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New Indicators of Innovation Activity in Economic Growth Models

Maria Reznakova, Stanislava Stefankova

Abstract

Our extensive literature review shows that innovations are fundamental to maintaining competitiveness at both micro- and macro-economic levels. In this study, we address how to improve the measurement of innovations and their impact on a country's competitiveness and economic growth. We provide an overview of indicators used to measure innovations and propose three new ones that are supposed to capture knowledge spillover: The Foreign Knowledge Inflow, Domestic Knowledge Outflow, and General Propensity to Patent. Innovation was proxied by the number of patent applications, which we supplemented with indexes measuring the origin of knowledge and its transfer. We employed the system GMM method on panel data of 56 countries for 2002–2019 to confirm and compare the informational value of standard innovation indicators and our indexes. Implementation of indexes revealed the counteracting impact of patenting on economic growth when the positive effect of innovation creation is weakened by knowledge disclosure. We provide evidence that a low propensity to patent facilitates growth. The impact of foreign knowledge on an economy is dependent on its technological capacity. The infusion of foreign knowledge boosts the growth of fast-growing economies but inhibits the growth of less technologically sophisticated ones. This supports our assumption that when researching the impact of innovations on economic growth, it is crucial to consider additional factors. Hence, index implementation appears to be the correct method.

Keywords: innovation, knowledge spillover, economic growth, generalized method of moments, propensity to patent
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1. INTRODUCTION

A theoretical link between innovation and economic growth was suggested as early as the 18th century by Adam Smith. However, technological change was formally incorporated into the Solow exogenous growth model more than 200 years later. Endogenous theories explaining technological change and considering innovation to be a key driver of growth arose at the end of the twentieth century (e.g., Romer, 1986). Innovations continue to fascinate researchers to this day and play a significant role in growth theories—including the more recent ones. Behind every innovation is a person with the ability to learn and innovate. Therefore, the recent theories have not neglected the human capital factor (e.g., Batabyal & Beladi, 2017). Thompson (2018) goes beyond human capital and emphasises the importance of social capital and its effect on innovations. Growth theories have provided the basis for extensive empirical research. Authors strive to explore whether innovation contributes to competitiveness and economic growth, and if so, then how and to what extent. Empirical evidence in this field indicates the fact that innovation activities tend to influence economic growth quite significantly. However, doubts remain regarding the capacity of current and future innovations to boost economic growth as in the past (Bayarçelik & Tasel, 2012; Gordon, 2018; Khalili et al., 2016). An individual examination of innovations, indispensable for economic growth, reveals significant differences between them. These differences lie in the degree of novelty, greatness, quality, or effect they bring. It is, therefore, only reasonable to assume that innovation may affect growth differently. The multifaceted nature of innovation requires careful thought about how to measure or proxy it. The commonly used proxies are often based on R&D or patenting, and despite the fact that their deficiencies have been well known for decades (i.e., Griliches, 1990), they are still widely used. Moreover, it is not only innovation but also knowledge accumulation which is crucial for sustained economic growth. Whilst the combined effect of these two elements is commonly agreed on, empirical studies tend to study the effects separately. We suspect that this is the reason for the ambiguity of results in empirical studies concerning innovation and growth. This study aims to fill this gap by improving existing innovation proxies so that they can capture not only the innovation itself but also the knowledge flow.

Based on a comprehensive literature review - presented in the second section - we examine patents as innovation proxies. The number of patent applications became our basic variable. Given the varying quality of patent systems worldwide, we found it necessary to consider the propensity to patent when modelling economic growth, as innovations can be protected by other forms of intellectual property protection. Furthermore, it also seemed significant to consider the effect of knowledge disclosure. This factor is particularly important given the enormous development of information technology and leads to convergence in the economic sense (Kijek & Matras-Bolibok, 2020). With this aim, we have created several indexes using data from global patent databases, enabling us to take the previously mentioned into account, thereby increasing the information value of standard innovation indicators. The methodology and data are described in the third section. The core empirical estimations and discussion of results are presented in the fourth section. In the fifth section, we concluded that the indexes we created made it possible to better detect the impact of innovation on the country's economic growth.

2. LITERATURE REVIEW: INNOVATION INDICATORS IN ECONOMIC GROWTH MODELS

The basic measures of innovations are R&D expenditures for the input and patents - either applications or grants - for the output of innovative activity; both are easily quantifiable. For instance, Bayarçelik & Tasel (2012) identified positive contributions of R&D expenditures and R&D personnel to economic growth in Turkey, while the patents' contribution was negative.

Saini & Jain (2011) indicated innovations' contribution to economic growth in technology-based countries, with relatively strong intellectual property protection. Conversely, Khalili et al. (2016) found a short-term negative impact of patenting on GDP in Japan; however, it positively contributed to the growth of manufacturing. Additionally, the impact of innovation on growth may occur outside the analysed economy because of widespread outsourcing (Khalili et al., 2016). Nevertheless, the variation of empirical results across countries is apparent and despite reasonable economic justifications, it still deserves further analysis. The growth theories developed during recent decades emphasise not only the significance of innovation but also its ability to positively influence subsequent innovation activities. Unlike earlier endogenous theories, they also incorporate the increasingly common non-physical essences of innovation (Marchese & Privileggi, 2016; Thompson, 2018). It might, hence, be important to empirically examine innovation and its impact on growth from a broader perspective -also considering the knowledge stock that it enriches and spreads, and not only the actual output and its quality.

