Impact of hard coal usage for metal production on economic growth of Poland

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1. Introduction

For many years the production of metals was one of the main applications of hard coal in Poland. This notion was especially emphasized during the period of communist rule. However, in the centrally planned economy there was a false allocation of coal resources among existing sectors. After the start of transition process from the centrally planned economy to the market economy the hard coal mining sector in Poland began restructuring in order to face new standards of economic activity.

In general, the transformation of hard coal mining sector in Poland has influenced the production of metals twofold. First, some fundamental changes were necessary to make Polish metal producers competitive in the global market. This process involved investments in new technologies, equipment and more efficient management. Second, since for over forty years the Soviet–type economy did not take any effort to protect the environment, most of state factories were operating without efficient pollution control. The transition process is naturally related with the fulfillment of many international laws regulating the emission of greenhouse gases and methods of waste neutralization. It is widely believed that adjusting the national energy structure in Poland is important in meeting the challenge of global climate change. 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 introduction of new management styles in hard coal mining sector in Poland had significant impact on employment in this sector. Although the financial state of hard coal sector was rather bad for many years, labour costs and the level of employment remained high, mainly due to strength of the coal–miners trade union. However, Polish governments have been performing the program of restructuring this sector. It was generally based on the closure of inefficient mines, and workforce reduction. 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.

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Despite the transition process Poland remained one of the largest consumers of hard coal in Europe. Moreover, the hard coal sector is still one of Poland's largest industries and employers. Therefore it is fully justified to ask about hard coal's importance for the economic growth of Poland on the example of the hard coal usage in production of metals. The motivation to examine this particular sector of Polish industry is twofold. First, in the last decade the production of metals in Poland has been dynamically changing. However, in recent years one could observe slight downward tendency. Second, many inefficient mines are or were subsidized by government. The justification was that increased coal production is essential for economic growth through the satisfaction of energy demand of industrial sector (including production of metals). However, one should examine whether increased production of hard coal is indeed economically justified and reasonable in this context. This paper contains the results of causality analysis which should (at least to some extent) help to answer this question. This research was aimed to check for dynamic interactions between GDP and hard coal consumption in production of metals in Poland.

Evidence on the direction of causality may have a significant impact on policy. For example, if there is a unidirectional causality (characterized by positive responses) running from consumption of hard coal in production of metals to economic growth, then a reduction in this usage could lead to a decline in economic growth. Naturally, this could also imply that government subsidies for hard coal mines are in line with principal country's economic interests. On the other hand, unidirectional causality from economic growth to coal consumption could imply that policies towards a reduction of coal usage in production of metals may be implemented without significant negative or adverse effects on the growth of economy. Moreover, this reduction would have a positive impact on environment.

Some of the most important studies will be reviewed in the next section.

2. Literature overview

In general, most of previous empirical studies related to investigations of energy–GDP causal links were conducted for aggregated energy usage and predominantly focused on the US economy or Asian Tigers. Kraft and Kraft [21] investigated the interdependency between economic growth and energy demand in USA. Using data for the period 1947–1974 they found that there was a relationship between GNP growth and energy consumption. They established that the rise in energy consumption was a consequence of increase in GNP. Yu and Choi [29] estimated the causal interdependency between the energy usage and gross national product of five countries. They found 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. In more recent study Glasure and Lee [8] found bidirectional causality between GDP and energy usage in South Korea and Singapore. On the other hand, Bowden and Payne [3] did not establish any causality between GDP and total energy consumption in the USA.

Large part of previous empirical investigations conducted for groups of countries provided mixed results. Contributions by Masih and Masih [24], Soytas and Sari [27] and Keppler [20] did not provide a common causal pattern for all analyzed countries. As one can see contributions related to GDP–energy links have focused on different countries, time periods, and have used different proxy variables for energy usage. The empirical outcomes of these contributions are not in line with each other and often just controversial.

In recent years only few papers empirically investigated causality issues between coal consumption and GDP. Yang [28] found unidirectional causality running from economic growth to coal consumption in Taiwan without a feedback effect which means that coal preservations have no destructive repercussions on the economic growth of this country. Jinke et al. [18] found unidirectional causality running from GDP to coal consumption in Japan and China, and no causal relationship between coal consumption and GDP in India, South Korea and South Africa.

To the knowledge of the author this paper is the first study which deals with the dynamic interaction between GDP, employment and the consumption of hard coal in a particular industry sector i.e. production of metals in Poland. Thus, one may expect outcomes of this paper to be helpful in judging whether increased consumption of hard coal in the production of metals will positively affect Polish economy.

The remainder of the paper is organized as follows. In the next section the applied dataset is presented. In section 4 the methodology is briefly described. The empirical results are presented and discussed in section 5. Section 6 concludes the paper.

