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TECHNOLOGICAL PROGRESS AND ECONOMIC GROWTH: EVIDENCE FROM POLAND

Summary: This paper presents the results of testing the causal interdependence between the number of patents, R&D outlays and GDP in Poland on the basis of quarterly data for the period Q1 2000-Q4 2009. We found the significant evidence of causality running from technological progress to GDP in Poland. In addition, we found that the number of patents is a causal factor for employment and that employment Granger causes R&D outlays. These findings indicate causality from patents to R&D expenditure, which was also detected by the analysis of a separate (two-dimensional) model. Although R&D outlays in Poland are still insufficient, our study indicates a significant contribution of technological progress to economic growth. One may claim that Polish government and private firms should invest more in R&D sector.

Keywords: patents, R&D sector, economic growth, Granger causality. **JEL classification:** C32; O31; O34; O40.

1. Introduction

The modern economic literature stresses the role of technological progress and human capital in long run economic growth. Technological progress depends on the quality of innovation and research and increases capital efficiency. However, the application of technological innovation and the results of scientific research depend on financial assets. Only rich countries can easily finance research and introduce its results into the economy.

Many empirical contributions emphasize that policies oriented towards innovation and the application of new technologies support economic growth and economic productivity in the long run. There is some evidence that countries where many innovations and new technologies are developed and used in production grow faster than other countries. Patents are probably the most important form of intellectual property and therefore they are widely used as a measure of the innovation level of an economy.

The European Union announced in Lisbon in March 2000 the goal of becoming the most competitive economy in the world by 2010. The EU authorities specified all necessary changes in policy to achieve this objective. This should be achieved due to a policy of capital accumulation in a different form and the support of technological progress in the member countries in order to establish a knowledge–based economy. This should take place because technological progress increases the productivity of production factors which has a positive effect on economic growth in the long run. This conviction was based on the theory of endogenous economic growth defined in [Romer 1986] and [Lucas 1988]. According to this theory R&D outlays generate new technological solutions, which speed up economic growth. Besides the "R&D expenditure" indicator also "number of researchers" and "investment in ICT" are recommended as benchmark indicators of innovation in the European economy [Eurostat 2008].

However, in many contributions the competitiveness of an economy, as mentioned above, is measured by patent applications. A high number of patents and the right patent law may encourage investors to invest more resources in R&D. Thus, both R&D outlays and patent applications seem to be good indicators of technical progress.

Although approximations of the rate of technological progress are far from precise, economists have no doubt that the contribution of new technologies to economic growth is very substantial. Nevertheless, the relative efficiency of promoting innovations and technology through large R&D programs in the EU in generating higher rates of GDP growth is still a subject of dispute among economists. The nature of the real impact of R&D outlays on the economic growth is still not clear. It is practically impossible to check directly effects of policies geared to introducing technological progress in order to stimulate economic growth.

From an empirical point of view it is more reasonable to first make an assumption that there exists a significant connection between technology policy and technology outcomes in terms of patent applications and R&D expenditure. Taking for granted these connections, a research question about the existence of effects (positive or negative) of R&D spending and patent applications on economic growth can be formulated.

In this paper the main interrelations between technical progress and economic growth of Poland in 2000-2009 are discussed. All computations are based on quarterly data of GDP, employment, number of patent applications and R&D outlays. The interrelations were tested in the framework of vector autoregression and error correction models by the application of recent linear and nonlinear tests for causality in short and long run.

The formulation of detailed hypotheses concerning interrelations between patent applications, R&D expenditure, employment and economic growth of Polish economy in the last decade was based on economic theory, visual inspection and descriptive statistics of the Polish macroeconomic data given in the dataset and main findings obtained for other countries in previous research.

We found strong evidence to claim that technical progress caused GDP growth in Poland in Granger sense in the period under study. The results of our research also supported unidirectional causality running from patent applications to outlays on R&D, i.e. the current effectiveness of the R&D sector was found to be a causal factor for its future funding.

The remainder of the paper is organized as follows. In the next section we give a literature overview finding that most of previous papers indicate an important role of technological innovations in economic development. In section 3 we formulate the main conjectures concerning the interrelations between technical progress and economic growth in Poland. In section 4 we review the recent and reliable dataset applied. In section 5 the methodology is briefly described with special attention paid to econometric analysis of short-length time series. Section 6 presents the empirical results and their discussion and section 7 gives conclusions.

2. Literature overview

One of the earliest studies on the role of innovations was that of the famous Austrian economist Joseph Schumpeter who gave an economic background to the exploration of the importance of new technology-based firms (NTBFs) in causing economic growth and development [Schumpeter 1911].

In the literature there have been many attempts to measure the contribution of R&D and patent applications to the economic growth of regions, countries or groups of countries. However, the research results differ very widely. All studies concerning the relations between technical progress and economic growth can be clustered into three groups [Griliches 1996]: historical case studies, analyses of invention counts and patent statistics, and econometric contributions relating productivity and economic growth to R&D outlays or similar variables. Recent theoretical growth models support (in general) the existence of a positive correlation between economic growth and technological progress, and especially outlays on learning [Firth and Mellor 2000]. However, there have been no empirical applications of these models. Therefore, the statistical testing of conjectures emerging from these models is impossible.

Economists mostly agree that there exist positive empirical correlations between expenditure on R&D (patent applications) and GDP growth [Freeman and Soete 1997; Falk 2006; Mansfield 1991a] but they also underline that the strength of these correlations depends on the specific sector, its size and the macroeconomic and political conditions in a country.

Early contributions [Terleckyj 1974, 1980; Lichtenberg and Siegel 1991; Griliches 1996] concerned with the analysis and assessment of private and social rates of returns on R&D outlays by measurements the number of patents were based on production functions. Although the computed coefficients for different economies were different across countries and sectors, there were some attempts to formulate general policy implications. Lipsey and Carlaw examined a number of contributions on well developed countries, predominantly for US economy, and found that approximated rate of return on R&D outlays lies between 0.2 and 0.5 [Lipsey and Carlaw 2001]. However, this result cannot be accepted without serious doubts because of the variations in the methodology applied in specific studies. According to an OECD study the elasticity of production with respect to domestic business is in most cases equal to 7 [OECD 2000]. However, there are significant differences across countries. In addition, the impact of foreign R&D on output was found to be significant and high.

The implications of public outlays on R&D are also not uniform. The rationale for government spending on R&D follows mainly from well documented market failures which characterise R&D process: imperfect practical application of R&D results which means that subsequent to the end results of R&D – patents and innovations – there is unintended spillover, for example in the form of inventions, which benefit rivals. This research is also high risk, which causes disincentives for the private sector to invest in R&D. The last fact is especially evident in the case of small firms which have limited financial assets. Because of these facts private firms invest less in R&D than would be desirable from a social point of view [Arrow 1962]. Governments invest in R&D through public funding and by incentives for firms to spend on R&D [Goel et al. 2008]. This can be done through direct support measures like grants, subsidies and public funding of research in universities and the public research institutes as well as indirect support via fiscal measures and tax credits. Usually indirect support is not reflected in official R&D statistics. Moreover, the higher the business R&D activity, the higher the apparent efficiency of public outlays on research.

Average returns on R&D are related to the concepts of spillover and positive externalities [Helpman and Coe 1995]. In some papers [Romer 1986; Bernstein and Nadiri 1988; Scherer 1993] it is stressed that the productivity of a firm or sector depends not only on its own R&D outlays, but also on technological improvements, the knowledge and information accessible to it.

Some contributors like Griliches, who examined empirically the existence of spillover effects, found that effects on R&D outlays at firm level are not significantly lower than of sector level [Griliches 1996]. Although this finding contradicts the existence of spillover, in general the cited case studies tend to support the presence of R&D spillover. The importance of technical progress at firm level in specific countries and time periods reflected in high R&D returns was also reported [Bean 1995; Griliches 1990; Griliches and Regev 1995; Hall and Mairesse 1995; Zif and McCarthy 1997]. One can expect not only high returns on R&D investment but also improvement in a firm's absorptive capacity, which allows making profits from externalities [Cohen and Levinthal 1989]. Both these positive results of R&D expenditure contribute to the economic growth of a specific country.

The role of R&D spillover through trade, especially in the IT sector, was underlined in [Madden and Savage 2000] and [Raa and Wolff 2000]. In the opinion of these authors outlays on technical progress introduced into modern sectors speed up GDP growth.

Tsipouri stresses that in previous investigations (conducted predominantly for the developed countries) which concerned effect of R&D outlays no general rate of return was found [Tsipouri 2004]. In specific studies a positive correlation between R&D and GDP growth was established. However, the results are applicable solely to countries with a similar economic structure.

In the one of the earliest contributions on the role of technical progress Solow stressed that technical change tends to support economic growth in the long run [Solow 1957]. This conviction was supported by Fagerberg, who found a significant correlation between GDP per capita and technical progress measured by R&D outlays or patent applications [Fagerberg 1988]. It was noticed that countries which focused on technologically advanced sectors reached higher rates of GDP growth than other countries. In his later contribution Fagerberg found that differences in productivity growth are larger among countries than across industries in the same country [Fagerberg 2000]. In the opinion of Branstetter technology spillover is predominantly of a national nature [Branstetter 2001]. Romer and Krugman as well, have drawn from this observation the conclusion that large countries should experience a higher GDP rate of growth than small countries [Romer 1986, 1990; Krugman 1990].

In this context important policy questions are related to the impact of technology policy on cohesion within the framework of the EU. Cohesion is being promoted in the Community through structural funds. Therefore, the possible trade off between economic growth and economic cohesion is a very important research question [Peterson and Sharp 1998; Pavitt 1998].

Our study belongs to the third group of contributions by the classification reported at the beginning of this section [Griliches 1996]. In the next section we formulate some conjectures with respect to the impact of technical progress on the growth of the Polish economy in last decade. As proxies for technical progress we use Polish quarterly data on the number of patents and outlays on R&D and then we relate them to GDP quarterly data.

The importance of labour as a production factor in both the long and short run is well known in the econometric literature. Thus, the employment variable plays an important role in our research. Moreover, it protects our study from the spurious causality analysis results reported in the literature because it solves the problem of omitting important variables. This problem can arise when using a simple two-dimensional approach.[1]

[1] It is possible to use other control variables with/instead of employment in the growth model. However, too many control variables may easily lead to serious multicollinearity and/or significantly reduce the number of degrees of freedom. On the other hand employment is often described as the only

The issues concerning factors of economic growth of Poland in recent years are widely discussed in the literature [e.g. Rapacki 2009; Bakalarczyk 2008]. The main macroeconomic data of Polish economy are provided in Statistical Yearbooks by Central Statistical Office of Poland.

