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An Alternative Approach towards the Knowledge Production Function on a Regional Level - Applications for the USA and Russia

Jens K. Perret*

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Abstract

The present study picks up on the aspect of knowledge generation - a key part of every national innovation system - in the context of the USA and the Russian Federation. Following Fritsch and Slavtchev (2006) a knowledge production function can be used to account for the efficiency of an innovation systems.

In detail this study provides a quantile regression estimation of the knowledge production function to account for a possible non-linear relationship between knowledge inputs and knowledge output. Using regional data for researchers, expenditures on R& D and patent grants for the USA and the Russian Federation - motivated by the results of a kernel density estimation and transition matrices - a quantile regression is performed for a basic knowledge production function design; for Russia as well for an extended design.

The results show that in both countries there exist groups of regions with smaller sized research systems that report significantly different dynamics and thus knowledge production functions than regions with larger sized research systems.

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1 Introduction

[1] In 1992 Lundvall introduced the concept of the national innovation system (NIS) into economic literature providing a comprehensive frame of reference to analyze the innovation dynamics in economies. Following the OECD's 1999 report on national innovation systems, regional innovation systems are the essential building blocks of any NIS. The analysis of an NIS is therefore inherently of a regional nature.

At the core of every NIS two concepts are of central importance: The generation and the diffusion of innovations and ergo knowledge; on the one hand inside the system itself and on the other across the system's borders.

The present study picks up on the aspect of knowledge generation in the context of the Russian Federation (RF)[2] and the USA[3]. Over the last two decades the RF experienced a transition from a Soviet centrally planned economy to a market economy, however it can still not be considered a fully developed knowledge society comparable to Western European economies where the terms of knowledge society or knowledge economy can be interchanged with the term NIS. On the other hand the US is considered to be one of the world's leading knowledge economies and to have every efficient and effective innovation system.

In this context the US and the Russian Federation offer an interesting comparison not only because they had a much different history and followed a different development path but also because they are politically and economically on different levels of development. An analysis of the US and the RF therefore allows us to take a look at how an innovation system - or at least the knowledge generation mechanism - in this type of a developing economy under specific restrictions looks and works and how it compares to the innovation system of a highly developed knowledge society and analyzed with the same methodology. Futhermore, this study can generate the first step in a more broader comparison or offer an analytical template for the study of other BRICS countries or countries at a similar level of development and comparable economic characteristics like Indonesia.

Fritsch and Slavtchev (2006) argue that estimating a knowledge production function (KPF) allows to test the efficiency of an NIS. The link between knowledge inputs and knowledge output basically coincides with the knowledge generation process in an NIS. The KPF approach is thus a suitable tool

[1]The author would like to thank Mr. David Hanrahan for editorial support.

[2]A comprehensive analysis of the knowledge generation and transmission process can be found in Perret (2013).

[3]Comparable studies here are for example Varga (2000), Audretsch and Stephan (1999a) or Ó hUallacháin and Leslie (2007)

to analyze the US and the Russian innovation system[4].

While studies like Fritsch and Franke (2004), Lee and Park (2005) or Wang and Huang (2007) operate on a firm basis, this study tackles the question from a regional perspective.

However, this study does not so much aim at simply applying the basic framework of the KPF to US and Russian data but tries to deduce in which areas the basic linear KPF framework needs adjustment to better fit the situation in the two countries and in which way the two countries differ from each other.

The study is structured in four sections. In the following second section the basic knowledge production function is introduced.

In the third section at first the quantile regression approach is motivated via the estimation of a kernel density function for the patent activities in both countries and via the calculation of a transition matrix. In a second part the quantile regression analysis is performed to account for the stability of regression coefficients and thus the linearity of the KPF and the potential of omitted variables. Using the regression results a non-linear version of the KPF specifically constructed around the present innovation data is deduced.

The study concludes in the fourth section with conclusions also picking up on policy and research implications.

2 Methodology - The Knowledge Production Function

In analogy to traditional production functions which describe the relation between economic input and output factors, a KPF describes the relation between knowledge inputs on the one hand and knowledge output on the other. Therefore, with K^I as knowledge inputs and K^O as knowledge output, a knowledge production function is a function $K^O(K^I)$. As knowledge inputs can be subsidized to a certain degree - e.g., researchers can be subsidized by additional expenditures on R&D as in the purchase of external knowledge - a KPF can be seen as a substitutional production function.

Additionally, a KPF does not have a theoretical maximum as the generation of knowledge is bounded only by the quantity of input factors.

It is thus reasonable to assume the form of a Cobb-Douglas-type production function when modeling a KPF:

$$K^O = a \cdot K_1^{I\alpha} \cdot K_2^{I\beta} ... \quad (1)$$

[4]Audretsch, D.; Lehmann and Wright (2014) provide a concise overview on the links between knowledge and innovation.

This line of argumentation leads to the basic form of a KPF as discussed and used in a similar fashion by Griliches (1979) when introducing the KPF concept into economics.

A KPF can however take different forms[5]. One of the main aims of the present study is to ascertain whether the assumption of a linear or log-linear form of the KPF is suitable when using the underlying data set.

In this study only researchers are considered as a basic input factor.

The discussion about the most suitable way to approximate knowledge output is as old as the idea of the KPF itself. Griliches himself[6] argued that the idea of using patent grants or applications is flawed, as patents only represent part of the codified knowledge. This link between patents and innovations is studied in more detail by Roper and Hewitt-Dundasa (2015) who argue that it might be a rather weak link.

However, in the absence of a more suitable indicator, this study uses the number of patent grants as an approximation of the stock of knowledge. Thus, it is in line with Verspagen and Schoenmakers (2004) who argue that patents can be seen as a noisy but usable approximation of the stock of knowledge.

The basic KPF therefore has the following form[7]:

$$PatentsGranted_t = a \cdot Researchers_t^{\alpha} \tag{2}$$

Abbreviating the patent grants with P and the number of researchers with R and taking the logarithm the function can be written as:

$$log(P) = log(a) + \alpha log(R) \tag{3}$$

Admittedly, patents are not granted instantaneously. Thus, we assume a time frame of one year for knowledge to be produced that can be patented accordingly.[8]

If, finally, new knowledge is generated, it needs to be submitted to the patent office for appraisal.

[5]For example Bitzer (2003) suggests a different approach to modeling a KPF. Additionally, it might be reasonable to include spatial effects in the analysis of the KPF as well. This has been done for example by Perret (2013).

[6]See Griliches (1979).

[7]Fritsch (2002) and Fritsch and Franke (2004) advocate the use of either researchers or R&D expenditures as knowledge inputs, though not both at the same time. As a large share of the R&D expenditures is used to pay for the researchers including both would lead to biases in the regression results.

[8]In some sectors, like pharmaceuticals, the time frame might be much longer, while in other sectors, like food products, it can be much shorter.

According to official statements by the EPO or Rospatent the patenting process in the Russian Federation officially should take between six months and two years[9]. For patent applications at the European Patent Office (EPO) one to two years can be seen as a reasonable assumption[10].

All told, a time lag of two or three years might be a suitable assumption[11].

So far it has been assumed that the knowledge production function possesses constant coefficients a and α. Considering the quantile regression approach, this assumption can be tested and, considering it does not hold true, the assumption can be relaxed and a becomes a function $a(P)$ of the patent grants and α function $\alpha(P)$.

The functions can be estimated by acknowledging that the quantile regression approach delivers a set of coefficients for each quantile of the patents variable. Calculating those quantiles explicitly it becomes possible to link patent values (the quantiles of the patent variable) with the estimated coefficient values from the quantile regression. Regressing the patent quantiles against these coefficient values delivers an estimate of the functions $a(P)$ and $\alpha(P)$.

Linear and log-linear coefficients While a solution for arbitrary functions $a(P)$ and $\alpha(P)$ cannot be calculated explicitly, a simple but useful case is to assume them to be linear or log-linear in logarithmized terms, respectively.

Both functions thus have the following forms:

$$a(P) = exp(a_1 log(P) + b_1) \quad (4)$$

$$\alpha(P) = a_2 log(P) + b_2 \quad (5)$$

The first equation can be logarithmized to read as follows:

$$log(a(P)) = a_1 log(P) + b_1 \quad (6)$$

The knowledge production function in this case reads as:

$$log(P) = a_1 log(P) + b_1 + (a_2 log(P) + b_2) log(R) \quad (7)$$

[9] See WIPO (2012b)

[10] Officially, an application should be processed after 18 months.