3. The dataset

This section contains the presentation of the dataset applied in further calculations. The descriptive analysis of all examined time series will be presented in subsection 3.1. Subsection 3.2 contains details of stationarity analysis which is a crucial precondition for causality testing.

3.1. Description

In this paper the dataset containing quarterly data on GDP, overall usage of hard coal in production of metals and employment in Poland in the period Q1 2000 to Q4 2009 was applied. 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 was provided by Energy Market Agency in Warsaw.[1]

In the initial step several transformations of examined dataset were performed. These transformations are believed to help avoiding spurious results of

[1] I would like to thank The Energy Market Agency in Warsaw for supplying the dataset on consumption of hard coal in production of metals in Poland. In addition, I also would like to acknowledge the help of the Statistical Office in Cracow in obtaining the macroeconomic data.

further causality analysis. Firstly, in order to filter out the impact of inflation the GDP was calculated at constant prices of year 2000. Secondly, since all examined variables were characterized by significant quarterly seasonality, the X–12 ARIMA procedure (which is currently used by US Census Bureau for seasonal adjustment) of Gretl software was applied to adjust each variable. Finally, each seasonally adjusted variable was transformed to logarithmic form, as this transformation (belonging to Box–Cox transformations) helps to stabilize variance, which is especially important for proper application of asymptotic theory. In this paper the abbreviations are used for all examined variables. Following table contains suitable details:

Table 1

Most previous contributions concerned with analysis of dynamic links between coal usage and GDP was based on application of annual data. However, for most post–Soviet economies (including Poland) reliable datasets cover only a few recent years and thus the causality analysis based on annual data cannot be carried out due to lack of degrees of freedom. Thus, all calculations of this paper were based on application of quarterly data. Moreover, the application of lower frequency data (e.g. annual) may seriously distort results of Granger causality analysis because some important interactions may stay hidden (for more details see e.g. [11]).

In order to analyze the properties of examined variables some descriptive statistics were calculated. The following table contains the results which were obtained for seasonally adjusted and logarithmically transformed data:

Table 2

From the table above one can already see some basic information about properties of analyzed data. However, in order to perform the comprehensive initial analysis suitable charts of examined time series are also required. Figure 1 shows the plots:

Figure 1

In general, Polish economy was growing in the period under study. The *GDP* was rising, especially between 2003 and 2008. This observation should be analyzed together with the fact that Poland was the only European country with positive GDP growth rate in 2008. The crisis of September 2008 caused only a slight slowdown of the pace of the growth of the Polish economy, which also can be seen from figure 1.

One can also easily see that, in general, *MCOAL* exhibited downward tendency. This tendency was especially significant after the third quarter of 2008. One may claim that the drop in hard coal consumption in production of metals in Poland was related to two facts. First, in recent years this sector of Polish industry has adopted new, more energy–efficient technologies in order to face number of international ecological requirements. Second, in the last decade the whole industry sector (including production of metals) in Poland has been eclipsed by expanding service sector.

On the other hand, the 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. This stage should be carried out with great precision as all further steps of causality analysis (including the choice of suitable testing method) strongly depend on it.

3.2. Testing the stationarity of the dataset

In this paper the stationarity analysis was performed on the basis of three well known unit root tests. The motivation to use three tests is twofold. First, each unit root test used in empirical research has got several drawbacks and thus in practise its indications are often confirmed by other unit root test. Second, since it is possible that two unit root tests lead to relatively different conclusions, one should use a third test to make a final decision about stationarity.

The following table contains results of stationarity analysis. Bold face indicates finding nonstationarity at 5% level:

Table 3

Results presented in table 3 lead to conclusion that all analyzed time series are nonstationary around constant at 5% significance level. For *GDP* and *MCOAL* this was confirmed by all three conducted tests while for *EMPL* this was confirmed by two of three tests. Some further calculations conducted for first differences of all time series confirmed that all examined variables are I(1).[2] It is also worth to note that none of three examined time series was found to be trend–stationary (at 5% level). This observation will be especially useful in further long–run causality analysis.

4. Methodology

In order to explore the dynamic relationships between GDP, overall usage of hard coal in production of metals and employment in Poland in period Q1 2000 – Q4 2009 several statistical methods were applied. Both the traditional econometric methods, like linear Granger causality tests based on asymptotic theory, as well as some recently developed instruments, like the Andrews and Buchinsky bootstrap algorithm and the Diks and Panchenko nonlinear Granger causality test were applied.

4.1. Cointegration and linear Granger causality

The concept of causality used in this paper was formulated by Granger [9]. Since this idea is well known and has been commonly used in previous research, I

[2] 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 the author upon request.

will not provide its detailed description. By and large, 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. The discussed definition was intentionally formulated for stationary series. Previous empirical studies (e.g. [12]) and theoretical deliberations (e.g. [25]) strongly suggested that if the time series under study are indeed nonstationary then the results of traditional linear causality tests may lead to spurious conclusions.

