Oil usage, gas consumption and economic growth: Evidence from Poland

Lach, Łukasz

AGH University of Science and Technology, Department of Applications of Mathematics in Economics

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Łukasz Lach
AGH University of Science and Technology,
Department of Applications of Mathematics in Economics, Gramatyka 10 st., 30–067 Cracow, Poland
tel.: +48 012 6174218, fax: +48 012 6367005, e-mail: llach@zarz.agh.edu.pl.

Abstract

This paper investigates causal links between economic growth, oil consumption and natural gas usage in Poland on the basis of quarterly data for the period Q1 2000 – Q4 2009. The application of the Toda–Yamamoto procedure, a nonlinear Granger causality test, bootstrap techniques and an analysis of VECM led to the conclusion that both oil and natural gas usage caused GDP growth in the short–term. However, in the long–term causality ran in the opposite direction. Both these findings are believed to be the consequence of the recent transformation of the Polish economy from energy intensive activities towards services, which in general are not energy–consuming.

Keywords: cointegration, economic growth, Granger causality, natural gas consumption, nonlinear causality test, oil consumption, residual–based bootstrap, Toda–Yamamoto method.

1. Introduction

The relationship between energy consumption and economic growth has received considerable attention in recent years, especially in developed economies. However, the lack of reliable datasets of sufficient size for post–Soviet countries mean that little attention has been paid to the emerging economies of Central and Eastern Europe. This paper fills this gap in the literature as it is aimed at an analysis of the causal links between oil usage, gas consumption and GDP in Poland for the period 2000–2009. This country was chosen for analysis as it is the largest in Central Europe. Moreover, in 1988 Poland was the first former Eastern Bloc country to start the transition process and was the only European country whose

GDP growth rate in 2008 remained positive despite the global economic crisis and minimal fiscal stimulus (as in most CESEE countries). To the best of the author's knowledge there are no similar contributions for a transitional country from Central Europe.

Although it is clear that any economy requires some oil and gas consumption, the impact of a reduction in the usage of these fuels on the GDP growth rate is worth investigating. If the level of energy consumption does not significantly affect the pace of economic growth, then certain policy implications arise. This seems to be especially important for Poland in terms of reducing its CO_2 emission level by 20%, which (according to the Polish government) should take place before 2020.

In the last decade there was a stable development of the Polish economy. This is clearly presented in figure 1 (all charts presented in this paper were created for seasonally adjusted (X–12 ARIMA) and logarithmically transformed time series):

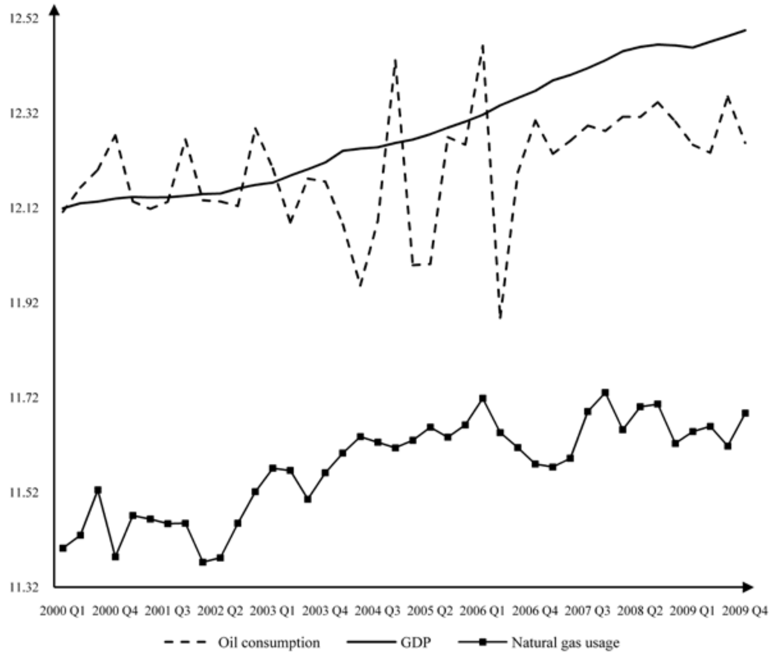

Figure 1: Plots of GDP and energy consumption series.

After the crisis of September 2008 GDP growth rate remained positive, but a slowdown was also reported. Figure 1 also shows that the usage of oil and natural gas rose significantly in 2000–2009. Thus, it seems to be interesting to investigate whether the Poland's economic growth was significantly related to the increase in oil and natural gas consumption. The answer to this question may be of interest to policy makers both in Poland (in terms of maintaining its economic development) as well as in other emerging economies.

