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Gurgul, Henryk and Lach, Łukasz

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Henryk Gurgul[a,*], **Łukasz Lach**[b]

[a]Department of Applications of Mathematics in Economics, Faculty of Management, AGH University of Science and Technology, Gramatyka 10 st., 30–067 Cracow, Poland, tel.: +48 012 6174310, fax: +48 012 6367005, e–mail: henryk.gurgul@gmail.com.

[b]Department of Applications of Mathematics in Economics, Faculty of Management, AGH University of Science and Technology, Gramatyka 10 st., 30–067 Cracow, Poland, tel.: +48 012 6174218, fax: +48 012 6367005, e–mail: lukilach1983@o2.pl.

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Abstract

The main goal of this paper is an analysis of the causal links between quarterly coal consumption in the Polish economy and GDP. For the sake of accurate computation an additional variable – employment – was also taken into account. Computations conducted for the period Q1 2000 to Q4 2009 by means of recent causality techniques confirmed the neutrality of hard coal usage with respect to economic growth. On the other hand, calculations for the pairs lignite–GDP and total coal consumption–GDP showed the existence of a significant nonlinear causality from coal usage to economic growth. This is clear evidence for claiming that lignite plays an important role in the

[*] Corresponding author.

economic growth of the Polish economy. Furthermore, each coal–related variable was found to have a nonlinear causal impact on employment. Because of the relatively short length of available time series we additionally applied bootstrap critical values. The empirical results computed by both methods did not exhibit significant differences.

These results have important policy implications. In general, our findings support the hypothesis that closing hard coal mines in Poland should have no significant repercussions on economic growth. However, this does not seem to be true for lignite mines.

Keywords: energy consumption, economic growth, Granger causality.

1. Introduction

The demand for coal stems mainly from its application to the generation of electricity and the production of steel. Although Poland had abundant supplies of some natural resources, including coal, the centrally planned system caused a false allocation of those resources and of investment funds to economic sectors. In addition, the cutting off of the most important industrial inputs from the former Soviet Union made a radical restructuring and rebalancing of all sectors, especially hard coal mining, inevitable.

In 1990 about 90 percent of the country's energy production was based on hard coal and lignite. By the end of 1991, however, the Polish coal industry was in serious economic trouble. Fifty six out of sixty seven mines showed losses in 1991 and only seven exhibited profits and were able to cover all their obligations. In 1998 still more than 66% of primary energy supplies in Poland originated from coal. Although Polish mining output has been continuously decreasing in relation to total industrial production in the transition period, it still accounted in 2003 for 4.5% of industrial production (at current prices). Also other indicators show that Poland has remained one of the world's largest coal producers and consumers. Poland's fuel and energy profile was dominated by coal, the only domestic energy source in abundance. The share of the coal sector (hard coal and lignite–often referred to as brown coal) in 2003 amounted to 3.4% of total industry sales but made up 8.1% of all industrial employment in that year. The deep–coal mining industry in Poland has been significantly reduced under market pressure since beginning of the transition process. The main reason was decreasing demand (i.e. an excess supply of coal). The most important customers of the coal industry in Poland are power stations. Their demand for coal between 1990 and 2003 reduced approximately by 36%. In this period labour costs and employment in the sector remained high, despite the sector's bad financial state. The main reason for this situation was the strength of the trade unions in the coal sector. Because of serious problems in the coal industry over next years the program of restructuring this industry (the closure of inefficient mines and workforce reduction) has been continued. In November 2003, the government introduced a second program in order to consolidate and reform Poland's coal sector – the Program of Restructuring the Hard Coal Mining Sector for 2003–2006. The program planned to close more inefficient mines and reduce employment on a voluntary basis. The government provided miners who voluntarily left the coal sector with other private sector employment and support such as early retirement pensions, retraining and social hardship allowances. The World Bank helped Poland in restructuring its mining industry with a loan. The plan conducted by the Polish government in cooperation with the World Bank led to a further deep fall in employment in the coal industry. The output of hard coal has decreased from a pre–transformation level of 193 million tonnes in 1988 to 101 million tonnes in 2004. The privatization of mines was, however, stopped by the Polish government in 2006. The World–Bank–supported restructuring program had been suspended by the Polish government by 2006. The reason was that the coal industry had that year become more profitable. Therefore only two mines had been closed through the project. The Polish government made a decision that any further mine closures would be handled by the mine companies. This was contrary to the former regulation where the Mine Restructuring Company was responsible for making decisions. The rise in demand in the following years protected the Polish coal industry from a sharp decrease in coal production.

In 2009 Poland produced 135.14 million tonnes of coal, i.e. 1.65% of the world total. In the same year Polish coal consumption amounted to 53.85 million tonnes oil equivalent, i.e. 1.64% of the world total. Poland is one of the largest consumers of coal in Europe. Coal recently (in 2009) accounted for 89.5% of the country's primary energy production and over 70% of total consumption. The greater part (55.84%) of coal–fuelled power generation is based on hard coal and the remainder is from lignite–fired capacity at mine–mouth captive power plants.

The commercially workable hard coal reserves are located in the Upper Silesian and the Lublin basins in the east of Poland (Bogdanka mine), with the Upper Silesian coalfield accounting for approximately 93% of the total. Lignite deposits in Poland are exclusively mined by opencast methods. Two of these operations are located in the centre of the country and a third one in the south–western region of Poland. In 2009, total lignite production in Poland dropped because of a fall in demand from 56.9 in 2008 to 54.4 million tonnes. Approximately 99.7% of this production was used by mine mouth power plants. Lignite–fired power stations generated in 2009 33.66% of total power generation in Poland. Lignite mines in Poland are willing to maintain their production capacity of 65–70 million tonnes per year. Moreover, lignite is expected to play an important role in the Polish energy sector until about 2035.

The main goals of the energy policy of the Polish government in recent years were the following: to assure the energy security of the country; to assure the growth of competitiveness and energy efficiency of the national economy; to protect the environment against the negative impact of the energy sector. In the framework of the third goal the need for sustainable development, i.e. the achievement of a balance between social, economic, technical and environmental conditions in the process of development, was established as a priority in the national energy policy. Eleven percent of Poland's surface is considered to be severely environmentally endangered (the most polluted region in Poland, designated *an area of the ecological disaster* is the Upper Silesia and Cracow region). However, approximately 27 percent of Polish land remains in an almost natural state. These circumstances demand a diverse regional and decentralized approach to environmental protection in the context of energy policy in Poland. Moreover, although fossil fuel power plants in Poland (old and using high sulphur brown coal) are a major source of industrial air pollution, coal smoke is also a cause for serious concern.

The mentioned general goals of energy policy in Poland are to be achieved by improving the legal and regulatory instruments of a balanced structure of the primary energy supply with a preference for using domestic coal and lignite resources. This usage should fulfil ecological requirements and assure a rational level of energy costs in the national economy through increasing its efficiency, also in the energy sector. Energy policy should combine the interests of energy consumers and suppliers in order to support security and the quality of the energy supply.

As we see from this short review the coal sector is still one of Poland's largest industries and employers. Therefore it is fully justified to ask about coal's importance for the economic growth of Poland in the language of causality notion. Also, converse questions concerning the impact of economic growth on the size of coal production may be of interest to the Reader. Many mines are or were subsidized by government. Thus, according to our prediction in times of fast economic growth the mines can receive more money from government as public help and in consequence can produce more coal. From a theoretical point of view also feedback cannot be excluded.

