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Abstract

The aim of this contribution is an investigation of causal interdependences between electricity consumption and GDP in Poland. Our research was conducted for total electricity consumption as well as for the industrial consumption of electricity. In order to reflect the causality between GDP and electricity consumption properly we performed our investigations in a three–dimensional framework with employment chosen as an additional variable. We used reliable quarterly data from the period Q1 2000 – Q4 2009. In order to check the stability of the causalities the investigations were performed on two samples: a full sample and a pre–crisis (i.e. Q1 2000 – Q3 2008) subsample. We applied both traditional methods as well as some recently developed econometric tools.

We found feedback between total electricity consumption and GDP as well as between total electricity consumption and employment. We also found unidirectional causality running from industrial electricity consumption to employment and no direct causal links between industrial electricity consumption and GDP. In addition, all these findings were, in general, not seriously affected by the financial and economic crisis of 2008. A significant exception is the causal effect of industrial electricity consumption on employment, which was more pronounced after the crisis of 2008.

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1. Introduction

Electricity has been the foundation of economic growth, and constitutes one of the most important infra–structural inputs in economic development. The growing interest in this area has largely been triggered by the growing demand for energy across the world, fuelled mainly by increasing economic activities across economies. A modern society implies growing reliance on networked information and communication technologies (ICTs), with more and more people using the Internet. Other ICTs such as cell phones, digital video recorders, digital music players, personal computers, and so on are quite common now. Therefore, companies, households and economies as a whole exhibit a demand for electricity. This demand is driven by such important factors as industrialization, extensive urbanization, population growth, and a rise in the standard of living.

In the past three decades, a number of studies have been performed in order to prove the interdependence between electricity consumption and economic growth. The findings show, in general, a strong relationship between electricity consumption and economic growth. However, the fact that there exists a strong relation between electricity usage and economic growth does not necessarily imply a causal dependence.

Moreover, some previous papers contain highly controversial results. This is why the previous literature that focused on the causal relationship between electricity consumption and economic growth was not able to provide general policy recommendations that could be applied across countries. Researchers indicate that many economists and policy makers were and still are concerned with the causal relationship between electricity consumption and economic growth because this relation has significant implications for governmental energy policy.

A major question is which variable should take precedence over the other, i.e. is electricity usage a stimulus for economic growth or does economic growth lead to an increase in electricity consumption? The answer to this question is the reason for categorization of published contributions concerning these relationships.

The main stream of literature concerning the causal relationship between electricity consumption and GDP growth can be divided into four groups. They are of great importance for electricity policy.

First, unidirectional causality running from electricity usage to GDP growth implies that restrictions on electricity may hamper economic growth while increases in electricity usage may contribute to economic growth. In the last years ecologists have increased pressure on governments to reduce carbon dioxide emissions in order to slow down the rate of climate change, and this pressure has especially intensified on developing countries. On the other hand, emerging economies worry about the negative impact on economic growth caused by the restricted consumption of fossil fuels, which are the main sources of electricity generation.

Second, unidirectional causality running from GDP growth to electricity usage could mean that electricity usage conservation policies may be justified with little or no negative repercussions on economic growth. This effect means that such an economy can be numbered among those which are non dependent on energy. In addition, a continuous increase in GDP may imply a permanent increase in electricity consumption.

Third, feedback (i.e. a bidirectional causal relationship between electricity usage and GDP growth) means that electricity consumption and economic growth are mutually affected and jointly determined at the same time. If bidirectional causality is found, economic growth may demand more electricity whereas more electricity consumption may induce economic growth.

Finally, a fourth (but less probable) scenario of lack of any causal relationship means that there is no interdependence between electricity consumption and GDP growth, so that neither expansive nor conservational policies with respect to electricity consumption have any effect on GDP growth.

The organization of the study is as follows. In the next section we give a literature overview. In the third section the main conjectures of the paper are formulated. The fourth section describes the dataset. In the fifth section the econometric methodology is explained. Section 6 contains empirical results. Section 7 concludes the paper.

2. Literature overview

The subject of the causal relationship between various forms of energy consumption and GDP growth has been well–documented in the econometric energy literature. The bulk of this literature focuses on developed countries. Different contributions 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. The findings differ even on the direction of both linear and nonlinear causality and its long–term versus short–term influence on energy policy. The type or lack of causal relationship has policy implications. In the next paragraphs we will review some of previous studies related to the causal links between economic growth and different forms of energy consumption (including electricity usage).

Yu and Choi (1985) examined the causal linkages between gross national product (GNP) and various types of energy consumption for a number of countries. They did not find any causal linkages for the USA, UK and Poland but they found a causal relationship from GNP to total energy consumption for South Korea and causality from total energy consumption to GNP for the Philippines. Yu and Jin (1992) examined monthly US data through cointegration analysis and concluded that energy consumption has no long–run causal links with income and employment.

The contribution by Cheng (1999) did not establish causality from energy consumption to economic growth but found causality from economic growth to energy consumption in the case of India. Cheng (1999) applied a Granger causality, cointegration and error correction approach. Fatai et al. (2004) analyzed the causal relationship between employment, energy consumption and economic growth in New Zealand. They were concerned not only with total energy consumption but also with disaggregated data, like the consumption of electricity, coal, oil and gas. They did not find causal relationships between total energy consumption, employment and economic growth. However, they found unidirectional causalities running from electricity consumption and oil usage to employment.

Chang and Wong (2001) investigated the relationship between poverty, energy and economic growth in Singapore. They reported unidirectional causality running from gross domestic product (GDP) to energy consumption with no feedback effect. Soytas and Sari (2003) studied causality between energy consumption and GDP for the G–7 countries and for the top 10 emerging economies excluding China. They found bidirectional causality for Argentina, unidirectional causality from GDP to energy consumption in Italy and Korea, and unidirectional causality from energy consumption to GDP in Turkey, France, Germany and Japan.

Electricity has become the preferred and dominant form of energy in the expanding areas of economic activity in industrial economies. It has been a major factor in the improvement of the standard of living, and has played a crucial role in technological and scientific progress. Therefore, this kind of energy is commonly thought to be especially important also for economic growth.

