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Abstract

The main aim of this contribution is an analysis of the causal relationship between the total energy consumption in the Polish economy and GDP. In order to assure the correctness of computations a third variable – employment – was included in the dataset. Calculations performed for the period Q1 2000 to Q4 2009 by means of recent econometric techniques indicated the existence of a significant causal relation from total energy consumption to GDP. In addition, some other causalities between employment and GDP for short– and long–run term were detected, which provided a basis for claiming that changes of energy use in Poland are related in the sense of Granger causality to the employment. Because of the relatively small dataset and possible problems with the proper application of asymptotic methods, we additionally applied bootstrap critical values. The results of both methods were generally in line with each other.

The results have important policy implications. The statistically significant causality from energy consumption to GDP means that energy is a very important factor in economic growth and therefore that energy policy in Poland cannot be neutral with respect to GDP growth.

Nomenclature

$ENERGY_{PL}$	Total quarterly energy consumption in Poland (in PJ)

[*] Corresponding author.

GDP_{PL}	Quarterly Gross Domestic Product in Poland (in millions PLN)
$EMPL_{PL}$	Employment in Poland based on quarterly Labour Force Survey (in thousands)
ADF	Augmented Dickey–Fuller unit root test
KPSS	Kwiatkowski, Phillips, Schmidt and Shin unit root test
PP	Phillips–Perron unit root test
AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion
HQ	Hannan–Quinn information criterion
SL	significance level
I(n)	integrated of order n
VAR	Vector AutoRegression model
VECM	Vector Error Correction Model
tr	transpose operator
OLS	Ordinary Least Squares methodology
$\hat{D}$	OLS estimator of D
$vec(\cdot)$	column stacking operator
$rwc(\cdot)$	row–wise concatenation operator
$0_{n\times m}$	$n\times m$ matrix filled with zeros
$\otimes$	Kronecker product
b_{DP}	bandwidth parameter of Diks and Panchenko nonlinear Granger causality test
l_{DP}	common lag parameter of Diks and Panchenko nonlinear Granger causality test
(G)ARCH	(Generalized) AutoRegressive Conditional Heteroscedasticity model
Δ	differencing operator
$x \neg\!\!\rightarrow y$	x does not Granger cause y

Keywords: energy consumption, economic growth, Granger causality, bootstrap techniques.

1. Introduction

For many years there have been investigations to clarify the relationship between economic growth and energy input in manufacturing processes. The extreme importance of energy for world economies has been apparent in the last five decades, especially as a result of the two energy crises in 1973 and 1979. Investigations have revealed a strong correlation between economic growth and energy consumption. Contributors have tried to establish whether this relationship is in fact causal, and if so, if it runs from energy towards the rate of economic growth or vice versa. Also, the existence of feedback between these two economic categories cannot be excluded.

Evidence on the direction of causality may have a significant impact on policy. For example, if there is unidirectional causality from energy consumption to economic growth, then a reduction of energy consumption could lead to a decline in economic growth. If there is unidirectional causality from economic growth to energy consumption, it could mean that policies towards reducing energy consumption may be implemented without significant negative or adverse effects on economic growth. Finally, no causality in either direction would also indicate that policies towards decreasing of energy consumption do not have any impact on economic growth.

The importance of energy supply for economic growth has been investigated not only by individual researchers, but also by major world financial institutions like the World Bank and the International Monetary Fund. The main object was to prove the impact of increasing energy prices, especially the oil price, on the rate of growth of the world economy.

Until the mid–1990's the dominant view in the economic literature was that economic growth implies an increase in demand for energy. This view was based on the assumption that increasing income is the source of rise in energy demand and declining income is the reason for decreasing energy consumption. Although the causal relationship between energy demand and economic growth has been extensively studied since the 70's, the empirical evidence concerning the direction of interdependency between economic growth and energy demand is still controversial. Although many contributions reported that the causal relation runs from economic growth towards energy consumption, numerous authors found that an increase in energy consumption can lead to economic growth. Some contributors have proved that the casual relationship between these two variables can be bidirectional, i.e. economic growth has an impact on energy consumption and vice versa. The positive impact of energy consumption on economic growth can be reflected indirectly in the positive impact of energy consumption on human resources, e.g. an increase in electricity consumption has a positive impact on population health (e.g. through increasing usage of washing machines, fridges etc.) and on education (telecommunication, radio, television etc.). An increase in human resources supports economic growth.

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

2. Literature overview

The first studies which dealt with the interdependency between economic growth and energy demand were predominantly focused on the US economy (i.e. [34], [2], [3], [50], [46], [47], [9], [10]). Kraft and Kraft ([34]) used US data for the period 1947–1974. The authors concluded that there is a relationship between Gross National Product (GNP) growth and energy consumption. They indicated that an increase in national income caused a rise in energy consumption. Yu and Choi ([50]) estimated the casual relationship between the energy consumption and GNP of five countries. They concluded that there was unidirectional causality from energy consumption to GNP in the Philippines and causality in the opposite direction i.e. from GNP to energy demand in South Korea. They found no causality in the USA, the UK and Poland.

The relationship between energy consumption and economic growth with respect to the direction of causality between these two variables was first investigated by Engle and Granger ([18]) by means of a new causality technique. Erol and Yu ([19]) investigated six industrialized countries, and based on the respective data they found no significant causal relationship between energy consumption and GDP growth or between energy consumption and employment. Yu et al. ([51]), in the case of the USA, found no interdependence between energy consumption and employment or between energy consumption and GNP. Cheng ([9]) by means of a multivariate approach could not find causality between energy and economic growth. In a study from 1997 Cheng ([10]) conducted an analysis by Hsiao's version of Granger causality, which he applied to Brazil, Mexico and Venezuela. However, he was unable to detect causal patterns between energy demand and economic growth in these three Latin countries. Stern ([47]) established cointegration between gross domestic product, capital, labour and energy consumption in the USA.

Some research has been performed in the past on basis of data for large groups of countries in order to prove the importance of energy consumption for their rate of economic growth. Ferguson et al. ([20]) conducted a study for the G–7 Group including the United States, Canada, Japan, Germany, France, Italy and the United Kingdom. The authors demonstrated that there is a strong dependency between electricity demand and wealth increase. They did not find any interdependence between total energy consumption and wealth. Ferguson et al. ([21]) extended their study from 1997 to more than 100 countries, comprising over 99% of global GDP. They concluded that wealthy countries exhibit a stronger dependency between electricity demand and wealth increase than between total energy consumption and wealth. Moreover, the authors found that in rich countries an increase in wealth over time relates to an increase in the proportion of the total primary energy supply consumed as electricity. An overview of the empirical results for Asian countries can be found in [44].