Most of previous papers examining causal links between energy usage and economic growth have been focused on the USA (see e.g. Kraft and Kraft (1978), Akarca and Long (1980) or more recent Bowden and Payne (2009)) or Asians Tigers (e.g. Glasure and Lee (1997), Yang (2000), Oh and Lee (2004)) and primarily based on the application of aggregated data. The major conclusion is that energy usage and economic growth are in general dynamically linked but the direction of the causal link is rather controversial.

Although the literature on the causal links between total energy usage and GDP is still expanding, there are not many papers dealing specifically with oil consumption and GDP for non–oil exporting countries. Yoo (2006) examined short– and long–run causal links between GDP and oil consumption in Korea using the two–dimensional VECM approach. He found a feedback relationship in the long–run and causality from GDP to oil consumption in the short–run. A similar result for the short–run was also reported by Yang (2000) in the case of Taiwanese data. However, in this case GDP and oil usage were not cointegrated. On the other hand, Yu and Choi (1985) found causality from liquid fuels to GNP in the case of Korea.

Yang's (2000) paper also contains the results of a causality analysis conducted for GDP and natural gas consumption. Natural gas consumption, as opposed to oil usage, was found to Granger cause GDP in the short–run. This finding was confirmed by Lee and Chang (2005), who examined the possibility of an endogenously determined structural break in testing for unit root and cointegration. Furthermore, a causal effect of gas consumption on GNP in the UK was reported by Yu and Choi (1985).

In recent years there have been only few papers investigating the causal links between energy usage and economic growth in Poland. Both Yu and Choi (1985) and Soytas and Sari

(2003) found no causal links between examined categories of energy consumption and economic growth in Poland.

In this paper the analysis of causal links between oil usage, natural gas consumption and GDP in Poland was performed based on recent and reliable quarterly data. This dataset covers the period 2000 – 2009.

The analysis of causal links between GDP and energy consumption has recently been conducted in a multivariate framework, since a simple two–dimensional approach can be seriously biased due to the possible omission of important variables. In this paper, taking into account macroeconomic theory and the experience of Chang et al. (2001), data on employment was chosen as an additional variable determining economic growth.

2. Main research objectives

Since the results of previous papers are in general mixed, it is hard to formulate a reliable hypothesis about the existence and directions of the causal links between aggregated or disaggregated energy consumption and economic growth in developing countries. This paper should be helpful in judging which of the four hypotheses tested in previous papers holds true in the case of the Polish economy:

The growth hypothesis – energy usage has a significant impact on the pace of economic growth, so that a reduction in energy usage may have serious repercussions on GDP growth;

The conservation hypothesis – energy consumption is Granger caused by economic growth and therefore a reduction in energy usage should not have an adverse impact on GDP;

The feedback hypothesis – causality between energy consumption and GDP runs in both directions so that fluctuations in these variables have a significant impact on each other;

The neutrality hypothesis – causality between energy usage and GDP does not run in any direction, which means these variables are not dynamically interdependent.

Although both of the Poland–related papers, i.e. Yu and Choi (1985) and Soytas and Sari (2003), provided evidence in favour of the neutrality hypothesis (in the case of total energy usage, oil usage and natural gas usage) they were based on an analysis of the data which was relatively out of date (before 1995) and unreliable (as it partly covered the period of communist rule). Since the recent and reliable data analyzed in this paper covers a crucial period for Poland (ongoing transformation, EU accession, world economic crisis) each of the four hypotheses is an open question in the case of Polish economy.

3. The dataset

The dataset used in this paper contains quarterly data on real GDP, oil consumption, natural gas consumption and employment in Poland for the period Q1 2000 – Q4 2009. All time series were seasonally adjusted and logarithmically transformed since both these transformations are believed to help in avoiding spurious results in further causality analysis. The following figure presents the graph of the time series of employment:

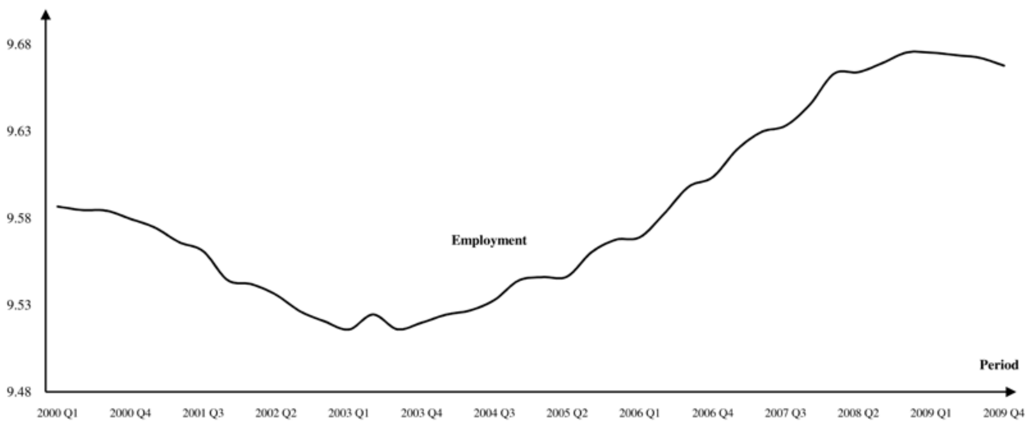

Figure 2: Plot of employment time series.

An analysis of the graphs presented in figures 1 and 2 leads to the conclusion that all the variables may indeed be nonstationary. In order to formally confirm this supposition three commonly used unit root tests were performed for each variable:

Test type[a] / Variable	Augmented Dickey-Fuller				Kwiatkowski-Phillips-Schmidt-Shin[e]		Phillips-Perron[e]	
	with constant		with constant and linear trend		with constant[c]	with constant and linear trend[d]	with constant	with constant and linear trend
	p-value	Optimal lag[b]	*p*-value	Optimal lag[b]	Test statistic		*p*-value	
GDP	0.99	1	0.19	1	1.08	0.23	0.98	0.52
Oil consumption	0.84	4	0.29	4	0.56	0.18	0.00	0.00
Natural gas usage	0.28	0	0.09	0	0.91	0.16	0.33	0.12
Employment	0.00	4	0.00	4	0.78	0.25	0.92	0.60

Table 1. Results of stationarity analysis.

[a] *Shading indicates finding nonstationarity at 5% significance level.*

[b] *Optimal lag was chosen on the basis of information criteria (namely the AIC, BIC, HQ, FPE).*

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

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

[e] *Bandwidth parameter was established according to Newey and West* (1987).

The results of the stationarity analysis presented in table 1 lead to the conclusion that all the time series are nonstationary around constant at a 5% significance level (for oil consumption and employment this was confirmed by two tests). Some further calculations performed for first differences confirm that all the variables are I(1). It is worth noting that the results of all computations which are not presented in the text in detailed form (usually to save space) are available from the author upon request.

4. Methodology

In this paper three econometric methods were applied in order to test for linear short– and long–run Granger causality – namely the Toda–Yamamoto method, a traditional analysis of VECM and the sequential elimination of insignificant variables in VECM. Toda and Yamamoto (1995) developed a method of testing for short–run Granger causality which has been commonly applied in recent empirical research (e.g. Keho (2007)), so a detailed description will not be presented in this paper (for details see e.g. Toda and Yamamoto (1995), Gurgul and Lach (2010)). By and large, this method allows for causality testing if the variables in question are characterized by different orders of integration or if the cointegration properties of the data are uncertain. This approach requires the establishment of a parameter p_1 (order of VAR model), parameter p_2 (highest order of integration of all examined variables) and then a calculation of the standard Wald test applied for the first p_1 lags of the augmented VAR(p_1+p_2) model.

Another well–known method of testing for short– and long–run causality between variables is the application of the VEC model (for details on this methodology see e.g. Granger (1988)). An important part of this procedure is the establishment of deterministic term in both the VAR model and the cointegrating equation using one of the famous *five cases* presented by Johansen (1995).

Finally, a sequential elimination of insignificant variables was 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 was omitted until all remaining variables had a *p*–value no greater than a fixed value (in this paper it was 0.05). This method may be especially useful when dealing with relatively small samples (like the one analyzed in this paper), as in such a case the estimation of the unrestricted VEC model may lead to disturbingly small number of degrees of freedom (for technical details see Gurgul and Lach (2010)).

In order to use the asymptotic statistics of all the methods some specific modelling assumptions should hold, which is relatively difficult to achieve while working with small samples (Lütkepohl (1993)). Thus, in this paper the bootstrap critical values were also calculated for each variant of linear causality test. In order to minimize the undesirable influence of heteroscedasticity, the bootstrap test was based on resampling leveraged residuals (for details see Davison and Hinkley (1999) or Hacker and Hatemi (2006)). The number of bootstrap replications (parameter *N*) was in each case established according to the method presented by Andrews and Buchinsky (2000). The value of parameter *N* was chosen to be large enough to ensure that the relative error of establishing the 5%–bootstrap critical value would not exceed 0.05 with a probability equal to 0.95. The relevant script written in Gretl (including all discussed linear methods) is available from the author upon request.