Knowledge flows - that is, spillovers - are economically significant; nevertheless, their effect is rather inconspicuous and generally characterised by international technology transfers (Kacprzyk & Doryń, 2017; Lee, 2021). More comprehensive access to knowledge may reduce future costs and the need to recreate what already exists elsewhere. Spillovers have been researched for decades, although initially, they were more intense at the local level (e.g., Jaffe et al., 1993). Recently, Goel & Saunoris (2017) identified that knowledge spillovers measured using patent data are considerably larger in economically freer states within the United States. Although it may seem that the effect of geographical distance in case of spillover from patent disclosure can nowadays be alleviated because of improved communication links, Kwon et al. (2020) revealed significant localisation effects of knowledge spillovers at both intra- and international levels in recent decades. Moreover, these localisation effects can even overshadow regional rivalries (Drivas, 2021).

Patent statistics is a recent and widely used tool to examine inventions and their underlying knowledge. Patent databases provide enormously rich patent information, not only about the invention itself but also about inventors, patent holders, and fields of technology to which the patents belong as well as where the owners operate. They also inform about predecessors and successors of inventions and patent families. However, these measures suffer from obvious deficiencies widely discussed in earlier studies (i.e., Crosby, 2000; Griliches, 1990). In short, the cost of creation hardly matches the value of innovation, considering that the potential future benefit and patent statistics omit innovations outside the patent system. Not all inventions are patented because not all of them meet the given criteria or because inventors may use other alternatives to protect their inventions. Patenting strategies or intellectual property protection preferences may make comparing patent statistics across countries difficult. Moreover, the patentability standards and other aspects of the patent systems may significantly vary across countries. As a result of increased internationalisation of R&D activities, resources may be invested in another country than the one which provides patent protection. As patents do not signify an innovation's value, a simple patent count introduces bias in the measurement of the output of innovation activities because many patents are used merely for blocking competitors (Torrisi et al., 2016). Additionally, patenting strategies are believed to be the reason for falling patent quality in recent decades (Marco et al., 2019). However, continued research in this field mitigated a few shortcomings. Table 1 provides a brief illustrative chronological overview of innovation indicators utilised in previous studies devoted to economic growth models. It also indicates gradual efforts to improve the innovation proxy.

Tab. 1 – Illustrative overview of innovation indicators utilised in earlier studies. Source: own research

Authors	Innovation indicators utilised
Crosby (2000)	Patent application: total, residential, and non-residential
Torun & Çiçekci (2007)	R&D expenditures; a number of triadic patent families; a number of researchers
Hasan & Tucci (2010)	R&D expenditure to GDP; the total number of patents granted to R&D expenses; the proportion of patents granted in the US; residual of the estimation of the total number of patents granted to R&D expenses on R&D expenditure to GDP
Saini & Jain (2011)	Number of patent applications
Bayarcelik (2012)	R&D expenditures; a number of R&D employees; a number of patents
Kim et al. (2012)	US patent grants
Wang (2013)	Patent and trademark applications
Khalili et al. (2016)	Patent applications
Khan et al. (2017)	Residential and non-residential patent applications; high-technology export; R&D expenditures; researchers in R&D
Jokanović et al. (2017) Simionescu et al. (2017)	R&D expenditure; scientific and technical journal articles; residential and non-residential patent applications; residential and non-residential trademark applications; researchers in the R&D sector; technicians in the R&D sector; high-technology exports
Kacprzyk & Doryń (2017)	R&D expenditures; EPO applications; USPTO patent grants by priority year at the national level, both annually and cumulatively
Raghupathi & Raghupathi (2017)	PCT patent applications; patents owned by non-residents; patent applications under PCT by the technology sector
Avila-Lopez et al. (2019)	Residential and non-residential patents; R&D expenditures to GDP (nominal and real); high-technology exports to real GDP; scientific and technical journal articles

As Table 1 indicates, R&D expenditures were supplemented, for instance, by the data on the number of employees engaged in R&D (i.e., Bayarcelik, 2012; Jokanović et al., 2017). Patent statistics underwent significant development to facilitate careful consideration of innovation diversity. Attention was mainly accorded to the varying quality of patented inventions, and it was empirically proven that countries with higher-quality patents tended to have higher growth rates (Hasan & Tucci, 2010; Torun & Çiçekci, 2007). However, there remain a few differences among countries based on their level of development. Due to differences in technological capabilities, growth in developing countries seems to be driven by utility models as a minor form of intellectual property rights. Utility models enable developing countries to build their technical capacity and support their competitiveness, whereas developed countries are well-equipped to produce patentable inventions (Kim et al., 2012). The quality of patents has been assessed using triadic patent families (Torun & Çiçekci, 2007) or by connection to the US patent system (Hasan & Tucci, 2010; Kacprzyk & Doryń, 2017; Kim et al., 2012). The innovative activity has been further assessed using, for instance, scientific and technical journal articles or high-technology exports (i.e., Avila-Lopez et al., 2019; Khan et al., 2017).

