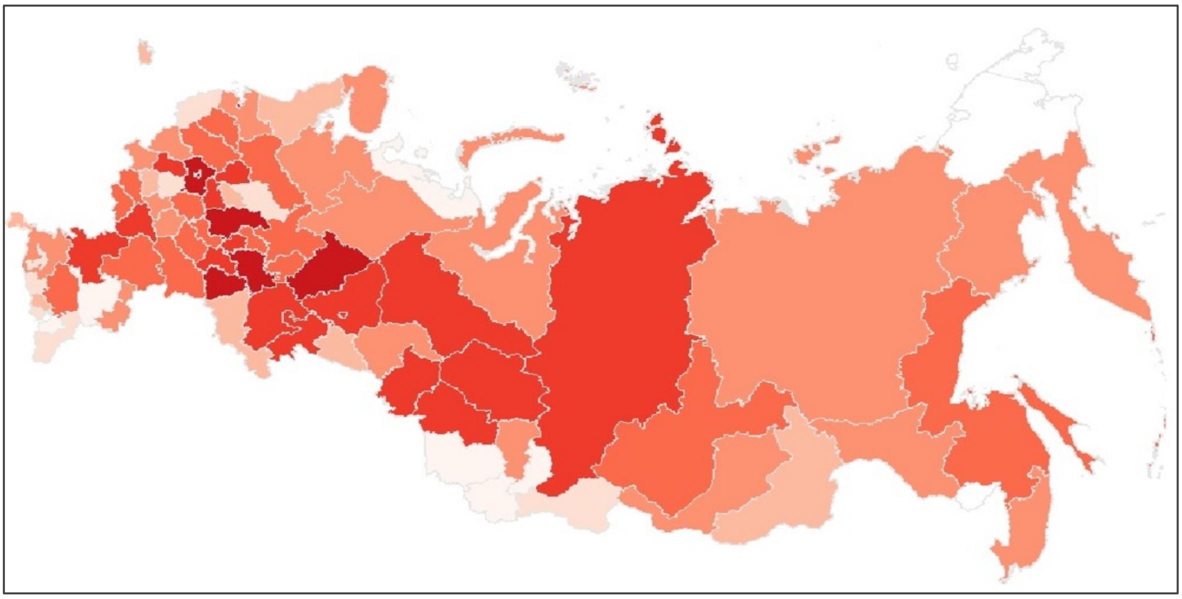


Figure 1c RIA index



We can also check of the meaningfulness of our results by comparing ECI results with other regional rankings such as the Higher School of Economics Russian Regional Innovations Index (HSE index) ranking and RIA Index of Scientific and Technological Development of Russian Regions (RIA index) ranking.[11,12] Both rankings are based on integral indexes that use a large collection of indicators measuring various aspects of regional R&D. While both rankings lack solid theoretical foundations and are based on strong assumption of perfect substitutability among the contributing indicators, they nevertheless capture a substantial part of regional variance in R&D performance.

Table 1 shows the Spearman correlation values among four rankings: ECI (based on both Russian customs and BACI CEPII data), ECICD (ECI with customs data only), and HSE and RIA rankings. Unlike ECICD, ECI has a much higher correlation with both the HSE and RIA indexes. This could indicate that ECI, which is based entirely on export data, captures a substantial part of variance related to various aspects of regional development. The result, while yet to be properly established, could reflect the fact that export data are useful in explaining inter-regional variances. These data, after all, reflect the availability of various export capabilities (e.g. R&D and infrastructure) of a particular region.

[11] URL: https://www.hse.ru/primarydata/rir2015
[12] URL: http://riarating.ru/regions_rankings/20161020/630044723.html