[11] While Fritsch and Slavtchev (2006) suggest that a three year lag offers the best alternative, Perret (2013) finds for the Russian Federation on a regional level a lag of two years to provide the best results.

The advantage is that this equation can explicitly be solved for the patents P[12] and therefore allows for an exact deduction of the KPF.

$$P = exp\left(-\frac{b_2}{a_2}\right) exp\left(-\left(log(R) + \frac{a_1 - 1}{a_2}\right)^{-1}\right)^{\frac{b_1 a_2 + b_2 - a_1 b_2}{a_2^2}} \tag{8}$$

While this equation seems at first to be bulky and unwieldy, in the course of the following analysis it will be useful to have it in this form.

Literature Review While this is not the first study to estimate a knowledge production function, among studies which have tested the KPF for specific regions or sectors, there are the only three studies with a focus on the Russian Federation; Roud (2007), Savin and Winker (2012) and Perret (2013) for the USA Varga (2000), Audretsch and Stephan (1999a), Ó hUallacháin and Leslie (2007) and Branstetter (2001) (US and Japan) can seen as an excerpt of studies with the respective focus.

Other studies on the topic can be roughly categorized into one of four categories.

In the first category, studies take a look at a specific group of countries: Madsen (2008) (OECD) or Buesca et al. (2010) (Europe / EU).

A second category consists of those studies that consider only individual countries. Besides the above cited ones for the US and Russia, there are, for example, studies by Ponds et al. (2010) (Netherlands), Buesca et al. (2006) (Spain), Andersson and Ejermo (2003) (Sweden), Ranga et al. (2004) (Belgium), Conte and Vivarelli (2005) (Italy), Fritsch and Franke (2004) (Germany), Wagner (2006) (Germany), Fischer and Varga (2003) (Austria), Masso and Vahter (2008) (Estonia) and Wu (2009) (China).

The third category is comprised of studies on specific sectors: Zucker et al. (2007) (Nanotechnology), Stephan et al. (2000) (Biotechnology), Ramani et al. (2008) (Biotechnology and Food) and Pardey (1989) (Agriculture).

Finally, the fourth group consists of those studies that have a more general focus unrelated to any sector or region. This category includes: Abdih and Joutz (2005) (Total Factor Productivity), Masso and Vahter (2008) (Total Factor Productivity) and Anselin et al. (1997) (State-level vs. Metropolitan-level) as well as, from a more theoretical perspective, Griliches and Mairesse (1998) and Acs et al. (2009).

[12] Note that in cases where a logarithm, aside from logarithm naturalis, has been implemented, the exponential function needs to be subsidized by a corresponding power function.

3 Analysis of the KPF

3.1 Variable Design

The basic KPF only includes researchers, therefore the problem of omitted variables is almost endemic, as shown by Perret (2013).

Considering that a significant part of the knowledge generation process is omitted, if only basic inputs are observed, the classical KPF usually needs to be extended through the introduction of additional variables. However as will be shown in the next section extending the KPF by including additional variable does not always solve the non-linearity of the coefficients only alleviates it a little. For the Russian Federation it will be shown in how far extending the KPF affects the stability of coefficients. Thus possible additional input factors need to be considered here as well.

Some of the aspects considered herein have already been implemented in other studies on the KPF approach. Following a broader perspective, as with the study by Asheim and Gertler (2005) or the seminal work on innovation systems by Lundvall (2010), where the KPF is described as a statistical representation of the national innovation system, underlines that a national innovation system cannot be described in its entirety by only one variable and region specific fixed effects.

While patents as indicators of knowledge output were available since 1987 from the EPO, Rospatent only began publishing patents on a regional level in 1997. Additionally, using a version of the Patstat database from Spring 2008 only allows to account for patents up to 2006. To limit biases due to data selection and as data for the dependent variables is only available since 1994, EPO patents were considered from 1994 to 2006 while Rospatent patents were considered from 1997 to 2012. For all dependent variables data has been available from 1994 to 2012[13].

The argument might be raised that EPO patent data - being used to represent Russia's internationally oriented innovation system - limits the results of the analysis to those firms that have a general interest in the European market. However, considering that the correlation between the patents from the EPO and the patents from Rospatent across all regions for the ten years

[13]Even though it is recognized that limiting the study to the year 2012 does exclude recent development trends from a purely formal perspective it is very convenient to stop in 2012. Until 2012 the regional layout across the Russian Federation has been relatively stable and all changes that did occur were only intra-regional or of an nominative nature. Stopping in 2012 excludes the regional re-allocations between Moscow city and the Moscow Oblast as well as having to argue the exclusion of the two de-facto objects of Crimea and Sevastopol - if data were available at all - as they would significantly bias the results.

from 1997 to 2006 amounts to 0.9245 it can be assumed that the distribution of international EPO patents across regions mirrors that of domestic Rospatent patents which should be less biased towards the European market[14]. Nevertheless, a suitable way to complement this study would be to use triad patents or at least Japanese or Chinese patent data; thereby covering for possible patenting in the Far Eastern regions which might be more oriented towards Asian markets than towards the European market.

Patents used herein represent patent grants and are assigned to specific years via their priority dates. As data from Rospatent is only available on a regional basis, EPO patents have been aggregated to the regional level using the official Russian classification of regions[15].

The analysis is focussed on the Russian perspective therefore only patents from inventors of Russian origin are considered and the assignment of patents to regions is performed on the basis of the inventors' addresses.

In all cases the base variable is the number of researchers[16]. It is complemented by control variables to account for the relative economical size of the regions; the regional real GRP with base year 1995[17].

In different studies[18] four channels of direct and indirect knowledge transfers are introduced - tacit knowledge spillovers via inventor or researcher movements, codified knowledge spillovers via patent citations and spillovers via trade and FDI - and since they provide to the generation of knowledge, they are considered as suitable controls. With tacit knowledge already accounted for by the researcher variable, the number of students per region adds to this aspects while accounting in some part for the institutional framework as well, as student numbers in Russia are highly correlated with universities. The regional imports[19] and the foreign direct investment inflows are added to the regression accounting for spillovers via trade and FDI[20]. As patent data

[14]Furthermore, this high correlation might be considered a first indicator that both parts of the Russian NIS are connected.

[15]The Nenetsia Autonomous Okrug is considered part of the Arkhangelsk Oblast and the Yamalia and Khantia-Mansia Autonomous Okrugs are considered parts of the Tyumen Oblast.

[16]All variables implemented in this section enter the regression in logarithmized terms, except for shares. It can be argued that scaling the researcher variable by using per capita values would be more suitable for the overall validity of the estimation, to ensure comparability with other studies of KPF however, absolute numbers are considered.

[17]Integrating the GRP also allows one to control for business cycle effects.

[18]See for example Kim (2010).

[19]Imports impact innovativeness as it relieves pressure from domestic firms to innovate and provide products for their home market. Lichtenberg, F.R. (1998) stresses that it is not so much the intensity of imports, but the distribution of the countries of the origin of imports that matters, however these effects are not accounted for in this study.

[20]It is noted that a feedback relation between the generation of knowledge via patents

has only been available for a restricted time horizon, the consistent calculation of a stock of patents as proxy for the availability of codified knowledge has not been possible.

Furthermore, the market structure is included in the model[21] via the shares of small and medium enterprises - an indicator in order to argue in line with Schumpeter (1911) that small and medium enterprises are more innovative than large enterprises and thereby generate more new knowledge. Additionally, following the ideas presented in Ayyagari et al. (2003), SME are correlated to the institutional framework of the region and the business environment; a higher share of SME indicates a more open and free business environment, while a lower share might be an indicator for a large share of the informal economy.

The number of government personnel is included to approximate the amount of corruption taking place - but also to account for government presence in general. As a proxy for corruption, the size of the government accounts indirectly for institutional efficiency. The choice of government personnel as an approximation for corruption has been made as a number of surveys taken in Russia[22] show that the highest amount of corruption is perceived in contexts with government officials like the police or members of the judicial and the education system. A higher number of government employees thus indicates a larger potential for corruption, which by itself would be harmful for knowledge generation as capital flows could be used more efficiently elsewhere. Secondly, state-owned businesses are considered to be less efficient than private businesses and therefore less innovative as well[23]. On a region-wide level a higher amount of government personnel might be an indicator for more state-owned businesses as well and therefore for more inefficiency and fewer innovations[24].