Despite the crisis of 2001 and 2008, Polish GDP has exhibited relatively stable and positive rate of growth, mainly due to rising private consumption, a jump in corporate investment, and European Union funds inflows. Since 2004, EU membership and access to EU structural funds have provided the major boost to the Polish economy.

3. Main research conjectures

In this paper we use abbreviations for all the variables. Table 1 contains some initial information:

Table 1. Units, abbreviations and short description of examined variables[2]

Description of variable	Unit	Abbreviation for seasonally adjusted and logarithmically transformed variable
Real quarterly gross domestic product in Poland	mln PLN	*GDP*
Employment in Poland based on quarterly Labour Force Survey	Thousands	*EMPL*
Quarterly number of patents registered in The Patent Office in Poland	Unit	*PAT*
Real quarterly R&D expenditures in Poland	mln PLN	*RD*

Source: material prepared by authors.

The hypotheses below are derived from economic theory, by visual inspection and descriptive statistics of the Polish macroeconomic data given in the dataset and previous empirical research conducted on technological progress-GDP links for other countries.

The probability of the existence of interdependencies between the technical progress related variables (*PAT* and *RD*), employment and GDP is considerable in the light of the literature overview presented in the previous section. However it is clear that transitional countries such as Poland (see R&D data in the next section) are not able to spend a similar amount of financial assets on R&D in comparison to other

variable production factor in the short run [Takayama 1985; Mansfield 1991b], which justifies its application in the growth equation.

[2] Details on applied dataset are presented in section 4.

highly developed OECD countries.[3] Therefore, the impact of the relatively moderate spending on R&D and patent applications on GDP in Poland is rather uncertain.

In the light of the literature (comp. e.g. [Griliches 1996; Freeman and Soete 1997; Falk 2006; Mansfield 1991a]) the significant impact of patent applications on GDP is more likely to exist since R&D outlays in Poland stem mainly from the state budget. The results concerning contribution of public R&D investments to economic growth are unclear and in some cases even controversial. As we cited in the introductory section, the EU applies as one of the possible proxies of technical progress the number of researchers (scientists and engineers). Behind this assumption there is a supposition that the more researchers there are the more likely there is the creation of inventions. One may wonder if an inverse relation is also probable: more inventions lead to a higher employment level not only in the R&D sector but also in other sectors, especially in NTBFs. Since patents stand for the "output" of the R&D sector, an increasing number of patents may suggest a rise in the efficiency of investments in the R&D sector and encourage government and firms to spend more money on further research which implies the increase of number of researchers. A more important supposition may be that developing new technology implies the birth of new competitive firms (for example in the ICT sector), which will employ new workers. This presumption is based on the observation that unemployment in most countries with a high level of technology is low. Therefore, we formulate a hypothesis concerning the role of patents in the growth of the Polish economy and employment in the form:

Conjecture 1: *There is a significant causal impact of the number of patents on GDP and employment in the Polish economy in the short and long run.*

Economic theory (production functions) predicts dependence between labour input and production output both in the short and long run. Therefore, by analogy, one can presume the existence of causality between these two variables in the Granger sense. Since this dependence is usually expressed by monotone increasing functions (with respect to employment) feedback (i.e. mutual Granger causality between employment and GDP) can be expected. Moreover, one can expect that the higher the employment in the whole economy, the higher the employment in the R&D sector and the last fact implies the necessity of higher R&D outlays. Therefore, we may formulate the following:

Conjecture 2: *There are some long run (short run) causalities between employment and GDP (changes in employment and changes in GDP). Moreover, employment causes changes in R&D outlays.*

It is the common view in the literature based on empirical results that patents (by definition a measure of innovations) contribute to economic growth. The existence

[3] In the period 2000-2009 the R&D expenditures in Poland were around 0.6-0.7% of GDP, while in the same time the EU average was at the level of around 2% of GDP.

of a connection between *PAT* and *RD* can be justified theoretically by taking into account that the *PAT* time series stands for the output of R&D investments (*RD*). This could be especially true in the case of Poland, where most registered patents result from research supported by the government.

Therefore, an indirect impact of R&D on GDP can be expected. In addition, R&D outlays support the growth of human capital, which according to economic theory contributes to GDP growth. In view of these facts, and results reported by some previous contributions related to R&D–GDP links we formulate hypothesis 4 in the form:

Conjecture 3: *There are linear and nonlinear Granger causalities from R&D expenditure to GDP in Poland.*

However, as stressed in the reviewed literature the empirical results concerning the impact of R&D on GDP are not uniform. In some empirical studies this impact is just neglected, especially the effect of government R&D spending. Moreover, in some contributions it is reported that registered patents are a causal factor for R&D, but not vice versa. This might be justified by the assumption that patents are proofs of the efficiency of researchers and R&D institutions. The more patents the more incentives in the future to invest in R&D by both the government and private firms. This may be the case especially for developing or emerging economies (like Poland) where only low or moderate financial assets can be invested in R&D. Thus, the following conjecture for the Polish R&D sector should also be tested:

Conjecture 4 *There is a causal relationship running from the number of registered patents to R&D outlays.*

The hypotheses listed above will be tested by some recent causality tests. The details of the testing procedures will be shown later. The test outcomes depend to some extent on the testing methods applied, thus testing the robustness of empirical findings is one of our main goals. Before describing the methodology, in the next section we will characterize the time series included in our sample.

4. The dataset and its properties

The first part of this section contains a description of the applied dataset. In subsection 4.2 the stationarity properties of all the time series are examined. The identification of the orders of integration of the time series under study is a crucial stage of causality analysis.

4.1. Description of the dataset

The chosen dataset includes quarterly data on GDP, R&D outlays, the number of patents registered in The Patent Office of Poland and employment in Poland in the period Q1 2000-Q4 2009. Thus, our dataset contains 40 observations. In order to remove the impact of inflation we calculated GDP at constant prices (year 2000).

The Central Statistical Office in Poland presents original data on R&D expenditure only on an annual basis. Therefore, in order to estimate the value of quarterly expenditures one is forced to use a suitable procedure for dividing the overall (annual) outlays. In this paper we used the following formula to calculate the estimates of quarterly R&D expenditure:

$$RD_q^x = \frac{RD^x(GP^x \cdot GCE^x + BP^x \cdot BCE^x)}{4} + RD^x \cdot GP^x \cdot \frac{SHE_q^x}{SHE^x} \cdot (1 - GCE^x) + RD^x \cdot BP^x \cdot \frac{INV_q^x}{INV^x} \cdot (1 - BCE^x) \tag{1}$$

where:[4] RD_q^x – R&D expenditures in quarter q in year x ($q \in \{1, 2, 3, 4\}$, $x \in \{2000, 2001, ..., 2009\}$);

RD^x – overall R&D expenditures in year x;

GP^x – share of government expenditures in R&D expenditures in year x;

BP^x – share of business (private) expenditures in R&D expenditures in year x;

GCE^x – share of current expenditures in government expenditures in R&D in year x;

BCE^x – share of current expenditures in business expenditures in R&D in year x;[5]

SHE_q^x – expenditures on science and higher education in quarter q in year x;

SHE^x – overall expenditures on science and higher education in year x;

INV_q^x – investment outlays for fixed assets in quarter q in year x;

INV^x overall investment outlays for fixed assets in year x.[6]

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[4] Quarterly data on the number of patents was obtained from The Patent Office of Poland. The quarterly data on budgetary expenditures was obtained from The Ministry of Finance of Poland. Quarterly time series of GDP, employment and annual time series of R&D expenditures were taken from the Central Statistical Office in Poland.

[5] GP^x, BP^x, GCE^x and BCE^x lie between 0 and 1. Moreover, $GP^x + BP^x = 1$ for all x since R&D outlays are either public or private.

[6] The Central Statistical Office and Ministry of Finance provides data on expenditure expressed in current prices. However, all the time series of expenditures (RD^x, SHE_q^x, SHE^x, INV_q^x, INV^x) are expressed in constant prices of year 2000 (due to the application of the inflation rate). Moreover, since data on investment outlays is presented by the Central Statistical Office only three times a year (first half-year, third quarter, fourth quarter) we assumed that $INV_1^x = INV_2^x$ for all x.

As we can see, the first component of the sum on the right side of equation (1) is exactly the same for each quarter of year *x*. This fact reflects the assumption that current expenditures, such as labour costs, energy and fuel costs, are generally constant over a year.[7] The second and third components represent the quarter dependent parts of R&D expenditure. We applied expenditures on science and higher education as well as investment outlays for fixed assets as the most suitable weights for the government and private components, respectively.

Since each variable used was characterized by significant quarterly seasonality, and this feature often leads to spurious results in causality analysis, the X–12 ARIMA procedure (which is currently used by the U.S. Census Bureau for seasonal adjustment) of Gretl software was applied to adjust each variable. Finally, each seasonally adjusted variable was transformed into logarithmic form, since this Box–Cox transformation may stabilize variance and therefore improve the statistical properties of the data, which is especially important for parametric tests.

The important point that distinguishes our paper from previous contributions on technological progress and economic growth is that we applied (less aggregated) quarterly data. This is partly because the data necessary covered only the recent few years and therefore a causality analysis based on annual data could not have been carried out due to lack of degrees of freedom. Moreover, as shown in some papers [Granger et al. 2000] the application of lower frequency data (for example annual) may seriously distort the results of Granger causality analysis because some important interactions may stay hidden.

The originality of this paper is also related to another important fact. As far as the authors know this is the first study which analyses dynamic interactions between technological progress and GDP in Poland, which is a leading country in the CEE region. The lack of reliable datasets of sufficient size is a common characteristic of most of post-Soviet economies and this can indeed be a serious problem for the researcher. However, the application of recent quarterly data and modern econometric techniques (described in section 5) provided a basis for conducting this leading research for one of the transitional European economies.

The initial part of our analysis contains some descriptive statistics of all the variables. Table 2 contains suitable results:

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[7] When this paper was being prepared the annual report *Science and technology in Poland in 2009* was still in production, thus it was impossible to get the RD^{2009}, GP^{2009}, BP^{2009}, GCE^{2009}, BCE^{2009} data directly from Central Statistical Office in Poland. However, for the sake of comparability with a model based on number of patents (it used data from 2009) we estimated quarterly R&D expenditures in 2009 using Eurostat data (RD^{2009}, GP^{2009} and BP^{2009} were attainable in this office). However, exact data on GCE^{2009} and BCE^{2009} was unattainable even in Eurostat databases, thus we used forecasts based on simple linear trend models estimated for GCE^{X} and BCE^{X} for years 2000-2008.