Ferguson et al. (2000) have studied the interdependences between electricity usage and economic growth in over 100 countries, and found that, as a whole, there is a strong correlation between these variables. Shiu and Lam (2004) investigated the relationship between electricity consumption and GDP growth for the Chinese economy using data for the 1971–2000 period. The authors found short–run unidirectional causality running from electricity consumption to economic growth. This implies that an increase in electricity consumption supported economic growth in China in the period under study. Later investigations by Yuan et al. (2007) performed for the period 1978–2004 are in line with contribution by Shiu and Lam (2004). Yang (2000) has found a bidirectional causal relationship between GDP and electricity consumption in Taiwan. Morimoto and Hope (2004) applied Yang's model to examine the impact of electricity supply on economic growth in Sri Lanka and found similar results. Jumbe (2004) showed that the Granger causality between GDP and electricity consumption for Malawian time series data over the period 1970–1999 runs in both directions (feedback). The error correction model, however, indicated only a unidirectional long–run relationship running from GDP to electricity consumption. Yoo (2005) performed an analogous analysis for Korea over the period 1970–2002 and found a short–run unidirectional causal relationship running from electricity consumption to GDP growth. Altinay and Karagol (2005) demonstrated that electricity consumption was a leading indicator of the economic growth of Turkey. Halicioglu (2007) in a more recent study for the period 1968–2005 demonstrated long–run causality running from income to electricity consumption in Turkey. However, in the short–run the results were inconclusive.

In contrast to the latest contributions, Narayan and Smyth (2005) established over the period 1966–1999 that real income Granger caused electricity consumption in Australia. On the other hand, Narayan and Singh (2007) in their contribution on Fiji found that in the long–run causality runs from electricity consumption and labour force to GDP, implying that Fiji is an energy–dependent country and thus energy conservation policies may have an adverse effect on Fiji's economic growth. Moreover, Narayan et al. (2008), Narayan and Smyth (2008) investigated interdependencies between electricity consumption and GDP for G7 countries (the largest economies in the world). The authors found that except for the USA, electricity consumption has a statistically significant positive effect on real GDP in the short–run. This finding implies that except for the USA, electricity conservation policies will hurt real GDP in the G7 countries. Ghosh (2009) found unidirectional short–run causality running from economic growth to electricity supply in India. He concluded that the absence of causality in the opposite direction implies that electricity demand and supply side measures can be adopted to reduce the wastage of electricity, which should not affect the future economic growth of India.

In a more extensive study Yoo (2006) tested Granger causality among real GDP and electricity consumption for four Asian countries: Indonesia, Malaysia, Singapore, and Thailand, over the period 1971–2002. The causality tests indicated a strong feedback relationship between electricity consumption and economic growth for Malaysia and Singapore. Causality running from economic growth to electricity consumption was reported for Indonesia and Thailand. This result means that energy conservation policies cannot dampen the economic growth of these two countries. To summarize, in all the four countries economic growth was found to stimulate electricity consumption. In a recent study performed on a group of countries Yoo and Lee (2010) found that both per–capita and total electricity consumption are expected to continuously increase for many years. Moreover, the authors expected that an increase in electricity consumption should be stimulated by growth in per–capita income.

In a recent study Wolde–Rufael (2006) applied a Toda–Yamamoto–based causality approach to test for dynamic dependences between electricity consumption and GDP for 17 African countries over the period 1971–2001. In general, results varied from country to country. However, all four possible relations mentioned in the introduction were detected. Squalli (2007) received similar range of causalities between electricity consumption and economic growth for 11 OPEC countries using time series data over the period 1980–2003.

Chen et al. (2007) tested causality for 10 Asian countries (China, Hong Kong, India, Indonesia, Korea, Malaysia, the Philippines, Singapore, Taiwan, and Thailand). The authors used panel causality tests based on the error correction model over the period 1971–2001. They found (except for China, Taiwan and Thailand) a unidirectional short–run causality running from economic growth to electricity consumption, and a feedback in the long–run. In a study from 2007 Mozumder and Marathe confirmed a unidirectional causality running from per capita GDP growth to per capita electricity consumption in Bangladesh over the period 1971–1999.

Lee and Chang (2008) examined 16 Asian countries and found that in general reducing energy consumption does not adversely affect GDP in the short–run but it does in the long–run. Thus, these countries should adopt a more vigorous energy policy.

In general, the bootstrap approach has been rarely used in previous energy literature. This approach is especially useful when analyzing small samples for which the application of the asymptotic theory of a traditional Granger causality test may lead to spurious results. Thus, the bootstrap approach used by Narayan and Prasad (2008) in their paper was likely to produce more efficient results compared with asymptotic–based tests for causality. They found evidence in favour of electricity consumption causing real GDP in the long–run in Australia, Iceland, Italy, the Slovak Republic, the Czech Republic, Korea, Portugal, and the UK. The implication is that electricity conservation policies may negatively impact real GDP in these countries. However, for the rest of the countries (approximately 73 percent of the OECD countries) their findings suggested that electricity conversation policies should not affect real GDP.

A comprehensive overview of results published in the literature is given by Yoo and Kwak (2010). On the other hand, the first study in the energy economics literature that investigates causality between electricity consumption and economic growth for a large group of transition countries is the one by Acaravci and Ozturk (2010). The goal of these authors was to examine whether there is any long–run relationship and causality between electricity consumption and economic growth for 15 European transition economies. By using Pedroni's panel cointegration tests (see Pedroni, 1999, 2004) for the period 1990–2006 they did not confirm long–term equilibrium relationship between electricity consumption per capita and the real GDP per capita. From this study it follows that electricity consumption policies have no effect on the level of real output in the long–run for these countries. The authors also conclude that the literature reports conflicting results and there is no consensus either on the existence or the direction of causality between electricity consumption and economic growth. However, they stress that the findings of their study have important policy implications for energy economics and show that this issue still deserves considerable attention.

To summarize, most of the recent contributors have found a positive causality running from electricity consumption to economic growth. Therefore, we may assume that, in general, the usage of electricity is a limiting factor in economic growth and that shocks to the energy supply can have significant repercussions on economic growth.

3. The main research hypotheses

The direction of causality between electricity consumption and economic growth in the light of the literature overview is not consistent and depends on different data sets, the characteristics of different countries and the different econometric methodologies applied. As we have already mentioned in previous sections, the prevailing point of view in the literature is that electricity consumption is a source of economic growth (this is in line with what is known as the *growth hypothesis*). However, for many countries the opposite direction of causality (which would support the *conservation hypothesis*) or even feedback (the *feedback hypothesis*) was reported. A *neutrality hypothesis* (no causality between electricity consumption and GDP in any direction) can also be found in the literature.

One of the main factors determining GDP is employment. In order to take this fact into account and avoid biased results of causality analysis involving electricity consumption and GDP we also included employment in our causality investigations.[1]

Taking into account results concerning other countries from Central and Eastern Europe, and the dominant role of electricity in Polish energy balance one may expect that the following hypothesis might hold true for Poland:

> <u>Conjecture 1:</u> *There was feedback between total electricity consumption and GDP as well as between total electricity consumption and employment in Poland in the years* 2000–2009 (*i.e. the feedback hypothesis held true*).