Since the results presented in subsection 3.2 provided relatively strong support for claiming that all analyzed time series are integrated of order one, an analysis of the cointegration properties of the dataset was also conducted. The motivation for performing long–run causality analysis is based on the fact that cointegration properties may be useful in describing long–term equilibrium relationships between variables. On the other hand, differencing the data or calculating growth rates usually solves the problem of nonstationarity and allows using traditional methods but it also leads to loss of important long–run information which in turn may simply distort results of causality tests.

To check the dimension of cointegration space the Johansen cointegration tests (Trace and Maximal Eigenvalue variants) were used. The application of this method comprises few steps. Firstly, the type of deterministic term was established. This was done through examination of famous *five cases* presented in Johansen [19]. Since none of time series was found to be trend–stationary the third case (i.e. presence of constant in cointegrating equation and in test VAR) was assumed. Next, the appropriate lag length was established through application of information criteria.

Finding cointegration relationship implies the existence of long–run Granger causality in at least one direction ([10]). In order to establish the direction of this causal link the suitable VEC model should be estimated. For example, testing for long–run Granger causality from variable A to variable B in two–dimensional VEC model is usually based on 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 (using F–test) provides a basis for examining short–run causalities between variables. The detailed description of this approach may be found in [14].

4.2. Bootstrap techniques

One cannot forget that discussed approach, like every parametric method, has some typical drawbacks. First of all, if some typical modelling assumptions do not hold, then the application of asymptotic theory may lead to misleading outcomes ([23]). Furthermore, the distribution of each test statistic may be markedly different from asymptotic pattern (i.e. F or t–Student) when dealing with small samples, even if all modelling conditions are generally fulfilled.

One possible way of overcoming these problems is the application of bootstrap methods. Bootstrapping is used to estimate the distribution of the test statistic by resampling the data. Therefore, one may expect bootstrapping to require vastly weaker assumptions in comparison to parametric methods. However, the application of bootstrap techniques does not guarantee a correct solution of all possible model specification problems and should not be used without second thought ([17]).

Since heteroscedasticity may cause a serious distortion of the results of the bootstrap procedure ([17]) the resampling algorithm applied in this paper was based on the application of leveraged residuals. The technical details of this resampling procedure may be found in [15] and [14]. In recent years the discussion on proper establishment of number of bootstrap replications has gained a considerable attention ([22]). In this paper the recently developed algorithm of choosing the number of bootstrap replications presented by Andrews and Buchinsky [1] was used. 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 author upon request.

4.3. Impulse response analysis

Standard Granger causality analysis provides an opportunity for the establishment of the direction of any linear causal link between examined variables, but it does not say anything about the signs of this relationship. Therefore, the linear Granger causality testing is usually supplemented with the impulse response (IR) analysis as it allows predicting reaction of the dynamic system to the shock in one or more variables ([11]). In order to examine the nature of this reaction (which is transmitted through the dynamic structure of the VEC model) an impulse response analysis based on one standard deviation shocks was used in this paper. It is also worth to note that impulse response analysis was performed only after finding significant evidence of causality. The lack of causal dependences implies that shock in one variable should not seriously affect the other one and thus IR analysis is unnecessary. The reader may find the theoretical background of this method in [23].

4.4 Nonlinear Granger causality test

In general, the motivation to use nonlinear causality test is twofold. Firstly, traditional linear Granger causality test is often found to have extremely low power in detecting certain kinds of nonlinear relationships ([4], [13]). Secondly, as the linear approach is based on testing the statistical significance of suitable parameters only in the mean equation causality in higher–order structure (e.g. causality in variance etc.) may not be found ([5]). One possible solution to these difficulties is the application of a nonlinear causality test. However, the interpretation of nonlinear causality running from one variable to another is not as simple as in the linear case. Since testing for linear causality is based on analysis of estimation results of specific equation one may also easily “measure” the impact of causal factor on caused variable (e.g. using impulse response analysis etc.). The existence of nonlinear causality informs about the direction of dynamic impact but provides no details about the way of transporting shocks.

In this article the nonlinear causality test proposed by Diks and Panchenko ([7]) was applied. Some representative (see e.g. [16], [6], [7], [13], [14]) values of the technical parameters of this method were used. Namely, the bandwidth parameter (denoted as ε) was set at level of 0.5, 1 and 1.5 for all conducted tests while common lag parameter (denoted as l) was established at the order of 1 and 2. The Reader may find more details about meaning of these technical parameters in [7].