There are many approaches to measure knowledge spillovers, based mainly on R&D or patent data (Lee, 2021) and supplemented by other macroeconomic indicators because knowledge also flows through licensing, human mobility, scientific publications and conferences, or imports and FDIs (Belitz & Mölders, 2015). Knowledge is often proxied by patent count (Goel & Saunoris, 2017) and knowledge flow is tracked by patent citation data (Kwon et al., 2020; Lee, 2021). These citations may be interpreted as spillovers from the knowledge described in the cited patent to the knowledge in the citing patent. Patent data and citations can reveal information about inventors, applicants, inventions, or assignees, as well as the technological field; it also facilitates knowledge spillover tracking in geographical, institutional, or technological dimensions (Lee, 2021). However, the patent citation may suffer from several drawbacks. Patent examiners tend to cite patent documents available in their native language or English more frequently (Ernst & Omland, 2011) and patent applicants tend to cite patents that support and do not compromise, the patentability of their inventions (Hedge & Sampat, 2009). Although patent citation helps track knowledge flow, it only reflects the flow resulting in patented technology. The enormity of patent literature makes it difficult for inventors and organisations to monitor relevant technological developments (Baruffaldi & Simeth, 2020); therefore, knowledge spillover might be limited by the attention scope and screening ability of the knowledge recipient. The present study aims to combine both the effect of innovation as well as the effect of knowledge spillover on economic growth by adjusting innovation proxies based on patent data.

3. RESEARCH METHODOLOGY

The use of patents in economic growth models as indicators of innovation is widespread. Research in recent decades has focussed on using qualitative characteristics of patents (e.g., patent applications by the technology sector, number of citations, number of scientific and technical journal articles, patent families, etc.). However, these efforts are constantly impacted by incompatibilities between national patent systems and inconsistent information sourcing. This significantly limits the use of qualitative patent information. Our goal is to create suitable innovation indicators based on patents for measuring the impact of innovation on economic growth in a larger sample of countries.

We used the Generalized Method of Moments (GMM) analyses for dynamic panel models (as in Evan et al., 2018; Gozgor et al., 2019; Hasan & Tucci, 2010; Kim et al., 2012). We chose the system GMM method (Blundell & Bond, 1998) because of the short time series dataset and because the studied variables are prone to be autoregressive. The system GMM estimator combines the regression in differences and regression in levels and employs a set of new instruments from within the system. Therefore, it is more efficient in the case of short time series observations. The consistency of GMM estimators depends on the validity of the instruments (i.e., instruments cannot be correlated to the error term) and in the absence of second-order serial correlation in the first difference of residuals, the first-order serial correlation is allowed (Hasan & Tucci, 2010). We tested the validity of the instruments with the Sargan test of over-identifying instruments with the null hypothesis of no correlation between the regressors and residuals and the autocorrelation with the Arellano–Bond test (AR), which examines the serial correlation of error terms with the null hypothesis of no serial correlation. We used the Wald test to investigate the significance of independent variables with the null hypothesis that the coefficient of an independent variable is not significantly different from zero.

3.1 Dependent variable

The dependent variable is the growth rate of annual per capita GDP in the country (ΔlnGDP). We operationalised the variable similarly to Hasan &Tucci (2010), as the change in the log of real per capita GDP in a local currency unit. We derived the real per capita GDP from the current per capita GDP by deflating it to the base year of 2001 using the annual GDP deflator obtained from the World Development Indicators (WDI, 2021) database. We worked with local currency units to prevent distortion by exchange rates.

3.2 Explanatory variables

In line with our goal, we created several indexes, which aim to proxy innovations more appropriately. When computing the indexes, we rely on the strengths of the patent and R&D data; however, unlike earlier studies, we do not focus on the patents, their quality, or R&D expenditure, as they may distort the diversity of either the innovations or countries. For instance, R&D expenditure is widely used as a proxy for input into an innovation activity and is considered a variable that can explain the production of new knowledge (Crosby, 2000). However, it can be assumed that similar amounts of investment in R&D produce fewer patents in developing countries compared to developed countries. This is because - as discussed above - developing countries are usually less technologically advanced in comparison to their developed counterparts, and in building their technological capacity, utility models play a significant role (Kim et al., 2012). Moreover, the strength and other aspects of the patent system are also significant factors in strategic decision-making related to intellectual property protection. That led us to focus on the propensity to patent and we created the General Propensity to Patent (GPP) index, computed as follows:

$$GPP_t = \frac{\left(1-(\frac{IEF_{PR_t}}{100})\right) \times \frac{PARW_t}{RD_t}}{MAX\left(\left(1-(\frac{IEF_{PR_t}}{100})\right) \times \frac{PARW_t}{RD_t}\right)} \tag{1}$$

where index t represents the year, $PARW_t$ represents the number of patent applications filed by residents worldwide, and RD_t represents the volume of expenditure on R&D in million USD. IEF_{PR} is the level of Property Rights freedom as a component of the Index of Economic Freedom. The protection of property rights is graded on a scale from 0 to 100 points: the higher the country's score, the more certain the legal protection of property rights. The propensity to patent is normalised by the maximum value in a sample.