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

In this article the nonlinear causality test proposed by Diks and Panchenko (2006) was used. The bandwidth parameter (b_{DP}) was set at a level of 0.5, 1 and 1.5 for all the tests and a common lag parameter (l_{DP}) was established in the order of 1 and 2 in each case. These values have been commonly used in previous papers (e.g. Hiemstra and Jones (1994), Diks and Panchenko (2006), Gurgul and Lach (2010)). More details about the meaning of these technical parameters and the form of test statistic may be found in Diks and Panchenko (2006).

5. Empirical results

The following table contains *p*–values obtained while testing for linear short–run Granger causality using the Toda–Yamamoto procedure. The research was performed for two three–dimensional VAR models constructed for GDP, employment and one energy–related variable (i.e. oil consumption or natural gas usage). The results are presented in the following table:

VAR model	Null hypothesis[b]	*p*-value[a]	
		Asymptotic distribution	Bootstrap distribution[c]
Constructed for natural gas usage, GDP and employment (p_1=5, p_2=1)[d]	Natural gas usage $\xrightarrow{no\ GC}$ GDP	0.35	0.42 (*N*=3299)
	GDP $\xrightarrow{no\ GC}$ Natural gas usage	0.58	0.51 (*N*=3359)
	Natural gas usage $\xrightarrow{no\ GC}$ Employment	0.05	0.04 (*N*=3519)
	Employment $\xrightarrow{no\ GC}$ Natural gas usage	0.17	0.15 (*N*=2519)
	GDP $\xrightarrow{no\ GC}$ Employment	0.27	0.24 (*N*=1979)
	Employment $\xrightarrow{no\ GC}$ GDP	0.72	0.76 (*N*=3059)
Constructed for oil consumption, GDP and employment (p_1=4, p_2=1)[d]	Oil consumption $\xrightarrow{no\ GC}$ GDP	0.84	0.86 (*N*=3379)
	GDP $\xrightarrow{no\ GC}$ Oil consumption	0.31	0.37 (*N*=3339)
	Oil consumption $\xrightarrow{no\ GC}$ Employment	0.87	0.82 (*N*=3419)
	Employment $\xrightarrow{no\ GC}$ Oil consumption	0.52	0.52 (*N*=2679)
	GDP $\xrightarrow{no\ GC}$ Employment	0.15	0.17 (*N*=2019)
	Employment $\xrightarrow{no\ GC}$ GDP	0.75	0.71 (*N*=3459)

Table 2. Results of Toda–Yamamoto causality test.

[a] *Shading indicates finding causality at 5% significance level.*

[b] *The notation " $x \xrightarrow{no\ GC} y$ " is equivalent to "x does not Granger cause y".*

[c] *N denotes number of bootstrap replications.*

[d] *p_1 was chosen on the basis of information criteria (namely the AIC, BIC, HQ, FPE).*

As we can see, in the period under study natural gas usage Granger caused employment while all other causal links were found to be insignificant at a 5% level (in the asymptotic and bootstrap variants). The next table contains the outcomes of Granger causality tests performed for the unrestricted VECMs as well as for sequentially restricted equations:

VEC model[d]	Null hypothesis[b]	*p*-value[a]							
		Short-run				Long-run			
		Unrestricted		Sequential		Unrestricted		Sequential	
		Asymptotic	Bootstrap[c]	Asymptotic	Bootstrap[c]	Asymptotic	Bootstrap[c]	Asymptotic	Bootstrap[c]
Constructed for natural gas usage, GDP and employment (Optimal lag[e] (levels): 5)	Natural gas usage $\xrightarrow{no\ GC}$ GDP	0.40	0.45	NCL	NCL	0.16	0.18	NCL	NCL
	GDP $\xrightarrow{no\ GC}$ Natural gas usage	0.48	0.51	0.05	0.04	0.03	0.02	0.00	0.00
	Natural gas usage $\xrightarrow{no\ GC}$ Employment	0.04	0.03	0.00	0.00	0.01	0.01	0.00	0.00
	Employment $\xrightarrow{no\ GC}$ Natural gas usage	0.09	0.07	0.01	0.02	0.03	0.04	0.00	0.00
	GDP $\xrightarrow{no\ GC}$ Employment	0.78	0.71	NCL	NCL	0.01	0.05	0.00	0.00
	Employment $\xrightarrow{no\ GC}$ GDP	0.12	0.15	NCL	NCL	0.18	0.24	NCL	NCL
Constructed for oil consumption, GDP and employment (Optimal lag[e] (levels): 4)	Oil consumption $\xrightarrow{no\ GC}$ GDP	0.60	0.43	NCL	NCL	0.16	0.25	NCL	NCL
	GDP $\xrightarrow{no\ GC}$ Oil consumption	0.27	0.29	NCL	NCL	0.00	0.00	0.00	0.00
	Oil consumption $\xrightarrow{no\ GC}$ Employment	0.80	0.69	NCL	NCL	0.60	0.72	NCL	NCL
	Employment $\xrightarrow{no\ GC}$ Oil consumption	0.54	0.61	NCL	NCL	0.00	0.00	0.00	0.00
	GDP $\xrightarrow{no\ GC}$ Employment	0.08	0.15	NCL	0.05	0.62	0.54	NCL	NCL
	Employment $\xrightarrow{no\ GC}$ GDP	0.58	0.59	NCL	NCL	0.10	0.17	NCL	NCL