An interesting question arises as to the stability of this feedback after the world economic crisis which began in 2008. Poland was the only European country with a positive rate of GDP growth in 2008. Therefore, in line with Conjecture 1, one might assume the stability of the feedback between total electricity consumption and GDP as well as between total electricity consumption and employment. Therefore our next hypothesis is of the form:

> <u>Conjecture 2:</u> *Feedback between total electricity consumption and GDP as well as between total electricity consumption and employment in Poland was robust in the face of the financial and economic crisis of* 2008.

Electricity is consumed by industries and by households. In recent decades there was no rise in the industrial usage of electricity in Poland conditional on technical progress. However, the usage of electricity by households (services sector) has been continuously increasing. Therefore, we may formulate the following:

> <u>Conjecture 3:</u> *In years* 2000–2009 *the interdependencies between industrial energy consumption, GDP and employment in Poland were not so strongly pronounced as in the case of total electricity consumption.*

The impact of the economic crisis of 2008 on the nature of the dynamic links between the usage of electricity in industry and GDP is also worth investigating. Taking into account the suspicions reflected in Conjecture 2, one may also formulate:

[1] Employment was often used in previous papers related to energy–GDP links (e.g. Chang et al., 2001).

Conjecture 4: *The crisis of* 2008 *had no impact on the structure of causal dependences between industrial energy consumption, GDP and employment in Poland.*

The above conjectures will be tested by different causality tests. A detailed description of these methods will be presented in section 5. In the next section we will first characterize the time series included in our sample.

4. The dataset and its properties

In the first part of this section we will present the applied dataset. Next, we will check the stationarity properties of all the time series. The identification of the orders of integration of all time series is a crucial stage of causality analysis.

4.1. Description of the dataset

The chosen dataset includes quarterly data on GDP, total electricity consumption, industrial electricity consumption and employment in Poland in the period Q1 2000 – Q4 2009.[2] Our dataset contains 40 observations. In order to avoid spurious results of further causality analysis 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, the X–12 ARIMA procedure (which is currently used by the U.S. Census Bureau for seasonal adjustment) of Gretl software was applied to adjust each variable. Finally, we transformed each seasonally adjusted variable into logarithmic form, since this operation (as one of the Box–Cox transformations) may stabilize variance and therefore improve the statistical properties of the data, which is especially important for parametric tests. Table 1 contains some initial information:

INSERT TABLE 1 AROUND HERE

One important point that distinguishes our paper from other contributions on electricity consumption and economic growth is that we applied less aggregated quarterly data. This is because the data necessary covered only the recent few years and thus a causality analysis

[2] 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, the help of the Statistical Office in Poland (Cracow Branch) in obtaining the applied macroeconomic data should be underlined.

based on annual data could not have been carried out due to lack of degrees of freedom.[3] Moreover, the application of lower frequency data (e.g. annual) may seriously distort the results of Granger causality analysis because some important interactions may stay hidden (for more details see e.g. Granger et al., 2000).

The originality of this paper is also related to another important fact. The methodology for conducting causality analysis does not allow an exploration of the dynamic links between Poland's GDP, electricity consumption and employment in the period after the bankruptcy of Lehman Brothers Bank (due to insufficient sample size), so we decided to use an alternative approach to examine the impact of the economic crisis of 2008 on the structure of the dynamic links between variables. That is, apart from the full sample, we additionally decided to examine the pre–crisis period (i.e. Q1 2000 – Q3 2008). It seems reasonable to expect this approach to be helpful in identifying the impact of the financial crisis on GDP–electricity usage relationships through the specification of differences in the structures of causal links between the variables for both samples under study. However, this method has a relatively serious drawback as the power properties of causality tests strongly depend on sample size.

The preliminary part of our analysis contains some descriptive statistics of all the variables. The following table contains suitable results. The results obtained for the pre–crisis subsample are presented in square brackets:

INSERT TABLE 2 AROUND HERE

In order to conduct a comprehensive initial analysis one should also make use of charts generated for all the variables under study. The following figure contains suitable plots:

INSERT FIGURE 1 AROUND HERE

In the period under study there was a relatively stable development of the Polish economy as *GDP* exhibited an upward tendency. The Polish economy was one of the few that managed to avoid undesirable consequences of the crisis of September 2008. However, after the third quarter of 2008 one could observe slight slowdown of the rate of development of the Polish economy. For *EMPL* in this period there was a stable rise between 2003 and 2008. However, before 2003 and after the crisis of September 2008 slight drops were also observed. It is also interesting to note that before the beginning of the world economic crisis the ELC_{TOT}

[3] The lack of reliable datasets of sufficient size is a common characteristic of most of post–Soviet economies.

exhibited a significant upward tendency while ELC_{IND} did not exhibit any type of time trend. Finally, we should note that figure 1 clearly shows the significant reaction of all examined variables to economic crisis of September 2008, which justifies the need to examine the impact of this shock on the structure of causal dependences between the variables. 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 stage of causality analysis.

4.2. Stationarity properties of the dataset

First, we conducted an Augmented Dickey–Fuller (ADF) unit root test. Before conducting the test, we set up a maximal lag length equal to 6 and then we used information criteria (namely, the AIC, BIC and HQ) to choose an optimal lag length from the set {0, 1, …, 6}. However, the results of an ADF test are relatively sensitive to any incorrect establishment of lag parameter. Moreover, this test tends to under–reject the null hypothesis pointing at nonstationarity too often (low power against stationary alternatives has been frequently reported by many authors, see e.g. Agiakoglu and Newbold, 1992). Therefore, to confirm the results of the ADF test a Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test was also conducted. Note that in contrast to the ADF test the null hypothesis of a KPSS test refers to the stationarity of time series.

Since it is possible that two unit root tests lead to relatively different conclusions, we used a third test to make a final decision about stationarity. In this paper we applied the Phillips–Perron (PP) test, which 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 following table contains the results of the stationarity analysis. The results obtained for the pre–crisis subsample are once again presented in square brackets. Bold face indicates finding nonstationarity at a 5% level:

INSERT TABLE 3 AROUND HERE

An analysis of the outcomes presented in table 3 shows that only ELC_{IND} was found to be stationary around constant at a 5% level (it was confirmed by two of three conducted tests) while all other time series were found to be nonstationary around constant (in some cases it also was confirmed by two of the three tests). Both these findings were obtained for the full sample and the pre–crisis subsample. Some further calculations (conducted for first differences) confirmed that all nonstationary variables are I(1) regardless of sample size.[4]

5. Methodology

In this paper we applied both linear and nonlinear Granger causality tests to explore the dynamic relationships between *GDP* and electricity consumption in Poland. The methodology of our research was a mixture of a traditional approach and some recent developments in econometric methods of analysing causal links. In general our research was conducted in two three–dimensional variants, each of which involved *GDP*, *EMPL* and one electricity–related variable (ELC_{TOT} or ELC_{IND}).