Employing the number of patent applications filed by residents worldwide enabled us to account for the varying value of inventions filed for patenting because applications from the same patent family are counted multiple times. A drawback of this approach is that applications from one family might be distributed over several subsequent years, as the filing of the first patent application triggers the right of priority, usually limited to 12 months. The ratio of the number of patent applications to millions of dollars invested in R&D shows the propensity to patent on the one hand and the efficiency of the millions invested in R&D on the other hand. These are two different aspects: first, inventors generally prefer patent protection over other forms of protection; second, inventors are better in terms of resource utilisation. To underline the propensity to patent, the proposed index also considers the level of property rights protection. Countries with poor protection of property rights generally experience a lower propensity to patent. We used the negation of the IEF_{PR} to mitigate this effect. Countries in our sample with the highest GPP produce the highest number of applications per invested dollar in R&D, which supports the validity of the GPP index.

As the propensity to patent provides information only about residents of a country, we created two more indexes to distinguish between domestic and foreign innovative activities and track knowledge flow. The Foreign Knowledge Inflow index (FKI) was computed as follows:

$$FKI_t = 1 - \frac{PAR_t}{PAT_t} = \frac{PAN_t}{PAT_t} \tag{2}$$

where t represents the year, PAR represents the number of patent applications filed by residents in a domestic country, and PAT represents the total number of patent applications filed at the national office. A similar index was proposed by Banerjee et al. (2000) to express the dependency of a country on foreign technology (instead of the number of applications, the authors employed the number of granted patents). This ratio illustrates what proportion of the total patent applications are filed by residents and suggests the technological self-sufficiency of a country. Additionally, it is closely related to how attractive a country is to foreigners. As the patentable inventions must be - among other things - non-obvious and novel worldwide, we believe that this index can also quite simply illustrate the source of the increase in knowledge stock and whether the increase was generated by domestic activities or the new knowledge was imported. The higher the index, the higher the level of knowledge inflow. The non-residential patent application extends the knowledge pool by importing it, bringing valuable opportunities for residents to use up domestic resources more effectively and maintain their competitiveness.

The Domestic Knowledge Outflow index (DKO) was computed as follows:

$$DKO_t = 1 - \frac{PAR_t}{PARW_t} \tag{3}$$

where t represents the year, PAR represents the number of patent applications filed by residents at the national office, and PARW represents the number of patent applications filed worldwide. This ratio illustrates the extent to which residents export their inventions. Thus, it indirectly captures the geographical reach of patent applications. Patents with greater geographical reach are considered to have higher quality and therefore, more valuable (e.g., Tahmooresnejad & Beaudry, 2019). Therefore, the proposed ratio may suggest the quality level of residential patent applications in a general sense. More importantly, we believe this ratio can capture the level of knowledge outflow. With the increase in geographical reach, there is certainly an increase in the number of languages in which knowledge beyond the invention is disclosed, as national patent offices usually require applications to be filed in a national language. However, the DKO ratio may misrepresent situations when a resident applies for patent protection only abroad. Nevertheless, it still has a decent denouncing ability about knowledge outflow. We presume that the ability to produce knowledge with worldwide reach is a competitive advantage, which positively contributes to economic growth.

We assessed the reliability of indexes by analysing the difference in ranking of individual countries when the time span was shortened. As the average difference observed was less than three, we consider them reliable. To test the suitability of proposed indexes, we set different explanatory variables utilised in previous studies, which we chose based on the literature review, re-running the regression analysis. We used the obtained results to compare and evaluate the information value of the suggested indicators.

3.3 Control variables

As control variables, we used human capital, investment, government spending, and openness. We controlled for the convergence effect by including the initial value of real GDP per capita in USD (inGDP), which we derived by deflating it to the base year of 2001 using the annual GDP deflator. The denomination in USD enables us to consider the varying level of development. As a proxy for human capital, we employed the Labour Force to Total Population ratio (LF). We expressed investment as the growth rate of Gross Capital Formation (change in the natural logarithm of real Gross Capital Formation in the local currency units). For government spending, we used the General Government Final Consumption to GDP variable (GGFC). Openness was measured as exports and imports of goods and services to GDP. The baseline model was set as follows:

$$\Delta lnGDP \sim \ln(inGDP) + LF + investment + GGFC + openess + FKI + GPP + DKO \tag{4}$$

3.4 Data

We examined 56 countries worldwide for the period 2002–2019. The only criterion for country selection was data availability. The list of the countries is presented in Table 2.

Tab. 2 – The list of countries and country codes in the sample. Source: own research

Argentina; Armenia; Austria; Azerbaijan; Belarus; Belgium; Brazil; Bulgaria; Canada; China; Colombia; Costa Rica; Croatia; Czech Republic; Denmark; Egypt, Arab Rep.; Estonia; Finland; France; Germany; Greece; Guatemala; Hong Kong SAR; China; Hungary; Iceland; India; Iran; Islamic Rep.; Israel; Japan; Kazakhstan; Korea, Rep.; Latvia; Lithuania; Luxembourg; Madagascar; Malaysia; Mexico; Moldova; Netherlands; Norway; Poland; Portugal; Romania; Russian Federation; Singapore; Slovak Republic; South Africa; Spain; Sweden; Thailand; Tunisia; Turkey; Ukraine; United Kingdom; United States; Uzbekistan

We collected the data from the WDI database provided by the World Bank and World Intellectual Property Organization (WIPO, 2021) statistics databases. Gross domestic expenditure on

R&D includes both capital and current expenditures in all sectors of performance. Patent data include worldwide patent applications filed by residents and non-residents through the Patent Cooperation Treaty procedure or with a national patent office. Moreover, we retrieved from the WIPO statistical database the number of patent applications filed by residents of a country worldwide. We have chosen the number of patent applications rather than the number of granted patents, given the possible time lag between application and grant across patents and countries. We believe that applications that have not led to patent grants also provide useful information about the activities of the applicant as well as about their preferences in intellectual property matters and, therefore, inform about the applicant's results of R&D activities. We supplemented the dataset with the Index of Economic Freedom (IEF) annually published by The Heritage Foundation. It covers 12 freedoms, one of which, The Property Rights Freedom, we have used in the computation of the General Propensity to Patent Index. The overall IEF index served us to divide our sample into sub-groups.