All calculations were performed for residual time series resulting from the examined VEC model. The residual time series are believed to reflect strict nonlinear dependencies, as the structure of linear links had been filtered out during linear causality analysis ([2]). The time series of residuals were all standardized, thus they shared a common scale parameter. In this paper the right–sided variant of Diks and Panchenko's test was used. There are at least two main reasons justifying this choice. Firstly, in empirical research the right–sided variant is often found to have greater power than a two-sided one ([26]). Secondly, despite the fact that significant negative values of test statistic provide a basis for rejection of the null hypothesis of Granger non–causality, they also indicate that knowledge of past values of one time series may interfere with the prediction of another one. In contrast, causality analysis is usually conducted to judge whether this knowledge is a help (not a hindrance) in the prediction process.

Finally, it should be noted that the former research has provided a solid basis for claiming that the considered nonlinear causality test tends to over–reject if there are heteroscedastic structures in analyzed time series ([7]). Thus, all residual time series were tested for the presence of unconstant variance. However, no significant evidence of the presence of any type of heteroscedasticity in the residuals of examined VEC model was found, thus no filtering was applied. It is also worth to note that each heteroscedasticity filtering (e.g. ARCH/GARCH one) should be carried out carefully as it may sometimes lead to a loss of power of the test, which may arise from the possible misspecification of the conditional heteroscedasticity model. This of course may simply lead to misleading results of discussed nonlinear testing procedure ([7]).

5. Empirical results

This section contains the outcomes of empirical analysis. It is divided into three parts, dedicated to results of linear causality tests, outcomes of IR analysis and results of nonlinear causality tests, respectively.

5.1. Linear Granger causality

In the first step the results of cointegration analysis are presented. As already mentioned, the presence of constant in both the cointegrating equation and test VAR was assumed (third Johansen's case). The maximal lag length (for levels) was set at a level of 6. BIC criterion pointed at one lag, but the results of Ljung–Box Q–

test excluded this possibility providing evidence of autocorrelation of residuals. The final lag length was established at a level of 5 as this value was indicated by all other applied information criteria. The results of Johansen cointegration tests are presented in the following table:

Table 4

The results of both variants of Johansen tests provided evidence to claim that for *GDP*, *MCOAL* and *EMPL* there is one cointegrating vector at 5% significance level. It is also worth to note that *GDP* and *MCOAL* coefficients in the cointegrating equation were both positive, which implies that in the long–run changes in one of these variables cause opposite changes of another one (e.g. after rise in *MCOAL* one could observe drop in *GDP*). This observation is in line with charts presented in figure 1.

After examining cointegration properties of analyzed dataset the suitable VEC model was estimated. Following table contains *p*–values obtained while testing for linear short– and long–run Granger causal effects by means of both the asymptotic– and bootstrap–based *F* and *t*–Student tests. Parameter *N* denotes number of bootstrap replications established after application of the Andrews and Buchinsky [1] procedure. Notation "$x \neg\rightarrow y$" is equivalent to "*x* does not Granger cause *y*". Bold face indicates finding causal link at 5% significance level:

Table 5

The results of both asymptotic– and bootstrap–based variants of short–run Granger causality tests provided basis to claim that in the period under study there was unidirectional linear causality running from *GDP* to *MCOAL*. The lack of causality in opposite direction implies that in the short–run changes of coal usage in production of metals in Poland had no impact on the rate of economic growth. On the other hand, the asymptotic variant of Granger test provided evidence to claim that fluctuations of *MCOAL* were found to have a short–run causal impact on employment. However, this was not confirmed by bootstrap–based procedure.

Both variants of *t*–test (asymptotic– and bootstrap–based) provided solid evidence to claim that error correction term of examined VEC model is statistically significant only in *GDP* and *EMPL* equations. This implies that both the GDP and employment react to fluctuations in the long–run equilibrium relationship between all three examined variables. In other words, the long–run causality from all variables to *GDP* and *EMPL* was found to be significant at 5% level.

5.2. Impulse response analysis

In previous subsection the evidence of existence of five statistically significant linear causal links was found. However, the analysis of linear Granger causality does not provide complete information about the dynamic interactions between examined variables. It provides details about directions of causal links but it does not tell anything about signs of these relationships. That is why an impulse response analysis was also performed. Every IR function illustrates the response of the caused variable to one s.d. (standard deviation) shock in the causal variable for

20 quarters. The residuals of examined VEC model were not found to be significantly correlated at 5% level, which excludes possibility of Wold instantaneous causality ([23]). Thus, before performing the impulse response analysis no orthogonal transformation of residuals was applied. The following figure contains illustration of all shock responses:

Figure 2

The one s.d. (0.09) shock from *EMPL* causes positive responses of *GDP* in all quarters. The one s.d. (0.12) shock from *GDP* causes positive response of *MCOAL* in the first five quarters with highest positive response (0.18) reported for the fourth quarter. The one s.d. shock from *GDP* causes positive response of *EMPL* in first five quarters. Starting from sixth quarter negative responses occur. On the other hand, the one s.d. (0.63) shock from *MCOAL* causes negative responses of *EMPL* from third quarter forward.