Evidence on the direction of causality may have a significant impact on policy. The results of the research presented in this paper should be helpful in judging which of the four hypotheses (Payne, 2009) tested in previous papers holds true in the case of the Polish economy:

Growth hypothesis – this implies that causality runs from energy consumption to economic growth. This suggests that energy consumption plays an important role in economic growth. Any reduction (increase) in energy consumption could lead to a fall (rise) in GDP growth.

Conservation hypothesis – this is based on unidirectional causality running from economic growth to energy consumption. This indicates that a country is not dependent on energy for growth and development and thus energy conservation policies will have little or no effect on economic growth. Furthermore, a permanent increase in economic growth may result in a permanent rise in energy consumption.

Feedback hypothesis – this asserts that there is two–way (bidirectional) causality between energy consumption and economic growth, i.e. energy and economic growth are interdependent and act as complements to each other.

Neutrality hypothesis– this would be supported by the absence of a casual relationship between energy consumption and economic growth, which means that neither conservative nor expansive policies in relation to energy consumption have any effect on economic growth.

Therefore, it is important to ascertain empirically whether there is a causal link between energy consumption and economic growth. The existence and directions of these causalities have crucial implications for energy policy and have been intensively examined by many authors. Some of the most important studies will be reviewed in the next section.

2. Literature overview

The early contributions concerned with relations between economic growth and energy demand were conducted predominantly for the US economy (e.g. Kraft and Kraft (1978), Akarca and Long (1979), Yu and Choi (1985), Stern (1993, 2000), Cheng (1995, 1997)). Kraft and Kraft (1978) investigated the interdependency between economic growth and energy demand. These authors on the basis of US data for the period 1947–1974 found that there is a relationship between GNP growth and energy consumption. They established that the increase in national income is the reason for the rise in energy consumption. Yu and Choi (1985) estimated the causal interdependency between the energy usage and gross national product (GNP) of five countries. The authors concluded that there was unidirectional causality from energy consumption to GNP in the Philippines, and causality in the opposite direction in South Korea. However, no causality was found in the case of USA, UK and Poland.

To summarize we give a short overview in the following table:

Author(s)	Analyzed countries and period of included data	Causal relation
Yu and Choi (1985)	South Korea, Philippines (1954–76)	Energy → GDP
Masih and Masih (1996)	Malaysia, Singapore, the Philippines, India, Indonesia, Pakistan (1955–90)	Mixed
Glasure and Lee (1997)	South Korea, Singapore (1961–90)	Energy ↔ GDP
Masih and Masih (1998)	Sri Lanka, Thailand (1955–91)	Energy → GDP
Asafu – Adjaye (2000)	India, Indonesia, Turkey (1973–95); Thailand, Philippines (1973–95)	Energy → GDP Energy↔GDP
Yang (2000)	Taiwan (1954–97)	GDP → coal consumption
Soytas and Sari (2003)	Argentina, South Korea, Turkey, Indonesia, Poland (1950–92)	Mixed
Fatai et al. (2004)	India, Indonesia, (1960–99); Thailand, Philippines (1960–99)	Energy → GDP Energy↔GDP
Jumbe (2004)	Malawi (1970–99)	GDP → Energy
Morimoto and Hope (2004)	Sri Lanka (1960–98)	Energy↔GDP
Oh and Lee (2004)	South Korea (1970–99)	Energy↔GDP
Paul and Bhattacharya (2004)	India (1950–96)	Energy↔GDP
Lee (2005)	18 countries (1975 – 2001)	Energy → GDP
Ambapour and Massamba (2005)	Congo (1960–99)	GDP → Energy
Keppler (2007)	Argentina, Brazil, Chile, China, Egypt, India, Indonesia, Kenya, South Africa, Thailand (1960/71–2002)	Mixed

Table 1: Summary and comparison of empirical results from causality tests.
Source: Gelo (2009), Lee (2005), Keppler (2007) and own sources.

As we see several studies in energy economics have examined the causal relationship between energy consumption and economic growth but only one of them (i.e. Yang (2000)) empirically investigated causality issues between coal consumption and GDP. Yang showed that Taiwanese data confirmed unidirectional causality from economic growth to coal consumption without a feedback effect. It results from Yang's computations that coal preservations have no destructive repercussions on the economic growth of Taiwan.

As we mentioned in the introductory section, economic considerations are not the only factors implying the necessity for reducing coal's input in energy generation. The obligations of governments to reduce CO_2 emission in the context of global climate change are also important factors for policy makers in the energy sector. It is widely believed that adjusting the national energy structure in Poland is important in meeting the challenge of climate change in connection with the greenhouse effect. This opinion is presented not only by independent economists, as official government documents by the Environmental Protection Agency share similar views. Thus, the reduction of higher carbon fuel (e.g. coal) consumption has become a central focus of energy and environmental policy in Poland. The last statement concerns in particular lignite production, whose share in electricity generation in Poland is still very high and exhibits no significant tendency to fall. Despite the rather common view in Poland that the hard coal sector should be reduced mostly because of economic inefficiency and for environmental reasons, the lignite sector is hardly diminishing, because the production of this kind of coal is less costly and more profitable from a solely economic point of view. However, lignite exploitation in open mines and its application for energy production has significant negative impact on the quality of the natural environment (e.g. it is one of the main sources of the acidification of the natural environment not only in Poland but also in other European countries). Moreover, lignite production has negative effects on the health of the local populations and their economic activity, especially in rural areas. It is also detrimental to protection of biodiversity included in the EU program NATURA 2000. Thus, it is not surprising that proposals to open any new lignite mine in Poland immediately cause local protests (especially among farmers) and from ecologists.

However, the main goal of this research, as stated in introductory section, is to test on the basis of recent data all four of Payne's hypotheses for Poland. Although environmental and social problems for Poland and Europe originating from coal use are very important, they are not the main subject of this paper. Therefore, they are mentioned in the paper but not deeply analyzed.

The remainder of the paper is organized as follows. In the next section we formulate the main conjectures concerning the interrelations between coal consumption and economic growth in Poland. In section 4 we review the applied dataset. In section 5 the methodology is briefly described. The empirical results are presented and discussed in section 6. Section 7 concludes the paper.

3. Main research conjectures

The main goal of this paper is to conduct empirical testing of causality between coal usage and economic growth in Poland. In later parts of this paper we use abbreviations for all examined variables. The following table contains the details:

Abbreviation	Description
GDP	Quarterly Gross Domestic Product in Poland (in millions PLN, constant prices of year 2000)
HCOAL	Quarterly consumption of hard coal in Poland (in TJ)
LGT	Quarterly consumption of lignite in Poland (in TJ)
SCOAL	SCOAL=HCOAL+LGT
EMPL	Employment in Poland based on quarterly Labour Force Survey (in thousands)

Table 2. Abbreviations and short descriptions of the variables.

In general, our investigation was performed in three variants: HCOAL versus GDP, LGT versus GDP and SCOAL versus GDP. In order to avoid spurious results of causality analysis we included EMPL as an additional variable in each variant. Since stationarity is the crucial precondition of traditional causality testing, we formulate the following:

Conjecture 1: The logarithms of coal–related time series, employment and GDP are stationary.

The existence of interdependencies between coal usage, employment and GDP in the light of the literature is uncertain. Therefore our null hypothesis concerning linear causality is of the form:

Conjecture 2: In each research variant (i.e. one coal–related variable, EMPL and GDP) there are no (pairwise) linear Granger causal links in any direction in the time period under study.