Some values were missing in the sample data. To construct a balanced panel, we imputed the missing data using the Expectation-Maximization with Bootstrapping (EMB) algorithm developed by Honaker & King (2010). This algorithm was designed to bridge data gaps using a predictive model. It creates separate datasets, where the observed data remain unchanged and missing values are filled in with different imputations. In this case, five separate datasets were created, and missing values were replaced by the mean of the imputed values - as recommended by the authors - followed by a verification of whether such an operation has changed the distribution of the initial sample. Furthermore, the data have been tested to exclude correlation. We verified the stationarity using the LLC (Levin et al., 2002) and IPS (Im et al., 2003) panel unit root tests. The LLC test has low power in small samples because of serial correlation, which cannot be eliminated even though it takes the heterogeneity among sections into account; the IPS test has a stronger ability to test small samples because it considers the heterogeneity among sections and eliminates serial correlation (Pradhan et al., 2017). Both tests provided similar results; except for the number of patent applications filed by residents, all other variables are stationary.

3.5 Sampling method

We divided the sample into 18 sub-samples based on nine criteria to determine how innovation and knowledge flow affect the growth in sub-samples that have certain features in common. When dividing the sample into two parts, similar values surrounding the threshold from both sides can skew the results. To avoid it, we ranked all 56 countries according to the average value of the chosen criteria and selected only the top (.t) and bottom (.b) 20 countries to ensure the groups were sufficiently differentiated. The selection criteria are as follows. First, we chose the level of GDP per capita and its annual growth rate. Second, we chose the level of technological sophistication of a country. We derived the level of technological sophistication from the Technology Index (TI) variable, which we constructed using the Min-Max normalisation method from six variables retrieved from the World Bank database, namely Fixed Telephone Subscriptions (per capita), Mobile Cellular Subscriptions (per capita), Electric Power Consumption (kWh per capita), Fixed Broadband Subscriptions (per capita), High-Technology Exports (per capita, current USD), and Individuals Using the Internet (% of the population). These or similar variables are commonly used as measures of the technological sophistication of the country (e.g., Hasan & Tucci, 2010;

Khan et al., 2017; Pradhan et al., 2017). This choice was inspired by Kim et al. (2012), who identified a varying degree of contribution of innovations to growth because of differences in countries' technological capabilities. Third, we chose the level of economic freedom expressed by the overall Index of Economic Freedom, inspired by the work of Goel & Saunoris (2017). They identified a connection between the extent of knowledge spillover and the level of economic freedom. We set two more criteria, namely, the level of expenditure on R&D as a percentage of GDP and whether the country was a spreader or recipient of knowledge. We considered the country in which non-residents' patent applications predominated throughout the entire period to be knowledge recipients; a country where residential applications predominated was considered a knowledge spreader. To assess robustness, we divided the sample based on our indexes. Table 3 shows the intersections among the sub-samples.

Tab. 3 – The intersections of sub-samples. Source: own research

	TI.t	RDE.t	IEF.t	PAN.t	GDP.t	AG.t	GPP.t	FKI.t	DKO.t
TI.t		18	18	7	18	1	2	7	16
RDE.t			17	5	18	1	3	6	15
IEF.t				6	17	2	2	6	15
PAN.t					6	5	5	18	9
GDP.t						0	2	7	17
AG.t							15	4	2
GPP.t								5	0
FKI.t									8
DKO.t									
	TI.b	RDE.b	IEF.b	PAN.b	GDP.b	AG.b	GPP.b	FKI.	DKO.b
TI.b									
RDE.b	15								
IEF.b	15	12							
PAN.b	5	8	7						
GDP.b	16	16	14	7					
AG.b	2	2	2	11	1				
GPP.b	2	1	1	8	0	14			
FKI.b	6	9	8	18	8	10	7		
DKO.b	14	13	15	8	15	0	1	9	
	TI.t	RDE.t	IEF.t	PAN.t	GDP.t	AG.t	GPP.t	FKI.t	DKO.t
TI.b		1	0	11	0	13	13	11	1
RDE.b	0		0	9	0	13	14	9	1
IEF.b	0	1		7	0	14	14	7	0
PAN.b	9	9	8		10	8	10	0	8
GDP.b	0	1	0	9		14	16	9	2
AG.b	14	15	13	5	16		2	7	14
GPP.b	15	14	16	8	15	1		7	15

FKI.b	7	7	6	0	8	10	10		7
DKO.b	1	2	1	5	1	14	16	5	

The intersections indicate that countries that are technologically more advanced are also characterised by higher investments in R&D, higher levels of GDP, and greater economic freedom. Conversely, these countries grow at lower annual rates, indicating the presence of the convergence effect - we have controlled for this effect. Additionally, the intersections reveal that technologically sophisticated countries are those whose knowledge flows out. Similarly, countries at lower technological levels are characterised by lower R&D expenditure, lower level of GDP per capita, but, on average, higher propensity to patent and higher knowledge inflow. The sub-samples under this division are more consistent and less scattered, which is a prerequisite for more plausible results of our analysis.