5.3. Outcomes of nonlinear causality tests

In this subsection the results of the nonlinear Granger causality tests conducted for residuals resulting from examined VEC model are presented. Once again the bold face was used to indicate the establishment of a causal link in examined direction at a 5% significance level and the notation $"x \neg\rightarrow y"$ is equivalent to "x does not Granger cause y:

Table 6

The analysis of results contained in table 6 lead to conclusion that in the period under study there was a nonlinear causal link running from *GDP* to employment. On the other hand, all other causal links were not found to be statistically significant even at 10% level.

6. Summary and conclusions

To the best knowledge of the author this is the first paper which examines the causal links between GDP, usage of hard coal in production of metals and employment in Poland on the basis of recent 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 empirical analysis was based on the application of linear short– and long–run Granger causality tests. Since examined sample was relatively small and this could cause problems with application of asymptotic distribution theory the residual–based bootstrap was additionally applied in this paper. In both research variants significant evidence of unidirectional short–run linear causality running from *GDP* to usage of hard coal in production of metals was found. Some weak evidence of causality running from *MCOAL* to employment was also found. On the other hand, each examined variable (i.e. *GDP*, *EMPL* and *MCOAL*) was found to have a significant long–run impact on *GDP* and *EMPL*.

After establishing directions of causalities between examined variables the impulse response analysis was performed to examine the signs of these relationships. In general, the outcomes of this part of empirical analysis provided basis to claim that a rise in usage of coal in production of metals leads to drops in both GDP and employment.

The main goal of the last part of empirical analysis was to examine strictly nonlinear Granger causal links between all the variables. The fluctuations of *GDP* were found to have a nonlinear causal impact on employment. On the other hand, all other strict nonlinear causal links were not found to be statistically significant.

The findings of this contribution imply some policy recommendations. Since in the short–run GDP was found to cause the usage of hard coal in production of metals and not vice versa, reducing the usage of this fuel in Polish metal industry should not have, in general, a significant negative impact on Polish GDP. This conclusion was also confirmed by results of impulse response analysis. Although one may claim that in the long–run *MCOAL* was found to cause both employment and GDP, the rise in hard coal usage in production of metals was accompanied with slowdown of economic growth and drop in overall employment. These results should be analyzed with two facts. First, in recent decade the share of industry sector (including production of metals) in Polish economy has significantly shrunk, as the process of transformation toward services–orientated economy has been taking place. Moreover, industrial sector has adopted new, more energy–efficient technologies in order to face number of international ecological requirements. This could explain both the reduction of the usage of hard coal in metal industry and no positive dynamic interactions with GDP or employment.

All these fact are strongly related to recently observed problems of Polish hard coal mines and ongoing process of their restructuring. Some of these mines do not bring any profit and must be even subsidised by central budget. The findings of this paper based on analysis of recent decade provided basis to claim that the common notion describing hard coal mines as extremely important for Polish economy (also in terms of industrial production) was rather false.

References:

[1] Andrews D.W.K., Buchinsky M., *A Three–Step Method for Choosing the Number of Bootstrap Repetitions*. Econometrica, 2000, Vol. 68, pp. 23–52.

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

[3] Bowden N., Payne J.E., *The causal relationship between U.S. energy consumption and real output: A disaggregated analysis*. Journal of Policy Modeling, 2009, Vol. 31, pp. 180-188.

[4] Brock W., *Causality, chaos, explanation and prediction in economics and finance*, in: Casti J., Karlqvist A. (Eds.), Beyond Belief: Randomness, Prediction and Explanation in Science, 1991, CRC Press, Boca Raton, Fla., pp. 230–279.

[5] Diks C.G.H., DeGoede J., *A general nonparametric bootstrap test for Granger causality*, in: Broer H.W., Krauskopf W., Vegter G. (Eds.), Global analysis of dynamical systems. Institute of Physics Publishing, 2001, Bristol, United Kingdom, pp. 391–403.

[6] Diks C.G.H., Panchenko V., *A note on the Hiemstra–Jones test for Granger non–causality*. Studies in Nonlinear Dynamics and Econometrics, 2005, Vol. 9, No. 2, Article 4.

[7] Diks C.G.H., Panchenko V., *A new statistic and practical guidelines for nonparametric Granger causality testing*. Journal of Economic Dynamics and Control, 2006, Vol. 30, pp. 1647–1669.

[8] Glasure Y.U., Lee A.R., *Cointegration, error–correction, and the relationship between GDP and electricity: the case of South Korea and Singapore*. Resource and Energy Economics, 1997, Vol. 20, pp. 17–25.

[9] Granger C.W.J., *Investigating causal relations by econometric models and cross spectral methods*. Econometrica, 1969, Vol. 37, pp. 424–438.

[10] Granger C.W.J., *Some recent developments in the concept of causality*. Journal of Econometrics, 1988, Vol. 39, pp. 199–211.