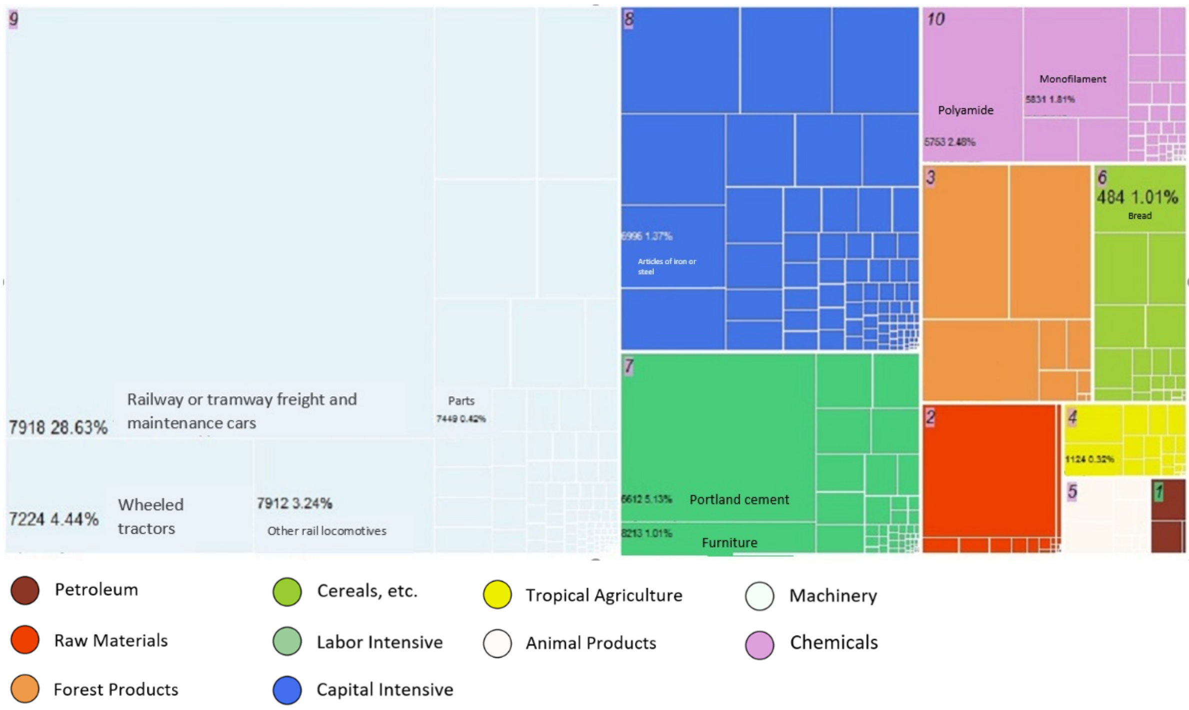
Table 1 Spearman correlation values, ECI, ECICD, HSE and RIA indexes

Spearman correlation	ECI	ECICD	HSE	RIA
ECI	1.0000			
ECICD	0.6529	1.0000		
HSE	0.5204	0.3364	1.0000	
RIA	0.5984	0.3441	0.8376	1.0000

While ECI could be useful as a measure of regional complexity, it is not useful if we need to know more about a particular regional economy. For example, it does not indicate the export structure of the regional economy or suggest how it might diversify its exports.

To obtain an understanding of the export structure of a particular region, we use an export treemap. In Fig. 2 below, the total area of the rectangle corresponds to 100% of the Bryansk region's[13] industrial export value. Each large block represents a particular product group according to Leamer (1984), while smaller blocks give a detailed composition of regional exports corresponding to 4-digit SITC codes (mentioned for some products) and their shares in the total value of regional exports. Colours are explained in the legend below the treemap.

Figure 2 Export treemap for Bryansk region representing its export structure in 2015



[13] We use Bryanskaya oblast as an example here, as its economy is relatively complex and well-diversified, which lets us provide better illustrations.

Looking closer at Fig. 2, the highest share of export value (over 50%) belongs to machinery (with railway or tramway freight and maintenance cars dominating), second- and third-largest shares correspond to capital intensive (with iron and steel as the leading products) and labour-intensive (especially cement) as major export group. Even though machinery is the leading export group in the Bryansk region, it does not export very complex products. This is consistent with its 16th place out of 85 in Russia's regional rankings (ECI = 0.7287).

As a visualization tool, the treemap gives only gives a static view of the composition of the regional export basket. It lets us visualize regional exports at the moment, but says little about what the region will export in the future.