The amount of oil and gas exploited in each region is included for two reasons. Studies show on the one hand that the level of corruption is much higher in this sector than in any other[25]. Furthermore, the sector itself is less

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and FDI flows seems highly likely even though respective tests do not yields corresponding results in this context.

[21]The link between the market structure and the innovative output, the innovativeness of a region, is argued in detail already by Mansfield (1981), Cohen and Levin (1987), Rothwell (1989) and Levin et al. (1991).

[22]See respective reports by Yuri Levada Analytical Center (2012) or Russian Public Opinion Research Center / VCIOM (2012).

[23]See Netter and Megginson (2001).

[24]As with the researchers, it can argued that it might be more prudent to use per capita values instead.

[25]Leite and Weidmann (1999) argues that corruption depends on natural resources, while Tompson (2006), a little less drastically, links corruption to large state-owned firms,

innovative than other sectors[26].

Finally, the base model includes the amount of exports and an indicator for economic openness[27]. The influence of exports can be motivated as export oriented firms are usually more successful, since they are more accustomed to competition. They need to be more modernized and more innovative to compete internationally and therefore are more likely to generate new patents. This argument can be backed up with studies by Podmetina et al. (2011) who show that export oriented firms are generally more innovative than firms oriented only towards their home market. Furthermore, Silva et al. (2010) as well as the literature cited in Wagner (2002) argue along the lines of learning-by-exporting and therefore the growth of knowledge through exporting.

A similar line of argumentation holds for the openness indicator, as regions that are more open to the world economy are confronted more with international competitive pressure and are therefore forced to innovate more[28].

In addition, Torkkeli et al. (2009) stresses the importance of FDI and trade flows on knowledge absorption and therefore the absorptive capacity in the Russian Federation. Including these trade variables into the model thereby automatically accounts in part for the absorptive capacity[29].

For the US it needs to be stressed that numbers on researchers are not available on a regional level and are subsidized by numbers of expenditures on R& D. A preliminary correlation analysis of both statistics on the national level shows that both statistics are highly correlated with a correlation coefficient of 0.9946. Additionally, using a simple OLS regression on both data series shows a positive linear relation with $R^2 = 0.9893$ and an F-statistic of $F = 1941.62$.

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which in Russia persist in the oil and gas industry.

[26]Note, in this context, also the proclaimed negative relation between resource endowments and economic growth which, in the literature, is referred to as the *resource curse*. See for a discussion of this phenomenon for example Auty (1993).

[27]The indicator is calculated as the relation of the sum of exports and imports against the GRP. Even though the exports are as well part of the openness indicator, multicolinearity is no problem in this context.

[28]The inclusion of the openness indicator might, however, not generate significant additional information as it basically replicates the effects of exports, imports and GRP in a composite form.

[29]All monetary variables including the GRP, the exports and imports as well as the FDI enter the model in real terms with the base year 1995.

3.2 Kernel Density Estimation and Markov Transition Matrices

Quah (1995) motivates and uses kernel density estimation to account for clubs in the context of interregional convergence. The same methodology is then taken up by other researchers in the same field to test whether economic convergence occurs uniformly across all regions or whether regions convergence to different steady states. The same approach can, however, also be applied to the question of whether within a group of countries there exists a common innovation system or if the countries, or in the present case regions, need to be divided into subgroups - with each subgroup forming its own innovation system.

In Quah (1995) he identifies different clubs via distinct peaks in the density function. However, it needs to be taken into account that in contrast to the question of convergence with the knowledge production function the identification might not be as clear and distinct. One would expect to find a rather fat tail instead of a second peak, in particular since US and Russian regions by themselves are rather heterogeneous. Thus, in this study we accept the presence of significantly fat tails as sufficient motivation against assuming the existence of only one common set of regions and thus of only one common innovation system.

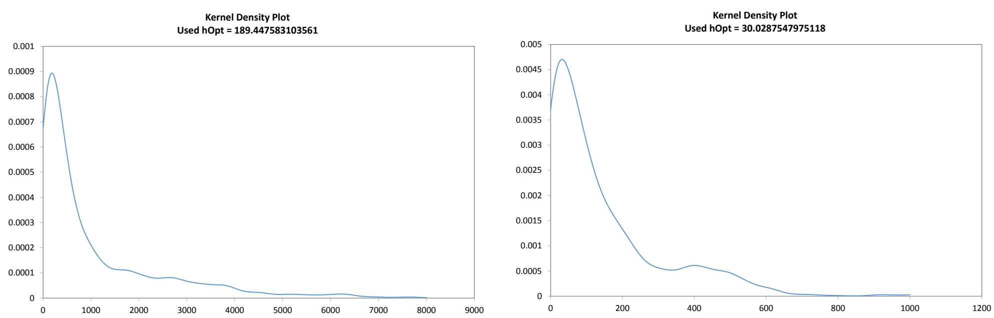

Figure 1: Kernel Density Estimation for US (left figure) and Russian (right figure) Patent Grants

As can be seen for both cases i.e. the US as well as the Russian case, the countries do not report a clear second peak but both of them report rather fat tails. In the right figure for the Russian Federation a very slight second peak is visible, however, it is no very distinct. Nonetheless, the two parts of Figure 1 are seen as first evidence in favor of additional heterogeneity in the context of the patenting activities and thus of the existence of more than one innovation system in each country[30].

Besides the number of innovation systems present, a second important question that needs to be asked beforehand is whether the adherence to one of the innovation systems is fixed over time or whether a high number of regions switch from one group to the other in the course of the analysis. This question can be studied easily by implementing the idea behind Markov transition matrices. Fingleton (1997) for example did some comparable work in the context of analyzing economic convergence.

		Quartile in 1963				
		1	2	3	4	
Quartile in 2015	1	9	4	0	0	13
	2	4	4	4	0	12
	3	0	4	6	3	13
	4	0	0	3	10	13
		13	12	13	13	51

		Quartile in 1997				
		1	2	3	4	
Quartile in 2012	1	14	6	0	0	20
	2	4	9	6	0	19
	3	0	3	14	2	19
	4	2	2	0	18	22
		20	20	20	20	80

Figure 2: Markov Transition Matrices for US (1963-2007, left figure) and Russian (1997-2012, right figure) Patent Grants

The two parts of Figure 2 show that while the borders of the innovation systems in the US and in Russia are not impervious to change, relatively speaking only a small number of regions change their adherence from one quartile to another. Additionally, all switches that do occur usually occur from one quartile to the next higher or lower quartile[31].

It can thus be reasoned that the specific groups within the two countries are relatively stable. This is an important insight regarding potential quantile regression analysis as too much volatility among regions would imply that the result could not be used to draw conclusions regarding any specific group of regions, as the groups would not remain consistent over time.

3.3 A Quantile Regression Approach

In contrast to classical mean-based estimation techniques, quantile regression allows to account for a number of additional aspects. The most important feature is that it allows to account for unequal variations caused by omitted variables - in other words, quantile regression models allow for different slopes, different coefficients calculated at given parts of the underlying distribution. Additionally, although not part of this study, results from quantile regression models can be used to generate weights for mean-based estimation techniques to counter biases of a non-linear relation.

[30]Note that in this figure only the case of Russian domestic patents at Rospatent is considered as it is later on shown that with Russian patents at the EPO no problems regarding the constancy of coefficients arises and thus quantile regression analysis in this case is not necessary and therefore no motivation thereof is needed.

[31]Analogously to the kernel density estimation, only Rospatent patents where considered for the RF.

In this section, a panel quantile estimator as proposed by Koenker (2004) is used to account at first for the Russian Federation for different slopes, on the one hand in the context of the basic KPF, on the other in the context of an extended KPF which includes, besides the researchers, all of the variables motivated in the beginning of this section[32]. In both cases Rospatent patent data is used in the analysis.