4. RESULTS AND DISCUSSION

The results of GMM analysis are presented in Table 4, showing the same baseline regression model on different sub-samples. We do not present results for sub-groups (RDE, IEF, GDP) that are extremely similar to TI sub-groups in composition. We altered the baseline model and employed the indexes separately to verify the accuracy of their simultaneous implementation.

Tab. 4 – Results of the system GMM regression analysis of respective sub-samples in columns. Source: own research

Variable	TI.t	TI.b	PAN.t	PAN.b	AG.t	AG.b
Initial Real Per Capita GDP	-0.005** (0.002)	0.007. (0.004)	0.007 (0.005)	-0.006 (0.005)	0.002 (0.004)	0.000 (0.001)
LF	0.114*** (0.029)	0.028 (0.057)	-0.003 (0.037)	0.158* (0.062)	0.101 (0.068)	0.045* (0.022)
Investment	0.196*** (0.038)	0.228*** (0.042)	0.194*** (0.043)	0.266*** (0.042)	0.258*** (0.032)	0.219*** (0.015)
GGFC	0.023 (0.044)	0.070 (0.165)	-0.081 (0.102)	0.114 (0.098)	-0.025 (0.117)	-0.067* (0.027)
Openness	0.006* (0.003)	0.005 (0.029)	-0.002 (0.007)	0.044** (0.014)	0.019 (0.027)	0.000 (0.002)
GPP	0.183** (0.065)	0.050 (0.043)	0.113 (0.174)	0.033 (0.043)	0.049 (0.034)	0.108** (0.033)
DKO	-0.010 (0.010)	-0.020 (0.027)	-0.035. (0.019)	-0.096*** (0.024)	-0.083* (0.036)	0.003 (0.004)
FKI	0.004 (0.005)	-0.034** (0.012)	0.007 (0.014)	0.036 (0.035)	0.042* (0.017)	0.004 (0.003)
Observations	660	660	660	660	660	660
Sargan test (p-value)	1.000	1.000	1.000	1.000	1.000	1.000
AR (1) (p-value)	.006	.061	.002	.062	.024	.003
Wald test (p-value)	<.001	<.001	<.001	<.001	<.001	<.001

Note: Standard errors are reported in parentheses. Significance codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1.

The results reveal a positive and statistically significant impact of propensity to patent on economic growth in countries where the propensity is low. Technologically advanced countries invest more in R&D and their economy is at a higher production level. These countries are also characterised by a higher level of outflow of domestic knowledge. More interestingly, the results presented in Table 5 indicate contradictory effects of knowledge flow variables and propensity to patent. When omitting the FKI and DKO variables, the positive and significant effect of propensity to patent was shown in all sub-samples with the only exception of knowledge recipients. It is evident that knowledge flow variables weaken the impact of GPP.

Tab. 5 – Results of the system GMM regression analysis of TI sub-samples. Source: own research

Variable	TI.t	TI.t	TI.t	TI.b	TI.b	TI.b
Initial Real Per Capita GDP	-0.005** (0.002)	-0.005* (0.002)	-0.004* (0.002)	0.003 (0.005)	0.006 (0.004)	0.005 (0.004)
LF	0.123*** (0.029)	0.125*** (0.033)	0.114*** (0.029)	0.020 (0.067)	0.030 (0.057)	0.008 (0.078)
Investment	0.196*** (0.037)	0.195*** (0.037)	0.197*** (0.038)	0.232*** (0.041)	0.237*** (0.041)	0.235*** (0.042)
GGFC	-0.012 (0.028)	-0.033 (0.037)	0.006 (0.034)	0.086 (0.193)	0.123 (0.156)	0.103 (0.190)
Openness	0.005** (0.002)	0.003. (0.002)	0.006* (0.002)	0.005 (0.031)	0.009 (0.026)	0.031 (0.031)
GPP	0.213*** (0.058)			0.106* (0.048)		
DKO			-0.016. (0.008)			-0.068** (0.024)
FKI		0.001 (0.005)			-0.047*** (0.009)	
Observations	660	660	660	660	660	660
Sargan test (p-value)	1.000	1.000	1.000	1.000	1.000	1.000
AR (1) (p-value)	.006	.006	.006	.073	.063	.045
Wald test (p-value)	<.001	<.001	<.001	<.001	<.001	<.001

Note: Standard errors are reported in parentheses. Significance codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1.