Table 2. Descriptive statistics of examined variables

Quantity \ Variable	*GDP*	*EMPL*	*PAT*	*RD*
Minimum	12.11	9.51	5.78	7.00
1st quartile	12.15	9.53	6.20	7.07
Median	12.26	9.57	6.42	7.19
3rd quartile	12.41	9.63	6.72	7.41
Maximum	12.49	9.68	7.17	7.61
Mean	12.28	9.58	6.45	7.25
Std. deviation	0.12	0.09	0.34	0.20
Skewness	0.27	0.48	–0.03	0.55
Excess kurtosis	–1.40	–1.12	–0.53	–1.10

Source: own calculations.

In order to conduct a comprehensive preliminary analysis the charts for all the variables under study should also be analyzed. The following figure contains suitable plots:

In years 2000-2009 there was relatively stable development of the Polish economy since *GDP* exhibited an upward tendency. One cannot forget that the Polish economy was one of the few that managed to avoid an undesirable impact of the crisis of 2008. However, after September 2008 one could observe the beginning of slight slowdown in the rate of growth of the Polish economy. For *EMPL* in the analyzed period there was a stable rise between 2003 and 2008. However, slight drops were also observed before 2003 and after the crisis of September 2008. Similar regularities were also observed for R&D expenditures. Between 2003 and 2008 *RD* exhibited a significant upward tendency. However, Figure 1 shows that the financial crisis of 2008 definitely caused an inhibition of the rate of growth of these expenditures. Finally, one should note that the *PAT* time series also exhibits an upward tendency. However, the slope of the trend line is relatively low in this case. Moreover, in comparison to other time series *PAT* is least smooth.[8] It is also worth noting that Figure 1 suggests positive causality between technological progress and economic growth in Poland in the period under study (which is clearly in line with economic theory).

The descriptive analysis of the time series included in our dataset will be extended in the next subsection by stationarity testing. This is a crucial stage of causality analysis.

[8] The range and variation of *PAT* are highest of all the time series. One may easily imagine a 50% drop (or rise) in the number of patents in quarters q and q+1. However, it is impossible to observe such a phenomenon for GDP, employment or R&D expenditures.

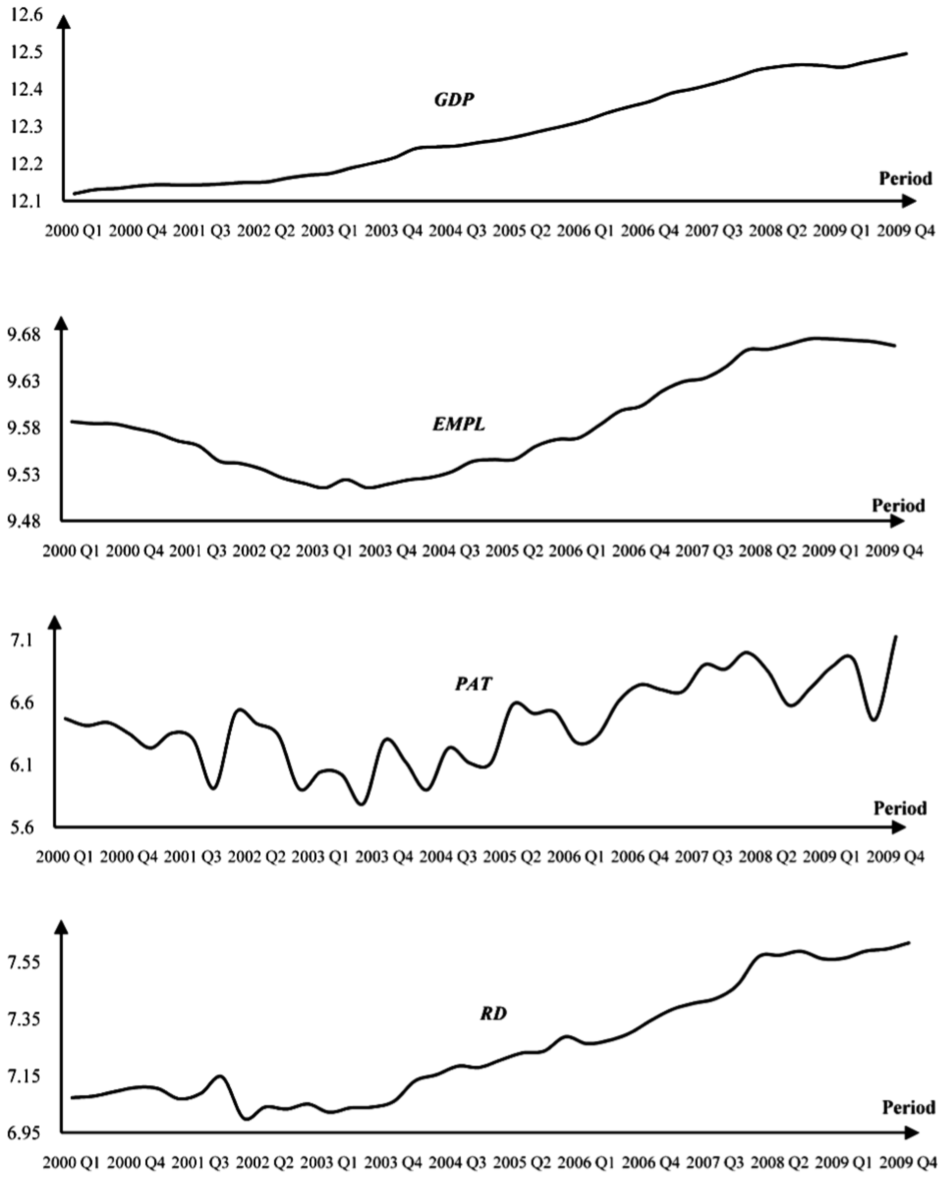

Figure 1. Plots of the time series[9]

Source: statistical data obtained by authors.

[9] Note that when data seems to be nonstationary (comp. e.g. Figure 1) the possibility of obtaining important conclusions based solely on calculation of descriptive statistics for variables in their levels (comp. e.g. Table 2) is rather small. However, descriptive statistics may provide some additional information on variables under study, especially if they exhibit significant and quite stable upward trends.

4.2. Stationarity properties of the dataset

In the first step of this part of research we conducted an Augmented Dickey–Fuller (ADF) unit root test.[10] However, the application of the ADF test involves two serious problems. Firstly, the outcomes of this test are relatively sensitive to an incorrect establishment of lag parameter. Secondly, the ADF test tends to under-reject the null hypothesis pointing at nonstationarity too often.[11] Therefore, the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test was applied to confirm the results of the ADF one. In contrast to the ADF test the null hypothesis of a KPSS test refers to the stationarity of the time series.

Since it is possible that two unit root tests lead to contradictory conclusions, a third test must be applied to make a final decision about the stationarity of time series. In this paper we additionally applied the Phillips–Perron (PP) test, which is based on a nonparametric method of controlling for serial correlation when testing for a unit root. The null hypothesis once again refers to nonstationarity.

Table 3 contains the results of the stationarity analysis. Bold face indicates finding nonstationarity at a 5% level:

Table 3. Results of stationarity analysis

Test type	ADF				KPSS		PP	
	with constant		with constant and linear trend		with constant[a]	with constant and linear trend[b]	with constant	with constant and linear trend
Variable	*p*-value	Optimal lag	*p*-value	Optimal lag	Test statistic		*p*-value	
GDP	**0.99**	1	**0.19**	1	**1.08**	**0.23**	**0.98**	**0.52**
EMPL	0.00	4	0.00	4	**0.78**	**0.25**	**0.92**	**0.60**
PAT	**0.83**	3	**0.59**	3	**0.52**	**0.16**	**0.35**	**0.07**
RD	**0.98**	0	**0.68**	0	**0.69**	**0.18**	**0.99**	**0.66**

[a] *critical values:* 0.347 (10%), 0.463 (5%), 0.739 (1%).
[b] *critical values:* 0.119 (10%), 0.146 (5%), 0.216 (1%).

Source: own calculations.

[10] Before conducting the test, the maximal lag length was set at a level of 6 and then the information criteria (namely, the AIC, BIC and HQ) were applied to choose the optimal lag. Since the application of information criteria does not automatically solve the problem of autocorrelation, we additionally re-examined the issue of autocorrelation of residuals of unit-root-related models. However, no evidence of significant (at 5% level) autocorrelation was found in any case, which in turn validated the information-criteria-based procedure of lag selection.

[11] Low power against stationary alternatives has been frequently reported by many authors, see, for instance [Agiakoglu and Newbold 1992].

An analysis of the outcomes presented in Table 3 shows that all time series were found to be nonstationary around constant at a 5% level.[12] Some further calculations (conducted for first differences) confirmed that all variables under study are I(1).[13]

5. Methodology

In this paper several econometric tools were applied to test for both linear and nonlinear Granger causality between GDP and technological progress in Polish economy. The main part of our research was conducted in two three-dimensional variants, each of which involved *GDP*, *EMPL* and one variable related to technological progress (i.e. *PAT* or *RD*).

5.1. Linear short and long run Granger causality tests

Since the concept of Granger causality [Granger 1969] is well known and has been commonly applied in previous empirical studies we will not explain it in detail. By and large, this idea is used to examine whether knowledge of the past and current values of one stationary variable is helpful in predicting the future values of another one or not (what matter most, only one period ahead). Stationarity is a crucial precondition for standard linear Granger causality tests. Nonstationarity of the time series under study may lead to false conclusions by a traditional linear causality test. This phenomenon has been investigated in previous empirical [Granger and Newbold 1974] and theoretical [Phillips 1986] deliberations. Since all the variables were found to be I(1) we applied three econometric methods suitable for testing for linear short and long run Granger causality in this context, namely, a traditional analysis of the vector error correction model (VECM), the sequential elimination of insignificant variables in VECM and the Toda–Yamamoto method.[14]

A cointegration analysis (based on the estimation of a VEC model) may be performed for variables which are integrated in the same order. As shown by Granger the existence of cointegration implies long run Granger causality in at least one direction [Granger 1988]. To establish the direction of this causal link one should es-

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[12] All three tests pointed at nonstationarity for every analyzed time series except for *EMPL*. In this case nonstationarity was confirmed by two of three conducted tests. To confirm the nonstationarity of *EMPL* we have additionally applied a GLS-ADF testing procedure, which has significantly greater power that ADF test. The results of GLS-ADF procedure were in line with KPSS and PP tests and confirmed nonstationarity at 5% level.