In classical economics, capital is one of the three (or four, in some formulations) 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 economic growth. Classical economic theory (comp. e.g. Shephard, 1970) assumes the amount of labour (determined by the level of employment) to be one of the most important production factors (inputs). Moreover, in the short run labour is the only variable production factor (so–called *one factor production functions* explain changes in output by means of changes in labour input solely). In the long run it is assumed that not only labour but also other production factors like capital goods can be changed. This fact is reflected in multivariate production functions e.g. the well known bivariate production functions: the linear, Cobb–Douglas and CES variants.

Labour is also an important input–variable in dynamic growth models. An extensive discussion concerning production functions and growth models is presented e.g. in Takayama (1985) and Mansfield (1991).

As one can see economic theory predicts a dependence between labour and output both in the short and long run. Since these dependences are in reasonable domain reflected by monotone increasing functions (with respect to employment) feedback, i.e. a mutual dependence in the sense of Granger causality between employment and GDP, can be expected. 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).

The lack of linear causality does not exclude the existence of nonlinear causality between the variables under study, which may be of interest from a practical point of view. Taking into account previous contributions related to coal–GDP links we formulate the next hypothesis in the form:

Conjecture 4: There are some nonlinear (pairwise) Granger causalities between variables of interest in each examined three–dimensional research variant.

Finally, one should notice that although hypothesis 3 is not directly related to coal consumption in Poland, the test results may be useful for Polish policy makers in the field of links between coal usage and output. Furthermore, we must remember that employment plays an important role in our research as it solves the problem of omitted variables, which was frequently reported in previous studies using a two–dimensional (only GDP and energy) approach (see e.g. Chang et al. 2001).

The above hypotheses will be tested by different causality tests. The details of the respective procedures will be presented later. The test results depend to some extent on the testing methods applied. Before describing the methodology, in the next section we will characterize the time series included in our sample.

4. Properties of the dataset

In this section the properties of the dataset are presented. In subsection 4.1 we present a general description of all time series under study while section 4.2 contains the results of stationarity tests.

4.1. Description of the dataset

In this paper we applied a dataset containing quarterly data on GDP, coal consumption (divided into hard coal, lignite and total (hard coal and lignite) coal consumption) and employment in Poland for the period Q1 2000 to Q4 2009. The data describing GDP and employment in Poland was collected from the Statistical Office in Cracow, while the data on the consumption of hard coal and lignite was acquired from Energy Market Agency in Warsaw.[1]

Before performing a stationarity analysis we conducted several transformations of our dataset, which are believed to help avoiding spurious results of causality analysis. Firstly, we calculated GDP at constant prices (year 2000) in order to filter out the impact of inflation. Secondly, since all examined variables were characterized by significant quarterly seasonality, the X–12 ARIMA procedure of Gretl software was applied to adjust each variable.[2] Finally, each seasonally adjusted variable was transformed to logarithmic form.[3]

In contrast with most previous contributions concerned with this topic in this paper quarterly data (instead of annual data) was applied. This way a dataset with highest possible frequency was used, since data on GDP is published once a quarter. The application of lower frequency data (e.g. annual data) may not be adequate for testing for Granger causality between chosen variables, as in such case some important interactions may stay hidden.[4]

The initial part of our analysis is based on a brief statistical description of all examined variables. The following table contains the results which were obtained for seasonally adjusted and logarithmically transformed data:

Variable / Quantity	ln(GDP)	ln(HCOAL)	ln(LGT)	ln(SCOAL)	ln(EMPL)
Minimum	12.11	12.58	11.66	12.94	9.51
1st quartile	12.15	13.01	11.74	13.26	9.53
Median	12.26	13.10	11.77	13.33	9.57
3rd quartile	12.41	13.15	11.78	13.30	9.63
Maximum	12.49	13.56	11.87	13.72	9.68
Mean	12.28	13.08	11.76	13.32	9.58
Std. deviation	0.13	0.16	0.04	0.12	0.09
Skewness	0.27	–0.08	0.28	0.09	0.48
Excess kurtosis	–1.40	2.80	0.79	2.95	–1.12

Table 3. Descriptive statistics.

Some basic information can be seen directly from this table. However, for the sake of comprehensiveness one should also analyze charts generated for all variables under study. Figure 1 shows the plots:

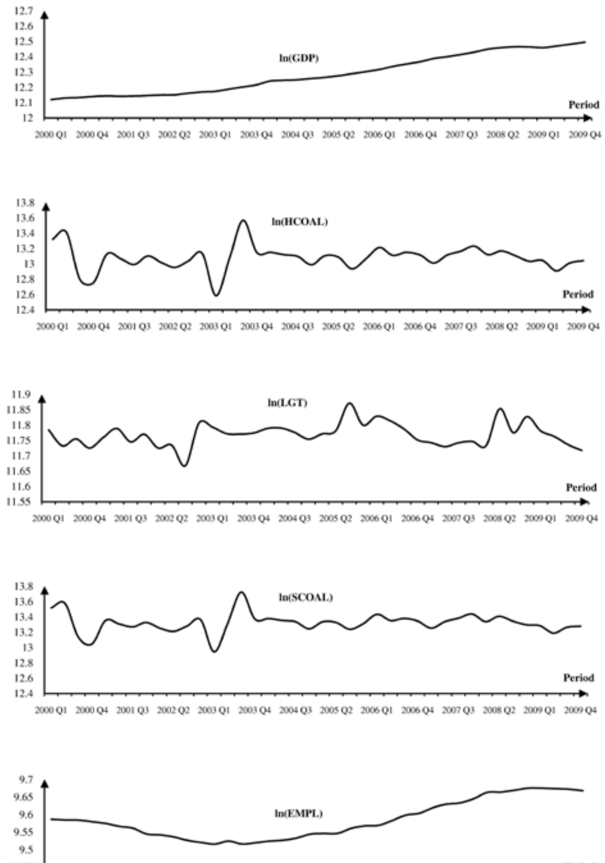

Figure 1. Graphs of analyzed time series.

As we can see, the period under study was a time of relatively stable development in the Polish economy, as ln(GDP) was generally rising, especially between 2003 and 2008. Despite the fact that, in general, the Polish economy (in comparison to other European countries) managed to avoid the negative impact of the outbreak of the financial crisis of September 2008 in Europe, a significant but rather gentle slowdown of the pace of the growth of the Polish economy was also reported after the third quarter of 2008. One can also easily see that neither ln(HCOAL), ln(LGT) nor ln(SCOAL) exhibited a significant upward or downward tendency in the period under study. However, for each coal–related time series several relatively significant shocks were observed (especially around 2003, 2006 and 2008). In analyzed period employment in Poland was rising between 2003 and 2008. However, slight drops were observed before 2003 and after the crisis of September 2008. In order to expand the preliminary statistical description of all time series a mandatory precondition for causality analysis i.e. stationarity testing, was also performed.

4.2. Testing the stationarity of the dataset

One must remember that the definition of Granger causality applied in this paper was intentionally formulated for stationary time series. Taking into account the results of previous empirical (Granger and Newbold, 1974) and theoretical (Phillips, 1986) deliberations, one may state that if the time series under study are indeed nonstationary then the outcomes of typical linear causality tests may lead to misleading conclusions. Thus, first we examined all time series for stationarity and identified their orders of integration. We did our best to carry out this part of the research with the greatest possible precision, since all further computations strongly depend on this stage.

