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Abstract

In this paper the results of testing the causal interdependence between technological progress and GDP in Poland are presented. The results obtained for quarterly data from the period Q1 2000 – Q4 2009 indicate causality running from technological progress to GDP in Poland. In addition, causality from number of patents to employment and from employment to R&D outlays is found, which indicates causality from patents to R&D expenditure. The robustness of these results is also approved.

The empirical findings of this paper imply some policy recommendations. Polish government and private firms should definitely increase investment in developing new technologies.

Keywords: Patents, R&D sector, economic growth, Granger causality.

JEL classification: C32; O31; O34; O40.

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1. Introduction

A growth in national income means that in a given economy the main macroeconomic indicators, namely production, employment, investment, consumption and exports grow. If in an economy quantitative changes are accompanied by qualitative changes, we observe economic development. A decrease in unemployment (increase in employment) may signal economic growth, but not necessarily economic development. The process of development is characterized not only by an increase in the number of employed workers but mainly by the improvement of their skills and qualifications. This is an important precondition for the improvement of existing capital – modernization by the introduction of technical progress. Economic development requires the restructuring of an economy – an increase in the proportion of modern sectors and a reduction of old and inefficient ones.

The improvement of the business cycle stimulates an increase in investment, employment, income, and output. Moreover, it supports the demand for production factors. Total expenditure consists of private consumption expenditure, government expenditure (on consumption and on investment), investment by the private sector and net exports. Each economy tends to balance aggregate demand and supply. A rise in aggregate demand is a precondition for a rise in aggregate supply, if there is spare production capacity. If there is no spare capacity, an increase in demand can start inflation processes.

These observations lead to the conclusion that economic policies should be oriented towards an increase in long run output capacity. The capacity of an economy depends on the size of production factors and the efficiency of their application to the production process. In classical economics, capital goods are one of three (or four) factors of production. The others are land, labour and (in some versions) organization, entrepreneurship, or management.

The modern economic literature stresses the role of technical progress and human capital in long run economic growth. Technical 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 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 word 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 technical 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 by 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 economic growth is still not clear. It is practically impossible to check directly effects of policies geared to introducing technical 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 we restrict our attention to an investigation of the effects (in the sense of Granger causality) of technical progress (represented by R&D expenditure and patent applications) on the growth rate of the Polish economy in the last decade.

The remainder of the paper is organized as follows. In the next section we give a literature overview finding that most of previous papers report important role of technological innovations in economic development. In section 3 we formulate the main conjectures concerning the interdependencies 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 discussion of empirical results. In last section, we conclude that the empirical results of this paper provide solid evidence for claiming that the growth of the Polish economy strongly depends on technological progress and we formulate recommendations for the future research in this field in Poland.

2. Literature overview

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

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 (1991)) 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 and 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 (2001) 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. 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 (2000) the elasticity of production with respect to domestic business is in most cases equal to 7. 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). Romer (1986), Bernstein and Nadiri (1988) and Scherer (1993) stress 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 (1996), 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. 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 reported by 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 ITT 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 (2004) 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. 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 (1957) stressed that technical change tends to support economic growth in the long run. This conviction was supported by Fagerberg (1988), who found a significant correlation between GDP per capita and technical progress measured by R&D outlays or patent applications. 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 (2000) found that differences in productivity growth are larger between countries than across industries in the same country. In the opinion of Branstetter (2001) technology spillover is predominantly of a national nature. Romer (1986 and 1990) and Krugman (1990) as well, have drawn from this observation the conclusion that large countries should experience a higher GDP rate of growth than small countries.

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) and 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 part of our study we formulate – on the basis of theoretical hypotheses and empirical results concerning the impact of technical progress on GDP growth for the specific countries reviewed in this chapter – some conjectures with respect to 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.

3. Main research conjectures

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

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*

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

The first step in causality analysis is test for the stationarity of the variables under study. This is the crucial precondition of traditional causality testing. Since it is unreasonable to expect that GDP, the situation in the labour market and the performance of R&D sector in Poland were generally changeless in the last decade, we may formulate the following:

Conjecture 1: All time series under study are nonstationary.

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 previous section. However, transitional countries like Poland are not able to spend a similar amount of financial assets on R&D in comparison to other highly developed OECD countries. 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 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

[1] The authors would like to thank The Ministry of Finance of Poland, The Patent Office of Poland, The Central Statistical Office in Poland and Eurostat for their help in obtaining the dataset.
[2] Details on applied dataset are presented in section 4.

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 is the creation of inventions. In our opinion 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 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:

> <u>Conjecture 2</u>: 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 a 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 – 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 3: 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 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 4: 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 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 5: 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:

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

where:[3]

[3] 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.

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; [4]

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.[5]

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, like labour costs, energy and fuel costs, are generally constant over a year.[6] 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

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[4] 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.