[11] Granger C.W.J., Huang B., Yang C., *A bivariate causality between stock prices and exchange rates: evidence from recent Asian Flu*. The Quarterly Review of Economics and Finance, 2000, Vol. 40, pp. 337–354.

[12] Granger C.W.J., Newbold P., *Spurious regression in econometrics*. Journal of Econometrics, 1974, Vol. 2, pp. 111–120.

[13] Gurgul H., Lach Ł., *Linear versus nonlinear causality of DAX companies*. Operations Research and Decisions, 2009, Vol. 3, pp. 27–46.

[14] Gurgul H., Lach Ł., *The causal link between Polish stock market and key macroeconomic aggregates*. Betriebswirtschaftliche Forschung und Praxis, 2010, Vol. 4, pp. 367–383.

[15] Hacker R.S., Hatemi–J A., *Tests for causality between integrated variables using asymptotic and bootstrap distributions: theory and application*. Applied Economics, 2006, Vol. 38, pp. 1489–1500.

[16] Hiemstra C., Jones J.D., *Testing for linear and nonlinear Granger causality in the stock price–volume relation*. Journal of Finance, 1994, Vol. 49, pp. 1639–1664.

[17] Horowitz J.L., *Bootstrap methods in econometrics: Theory and numerical performance*, in: Kreps D.M., Wallis K.F. (Eds.), Advances in Economics and Econometrics: Theory and Applications, 1995, Cambridge University Press, Cambridge, pp. 188–232.

[18] Jinke L., Hualing S., Dianming G., *Causality relationship between coal consumption and GDP: difference of major OECD and non-OECD countries*, Applied Energy, 2008, Vol. 8, pp. 421–429.

[19] Johansen S., *Likelihood–based Inference in Cointegrated Vector Autoregressive Models*, 1995, Oxford University Press, Oxford.

[20] Keppler J.H., *Causality and Cointegration between Energy Consumption and Economic Growth in Developing Countries*, in: Keppler J.H., Bourbonnais R., Girod J. (Eds.), The Econometrics of Energy Systems, 2007, Palgrave Macmillan, New York, pp. 75–97.

[21] Kraft J., Kraft A., *On the relationship between energy and GNP*. The Journal of Energy and Development, 1978, Vol. 3, pp. 401–403.

[22] Lach Ł., *Application of bootstrap methods in investigation of size of the Granger causality test for integrated VAR systems*. Managing Global Transitions, 2010, Vol. 8, pp. 167–186.

[23] Lütkepohl H., *Introduction to Multiple Time Series Analysis, second ed.*, 1993, Springer–Verlag, New York.

[24] Masih A.M.M., Masih R., *Energy consumption, real income and temporal causality: results from a multi–country study based on cointegration and error–correction modelling techniques*. Energy Economics, 1996, Vol. 18, pp. 165–183.

[25] Phillips P.C.B., *Understanding the spurious regression in econometrics*. Journal of Econometrics, 1986, Vol. 33, pp. 311–340.

[26] Skaug H.J., Tjøstheim D., *Nonparametric tests of serial independence*, in: Subba Rao T. (Ed.), Developments in Time Series Analysis, 1993, Chapman and Hall, London , pp. 207–229.

[27] Soytas U., Sari R., *Energy consumption and GDP: causality relationship in G–7 countries and emerging markets*. Energy Economics, 2003, Vol. 26, pp. 33–37.

[28] Yang H.Y., *A note on the causal relationship between energy and GDP in Taiwan*. Energy Economics, 2000, Vol. 22, pp. 309–317.

[29] Yu E., Choi J., *The causal relationship between energy and GDP, an international comparison*. The Journal of Energy and Development, 1985, Vol. 10, pp. 249–272.

Table 1.

Units, abbreviations and short description of examined variables.

Description of variable	Unit	Abbreviation for seasonally adjusted and logarithmically transformed variable
Actual quarterly gross domestic product in Poland	mln PLN	*GDP*
Employment in Poland based on quarterly Labour Force Survey	thousands	*EMPL*
Quarterly consumption of hard coal in production of metals in Poland	TJ	*MCOAL*

Source: own calculations.

Table 2.

Descriptive statistics of examined variables.

Quantity \ Variable	*GDP*	*EMPL*	*MCOAL*
Minimum	12.11	9.51	3.94
1st quartile	12.15	9.53	5.11
Median	12.26	9.57	6.38
3rd quartile	12.41	9.63	7.02
Maximum	12.49	9.68	7.26
Mean	12.28	9.58	6.26
Std. deviation	0.12	0.09	0.63
Skewness	0.27	0.48	−1.63
Excess kurtosis	−1.40	−1.12	3.64

Source: own calculations.

Table 3.

Results of stationarity analysis.

