Modelling the Innovative Performance of Resource Areas: Analysis of 22 Russian Regions

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Abstract

Purpose. Regions with a high share of the resource sector in the economy tend to show weak innovative performance and rely on the exploitation of nature wealth. Transition to sustainable development requires special measures to stimulate innovation activity. The main purpose of our study is to find key drivers of innovative performance for resource abundant regions. Awareness of the essential determinants of innovative activity in “resource regions” is crucial for policy-makers in planning the strategy of regional sustainable development.

Methods. We used knowledge production function to create our own model of innovative performance. We tested our model on the empirical data from Russian resource-rich regions to reveal key drivers of innovative performance for resource regions.

Results. Regression analysis showed that the same basic patterns of knowledge generation are relevant for resource abundant regions and for developed countries. We also discovered that financial independence of the region and entrepreneurial activity are crucial factors of innovative performance for resource-rich regions.

Conclusions. Our findings can be used to form an effective regional policy that ensures sustainable socio-economic development of resource-rich regions through the transition from mining to deep processing based on the use of high technology (innovation).

Keyword: innovative performance; “resource curse”; innovative capacity; modeling; regional policy.

Introduction

Natural resources can be a “blessing” for economic development (Fleming et al 2015; Allcott and Keniston 2017) but sometimes become a “curse” for the regions with high resource endowment (Van Der Ploeg and Poelhekke 2017; Corey and McMahon 2009). Papyrakis and Gerlagh (2004) provides evidence from the US states to prove that resource rich regions are less successful in economic growth than regions poor in natural wealth. The economy in such regions relies on the exploitation of natural treasures and the resource sector dominates in the economy structure. Such ways of development are unsustainable, especially for the case of exhaustible (mineral) resources. Transition to more sustainable economic growth requires measures for stimulating innovation activity and encouraging entrepreneurship in the territory (Sevastyanova 2017). At the same time resource regions are under pressure of several negative factors. The first group of factors are national factors of “resource curse” and “Dutch disease”: overvaluation and volatility of the national currency (Corden and Neary 1984); rent-seeking behavior and corruption (Van Der Ploeg and Poelhekke 2017); false sense of security that causes a lack of incentives for learning and development (Gylfason 2001). The second group of factors is linked to regional specificities of resource regions. Even if the country managed to overcome negative effects of resource abundance some regions can face regional-scale problems. First, resources are dispersed unequally around the world and very often concentrate in the territories with hard climate conditions which are far from the main markets, financial and research centers (Kinnear 2014). Secondly, high volatility in commodity markets generates instability of the employment in the resource sector that can cause socio-economic problems at a local level (Fleming et al 2015). Moreover, uncertainty of long-term benefits from resource extraction negatively affects long-term investments (Ivanova and Leydesdorff 2014). Local resource companies are integrated in national or transnational corporations that attract a major share of the natural rent leaving regional authorities to solve local problems (Krjukov et al 2017). All these negative effects, both national and regional, make barriers for innovative activity in resource regions.

Despite those barriers there are several examples of Russian (Sevastyanova 2017), and Australian (Kinnear 2014) resource regions that demonstrate high innovative performance. Positive cases of resources “innovative-leaders” inspire a question, what are the drivers of innovative success for resource-based local economies?

To answer this question, we conducted an econometric analysis of innovative performance factors based on knowledge production function (Romer 1990) and our own regressive model. Calculations were carried out using the official statistics on Russian resource regions for a ten-year period (2006-2016).

In the first part of our paper we introduce a definition of a raw material region used in the context of this paper. We also analyze the features of the socio-economic development of resource-rich Russian regions. Section 4 tests Romer’s model on the empirical data from Russian resource abundant regions to clarify whether fundamentals of knowledge production are relevant for these territories. We run regression analysis in Secion 4 to find the essential drivers of innovative performance for resource-rich regions.

Literature Review

Since innovations became a synonim of economic development (Schumpeter 2017) the interest to the sources of innovative success increase. Measuring innovative performance on macro, local and micro levels gives awareness of the main drivers of innovative activity and it can form the basis for strategy development. The first source of information about the determinants of innovative performance is presented by various national and regional ratings. Most rankings are based on the innovative system framework (Nelson 1993, Edquist 2010, Lundwall 2010) and consist of two part: resources for innovations (inputs) and innovative performance (output) (see, for example, Index G.I. 2017). Ranking provides information about the elements of innovation system and its productivity separately and without taking into account specific features of assessing economies (Sevastyanova 2017).