[5] 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.

[6] 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.

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 (such as 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:

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

Table 2. Descriptive statistics of examined variables.

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:

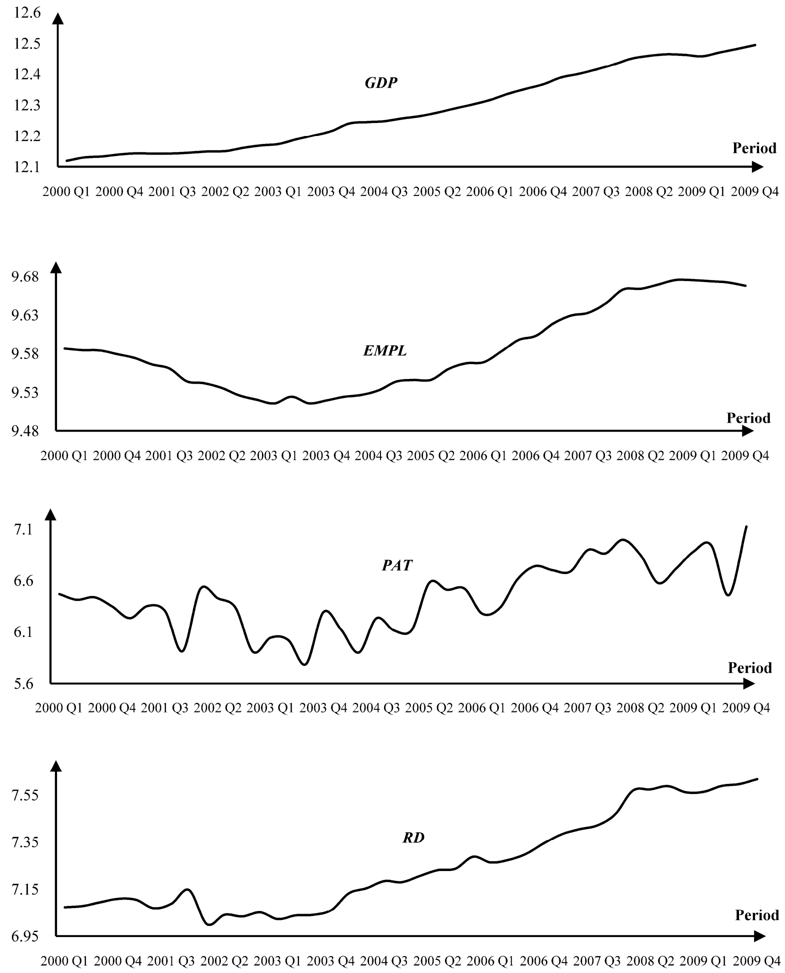

Figure 1. Plots of the time series.

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.[7]

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.

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.[8] 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.[9] Therefore, the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test was conducted 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:

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[7] 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.

[8] 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.

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

Test type / Variable	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
	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**

Table 3. Results of stationarity analysis.

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

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.[10] Therefore, conjecture 1 should be accepted. Some further calculations (conducted for first differences) confirmed that all variables under study are I(1).[11]

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 (that is *PAT* or *RD*).

5.1. Linear short and long run Granger causality tests

Since the concept of Granger (1969) causality 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 a knowledge of the past and current values of one stationary variable is helpful in predicting the future values of another one or not. Stationarity is a crucial precondition for standard linear Granger causality tests. Nonstationarity of the time series

[10] 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.
[11] 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.

under study may lead to misleading 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.

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 (1988) the existence of cointegration implies long run Granger causality in at least one direction. To establish the direction of this causal link one should estimate 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.

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 by 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.[12] 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 a 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 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).

[12] It is possible that results of stationarity and cointegration analysis are partly false and thus causality analysis performed in VEC framework is also partly incorrect. We believe that TY approach may provide a basis to confirm or undermine the VEC–based results.

The application of these parametric methods has got two serious drawbacks. Firstly, if suitable modelling assumptions do not hold 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.[13] 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 by 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.[14]

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, for example, Brock, 1991) the traditional linear Granger causality test tends to have extremely low power in detecting certain kinds of

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

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

nonlinear causal interrelations. Second, linear methods are mainly based on testing the statistical significance of suitable parameters only in a mean equation, thus causality in any higher–order structure (such as variance) cannot be explored (Diks and DeGoede, 2001).

In this paper we applied the nonlinear causality test proposed by 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, for example, Diks and Panchenko (2006), Gurgul and Lach (2010)). We set up the bandwidth (denoted as ε) at a level of 0.5, 1 and 1.5 while the common lag parameter (denoted as l) was set at the order of 1 and 2. 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).[15]

Since previous studies (Diks and Panchenko, 2006) provided evidence that the presence of heteroscedasticity leads to over–rejection of the discussed nonlinear test, 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).