In an earlier contribution Masih and Masih ([39]) concluded the existence of a cointegrating relationship between energy demand and GDP in India, Pakistan and Indonesia, but they did not find such evidence in the case of Malaysia, Singapore or the Philippines. Yang ([49]) investigated the causal interdependence between GDP and energy demand including coal, natural gas and electricity. He tested for causality between aggregated as well several disaggregated economic variables. He found bidirectional causality between energy consumption and GDP in India. However, in the case of Pakistan and Indonesia, the causality ran only in one direction, namely from GDP to energy consumption. A similar study by Masih and Masih ([40]) concerning the causal relationship between energy consumption, real income and prices conducted for South Korea and Taiwan confirmed that there exists a long–run equilibrium relationship between all three variables and a feedback between energy consumption and real income for both South Korea and Taiwan.

In a more recent study by Chang et al. ([7]) based on VECM analysis the authors suggested for Taiwanese data bidirectional Granger causality for the employment–output and employment–energy consumption variables, but only unidirectional causality running from energy consumption to output.

Gelo ([22]) investigated causality between GDP and total primary energy consumption in Croatia for the time period 1953 to 2005. The main conclusion of the paper is that VAR model evaluation demonstrates that change in GDP of 1% in period t–1 would affect the annual total primary energy consumption by 0.509% in period t.

As we can see, the direction of causality between energy consumption and economic growth is highly controversial. Some authors argue that the relationship may very well run from economic growth to energy consumption while others found causality from energy consumption to economic growth or even feedback.

While there have been a number of studies dealing with causality tests on energy consumption and economic growth, little attention has been paid to the emerging economies of Central and Eastern Europe. We will fill this gap with a causality analysis of energy usage and economic growth based on Polish data.

One possible approach to energy–GDP links is to conduct simple research based only on two variables. As we see from the comprehensive literature overview this was especially popular in early studies concerning GDP–energy links. However, any results provided by such a simple approach may be seriously biased due to the possible omission of important variables. Thus, it is not surprising that in recent years the analysis of causal links between GDP and energy has often been conducted in a multivariate framework as in [7]. In this paper, taking into account macroeconomic theory and the experience of Chang et al. ([7]), we chose data on employment as an additional variable determining economic growth.

The objective of this paper is to establish the causality between energy consumption and economic growth in Poland as an emerging economy, by employing recent advances in causality testing techniques. Section 3 describes the main research hypotheses, section 4 contains a description of the dataset and in section 5 the applied methodology is reviewed. In section 6 the computed results are presented and discussed. Section 7 concludes the paper.

3. Main conjectures

It is not easy to formulate a general assumption about the interdependence between economic growth and energy usage taking into account the results reported in the literature. The empirical results presented in the last section are very often contradictory. Moreover, as we saw in section 2 early contributions were based on computations concerning GDP–energy interdependence in a two–dimensional framework. However, more recent studies have shown that results by this simple approach were biased because important variables were omitted. Therefore, in recent papers the causal links between GDP and energy are usually examined with a multivariate framework. The most frequently used additional variables are employment, capital or prices. Economic theory suggests that each of them can have explanatory power in the detection of relationships between GDP and energy consumption. In our study we applied quarterly data on employment. Employment alongside capital is (according to economic theory) an important factor in economic growth. Although we are interested primarily in an examination of causality between energy consumption and economic growth, two other causalities between the remaining two pairs (i.e. employment–energy consumption and employment–GDP) are also tested. On the basis of results shown in a contribution by Yu and Choi ([50]) for Poland and results for other developing economies or emerging markets reviewed in the previous section, we formulate the following hypothesis:

> **Conjecture 1:** $ENERGY_{PL}$, $EMPL_{PL}$ and GDP_{PL} are not dynamically (pairwise) interdependent, i.e. they are no (pairwise) linear Granger causal links in any direction in the time period under study.

Linear causality may be of interest for policy makers, but nonlinear interdependences can also occur, which in turn might also be important in the context of decision making. In most cases a lack of linear dynamic dependencies implies a lack of nonlinear causalities. Therefore, we formulate the next hypothesis in an analogous form:

Conjecture 2: There are no nonlinear (pairwise) Granger causalities between $ENERGY_{PL}$, $EMPL_{PL}$ and GDP_{PL} in any direction.

These hypotheses are tentative, because the research by Yu and Choi ([50]) on the relation between total energy consumption and GDP was conducted many years ago. Moreover, in those years the Polish economy was among the *centrally planned* (or *Soviet type*) *economies* and therefore our prediction based on results reported by these authors may be compromised.

As we have just stressed the amount of labour (determined by the level of employment) is one of the most important production factors. Moreover, in the short–run labour can be treated as the only production factor (by using what is known in the literature as *one factor production functions*, which explain output by means of labour input solely). In the long–run labour and capital are two common inputs which are related to output. Economic theory predicts a strong dependence between labour and output with both in the short– or long–run. In addition, because these dependences are monotone increasing functions with respect to employment inverse functions exist, i.e. a mutual dependence between employment and GDP can be expected.

Thus, the following hypothesis might hold true:

Conjecture 3: There is feedback in the short–run between the size of $EMPL_{PL}$ and GDP_{PL}.

A very similar hypothesis for the long–run term concerning employment and the growth of GDP is given by:

Conjecture 4: There is feedback in the long–run between the size of $EMPL_{PL}$ and GDP_{PL}.

One should notice that although hypotheses 3 and 4 are not directly related to energy use in Poland, testing them may also lead to the establishment of some potentially important conclusions also for Polish policy makers in the field of energy consumption and output. The above hypotheses will be probed by different causality tests. The details of the respective procedures will be shown in section 5, which deals with methodology. The test results depend to some extent on the testing methods applied. Before describing the research methodology, in the next section we will characterize the time series included in our sample.

4. The dataset and its properties

In this section we present a brief description and analysis of the stationarity properties of the time series included in the dataset and used in causality computations. It is important to mention that the definition of Granger causality was intentionally formulated for stationary time series. Previous empirical studies (i.e. [26]) and theoretical deliberations (i.e. [43]) strongly suggest that if the time series under study are indeed nonstationary then the results of traditional linear causality tests may lead to spurious conclusions. Therefore, the initial part of our causality analysis includes testing time series for stationarity and identifying their orders of integration. Since this stage of the research is extremely important for further computations, it should be carried out with great precision. We will conduct testing for stationarity and the identification of orders of integration in subsection 4.2.