4.2.1. ADF unit root test

In order to examine the stationarity properties of our dataset we firstly applied an Augmented Dickey–Fuller (ADF)[5] unit root test. First, we set up a maximal lag length equal to 6 and then we used information criteria (namely the AIC, BIC and HQ) in order to choose the optimal lag length from the set {0, 1, …, 6}. The next table contains the outcomes of the ADF test:

Variable	ADF with constant		ADF with constant and linear trend	
	Test statistic (*p*–value)	Optimal lag	Test statistic (*p*–value)	Optimal lag
ln(GDP)	0.73 (0.99)	1	–2.81 (0.19)	1
ln(HCOAL)	–6.71 (0.00)	1	–6.92 (0.00)	1
ln(LGT)	–2.99 (0.03)	2	–2.86 (0.17)	2
ln(SCOAL)	–6.24 (0.00)	1	–6.67 (0.00)	1
ln(EMPL)	–3.74 (0.00)	4	–4.34 (0.00)	4

Table 4. Results of ADF test (levels).

One can easily see that of all the variables only the ln(GDP) was found to be nonstationary (at a 5% significance level), regardless of the form of deterministic term. At each common significance level all other time series were found to be stationary around constant (except for ln(LGT) at 1% level). All time series, except for ln(GDP) and ln(LGT), were found to be stationary also when the time trend was additionally taken into account.

4.2.2. KPSS unit root test

When interpreting the outcomes of the ADF test one should bear in mind two crucial facts. Firstly, the ADF test is relatively sensitive to an incorrect establishment of the lag parameter. Secondly, as it was shown by Agiakoglu and Newbold (1992) this test is often characterized by significant under–rejection. Thus, in order to confirm the outcomes of the ADF test the Kwiatkowski, Phillips, Schmidt and Shin (KPSS)[6] test is usually additionally conducted. Contrary to the ADF test the null hypothesis of this test refers to the stationarity of the variable. The results of KPSS test are presented in the following table:

Variable	KPSS test statistic (with constant[a])	KPSS test statistic (with constant and linear trend[b])
ln(GDP)	1.08	0.23
ln(HCOAL)	0.07	0.06
ln(LGT)	0.07	0.07
ln(SCOAL)	0.06	0.05
ln(EMPL)	0.78	0.25

Table 5. Results of KPSS test (levels).

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

This time not only ln(GDP), but also the ln(EMPL), was found to be nonstationary, while for all coal–related variables the null hypothesis of the KPSS test could not be rejected (at all standard significance levels). Moreover, all these findings were reported regardless of the form of the deterministic term which was assumed during testing.

4.2.3. PP unit root test

The different results of the ADF and KPSS tests forced us to use another test in order to make a final decision about the stationarity of the variables, so the Phillips–Perron (PP)[7] test was applied. This approach makes use of a specific nonparametric method of controlling for serial correlation. Once again the null hypothesis refers to nonstationarity. The following table contains the results of the PP test:

Variable	PP test *p*–value (with constant)	PP test *p*–value (with constant and linear trend)
ln(GDP)	0.98	0.52
ln(HCOAL)	0.00	0.00
ln(LGT)	0.00	0.00
ln(SCOAL)	0.00	0.00
ln(EMPL)	0.92	0.60

Table 6. Results of PP test (levels).

As we can see, the conclusion based on outcomes presented in table 6 is in line with the results of the KPSS test. Thus, in further computations only the ln(GDP) and ln(EMPL) time series were assumed to be nonstationary around constant, while each coal–related variable was found to be stationary. This means that Conjecture 1 is false. We conducted some further calculations for first differences of the ln(GDP) and ln(EMPL) time series finding that these two variables are I(1).[8]

5. Methodology

In order to explore the dynamic relationships between GDP, coal consumption (hard coal, lignite and total coal consumption) and employment in Poland several econometric tools were applied. We used both traditional econometric methods, like linear Granger causality test based on asymptotic theory, as well as some recently developed instruments, like the Toda–Yamamoto procedure, the Andrews and Buchinsky bootstrap algorithm and the Diks and Panchenko nonlinear Granger causality test.

5.1. Toda–Yamamoto testing procedure

In this paper we use the idea of causality formulated by Granger (1969). Since this concept is well known and has been commonly used in previous research, we will not provide a detailed description. Generally, it is used in order to examine if the current and past values of one stationary variable are helpful in predicting the future values of another one.

Toda and Yamamoto (1995) developed a method of testing for Granger causality which has been commonly applied in recent empirical research (e.g. Keho, 2007), so a detailed description will not be presented in this paper (for details see e.g. Toda and Yamamoto (1995), Gurgul and Lach (2010)). This method allows for causality testing even if the variables in question are characterized by different orders of integration[9] or if the cointegration properties of the data are uncertain. Moreover, the Toda–Yamamoto (TY) method is relatively simple to perform and free of complex pretesting procedures (like initial tests, arbitrary decisions etc.), which may seriously distort the test results and hinder their interpretation, especially when some examined variables are indeed integrated. The first step of the TY approach requires the construction of a VAR(p) model for all examined variables. If the order of the process (parameter p) is unknown then it should be established by means of suitable statistical methods, e.g. the application of consistent model selection criteria.[10] Next, one should establish the highest order of integration of all examined variables (parameter *d*). In the final step an augmented VAR(*p*+*d*) model should be estimated. The Toda–Yamamoto test statistic (TY_{test}) is just the standard Wald test applied for the first *p* lags of the augmented VAR(*p*+*d*) model. The TY_{test} is asymptotically $\chi^2(p)$ distributed.

5.2. Bootstrap techniques

One cannot forget that the TY approach, like every parametric method, has some typical drawbacks. First of all, if some typical modelling assumptions[11] do not hold, then the application of asymptotic theory may lead to misleading outcomes. Furthermore, the distribution of the TY_{test} statistic may be markedly different from χ^2 when dealing with small samples, even if all modelling conditions are generally fulfilled.

The application of bootstrap methods provides one possible way of overcoming these problems. By and large, the bootstrap idea is used to estimate the distribution of the test statistic by resampling the data. Thus, the calculated distribution depends mainly on the available dataset and one may expect bootstrapping to require vastly weaker assumptions in comparison to parametric methods. It is also worth underlining that both the size and power properties of bootstrap–based causality procedure remain quite satisfactory, even for nonstationary or heteroscedastic data.[12] However, the application of bootstrap techniques does not guarantee a correct solution of all possible model specification problems.[13]

Since heteroscedasticity may cause a serious distortion of the results of the bootstrap procedure[14] we based our research on approach commonly used on this field, namely the application of leveraged residuals.[15] In order to create a bootstrap–based TY_{test} distribution we first estimated each[16] non–augmented trivariate VAR model by means of OLS methodology assuming that the null hypothesis (that one variable does not Granger cause the other one) holds true. Next, leverages were applied to transform regression raw residuals ($\{\hat{\varepsilon}_i^m\}_{i=v_0,\dots,T} = \left\{\begin{bmatrix}\hat{\varepsilon}_{1,i}^m \\ \hat{\varepsilon}_{2,i}^m \\ \hat{\varepsilon}_{3,i}^m\end{bmatrix}\right\}_{i=v_0,\dots,T}$ denotes the set of leverage–modified vectors of the residuals, T denotes sample size, v_0 is equal to VAR lag length plus one). Finally, we conducted the following algorithm (ALG):[17]