[13] We would like to underline that detailed results of all computations which are not presented in the text (usually to save space) in detailed form are available from authors upon request.

[14] The concept of long run causality applied in this research is due to [Granger 1988]. This idea extends the standard (short run) definition allowing the causal variable to have long-lasting causal effect on the caused one. A shock in a causal variable implies a disturbance in cointegrating relationship, which in turn implies subsequent changes in the caused variable, as the cointegrating equation returns to the equilibrium state.

timate a suitable VEC model and check (using a t-test) the statistical significance of the error correction terms. Testing the joint significance (using an F-test) of lagged differences provides a basis for short run causality investigations.[15]

However, causality testing based on the application of an unrestricted VEC model has got a serious drawback. Namely, in practice it is often necessary to use a relatively large number of lags in order to avoid the consequences of the autocorrelation of residuals. On the other hand, a large number of lags may lead to a significant reduction in the number of degrees of freedom, which in turn has an undesirable impact on test performance, especially for small samples. Moreover, testing for linear causality using a traditional Granger test often suffers because of possible multicollinearity. Therefore, in order to test for short and long run linear Granger causality a sequential elimination of insignificant variables was additionally applied for each VECM equation separately. At each step of this procedure the variable with the highest p-value (t-test) was omitted until all remaining variables have a p-value no greater than a fixed value (in this paper it was 0.10). The reader may find more technical details of this approach in [Gurgul and Lach 2010].

Another approach for testing for linear Granger causality was formulated in [Toda and Yamamoto 1995]. This method has been commonly applied in recent empirical studies (see, for example [Mulas-Granados and Sanz 2008]) since it is relatively simple to perform and free of complicated pretesting procedures, which may bias the test results, especially when dealing with nonstationary variables. The most important feature of the Toda–Yamamoto (TY) approach is the fact that this procedure is applicable even if the variables under study are characterized by different orders of integration.[16] In such cases a standard linear causality analysis cannot be performed by the direct application of a basic VAR or VEC model. On the other hand, differencing or calculating the growth rates of some variables allows the use of the traditional approach, but it may also cause loss of long run information and lead to problems with the interpretation of test results.

The idea behind the Toda and Yamamoto approach for causality testing is relatively simple as it is just a modification of the standard Wald test. To shed light on this procedure let us assume that the true DGP is an n-dimensional VAR(p) process. If the order of this process (p) is unknown, it may be established with the help of standard model selection criteria (for more details see [Paulsen 1984]). In the next step the

[15] The traditional approach to testing for long run causality used in this paper (based on significance tests in VECM framework) has been often applied in recent empirical papers as it is simple to perform and relatively easy to interpret. However, since the work of [Granger 1988] the concept of long run causality has been an object of many statistical modifications and extensions (for more detailed discussion see e.g. [Bruneau and Jondeau 1999]).

[16] It is possible that the results of stationarity and cointegration analysis are partly false and thus causality analysis performed in VEC framework is also partly incorrect. TY approach may provide a basis to confirm or undermine the VEC-based results (for more details see e.g. [Gurgul and Lach 2011]).

highest order of integration of all the variables in the VAR model (let d denote this value) should be established. Finally, the augmented VAR($p + d$) model should be fitted to the dataset. A Toda–Yamamoto test statistic is just a standard Wald test applied to test null restrictions only for the first p lags of the augmented VAR model. If some typical modelling assumptions (for instance, the error term being white noise) hold true for the augmented model then the test statistic has the usual asymptotic $\chi^2(p)$ distribution [Toda and Yamamoto 1995]. However, since we dealt with relatively small samples we applied the TY test statistic in its asymptotically F-distributed variant, which performs better for small samples [Lütkepohl 1993].

The application of these parametric methods has got two serious drawbacks. Firstly, if suitable modelling assumptions are not satisfied, the application of asymptotic theory may lead to spurious results. Secondly, regardless of the modelling assumptions, the distribution of the test statistic may be significantly different from an asymptotic pattern when dealing with extremely small samples. The application of the bootstrap technique provides one possible way of overcoming these difficulties. Bootstrapping is used for estimating the distribution of a test statistic by resampling data. It seems reasonable to expect that the bootstrap procedure does not require such strong assumptions as parametric methods, since the estimated distribution depends only on the available dataset. However, bootstrapping is likely to fail in some specific cases and therefore cannot be treated as a perfect tool for solving all possible model specification problems [Horowitz 1995].

In order to minimize the undesirable influence of heteroscedasticity, the bootstrap test was based on resampling leveraged residuals.[17] Academic discussion on the establishment of the number of bootstrap replications has attracted considerable attention in recent years [Horowitz 1995]. In this paper the recently developed procedure of establishing the number of bootstrap replications presented in [Andrews and Buchinsky 2000] was applied. In all cases we aimed to choose such a value of number of replications which would ensure that the relative error of establishing the critical value (at a 10% significance level) would not exceed 5% with a probability equal to 0.95.[18]

5.2. Nonlinear Granger causality test

In general, the application of nonlinear methods in testing for Granger causality is based on two facts. First, as shown in some papers (see e.g. [Brock 1991]) the traditional linear Granger causality test tends to have extremely low power in detecting certain kinds of nonlinear causal interrelations. Second, linear methods are mainly

[17] The detailed description of resampling procedure applied in this paper may be found in [Hacker and Hatemi 2006].

[18] The Gretl script including the implementation of all mentioned linear methods with asymptotic and bootstrap-based variants is available from the authors upon request.

based on testing the statistical significance of suitable parameters only in a mean equation, thus causality in any higher-order structure (for example variance) cannot be explored [Diks and DeGoede 2001].

In this paper we applied the nonlinear causality test presented in [Diks and Panchenko, 2006]. We applied some typical values of the technical parameters of this method, which have been commonly used in previous papers (see e.g. [Diks and Panchenko 2006], [Gurgul and Lach 2010]). We set up the bandwidth (denoted as b_{DP}) at a level of 0.5, 1 and 1.5 while the common lag parameter (denoted as l_{DP}) was set at the order of 1 and 2.[19] The reader may find a detailed description of the role of these technical parameters and the form of test statistic in [Diks and Panchenko 2006].[20]

Since previous studies provided evidence that the presence of heteroscedasticity leads to over-rejection of the discussed nonlinear test [Diks and Panchenko 2006], we additionally decided to test all examined time series for the presence of various heteroscedastic structures (using, inter alia, White's test and a Breusch–Pagan test).

It is important to note that all the test outcomes depend to some extent on the testing methods applied. This fact is the reason for using a variety of econometric methods in order to ensure the robustness of empirical findings and rigorous statistical verification of all hypotheses listed in section 3. Nevertheless using carefully selected econometric procedures, one should bear in mind that obtaining spurious results of causality analysis is still possible, which implies that empirical results should be analyzed with a measure of caution, especially for samples as small as the one analyzed in this paper.

6. Empirical results

In this section the results of short and long run linear Granger causality analysis as well as the outcomes of nonlinear causality tests are presented. The main goal of these empirical investigations was to examine the structure of the dynamic relationships between different measures of technological progress and GDP in Poland in the period Q1 2000-Q4 2009. As already mentioned, the main part of the research was performed in a three-dimensional framework, since fluctuations in employment may have a significant impact on the structure of technology-GDP links.[21]

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[19] One should note that the nonlinear causality between two variables is significant if it is confirmed by results of nonlinear test for at least one combination of parameters b_{DP} and l_{DP} [Diks and Panchenko 2006].

[20] We applied Diks and Panchenko's nonlinear procedure using all practical suggestions presented in [Gurgul and Lach 2010].

[21] We examined two sets of variables, each of which contained GDP, employment and one measure of technological progress (number of patents or B&R spending).

6.1. Number of patents and GDP

Since *PAT, GDP* and *EMPL* were all found to be I(1) we first performed a cointegration analysis for these variables. We analyzed the possibilities listed in [Johansen 1995] to specify the type of deterministic trend. In view of the results presented in subsection 4.2 (no trend-stationarity) the Johansen's third case was assumed, that is the presence of a constant in both the cointegrating equation and the test VAR. In the next step, the information criteria (namely, AIC, BIC, HQ) were applied to establish the appropriate number of lags. The final lag length was set at a level of 5.[22] The following table contains the results of Johansen cointegration tests:

Table 4. Results of cointegration analysis for *PAT*, *GDP* and *EMPL* variables

		Johansen Trace test		Johansen Maximal Eigenvalue test	
Hypothesized number of cointegrating vectors	Eigenvalue	Trace statistic	*p*-value	Maximal Eigenvalue statistic	*p*-value
Zero	0.59	44.73	0.00	34.27	0.00
At most one	0.23	10.46	0.24	10.14	0.20
At most two	0.01	0.313	0.57	0.31	0.57

Source: own calculations.

One can see that both variants of Johansen test provided solid evidence (at all typical significance levels) for claiming that for these variables the dimension of cointegration space is equal to one. Moreover, the hypothesis that the smallest eigenvalue is equal to zero was accepted (last row of table 4), which additionally validates the results of the previously performed unit root tests.[23] Next, we estimated a suitable VEC model assuming 4 lags (for first differences) and one cointegrating vector. Table 5 contains *p*-values obtained while testing for linear short and long run Granger causality using an unrestricted VEC model and the sequential elimination of insignificant variables:[24]

The results obtained for the unrestricted VEC model provided a basis for claiming that *PAT* Granger caused *EMPL* in the short run in the period under study. On the

[22] We set the maximal lag length (for levels) at a level of 6. BIC criterion pointed at one lag, however, the results of Ljung–Box Q-test confirmed that in the case of one lag residuals were significantly autocorrelated, which in turn may lead to serious distortion of the results of the causality analysis.

[23] It is a well known fact that the case of full rank refers to stationarity of all considered time series [Lütkepohl 1993].

[24] Through this paper the notation "$x \neg\!\!\rightarrow y$" is equivalent to "*x* does not Granger cause *y*". Moreover, the symbol "NCL" is the abbreviation of "No coefficients left". Finally, bold face always indicates finding a causal link in a particular direction at a 10% significance level.