5.1. Linear short– and long–run Granger causality tests

Since the idea of Granger (1969) causality is well known and has been widely used in previous studies we will not explain it in detail. By and large, this concept is used to investigate whether a knowledge of the past and current values of one stationary variable is helpful in predicting the future values of another one or not. If the time series under study are nonstationary then the outcomes of typical linear causality tests may lead to misleading conclusions, which has been shown in previous empirical (Granger and Newbold, 1974) and theoretical (Phillips, 1986) deliberations. Since all but one examined variable were found to be I(1) we applied three econometric methods suitable for testing for linear short– and long–run Granger causality in this context, namely, a traditional analysis of the vector error correction model (VECM), the sequential elimination of insignificant variables in VECM and the Toda–Yamamoto method.

If variables are integrated in the same order one may perform a cointegration analysis. The existence of cointegration implies long–run Granger causality in at least one direction (Granger, 1988). The direction of this causality may be examined through an estimation of a suitable VEC model and a test (using *t*–test) of the statistical significance of the error correction terms. Checking joint significance (using *F*–test) of lagged differences allows for short–run causality testing in a VEC framework. The application of an unrestricted VEC model has got some drawbacks, however. In practical research it is often necessary to consider a relatively large number of lags in order to avoid the problem of the autocorrelation

[4] 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.

of residuals. On the other hand, a large number of lags may significantly reduce the number of degrees of freedom, which in turn has an undesirable impact on test performance, especially for small samples. Thus, a sequential elimination of insignificant variables was additionally applied for each VECM equation separately to test for short– and long–run Granger causality. At each step the variable with the highest p–value (t–test) was omitted until all remaining variables have a p–value no greater than a fixed value (in this paper it was 0.10). More technical details of this approach may be found in Gurgul and Lach (2010).

The Toda–Yamamoto (1995) approach for testing for Granger causality has been commonly applied in recent empirical studies (see e.g. Keho, 2007) 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) testing method is applicable even if variables are characterized by different orders of integration (which is true in the case of ELC_{IND}). As we have already mentioned, in such cases a standard linear causality analysis cannot be performed by the direct application of a traditional vector autoregression (VAR) or VEC model. On the other hand, differencing or calculating the growth rates of some variables allows the use of the traditional approach, but it may also cause a loss of long–run information and lead to problems with the interpretation of test results.

Since the TY methodology is also well known we will only provide a brief description (for a comprehensive description see e.g. Toda and Yamamoto, 1995). In order to use this procedure one should assume that the order (denote this lag parameter p_1) of the VAR model is known. If not, it should be established by means of some standard statistical methods (e.g. the application of a consistent model selection criterion etc., for details see Paulsen, 1984). Next, one should establish the highest order of integration of all variables (denote this parameter p_2). According to Toda and Yamamoto (1995) parameter p_2 is an unrestricted variable since its role is to guarantee the use of asymptotic theory. Finally, after the estimation of an augmented VAR(p_1+p_2) model one should apply a standard Wald test to check the statistical significance of the first p_1 lags obtained from an augmented model. If some specific modeling assumptions (e.g. whiteness of error term etc., for more details see Lütkepohl, 1993) hold true then the TY test statistic is asymptotically $\chi^2(p_1)$ distributed. Since we dealt with relatively small samples we applied the TY test statistic in its asymptotically F–distributed variant, which performs better for small samples (for more details see e.g. Lütkepohl, 1993).

All three linear methods described above have several drawbacks, which are typical of parametric tests. Firstly, the application of asymptotic theory may lead to spurious results if suitable modeling assumptions do not hold. Secondly, even if all modeling assumptions are generally fulfilled, the distribution of the test statistic may still be significantly different from an asymptotic pattern when dealing with extremely small samples. One possible way of overcoming these difficulties is the application of the 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. 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 second thought (see e.g. Horowitz, 1995).

In this paper we applied a bootstrap based on leveraged residuals.[5] In recent years the academic discussion on the establishment of the number of bootstrap replications has attracted considerable attention (see e.g. Horowitz, 1995; Lach, 2010). In our research we applied the recently developed procedure of establishing the number of bootstrap replications presented by Andrews and Buchinsky (2000). In all cases our goal was to choose such a value of number of replications which would ensure that the relative error of establishing the critical value (at a 10% significance level) would not exceed 5% with a probability equal to 0.95. The Gretl script including all mentioned linear methods with asymptotic– and bootstrap–based variants is available from the authors upon request.

5.2. Nonlinear Granger causality test

Generally, the motivation to use nonlinear methods in testing for causality is twofold. Firstly, the traditional linear Granger causality test has been found to have extremely low power in detecting certain kinds of nonlinear causal relationships (see e.g. Brock, 1991; Gurgul and Lach, 2009). Secondly, since linear methods depend on testing the significance of suitable parameters only in a mean equation, causality in any higher–order structure (like causality in variance etc.) cannot be explored (Diks and DeGoede, 2001).

In this paper the nonlinear causality test proposed by Diks and Panchenko (2006) was applied. We decided to use some typical values of the technical parameters of this method, which have been commonly used in previous papers (e.g. Diks and Panchenko, 2005, 2006;

[5] The technical details of resampling procedure applied in our bootstrap research may be found in Hacker and Hatemi (2006).

Hiemstra and Jones, 1994; Gurgul and Lach, 2010). The bandwidth (denoted as b_{DP}) was set at a level of 0.5, 1 and 1.5 while the common lag parameter (denoted as l_{DP}) was set at the order of 1 and 2. A detailed description of the role of these technical parameters and the form of test statistic may be found in Diks and Panchenko (2006).

Diks and Panchenko (2006) also provided evidence that the presence of heteroscedasticity leads to over–rejection of this nonlinear test. Thus, we additionally decided to test all examined time series for the presence of various heteroscedastic structures. However, the results of the heteroscedasticity tests (like Breusch–Pagan test etc.) provided no significant proofs of the presence of heteroscedasticity, thus we did not re–run the nonlinear causality analysis for filtered time series.[6]

6. Empirical results

In this section we present the results of short– and log–run linear Granger causality tests as well as the outcomes of nonlinear causality analysis. Our goal was to examine the nature of the dynamic links between electricity consumption and GDP in Poland in the periods Q1 2000 – Q4 2009 (full sample) and Q1 2000 – Q3 2008 (pre–crisis subsample). As we have already mentioned, our research was performed in a three–dimensional framework, as fluctuations of employment may have a significant impact on the structure of electricity usage–GDP links. We examined two sets of variables, each of which contained GDP, employment and one electricity–related variable.