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.[16]

[15] We applied Diks and Panchenko's (2006) nonlinear procedure using all practical suggestions presented in Gurgul and Lach (2010).

[16] 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.[17] The following table contains the results of Johansen cointegration tests:

		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

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

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.[18] Next, we estimated a suitable VEC model assuming 4 lags (for first differences) and one cointegrating vector. Table 5 contains *p*–values obtained while

[17] 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.
[18] It is a well known fact that the case of full rank refers to stationarity of all considered time series (Lütkepohl, 1993).

testing for linear short and long run Granger causality using an unrestricted VEC model and the sequential elimination of insignificant variables:[19]

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**					

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

[a] *Number of bootstrap replications established using Andrews and Buchinsky* (2000) *method varied between* 1469 *and* 2699.

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 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.

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

[19] 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.

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.[20] For each combination of ε and l three p–values are presented according to the following rule:

p–value for residuals of unrestricted VEC model	p–value for residuals of sequentially restricted equations
p–value for residuals of TY procedure	

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

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	
$PAT \neg\rightarrow GDP$	**0.08**	**0.03**	0.43	0.13	0.22	0.19	0.26	**0.08**	**0.07**	**0.04**	**0.09**	0.15
	0.38		0.51		0.42		**0.09**		0.67		0.43	
$GDP \neg\rightarrow PAT$	0.34	0.42	0.65	0.35	0.62	0.28	**0.08**	0.16	0.73	0.32	0.67	0.27
	0.84		0.82		0.79		0.82		0.72		0.62	
$PAT \neg\rightarrow EMPL$	**0.09**	0.13	**0.06**	0.25	0.21	0.28	0.42	0.53	0.18	0.46	**0.08**	0.58
	0.32		**0.05**		0.42		0.78		0.72		0.62	
$EMPL \neg\rightarrow PAT$	0.23	0.35	0.76	0.46	0.65	0.59	0.23	0.38	0.73	0.61	0.65	0.55
	0.21		0.46		0.67		0.44		0.69		0.73	
$GDP \neg\rightarrow EMPL$	0.57	0.23	0.65	0.19	0.25	0.54	0.15	0.42	0.26	0.25	0.23	0.29
	0.84		0.45		0.38		0.19		0.43		0.31	
$EMPL \neg\rightarrow GDP$	0.25	0.36	0.49	0.48	0.54	0.39	0.23	0.27	0.63	0.44	**0.10**	0.29
	0.92		0.58		0.53		**0.07**		0.55		0.33	

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

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.

[20] 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).

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 2 should also 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:

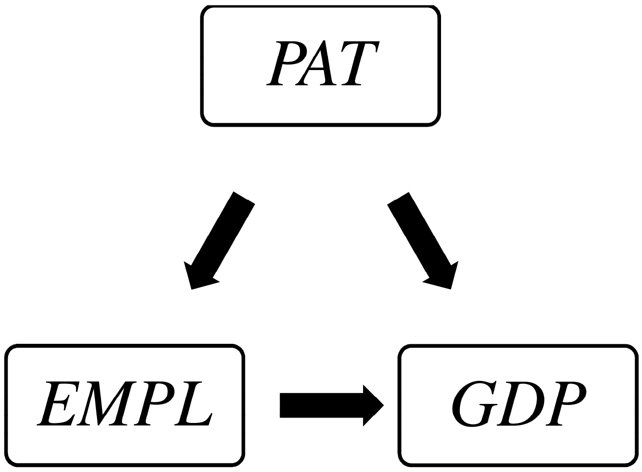

Figure 2. The structure of causal links between the *PAT*, *EMPL* and *GDP*.

We must remember that figure 2 present 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.[21] 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):

		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

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

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) 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.[22] 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:

Short run				
Null hypothesis	*p*–value			
	Unrestricted		Sequential	
	Asymptotic	Bootstrap[a]	Asymptotic	Bootstrap[a]
RD ¬→ *GDP*	0.16	0.18	**0.07**	**0.03**
GDP ¬→ *RD*	0.48	0.33	0.35	0.49
RD ¬→ *EMPL*	0.84	0.88	0.46	0.37
EMPL ¬→ *RD*	0.21	0.19	**0.06**	**0.03**
GDP ¬→ *EMPL*	0.44	0.38	0.13	**0.09**
EMPL ¬→ *GDP*	**0.03**	**0.08**	**0.02**	**0.07**

Long run								
Equation	*p*–value of EC_1 component				*p*–value of EC_2 component			
	Unrestricted		Sequential		Unrestricted		Sequential	
	Asymptotic	Bootstrap[a]	Asymptotic	Bootstrap[a]	Asymptotic	Bootstrap[a]	Asymptotic	Bootstrap[a]
GDP	**0.03**	**0.05**	**0.01**	**0.05**	0.41	0.38	0.38	0.67
RD	**0.01**	**0.00**	**0.00**	**0.00**	**0.01**	**0.00**	**0.06**	**0.04**
EMPL	0.23	0.38	**0.01**	**0.03**	0.12	**0.06**	**0.02**	**0.02**

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

[a] *Number of bootstrap replications established using the Andrews and Buchinsky* (2000) *method varied between* 1589 *and* 2939.