Another approach to measuring innovative process is based on the case study method. It gives more information about the peculiarities of a particular economy but you cannot generalize about the common principles of innovative process (see, for example Cavallo et al 2014).

The third way to explore the sources of innovation development is econometrical modeling. Regression analysis demonstrates the influence of significant “inputs” on innovative performance. Modeling innovative performance relies on the knowledge production function framework introduced by Griliches (1979) to estimate the influence of R&D efforts to productivity growth. He assumed that new knowledge was a function of special “input”, namely R&D expenditures, and other unmeasured inputs. Another important assumption is that “knowledge output” is behind “inputs” in time. So, one should apply a relevant lag while measuring the effects of knowledge inputs. Later, Romer (1990) introduced the ideas production model with the two main factors of knowledge creation, such as human capital employed in research and current knowledge stock:

$$\dot{A}_t = \delta H_{A,t}^{\gamma} A_t^{\varphi}, (1)$$

$\dot{A}_t$ – new knowledge and technologies, produced in year *t*; A_t – knowledge and technologies stock: H_A – researchers, involved in the generation of new knowledge and technologies (human capital).

Although there is an ongoing discussion about the form of ideas production model (Grossman and Helpman 1991), there is empirical evidence that those ”inputs” are crucuial for new knowledge creation (Furman et al 2002). Additional factors of innovative process appeared in the innovative capacity framework (Furman et al 2002). The innovative capacity framework combined the Romer model, the concept of innovative systems (Nelson 1993) and the Porter cluster theory (Porter 1998). According to the authors, there are three more components that infuence innovative capacity (innovative performance). The first component is the common innovation infrastructure or conditions for new knowledge production. The second component characterizes the level of development of innovative clusters. The strength of the relationships between the innovation infrastructure and clusters forms the third component of the model:

$$\dot{A}_{j,t} = \delta_{j,t}(X_{j,t}^{INF}, Y_{j,t}^{CLUS}, Z_{j,t}^{LINK})H_{j,t}^{A,\gamma} A_{j,t}^{\varphi}, \quad (2)$$

$\dot{A}j,t$ – new knowledge and technologies, created by the country j in year t; $H_{j,t}^{A\lambda}$ – human capital, engaged in the process of generation of new knowledge and technologies; $A_{j,t}^{\Phi}$ – knowledge and technology reserve, which the country jhas in the yeart-1; $X_{j,t}^{INF}$–the quality of the general innovational infrastructure; $Y_{j,t}^{CLUS}$ – characteristic of the industrial cluster environment in the economics; $Z_{j,t}^{LINK}$ – the strength of the relationships between the innovational infrastructure and the national industrial clusters.

Innovative capacity model does not only include the knowledge creation process but takes into account the conditions under which new knowledge becomes an innovation. Additional factors show how policy choices affect innovative performance. This method has several limitations. First, innovative performance (or new knowledge) is measured by the number of granted patents (Acs et al 2002, Furman et al 2002, Autant-Bernard and LeSage 2011). As Griliches (1991) notes, “not all inventions are patentable, not all inventions are patented, and the inventions that are patented differ greatly in ‘quality’, in the magnitude of inventive output associated with them”. Patents could be a measure of new knowledge but do not measure innovative performance directly. Patents influence innovative performance as an “input” for further innovations.

The second limitation is about additional factors of clusters, innovative infrastructure and quality of linkages. These factors were empirically tested on the data from well-developed countries (Furman et al 2002) but not on regional levels and not for a special case of resource regions.

We modified the innovative capacity model as follows:

$$IP_r = \dot{A}(P^{\alpha}E^{\beta}) \ (6)$$

where $\dot{A}$ is a new knowledge, created in regional economy, P and E are the specific factors of innovative capacity for resource regions, α and β are the elasticities of specific factors. Factor P evaluates regional policy efforts for innovative development. It corresponds to

X^{INF} – the factor of common infrastructure quality from the innovative capacity model (2). Factor E corresponds to Y^{CLUS} – the characteristic of innovative environment. Variable Z^{LINK} doesn't have a relevant indicator at a regional level. Ivanova and Leydesdorff (2014) developed a theoretical model of the linkages impact and implemented it in the case of Arctic resource regions (Carayannis et al 2017). We did not include linkages variables into the model.

We suggest measuring innovative performance (IP variable) with the flow of innovative goods and services produced in the regional economy. This indicator better estimates the result of innovative processes than patents, while patents become an innovative input in the model. Thus, this model explains the variation in innovative performance across resource regions under the influence of internal factors, such as patents granted in the region, regional innovative policy and the quality of innovative environment without external influences.