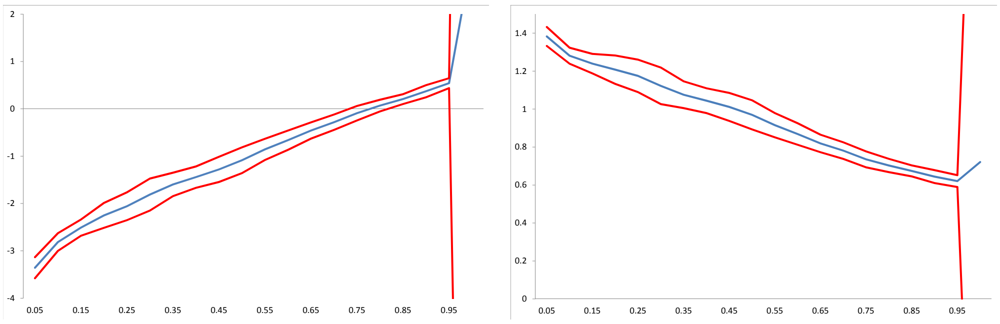

Figure 3: Quantile Regression for RP Patents - Intercept (left) and Slope (right) Coefficient of Basic Model

Figure 3 shows the different coefficients calculated for equally weighted quantiles with a distance of five percentage points. Additionally, the figure contains a 95 percent confidence interval generated via 500 bootstrap repetitions. The right part of the figure in particular reveals that the relation between researchers and Rospatent patents is not linear. In specific, the results show that at lower quantiles the coefficients are larger and are steady declining indicating that the researcher variable exerts not only a change in the means of the patent variable but on its variance as well.

Applied to the underlying data, this signifies that decreasing returns to scale - concerning patenting - for the input of research personnel are present across the regions of the Russian Federation.

The constant left part of both parts of Figure 4 can be readily explained by the presence of zero-inflation in the data as a large number of regions did not own an European patent. Disregarding the values for the lower quantiles up to the 50 percent quantile, it is interesting to note that for the higher quantiles the intercept is more or less linearly increasing and the slope is constant.

This signifies that the researcher variable exerts an impact on the mean of the patenting variable - there are constant returns to scale of the researcher

[32]Estimations have been carried out for a two and a three year time lag. In both cases the results look almost identical. Therefore, only the results for two year time lag are presented herein.

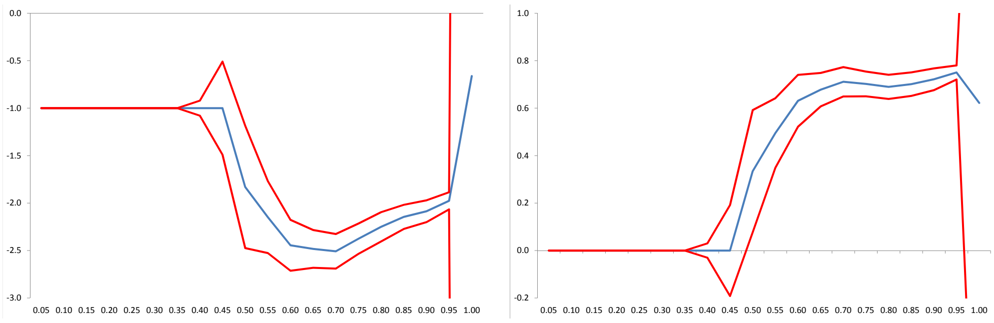

Figure 4: Quantile Regression for EPO Patents - Intercept (left) and Slope (right) Coefficient of Basic Model

inputs when considering EPO patents.

Furthermore, this result indicates that the basic KPF suffices when trying to describe international oriented patenting activity across the Russian regions. In other words, the single most important factor for patenting at the EPO is being one of the regions with large research centers and thus possessing the largest research potential, i.e. that which matters most on an international level.

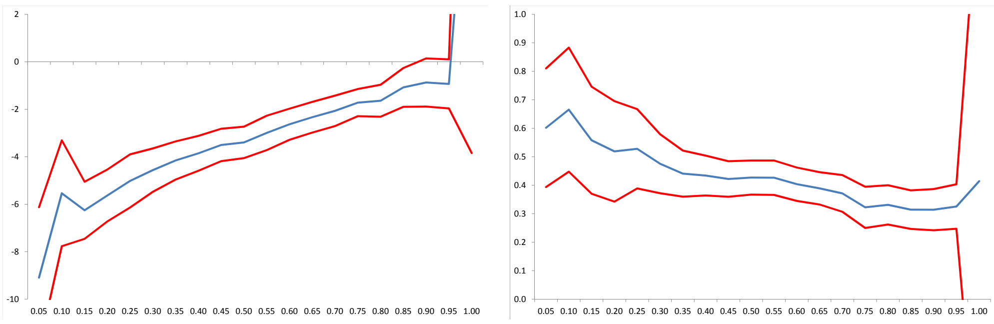

Figure 5: Quantile Regression for RP Patents - Intercept (left) and Slope (right) Coefficient of Extended Model

Switching from the basic to the extended model, it can be seen from Figure 5 that while the results inherently do not change between the basic and the extended model, the right part of the figure shows that the decrease in the slope in less pronounced, however, it does not disappear completely. The additional variables thus capture, while not all of it, at least a significant part of the unexplained variance in the dependent variable.

However, as has already been mentioned in Perret (2013), there is still a large part of unexplained variance due to the lack of relevant variables or due to a non-linearity of the model.

For EPO patents, similar to the results for the basic model, starting from the 60 percent quantile the slope can be considered to be more or less constant, while in comparison to Figure 4 it becomes more rugged. This indicates that while extending the model might have a positive effect concerning the intercept, the layout of the basic model might already suffice and yield more stable results than the extended model[33].

Summarizing, when considering Rospatent data the results mirror those of a typical location-scale model with a decreasing slope parameter indicating that the model still contains a lot of unexplained variance that needs to be accounted for via additional variables.

Furthermore, as especially consistent Russian regional panel data, aside from the one already implemented in the context of the extended model, is hard to come by, it seems a prudent choice to use the results above to generate weights for usage by standard panel estimators to counter the bias that is still present even in the extended model.

For the international perspective, and considering EPO patents, the figures point to the conclusion that the basic KPF already suffices and extending the model might only destabilize the slope coefficients. In this context, in the next section only the KPF using Rospatent data is considered any longer as the basic KPF design suffices for the EPO-based one.

Nonetheless, in a second step we might still consider the results for US patent data at the USPTO and expenditures on R&D.

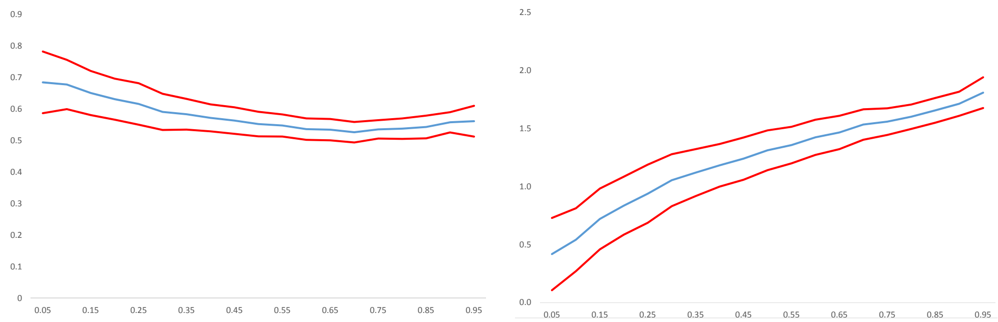

Figure 6: Quantile Regression for US USPTO Patents - Intercept (left) and Slope (right) Coefficient of Basic Model

Figure 6 summarizes the results of the quantile regression, run this time with data for the US[34].

[33] Figures for the extended model are not included here.

[34] Note that for reasons of data availability we only consider the basic version of the US KPF herein.

The results are comparable to those from the Russian case with patents from Rospatent. The only difference is that the intercept in this case is monotonously increasing while the slope parameter represents a more or less quadratical relationship. Thus, the non-linear and non-constant slope parameter in particular gives rise to the need to analyse the relationship in more detail as well.

3.4 Extending the basic knowledge production function

In the previous section it has been shown that adding variables to the KPF design might help to alleviate some of its design flaws but not all of them. Therefore, in this section the results from the previous section, in particular those for the basic cases, are taken and used to construct an alternative KPF design for the USA and the Russian Federation, respectively.