4.1 Description of dataset

The chosen dataset includes quarterly data of GDP, total energy consumption and employment for the period Q1 2000 to Q4 2009. Our dataset contains 40 observations. The data describing GDP_{PL} and $EMPL_{PL}$ was obtained from the Statistical Office in Cracow, while data on $ENERGY_{PL}$ was from The Energy Market Agency in Warsaw.

In order to avoid spurious results we conducted several transformations of our dataset. Firstly, in order to remove the impact of inflation we calculated GDP at constant prices (year 2000). Secondly, since each variable used was characterized by significant quarterly seasonality and this property may distort the results of the causality analysis, the X–12 ARIMA procedure of Gretl software was applied to adjust each variable (note that this procedure is currently used by the U.S. Census Bureau for seasonal adjustment). Finally, each seasonally adjusted variable was transformed to logarithmic form as this operation (Box–Cox transformation) may stabilize variance and therefore improve the statistical properties of the data.

An important fact that distinguishes this paper from previous contributions is the application of quarterly data. The data on GDP_{PL} is published once a quarter, so that the application of higher frequency data is not possible. On the other hand, many previous papers concerning GDP–energy links was based on applications of annual data, although the application of lower frequency data may not be adequate for testing for Granger causality between variables because some important interactions may stay hidden (for more details see e.g. [24]).

The preliminary part of our analysis contains some descriptive statistics of all examined variables. These quantities may be useful for describing some basic properties of the dataset. At this point some typical statistics were calculated for each variable. The following table contains suitable results obtained for seasonally adjusted and logarithmically transformed data:

INSERT TABLE 1 AROUND HERE

There is already some interesting information in this table. However, a comprehensive initial analysis should also make use of charts generated for all the variables under study. Figure 1 contains suitable plots:

INSERT FIGURE 1 AROUND HERE

Firstly, we can see a relatively stable development of the Polish economy since ln(GDP_{PL}) exhibits an upward tendency (especially after 2003). Although the Polish economy was one of the few that did not suffer significantly because of the crisis of September 2008, one can observe slight slowdown of the rate of development of the Polish economy after the third quarter of 2008. It is also clear that $ENERGY_{PL}$ in the period under study did not exhibit any significant upward or downward tendency. However, there were several significant shocks (especially between 2004 and 2006). For $EMPL_{PL}$ in this period there is a stable rise between 2003 and 2008. However, before 2003 and after the crisis of September 2008 slight drops are also observed. The descriptive analysis of the time series included in our dataset will be extended in the next subsection by stationarity testing, which is a crucial precondition for causality analysis.

4.2 Stationarity properties of the dataset

Firstly we conducted an ADF unit root test. Before conducting the test, we set up a maximal lag length equal to 6 and then we used information criteria (AIC, BIC, HQ) to choose an optimal lag length from the set {0, 1, …, 6}. The following table contains the results of the ADF test with a deterministic term including only constant as well as constant and linear trend:

INSERT TABLE 2 AROUND HERE

From table 2 it is obvious that only ln(GDP_{PL}) was found to be nonstationary (even at 10% SL), whatever the form of the deterministic term. Two other time series were found to be stationary (at each typical SL). However, when interpreting the results of an ADF test one should bear in mind two important facts. Firstly, the results of an ADF test are relatively sensitive to any incorrect establishment of lag parameter. Secondly, as shown in some papers[1], this test tends to under–reject the null hypothesis pointing at nonstationarity too often. Therefore, to confirm the results of the ADF test a KPSS test was additionally conducted. Note that in contrary to the ADF test the null hypothesis of a KPSS test refers to the stationarity of time series. The results of this test are presented in the following table:

INSERT TABLE 3 AROUND HERE

The results presented in table 3 lead to relatively different conclusions than the outcomes contained in table 2. This time only ln($ENERGY_{PL}$) was found to be stationary (at each typical SL), while for the other time series the null hypothesis of the KPSS test was clearly rejected. It is worth mentioning that both these findings were reported regardless of the form of the deterministic term.

The relatively different results of both tests forced us to use a third test, namely the PP test. This test is based on a nonparametric method of controlling for serial correlation when testing for a unit root. As with ADF the null hypothesis refers to nonstationarity. The results of the PP test are presented in the following table:

INSERT TABLE 4 AROUND HERE

Analysis of the outcomes presented in table 4 shows that they are in line with the results presented in table 3. Therefore, for our further calculations we assumed that only ln($ENERGY_{PL}$) is a stationary time series while the two other series are nonstationary around constant. Some further calculations (conducted for first differences of ln(GDP_{PL}) and ln($EMPL_{PL}$) time series) confirmed that these two variables are I(1).[2]

5. Methodology

In order to explore the dynamic relationships between GDP and total energy consumption in Poland both linear and nonlinear Granger causality tests were applied in this paper. The main goal of our analysis was to examine

[1] Low power against stationary alternatives has been frequently reported by many authors, see e.g. [1].
[2] The results of unit root tests conducted for differenced data are not presented here to save space. We would like to underline that detailed results of all computations which are not presented in the text (usually to save space) in detailed form are available from authors upon request.

the research hypotheses formulated in section 3. For this purpose we applied both a traditional approach as well as some recent developments in econometric methods of analysing causal links between the variables.

The concept of causality used in this paper is due to Granger ([25]). This idea is well known and it has been widely used in previous studies therefore we will not explain it in detail. By and large, this concept is used to investigate whether a knowledge of past and current values of one stationary variable is helpful in predicting future values of another one or not.

In order to examine short–run linear Granger causality between all three variables and taking into account the results of stationarity analysis from the previous subsection the Toda–Yamamoto ([48]) approach was applied in this paper. This method has been commonly applied in recent empirical studies (see e.g. [33]) since it is relatively simple to perform and free of complicated pretesting procedures, which may bias the test results, especially when dealing with nonstationary variables. The most important feature of this concept is the fact that the Toda–Yamamoto (TY) method is useful for testing for causality between variables which are characterized by different orders of integration. As already mentioned, in such cases a traditional linear causality analysis cannot be performed by the direct application of a basic VAR or VEC model. On the other hand, differencing integrated variables, although leading to stationarity and allowing the use of the standard approach, may lead to a loss of the long–run properties of the data and cause a problem with the interpretation of test results.