ALG 1. Random draw – draw randomly with replacement (all points have equal probability $p_0 = \frac{1}{T - v_0 + 1}$) from the set $\{\hat{\varepsilon}_i^m\}_{i=v_0,\dots,T}$ (as a result the set $\{\hat{\varepsilon}_i^{**}\}_{i=v_0,\dots,T}$ was obtained);

ALG 2. Subtract the mean – this step guarantees that the mean of bootstrap residuals is zero (this way we create the set $\{\hat{\varepsilon}_i^*\}_{i=v_0,\dots,T}$, such that $\hat{\varepsilon}_{k,i}^* = \hat{\varepsilon}_{k,i}^{**} - \frac{\sum_{j=v_0}^{T} \hat{\varepsilon}_{k,j}^{**}}{T - v_0 + 1},\ i = v_0, \dots, T,\ \ k = 1, 2, 3$);

ALG 3. Generate the data – through the use of original data, coefficient estimates from the regression of a restricted non–augmented VAR model and the bootstrap residuals $\{\hat{\varepsilon}_i^*\}_{i=v_0,\dots,T}$ we were able to create simulated time series;

ALG 4. Conduct TY test – we performed the TY procedure for data generated at step ALG 3.

The creation of the empirical distribution of the TY_{test} statistic and the establishment of bootstrap critical values requires repeating the ALG procedure N times. In this paper we applied the recently developed algorithm of choosing the number of bootstrap replications presented by Andrews and Buchinsky (2000). For each resampling procedure the number of replications was set at such a level that would guarantee that the relative error of establishing the bootstrap critical value (at a 5% significance level) would not exceed 0.05 with a probability equal to 95%.

The appropriate Gretl script, including the Andrews and Buchinsky procedure, is available from the authors upon request.

5.3. Long run Granger causality

The results of the stationarity analysis (subsection 4.2) provided a strong basis for claiming that the two analyzed time series are I(1), so cointegration analysis was additionally performed for this pair of variables. Previous studies (e.g. Granger (1988), Cheng et al. (2007), Gurgul and Lach (2010)) have shown that cointegration is a sufficient condition to establish a long run causality in at least one direction. In this paper we applied Johansen cointegration tests (both the Trace and Maximal Eigenvalue variants).

Testing for long run Granger causality from variable *A* to variable *B* was based on estimating a suitable VEC model (using results of Johansen cointegration analysis) and checking (using *t*–test) whether the coefficient of the error term on the right side of appropriate equation (in this case with *B* on left side) is statistically significant. If this coefficient is indeed significant then one may say that *A* long run Granger causes *B*. Testing the joint significance of suitable lagged differences provides a basis for examining short run causalities between variables.

5.4. Sequential elimination of insignificant variables

Apart from the application of traditional linear tests for both short and long run Granger causality we additionally performed a sequential elimination of insignificant variables in both equations resulting from the examined two–dimensional VECM. At each step of this procedure the variable with the highest *p*–value was omitted until all remaining variables had a *p*–value no greater than a fixed value (in our case 0.05). This re–estimation was applied for each equation separately, thus all insignificant variables were omitted. The sequential elimination of insignificant variables seems to be especially useful in our research since we dealt with a relatively small sample and therefore the impact of insignificant (lagged) variables could considerably distort the results of a traditional causality test.[18] In both the traditional and sequential variants of VECM–based causality tests the bootstrap critical values were also calculated. The leverage transformation and the methodology of establishing number of replications proposed by Andrews and Buchinsky were applied once again.

5.5. Nonlinear Granger causality test

Alongside the bootstrap–based linear short and long run causality analysis a nonlinear test for Granger causality was also used in this paper, as it performs relatively better than linear methods in detecting certain kinds of nonlinear causal relationships (Brock (1991), Gurgul and Lach (2009)) and it is not restricted to causality analysis only in the mean equation (causality in any higher–order structure may also be explored, see e.g. Diks and DeGoede (2001)).

For the use of this article the nonlinear Granger causality test proposed by Diks and Panchenko (2006) was applied. By and large, this concept is an extension of ideas formulated by Baek and Brock (1992) and Hiemstra and Jones (1994). We used typical values of the technical parameters of this method. The bandwidth (denoted as ε) was set at a level of 0.5, 1 and 1.5 for each test, since these values have commonly been used in previous papers (e.g. Gurgul and Lach (2010), Diks and Panchenko (2005, 2006), Hiemstra and Jones (1994)). For every pair of time series a common lag parameter (denoted as CL) was set at the order of 1 and 2.[19]

By means of the White and Breusch–Pagan tests all residual time series under study were examined for the presence of heteroscedastic structures, since previous research has proved that this nonlinear causality procedure leads to spurious results when the assumption of constant variance does not hold (see e.g. Diks and Panchenko (2006)). In some cases significant evidence of the presence of heteroscedasticity in the residuals of examined autoregression models were found, and therefore the nonlinear causality analysis was re–run for GARCH–filtered series of residuals.[20] The next section contains a comprehensive presentation of main empirical findings of this contribution.

6. Empirical results

In this section the outcomes of both short and long run linear Granger causality tests as well as the results of the analysis of nonlinear Granger causal links are presented. This section is divided into several parts, each of which is dedicated to the application of one of the econometric methods described in previous section.

6.1. Outcomes of Toda–Yamamoto tests

Before testing for linear causality, a number of lags (parameter *p*) was established for each of the three non–augmented VAR models.[21] The following table contains a summary of this preliminary analysis as well as a brief description of the models used in causality analysis:

VAR model	Description	Parameters for TY procedure
Model 1	Constructed for ln(GDP), ln(EMPL) and ln(HCOAL)	p=5, d=1
Model 2	Constructed for ln(GDP), ln(EMPL) and ln(LGT)	
Model 3	Constructed for ln(GDP), ln(EMPL) and ln(SCOAL)	

Table 7. Description of VAR models applied for TY procedure.

In table 8 the *p*–values obtained while testing for linear Granger causal effects by means of both the asymptotic– and bootstrap–based TY tests are presented. In each case parameter *N* stands for the number of bootstrap replications established after application of the Andrews and Buchinsky procedure. Notation $x \xrightarrow{no\ GC} y$ is equivalent to "*x* does not Granger cause *y*".[22]