Referring to Figures 3 and 6, it can be seen that the coefficients, with the exception of the US slope parameter, show a more or less linear pattern. However, it is not certain that the quantiles are equidistant. Thus, as motivated above in Figures 7 and 8, quantiles for the patent variable have been calculated and were plotted against the coefficient values.

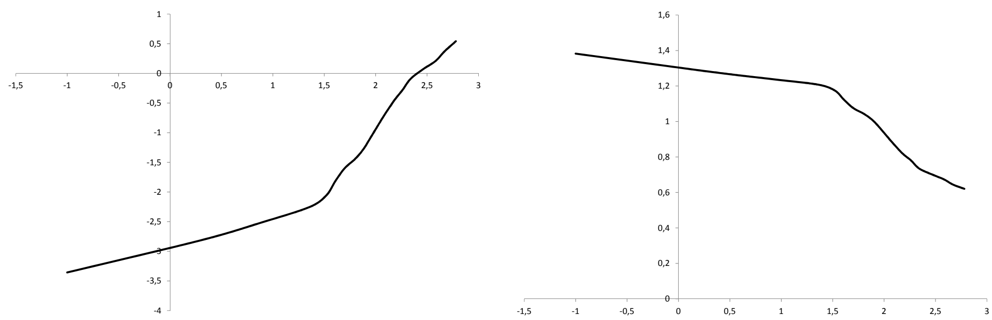

Figure 7: Quantile Regression for Rospatent Patents (Distance corrected) - Intercept (left) and Slope (right) Coefficient

While these plots can be decently approximated by a polynomial of the fifth order, it seems to be more prudent to assume both coefficients to be piecewise linear functions with a break at either approximately 0.9 or 1.4, respectively. Considering that these values refer to the logarithmized patent numbers (to the base of 10), the break would occur at approximately 8 or 25 patents.

Comparable to the results presented in Figure 6, Figure 8 illustrates that the coefficient for the US intercept can be approximated by a linear function

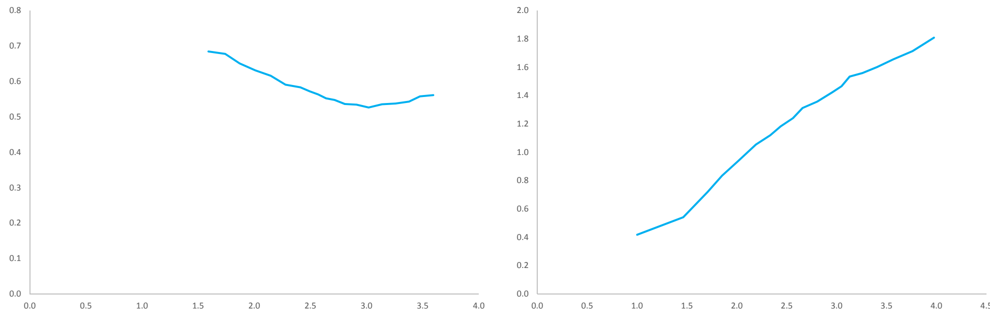

Figure 8: Quantile Regression for USPTO Patents (Distance corrected) - Intercept (left) and Slope (right) Coefficient

while the best fit for the slope parameter can be achieved via a quadratic equation. For reasons of simplicity and being able to solve the KPF analytically, the slope parameter here is also approximately by a piecewise linear function.

Thus, using linear functions for approximating the slope and intercept can be used in both cases, i.e. for the US and for the Russian Federation. Therefore, the necessary steps discussed below relating to the Russian Federation are exemplary, the same steps are performed analogously for the US. In the end, only the final KPF function will be reported and illustrated for the US.

Figure 9 reports the intercept $log(a(P))$ and the slope parameter $\alpha(P)$ for the upper linear piece of the KPF (for 8 or more patents) while Figure 10 reports the functions for the lower linear pieces. The figures also include a regression line for the functions to graphically illustrate the fit[35].

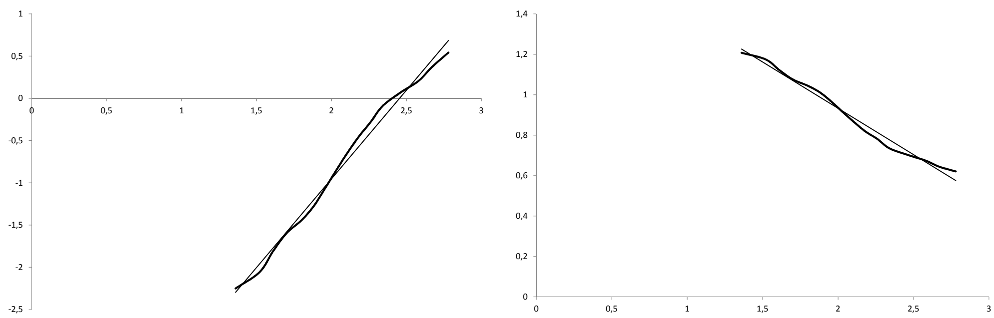

Figure 9: Piecewise Regression of Intercept (left) and Slope (right) Coefficients - Upper Piece

[35] A figure for the case with a break at 25 patents has not been presented separately as the results would more or less copy Figures 9 and 10. Table 1 furthermore underlines the similarity of both cases.

	Intercept	Slope	R^2	F-Test Sig. Level
8 Patents				
Slope Upper Piece	1.8488	-0.458	0.9841	***
Intercept Upper Piece	-5.1514	2.0991	0.9902	***
Slope Lower Piece	1.306	-0.0757	0.9992	**
Intercept Lower Piece	-2.9229	0.4414	0.9976	**
25 Patents				
Slope Upper Piece	1.864	-0.4645	0.9816	***
Intercept Upper Piece	-5.1888	2.1153	0.9882	***
Slope Lower Piece	1.3066	-0.0743	0.999	**
Intercept Lower Piece	-2.9137	0.4634	0.9953	**

Table 1: Regression Results: Intercept-and Slope-Functions

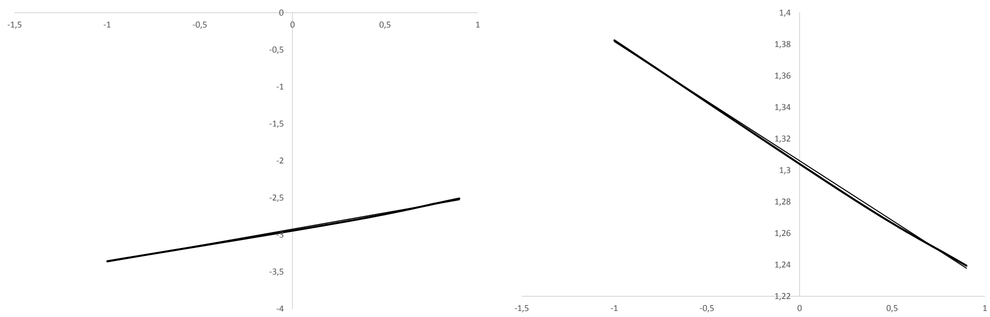

Figure 10: Piecewise Regression of Intercept (left) and Slope (right) Coefficients - Lower Piece

Table 1 reports the equations for the regression lines as well as the R^2 statistics and the significance levels according to an F-test[36] both for the case with a break at 8 patents and a break at 25 patents; in both cases for the upper as well as for the lower parts of the piecewise functions.

Using these estimates of the intercept and slope functions and referring to the results of the exercise in Section 2, the knowledge production function for the break at 8 patents can be given as[37]:

$$P = \left(\begin{array}{ll} 10^{17.2523} 10^{-165,9186(log(R)+7,3791)^{-1}} & for P < 25 \\ 10^{4.0367} 10^{-1,5604(log(R)-2,3998)^{-1}} & for P \geq 25 \end{array} \right. \tag{9}$$

To test for stability, the alternative break at 25 patents has been consid-

[36]Asterisks are used to signify significance. * is an error margin of 10 percent, ** of 5 percent and *** of 1 percent.