To throw some light on the concept of TY approach for causality testing consider the following n–dimensional VAR(p) process:

$$y_t = c + \sum_{i=1}^{p} A_i y_{t-i} + \varepsilon_t \ , \tag{1}$$

where $y_t = (y_t^1, \ldots, y_t^n)^{tr}$, $c = (c_1, \ldots, c_n)^{tr}$ and $\varepsilon_t = (\varepsilon_{1,t}, \ldots, \varepsilon_{n,t})^{tr}$ are n–dimensional vectors and $\{A_i\}_{i=1}^{p}$ is a set of $n \times n$ matrices of parameters for appropriate lags. Let d denote the highest order of integration of all variables $y^1, \ldots, y^n$. According to Toda and Yamamoto this parameter (d) is an unrestricted variable since its role is to guarantee the use of asymptotic theory. The order p of the process is assumed to be known otherwise it may be established by means of some standard statistical methods (e.g. the application of a consistent model selection criterion etc., more details can be found in [42]). The TY idea of testing for causal effects is based on estimating the augmented VAR(p+d) model:

$$y_t = c' + \sum_{i=1}^{p+d} A_i' y_{t-i} + \varepsilon_t' \ . \tag{2}$$

Some specific conditions need to be assumed in order to use Toda–Yamamoto method. Firstly, we shall assume that the error vector ε' is an independent white noise process with a nonsingular covariance matrix $\Sigma_{\varepsilon'}$ (its elements are assumed to be constant over time). Secondly, the condition $E\left|\varepsilon'_{k,t}\right|^{2+s} < \infty$ is expected to hold true for all k=1,…, n and some s>0. One may say that the k–th element of y_t does not Granger cause the j–th element of y_t (where $k, j \in \{1,...,n\}$) if there is no reason for the rejection of following null hypothesis:

$$\text{H}_0\text{:}\ \ a^s_{jk} = 0 \quad \text{for } s=1, \ldots, p, \tag{3}$$

where $A_s = \left[a^s_{pq}\right]_{p,q=1,...,n}$ for s=1, ..., p. Note that the hypothesis of non–causality refers to a non–augmented VAR model. Next, we shall define (T stands for sample size) the $n\times T$ matrix $Y := (y_1,...,y_T)$, the $n\times(1+n(p+d))$ matrix $\hat{D} := (\hat{c},\hat{A}_1,...,\hat{A}_p,...,\hat{A}_{p+d})$, the $(1+n(p+d))\times 1$ matrix $Z_t := rwc(1,y_t,y_{t-1},...,y_{t-p-d+1})$, where t=1,…,T, the $(1+n(p+d))\times T$ matrix $Z := (Z_0,...,Z_{T-1})$ and finally the $n\times T$ matrix $\hat{\delta} := (\varepsilon'_1,...,\varepsilon'_T)$.

The Toda–Yamamoto procedure goes as follows. The first point requires the calculation of $V_U := \frac{\hat{\delta}\hat{\delta}^{tr}}{T}$ – the variance–covariance matrix of residuals from the unrestricted augmented VAR model (i.e. model (2)). Next, after defining $\alpha := vec(c,A_1,...,A_p,0_{n\times nd})$ and $\hat{\alpha} := vec(\hat{c},\hat{A}_1,...,\hat{A}_p,...,\hat{A}_{p+d})$ one can write the TY test statistic for testing causal effects between variables in y_t in the following form:

$$TY_{test} := (R\hat{\alpha})^{tr}\left(R\left(\left(ZZ^{tr}\right)^{-1}\otimes V_U\right)R^{tr}\right)^{-1}(R\hat{\alpha}) \tag{4}$$

where R is the matrix of linear restrictions. In order to test for causality from y^k to y^j we shall assume that R is a $p\times(1+n(p+d))$ matrix whose elements take only the value of zero or one. Each row of matrix R corresponds to the restriction of one parameter in α. The value of every element in each row of R is one if the associated parameter in α is zero under the null hypothesis, otherwise it is zero. There is no association between matrix R and the last n^2d elements in α. This approach allows us to formulate the null hypothesis of Granger non–causality in the following form:

$$\text{H}_0\text{:}\ \ R\alpha^{tr} = 0 \tag{5}$$

If the modeling assumptions (like the properties of the error term, etc.) are fulfilled, then TY_{test} is asymptotically $\chi^2(p)$ distributed. In other words, the TY approach is just a standard Wald test applied to the first p lags obtained from an augmented VAR(p+d) model.

However, this method of testing for Granger causality has several drawbacks, which are typical of parametric tests. Firstly, the application of asymptotic theory may lead to spurious results if the modeling assumptions do not hold. Secondly, even if these assumptions are generally fulfilled, the distribution of TY_{test} may still be significantly different from suitable chi–square when dealing with extremely small samples. One possible way of overcoming these difficulties is the application of bootstrap technique. This method is used for estimating the distribution of a test statistic by resampling data. Since the estimated distribution depends only on the available dataset, it may be reasonable to expect that the bootstrap approach does not require such strong assumptions as parametric methods. Furthermore, the size and power properties of a causality test based on bootstrap techniques remain relatively good even in cases of nonstationarity and various schemes of error term structure (including untypical heteroscedasticity etc., for more details see [17], [38], [29] and [35]). However, bootstrap methods cannot be treated as perfect tools for solving all possible model specification problems. This approach is likely to fail in some specific cases and therefore should not be used without thought (see e.g. [31] and [12]).