Table 5. Analysis of causal links between *PAT*, *GDP* and *EMPL* variables (VEC models)

Short run					Long run				
Null hypothesis	*p*-value				Equation	*p*-value of error correction component			
	Unrestricted		Sequential			Unrestricted		Sequential	
	Asymptotic	Bootstrap[a]	Asymptotic	Bootstrap[a]		Asymptotic	Bootstrap[a]	Asymptotic	Bootstrap[a]
PAT $\neg\!\rightarrow$ GDP	0.29	0.23	**0.09**	**0.08**	*GDP*	0.11	**0.08**	**0.02**	**0.00**
EMPL $\neg\!\rightarrow$ GDP	0.24	0.18	NCL	NCL					
GDP $\neg\!\rightarrow$ PAT	0.47	0.52	NCL	NCL	*PAT*	0.51	0.46	NCL	NCL
EMPL $\neg\!\rightarrow$ PAT	0.34	0.27	**0.08**	**0.05**					
GDP $\neg\!\rightarrow$ EMPL	0.25	0.22	NCL	NCL	*EMPL*	**0.00**	**0.00**	**0.00**	**0.00**
PAT $\neg\!\rightarrow$ EMPL	0.02	0.01	0.07	0.03					

[a] *Number of bootstrap replications established using Andrews and Buchinsky method varied between* **1469** *and* **2699**.

Source: own calculations.

other hand, the sequential elimination of insignificant variables led to the conclusion that in the short run there was feedback between these variables. Moreover, *PAT* was found to Granger cause *GDP*. It is worth mentioning that all these results were found in asymptotic and bootstrap-based research variants.

In all the research variants (except for the asymptotic-based variant in an unrestricted model) the error correction component was found to be significant in the *GDP* and *EMPL* equations, which provides a basis for claiming that for *GDP* and employment there was feedback in the long run. Furthermore, the number of patents was found to Granger cause *GDP* and *EMPL* in the long run.[25]

For the sake of comprehensiveness we additionally applied the Toda–Yamamoto approach for testing for causal effects between *PAT*, *GDP* and *EMPL.* The outcomes of the TY procedure provided no basis for claiming that linear causality runs in any direction for the variables (at a 10% significance level), thus we do not present them in a separate table.

In the last step of the causality analysis, a nonlinear test was performed for the residuals resulting from all linear models, namely, the residuals of unrestricted VECM, the residuals resulting from individually (sequentially) restricted equations and the residuals resulting from the augmented VAR model applied in the Toda–Yamamoto method.[26] For each combination of b_{DP} and l_{DP} three *p*-values are presented according to the following rule:

<table>
<tr><td>p-value for residuals of unrestricted VEC model</td><td>p-value for residuals of sequentially restricted equations</td></tr>
<tr><td colspan="2">p-value for residuals of TY procedure</td></tr>
</table>

Since in all examined cases no significant evidence of heteroscedasticity was found, no filtering was used. Following table contains suitable results: [27]

[25] It should be noted that scarcity of statistical data (which covers only 10 years) may lead to some doubts on the validation of established long run causal dependences. However, all coefficients in cointegrating equation were found to be significant at 10% level. Moreover the signs of *PAT* and *GDP* coefficients were different, implying that a rise (drop) in one variable is related with a long run rise (drop) in the other, which is in line with both the economic theory and the visual inspection of variables under study (comp. Figure 1).

[26] Since the structure of linear connections had been filtered out after an analysis of linear models, the residuals are believed to reflect strict nonlinear dependencies [Baek and Brock 1992].

[27] As already mentioned the main goal of our research is to seek for the evidence of causal relationship between technological progress and economic growth. Therefore, the presentation of the empirical results is oriented mainly towards analysing suitable *p*-values of causality tests. For the sake of transparency, we do not present the full outcomes of all auxiliary estimations and calculations. The complete results are available from authors upon request.

Table 6. Analysis of nonlinear causal links between *PAT*, *GDP* and *EMPL* variables

<table>
<tr><th rowspan="2">Null hypothesis</th><th colspan="12">p-value</th></tr>
<tr><th colspan="2">$b_{DP}=0.5$, $l_{DP}=1$</th><th colspan="2">$b_{DP}=1$, $l_{DP}=1$</th><th colspan="2">$b_{DP}=1.5$, $l_{DP}=1$</th><th colspan="2">$b_{DP}=0.5$, $l_{DP}=2$</th><th colspan="2">$b_{DP}=1$, $l_{DP}=2$</th><th colspan="2">$b_{DP}=1.5$, $l_{DP}=2$</th></tr>
<tr><td rowspan="2">$PAT \neg\rightarrow GDP$</td><td>0.08</td><td>0.03</td><td>0.43</td><td>0.13</td><td>0.22</td><td>0.19</td><td>0.26</td><td>0.08</td><td>0.07</td><td>0.04</td><td>0.09</td><td>0.15</td></tr>
<tr><td colspan="2">0.38</td><td colspan="2">0.51</td><td colspan="2">0.42</td><td colspan="2">0.09</td><td colspan="2">0.67</td><td colspan="2">0.43</td></tr>
<tr><td rowspan="2">$GDP \neg\rightarrow PAT$</td><td>0.34</td><td>0.42</td><td>0.65</td><td>0.35</td><td>0.62</td><td>0.28</td><td>0.08</td><td>0.16</td><td>0.73</td><td>0.32</td><td>0.67</td><td>0.27</td></tr>
<tr><td colspan="2">0.84</td><td colspan="2">0.82</td><td colspan="2">0.79</td><td colspan="2">0.82</td><td colspan="2">0.72</td><td colspan="2">0.62</td></tr>
<tr><td rowspan="2">$PAT \neg\rightarrow EMPL$</td><td>0.09</td><td>0.13</td><td>0.06</td><td>0.25</td><td>0.21</td><td>0.28</td><td>0.42</td><td>0.53</td><td>0.18</td><td>0.46</td><td>0.08</td><td>0.58</td></tr>
<tr><td colspan="2">0.32</td><td colspan="2">0.05</td><td colspan="2">0.42</td><td colspan="2">0.78</td><td colspan="2">0.72</td><td colspan="2">0.62</td></tr>
<tr><td rowspan="2">$EMPL \neg\rightarrow PAT$</td><td>0.23</td><td>0.35</td><td>0.76</td><td>0.46</td><td>0.65</td><td>0.59</td><td>0.23</td><td>0.38</td><td>0.73</td><td>0.61</td><td>0.65</td><td>0.55</td></tr>
<tr><td colspan="2">0.21</td><td colspan="2">0.46</td><td colspan="2">0.67</td><td colspan="2">0.44</td><td colspan="2">0.69</td><td colspan="2">0.73</td></tr>
<tr><td rowspan="2">$GDP \neg\rightarrow EMPL$</td><td>0.57</td><td>0.23</td><td>0.65</td><td>0.19</td><td>0.25</td><td>0.54</td><td>0.15</td><td>0.42</td><td>0.26</td><td>0.25</td><td>0.23</td><td>0.29</td></tr>
<tr><td colspan="2">0.84</td><td colspan="2">0.45</td><td colspan="2">0.38</td><td colspan="2">0.19</td><td colspan="2">0.43</td><td colspan="2">0.31</td></tr>
<tr><td rowspan="2">$EMPL \neg\rightarrow GDP$</td><td>0.25</td><td>0.36</td><td>0.49</td><td>0.48</td><td>0.54</td><td>0.39</td><td>0.23</td><td>0.27</td><td>0.63</td><td>0.44</td><td>0.10</td><td>0.29</td></tr>
<tr><td colspan="2">0.92</td><td colspan="2">0.58</td><td colspan="2">0.53</td><td colspan="2">0.07</td><td colspan="2">0.55</td><td colspan="2">0.33</td></tr>
</table>

Source: own calculations.

As one can see nonlinear causality running from *PAT* to *GDP* was confirmed by all nonlinear tests (for residuals from unrestricted VECM feedback was even detected). Moreover, we found strong support for claiming that there is nonlinear unidirectional causality from the number of patents to employment. This was confirmed by an analysis of the residuals of unrestricted VEC model and the residuals of the augmented model applied in the TY procedure.

The results of all the methods provided relatively strong support for claiming that the number of patents registered in The Patent Office of Poland is a causal factor for movements of real GDP and employment both in the short and long run. Therefore, conjecture 1 should be accepted. Moreover, this conclusion, in general, was confirmed by the results of two completely different methods (a two-stage analysis of the VEC model and the TY approach with respective nonlinear tests), which validates this major conclusion and confirms its robustness when exposed to statistical tools. Another important conclusion supported by the results of both econometric approaches is the causal influence of employment on *GDP*. Therefore, we found that *PAT* causes *GDP* directly and indirectly (through a causal influence on employment). To summarize one may present the structure of causal dependences between *PAT*, *EMPL* and *GDP* in the following figure:

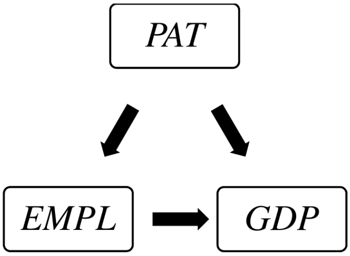

Figure 2. The structure of causal links between the *PAT*, *EMPL* and *GDP*

Source: material prepared by authors.

We must remember that Figure 2 presents the structure of causal dependencies between *PAT*, *EMPL* and *GDP*, which was evidently supported by our empirical results. Some other causalities (the short run impact of employment on *PAT*, causality from *GDP* to *EMPL*) were also reported, but they were not supported by the results of both econometric procedures applied in this paper. There is no reason to treat these causal links as unimportant, although they were found to be far less significant than those presented in Figure 2.

6.2. R&D expenditures and GDP

As in the previous case (subsection 6.1), in the first step cointegration analysis was carried out for the *RD*, *GDP* and *EMPL* variables.[28] The following Table contains the results of cointegration tests performed under the assumption of Johansen's third variant and 4 lags (for variables in first differences):

Table 7. Results of cointegration analysis for the *RD*, *GDP* and *EMPL* variables

		Johansen Trace test		Johansen Maximal Eigenvalue test	
Hypothesized number of cointegrating vectors	Eigenvalue	Trace statistic	*p*-value	Maximal Eigenvalue statistic	*p*-value
Zero	0.41	34.45	0.01	18.60	0.09
At most one	0.36	15.95	0.04	15.95	0.02
At most two	0.00	0.00	0.97	0.00	0.97

Source: own calculations.