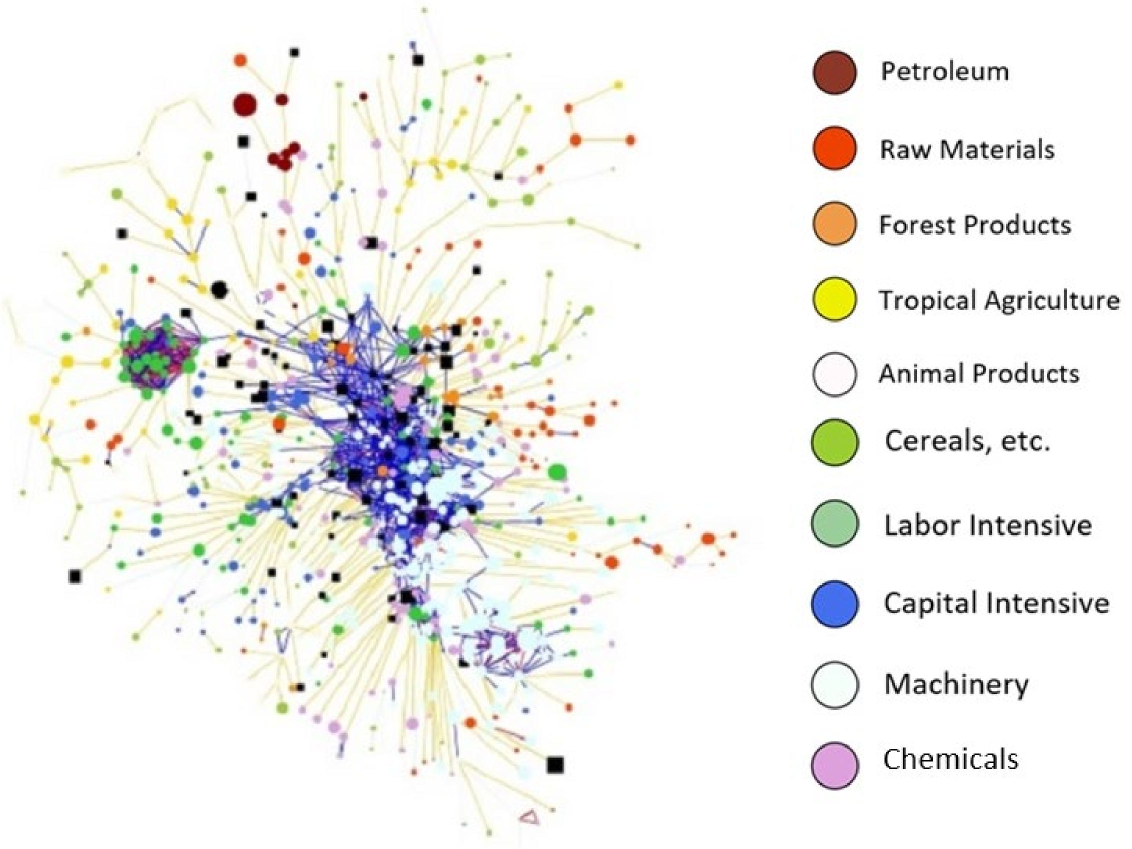
To see what a region might export tomorrow, we use an advanced visualization tool representing a network, whereby internationally exported products are linked to each other. The Maximum Spanning Tree (MST) algorithm makes a "skeleton" of the network, where exported goods with RCA play the role of nodes, and proximities defined in equation (13) serve as links. MST maximizes the sum of links, i.e. the sum of proximities connecting nodes representing products. A force spring algorithm is applied to achieve a better visualization of the network.[14]

This network, i.e. the product space (Hausmann et al., 2011) is depicted at Fig. 3. Nodes reflect exported products grouped into 10 product groups and listed on the right-hand side of Fig. 3 according to Leamer (1984). Each colour corresponds to a particular product group, and black squares indicate which products are already exported effectively (i.e. with RCA) by the Bryansk region.

Unlike the treemap, which is simply a collection of products Bryansk region exports in 2015, the product space gives some insights regarding how Bryansk might potentially diversify. As it exports products belonging to machinery and capital intensive sectors, it could use the respective capabilities to export more products related to these product groups.