6.1. Total electricity consumption and GDP

Since ELC_{TOT}, GDP and $EMPL$ were all found to be I(1) we first performed a cointegration analysis. The type of deterministic trend was specified using the possibilities listed in Johansen (1995). Taking into account the results presented in subsection 4.2 (no trend–stationarity) we assumed the third case, i.e. the 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.[7] The final lag length was established at a level of 5. It should be noted that the same lag parameter was found to be the most suitable for the pre–crisis subsample. The results of Johansen cointegration tests are presented in the

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

[7] The maximal lag length (for levels) was set at a level of 6. BIC pointed at one lag, but the results of Ljung–Box Q–test confirmed that in the case of one lag residuals were significantly autocorrelated, which in turn may seriously distort the results of the causality analysis.

following table (once again results referring to the reduced sample are presented in square brackets):

INSERT TABLE 4 AROUND HERE

As we can see both variants of Johansen test (i.e. Trace and Maximal Eigenvalue) provided solid evidence for claiming that for both samples the dimension of cointegration space was equal to two (at 10% level). Next, we estimated suitable VEC models using the full sample and the pre–crisis subsample. In both cases we assumed 4 lags (for first differences) and two cointegrating vectors.[8] The following table contains *p*–values obtained while testing for linear short– and long–run Granger causality using unrestricted VEC models and the sequential elimination of insignificant variables (*p*–values referring to the reduced sample are presented in square brackets, bold face indicates finding a causal link in a given direction at a 10% level):

INSERT TABLE 5 AROUND HERE

The results obtained for the unrestricted VEC model provided a basis for claiming that ELC_{TOT} Granger caused *GDP* in the short–run in the period Q1 2000 – Q4 2009 (this was confirmed only by a bootstrap–based test). On the other hand, the sequential elimination of insignificant variables led to the conclusion that in the short–run there was feedback between these variables (which was confirmed by asymptotic– and bootstrap–based test). Moreover, the analysis of pre–crisis subsample led to similar results.

Despite the sample, and the type of critical values used we found unidirectional short–run linear causality running from employment to total electricity consumption. On the other hand the structure of short – run causal links between *GDP* and *EMPL* was found to be influenced by the analyzed period and testing method used.

In all the research variants the EC_1 component was found to be significant in *GDP* and ELC_{TOT} equations, which provides a basis for claiming that for total electricity consumption and output there was feedback also in the long–run. Furthermore, the sequential elimination indicated the existence of feedback between ELC_{TOT} and *EMPL* and unidirectional causality from *GDP* to *EMPL* in the long–run.

[8] The first vector (denoted as EC_1) involved *GDP* and ELC_{TOT} while the second one (EC_2) involved *EMPL* and ELC_{TOT}.

In general, the results for the pre–crisis subsample led to a conclusion similar to the analysis of the full sample. We should just mention that before the crisis the impact of *EMPL* on *GDP* (short–run) and ELC_{TOT} (long–run) was rather weak (it was not confirmed during an analysis of the unrestricted VEC model). On the other hand, long–run causality from *GDP* and total electricity consumption to employment was found to be stronger before September 2008.

For the sake of comprehensiveness we additionally applied a Toda–Yamamoto approach for testing for causal effects between ELC_{TOT}, *GDP* and *EMPL.* Cointegration methodology was not applicable to ELC_{IND}, *GDP* and *EMPL,* thus the differences in structures of linear causal links between *GDP* and ELC_{TOT} as well as between *GDP* and ELC_{IND} could be compared only on the basis of the TY approach.

The following table contains *p*–values obtained while testing for linear short–run Granger causality between ELC_{TOT}, *GDP* and *EMPL* using the Toda–Yamamoto approach. It seems interesting to see if the results of the TY approach are in line (at least to some extent) with outcomes obtained after an analysis of the VEC model (in unrestricted and sequentially–eliminated variants), which is especially important in terms of the robustness and validation of the empirical results. Whenever test results indicated the existence of a causal link in a given direction (at 10% level) bold face was used to mark this finding. Results referring to the reduced sample are presented in square brackets:

INSERT TABLE 6 AROUND HERE

As we can see, before the crisis of September 2008 *GDP* was found to Granger cause total electricity consumption. This result was obtained only by the bootstrap–based TY procedure. There were no other linear causal links significant at a 10% level for the pre–crisis subsample. However, when the full sample was considered the causalities from *GDP* and *EMPL* to ELC_{TOT} were found to be significant at a 10% level in asymptotic– and bootstrap–based variants.

Finally, a nonlinear causality analysis was performed for the residuals resulting from all linear models, i.e. the residuals of unrestricted VECM, the residuals resulting from individually (sequentially) restricted equations and the residuals resulting from the augmented VAR model applied in the Toda–Yamamoto method.[9] In all cases no significant

[9] Residuals are believed to reflect strict nonlinear dependencies since the structure of linear connections had been filtered out after an analysis of linear models (Baek and Brock, 1992).

evidence of heteroscedasticity was found, therefore no filtering was applied. Since for the residuals of the unrestricted VECM and the residuals resulting from individually (sequentially) restricted equations no significant (at a 10% level) nonlinear links were found, we did not find a reason to present these results in separate tables.

However, some statistically significant nonlinear relations were found for the residuals of the augmented VAR applied in the TY method. The following table presents *p*–values obtained while testing for nonlinear Granger causality between ELC_{TOT}, *GDP* and *EMPL* (bold face was used to mark finding causality at a 10% level, *p*–values referring to the reduced sample are once again presented in square brackets):

INSERT TABLE 7 AROUND HERE

This time the results obtained for the two samples were relatively different. Before the crisis one could observe feedback between *GDP* and ELC_{TOT} and unidirectional causality from *EMPL* to ELC_{TOT}. On the other hand causality from ELC_{TOT} to *GDP* and *EMPL* was found to be statistically significant for the full sample.

In general, the results of all the methods provided relatively strong support for claiming that for total electricity consumption and *GDP* as well as for ELC_{TOT} and employment Granger causality runs in both directions. This result was found for both periods. Moreover, it is worth noting that this conclusion, in general, was confirmed by the results of two completely different methods, namely a two–stage analysis of the VEC model and the TY approach (with a post–TY nonlinear test), which somewhat confirms the robustness of this major conclusion when exposed to the statistical tools. Therefore, we found strong support for claiming that Conjecture 1 and Conjecture 2 are both true.