Variable \ Test type	ADF				KPSS		PP	
	with constant		with constant and linear trend		with constant[a]	with constant and linear trend[b]	with constant	with constant and linear trend
	p–value	Lag	*p*–value	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**
MCOAL	**0.96**	4	**0.84**	4	**0.84**	**0.19**	**0.53**	**0.17**

Source: own calculations.

[a] critical values: 0.347 (10%), 0.463 (5%), 0.739 (1%).

[b] critical values: 0.119 (10%), 0.146 (5%), 0.216 (1%).

Table 4.

Results of cointegration analysis for *GDP*, *EMPL* and *MCOAL* variables.

		Johansen Trace test		Johansen Maximal Eigenvalue test	
Hypothesized number of cointegrating vectors	Eigenvalue	Trace statistic	*p*–value	Maximal Eigenvalue statistic	*p*–value
Zero	0.47	36.61	0.00	21.13	0.02
At most one	0.28	13.83	0.08	14.27	0.12
At most two	0.06	2.26	0.13	3.84	0.13

Source: own calculations.

Table 5.

Results of linear causality analysis for *GDP*, *EMPL* and *MCOAL* variables.

Short–run causality		
Null hypothesis	*p*–value (asymptotic)	*p*–value (bootstrap)
MCOAL $\neg\rightarrow$ *GDP*	0.13	0.15 (*N*=3519)
GDP $\neg\rightarrow$ *MCOAL*	**0.01**	**0.01** (*N*=3239)
EMPL $\neg\rightarrow$ *GDP*	0.11	0.13 (*N*=2659)
GDP $\neg\rightarrow$ *EMPL*	0.52	0.48 (*N*=2279)
MCOAL $\neg\rightarrow$ *EMPL*	**0.04**	0.12 (*N*=3399)
EMPL $\neg\rightarrow$ *MCOAL*	0.23	0.30 (*N*=3239)
Long–run causality		
Null hypothesis	*p*–value (asymptotic)	*p*–value (bootstrap)
MCOAL $\neg\rightarrow$ *GDP*	**0.02**	**0.00** (*N*=2739)
GDP $\neg\rightarrow$ *MCOAL*	0.15	0.45 (*N*=3339)
EMPL $\neg\rightarrow$ *GDP*	**0.02**	**0.00** (*N*=2939)
GDP $\neg\rightarrow$ *EMPL*	**0.00**	**0.00** (*N*=3439)
MCOAL $\neg\rightarrow$ *EMPL*	**0.00**	**0.00** (*N*=2079)
EMPL $\neg\rightarrow$ *MCOAL*	0.15	0.45 (*N*=3319)

Source: own calculations.

Table 6.

Analysis of nonlinear causal links between *GDP*, *EMPL* and *MCOAL* variables

Null hypothesis	p–value					
	ε=0.5, l=1	ε=1, l=1	ε=1.5, l=1	ε=0.5, l=2	ε=1, l=2	ε=1.5, l=2
$MCOAL \neg\rightarrow GDP$	0.76	0.87	0.86	0.43	0.65	0.89
$GDP \neg\rightarrow MCOAL$	0.43	0.67	0.76	0.45	0.68	0.59
$EMPL \neg\rightarrow GDP$	0.40	0.38	0.40	0.45	0.47	0.59
$GDP \neg\rightarrow EMPL$	0.08	0.14	**0.04**	0.31	0.17	0.09
$MCOAL \neg\rightarrow EMPL$	0.82	0.38	0.48	0.65	0.65	0.35
$EMPL \neg\rightarrow MCOAL$	0.87	0.43	0.86	0.71	0.77	0.86

Source: own calculations.