The outflow of domestic knowledge seems to have a negative impact on economic growth when statistically significant. The effect is most evident without the effect of the other two explanatory variables and strongest in the sub-group of knowledge spreaders. Patent protection increases the incentives to create and patent knowledge on the one hand, but on the other hand, it reduces the incentives to commercialise it. This effect may overtake the growth-enhancing effect of R&D and reduce the aggregate rate of growth (Acs & Sanders, 2012). The effect of the foreign knowledge inflow is two-fold. In less technologically and economically developed countries, the inflow of knowledge seems to inhibit economic growth. However, in fast-growing countries, which are also characterised by a high propensity to patent and high knowledge outflow, the growth is supported by foreign knowledge inflow. These implications are in line with Kim et al.'s (2012) conclusions that for developing countries, minor inventions are more important for building their technological capacity. The infusion of foreign technology is essential for a country to sustain its economic vitality and growth, especially in the case of a country with a mature domestic technological infrastructure. Table 6 shows results for sub-samples based on our indexes; it supports the robustness of presented results, as it shows, for instance, a strong positive effect of low propensity to patent.

Tab. 6 – Results of the system GMM regression analysis of respective sub-samples in columns. Source: own research

Variable	GPP.t	GPP.b	FKI.t	FKI.b	DKO.t	DKO.b
Initial Real Per Capita GDP	-0.002 (0.004)	-0.006** (0.002)	0.005 (0.004)	-0.002 (0.005)	-0.008** (0.002)	0.001 (0.004)
LF	0.082 (0.059)	0.144*** (0.038)	-0.058 (0.046)	0.143* (0.071)	0.154*** (0.042)	0.074 (0.049)
Investment	0.243*** (0.041)	0.202*** (0.034)	0.197*** (0.050)	0.276*** (0.043)	0.192*** (0.035)	0.241*** (0.044)
GGFC	0.051 (0.143)	0.004 (0.026)	-0.075 (0.097)	-0.076 (0.131)	0.020 (0.051)	0.035 (0.147)
Openness	0.045. (0.027)	0.006*** (0.002)	-0.003 (0.005)	0.030 (0.022)	0.005 (0.003)	0.037 (0.031)
GPP	0.086. (0.046)	1.495*** (0.430)	0.079 (0.176)	0.055 (0.046)	1.082** (0.383)	0.071 (0.044)
DKO	-0.068. (0.037)	-0.016* (0.007)	-0.034* (0.017)	-0.074* (0.029)	-0.011 (0.014)	-0.089. (0.053)
FKI	0.004 (0.015)	0.003 (0.004)	0.050** (0.017)	0.054. (0.030)	0.008 (0.006)	-0.015 (0.015)
Observations	660	660	660	660	660	660
Sargan test (p-value)	1.000	1.000	1.000	1.000	1.000	1.000
AR (1) (p-value)	.025	.009	.005	.080	.007	.023
Wald test (p-value)	<.001	<.001	<.001	<.001	<.001	<.001

Note: Standard errors are reported in parentheses. Significance codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1.

The relatively large number of sub-samples provides additional essential information. Considering the economic growth driven by innovations and knowledge, the level of economic freedom is not determining, contrary to the conclusions of Goel & Saunoris (2017). Similarly, it does not matter whether residential or non-residential patent applications predominate in the economy, unlike shown by Khan et al. (2017). What determines the effect of innovation and knowledge is the level of technological sophistication, which is closely related to the level of investment in R&D and the production level of an economy. The results, in line with those of Kim et al. (2012), indicate that innovations have a stronger impact on more developed countries, which are technologically more advanced and invest more in R&D. However, our indexes are inter-connected and need to be assessed concerning that. The filing of application - incorporated in the propensity to patent index - showed a positive impact on economic growth, similar to Saini & Jain (2011). Interestingly, developing countries are more prone to patent; however, the positive effect is counter-balanced by knowledge flow. Conversely, the growth of developed countries seems to be driven by a low propensity to patent. It indicates that residents of developed countries prefer different forms of protection for intellectual property, as they are more active in R&D than developing countries. The current pace of technological advancement is so fast that the cost of patent protection, including potential litigation cost, seemingly exceeds the potential benefits for profit-seeking firms.

Additionally, when these firms proceed to patent, they also tend to expand the protection to other countries. However, the outflow of knowledge from developed countries does not have a significant effect on their economic performance. The threat of imitation from developing markets might be a strong motivation for expanding patent protection (Cai et al., 2020). As the demand for the latest and most advanced technologies is growing worldwide, it is important to adopt all possible means to sustain one's competitive advantage. One of the options is blocking competitors through strategic patenting (Torrisi et al., 2016) rather than commercialising in less attractive developing markets.

The territorial nature of patent protection justifies the growth-inhibiting effect of foreign knowledge inflow in developing counties. The technology can be utilised free of cost, unless patented in the given market. According to Haruyama & Hashimoto (2020), it adversely affects incentives for innovative R&D and, at the same time, promotes industrialisation in developing countries. The knowledge stock is increasing at a rate that limits the ability to track technological development by recipients' attention scope (Baruffaldi & Simeth, 2020). This could be why competitors cannot use the knowledge to improve the quality of their own subsequent patents (Acosta, 2021) and why the impact of knowledge flows is not as significant as expected.

To credibly answer our research question, we substituted the proposed indexes, re-ran the regression analysis, and compared the results. As explanatory variables, we employed R&D expenditure (RDE to GDP), the total number of patent applications in natural logarithm (ln of PAT), and the proportion of worldwide patent applications of residents of a country filed in the US (USPA to PARW). Table 7 presents results only for the sub-samples, where these explanatory variables were statistically significant.