We start with an empirical test of knowledge production function to find out whether the main drivers of knowledge creation are relevant for resource-rich regions. Then we run regression analysis of the model (6) to identify the essential drivers that influence innovative performance in resource regions.

Methods

This study is on the regional economies that suffer from natural resource abundance. Negative effects from natural wealth are associated with the "natural dependence" notion, when the resource sector dominates in the economy (Corden and Neary 1982). We distinguish "resource endowment" from "resource dependence" (Kuleshov et al 2017) or "resource abundance" (Sachs and Warner 2001). Natural wealth per se does not cause a threat for economic growth (Stijns 2001, Gylfason 2001). A threat is the predominance of the resource sector that leads to negative effects which were discussed in the first part of this study.

Different approaches exist to classify an economy as "resource dependent" or "resource abundant". Sachs and Warner (2001) use a share of primary export in GDP as a measure of resource abundance. This indicator is not good in the case of regions because regional economy is an open system and export flows can concentrate at a national level. Another approach relies on the locational quotient analysis that measures the share of resource in employment, GRP and other indicators (Kinnear 2014). We apply a single locational index, the share of extracting industry in GRP because it demonstrates the impact of the resource sector in regional development:

$$F_r = \frac{EAV_r}{AV_r} \quad (3)$$

where EAV_r – added value of the extracting sector in the region, AV_r – gross added value of the region.

Then we compare the regional index with the national index (F_c):

$$F_c = \frac{EAV_c}{AV_c} \quad (4)$$

$$K_r = \frac{F_r}{F_c} = \frac{EAV_r}{AV_r} * \frac{AV_c}{EAV_c} \quad (5)$$

where Fc – the share of extracting industry for added value of the country; EAV_c – added value of the extracting sector in a national economy, AV_r – gross added value of the country; K_r – localization index of the region,.

If index K_r is more than one, regional economy is more ”resource-oriented” than national economy and we will call it ”resource” or ”resource abundunt” region.

We rely our analysis of resource regions on the statistical data from the Russian Federation for two reasons. First, the Russian Federation is a ”resource abundant” country. Mineral resources dominate in the national exports and their share increased over the past ten years up to 59% in 2016 (Surinov, 2017). Second, the sample of resource regions in the Russian Federation is representative: 22 of 85 regions can be classified as resource ones if we use the localization index (5) (Figure 1).

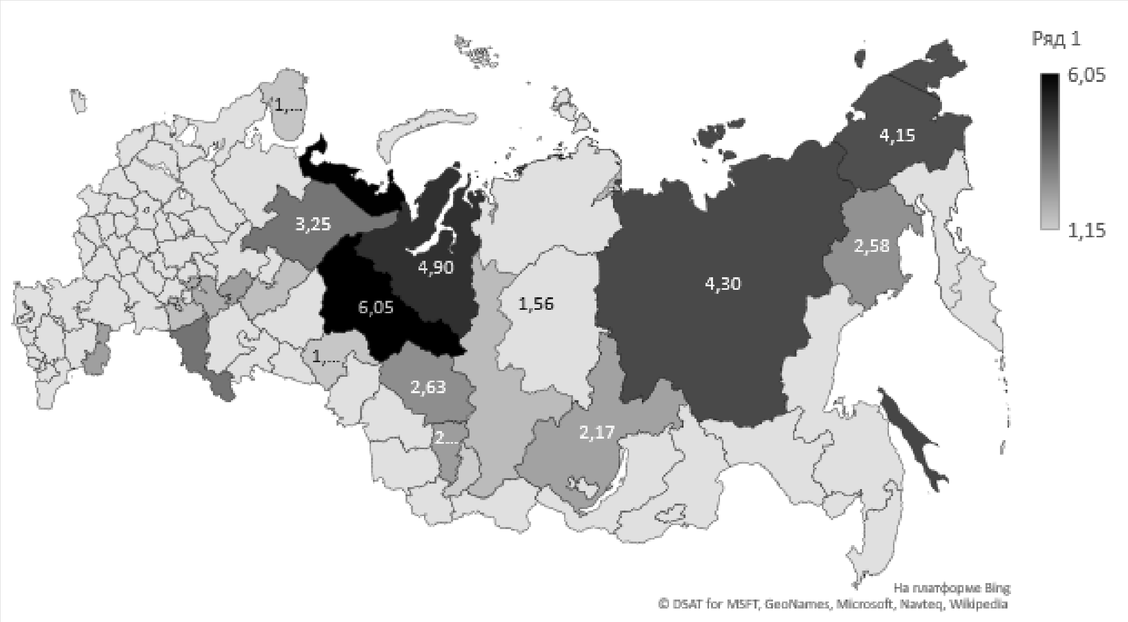

Figure 1. Resource abundant regions of the Russian Federation by localization index (Zimnyakova and Samusenko 2017)