In order to minimize the risk of the undesirable influence of heteroscedasticity on the results of the bootstrap test we based our research on resampling leveraged residuals. Bootstrap based on leveraged residuals has commonly been used in previous papers (see e.g. [29] and [28]). More details on leverages may be found in [13]. First, we estimated a non–augmented trivariate VAR model through OLS methodology with the assumed null hypothesis that one variable does not Granger cause the other one. In fact this means that some elements of the coefficient matrices were restricted to zero. Next, we used leverages to transform regression raw residuals (the set of the vectors of the residuals modified by this transformation will be denoted $\{\hat{\varepsilon}_i^m\}_{i=i_0,\ldots,T}$, T stands for sample size, i_0 is equal to VAR lag length plus one). Finally, the following algorithm was conducted (note that the described algorithm may be easily adopted for cases concerning different dimensions e.g. bivariate models, single equation models etc.):

Step 1. Drawing randomly with replacement (each point has the same probability $\frac{1}{T-i_0+1}$) from the set $\{\hat{\varepsilon}_i^m\}_{i=i_0,\ldots,T}$ (as a result we get the set $\{\hat{\varepsilon}_i^{**}\}_{i=i_0,\ldots,T}$);

Step 2. Subtracting the mean in order to guarantee the mean of bootstrap residuals is zero (this way we create the set $\{\hat{\varepsilon}_i^{*}\}_{i=i_0,\ldots,T}$, such that $\hat{\varepsilon}_{k,i}^{*}=\hat{\varepsilon}_{k,i}^{**}-\frac{\sum_{j=i_0}^{T}\hat{\varepsilon}_{k,j}^{**}}{T-i_0+1}$, $i=i_0,\ldots,T$, $k=1,2,3$);

Step 3. Generating the simulated data through the use of original data, coefficient estimates from the regression of restricted non–augmented VAR model and the bootstrap residuals $\{\hat{\varepsilon}_i^*\}_{i=i_0,\dots,T}$;

Step 4. Performing the TY procedure (for simulated data).

In order to create the empirical distribution of TY_{test} and get empirical critical values (bootstrap critical values) one should repeat this procedure *N* times. Academic discussion on how the number of bootstrap replications (parameter *N*) may affect the performance of bootstrap techniques has attracted considerable attention in recent years (see e.g. [31] and [35]). This paper uses the recently developed procedure of establishing the number of bootstrap replications presented by Andrews and Buchinsky ([4]). In each case we aimed to apply such a value of parameter *N* which would ensure that the relative error of establishing the critical value (at 5% SL) would not exceed 5% with probability equal to 0.95. The following formula displays this idea:

$$P^*\left(\frac{|cr_b-cr|}{cr}\le 0.05\right)=0.95, \tag{6}$$

where P^* stands for probability with respect to randomness in the bootstrap samples, cr_b denotes bootstrap critical value (for 5% SL and *N* replications) and *cr* stands for the *ideal* (i.e. after an infinite number of replications) bootstrap critical value (for 5% SL). The suitable procedure (including the Andrews and Buchinsky method) written in the Gretl program is available from the authors upon request.

Since we found relatively strong support for claming that the two examined variables are integrated in the same order (i.e. I(1)) we additionally decided to perform a cointegration analysis for these two variables. As shown by several authors (e.g. [23], [11] and [28]) if variables are indeed cointegrated it is sufficient to establish long–run causality in at least one direction. In order to test for cointegration we applied Johansen Trace and Maximal Eigenvalue tests. In order to test for long–run Granger causality from variable *X* to variable *Y* one should estimate a suitable VEC model (assuming previously established cointegration properties), then consider an appropriate equation (with *Y* on the left side) and finally test whether the coefficient of the error term on the right side of the equation is statistically significant. If this is true then one may say that *X* long–run Granger causes *Y*. The procedure of testing for short–run causality from one variable to another is based on checking the joint significance of suitable lagged differences.

Besides this classical approach for testing for short– and long–run causality in terms of unrestricted VECM, we additionally performed a sequential elimination, which at each step omits the variable with the highest *p*–value until all remaining variables have a *p*–value no greater than 0.05. We had omitted all insignificant variables, since this re–estimation was applied for each equation separately. Sequential elimination of insignificant variables may be especially useful when dealing with relatively small samples (which is true of our research). The Reader may find comprehensive technical details of each (classical and sequential) approach in [28]. Furthermore, taking into account all the previously mentioned problems of a parametric approach (the validity of asymptotic distributions, small sample problems etc.) we decided to use bootstrap critical values for each causality (significance) test conducted for our VECM (traditional and sequential variant). We precisely followed a previously described bootstrap procedure (i.e. the application of leverages and the methodology for establishing the number of replications proposed by Andrews and Buchinsky).

Alongside the bootstrap–based linear causality test a nonlinear test for Granger causality was also used in this paper, both in the three– (VAR model) and two–dimensional (VEC model) case. There are a number of reasons to justify the application of nonlinear methods. Let us mention just two of them, which are mostly cited in the literature. Firstly, the traditional linear Granger causality test performs relatively poorly (extremely low power) in detecting certain kinds of nonlinear causal relationships (see e.g. [6] and [26]). Secondly, since the standard linear procedure is based on testing the statistical significance of suitable parameters only in a mean equation, causality in any higher–order structure (e.g. causality in variance etc.) cannot be explored (see e.g. [14]). The application of a nonlinear approach is believed to provide a solution to this problem as it allows the researcher to explore complex dynamic links between variables.

In this article we apply the nonlinear causality test proposed by Diks and Panchenko ([16]). This idea is largely a continuation of concepts formulated by Baek and Brock ([5]) and Hiemstra and Jones ([30]). In our research we decided to use some typical values of the technical parameters of this method. Namely, the b_{DP} was set at a level of 0.5, 1 and 1.5 for all conducted tests. These values have been commonly used in previous papers (e.g. [30], [15], [16] and [27]). We also decided to use the same lags for every pair of time series being analyzed establishing l_{DP} at the order of 1 and 2. More details about the meaning of these technical parameters and the form of test statistic may be found in [16].

Since the structure of linear dependences had been filtered out after an analysis of suitable autoregression models, a nonlinear causality test was performed for residual time series. In this case residual time series are believed to reflect strict nonlinear dependencies (for more details see e.g. [5] and [8]). All time series of residuals were standardized, thus they shared a common scale parameter. In this paper we used a one–side test rejecting the null hypothesis whenever the test statistic was significantly large. The motivation to do so is twofold. Firstly, in practical applications a one–sided test is often found to have larger power than a two–sided one (see e.g. [45]).

Secondly, although significant negative values of test statistic also provide a basis for rejection of Granger non–causality, they additionally indicate that a knowledge of the past values of one time series may seriously aggravate the prediction of another one. This is contrary to the idea of causality analysis, which is usually conducted to judge whether this knowledge is helpful (not aggravating) for prediction issues or not.

As former research has provided evidence that the applied nonlinear causality test tends to over–reject in cases of the presence of heteroscedastic structures in analyzed time series (comp. [16]), we additionally decided to test all residual time series for the presence of heteroscedastic structures using White and Breusch–Pagan tests. However, we did not find any significant proofs of the presence of heteroscedasticity in the residuals of each model and therefore we did not re–run nonlinear causality analysis for filtered series of residuals. One should bear in mind that heteroscedasticity filtering (e.g. by ARCH/GARCH filtering) should be used only when it is strongly justified. A possible misspecification of the conditional heteroscedasticity model may sometimes lead to loss of power of the test, which in turn may simply lead to spurious results of the testing procedure (for some additional information see [16]).