[14]URL: http://chidalgo.org/productspace/network.htm

Figure 3 Visualization of the Bryansk region's export in the product space in 2015. Black rectangles represent products exported effectively (i.e. with RCA)



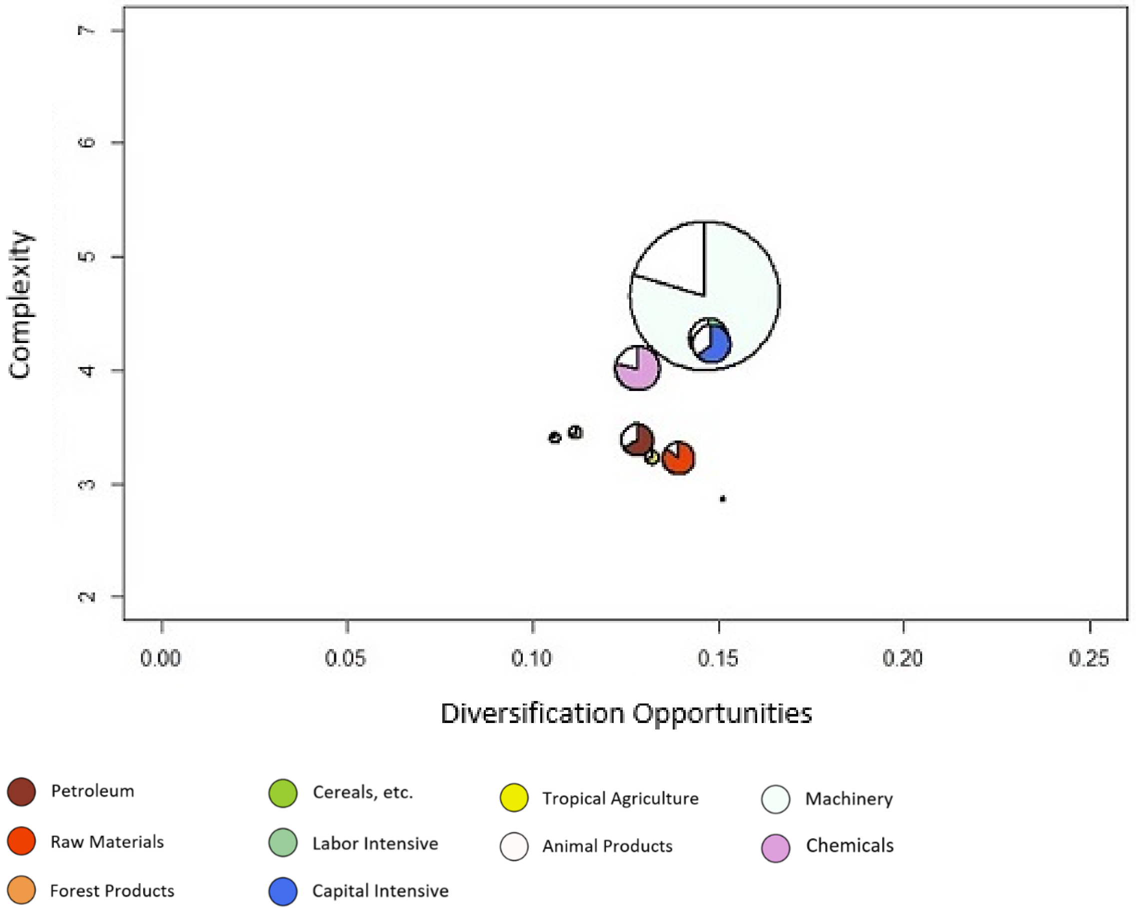
The product space is a visualization, not an analytical tool. It can help one see how well a region is positioned in the network of effectively exported products to make very rough estimates of how its economy might diversify in the future.

We need an *explicit* analytical tool to estimate a particular region's opportunity to diversify into new sectors. Following Hausmann et al. (2011) we use equation (13) to measure the proximity between the nowadays export basket of a particular region and each of ten product groups defined according to Leamer (1984). This approach to measuring diversification opportunities is intuitive. If a particular economy is an exporter of many complex products, it should be easier for it to diversify into other complex industries.

The horizontal axis of Fig. 4 reflects a proximity-based probability measure that shows how likely is that Bryansk region will be able to diversify into a particular group It also shows, using products' PCIs defined in equation (12), the complexity of these groups. The size of groups is proportional to their share of world exports. Finally, white slices correspond to the shares Bryansk region already held in 2015 has in each of the 10 groups.

From Fig. 4, we can conclude that the most promising directions of diversification are related to machinery, capital-intensive and labour-intensive product groups, as well as the chemical industry. Note, however, that the Bryansk region's share in each of these groups is low, indicating that the Bryansk region is yet to become an exporter of these product groups' most complex products.