VAR model	Null hypothesis	*p*–value	
		Asymptotic	Bootstrap
Model 1	ln(GDP) $\xrightarrow{no\ GC}$ ln(HCOAL)	0.25	0.34 (*N*=3219)
	ln(HCOAL) $\xrightarrow{no\ GC}$ ln(GDP)	0.16	0.18 (*N*=3539)
	ln(EMPL) $\xrightarrow{no\ GC}$ ln(HCOAL)	0.22	0.35 (*N*=3319)
	ln(HCOAL) $\xrightarrow{no\ GC}$ ln(EMPL)	0.16	0.14 (*N*=3259)
	ln(GDP) $\xrightarrow{no\ GC}$ ln(EMPL)	0.14	0.22 (*N*=2579)
	ln(EMPL) $\xrightarrow{no\ GC}$ ln(GDP)	0.18	0.19 (*N*=1919)
Model 2	ln(GDP) $\xrightarrow{no\ GC}$ ln(LGT)	0.31	0.58 (*N*=3139)
	ln(LGT) $\xrightarrow{no\ GC}$ ln(GDP)	0.67	0.86 (*N*=3439)
	ln(EMPL) $\xrightarrow{no\ GC}$ ln(LGT)	0.31	0.65 (*N*=3299)
	ln(LGT) $\xrightarrow{no\ GC}$ ln(EMPL)	0.45	0.68 (*N*=3489)
	ln(GDP) $\xrightarrow{no\ GC}$ ln(EMPL)	0.45	0.70 (*N*=2319)
	ln(EMPL) $\xrightarrow{no\ GC}$ ln(GDP)	0.80	0.91 (*N*=2139)
Model 3	ln(GDP) $\xrightarrow{no\ GC}$ ln(SCOAL)	0.43	0.49 (*N*=3519)
	ln(SCOAL) $\xrightarrow{no\ GC}$ ln(GDP)	0.17	0.19 (*N*=3039)
	ln(EMPL) $\xrightarrow{no\ GC}$ ln(SCOAL)	0.25	0.33 (*N*=3259)
	ln(SCOAL) $\xrightarrow{no\ GC}$ ln(EMPL)	0.12	0.15 (*N*=3539)
	ln(GDP) $\xrightarrow{no\ GC}$ ln(EMPL)	0.14	0.21 (*N*=2499)
	ln(EMPL) $\xrightarrow{no\ GC}$ ln(GDP)	0.25	0.29 (*N*=1999)

Table 8. Results of TY procedure.

As we can see, for all three VAR models the test results provided no basis for claiming that linear Granger causality runs in any direction at a 5% significance level. This finding was established for both the asymptotic– and bootstrap–based TY procedures. Thus, Conjecture 2 should be accepted. However, in a few cases the causal links were relatively close to statistical significance. We underline that relatively small *p*–values (around 0.15) were gained while testing for causality from hard coal consumption to employment as well as from total coal consumption to employment. In contrary, the hypothesis that ln(LGT) does not Granger cause ln(EMPL) was clearly accepted. Similar results were gained for coal consumption and GDP (i.e. an almost significant impact of HCOAL and SCOAL on GDP, no impact of lignite). We should also note that for Model 1 and Model 3 the *p*–values obtained while testing for causality from GDP to employment were both relatively small.

6.2. Results of cointegration testing and long run causality analysis

As ln(GDP) and ln(EMPL) were both found to be I(1), a cointegration analysis was additionally conducted for this pair of variables. This kind of research may extend the previously performed short run examination as it allows us to explore the long run properties of the data. Despite the fact that all coal–related variables could not be taken into consideration for this part of the research (since they were found to be stationary), the results of the cointegration analysis together with the results of short run analysis may also lead to vital conclusions related to the role of different forms of coal usage.

The starting point of cointegration analysis requires a specification of the type of deterministic trend. This is usually performed through the application of one of five possibilities presented in Johansen (1995). The fact that neither of I(1) time series were found to be trend–stationary (see subsection 4.2) convinced us to use the third case, i.e. we assumed the presence of a constant in the cointegrating equation and the test VAR. Next, the appropriate number of lags was established through the application of information criteria (namely the AIC, BIC and HQ).[23] The following table contains the results of Johansen cointegration tests:[24]

		Johansen Trace test		Johansen Maximal Eigenvalue test	
Hypothesized number of cointegrating vectors	Eigenvalue	Trace statistic	*p*–value	Maximal Eigenvalue statistic	*p*–value
Zero	0.33	13.58	0.09	13.56	0.06
At most one	0.00	0.01	0.90	0.01	0.90

Table 9. Results of cointegration analysis for ln(GDP) and ln(EMPL).

One can easily see that at 10% significance levels both tests indicate that the variables are indeed cointegrated. After defining the dimension of the examined cointegration space, suitable unrestricted VEC model (including four lags of first differences of each variable and one cointegrating vector) was estimated. Next, tests for short and long run linear Granger causality between ln(GDP) and ln(EMPL) were conducted. Finding the causal link in a chosen direction (at a 5% significance level) is always marked by bold face. Parameter *N* plays an analogous role to the case of table 8:

Type of causality analysis	Null hypothesis	asymptotic *p*–value	bootstrap *p*–value
Short run (*F* test)	$\Delta\ln(GDP) \xrightarrow{no\ GC} \Delta\ln(EMPL)$	0.35	0.41 (*N*=2119)
	$\Delta\ln(EMPL) \xrightarrow{no\ GC} \Delta\ln(GDP)$	0.16	0.14 (*N*=1979)
Long run (*t*–test)	$\ln(GDP) \xrightarrow{no\ GC} \ln(EMPL)$	**0.00**	**0.01** (*N*=1999)
	$\ln(EMPL) \xrightarrow{no\ GC} \ln(GDP)$	0.16	**0.04** (*N*=1939)

Table 10. Results of causality analysis based on unrestricted VECM for ln(GDP) and ln(EMPL).

After analyzing the outcomes presented in table 10 one may easily see that in general the results of testing for short run effects are in line with the corresponding outcomes contained in table 8. Short run linear Granger causality was not reported in any direction, although we were relatively close to rejecting the hypothesis that Δln(EMPL) does not cause Δln(GDP). On the other hand, an analysis of the results of suitable *t*–tests led to the conclusion that there may exist a long run Granger causal link from ln(GDP) to ln(EMPL) (asymptotic variant) or maybe even a feedback relationship (bootstrap variant). Thus, Conjecture 3 is partly true.

In the next step, a causality analysis based on the sequential elimination of insignificant variables (precisely described in subsection 5.4) was performed separately for each equation resulting from the examined VEC model. The following table contains suitable outcomes (bold face plays an analogous role to previous cases):

Type of causality analysis	Null hypothesis	Final asymptotic *p*–value	Final bootstrap *p*–value
Short run	$\Delta\ln(GDP) \xrightarrow{no\ GC} \Delta\ln(EMPL)$	No coefficients left.	No coefficients left.
	$\Delta\ln(EMPL) \xrightarrow{no\ GC} \Delta\ln(GDP)$	**0.04**	**0.02**
Long run	$\ln(GDP) \xrightarrow{no\ GC} \ln(EMPL)$	**0.00**	**0.01**
	$\ln(EMPL) \xrightarrow{no\ GC} \ln(GDP)$	**0.05**	**0.01**

Table 11. The results of sequential elimination of insignificant variables.

The results presented in table 11 provided a solid basis for claiming that for ln(GDP) and ln(EMPL) there exists a feedback relation in the long–term, which was confirmed by both asymptotic– and bootstrap–based sequential procedures. Furthermore, the short run causality running from employment to GDP was also found to be statistically significant at a 5% level, which partly supports Conjecture 3. On the other hand, the application of both asymptotic–and bootstrap–based sequential procedures led to the elimination of all lagged coefficients of Δln(GDP) in the Δln(EMPL) equation. So some solid evidence in favour of Conjecture 3 was also found.