6. Empirical results

In this section the results of short– and log–run linear Granger causality tests as well as the outcomes of nonlinear causality analysis are presented. These findings may be helpful in describing the structure of dynamic links between GDP and energy use in Poland in the period under study. As we have already mentioned, our research also takes into consideration fluctuations in $EMPL_{PL}$, which may have an important impact on the structure of $ENERGY_{PL}$–GDP_{PL} links. One may also expect these outcomes to provide a basis for judging which of the research hypotheses presented in section 3 should be accepted and which not. We shall start the presentation of results of our research from outcomes obtained during the analysis of linear Granger causality for a three–dimensional VAR model. The following table contains p–values obtained while testing for linear Granger causality through the application of an asymptotic– and bootstrap–based Toda–Yamamoto procedure. The value of the N parameter denotes the number of bootstrap replications used to construct the distribution of TY_{test} statistic according to the Andrews and Buchinsky method. Before conducting the TY procedure, we established the number of lags (parameter p) in the nonaugmented three–dimensional VAR model. For this purpose we followed a simple procedure. We set up a maximal possible lag length at the level of 6 and then we used several information criteria (namely, AIC, BIC, HQ) in order to choose the optimal lag length. Although the BIC criterion pointed at one lag (other criteria pointed at five lags), the results of a Ljung–Box Q–test provided a strong basis for claiming that, in the case of one lag, the residuals were significantly autocorrelated, which in turn may seriously distort the results of the causality analysis. Therefore, the optimal lag was set at five. Since the ln(GDP_{PL}) and ln($EMPL_{PL}$) time series were found to be I(1), parameter d was set at one.

Whenever test results indicate the existence of a causal link in a given direction (at 5% SL) bold face is used to mark this finding. The following table contains results computed by the VAR model constructed for ln(GDP_{PL}), ln($ENERGY_{PL}$) and ln($EMPL_{PL}$) time series[3]:

INSERT TABLE 5 AROUND HERE

As we can see the test results strongly support the hypothesis that total energy consumption Granger causes GDP, which means that conjecture 1 is not true at least for these two variables. The test results provided no basis for claiming that linear Granger causality runs in any other direction (at 5% SL). However, we should underline the relatively small p–values obtained after testing causality from ln($EMPL_{PL}$) to ln(GDP_{PL}). Finally, it should be noted that all these findings were shown by the results of both the asymptotic– and bootstrap–based TY procedure.

The next table contains the results of nonlinear Granger causality tests conducted for residuals resulting from an augmented three–dimensional VAR model. As above, whenever the test results indicated the existence of causal link in a given direction (at 10% SL) bold face was used to mark this finding:

INSERT TABLE 6 AROUND HERE

As we can see the test results support to some extent the hypothesis that total energy consumption Granger causes employment, which partly contradicts conjecture 2. Furthermore, the test results provided no basis for claiming that nonlinear Granger causality runs in any other direction (at 10% SL).

Since we found strong support for saying that ln(GDP_{PL}) and ln($EMPL_{PL}$) are both I(1), we additionally decided to perform a cointegration analysis for these two variables. This kind of research may provide additional information for our empirical analysis, as it allows an exploration of the long–run properties of the data.

[3] Since we dealt with relatively small samples we transformed a modified Wald statistic in order to use critical values from a suitable F–distribution. Namely, we applied a $TY^{*}_{test} = \frac{TY_{test}}{p}$ statistic, which is asymptotically $F(p, T - n(p+d) - 1)$ distributed and performs better for small samples (for more details see [36]). The meaning of parameters T, n, p and d is the same as in section 5.

Although this research was performed only for two variables (as ln($ENERGY_{PL}$) was found to be stationary), combining the results of the cointegration analysis with previously presented outcomes of the TY procedure may lead to interesting conclusions concerning the role of energy use. Before conducting an analysis of cointegration properties there are some preliminary steps. Firstly, the type of deterministic trend should be specified using one of five possibilities listed in [32]. Taking into account the results presented in subsection 4.2 we assumed the third case, i.e. presence of a constant in both the cointegrating equation and the test VAR. Next, we used information criteria (i.e. AIC, BIC, HQ) to establish the appropriate number of lags. The maximal value (for levels) was once again set at a level of 6. BIC pointed at one lag, but a significant autocorrelation of residuals (using Ljung–Box Q–test) was shown once again. Therefore the final lag length was established at a level of 5. The results of Johansen cointegration tests are presented in the following table:

INSERT TABLE 7 AROUND HERE

Critical values were taken from [37]. As we can see both tests indicate (at 10% SL) that the variables are cointegrated. Similar results (i.e. the existence of one cointegrating vector) were shown using critical values proposed in [41].

Next, we estimated an unrestricted VEC model assuming 4 lags (for first differences) and one cointegrating vector. The results of this estimation were used to test for short– and long–run causality between the variables. Bold face was used to indicate finding a causal link in a given direction (at 5% SL). The following table contains suitable results (N denotes the number of bootstrap replications established by mean of the Andrews and Buchinsky procedure):

INSERT TABLE 8 AROUND HERE

As we can see the results of causality tests conducted on the basis of an estimation of an unrestricted VEC model confirmed the findings obtained after the application of the Toda–Yamamoto method. Short–run Granger causality was not reported in any direction between the variables, which contradicts conjecture 3. On the other hand using a t–test with asymptotic critical values led us to the conclusion that GDP_{PL} long–run Granger causes $EMPL_{PL}$. The dynamic links between these two variables were found to be even stronger when we look at the result of a *t*–test with bootstrap critical values, which show a bidirectional long–run relationship,[4] which is in line with conjecture 4.