Figure 4 Visualization of relationship between the probability of joining certain product group and this group's complexity. Each product is exported effectively (i.e. with RCA)



Finally, we consider that merging or expanding into different group provides further opportunities for a longer run diversification. If a region has high chances to diversify into, say, machinery and forestry, then it is probably better to use the former opportunity as it gives more opportunities to expand into other complex sectors and increase the overall level of economic complexity of the region.

We therefore measure the average proximity between each product group defined according to Leamer (1984) and the basket of all products not currently exported with RCA by a particular region. However, as estimating distant diversification opportunities is conceptually similar to estimating proximate diversification opportunities,[15] we do not give an example here. For readers of Russian, such examples are plentiful in our *Atlas of Economic Complexity: Russian regional pages*.[16]

Overall, the diversification prospects of Russian regions are limited. Diversification opportunities are smaller than 5% for near half of Russian regions, with the value of 0 for 12 of them (Jewish Autonomous Region, Kamchatka Territory, Magadan region, Republic of Ingushetia, Komi Republic, Republic of Sakha (Yakutia), Republic of Tuva, Republic of Khakassia, Sakhalin region, Tyumen region, Chechen Republic and Chukotka Autonomous Region). As for the rest, in their case the diversification opportunities are not higher than 0.15, except for Moscow and Smolensk regions (0.25-0.3), as well as for Novosibirsk and Omsk regions (0.2).

This result may indicate that Russian regions would have greater chances to diversify if they joined global value-added chains rather than they try to develop and export entirely new products. Moreover, regions may find it more effective to cooperate and develop joint diversification strategies. In many cases, a single region in Russia has relatively few capabilities, but two or more regions with complementary capabilities could develop a joint diversification strategy that would enhance their diversification opportunities. Here, we refrain from making specific suggestions as to which regions might form coalitions with each other as it would require complementary methods beyond this paper's focus.

Concluding remarks

In this paper, we applied a network approach to evaluate the level of complexity of Russian regions and their export opportunities. Using the same approach as in Hausmann et al. (2011) and combining Russian customs data with BACI CEPII data on international exports, we calculated Economic Complexity Index (ECI) values for all 85 Russian regions. The ECI reflects the complexity of products exported by these regional economies.

The key assumption of our approach is that export data reflect the presence of various capabilities such as property rights protection, know-how, infrastructure, availability of credit and marketing skills. More complex goods require more such capabilities, while simple products can be

[15] The basket of products exported with RCA by a region and the basket of products not exported with RCA by the same region can be considered as two endpoints of an ideal diversification path.
[16] https://docs.wixstatic.com/ugd/9db2e8_17a1d03200d646b7860d7826336898bf.pdf

produced and exported with fewer capabilities. One can therefore consider products as nodes in a network in which the product is directly linked to another product when both are the result of similar capabilities or skills sets. A complex product such as a nuclear power plant requires a vast variety of capabilities, so it is linked to many products, both complex and simple. In contrast, a simple product such as tomato uses a small set of much simpler capabilities, and therefore it might be barely linked to other products. One can use a centrality measure to rank products according to the level of centrality that also reflects complexity. The same logic applies to economies, because a particular economy can be treated as a "basket" of products it exports.

Our findings indicate that western and central regions of Russia are more complex than the northern and eastern regions, while a group of southern regions is positioned somewhere in the middle. We compare ECI with other regional indexes such as the HSE and RIA R&D-related indexes, both calculated as averages of a large group of relevant indicators. We find that ECI and the two other indexes are strongly correlated, implying that ECI seems to capture important information on R&D activities even though it uses no data explicitly related to R&D. While preliminary and yet to be properly established, this finding supports the view that export data may reflect the presence of various export capabilities.

We then use two visualization tools, a treemap and a product space visualization, to give a more detailed view of what a particular region exports and to help interpret the implications of its ECI levels.

Finally, we estimate export opportunities of Russian regions by measuring how far their current export baskets are from 10 large product groups. We find that on average Russian regions have relatively weak opportunities to diversify. This may suggest that Russian regions might be better off if they seek to integrate with global value-added chains rather than try to develop and export novel products. Regions may also form pursuing export strategies based on cooperation with each other as individual regions may lack sufficient capabilities to exploit diversification opportunities.

We emphasize that the quality of data has reduced the precision of these results. Even though we manage demonstrate an improvement in quality, we by no means come close to solving the myriad of data-related problems that present challenges for many years ahead. Perhaps the best we can say is that our estimates here are *tolerably* biased.