These regions are mainly located at a considerable distance from the central part of the country which is densely populated. Taken together, 22 resource abundant regions extract 83.42% of all mineral resources of the country, they occupy 64.4% of the territory, they bring 43.15% of tax payments to budgets at all levels. At the same time, these regions include only 21.55% of the population, 9.5% of budgets spendings and 3.66% of investments across the country (Statistical data come from Suri)

Resource regions differ in innovative performance (Table 1).

Table 1 Resource regions in the National Innovation Rating, 2016[1]

Region	Place	Region	Place	Region	Place
Tatarstan	3	Astrakhanskaya oblast	32	Sakhalinskaya oblast	73
Tomskaya oblast	4	Yakutiya	42	Khakasiya republic	74
Samarskaya oblast	9	Komy republic	54	Yamalo-Nenetski AO	75
Tumenskaya oblast	14	Murmanskaya oblast	57	Amurskaya oblast	78
Krasnoyarski krai	16	Kemerovskaya oblast	61	Nenetski AO	82
Permski krai	18	Orenburgskaya oblast	62	Chukotski AO	85
Udmurtskaya republic	29	Khanty-Mansisky AO	66		
Irkutskaya oblast	31	Magadanskaya oblast	68		

[1] Rating of Russian innovative regions (Association, 2017) is counted by Russian Innovative Regions Association according to the methodology of Global Innovative Index (Index G.I., 2017)

To find the drivers of innovative performance asymmetry we run two regression models, model (1) and model (6). We used panel data from 22 Russian resource regions from 2003 till 2016. The data was taken from the web site of the Russian Federal State Statistic Service. To follow the assumption that knowledge creation "inputs" do not affect 'outputs' simultaneously, we applied a 3-year lag for the "input" variables (Table 2).

Table 2. Variable sample for knowledge production function

Variable	Index	Definition
$\dot{A}$	Patents (Pt)	Patents granted in the region *j* in the year (*t+3*); (2006-2016)
A	Patent Stock (PS)	Cumulative patents in the region *j* before year (*t-1*) cumulatively; (2003-2013)
H_A	RND Personnel (RP)	Full-time employed scientists and engineers in the region *j* in year *t*; (2003-2013)
H_A	RND Expenditure (RE)	R&D expenditures in all sectors of the region *j* in year *t*, adjusted to the prices of 2003; (2003-2016)

We took the number of patents granted in the region (Pt) as an "output" measure of knowledge creation like in (Furman et al 2002 and Fritch 2002). To estimate knowledge stock we counted the patents granted in the region *j* from 1990 to year (t-1) cumulatively. We chose two variables to measure human capital. They are the number of personnel employed in R&D and R&D expenditures adjusted to the prices of 2003. Then we applied the natural logarithm to all variables to provide the transition to the additive regression model. Correlation control for variables is presented in table 3.

Table 3. Correlations matrix for the knowledge production function variables

	(Pt)	(PS)	(RP)	(RE)
(Pt)	1	$0{,}913^{*}$	$0{,}854^{*}$	$0{,}760^{*}$
(PS)	$0{,}913^{*}$	1	$0{,}825^{*}$	$0{,}759^{*}$
(RP)	$0{,}854^{*}$	$0{,}825^{*}$	1	$0{,}955^{*}$
(RE)	$0{,}760^{*}$	$0{,}759^{*}$	$0{,}955^{*}$	1

* Correlation is significant at 0.01 level (Pirson's correlation); the number of observations = 242

Table 3 demonstrates a high correlation between the numder of patents granted in year *t+3* and knowledge creation inputs. Input variables also significantly correlate and correlation coefficients exceed 0,76. Therefore we will run regression analysis separately for each variable (see Results section).

Variables for the second model are presented in Table 4.