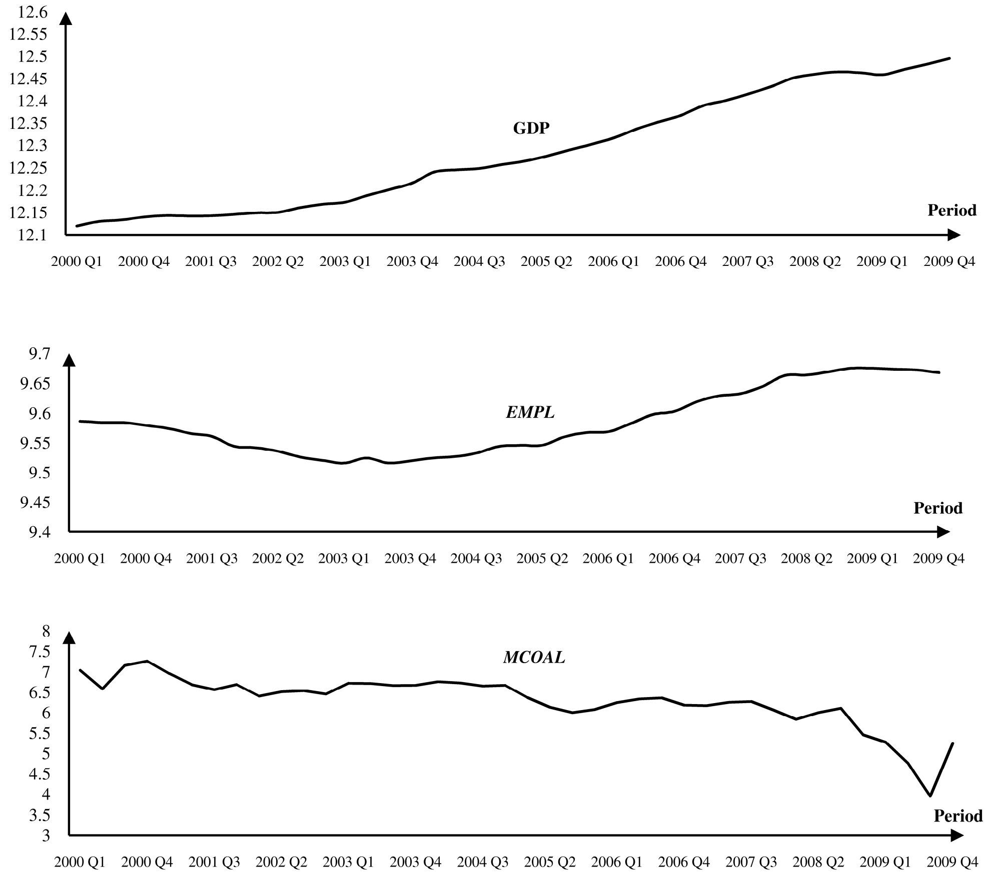

Figure 1. Plots of examined times series.

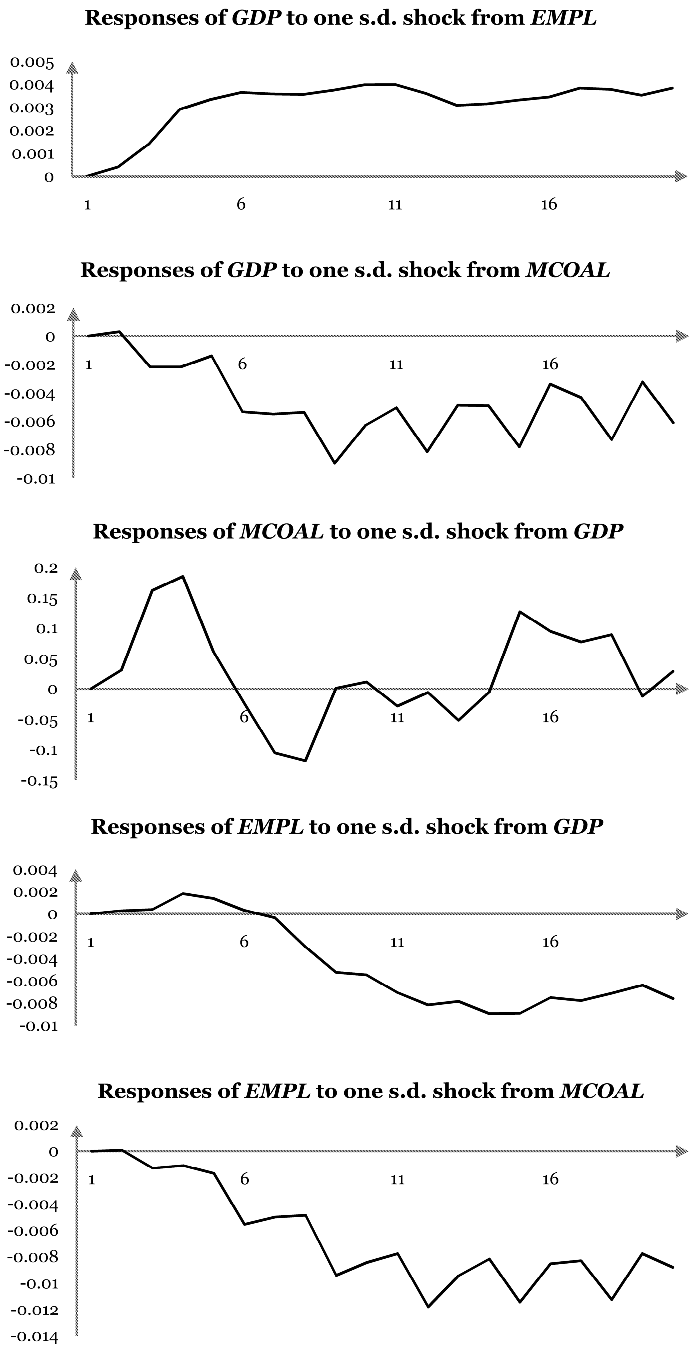

Figure 2. Impulse response analysis.