6.2. Industrial electricity consumption and GDP

Since ELC_{IND} was found to be stationary (in both periods) a cointegration analysis could not be carried out for the ELC_{IND}, *GDP* and *EMPL* variables. In this case the Toda–Yamamoto procedure was the only applicable method for testing for linear Granger causality in a three–dimensional framework. Therefore, the differences in the structures of linear causal links between economic growth and both electricity–related variables could be compared only on the basis of this approach. The optimal lag length for the unrestricted VAR model was once again set at the level of five (for both samples). The following table contains *p*–values obtained while testing for linear short–run Granger causality using the Toda–

Yamamoto approach. Whenever test results indicated the existence of a causal link in a given direction (at a 10% level) bold face was used to mark this finding. The results referring to the reduced sample are presented in square brackets:

INSERT TABLE 8 AROUND HERE

Regardless of the type of critical values used no causal links were found for the pre–crisis subsample. On the other hand, causality from ELC_{IND} to employment was found to be statistically significant for the full sample. This result may be interpreted as proof of the fact that during the period of economic crisis industrial electricity consumption had an extremely significant impact on employment in Poland.

A nonlinear causality analysis was also performed for the residuals resulting from the augmented VAR model applied in the Toda–Yamamoto method. No significant evidence of heteroscedasticity was found, therefore once again no filtering was applied. The following table presents *p*–values obtained while testing for nonlinear Granger causality between ELC_{IND}, *GDP* and *EMPL* (bold face was used to mark finding causality at a 10% level, *p*–values referring to the reduced sample are presented in square brackets):

INSERT TABLE 9 AROUND HERE

This time causality from ELC_{IND} to employment was found to be significant at a 10% level in both periods. However, this is not contrary to the conclusion formulated after an analysis of the results of the linear TY procedure (table 8) because evidence of causality in the pre–crisis subsample was clearly weaker than in a full sample (e.g. it was not statistically significant at 5% level). In general, the results of this part of our research provided solid evidence in favour of Conjecture 3. On the other hand, Conjecture 4 should rather be rejected.

7. Concluding remarks

The main goal of this paper was the examination of causal interdependences between electricity consumption and GDP in Poland. We performed our research on total electricity consumption as well as on industrial electricity consumption. Our research was performed in a three–dimensional framework with employment chosen as an additional variable, since a simple two–dimensional approach involving only GDP and electricity consumption may be seriously biased due to the omission of important variables. We applied reliable quarterly data covering the period Q1 2000 – Q4 2009. However, we additionally examined the case of a reduced sample to investigate the possible impact of the world economic crisis on the structure of dynamic links between the variables. In order to test for causality we applied both traditional methods as well as some recently developed econometric tools.

We found relatively strong support for claiming that there was feedback between total electricity consumption and GDP as well as between total electricity consumption and employment in both periods. This may be interpreted as evidence of the fact that this structure of causal dependences between variables was relatively strong as it was not seriously disrupted during the crisis of 2008. It is also worth noting that this result was, in general, confirmed by two completely different econometric methods, which is especially important in terms of the validation and robustness of the empirical findings.

In contrast to total electricity consumption, we did not find such strong causal connections with other variables for industrial electricity usage in both periods, which was partly the consequence of the fact that in this case cointegration analysis could not be carried out in a three–dimensional framework. However, the data and computations showed evidence for claiming that the economic crisis of 2008 significantly supported the causal impact of industrial electricity consumption on employment.

To summarize, the results of our research provided a solid basis for accepting the feedback hypothesis for total electricity consumption and GDP as well as for total electricity consumption and employment in Poland. This result was robust in the face of the impact of the economic crisis and the type of econometric method used and proves that total electricity consumption is an important factor determining fluctuations in economic growth and employment in Poland. On the other hand, industrial electricity consumption was found to have a direct causal impact on employment but not on GDP. We found especially strong evidence of the existence of this link when the crisis period was also taken into consideration.

In general, one may claim that these results lead to the conclusion that in the recent decade the economic growth of Poland was dynamically linked by changes of electricity usage mostly in the non–industrial sector (residential usage, usage for commercial and public services etc.). This observation should be analyzed together with two facts. First, in the recent decade Polish industry has adopted new, more energy–efficient technologies in order to face a number of international ecological requirements. This could explain why growth in electricity consumption in this sector was not reported although there was a growth in the value of sold industrial production. Secondly, in recent years the share of the service sector in Polish GDP and employment has significantly risen. Thus, it is not surprising that increasing electricity consumption in this sector was significantly related to the economic growth of Poland.

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Figures:

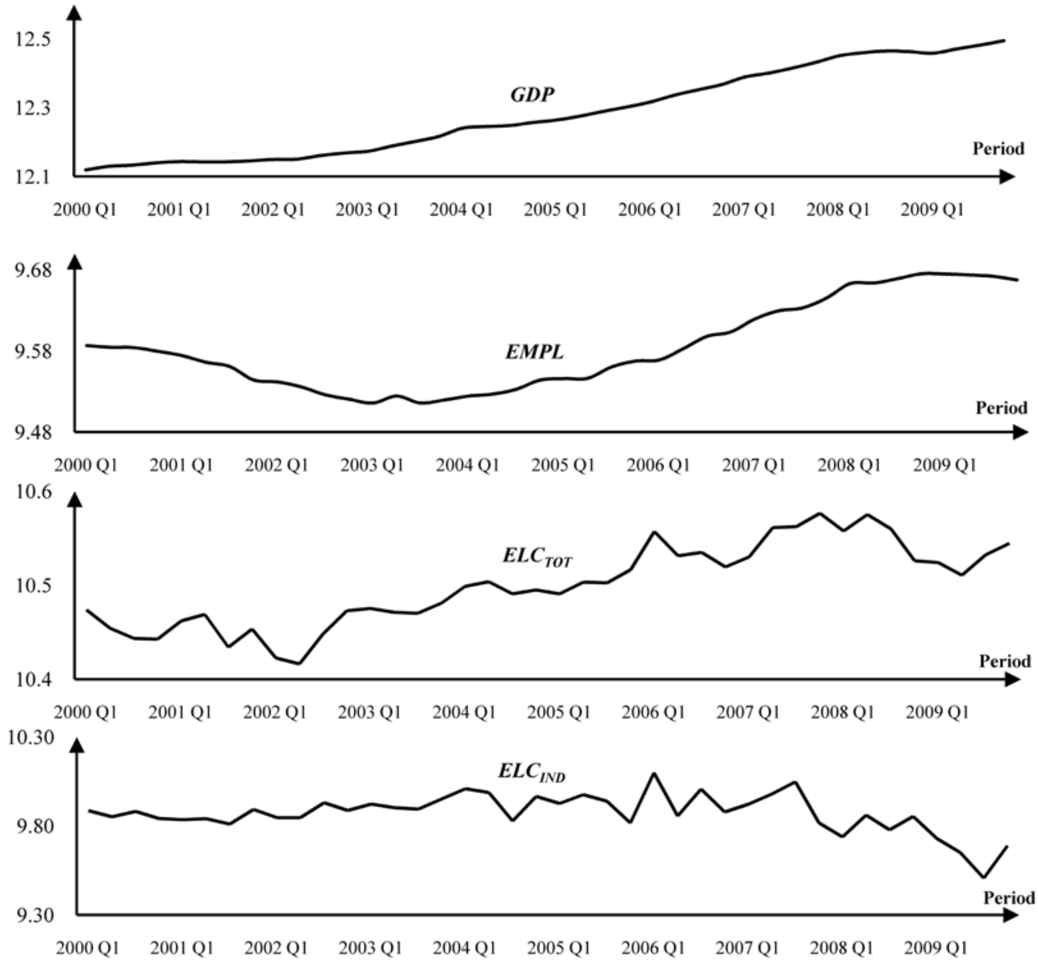

Figure 1: Plots of examined time series.

Description of variable	Unit	Abbreviation for seasonally adjusted and logarithmically transformed variable
Real quarterly gross domestic product in Poland	mln PLN	*GDP*
Employment in Poland based on quarterly Labour Force Survey	thousands	*EMPL*
Quarterly total electricity consumption in Poland	GWh	ELC_{TOT}
Quarterly industrial electricity consumption in Poland	GWh	ELC_{IND}

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

Quantity \ Variable	*GDP*	*EMPL*	ELC_{TOT}	ELC_{IND}
Minimum	12.11 [12.11]	9.51 [9.51]	10.41 [10.41]	9.50 [9.73]
1st quartile	12.15 [12.14]	9.53 [9.53]	10.46 [10.46]	9.82 [9.84]
Median	12.26 [12.24]	9.57 [9.56]	10.50 [10.49]	9.88 [9.88]
3rd quartile	12.41 [12.35]	9.63 [9.59]	10.53 [10.53]	9.93 [9.95]
Maximum	12.49 [12.46]	9.68 [9.66]	10.57 [10.57]	10.09 [10.09]
Mean	12.28 [12.25]	9.58 [9.57]	10.50 [10.48]	9.87 [9.89]
Std. deviation	0.12 [0.11]	0.09 [0.04]	0.04 [0.04]	0.10 [0.07]
Skewness	0.27 [0.48]	0.48 [0.71]	0.01 [0.20]	–0.87 [0.44]
Excess kurtosis	–1.40 [–1.09]	–1.12 [–0.62]	–0.61 [–0.96]	1.93 [–0.01]

Table 2. Descriptive statistics of examined variables.

Test type \ Variable	ADF				KPSS[c]		PP[c]	
	with constant		with constant and linear trend		with constant[a]	with constant and linear trend[b]	with constant	with constant and linear trend
	p–value	Optimal lag	*p*–value	Optimal lag	Test statistic		*p*–value	
GDP	**0.99 [0.91]**	1 [1]	**0.19 [0.23]**	1 [1]	**1.08 [0.94]**	**0.23 [0.22]**	**0.98 [0.94]**	**0.52 [0.43]**
EMPL	0.00 [**0.13**]	4 [4]	0.00 [**0.35**]	4 [4]	**0.78 [0.53]**	**0.25 [0.24]**	**0.92 [0.97]**	**0.60 [0.95]**
ELC_{TOT}	**0.68 [0.81]**	0 [0]	**0.16 [0.15]**	0 [0]	**0.93 [0.63]**	0.12 [0.13]	**0.76 [0.89]**	**0.16 [0.12]**
ELC_{IND}	**0.24** [0.00]	1 [0]	**0.35 [0.19]**	4 [4]	0.33 [0.25]	**0.23 [0.18]**	0.03 [0.00]	**0.09** [0.00]

Table 3. Results of stationarity analysis.

[a] *critical values:* 0.347 (10%), 0.463 (5%), 0.739 (1%).
[b] *critical values:* 0.119 (10%), 0.146 (5%), 0.216 (1%).
[c] *Bandwidth parameter was established according to Newey and West* (1987).

		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 [0.58]	38.13 [39.54]	0.00 [0.00]	22.78 [26.24]	0.02 [0.00]
At most one	0.33 [0.35]	15.35 [13.29]	0.05 [0.10]	14.31 [12.95]	0.04 [0.07]
At most two	0.02 [0.01]	1.03 [0.33]	0.30 [0.56]	1.03 [0.33]	0.30 [0.56]

Table 4. Results of cointegration analysis for ELC_{TOT}, GDP and $EMPL$ variables.

Short–run				
Null hypothesis[a]	p–value[c]			
	Unrestricted		Sequential	
	Asymptotic	Bootstrap[b]	Asymptotic	Bootstrap[b]
$ELC_{TOT} \neg\rightarrow GDP$	0.15 [0.14]	**0.09 [0.10]**	**0.01 [0.00]**	**0.02 [0.03]**
$GDP \neg\rightarrow ELC_{TOT}$	0.12 [0.16]	0.16 [0.21]	**0.01 [0.02]**	**0.04 [0.04]**
$ELC_{TOT} \neg\rightarrow EMPL$	0.55 [0.51]	0.43 [0.53]	NCL [NCL]	NCL [NCL]
$EMPL \neg\rightarrow ELC_{TOT}$	**0.00 [0.01]**	**0.00 [0.02]**	**0.00 [0.00]**	**0.01 [0.00]**
$GDP \neg\rightarrow EMPL$	0.69 [0.67]	0.61 [0.73]	**0.08 [0.09]**	**0.02 [0.01]**
$EMPL \neg\rightarrow GDP$	**0.10** [0.16]	**0.07** [0.14]	**0.00 [0.00]**	**0.00 [0.00]**

Long–run								
Equation	p–value of EC_1 component[c]				p–value of EC_2 component[c]			
	Unrestricted		Sequential		Unrestricted		Sequential	
	Asymptotic	Bootstrap[b]	Asymptotic	Bootstrap[b]	Asymptotic	Bootstrap[b]	Asymptotic	Bootstrap[b]
ELC_{TOT}	**0.00 [0.00]**	**0.01 [0.00]**	**0.05 [0.00]**	**0.02 [0.00]**	**0.10** [0.15]	**0.09** [0.17]	**0.00 [0.07]**	**0.00 [0.01]**
GDP	**0.04 [0.02]**	**0.08 [0.01]**	**0.01 [0.03]**	**0.04 [0.04]**	0.94 [0.95]	0.73 [0.68]	NCL [NCL]	NCL [NCL]
$EMPL$	0.18 [**0.08**]	0.25 [**0.04**]	**0.02 [0.01]**	**0.05 [0.04]**	**0.01 [0.00]**	**0.00 [0.00]**	**0.00 [0.00]**	**0.00 [0.00]**

Table 5. Analysis of causal links between ELC_{TOT}, GDP and $EMPL$ variables (VEC models).