Table 4. Variable sample for innovative performance

Variable	Index	Definition
IP	Innovative performance (IP)	Innovative products and services produced in the region *j* in the year (*t+3*) adjusted to the prices of 2003; (2006-2016)
$\dot{A}$	Patents (Pt)	Patents granted in the region *j* in the year *t*; (2003-2013)
P	Regional policy (Po)	Regional budget income without federal transfers in the region *j* in the year *t* adjusted to the prices of 2003; (2003-2013)
E	Small and medium enterprises (SME)	The number of small and medium enterprises in the region *j* in year *t*; (2003-2013)

Now we apply a shift to innovation performance variable (IP) because there is a lag between knowledge creation and its commercialization. The policy choise variable (P) is measured by the ammount of the budget incomes that are left in the region and provide sources for independent policy of innovation development (Po). It might be surprising but resource regions that provide almost a half of all tax flows across the country have budget deficits. There are two main reasons for that. First, it is the rules of taxation system where the main part of obligatory payments are concentrated on national level. Some regions (like Tatarstan) had an agreement with federal athorities which leaves a greater share of taxes in the region. The agreement was not prolonged in 2017. Secondly, a major part of extracting enterprises belong to national companies and that results in accumulating all income flows in central, more developed regions.

We measure the innovative environment of resource regions with the number of small and medium enterprises (SME). Greater number of SME means a better entrepreneurial climate in the region.

Correlation analysis is presented in Table 5.

Table 5. Correlations matrix for innovative performance variables

	(IP)	(Pt)	(Po)	(SME)
(IP)	1	0,736*	0,678*	0,465*
(Pt)	0,736*	1	0,652*	0,461*
(Po)	0,678*	0,652*	1	0,369*
(SME)	0,465*	0,461*	0,369*	1

* Correlation is significant at 0.01 level (Pirson's correlation); the number of observations = 242

Factor variables highly correlated with innovative performance (IP). Mutual correlations don't exceed 0,70 so all variables can be included in the regression model.

Results

First, we run regressions for knowledge creation inputs separately. The results are presented in Table 6.

Table 6. Knowledge production function models (dependent variable is (Pt))

Variable		Coefficients (standard error)		
		Patent Stock	R&D Personnel	R&D Expenditure
A	PS	0,698 (0,020)**		
H_A	RP		0,973 (0,038)**	
H_A	RE			0,830 (0,046)**
(Constant)		0,303 (0,125)*	-2,804 (0,285)**	-6,502 (0,598)**
R^2		0,834	0,729	0,92

*,** significant at 5% and 1% level

Pairwise regression analysis showed a significant relationship between knowledge output and its main factors. Existing knowledge, the number of scientists and researchers and R&D expenditures are highly connected with each other and explain the most part of the knowledge production process. Individually each variable explains more than 80% of overall variations of ideas creation. This means the evidence for knowledge creation function is relevant for the case of resource regions as well as for OECD countries (Furman et al 2002).

As mentioned above, new knowledge is only one of the drivers of innovation performance. It may become an innovation after its commercial use. We run another regression for the main factors of innovation process (Table 7).

Table 7. The determinants of innovative performance (dependent variable is (IP))

Variable		Coefficients (standard error)			
		Patent Flow	Regional Policy	Small&medium enterprises	Multiple regression
Ȧ	Pt	0,898 (0,054)**			0,565 (0,067)**
P	Po		1,897 (0,133)**		0,933 (0,147)**
E	SME			0,894 (0,110)**	0,240 (0,087)**
(Constant)		3,780 (0,25)**	-2,804 (0,285)**	4,074 (0,450)**	-5,078 (1,311)**
R^2		0,541	0,459	0,216	0,624
Adj. R^2		0,539	0,457	0,213	0,620

*,** significant at 5% and 1% level

Multiple regression demonstrates a significant connection of all variables with innovative performance. Together all factors explain more than 60% of variations of innovative output. The impact of each determinant is disscussed below.

Innovative capacity (IP) of resource regions is determined by patents granted on their territory. Thus the presence of local knowledge creation is crutial for innovative development.

Small and medium entreprises contribute to innovative capacity of resource regions. (Bukharova et al 2018). This factor has the lowest elasticity, but is still significant in multiple regression.

Financial independency (Po) has the highest regressional coefficient of 0,933. It means that 10% change in the regional budget income leads to 9% change of innovative output. Financial sufficiency is a problem for Russian resource regions and many other regions in the country. Nineteen resource-rich regions out of twenty two resource-abundant territories have budget deficit, while the national budget is surplus (Table 8).