Regardless of the type of test used the dimension of cointegration space was found to be equal to two (at 10% significance level). As in the previous case (Table 4)

[28] The preliminary part of cointegration analysis (specification of the type of deterministic trend, lag selection procedure) was performed in exactly the same way as in the case of *PAT*, *EMPL* and *GDP* variables.

the nonstationarity of all variables was once again confirmed. In the next step we estimated a suitable VEC model assuming 4 lags (for first differences) and two cointegrating vectors.[29] Table 8 contains *p*-values obtained while testing for linear short and long run Granger causality using unrestricted VEC model and the sequential elimination of insignificant variables:

Table 8. Analysis of causal links between *RD*, *GDP* and *EMPL* variables (VEC model)

<table>
<tr><td colspan="9">Short run</td></tr>
<tr><td rowspan="3">Null hypothesis</td><td colspan="8">p-value</td></tr>
<tr><td colspan="4">Unrestricted</td><td colspan="4">Sequential</td></tr>
<tr><td colspan="2">Asymptotic</td><td colspan="2">Bootstrap[a]</td><td colspan="2">Asymptotic</td><td colspan="2">Bootstrap[a]</td></tr>
<tr><td>RD ¬→ GDP</td><td colspan="2">0.16</td><td colspan="2">0.18</td><td colspan="2">0.07</td><td colspan="2">0.03</td></tr>
<tr><td>GDP ¬→ RD</td><td colspan="2">0.48</td><td colspan="2">0.33</td><td colspan="2">0.35</td><td colspan="2">0.49</td></tr>
<tr><td>RD ¬→ EMPL</td><td colspan="2">0.84</td><td colspan="2">0.88</td><td colspan="2">0.46</td><td colspan="2">0.37</td></tr>
<tr><td>EMPL ¬→ RD</td><td colspan="2">0.21</td><td colspan="2">0.19</td><td colspan="2">0.06</td><td colspan="2">0.03</td></tr>
<tr><td>GDP ¬→ EMPL</td><td colspan="2">0.44</td><td colspan="2">0.38</td><td colspan="2">0.13</td><td colspan="2">0.09</td></tr>
<tr><td>EMPL ¬→ GDP</td><td colspan="2">0.03</td><td colspan="2">0.08</td><td colspan="2">0.02</td><td colspan="2">0.07</td></tr>
<tr><td colspan="9">Long run</td></tr>
<tr><td rowspan="3">Equation</td><td colspan="4">p-value of EC_1 component</td><td colspan="4">p-value of EC_2 component</td></tr>
<tr><td colspan="2">Unrestricted</td><td colspan="2">Sequential</td><td colspan="2">Unrestricted</td><td colspan="2">Sequential</td></tr>
<tr><td>Asymptotic</td><td>Bootstrap[a]</td><td>Asymptotic</td><td>Bootstrap[a]</td><td>Asymptotic</td><td>Bootstrap[a]</td><td>Asymptotic</td><td>Bootstrap[a]</td></tr>
<tr><td>GDP</td><td>0.03</td><td>0.05</td><td>0.01</td><td>0.05</td><td>0.41</td><td>0.38</td><td>0.38</td><td>0.67</td></tr>
<tr><td>RD</td><td>0.01</td><td>0.00</td><td>0.00</td><td>0.00</td><td>0.01</td><td>0.00</td><td>0.06</td><td>0.04</td></tr>
<tr><td>EMPL</td><td>0.23</td><td>0.38</td><td>0.01</td><td>0.03</td><td>0.12</td><td>0.06</td><td>0.02</td><td>0.02</td></tr>
</table>

[a] *Number of bootstrap replications established using the Andrews and Buchinsky method varied between 1589 and 2939.*

Source: own calculations.

As we can see, this time the results obtained for the unrestricted VEC model provided a basis for claiming that there is unidirectional short run causality running from employment to GDP. No other short run dependencies were found for the unrestricted model, although in two cases (testing causality from *RD* to *GDP* and from

[29] The first vector (denoted as EC_1) involved *GDP* and *RD* while the second one (EC_2) involved *EMPL* and *RD*. All coefficients in EC_1 and EC_2 were found to be significant at 5% (EC_1) and 10% (EC_2). Moreover, the signs of *RD* coefficients were different than those of *GDP* (EC_1) and *EMPL* (EC_2), which also seems to be quite reasonable and reflects the upward trends in all time series under study (comp. Figure 1 and footnote 26).

EMPL to *RD*) the *p*-values were relatively small. The results obtained for sequentially restricted equations confirmed the existence of short run causality from *EMPL* to *GDP*. However, this time causality from *RD* to *GDP* and from *EMPL* to *RD* was found to be significant at a 10% level. On the other hand, both methods applied to the VEC model provided relatively solid evidence for the existence of long run feedback between quarterly R&D expenditures and employment as well as between *RD* and *GDP*. The long term impact of *GDP* on *EMPL* was found to be statistically significant only after the sequential elimination.

As in subsection 6.1, the Toda–Yamamoto approach was also applied to the *RD*, *GDP* and *EMPL* variables. The following Table contains the outcomes of the TY procedure:

Table 9. Analysis of causal links between *RD*, *GDP* and *EMPL* variables (TY approach)

Null hypothesis	*p*-value	
	Asymptotic	Bootstrap[a]
$RD \neg\rightarrow GDP$	**0.06**	**0.08** ($N = 1679$)
GDP ¬→ RD	0.76	0.81 ($N = 2179$)
RD ¬→ EMPL	0.83	0.75 ($N = 1839$)
EMPL ¬→ RD	0.15	0.11 ($N = 1659$)
GDP ¬→ EMPL	0.45	0.39 ($N = 1659$)
EMPL ¬→ GDP	0.23	0.19 (N = 2059)

[a] *Parameter N denotes the number of bootstrap replications established according to the Andrews and Buchinsky procedure.*

Source: own calculations.

The analysis of outcomes presented in Table 9 leads to the conclusion that R&D expenditures Granger cause GDP. Although the *p*-values obtained while testing for causality in other directions were greater than 0.10, the dynamic impact of *EMPL* on *RD* was found to be "almost" significant (*p*-value at the level of 0.11 in the bootstrap variant).

The last stage of causality analysis was based on the application of Diks and Panchenko's nonlinear test. As in the previous case, the test was performed for the time series of residuals. Since no significant evidence of heteroscedasticity was found, no filtering was used. Table 10 presents the *p*-values obtained while testing for nonlinear Granger causality between *RD*, *GDP* and *EMPL*. The test outcomes are presented according to the rule preceding presentation of Table 6:

Table 10. Analysis of nonlinear causal links between the *RD*, *GDP* and *EMPL* variables

Null hypothesis	*p*-value											
	b_{DP}=0.5, l_{DP}=1		b_{DP}=1, l_{DP}=1		b_{DP}=1.5, l_{DP}=1		b_{DP}=0.5, l_{DP}=2		b_{DP}=1, l_{DP}=2		b_{DP}=1.5, l_{DP}=2	
RD ¬→ *GDP*	0.48	0.53	0.44	0.28	0.61	0.36	0.43	0.53	0.26	0.47	0.34	0.84
	0.69		0.34		0.31		0.72		0.29		0.23	
GDP ¬→ RD	0.69	0.43	0.17	0.27	0.58	0.73	0.81	0.62	0.71	0.53	0.81	0.76
	0.71		0.21		0.55		0.62		0.28		0.45	
RD ¬→ EMPL	0.81	0.75	0.74	0.67	0.65	0.62	0.36	0.48	0.43	0.29	0.49	0.71
	0.42		0.41		0.61		0.50		0.35		0.43	
EMPL ¬→ RD	**0.08**	0.19	**0.06**	0.32	0.21	0.37	0.22	0.72	0.21	0.63	0.47	0.59
	0.09		0.34		0.44		0.21		0.27		0.29	
GDP ¬→ EMPL	0.24	0.83	0.92	0.72	0.31	0.49	0.81	0.67	0.55	0.42	0.23	0.44
	0.36		0.18		0.28		0.31		**0.06**		0.37	
EMPL ¬→ GDP	0.27	0.57	0.73	0.69	0.63	0.31	0.14	0.38	0.63	0.46	0.71	0.52
	0.30		0.63		**0.08**		0.57		**0.09**		0.15	

Source: own calculations.

This time nonlinear causality running from *EMPL* to *RD* was confirmed by all but one test (for residuals from sequentially restricted VECM no nonlinear causality was reported). Moreover, the analysis of the residuals from the augmented model applied in the TY procedure provided a basis for claiming that there is nonlinear feedback between *GDP* and *EMPL*.

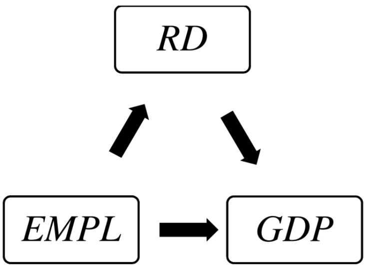

Figure 3. The structure of causal links between the *RD*, *EMPL* and *GDP*

Source: material prepared by authors.

Generally, the results of all the methods provided relatively strong support for claiming that R&D expenditure is a causal factor for movements of real GDP both in the short and long run, which supports conjecture 3. Moreover, employment was found to Granger cause *RD* and *GDP*, which additionally provides a basis for accepting conjecture 2. These conclusions, in general, were once again confirmed by the results of the two econometric methods applied, which is especially important in terms of the validation and robustness of the empirical results. To summarize one may present the structure of causal dependences between *RD*, *EMPL* and *GDP* in the following Figure 3.

We should once again stress that Figure 3 presents the structure of causal dependences between *RD*, *EMPL* and *GDP* which was evidently supported by our empirical results. Some other causalities (in opposite directions to those presented in Figure 3) were also reported (mostly in the long term). However, these results were not confirmed by both econometric procedures applied in this paper, which leads to some doubt about their existence.

6.3. Outlays on R&D versus number of patents

The results presented in subsections 6.1 and 6.2 provided evidence for claiming that conjecture 4 is true, in other words there is Granger causality running from the number of patents to R&D expenditure (indirectly, as *PAT* causes employment and employment causes *RD*). This conclusion is of great importance for a number of social groups related to the R&D sector (researchers, politicians, investors). However, it is based on results obtained for two different econometric models. Therefore, in order to confirm or contradict this finding we additionally performed an analysis of causal dependences between *PAT* and *RD* using a model which involves both these variables.