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Appendix I

Table A1 ECI Index (based on Russian customs and BACI CEPII country data), ECI index (based on customs data alone), HSE index and RIA index

Regions	ECI (regions & countries)	ECI (regions without countries)	Russian Regional Innovations Index (HSE index)	Index of Scientific and Technological Development of Russian Regions (RIA index)
Moscow Region	1.9007	1.5514	0.4136	61.64
Moscow	1.5536	0.4108	0.5530	80.06
Sverdlovsk Region	1.1789	0.0871	0.4263	54.64
Nizhny Novgorod Region	1.1233	0.3245	0.4749	65.35
St. Petersburg	1.0724	0.4335	0.5413	71.47
Smolensk Region	1.0343	1.1128	0.3271	32.12
Republic of Tatarstan	0.9371	0.4008	0.5625	65.53
Chuvash Republic	0.9180	0.8153	0.4645	47.07
Ulyanovsk Region	0.8717	0.4584	0.4137	53.81
Chelyabinsk Region	0.8519	0.4919	0.4036	49.98
Novosibirsk Region	0.8246	0.4847	0.4389	53.55
Vladimir Region	0.7804	0.5216	0.3482	49.59
Omsk Region	0.7714	-0.7883	0.3243	46.30
Kaluga Region	0.7542	0.2555	0.4812	48.88
Rostov Region	0.7408	0.5770	0.3664	51.47
Bryansk Region	0.7287	0.8438	0.2985	31.78
Samara Region	0.7211	-0.0104	0.3941	63.74
Penza Region	0.7078	0.4108	0.4411	45.14
Volgograd Region	0.6784	0.4846	0.3627	36.67
Republic of Buryatia	0.6760	0.3583	0.3377	32.60
Tver Region	0.6737	-0.5460	0.3715	37.05
Ryazan Region	0.6508	0.3383	0.3250	44.38
Yaroslavl Region	0.6369	0.2569	0.3963	49.44
Pskov Region	0.5710	-0.2736	0.2080	18.02
Orenburg Region	0.5631	-0.2872	0.3222	25.30
Altai Territory	0.5288	0.5484	0.3673	32.31
Stavropol Territory	0.5221	0.5097	0.3960	37.28
Udmurt Republic	0.5156	0.2444	0.2947	38.74
Kurgan Region	0.5112	0.3241	0.2817	26.60
Kirov Region	0.5010	0.3001	0.3488	37.06
Orel Region	0.4641	0.2838	0.2878	28.40
Republic of Dagestan	0.4539	0.2153	0.2808	17.76
Saratov Region	0.4403	0.1372	0.3396	42.69
Perm Territory	0.4188	0.3249	0.4007	59.99
Ivanovo Region	0.4080	0.4296	0.2881	27.61
Belgorod Region	0.3779	-0.4722	0.3947	35.31
Tyumen Region	0.3688	0.1060	0.3988	47.48