[a] *The notation "$x \neg\rightarrow y$" is equivalent to "x does not Granger cause y".*
[b] *Number of bootstrap replications established using Andrews and Buchinsky* (2000) *method varied between* 1769 *and* 3119.
[c] *The symbol NCL is the abbreviation of "No coefficients left".*

Null hypothesis[a]	p–value	
	Asymptotic	Bootstrap[b]
$ELC_{TOT} \neg\rightarrow GDP$	0.27 [0.43]	0.41(N=2099) [0.52 (N=2279)]
$GDP \neg\rightarrow ELC_{TOT}$	**0.05** [0.15]	**0.07** (N=2659) [**0.05** (N=3019)]
$ELC_{TOT} \neg\rightarrow EMPL$	0.71 [0.65]	0.58 (N=2219) [0.53 (N=2739)]
$EMPL \neg\rightarrow ELC_{TOT}$	**0.03** [0.18]	**0.02** (N=2019) [0.24 (N=2559)]
$GDP \neg\rightarrow EMPL$	0.72 [0.86]	0.64 (N=1679) [0.77 (N=1859)]
$EMPL \neg\rightarrow GDP$	0.53 [0.48]	0.42 (N=2219) [0.41 (N=2759)]

Table 6. Analysis of causal links between ELC_{TOT}, GDP and $EMPL$ variables (TY approach).

[a] *The notation "$x \neg\rightarrow y$" is equivalent to "x does not Granger cause y".*
[b] *Parameter N denotes the number of bootstrap replications established according to Andrews and Buchinsky* (2000) *procedure.*

Null hypothesis[a]	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
$ELC_{TOT} \neg\rightarrow GDP$	0.67 [0.43]	0.61 [0.35]	**0.08** [0.20]	0.72 [0.56]	0.26 [**0.09**]	0.42 [0.59]
$GDP \neg\rightarrow ELC_{TOT}$	0.51 [0.35]	0.32 [0.57]	0.76 [0.46]	0.41 [0.64]	0.61 [**0.05**]	0.81 [0.77]
$ELC_{TOT} \neg\rightarrow EMPL$	0.62 [0.57]	0.72 [0.58]	0.16 [0.23]	0.52 [0.59]	0.73 [0.66]	**0.06** [0.29]
$EMPL \neg\rightarrow ELC_{TOT}$	0.55 [0.26]	0.81 [0.92]	0.34 [0.37]	0.29 [0.44]	0.76 [0.49]	0.17 [**0.09**]
$GDP \neg\rightarrow EMPL$	0.49 [0.47]	**0.09** [0.19]	0.81 [0.76]	0.43 [0.32]	0.30 [0.28]	0.70 [0.83]
$EMPL \neg\rightarrow GDP$	0.68 [0.58]	0.17 [0.36]	0.45 [0.42]	0.38 [0.26]	0.56 [0.82]	0.31 [0.27]

Table 7. Analysis of nonlinear causal links between ELC_{TOT}, GDP and $EMPL$ variables (post–TY residuals).

[a] *The notation "$x \neg\rightarrow y$" is equivalent to "x does not Granger cause y".*

Null hypothesis[a]	p–value[b]	
	Asymptotic	Bootstrap[b]
$ELC_{IND} \neg\rightarrow GDP$	0.22 [0.72]	0.24(N=1879) [0.53 (N=2099)]
$GDP \neg\rightarrow ELC_{IND}$	0.61 [0.86]	0.66 (N=2579) [0.72 (N=2819)]
$ELC_{IND} \neg\rightarrow EMPL$	**0.06** [0.28]	**0.04** (N=2019) [0.35 (N=2359)]
$EMPL \neg\rightarrow ELC_{IND}$	0.48 [0.65]	0.57 (N=1919) [0.72 (N=2139)]
$GDP \neg\rightarrow EMPL$	0.54 [082]	0.39 (N=1999) [0.57 (N=2279)]
$EMPL \neg\rightarrow GDP$	0.67 [0.88]	0.79 (N=2239) [0.72 (N=2439)]

Table 8. Analysis of causal links between ELC_{IND}, GDP and $EMPL$ variables (TY approach).

[a] *The notation "$x \neg\rightarrow y$" is equivalent to "x does not Granger cause y".*
[b] *Parameter N denotes the number of bootstrap replications established according to Andrews and Buchinsky* (2000) *procedure.*

Null hypothesis[a]	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
$ELC_{IND} \neg\rightarrow GDP$	0.76 [0.49]	0.84 [0.54]	0.83 [0.45]	0.25 [0.32]	0.81 [0.52]	0.76 [0.64]
$GDP \neg\rightarrow ELC_{IND}$	0.19 [0.42]	0.82 [0.67]	0.13 [0.24]	0.73 [0.67]	0.69 [0.71]	0.43 [0.55]
$ELC_{IND} \neg\rightarrow EMPL$	0.23 [0.35]	0.47 [0.79]	0.19 [0.34]	0.69 [0.43]	0.18 [0.40]	**0.04** [**0.09**]
$EMPL \neg\rightarrow ELC_{IND}$	0.34 [0.19]	0.63 [0.81]	0.45 [0.58]	0.70 [0.62]	0.92 [0.67]	0.52 [0.37]
$GDP \neg\rightarrow EMPL$	0.65 [0.77]	0.46 [0.34]	0.65 [0.38]	0.45 [0.82]	0.78 [0.83]	0.65 [0.72]
$EMPL \neg\rightarrow GDP$	0.82 [0.39]	0.78 [0.65]	0.82 [0.72]	0.67 [0.34]	0.82 [0.49]	0.52 [0.63]

Table 9. Analysis of nonlinear causal links between ELC_{IND}, GDP and $EMPL$ variables (post–TY residuals).

[a] *The notation "$x \neg\rightarrow y$" is equivalent to "x does not Granger cause y".*