Since *RD* and *PAT* were found to be nonstationary we first performed a cointegration analysis for these variables.[30] After establishing one cointegration vector (at 10% significance level) suitable VEC model was estimated. The results of this estimation provided evidence of long run feedback between *RD* and *PAT* (at 10% level in asymptotic and bootstrap-based variants).[31] Moreover, the analysis of residuals from the VEC model provided evidence for claiming that nonlinear causality runs from *PAT* to *RD*. The findings obtained in the VEC-based procedure (that is linear (long run) and nonlinear unidirectional causality from patents to R&D expenditures) were confirmed after the application of the TY-based method.[32] The following Table contains a summary of the causality analysis conducted for the *RD* and *PAT* variables in a two-dimensional framework:

[30] We followed the procedure applied in subsections 6.1 and 6.2 (specification of the type of deterministic trend, lag selection procedure). All information criteria (AIC, BIC, HQ) pointed at one lag (for levels). Thus, in the next step both Johansen's tests were applied to examine cointegration properties in a model with one lag.

[31] The cointegrating equation was of the form $EC_t = PAT_t - 1.28RD_t + 2.9$ with all components significant at 10% level.

[32] It is worth noting that statistical properties of both models (VEC model and augmented VAR model applied in TY method) were relatively satisfying (for example, whiteness of error term).

Table 11. Analysis of causal links between *RD* and *PAT* based on models with one lag

Null hypothesis	VEC-based procedure[a]			TY-based procedure[a]		
	Linear test[b]		Nonlinear test	Linear test		Nonlinear test
	Asymptotic	bootstrap[c]		asymptotic	bootstrap[c]	
$RD \neg\rightarrow PAT$	Do not reject	Do not reject	Do not reject	Do not reject	Do not reject	Do not reject
$PAT \neg\rightarrow RD$	**Reject**	**Reject**	**Reject**	**Reject**	**Reject**	Do not reject

[a] *Assumed significance level is* 10%*, bold face indicates finding a significant causal link.*

[b] *Since only one lag was examined (in levels) short run causality could not be examined.*

[c] *Number of bootstrap replications established using the Andrews and Buchinsky method varied between 1769 and 2659.*

Source: own calculations.

The analysis of models based on one lag provided solid evidence for claiming that there is unidirectional Granger causality running from the number of patents to R&D expenditure. This finding was confirmed by different econometric methods, which is clear evidence of robustness and surely validates this result. Although the choice of one lag (justified by information criteria) did not lead to significant statistical difficulties in either method, it also has got a serious drawback. A period of only one quarter seems to be definitely too short to capture all the possible interactions between these variables, since previous studies dealing with similar issues (e.g. [Jalles 2010]) provided a basis for claiming that this period should cover about 1-2 years. Therefore, we additionally conducted an examination of causality between *RD* and *PAT* assuming 4 and 6 lags for variables in their levels (in the VEC model and nonaugmented VAR model used in the TY method).[33] We followed previously used procedure (linear VEC and TY-based procedures, both supplemented with Diks and Panchenko nonlinear tests). The following Table presents a summary of the results.

Both these methods provided solid evidence for claiming that the number of patents registered in The Patent Office of Poland Granger causes R&D expenditure, in other words conjecture 4 should clearly be accepted. This major finding confirms the results obtained in both three-dimensional models (subsections 6.1 and 6.2) and one-lag-based models, which is important in terms of robustness and the validation of empirical findings. Moreover, we found strong support for claiming that current R&D expenditures are especially sensitive to fluctuations in the number of patents from the two previous quarters.[34] As with previous results, the outcomes presented in

[33] The arbitrary establishment of lag parameter is an alternative method to the application of popular model selection criteria and it has been commonly used in previous papers (see, for example, [Granger et al. 2000]). Moreover, we did not consider more than 6 lags due to the size of examined sample.

[34] This was reflected in detailed estimation results, especially in sequential elimination variant.

Table 12. Analysis of causal links between *RD* and *PAT* based on models with arbitrarily chosen lags

<table>
<tr><td colspan="8">VEC-based procedure[a]</td></tr>
<tr><td rowspan="3">Number of lags (levels)</td><td rowspan="3">Null hypothesis</td><td colspan="4">Linear test[b]</td><td colspan="2">Nonlinear test</td></tr>
<tr><td colspan="2">unrestricted</td><td colspan="2">sequential</td><td rowspan="2">post-unrestricted</td><td rowspan="2">post-sequential</td></tr>
<tr><td>asymptotic</td><td>bootstrap[c]</td><td>asymptotic</td><td>bootstrap[c]</td></tr>
<tr><td rowspan="2">4</td><td>RD ¬→ PAT</td><td>Do not reject</td><td>Do not reject</td><td>Do not reject</td><td>Do not reject</td><td>Do not reject</td><td>Do not reject</td></tr>
<tr><td>PAT ¬→ RD</td><td>Reject</td><td>Reject</td><td>Reject</td><td>Reject</td><td>Do not reject</td><td>Do not reject</td></tr>
<tr><td rowspan="2">6</td><td>RD ¬→ PAT</td><td>Do not reject</td><td>Do not reject</td><td>Do not reject</td><td>Do not reject</td><td>Do not reject</td><td>Do not reject</td></tr>
<tr><td>PAT ¬→ RD</td><td>Reject</td><td>Reject</td><td>Reject</td><td>Reject</td><td>Do not reject</td><td>Do not reject</td></tr>
<tr><td colspan="8">TY–based procedure[a]</td></tr>
<tr><td rowspan="2">Number of lags (levels of nonaugmented model)</td><td rowspan="2">Null hypothesis</td><td colspan="4">Linear test</td><td colspan="2" rowspan="2">Nonlinear test</td></tr>
<tr><td colspan="2">asymptotic</td><td colspan="2">bootstrap[c]</td></tr>
<tr><td rowspan="2">4</td><td>RD ¬→ PAT</td><td colspan="2">Do not reject</td><td colspan="2">Do not reject</td><td colspan="2">Do not reject</td></tr>
<tr><td>PAT ¬→ RD</td><td colspan="2">Reject</td><td colspan="2">Reject</td><td colspan="2">Do not reject</td></tr>
<tr><td rowspan="2">6</td><td>RD ¬→ PAT</td><td colspan="2">Do not reject</td><td colspan="2">Do not reject</td><td colspan="2">Reject</td></tr>
<tr><td>PAT ¬→ RD</td><td colspan="2">Reject</td><td colspan="2">Reject</td><td colspan="2">Do not reject</td></tr>
</table>

[a] *The significance level is* 10%, *bold face indicates finding a significant causal link.*
[b] *In both cases no evidence of cointegration (at* 10% *level) was found, thus long run causality could not be examined.*
[c] *Number of bootstrap replications established using the Andrews and Buchinsky method varied between* 1649 *and* 3019.

Source: own calculations.

Table 12 confirmed that evidence for causality running in the opposite direction (that is from *RD* to *PAT*) is markedly weak.

7. Concluding remarks

The main goal of this paper is the examination of causal interdependencies between different measures of technological progress and GDP in Poland on the basis of quarterly data for the period Q1 2000-Q4 2009. We performed our research on the number of patents registered in The Patent Office of Poland as well as on R&D expenditures. The empirical research was performed in a three-dimensional framework with employment chosen as an additional variable, since a two--dimensional approach involving only GDP and one of the measures of technological progress may be seriously biased due to the omission of important variables. In order to conduct a comprehensive causality analysis we applied both traditional methods as well as some recently developed econometric tools.

We found strong evidence for claiming that technological progress caused GDP in Poland in the period under study. This important conclusion was supported by results obtained for two analyzed measures of technological progress and two (different) econometric techniques (the concept of cointegration and the idea of Toda–Yamamoto, both supplemented by Diks and Panchenko's nonlinear test), which surely is a solid proof of robustness. Moreover, our empirical research provided solid evidence for the robustness of the causality running from employment to GDP. However, the analysis of the models provided mixed results on causality between both measures of technological progress and employment. Patents are usually thought of as the fruition of R&D spending and as a measure of technological progress. In general, the number of patents was found to cause employment while for R&D expenditures causality runs in the opposite direction. This may somehow be interpreted as evidence of (indirect) causality running from patents (the output of the process of scientific and technological development) to R&D expenditures (the input of this process). Since the direction of causality between these variables is of great importance, we additionally conducted separate research involving only these variables. The results of this research confirmed unidirectional causality from patent applications to outlays on R&D. In other words, the level of effectiveness of the R&D sector is a causal factor for the future of its budget. The more registered innovations and the greater their importance (profitability) to manufacturers, the higher R&D outlays can be expected in the following periods. Moreover, the ratio of patents to R&D spending in the Polish economy did not exhibit large fluctuations over the same quarters in the decade under study.

We also found evidence for claiming that the common opinion that there should be a strong causal link in the opposite direction (from input to output in the R&D sector) is rather naive. First of all, the entire lag between the moment when R&D is conducted and when the research bears fruit (patents) can be long and variable.

The size of R&D expenditures does not have to be a determiner of the number of patents, since it is impossible to say that progress in science and technology is proportional to available funds. The latter seems to be especially evident in the case of Poland where public R&D spending dominates. Although high technological standards lead to the achievement of an advantage on the market, they are also related to risk as the results of scientific research (despite high budgets) may be unsatisfactory or unprofitable. Another general reason for lack of causality from R&D to patents may be explained by the fact that the propensity to patenting is decreasing with time. Patents are being increasingly superseded by other means of obtaining returns from the R&D investment of companies (for example secrecy).

In general, the results of this paper provide solid evidence for claiming that the growth of the Polish economy is strongly related to technological progress. Although in the period under study the rate of growth of R&D expenditure in Poland was generally similar to the GDP growth rate, its absolute size is still small. The results of this research also have important policy implications. They strongly suggest that a significant increase in public and private involvement in supporting scientific and technological research should bring essential advantages (with respect to the level of employment and the level of output).

There is a common view that firms and government invest their financial assets in order to develop new products or services. Usually, the results can be achieved sporadically since the process of developing inventions is not a continuous one and is charged with a relatively high level of risk. The fact that innovations spread through the economy as a result of imitation is commonly accepted in the literature. Many firms and countries devote large resources to achieve the imitation of new products. This is especially reasonable in the case of less developed countries since discovering new products is costly, takes time and includes uncertainty. Therefore, future research of the impact of R&D and the volume of investment outlays on GDP growth in countries like Poland should try to delineate the effects of inventions and the effects of imitations.

Another problem for future research on the impact of technology on economic growth follows from fast growing share of services in the most highly developed economies, which makes R&D expenditure and the number of patents biased measures of technological changes. Thus, it seems necessary to supplement future research on R&D spending and the number of patents as measures of technological progress in Poland with more relevant indicators also taking into account the improvement of the quality of services.