Khanty-Mansi Autonomous Area – Yugra	0.3688	0.1060	0.3225	34.56
Yamal-Nenets Autonomous Area	0.3688	0.1060	0.3775	28.15
Republic of Bashkortostan	0.3638	0.2181	0.4200	50.38
Astrakhan Region	0.3453	0.0477	0.3250	29.74
Republic of Mari El	0.3407	0.0806	0.3438	34.64
Republic of Mordovia	0.3235	-0.0994	0.4930	40.49
Voronezh Region	0.3088	0.2020	0.4002	51.43
Leningrad Region	0.3029	0.1490	0.3154	31.47
Tula Region	0.3028	0.1241	0.3356	52.23
Irkutsk Region	0.2751	-0.1781	0.3511	38.74
Kursk Region	0.2686	-0.4329	0.3769	37.05
Kostroma Region	0.2457	0.2408	0.2161	20.75
Vologda Region	0.2420	-0.0716	0.3141	34.87
Kemerovo Region	0.2351	-0.0160	0.3481	31.99
Lipetsk Region	0.2289	0.2380	0.4261	34.17
Komi Republic	0.2091	0.0539	0.3368	31.33
Kaliningrad Region	0.1867	-0.1214	0.2055	25.70
Novgorod Region	0.1842	0.1017	0.2979	40.36
Krasnodar Territory	0.1542	0.0941	0.3315	30.73
Arkhangelsk Region	0.1480	0.0806	0.2896	34.08
Nenets Autonomous Area	0.1480	0.0806	0.1958	13.32
Tambov Region	0.1352	0.2831	0.3775	32.07
Kabardino-Balkaria Republic	0.0919	0.1450	0.3075	22.91
Republic of Karelia	0.0897	0.1504	0.3145	21.31
Republic of Ingushetia	0.0753	0.0189	0.1909	7.77
Republic of Kalmykia	0.0680	-0.0103	0.1969	13.18
Republic of Tuva	0.0578	0.0946	0.2586	16.62
Tomsk Region	0.0321	0.0007	0.4652	54.18
Kamchatka Territory	0.0287	-0.5210	0.2611	28.39
Karachayevo-Cherkessia Republic	0.0205	0.1310	0.2033	17.54
Republic of Sakha (Yakutia)	0.0155	0.0291	0.3298	32.99
Sakhalin Region	0.0139	-0.1140	0.3162	45.61
Chukotka Autonomous Area	0.0096	0.0285	0.2372	na
Republic of Khakassia	-0.0052	-0.2943	0.2717	13.64
Magadan Region	-0.0085	-0.0176	0.3246	30.49
Republic of North Ossetia – Alania	-0.0088	0.2044	0.2809	20.44
Khabarovsk Territory	-0.0093	-0.2145	0.4498	43.66
Republic of Adygea	-0.0195	0.1310	0.2766	16.95
Krasnoyarsk Territory	-0.0266	-0.3026	0.4382	48.24
Chechen Republic	-0.0403	-0.5554	0.1915	10.34
Amur Region	-0.0696	-1.1271	0.2913	28.41
Trans-Baikal Territory	-0.0902	-0.9650	0.2358	25.50
Republic of Altai	-0.0940	0.1820	0.3067	14.17
Jewish Autonomous Region	-0.1267	-0.2858	0.1592	na
Murmansk Region	-0.1875	-7.9208	0.3464	30.71
Primorye Territory	-0.1925	-1.9891	0.3102	34.62

Appendix II

Table A2 PCI (Russian customs data, no BACI CEPII country data). Products that do not fit the respective part of PCI ranking with respect to their level of complexity are bolded

Code SITC	Product names	PCI
8746	Automatic regulating or controlling instruments and apparatus	1,5694
6942	**Screws, bolts, nuts, coach screws, screw hooks, rivets, etc.**	**1.3509**
7449	Parts suitable for use solely or principally with the machinery	1.2621
7725	Electrical apparatus for switching or protecting electrical circuits	1.2482
7843	Other parts and accessories of the motor vehicles	1.2211
7471	Pressure-reducing valves	1.1423
484	**Bread. pastry, cakes, biscuits and other bakers' wares, etc.**	1.1333
6911	Structures and parts of structures	0.9790
7421	Pumps fitted or designed to be fitted with a measuring device	0.8463
6764	**Other bars and rods of iron and steel**	0.8398
6974	**Table, kitchen or other household articles and parts thereof, n.e.s.**	0.8372
7161	Electric motors of an output not exceeding 37.5 W	0.8134
7435	Centrifuges (including centrifugal driers), n.e.s.	0.7351
5334	Paints and varnishes (including enamels, lacquers and distempers), etc.	0.7278
6795	Tube or pipe fittings (e.g., couplings, elbows, sleeves), of iron or steel	0.7256
6343	**Plywood, veneered panels and similar laminated wood**	0.6999
6794	Other tubes, pipes and hollow profiles, of iron or steel	0.6923
6732	Flat-rolled products of iron or non-alloy steel, not clad, plated or coated	0.6913
8212	**Mattress supports; articles of bedding or similar furnishings, etc.**	0.6882
6768	Angles, shapes and sections (excluding rails) and sheet piling, of iron or steel	-1.1527
6575	Twine, cordage, ropes and cables and manufactures thereof	-1.1829
2875	Zinc ores and concentrates	-1.4278
814	Flours, meals and pellets, of meat or meat offal, of fish or of crustaceans	-1.4513
2874	Lead ores and concentrates	-1.5871
812	Bran, sharps and other residues, whether or not in the form of pellets	-1,6170
363	Molluscs and aquatic invertebrates, fresh, chilled, frozen, dried, salted or in brine	-1.7677
342	Fish, frozen (excluding fillets and minced fish)	-1.9120
6341	Sheets for veneering (including those obtained by slicing laminated wood)	-2.5010
2482	Wood of coniferous species, sawn or chipped lengthwise, sliced or peeled	-3.4296
7861	**Trailers and semi-trailers of the caravan type, for housing or camping**	-5.9950
2723	Natural calcium phosphates, natural aluminium calcium phosphates	-6.2541
6832	Nickel and nickel alloys, worked (excluding electroplating anodes)	-6.2541
7935	**Light vessels, fire-floats, dredgers, floating cranes**	-6.2541
344	Fish fillets, frozen	-6.8039
6842	Aluminium and aluminium alloys, worked	-6.9798
2815	Iron ore and concentrates, not agglomerated	-7.0142
2878	Ores and concentrates of molybdenum, niobium, tantalum, titanium, vanadium	-7.0631
361	Crustaceans, frozen	-7.6819
351	Fish, dried, salted or in brine, but not smoked	-8.5991