[21] 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

[22] The first vector (denoted as EC_1) involved *GDP* and *RD* while the second one (EC_2) involved *EMPL* and *RD*.

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 *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:

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

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

[a] *Parameter N denotes the number of bootstrap replications established according to the Andrews and Buchinsky* (2000) *procedure.*

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:

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	
$RD \neg\rightarrow GDP$	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	
$GDP \neg\rightarrow RD$	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	
$RD \neg\rightarrow EMPL$	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	
$EMPL \neg\rightarrow RD$	**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	
$GDP \neg\rightarrow EMPL$	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	
$EMPL \neg\rightarrow GDP$	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	

Table10. Analysis of nonlinear causal links between the *RD*, *GDP* and *EMPL* variables.

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, 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*.

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 4. Moreover, employment was found to Granger cause *RD* and *GDP*, which additionally provides a basis for accepting conjecture 3. 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:

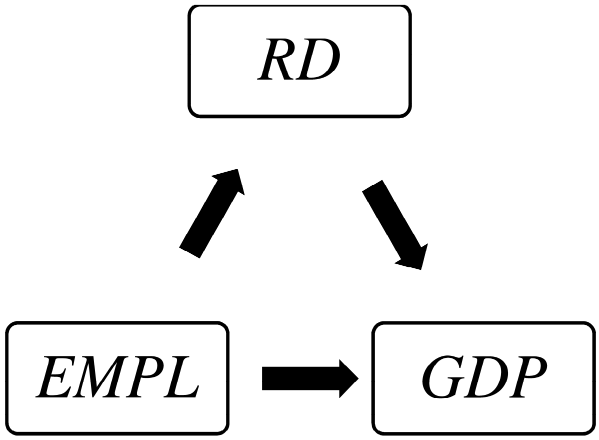

Figure 3. The structure of causal links between the *RD*, *EMPL* and *GDP*.

We should once again underline that figure 3 present 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 5 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.[23] 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).[24] 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.[25] The following table contains a summary of the causality analysis conducted for the *RD* and *PAT* variables in a two–dimensional framework:

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

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

[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* (2000) *method varied between* 1769 *and* 2659.

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

[23] 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 of Johansen's tests were applied to examine cointegration properties in a model with one lag.

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

[25] It is worth to note 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.).

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[26] 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).[27] 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:

VEC–based procedure[a]

Number of lags (levels)	Null hypothesis	Linear test[b]				Nonlinear test	
		unrestricted		sequential		post–unrestricted	post–sequential
		asymptotic	bootstrap[c]	asymptotic	bootstrap[c]		
4	$RD \neg\rightarrow PAT$	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**	Do not reject	Do not reject
6	$RD \neg\rightarrow PAT$	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**	Do not reject	Do not reject

TY–based procedure[a]

Number of lags (levels of nonaugmented model)	Null hypothesis	Linear test		Nonlinear test
		asymptotic	bootstrap[c]	
4	$RD \neg\rightarrow PAT$	Do not reject	Do not reject	Do not reject
	$PAT \neg\rightarrow RD$	**Reject**	**Reject**	Do not reject
6	$RD \neg\rightarrow PAT$	Do not reject	Do not reject	**Reject**
	$PAT \neg\rightarrow RD$	**Reject**	**Reject**	Do not reject

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

[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* (2000) *method varied between* 1649 *and* 3019.

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 5 should clearly be accepted. This major finding confirms the results obtained in both three–

[26] See, for instance, Jalles (2010).
[27] 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.

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.[28] As with previous results, the outcomes presented in 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 was 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

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

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 run 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 in the following periods can be expected. 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 (such as 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 the Polish R&D sector has been systematically growing in the recent decade, its size is still too small. In the period under study the rate of growth of R&D expenditure in Poland was generally similar to the GDP growth rate, which was a reason why Poland was unable to meet the requirements of Lisbon Strategy. 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 lead to real profits (with its impact on the level of employment and the level of output). Moreover, the increase in the standard of living (information and communication technologies, heath care, public security, white goods and entertainment) is also worth considerable attention.

There is a common view that firms and government invest their financial assets in order to develop new products or services. The results can be achieved sporadically since the process of developing inventions is not a continuous one and is charged with a 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 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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