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Literature

Agiakoglu C., Newbold P., *Empirical Evidence on Dickey–Fuller Type Tests*, "Journal of Time Series Analysis", Vol. 13, 1992.

Andrews D.W.K., Buchinsky M., *A Three-Step Method for Choosing the Number of Bootstrap Repetitions*, "Econometrica", Vol. 68, 2000.

Arrow K., *The Economic Implications of Learning by Doing*, "Review of Economic studies", Vol. 29, 1962.

Baek E.G., Brock W.A., *A general test for Granger causality: Bivariate model*, "Technical Report", Iowa State University and University of Wisconsin, Madison, 1992.

Bakalarczyk S., *Diagnosis of the Polish economy. Present state and perspectives*, Difin, Warszawa, 2008.

Bean A.S., *Why some R&D organizations are more productive than others*, "Research and Technology Management", Vol. 38, 1995.

Bernstein J.I., Nadiri I.M., *Inter-industry R&D spillovers, rates of return and production in high-tech industries*, "American Economic Review, Papers and Proceedings", Vol. 78, 1988.

Branstetter L.G., *Are Knowledge Spillovers International or Intranational in Scope? Microeconometric Evidence from the U.S. and Japan*, "Journal of International Economics", Vol. 53, 2001.

Brock W.A., Causality, chaos, explanation and prediction in economics and finance, [in:] *Beyond Belief: Randomness, Prediction and Explanation in Science*, eds. Casti J., Karlqvist A., CRC Press, Boca Raton 1991.

Bruneau C., Jondeau E., *Long-Run Causality, with an Application to International Links Between Long-Term Interest Rates,* "Oxford Bulletin of Economics and Statistics", Vol. 61(4) 1999.

Cohen W.M., Levinthal D.A., *Innovation and Learning: The Two Faces of R&D*, "The Economic Journal", Vol. 99, 1989.

Diks C.G.H., DeGoede J., A general nonparametric bootstrap test for Granger causality, [in:] *Global analysis of dynamical system*, eds. Broer, H.W., Krauskopf, B., Vegter G., Institute of Physics Publishing, Bristol 2001.

Diks C.G.H., Panchenko V., *A new statistic and practical guidelines for nonparametric Granger causality testing,* "Journal of Economic Dynamics and Control", Vol. 30, 2006.Eurostat, *Patents and R&D personnel*, "Statistics in Focus", 107, 2008.

Fagerberg J., *International Competitiveness*, "The Economic Journal", Vol. 98, 1988.

Fagerberg J., *Technological progress, structural change and productivity growth: a comparative study,* "Structural Change and Economic Dynamics", Vol. 11, 2000.

Falk M., *What drives business research and development (R&D) intensity across Organisation for Economic Cooperation and Development (OECD) countries,* "Applied Economics", Vol. 38, 2006.

Firth L., Mellor D., *Learning and new growth theories*, "Research Policy", Vol. 29, 2000.

Freeman C., Soete L., *The Economics of Industrial Innovation*, MIT Press, Massachusetts, 1997.

Goel R.K., Payne J.E., Ram R., *R&D expenditures and U.S. economic growth: A disaggregated approach,* "Journal of Policy Modeling", Vol. 30, 2008.

Granger C.W.J., Huang B., Yang C., *A bivariate causality between stock prices and exchange rates: evidence from recent Asian Flu*, "The Quarterly Review of Economics and Finance", Vol. 40, 2000.

Granger C.W.J., *Investigating causal relations by econometric models and cross spectral methods*, "Econometrica", Vol. 37, 1969.
Granger C.W.J., Newbold P., *Spurious regression in econometrics*, "Journal of Econometrics", Vol. 2, 1974.
Granger C.W.J., *Some recent developments in the concept of causality*, "Journal of Econometrics", Vol. 39, 1988.
Griliches Z., *Patent Statistics as Economic Indicators: A Survey*, "Journal of Economic Literature", Vol. 28, 1990.
Griliches Z., *R&D and Productivity: Econometric Results and Measurement Issues*, [in:] *Handbook of the Economics of Innovation and Technological Change*, ed. Stoneman, P., Blackwell, Oxford 1996.
Griliches Z., Regev H., *Firm productivity in Israeli industry 1979–1988*, "Journal of Econometrics", Vol. 65, 1995.
Gurgul H., Lach Ł., *The causal link between Polish stock market and key macroeconomic aggregates,* "Betriebswirtschaftliche Forschung und Praxis", Vol. 4, 2010.
Gurgul H., Lach Ł., *The role of coal consumption in the economic growth of the Polish economy in transition,* "Energy Policy", Vol. 39, 2011.
Hacker S.R., Hatemi–J A., *Tests for causality between integrated variables using asymptotic and bootstrap distributions: theory and application*, "Applied Economics", Vol. 38, 2006.
Hall B., Mairesse J., *Exploring the relationship between R&D and productivity in French manufacturing firms,* "Journal of Econometrics", Vol. 65, 1995.
Helpman E., Coe D.T., *International R&D Spillovers*, "European Economic Review", Vol. 39, 1995.
Horowitz J.L., Bootstrap methods in econometrics: Theory and numerical performance, [in:] *Advances in Economics and Econometrics: Theory and Applications*, eds. Kreps, D.M., Wallis, K.F., Cambridge University Press, Cambridge 1995.
Jalles J.T., *How to measure innovation? New evidence of the technology-growth linkage*, "Research in Economics", Vol. 64, 2010.
Johansen S., *Likelihood-based Inference in Cointegrated Vector Autoregressive Models*, Oxford University Press, Oxford 1995.
Krugman P., *Rethinking International Trade*, MIT Press, Cambridge 1990.
Lichtenberg F.R., Siegel D., *The impact of R&D investment on productivity: new evidence using R&D–LRD data*, "Economic Inquiry", Vol. 29, 1991.
Lipsey R.G., Carlaw K. *What does total factor productivity measure?* (available at http://www.csls.ca/ipm/1/lipsey-e.pdf), 2001.
Lucas R., *On the Mechanics of Economic Development*, "Journal of Monetary Economics", Vol. 22, 1988.
Lütkepohl H., *Introduction to Multiple Time Series Analysis,* Springer–Verlag, New York 1993.
Madden G., Savage S.J., *R&D spillovers, information technology and telecommunications, and productivity in Asia and the OECD,* "Information Economics and Policy", Vol. 12, 2000.
Mansfield E., *Academic Research and Industrial Innovations*, "Research Policy", Vol. 20, 1991a.
Mansfield E., *Microeconomics: Theory and Application*, Norton & Company, Inc., New York 1991b.
Mulas-Granados C., Sanz I., *The dispersion of technology and income in Europe: Evolution and mutual relationship across regions*, "Research Policy", Vol. 37, 2008.
OECD. *Science, technology and industry outlook 2000 – Chapter II: Science, technology and innovation policy in OECD countries – A review of recent developments*, OECD, Paris 2000.
Paulsen J., *Order determination of multivariate autoregressive time series with unit roots,* "Journal of Time Series Analysis", Vol. 5, 1984.
Pavitt K., *The inevitable limits of EU R&D funding*, "Research Policy", Vol. 27, 1998.
Peterson J., Sharp M., *Technology Policy in the European Union*, Macmillan Press, London 1998.

Phillips P.C.B., *Understanding the spurious regression in econometrics*, "Journal of Econometrics", Vol. 33, 1986.

Raa T., Wolff E., *Engines of growth in the US economy*, "Structural Change and Economic Dynamics", Vol. 11, 2000.

Romer P., *Endogenous technological change*, "Journal of Political Economy", Vol. 98, 1990.

Romer P., *Increasing Returns and Long-Run Growth*, "Journal of Political Economy", Vol. 94, 1986.

Scherer F.M., *Lagging productivity growth measurement, technology and shock effects*, "Empirica", Vol. 20, 1993.

Schumpeter J., *Theorie der wirtschaftlichen Entwicklung*; Neuausgabe hrgg. von Röpke J. und Stiller O., Berlin 2006, 1911.

Solow R., *Technical change and the aggregate production function*, "Review of Economics and Statistics", Vol. 34, 1957.

Takayama A., *Mathematical Economics*, Cambridge University Press, Cambridge, 1985.

Terleckyj N.E., Direct and indirect effects of industrial R&D on the productivity growth of industries, [in:] *New Developments in Productivity Measurement and Analysis*, eds. Kendrik, J.N., Vaccara B.N., University Chicago Press, Chicago 1980.

Terleckyj N.E., *Effect of R&D on the Productivity Growth of Industries*, National Planning Association, Washington D.C. 1974.

Toda H.Y., Yamamoto T., *Statistical inference in vector autoregressions with possibly integrated processes*, "Journal of Econometrics", Vol. 66, 1995.

Tsipouri L.J., *Innovations for European competitiveness and cohesion: opportunities and difficulties of co-evolution,* "Science and Public Policy", Vol. 31, 2004.

Wzrost gospodarczy w krajach transformacji: konwergencja czy dywergencja, ed. R. Rapacki, PWE, Warszawa 2009.

Zif J., McCarthy D., *R&D cycle: The influence of product and process R&D on short-term ROI*, "IEEE Transactions on Engineering Management", Vol. 44, 1997.

POSTĘP TECHNICZNY A WZROST GOSPODARCZY: PRZYPADEK POLSKIEJ GOSPODARKI

Streszczenie: W artykule przedstawiono wyniki testowania przyczynowości w sensie Grangera pomiędzy liczbą patentów, nakładami na BiR i PKB w Polsce w oparciu o dane kwartalne dla okresu 2000 Q1-Q4 2009. Wyniki badań potwierdziły istotny wpływ postępu technicznego na PKB w Polsce. Co więcej, stwierdzono, iż liczba patentów jest przyczyną zmian wielkości zatrudnienia, która z kolei wpływa na poziom nakładów na BiR. Wpływ liczby patentów na wielkość wydatków na BiR został także potwierdzony poprzez analizę dodatkowego dwuwymiarowego modelu. Pomimo, iż nakłady na BiR w Polsce są wciąż niskie, przeprowadzone badania dostarczyły dowodów potwierdzających istotny wpływ postępu technicznego na wzrost PKB. Wzorem innych wysoko rozwiniętych krajów OECD tak rząd jak i prywatni przedsiębiorcy powinni zwiększyć wielkość inwestycji w sektorze BiR polskiej gospodarki.

Słowa kluczowe: patenty, sektor BiR, wzrost gospodarczy, przyczynowość w sensie Grangera. **Klasyfikacja JEL:** C32; O31; O34; O40.