Although short–run causality from employment to GDP was not found as statistically significant by means of either method (the TY procedure and an analysis of unrestricted two–dimensional VECM), the suitable *p*–values were generally small (around 0.15). Furthermore, in both cases relatively large numbers of lags had to be used in order to model properly the dynamic structure of the variables. This in turn may distort the results of the causality analysis, as some potentially insignificant (lagged) variables could have been taken into account. In order to examine this issue a sequential elimination (described in detail in a previous section) was additionally performed for each equation of the bivariate VEC model. The results of causality tests performed after this elimination are presented in the following table (once again the bold face refers to finding a causal link at 5% SL):

INSERT TABLE 9 AROUND HERE

As we can see the previously established bidirectional long–run causal relationship between the variables (i.e. conjecture 4) was once again confirmed, this time by both asymptotic– and bootstrap–based procedures. In addition, after eliminating insignificant variables, short–run causality from $EMPL_{PL}$ to GDP_{PL} was found to be significant at 5% SL, which partly supports conjecture 3. On the other hand, all lagged coefficients of $\Delta\ln(GDP_{PL})$ were eliminated in $\Delta\ln(EMPL_{PL})$ equation. These findings were once again established regardless of the type of sequential analysis (asymptotic– or bootstrap–based).

Finally, a nonlinear causality analysis was also performed for residuals of unrestricted VECM and residuals resulting from individually (sequentially) restricted equations. In both cases no significant evidence of heteroscedasticity was found, therefore no filtering was applied. Combinations of b_{DP} and l_{DP} were exactly the same as in previous research (see table 6). In both cases no evidence of nonlinear Granger causality in any direction between GDP and employment was found. Since all *p*–values were greater than 0.50, we did not find a reason to present these results in separate tables.

7. Conclusions

[4] The significant difference in the indications of the bootstrap and asymptotic test is worth underlining.

The factors determining economic growth are the subject of numerous theoretical and empirical studies. The majority of these contributions are related to highly developed market economies. For these countries time series of sufficient length are available. In former centrally planned economies causality analyses have to be restricted to much shorter time series. In order to avoid the problem of the scarcity of data we used quarterly data in our contribution.

The application of recent causality methodology, such as asymptotic– and bootstrap–based TY procedures, allowed some conclusions to be drawn concerning causal interdependencies between energy consumption and GDP. To summarise, the results of the TY procedure provided a solid basis for claiming that energy consumption Granger caused GDP in Poland in the last decade. This is most important finding in our study. Furthermore, the application of a cointegration approach led us to the conclusion that for employment and GDP there existed a bidirectional long–run Granger causal link. There was also some evidence (in a statistical sense) for the short–run impact of employment on GDP. If we combine the results of both methods we may also state that energy consumption was an indirect causal factor for employment since energy use directly caused GDP, which in turn was found to be cointegrated with employment. The analysis of nonlinear causal interdependencies also led to the conclusion that energy consumption Granger caused employment in Poland in the period under study.

Some policy recommendations arise from the results of these computations. Contrary to findings for some other countries mentioned in section 2 unidirectional causality running from energy consumption to economic growth implies that the reduction of energy consumption could lead to a decline in economic growth. Thus, the further economic growth of the Polish economy seems to require increased supplies of energy. However, our computations do not take into account possible technical progress. It may be that, given technical progress, the same amount or even more goods and services could be produced by the same supplies of energy.

In addition, the results of different versions of asymptotic causality tests were – in view of the scarcity of data – compared with findings based on bootstrapping methods. In general, the results based on asymptotic theory and bootstrap techniques were relatively similar. The moderate size of the dataset means that such analysis should be repeated after some years.

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The authors would like to thank The Energy Market Agency (in Polish *Agencja Rynku Energii*, *ARE*) in Warsaw for supplying the extensive dataset on energy production and consumption in Poland. The interest of this institution in supporting academic research is worth special attention and should be highly praised. In addition, we would also like to acknowledge the help of the Statistical Office in Poland (Cracow Branch) in obtaining the dataset including macroeconomic data.

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Vitae

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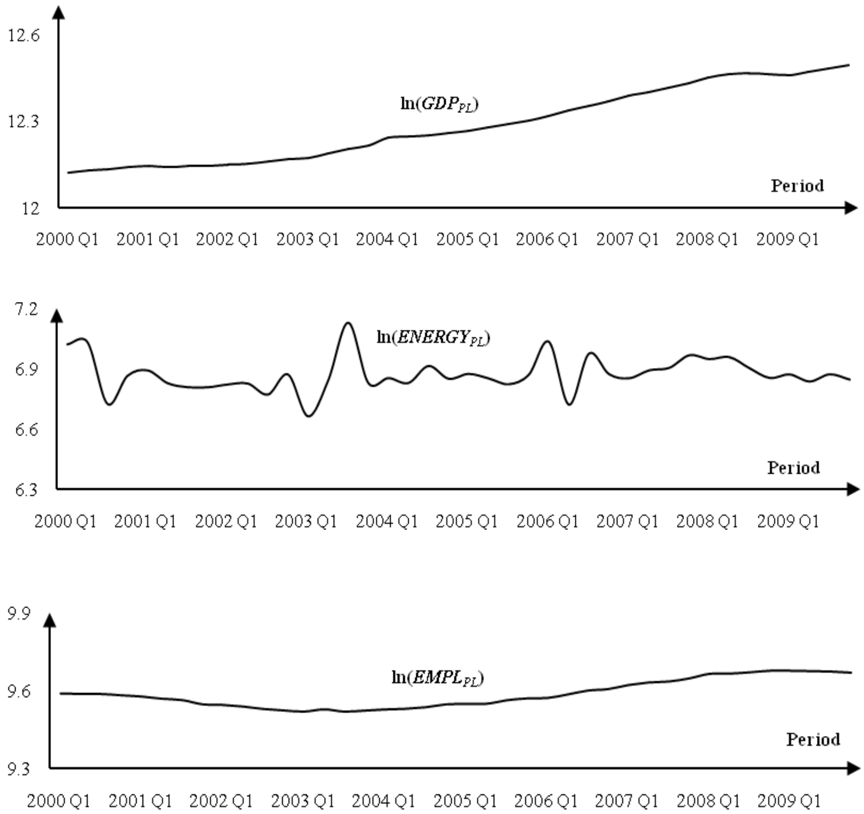
Figure captions

Figure	Description
1	Graphs of time series used in further computations.