Tab. 7 – Results of the system GMM regression analysis of respective sub-samples with substituted explanatory variables. Source: own research

Variable	TI.b	PAN.b	PAN.b	IEF.b	AG.t	AG.t
Initial Real Per Capita GDP	0.003 (0.005)	-0.018*** (0.003)	-0.003 (0.007)	-0.010* (0.005)	-0.005 (0.004)	0.003 (0.004)
LF	0.003 (0.083)	0.214*** (0.055)	0.189* (0.078)	0.034 (0.050)	0.068 (0.055)	0.115* (0.053)
Investment	0.244*** (0.041)	0.275*** (0.039)	0.280*** (0.038)	0.258*** (0.040)	0.269*** (0.030)	0.275*** (0.031)

GGFC	0.132 (0.195)	0.069 (0.106)	-0.102 (0.122)	0.185 (0.143)	0.172 (0.114)	0.028 (0.121)
Openness	0.034 (0.034)	0.039** (0.012)	0.036** (0.014)	0.054* (0.026)	0.025 (0.024)	0.009 (0.022)
RDE to GDP	0.272 (1.321)	-1.813*** (0.437)	-0.450 (0.289)	-6.281*** (1.831)	-4.557*** (1.014)	-2.048* (0.864)
ln of PAT		0.010*** (0.002)		0.014*** (0.004)	0.008*** (0.002)	
USPA to PARW	-0.061* (0.027)		-0.225** (0.086)			-0.082** (0.030)
Observations	660	660	660	660	660	660
Sargan test (p-value)	1.000	1.000	1.000	1.000	1.000	1.000
AR (1) (p-value)	.057	.094	.081	.042	.039	.038
Wald test (p-value)	<.001	<.001	<.001	<.001	<.001	<.001

Note: Standard errors are reported in parentheses. Significance codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1.

The RDE to GDP variables attained statistical significance in several sub-samples; however, the coefficients are highly scattered, which makes results difficult to interpret. When proxying the innovations with the total number of patents, the results show a positive and significant effect in the case of less developed, fast-growing countries where residential patent applications are predominant. When we consider the quality of domestic innovations, results indicate their growth-inhibiting effect in less technologically and economically advanced countries. Comparing the outcome of the two presented analyses, the results achieved using the proposed indexes are more consistent, reasonable, and in line with previous research, which supports their suitability.

5. CONCLUSION

We analysed the link between innovations and economic growth. Inspired by many studies in this field and their varying results, we focussed on patents and their suitability as innovation proxy in economic growth models. We created three indexes: the General Propensity to Patent (GPP, which combine the level of the legal protection of property right, the efficiency of R&D expenditures, and preferences for patenting in the country); Foreign Knowledge Inflow (FKI, which suggests the technological self-sufficiency of the country), and Domestic Knowledge Outflow (DKO, which illustrates the extent to which residents export their inventions abroad) to identify the differential impact of innovation on a country's economic growth. Their construction preserves the advantages of data accessibility and aims for better comparability at the country level. The indexes, unlike prior innovation indicators based on patent data, do not focus on the innovation itself but extract information from the patent system about knowledge creation and flow.

Based on the GMM estimation method, we may conclude that innovations, indicated by the propensity to patent, boost economic growth. However, the outflow of disclosed knowledge has the opposite effect on growth. This counteracting effect is hidden when utilising only patent statistics, regardless of its quality-enhancing alterations. Interestingly, despite more technologically advanced countries having better property right protection, their residents patent less per million invested in R&D. Either they invest in more resource-intensive R&D activities - and every invention they patent is more expensive, or they prefer a different form of protection and choose to patent only ground-breaking inventions worth worldwide protection. Furthermore, we identified the negative effect of the inflow of foreign knowledge into less technologically and economically developed countries, suggesting that these countries lack the ability to exploit the knowledge for their benefit.

Technological progress has shifted from tangible inventions to intangible improvements in everyday processes. It is necessary to search tirelessly for more suitable measurements of innovations as they are constantly evolving in terms of content and form. We conclude that our indexes are suitable proxies of innovation, as they balance the disproportion of innovation inside and outside the patent system to some extent. Their implementation helped combine the effect of innovations and knowledge accumulation and reveal otherwise unidentifiable counteracting effects of knowledge creation and disclosure. This study has a few limitations. We did not examine the impact of utility models; their analysis may provide a complementary explanation. Additionally, we did not track the number of patents granted out of the patent applications included in our research. A significant question engendered by this research is: where does economic growth actually occur and how many economies can benefit from innovative activities occurring in one country? We firmly believe that along with the innovations themselves and the disclosed knowledge, the knowledge kept outside the patent system, or secret, also plays an important role in economic growth. These questions can be answered by focussing on individual firms rather than entire economies. However, our results seem consistent and may serve as the basis for further research.

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Contact information

prof. Ing. Maria Reznakova, CSc.
Brno University of Technology
Faculty of Business and Management
Department of Finance
Czech Republic
E-mail: reznakova@vutbr.cz
ORCID: 0000-0002-7261-607X

Ing. Stanislava Stefankova
Brno University of Technology
Faculty of Business and Management
Department of Finance
Czech Republic
E-mail: stanislava.stefankova@vutbr.cz
ORCID: 0000-0002-3950-75331