[37]It is taken into account that piecewise functions are regularly defined via the independent variable and not as has been the case here via the dependent variable.

ered as well. Using the same procedure as above, the resulting KPF is given below. It can be seen that both pieces are comparable to the equation above.

$$P = \begin{pmatrix} 10^{17.5855} 10^{-166,2188(log(R)+7,2221)^{-1}} & for P < 25 \\ 10^{4.0129} 10^{-1,5353(log(R)-2,4011)^{-1}} & for P \geq 25 \end{pmatrix} \tag{10}$$

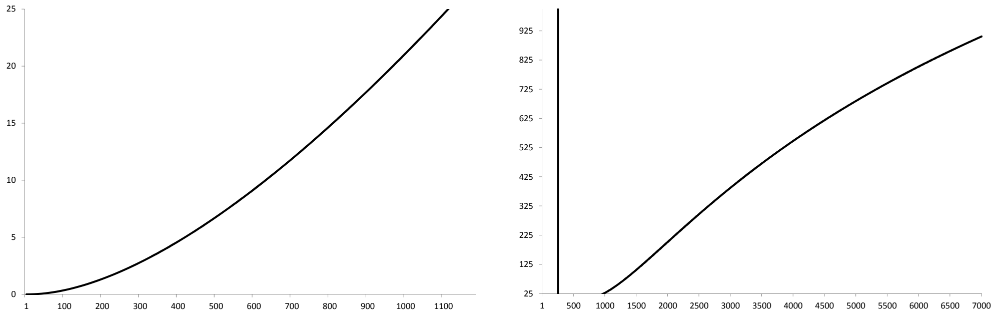

Figure 11: Knowledge Production Function - Lower (left) and Upper (right) piece

If equation 10 is plotted it results in Figure 11. The figure illustrates that there is a definitive gap in the definition. For the approximate interval $R \in (980; 1110)$ this KPF is not defined. Returning to the raw data, this translates into 72 observations which equals about 4.74 percent of total observations. Switching to the original version with a break at 8 patents, the gap would shift to the approximate interval $R \in (585; 790)$ which translates into 107 observations which equals about 7.04 percent of total observations.

To close these gaps in the definition consider that the intercept and the slope function have been deconstructed into two disjoint functions. Following this logic it becomes evident that the two parts of the function need an artificial link to connect both of them. This artificial link needs to be a patent value between 8 and 25. To construct this value the average of the coefficients for both intercept and both slope function are taken to construct an average knowledge production function which reads as follows:

$$P = \begin{pmatrix} 10^{17.4189} 10^{-166.0687(log(R)+7.3006)^{-1}} & Lower\ part \\ 10^{4.0248} 10^{-1.5479(log(R)-2.4005)^{-1}} & Upper\ part \end{pmatrix} \tag{11}$$

Both parts of the resulting KPF are then equalized. Solved for the number of researchers results in a quadratic equation:

$$log^2(R) - 7.383 log(R) + 13.0816 = 0 \tag{12}$$

This equation sports two solutions for R. The first solution is situated at $R = 897.188$ resulting in a number of patents of $P = 16.6947$. The second solution is situated at $R = 26,921.324$ resulting in a number of patents of $P = 1,828.673$. As the number of patents is assumed to be between 8 and 25 the second solution is discarded and it is assumed that the first solution describes the true break in the KPF[38].

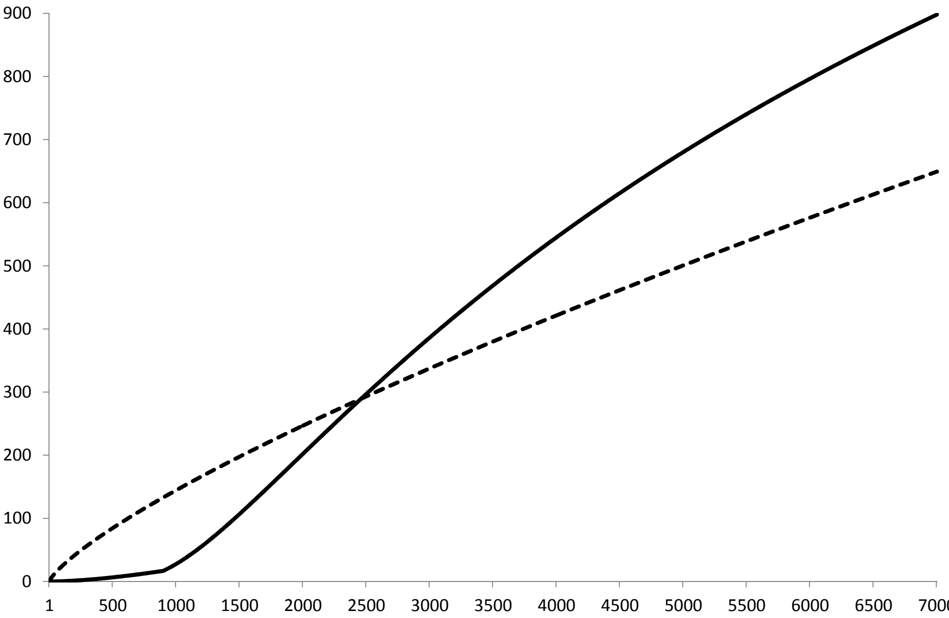

Figure 12: Fully Combined KPF versus Traditional Form KPF - Russia

The final KPF is given in Figure 12 by the continuous line. The dotted line gives the traditional basic KPF as deduced by Perret (2013). It can be seen that the traditional form overestimates patent output for regions with smaller research systems while it underestimates the output for regions with larger research systems[39].

While the quantile regression analysis only delivers information on the fact that regions with less developed (smaller) research systems, as measured via the number of active researchers, innovate differently, this detailed estimation shows in particular that in the less developed regions the marginal rate of research is much higher (and indeed increasing) than in regions with

[38]While this procedure makes the KPF continuous at the value $R = 897.188$ it still remains non-differentiable. This design flaw needs to be remarked upon as the basic KPF has been noted in its log-linear form, and the logarithm as well as the first order derivative are linked to the growth rate of the function. This problem, however, will not be treated in the present study.

[39]Note that in both cases a fixed effects estimator has been implemented and thus the resulting KPFs are comparable.

more developed (larger) research systems where the marginal rate of research is actually decreasing. In light of the typical design of a KPF as a Cobb-Douglas-type production function the form of the upper part of the function with decreasing returns to scale of research is not surprising; only the overall design of the function deviates from the theoretical basic KPF model not so much the underlying assumptions about its form. It is rather the lower part of the KPF with increasing returns to scale that surprises.

Returning to the deliberation that the Russian regional research and innovation systems are influenced significantly by cultural and societal effects, it seems plausible that once an innovation system reaches a certain size its potential for rent-seeking opportunists becomes obvious and their entrance into the innovation system reduces its effectiveness.

The threshold for a change in the structure of the innovation system as seen above lies at a size of around 900 researchers which refers to approximately 44.8 percent of all observations[40]. This result gives hope insofar as it shows that a lot of Russia's regions are sporting an innovation system with increasing marginal rates of research and therefore offer a suitable basis to finally start on the path to a more sustainable economic development beyond natural resources.

Switching from the analysis of the Russian case to the US case, it can be restated that the steps performed for the US case basically mirrors the Russian case with the only exception being that the intercept function remains identical for both the upper and the lower part of the function. Thus the final function reads as:

$$P = \left(\begin{array}{lll} 10^{0.8712log(R)-0.0631} 10^{-0.1185log(R)-0.5079} & Lower\ part \\ 10^{0.3408log(R)-0.0631} 10^{0.0612log(R)-0.5079} & Upper\ part \end{array} \right. \qquad (13)$$

The equation shows that the structure for the KPF for the US is inherently similar to the one for Russia. The main difference becomes obvious when the function is plotted together with the classical version of the KPF, that results from a fixed effects GMM estimation of the function.

When comparing the new US and the new Russian KPF, two aspects are worth mentioning.

First, it is quite obvious that the first part of the US' KPF shows decreasing returns to scale, a declining function, while the second part of the US' KPF shows increasing returns to scale, an inclining function. In other words, this means that for US regions, a certain size of the research sector is

[40]Note that these observations relate mostly to specific smaller regions which report consistently small values and are not limited to the years of the 1990s and thus to effects of the transition recession.