Table A3 PCI: Russian customs data and BACI. CEPII country data products that do not fit the respective part of PCI ranking with respect to their level of complexity are bolded

Code SITC	Product Names	PCI
7725	Electrical apparatus for switching or protecting electrical circuits	3.2567
7471	Pressure-reducing valves	2.8701
7421	Pumps fitted or designed to be fitted with a measuring device	2.8046
6942	**Screws, bolts, nuts, coach screws, screw hooks, rivets, cotters, cotter pins**	2.4158
8746	Automatic regulating or controlling instruments and apparatus	2.3948
7435	Centrifuges (including centrifugal driers), n.e.s.	2.3416
7449	Parts suitable for use solely or principally with the machinery	2.2532
6764	**Other bars and rods of iron and steel**	2.0471
7161	Electric motors of an output not exceeding 37.5 W	1.8287
7522	Portable automatic data processing machines, weighing not more than 10 kg	1.7919
7712	Other electric power machinery; parts of the electric power machinery	1.7543
6911	Structures and parts of structures	1.6741
7843	Other parts and accessories of the motor vehicles	1.6153
7861	Trailers and semi-trailers of the caravan type, for housing or camping	1.5753
7456	Mechanical appliances for projecting, dispersing or spraying liquids or powders	1.5290
7752	Household-type refrigerators and food freezers (electrical and other)	1.5200
6299	Hard rubber; articles of hardened rubber or of unhardened vulcanized rubber	1.4775
7787	Electrical machines and apparatus, having individual functions, n.e.s.	1.4728
7272	Other food-processing machinery and parts thereof, n.e.s.	1.4694
7811	Vehicles specially designed for travelling on snow	1.4480
711	Coffee, not roasted, whether or not decaffeinated	-2.5463
6116	Goat- or kidskin leather, without hair on, whether or not split	-2.5604
2911	Bones, horns, ivory, hooves, claws, coral, shells and similar products	-2.6446
2119	Hides and skins, n.e.s.; waste and used leather	-2.6506
2922	Lac; natural gums, resins, gum resins, and balsams	-2.7050
361	Crustaceans, frozen	-2.7469
363	Molluscs and aquatic invertebrates, fresh, chilled, frozen, dried, salted or in brine	-2.8223
812	Bran, sharps and other residues, whether or not in the form of pellets	-2.8604
6115	Sheep- or lambskin leather, without wool on, whether or not split	-2.9536
6674	Synthetic or reconstructed precious or semiprecious stones, whether or not worked	-2.9669
8961	Paintings, drawings and pastels, executed entirely by hand	-3.0346
342	Fish, frozen (excluding fillets and minced fish)	-3.0389
19	Live animals, n.e.s.	-3,0854
2632	Cotton linters	-3,1296
341	Fish, fresh (live or dead) or chilled (excluding fillets and minced fish)	-3,1508
2473	Wood in the rough (whether or not stripped of bark or sapwood) or roughly squared	-3.2637
577	Edible nuts (excluding nuts chiefly used for the extraction of oil), fresh or dried	-3,2844
579	Fruit, fresh or dried, n.e.s.	-3.3878
2237	Oil-seeds and oleaginous fruits, n.e.s.	-3.6968
2924	Plants and parts of plants (including seeds and fruits) of a kind used primarily	-4.1954

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