Figure 1


12.6
12.3
12
ln(GDP_{PL})
Period
2000 Q1
2001 Q1
2002 Q1
2003 Q1
2004 Q1
2005 Q1
2006 Q1
2007 Q1
2008 Q1
2009 Q1
7.2
6.9
6.6
6.3
ln($ENERGY_{PL}$)
Period
2000 Q1
2001 Q1
2002 Q1
2003 Q1
2004 Q1
2005 Q1
2006 Q1
2007 Q1
2008 Q1
2009 Q1
9.9
9.6
9.3
ln($EMPL_{PL}$)
Period
2000 Q1
2001 Q1
2002 Q1
2003 Q1
2004 Q1
2005 Q1
2006 Q1
2007 Q1
2008 Q1
2009 Q1

List of Tables

Statistic \ Variable	ln($ENERGY_{PL}$)	ln(GDP_{PL})	ln($EMPL_{PL}$)
Minimum	6.66	12.11	9.51
1st Quartile	6.82	12.15	9.53
Median	6.86	12.26	9.57
3rd Quartile	9.91	12.41	9.63
Maximum	7.13	12.50	9.69
Mean	6.87	12.28	9.59
Standard deviation	0.11	0.13	0.09
Skewness	0.52	0.27	0.48
Kurtosis	1.23	–1.40	–1.12

Table 1. Descriptive statistics of analyzed variables.

Variable	ADF with constant		ADF with constant and linear trend	
	Test statistic (p–value)	Optimal lag	Test statistic (p–value)	Optimal lag
ln($ENERGY_{PL}$)	–6.67 (0.00)	0	–6.83 (0.00)	0
ln(GDP_{PL})	0.73 (0.99)	1	–2.81 (0.19)	1
ln($EMPL_{PL}$)	–3.74 (0.00)	4	–4.34 (0.00)	4

Table 2. Results of ADF test of variables (levels).

Variable	KPSS test statistic (with constant[a])	KPSS test statistic (with constant and linear trend[b])
ln($ENERGY_{PL}$)	0.17	0.08
ln(GDP_{PL})	1.08	0.23
ln($EMPL_{PL}$)	0.78	0.25

Table 3. Results of KPSS test of variables (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%)

Variable	PP test p–value (with constant)	PP test p–value (with constant and linear trend)
ln($ENERGY_{PL}$)	0.00	0.00
ln(GDP_{PL})	0.98	0.52
ln($EMPL_{PL}$)	0.92	0.60

Table 4. Results of PP test of variables (levels).

	p–value	
Null hypothesis	Asymptotic distribution	Bootstrap distribution
$\ln(ENERGY_{PL})\neg\rightarrow\ln(GDP_{PL})$	**0.01**	**0.03** (N=3519)
$\ln(GDP_{PL})\neg\rightarrow\ln(ENERGY_{PL})$	0.45	0.67 (N=3539)
$\ln(ENERGY_{PL})\neg\rightarrow\ln(EMPL_{PL})$	0.24	0.21 (N=1979)
$\ln(EMPL_{PL})\neg\rightarrow\ln(ENERGY_{PL})$	0.28	0.31 (N=2059)
$\ln(GDP_{PL})\neg\rightarrow\ln(EMPL_{PL})$	0.47	0.41 (N=3339)
$\ln(EMPL_{PL})\neg\rightarrow\ln(GDP_{PL})$	0.19	0.16 (N=3379)

Table 5. Results of Toda–Yamamoto causality analysis.

Null hypothesis	p–value					
	b_{DP}=0.5, l_{DP}=1	b_{DP}=1, l_{DP}=1	b_{DP}=1.5, l_{DP}=1	b_{DP}=0.5, l_{DP}=2	b_{DP}=1, l_{DP}=2	b_{DP}=1.5, l_{DP}=2
$\ln(ENERGY_{PL})\neg\rightarrow\ln(GDP_{PL})$	0.65	0.78	0.84	0.78	0.92	0.81
$\ln(GDP_{PL})\neg\rightarrow\ln(ENERGY_{PL})$	0.34	0.31	0.76	0.65	0.86	0.59
$\ln(ENERGY_{PL})\neg\rightarrow\ln(EMPL_{PL})$	0.64	0.72	0.35	0.19	**0.07**	**0.09**
$\ln(EMPL_{PL})\neg\rightarrow\ln(ENERGY_{PL})$	0.68	0.49	0.25	0.58	0.36	0.49
$\ln(GDP_{PL})\neg\rightarrow\ln(EMPL_{PL})$	0.54	0.39	0.23	0.38	0.47	0.37
$\ln(EMPL_{PL})\neg\rightarrow\ln(GDP_{PL})$	0.76	0.39	0.65	0.71	0.75	0.25

Table 6. Results of nonlinear causality analysis performed for residuals for augmented three–dimensional VAR model.

		Trace test		Maximal Eigenvalue test	
Hypothesized number of cointegrating equations	Eigenvalue	Trace statistic	p–value	Maximal Eigenvalue statistic	p–value
Zero	0.3290	13.58	0.09	13.56	0.06
At most one	0.0004	0.015	0.90	0.015	0.90

Table 7. Results of cointegration analysis for $\ln(GDP_{PL})$ and $\ln(EMPL_{PL})$ variables.

Short–run causality			Long–run causality		
Null hypothesis	p–value (asymptotic)	p–value (bootstrap)	Null hypothesis	p–value (asymptotic)	p–value (bootstrap)
$\Delta\ln(GDP_{PL})\neg\rightarrow\ln(EMPL_{PL})$	0.354	0.413 (N=1919)	$\ln(GDP_{PL})\neg\rightarrow\ln(EMPL_{PL})$	**0.001**	**0.008** (N=1899)
$\ln(EMPL_{PL})\neg\rightarrow\Delta\ln(GDP_{PL})$	0.167	0.149 (N=1959)	$\ln(EMPL_{PL})\neg\rightarrow\ln(GDP_{PL})$	0.163	**0.047** (N=1919)

Table 8. Results of causality analysis based on unrestricted VECM constructed for $\ln(GDP_{PL})$ and $\ln(EMPL_{PL})$.

Short–run causality			Long–run causality		
Null hypothesis	Final p–value (asymptotic)	Final p–value (bootstrap)	Null hypothesis	Final p–value (asymptotic)	Final p–value (bootstrap)
$\Delta\ln(GDP_{PL})\neg\rightarrow\ln(EMPL_{PL})$	No coefficients left.	No coefficients left.	$\ln(GDP_{PL})\neg\rightarrow\ln(EMPL_{PL})$	**0.001**	**0.010**
$\ln(EMPL_{PL})\neg\rightarrow\Delta\ln(GDP_{PL})$	**0.041**	**0.022**	$\ln(EMPL_{PL})\neg\rightarrow\ln(GDP_{PL})$	**0.049**	**0.015**

Table 9. Results of causality analysis based on sequential elimination of insignificant variables.