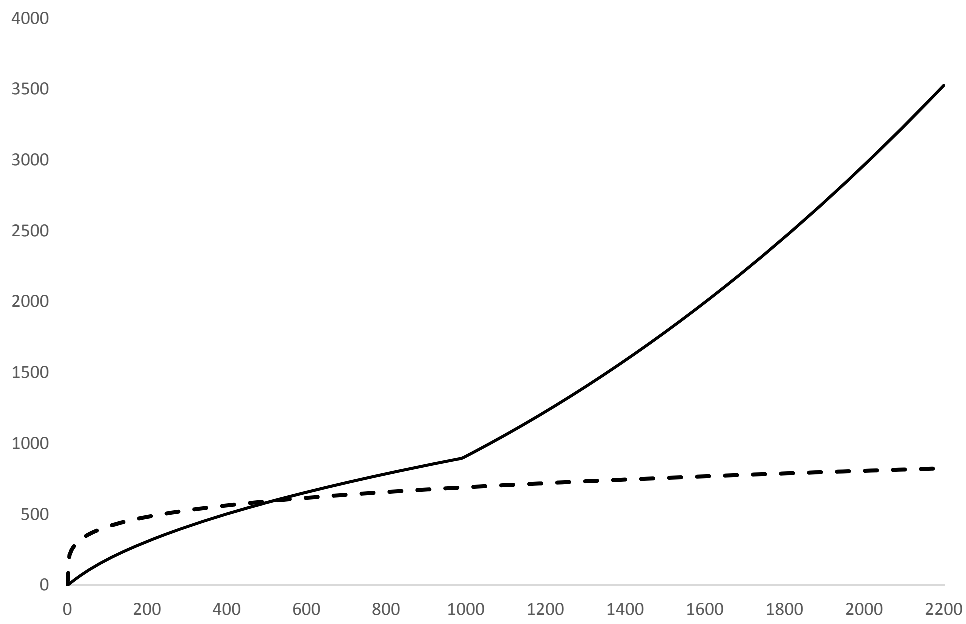

Figure 13: Fully Combined KPF versus Traditional Form KPF - USA

essential to avoid decreasing returns to scale.

For the Russian Federation, as discussed already above, the picture is the exact opposite. The first half, regions with small research systems, report increasing returns to scale while the second half, regions with bigger research systems, report decreasing returns to scale. It can thus be stated that the dynamics and potential efficiency gains via the innovation and research systems work exactly opposite in the US and in Russia.

Relating this to economic policy means that innovation and knowledge based growth, the archetypical approach to sustainable growth, via investments in the research infrastructure and investments in R&D, seem to be a suitable beneficial long term solution for the US, whereas for the Russian Federation, investments that enlarge research systems and attract researchers might in the long run be harmful for the efficiency of the regional innovation systems. Thus, realizing growth through innovations and research policy will be much harder for Russia than for the US.

Contrary to the last paragraphs, a second aspect worth mentioning highlights commonalities between the US and the Russian innovations systems. In both cases the critical point at which the efficiency of the innovation system changes lies at approximately 900 researchers. While the amount of patents these researchers generate, i.e. the efficiency of the innovation system differs, the number of researchers is rather stable and begs the question of whether this is just a statistical artifact or if it could be reduced to some basic underlying characteristics of innovation systems per se.

As a side-note, it is worth mentioning that in light of the still ongoing sanctions of the Western countries (as of early 2016) which hit high-tech imports in particular, the goal, as stated by President Putin, to restructure the Russian economy and foster its national innovation system, and thus its regional innovation systems, becomes even more important for an economic turn-around. Assuming that, and despite a time lag of approximately three to four years which exists between the results of this paper and the reality, hope still persists that the potential of smaller regions with less developed innovation systems in particular might (if fostered correctly by the policy makers) have a significant impact on regional and thus national development.

4 Conclusions

In the present study, the aim has been to shed additional light on the structure of the KPF - describing the relation between knowledge inputs and outputs.

While previous analyses focussed on fitting data to the KPF layout, this study can be seen as a first step in trying to allow the KPF structure to be more accommodating to the underlying data and thereby offering a better description of the structure of the respective NIS.

In the analysis, a panel quantile regression approach has been used to account for the possible non-linearity of the relation between researchers or expenditures on R&D respectively and patents. For Russia, it has been shown that, for the patents at Rospatent, decreasing returns of scale for the input of researchers exist which diminish when the basic KPF model is extended by additional variables. For patents at the EPO starting from the 50 percent quantile - due to considerable zero-inflation - a stable linear relation exists.

Decreasing returns of researcher input signify that regions with a large developed research system work less efficiently than regions with smaller research institutions. The goal of innovation politics should therefore aim at working on abolishing the inefficiency of large research centers. A second way to proceed can be seen in fostering the potential of regions with smaller, less developed innovation systems which, however, work more efficiently; it has been shown that this refers to at least about 45 percent of all observations and, in light of the fact that the regional innovation systems are rather path-dependent, it can roughly be translated into 45 percent of all regions. This would seem to call for a decentralization of the innovation system, however, taking the developments of the last decade into account, this does not seem to be the aim of policy makers in Russia.

While not made explicit by this study, these results seem to indicate however existing problems of corruption and institutional failure which increase with the size of the research sectors. A detailed analysis of this problem is, however, not a part of this study and, considering the data used herein, also not possible. This would be an interesting topic for future research.

For the US, it has been shown that the opposite case is true and starting at approximately 900 researchers per region the innovation system reports increasing returns to scale for the researcher input. Thus, for the US, a research oriented policy will in the long run be more sustainable and beneficial.

The results also show that the classical KPF design not only fits the underlying data in a worse way than the newly generated one, it also underestimates the efficiency of large research systems and leads to wrong assumptions especially regarding large, elite research regions or establishments.

References

Ó hUallacháin, B. and Leslie, T.F. (2007), "Rethinking the Regional Knowledge Production Function", *Journal of Economic Geography*, 7, 737–752.

Abdih, Y. and Joutz, F. (2005), "Relating the Knowledge Production Function to Total Factor Productivity: An Endogenous Growth Puzzle", *IMF Working Paper*, WP/05/74.

Acs, Z.J.; Braunerhjelm, P.; Audretsch, D.B. and Carlsson, B. (2009), "The Knowledge Spillover Theory of Entrepreneurship", *Small Business Economics*, 32, 15–30.

Andersson, M. and Ejermo, O. (2003), "Knowledge Production Function in Swedish Functional Regions 1993-1999", *CESPRI Working Paper*, 139.

Anselin, L.; Varga, A. and Acs, Z. (1997), "Local Geographic Spillovers between University Research and High Technology Innovations", *Journal of Urban Economics*, 42, 422–448.

Asheim, B.T. and Gertler, M.S. (2005), "The Geography of Innovation: Regional Innovation Systems", in Fagerberg, J.; Mowery, D.C. and Nelson, R.R., eds., "The Oxford Handbook of Innovation", 291–317, Oxford University Press, Oxford, 1. edition.

Audretsch, D. and Stephan, P. (1999a), "How and why does Knowledge Spill over in Biotechnology?", in Audretsch, D. and Thurik, R., eds., "Innovation, Industry Evolution, and Employment", 216–229, Cambridge University Press.

Audretsch, D.; Lehmann, E. and Wright, M. (2014), "Technology Transfer in a Global Economy", *The Journal of Technology Transfer*, 39, 301–312.

Auty, R.M. (1993), Sustaining Development in Mineral Economies: The Resource Course Thesis, Routledge, 1. edition.

Ayyagari, M.; Beck, T. and Demirgüç, A. (2003), "Small and Medium Enterprises Across the Globe: A New Database", *Worldbank Policy Research Working Paper*, 3127.

Bitzer, J. (2003), Technologische Spillover-Effekte als Determinanten des Wirtschaftswachstums, volume 532 of *Volkswirtschaftliche Schriften*, Duncker & Humblot, Berlin, 1. edition.

Branstetter, L.G. (2001), “Are Knowledge Spillovers International or Intranational in Scope?: Microeconometric Evidence from the U.S. and Japan”, *Journal of International Economics*, 53, 53–79.

Buesca, M.; Heijs, J. and Baumert, T. (2010), “The Determinants of Regional Innovation in Europe: A Combined Factorial and Regression Knowledge Production Function Approach”, *Research Policy*, 39, 722–735.

Buesca, M.; Heijs, J; Martinez Pellitero, M. and Baumert, T. (2006), “Regional Systems of Innovation and the Knowledge Production Function: The Spanish Case”, *Technovation*, 26, 463–472.