6.3. Outcomes of nonlinear causality tests

In this subsection the results of the nonlinear Granger causality tests conducted for residuals resulting from all augmented three–dimensional VAR models are presented. Based on the results of tests of heteroscedasticity, the residuals resulting from augmented Model 2 were additionally GARCH(1,1)–filtered. Thus, in this case two sets of results are presented, namely the results obtained for unfiltered as well as GARCH(1,1)–filtered residuals.[25] This time bold face was used to indicate the establishment of a causal link in examined direction at a 10% significance level:

VAR model	Null hypothesis	*p*–value					
		ε=0.5, CL =1	ε =1, CL =1	ε =1.5, CL =1	ε =0.5, CL =2	ε =1, CL =2	ε =1.5, CL=2
Model 1	ln(GDP) $\xrightarrow{no\ GC}$ ln(HCOAL)	0.36	0.15	**0.09**	0.81	0.31	**0.09**
	ln(HCOAL) $\xrightarrow{no\ GC}$ ln(GDP)	0.63	0.42	0.18	0.72	0.62	0.45
	ln(EMPL) $\xrightarrow{no\ GC}$ ln(HCOAL)	0.47	0.34	0.41	0.60	0.54	0.42
	ln(HCOAL) $\xrightarrow{no\ GC}$ ln(EMPL)	0.61	0.14	**0.02**	0.42	0.17	**0.05**
	ln(GDP) $\xrightarrow{no\ GC}$ ln(EMPL)	0.67	0.72	0.29	0.18	0.23	**0.09**
	ln(EMPL) $\xrightarrow{no\ GC}$ ln(GDP)	0.74	0.65	0.37	0.21	0.22	0.21
Model 2	ln(GDP) $\xrightarrow{no\ GC}$ ln(LGT)	0.32 [0.16]	0.41 [0.29]	0.15 [0.57]	0.43 [0.67]	0.49 [0.30]	0.41 [0.29]
	ln(LGT) $\xrightarrow{no\ GC}$ ln(GDP)	0.14 [0.40]	**0.08** [0.14]	**0.01** [0.18]	0.51 [0.71]	**0.08** [**0.08**]	**0.01** [**0.08**]
	ln(EMPL) $\xrightarrow{no\ GC}$ ln(LGT)	0.54 [0.71]	**0.07** [0.45]	0.41 [0.71]	0.61 [0.77]	0.51 [0.45]	0.27 [0.29]
	ln(LGT) $\xrightarrow{no\ GC}$ ln(EMPL)	0.57 [0.64]	0.63 [0.67]	0.32 [0.84]	0.82 [0.82]	0.42 [**0.07**]	**0.07** [**0.09**]
	ln(GDP) $\xrightarrow{no\ GC}$ ln(EMPL)	0.42 [0.49]	0.19 [0.75]	0.43 [0.22]	0.32 [0.76]	0.21 [0.25]	0.46 [0.45]
	ln(EMPL) $\xrightarrow{no\ GC}$ ln(GDP)	0.63 [0.78]	0.72 [0.36]	0.51 [0.35]	0.75 [0.63]	0.32 [0.19]	0.51 [0.48]
Model 3	ln(GDP) $\xrightarrow{no\ GC}$ ln(SCOAL)	0.24	**0.04**	0.15	0.45	**0.09**	**0.06**

	ln(SCOAL) $\xrightarrow{no\ GC}$ ln(GDP)	0.65	**0.08**	**0.09**	0.64	0.24	0.33
	ln(EMPL) $\xrightarrow{no\ GC}$ ln(SCOAL)	0.32	0.33	0.41	0.32	0.61	0.69
	ln(SCOAL) $\xrightarrow{no\ GC}$ ln(EMPL)	0.64	**0.08**	**0.01**	0.68	0.27	0.19
	ln(GDP) $\xrightarrow{no\ GC}$ ln(EMPL)	0.61	0.78	0.42	**0.09**	0.56	0.19
	ln(EMPL) $\xrightarrow{no\ GC}$ ln(GDP)	0.42	0.47	0.46	0.16	0.47	**0.08**

Table 12. Results of nonlinear causality analysis.

Unidirectional nonlinear Granger causal links from GDP to hard coal consumption as well as a feedback relation between ln(GDP) and ln(SCOAL) were found to be statistically significant at a 10% level. Moreover, the usage of lignite was found to be a causal factor for fluctuations of GDP. Furthermore, all coal–related variables were found to Granger cause employment (for lignite usage even feedback was detected). Finally, the test results obtained for Model 1 and Model 3 provided a basis for claiming that GDP Granger causes employment (an analysis of the residuals of Model 3 showed feedback). Therefore we found strong support for the acceptance of Conjecture 4.

Nonlinear Granger causality tests were also conducted for residuals resulting from the unrestricted VEC model as well as for residuals obtained after sequential elimination (see subsection 6.2). In both cases no significant evidence of heteroscedasticity was found, therefore no filtering was applied. In the case of each nonlinear test the null hypothesis of Granger non–causality was clearly accepted (*p*–value greater than 0.4). Since in all analyzed cases no signs of existence of causal links were found, we did not present these results in a separate table.

7. Summary and conclusions

Coal and lignite are dominating fuels for Polish power generation, which has been expanded on the basis of solid fuels from domestic sources. Coal and lignite's share in the power generating industry is now prevalent. This situation is expected to be maintained in the long–term. More than 50% of the power stations are over 25 years old, while about 25% have been in usage for more than 30 years. The lignite–fired power plants belong to the newest in Poland. They are subject to remanufacturing in order to meet European environmental standards.

The originality of this contribution is mainly related to two facts. Firstly, it was performed for one of the Central European emerging economies and therefore it fills a gap in the literature, which in the past mainly concentrated on developed countries. Secondly, to the best knowledge of the authors this is the first paper which examines the causal links between all variables on the basis of recent and reliable quarterly data. In the case of post–Soviet economies reliable datasets of sufficient size are not easy to obtain, which makes econometric research (especially based on annual data) difficult or even impossible to perform.

The first part of our Granger causality analysis was based on the application of linear tests by means of both asymptotic– and bootstrap–based Toda–Yamamoto procedures. We analyzed three cases, each of which involved GDP, employment and one coal–related variable (i.e. hard coal consumption, lignite consumption and total coal consumption). Regardless of the type of critical values used, no statistically significant linear links were found in any direction for any of the three cases. In few cases testing for causality led to relatively small *p*–values (around 0.15).

In the next part of our research cointegration–based causality tests were conducted in two–dimensional framework for GDP and employment. The results of this research (especially for the sequential elimination variant) led to the conclusion that there may indeed exist a short run causality from employment to GDP. Furthermore, in the long run a feedback causal relationship was also reported.

The main goal of the last part of our empirical analysis was to examine strictly nonlinear Granger causal links between all the variables, based on residuals from models used in the linear test. All coal–related variables were found to Granger cause employment (for lignite usage even feedback was detected). Moreover, GDP was found to cause hard coal consumption and total coal consumption (in this case feedback was reported). In contrast, the usage of lignite was found to be a causal factor for GDP. Finally, GDP was once again found to cause employment (for one model even feedback was detected).

The findings of this contribution imply some policy recommendations. Since GDP directly causes hard coal consumption and not vice versa, the closure of hard coal mines in Poland (some of them do not bring any profit and even have to be subsidised by the central budget) should not have, in general, a significant negative impact on Polish GDP. In other words our major finding supports the conservation hypothesis of hard coal consumption with respect to economic growth in Poland. Evidence supporting the existence of an indirect causal link from hard coal usage to GDP was relatively weak (it was not supported by the results of the estimation of unrestricted VECM) and cannot change the major conclusion of this part of our research. However, this important conclusion should also be examined in future (interdisciplinary) research in relation to both short– and long–term economic growth on a regional scale, focused on an increase in unemployment as well as all other possible social and political implications of closing hard coal mines (including the important contribution of miners, their families and people employed in related services in local populations). The necessity for such investigations also follows from the above–mentioned Granger causality running from all coal–related variables (i.e. coal consumption) to employment.