Table 8 Resource region budget deficit in 2016[2]

Region	Deficit (% of GRP)	Region	Deficit (% of GRP)	Region	Deficit (% of GRP)
Tomskaya oblast	3,1	Astrakhanskaya oblast	19,7	Kemerovskaya oblast	25,8
Samarskaya oblast	17,2	Yakutiya	41,4	Sakhalinskaya oblast	12,8
Krasnoyarski krai	37,4	Komy republic	47,7	Khakasiya republic	165,1
Permski krai	2,4	Kemerovskaya oblast	25,8	Yamalo-Nenetski AO	0,9
Udmurtskaya republic	63,7	Orenburgskaya oblast	3,6	Nenetski AO	64,5
Permski krai	2,4	Khanty-Mansisky AO	11,5		
Udmurtskaya republic	63,7	Magadanskaya oblast	26,2		

The size of the budget deficit exeeds 3% of GRP in 16 regions, and is critical in Khakasiya republic. Natural wealth flows away from the resource territories. This undermines the ability of regional authorities to maintain local innovative systems. The most part of R&D expenditures are conducted in central Russian regions. Three central regions (Moscow, St-Petersburg and Moscovskaya oblast) concentrate more than 39% of all expenditures for new technologies. Meanwhile, the share of 22 resource regions is only 25%.

Discussion

We used regression analysis to find the essential drivers of innovative capacity for resource regions. This method gives a confirmation of the hypothesis about the main principles of innovation development. Regression analysis was widely used in the economic growth studies (Sachs and Warner 2001, Sala-i-Martin 1997), in knowledge production studies (Rodrigues Pose and Crescenzi 2008) and in innovative capacity studies (Furman et al 2002). This method has some limitations. First, real economy is a complex system and its factors are highly connected with each other, which results in collinearity problems. Furthermore, regression results depend on the data period. The data from different periods can demonstrate various results. We tried to solve these two problems. The variables we used in multiple regression significantly correlate with the

[2] Statistical data goes from (Surinov, 2017)

dependent variable but mutual correlations do not exceed 0,70. As for the data period, we used all the available regional data on innovations. The first year when the Russian Federal State Statistics Service collected the data of innovative output was 2006. The data period for the dependent value starts in 2006. The regression model can be recalculated through the time when the data is supplemented.

The main drivers of innovative performance for resource regions are new knowledge production, financial independency and entrepreneurial climate. The first factor, new knowledge production, demonstrates the importance of local innovative system existence. The competences for new knowledge production concentrated in the region, contribute to its innovative capacity.

The second innovative performance driver is the financial independency of the regional budget. The more freedom the regional authorities have in strategical issues, the greater the incentives for intensive development are (Coase and Wang 2016). Vertical integrated extracting companies have a lack of interest in innovative development of the regions. They concentrate funds in the regions where the head offices are located. Thus, the regions with a greater part of their budget income have more spare funds to maintain economy and local innovative system (Popodko and Zimnyakova 2018). Local links between the members of innovative process (Triple Helix), business, science and government, are crucial for innovative performance (Etkowits and Ranga 2015).

Small and medium enterprises is the third driver of innovative performance of resource regions. First, the presence of SME in the region means good conditions for entrepreneurship. Furthermore, small businesses are more flexible for new technologies and innovations.

Our innovative capacity model has a medium R^2. It can be supplemented by additional factors to increase its quality. Further analysis can be conducted for another group of regions, for example, the regions without extracting industries. The comparison of elasticities coefficients can give more information about the relevance of innovative capacity factors for non-resource regions.

Conclusion

Economies related to resource extracrion are under the risk of the “resource curse”. Rent seeking behavior, natural wealth depletion generates serious threats for sustainability of regional development. Inspiring examples of countries and regions that managed to escape the curse of natural resources and create the economy based on innovations make scholars and policy makers search for the drivers of innovative development for resource economies.

Our study confirmed the relevance of the main drivers of knowledge creation for resource-rich regions. New ideas production depends on the knowledge stock, human capital and R&D expenditures for both resource-rich and resource poor economies. New knowledge in its turn constitutes one of the main drivers of innovative capacity of resource regions. The results of our regressive analysis confirmed that fact. Additional factors on innovative capacity are financial independency of the regional budget and entrepreneurial conditions.

Our regressive analysis has some limitations. First, we didn't mention marketing and organizational innovations, taking into account only innovative output as the innovative capacity characteristic. Other types of innovations and their drivers can be a topic for further studies. Our model can be expanded by additional factors of innovative performance and can be applied to other economies. Our results can contribute to developing innovation strategy of resource region.

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