Cohen, W.M. and Levin, R.C. Mowery, D.C. (1987), “Firm Size and R&D Intensity: A Re-Examination”, *The Journal of Industrial Economics*, 35, 543–565.

Conte, A. and Vivarelli, M. (2005), “One or Many Knowledge Production Functions? Mapping Innovative Activity Using Microdata”, *IZA Discussion Paper*, 1878.

Fingleton, B. (1997), “Specification and Testing of Markov Chain Models: An Application to Convergence in the European Union”, *Oxford Bulletin of Economics and Statistics*, 59, 385–403.

Fischer, M.M. and Varga, A. (2003), “Spatial Knowledge Spillovers and University Research: Evidence from Austria”, *The Annals of Regional Science*, 37, 303–322.

Fritsch, M. (2002), “Measuring the Quality of Regional Innovation Systems: A Knowledge Production Function Approach”, *International Regional Science Review*, 25, 86–101.

Fritsch, M. and Franke, G. (2004), “Innovation, Regional Knowledge Spillovers and R&D Cooperation”, *Research Policy*, 33, 245–255.

Fritsch, M. and Slavtchev, V. (2006), “Universities and Innovation in Space”, *Industry and Innovation*, 14, 201–218.

Griliches, Z. (1979), “Issues in Assessing the Contribution of R&D to Productivity Growth”, *The Bell Journal of Economics*, 10, 92–116.

Griliches, Z. and Mairesse, J. (1998), “Production Functions: The Search for Identification”, in Strom, S., ed., “Econometrics and Economic Theory in the 20th Century: The Ragnar Frisch Centennial Symposium”, 169–203, Cambridge University Press, Cambridge, 1. edition.

Kim, M. J. (2010), “Corruption and Economic Growth”, *EACGS Conference*.

Koenker, R. (2004), “Quantile Regressions for Longitudial Data”, *Journal of Multivariate Analysis*, 91, 74–89.

Lee, H.-Y. and Park, Y.-T. (2005), “An International Comparison of R&D Efficiency: DEA Approach”, *Asian Journal of Technology Innovation*, 13, 207–222.

Leite, C. and Weidmann, J. (1999), “Does Mother Nature Corrupt? Natural Resources, Corruption, and Economic Growth”, *IMF Working Paper*, WW/99/85.

Levin, R.; Klevorick, A.K.; Nelson, R.R.; Winter, S.G.; Link, A.N. and Bozeman, B. (1991), “Innovative Behavior in Small-Sized Firms”, *Small Business Economics*, 3, 179–184.

Lichtenberg, F.R., van Pottelsberghe de la Potterie B. (1998), “International R&D Spillovers: A Comment”, *European Economic Review*, 42, 1483–1491.

Lundvall, B.-A. (Ed.) (2010), National Systems of Innovation: Toward a Theory of Innovation and Interactive Learning, Anthem Press, 1. edition.

Madsen, J.B. (2008), “Semi-Endogenous Versus Schumpeterian Growth Models: Testing the Knowledge Production Function Using International Data”, *Journal of Economic Growth*, 13, 1–26.

Mansfield, E. (1981), “Composition of R&D Expenditures: Relationship to Size of Firm, Concentration and Innovative Output”, *The Review of Economic and Statistics*, 63, 610–615.

Masso, J. and Vahter, P. (2008), “Technological Innovation and Productivity in Late-Transition Estonia: Econometric Evidence from Innovation Surveys”, *The European Journal of Development Research*, 20, 240–261.

Netter, J.M. and Megginson, W.L. (2001), “From State to Market: A Survey of Empirical Studies on Privatization”, *Journal of Economic Literature*, 39, 321–389.

Pardey, P.G. (1989), “The Agricultural Knowledge Production Function: An Empirical Look”, *The Review of Economics and Statistics*, 71, 453–461.

Perret, J.K. (2013), Knowledge as a Driver of Regional Growth in the Russian Federation, Springer, Heidelberg, 1. edition.

Podmetina, D.; Vaatanen, J. and Smirnova, M.M. (2011), “Open Innovation in Russian Firms: An Empirical Investigation of Technology Commercialization and Acquisition”, *International Journal of Business Innovation and Research*, 5, 298–317.

Ponds, R.; van Oort, F. and Frenken, K. (2010), “Innovation, Spillovers and University-Industry Collaboration: An Extended Knowledge Production Function Approach”, *Journal of Economic Geography*, 10, 231–255.

Quah, D.T. (1995), “Regional Convergence Clusters Across Europe”, *Centre for Economic Performance Discussion Paper*, 274.

Ramani, S.V.; El-Aroui, M.-A. and Carrère, M. (2008), “On Estimating a Knowledge Production Function at the Firm and Sector Level Using Patent Statistics”, *Research Policy*, 37, 1568–1578.

Ranga, L.M.; Debackere, K. and von Tunzelmann, N. (2004), “Entrepreneurial Universities and the Dynamics of Academic Knowledge Production: A Case Study of Basic vs. Applied Research in Belgium”, *Scientometrics*, 58, 301–320.

Roper, S. and Hewitt-Dundasa, N. (2015), “Knowledge stocks, knowledge flows and innovation: Evidence from matched patents and innovation panel data”, *Research Policy*, 44, 1327–1340.

Rothwell, R. (1989), “Small Firms, Innovation and Industrial Change”, *Small Business Economics*, 1, 51–64.

Roud, V. (2007), “Firm-Level Research on Innovation and Productivity: Russian Experience”, *ISSEK Working Paper*.

Russian Public Opinion Research Center / VCIOM (2012), About Us.

Savin, I. and Winker, P. (2012), “Heuristic Optimization Methods for Dynamic Panel Data Model Selection: Application on The Russian Innovative Performance”, *Computational Economics*, 39, 337–363.

Schumpeter, J.A. (1911), Theorie der wirtschaftlichen Entwicklung, eine Untersuchung über Unternehmergewinn, Kapital, Kredit, Zins und den Konjunkturzyklus, Harvard University Press, MA, 2. edition.

Silva, A.; Afonso, O. and Africano, A.P. (2010), “Learning-by-Exporting: What we Know and What we Would Like to Know”, *The International Trade Journal*, 26, 255–288.

Stephan, P.; Audretsch, D. and Hawkins, R. (2000), “The Knowledge Production Function Lessons from Biotechnology”, *International Journal of Technology Management*, 19, 165–178.

Tompson, W. (2006), “A Frozen Venezuela? The Resource Curse and Russian Politics”, in Ellman, M., ed., “Russia’s Oil and Natural Gas: Bonanza or Curse?”, 189–212, Anthem Press, London, 1. edition.

Torkkeli, M.T.; Podmetina, D.; Ylä-Kojola, A.-M. and Väätänen, J. (2009), "Knowledge Absorption in an Emerging Economy - The Role of Foreign Investments and Trade Flows in Russia", *International Journal of Business Excellence*, 2, 269–284.

Varga, A. (2000), "Local Academic Knowledge Spillovers and the Concentration of Economic Activity", *Journal of Regional Science*, 40, 289–309.

Verspagen, B. and Schoenmakers, W. (2004), "The Spatial Dimension of Patenting by Multinational Firms in Europe", *Journal of Economic Geography*, 4, 23–42.

Wagner, J. (2002), "Exports and Productivity: A Survey of the Evidence from Firm-Level Data", *The World Economy*, 30, 60–82.

Wagner, J. (2006), "International Firm Activities and Innovation Evidence from Knowledge Production Functions for German Firms", *MPI Discussion Papers on Entrepreneurship, Growth and Public Policy*, 1506.

Wang, E. and Huang, W. (2007), "Relative Efficiency of R&D Activities: A Cross-Country Study Accounting for Environmental Factors in the DEA Approach", *Research Policy*, 36, 260–273.

WIPO (2012b), Patent System in Russia, WIPO.

Wu, Y.-M. (2009), "An Empirical Analysis of R&D Cooperation and Regional Knowledge Spillovers Based on Knowledge Production Function", *Studies in Science of Science*, 2009-10.

Yuri Levada Analytical Center (2012), Levada Center.

Zucker, L.G.; Darby, M.R.; Furner, J.; Liu, R.C. and Ma, H. (2007), "Minerva Unbound: Knowledge Stocks, Knowledge Flows and New Knowledge Production", *Research Policy*, 36, 850–863.