Preliminary comparative analyses of prices have shown that the prices of Polish steam coal in the first six months of 2008, as against the price of ARA (the Amsterdam–Rotterdam–Antwerp) ports were competitive, while in the first six months of 2009 the prices were uncompetitive and this tendency continued in 2010, which tends to support our empirical findings. Therefore, in our opinion the Polish government should continue the policy started in the first half of this decade to provide miners who voluntarily left the coal sector with other private sector employment. The Polish authorities should support miners leaving hard coal sector with early retirement pensions, retraining and social hardship allowances. These recommendations are in line with EU energy policy, which proposes a reduction in hard coal production in member states. Moreover, they are aimed at cushioning the social consequences of restructuring the coal sector (early retirement, retraining etc.). As already mentioned some interdisciplinary studies should be carried out to test whether government energy policy (including its social aspects) is indeed meeting the expectations of local society.

On the other hand, the detection of a direct nonlinear causal link from lignite consumption to GDP means that the consumption of lignite contributes significantly to economic growth in Poland. In other words the use of this fuel is economically reasonable and important (especially in the production of electricity which plays a crucial role in economic growth). However, the problem of economic rationality, i.e. the issue of the costs and prices of lignite use in Poland with reference to the connection between lignite mining and electric power stations in market conditions, is very complex. Lignite mines can not choose the recipient of their product. It will be an electric power station which is associated with lignite mines. The exploitation costs of lignite production in Poland are determined mainly by lignite deposits and other geological factors, the electric energy price as well as technological and organizational circumstances. The electric energy price, which has an indirect impact on the lignite price (i.e. a higher electricity price causes a higher lignite price) plays an important role. Thorough analyses show that electricity produced on the basis of lignite is approximately 30% cheaper than electricity generated by a power station fired by hard coal.

The key problem related to lignite exploitation is the acidification of the environment. The major pollutants from power stations based on lignite are CO_2, SO_2, nitric oxides, O_3, air particles, and sediments. Facing significantly lower CO_2 limits than are necessary, power stations that need to increase their CO_2 emission permits must buy permits from those who require fewer permits. The transfer of permits is referred to as a trade. This is a result of EU restrictions oriented towards a reduction of CO_2 emission just in some European countries, without any real contribution from countries which on the global scale are the main sources of the emission of greenhouse gases. Therefore, this measure can not significantly contribute to environmental improvement on a global scale. However, this EU restriction substantially diminishes the competitiveness of electricity generation based on coal, especially on lignite.

In addition, we should once again stress that mining projects, especially lignite opencast exploitation, are usually not accepted by society. Social acceptance for the development of new lignite deposits and for new lignite–based power plants in Poland is very low, which is caused by common opinion about the enormous negative environmental effects of the extractive industry. The improvement of the power generation process, the application of modern environmental protection methods in lignite power plants, the contribution of lignite plants to regional prosperity and the living standards of residents could somewhat change this negative attitude to lignite mines in Poland, at least to some extent.

To summarize, interdisciplinary case studies related to the above–mentioned risk factors associated with the development of lignite production are necessary. A review of preventive technologies and their cost–benefit analyses (including ecological and health aspects) also deserve considerable attention.

The findings of this paper obtained for hard coal and lignite seem to be confirmed by results gained after an analysis of the causal relationships between total coal consumption (hard coal and lignite) and GDP. In this case nonlinear feedback was observed, which may be interpreted as an implication of unidirectional links (the dynamic impact of GDP on hard coal usage, and the causal influence of lignite consumption on GDP).

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Footnotes:

[1] There we would like to thank The Energy Market Agency in Warsaw for supplying the extensive dataset on production and consumption of coal energy in Poland. We are impressed with the commitment of this institution to supporting scientific research. In addition, we also would like to acknowledge the help of the Statistical Office in Cracow in obtaining the macroeconomic data.

[2] Significant seasonality may distort the overall result of causality analysis. The X–12 ARIMA procedure is one of most common approaches for seasonal adjustment (it is currently used by the U.S. Census Bureau).

[3] The logarithm belongs to Box–Cox transformations and helps to stabilize the variance, thus the transformed time series becomes closer to normally distributed, which is especially desired for the application of standard statistical methods.

[4] See Granger et al. (2000).

[5] For more details see Dickey and Fuller (1979) and Said and Dickey (1984).

[6] For more details see Kwiatkowski et al. (1992).

[7] For more details see Phillips and Perron (1988).

[8] The results of all computations conducted for the use of this paper, which are not presented in the text in detailed form (usually to save the space), are available from authors upon request.

[9] In such cases (different orders of integration) traditional linear causality analysis (based on direct application of simple VAR or VEC model) cannot be performed. One may state that differencing integrated variables is a possible solution to this problem as it leads to stationarity and allows the use of the standard approach. However, differencing may also lead to a loss of the long run properties of data and cause serious difficulties with the interpretation of test outcomes.

[10] More details can be found in Paulsen (1984).

[11] The list of these assumptions may be found in Lütkepohl (1993).

[12] For some additional details see Dolado and Lütkepohl (1996), Hacker and Hatemi (2006), Lach (2010).

[13] Bootstrap is likely to fail in some specific cases and thus it should not be used without due consideration (see e.g. Horowitz (1995) and Chou and Zhou (2006)).

[14] See e.g. Horowitz (1995).

[15] See e.g. Hacker and Hatemi (2006), Gurgul and Lach (2010). Technical details on leverages may be found in Davison and Hinkley (1999).

[16] In this paper we apply TY methodology for three VAR models. Details are presented in table 7 in subsection 6.1.

[17] Data preparation procedure and ALG may be easily adopted for bivariate models, single equation models etc.

[18] For comprehensive technical details of both the traditional and sequential long run causality tests see e.g. Gurgul and Lach (2010).

[19] Taking into consideration suggestions of Baek and Brock (1992) and Chen and Lin (2004) we applied nonlinear causality test for suitable residual time series. Moreover, we used right–sided version of the test following Skaug and Tjøstheim (1993) suggestions. The Reader may find detailed technical description of discussed nonlinear test in Diks and Panchenko (2006).

[20] For each heteroscedastic residual time series the GARCH(1,1) model was found to have the best fit to data.

[21] In all cases the maximal possible lag length was set up a level of 6 and then the final lag was established through the application of several information criteria (namely, AIC, BIC and HQ). Although for all VAR models the BIC criterion pointed at one lag (other criteria pointed at five lags), the results of the Ljung–Box Q–test ensured that in the case of one lag the residuals were significantly autocorrelated, which in turn may cause a distortion of the outcomes of TY analysis. Therefore, the optimal lag was set at five in all cases.

[22] All p–values presented in table 8 were calculated on the basis of $TY_{test}^{F} := \frac{TY_{test}}{p}$ statistic, which is asymptotically $F(p, T - n(p + d) - 1)$ distributed (T denotes sample size, n stand for VAR dimension, p and d are the same as in section 5). This modification of TY_{test} statistic performs relatively better for samples as small as the one analyzed in this paper (for more details see Lütkepohl (1993)).

[23] The final lag (for levels) was once again found to be equal to 5 (contrary to all other criteria, the BIC criterion once again pointed at only one lag, but the results of the Ljung–Box Q–test clearly excluded this possibility).

[24] For critical values we referred to MacKinnon et al. (1999). A similar conclusion (i.e. one cointegrating vector) was reported after the use of critical values presented in Osterwald–Lenum (1992).

[25] Results for GARCH–filtered data are presented in square brackets.