Table 3. Analysis of causal links based on examination of VEC models.

[a] *Shading indicates finding causality at* 5% *significance level,* NCL *is the abbreviation for "no coefficients left".*

[b] *The notation " $x \xrightarrow{no\ GC} y$ " is equivalent to "x does not Granger cause y".*

[c] *The number of bootstrap replication established according to Andrews and Buchinsky* (2000) *procedure varied between* 1989 *and* 3619.

[d] *For both VEC models Johansen's Trace and Maximal Eigenvalue tests pointed at one cointegrating vector at* 5% *significance level.*

[e] *Optimal lag was chosen on the basis of information criteria (namely the AIC, BIC, HQ, FPE).*

Examined residuals[c]	Null hypothesis[b]	*p*-value[a]					
		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
Resulting from unrestricted VECM constructed for natural gas usage, GDP and employment	Natural gas usage $\xrightarrow{no\ GC}$ GDP	0.17	0.04	0.02	0.72	0.46	0.67
	GDP $\xrightarrow{no\ GC}$ Natural gas usage	0.15	0.42	0.35	0.65	0.34	0.54
	Natural gas usage $\xrightarrow{no\ GC}$ Employment	0.16	0.46	0.56	0.59	0.33	0.76
	Employment $\xrightarrow{no\ GC}$ Natural gas usage	0.51	0.56	0.28	0.29	0.51	0.49
	GDP $\xrightarrow{no\ GC}$ Employment	0.75	0.64	0.84	0.76	0.30	0.58
	Employment $\xrightarrow{no\ GC}$ GDP	0.72	0.71	0.79	0.77	0.90	0.55
Resulting from unrestricted VECM constructed for oil consumption, GDP and employment	Oil consumption $\xrightarrow{no\ GC}$ GDP	0.51	0.42	0.80	0.19	0.31	0.43
	GDP $\xrightarrow{no\ GC}$ Oil consumption	0.76	0.31	0.21	0.34	0.56	0.79
	Oil consumption $\xrightarrow{no\ GC}$ Employment	0.37	0.08	0.09	0.31	0.24	0.27
	Employment $\xrightarrow{no\ GC}$ Oil consumption	0.86	0.71	0.73	0.16	0.17	0.63
	GDP $\xrightarrow{no\ GC}$ Employment	0.75	0.31	0.81	0.84	0.73	0.64
	Employment $\xrightarrow{no\ GC}$ GDP	0.40	0.08	0.28	0.34	0.36	0.29

Table 4. Results of nonlinear Granger causality test.

[a] *Shading indicates finding causality at 10% significance level.*

[b] *The notation " $x \xrightarrow{no\ GC} y$ " is equivalent to "x does not Granger cause y".*

[c] *Taking into account the results of applied heteroscedasticity tests (e.g. Breusch–Pagan test, White's test) no heteroscedasticity filtering was used.*

For both sets of variables Johansen's (1995) third case (constant in VAR and cointegrating equation) was assumed. In both cases one cointegrating vector was found. The causality from GDP to natural gas usage (but only in sequential variant) and a feedback between natural gas consumption and employment were found. There were no short–run causal links between oil usage and GDP or employment. In the long–run there was feedback between gas consumption and employment and unidirectional causality from GDP to natural gas usage. Finally, both GDP and employment were found to Granger cause oil usage in the long–run.

Table 4 contains the results of nonlinear short–run causality tests conducted for the residuals of both unrestricted VECMs. First it should be mentioned that an analysis of the residuals from the augmented Toda–Yamamoto model and restricted VECM led to a conclusion analogous to the outcomes presented in table 4. As we can see this time both oil usage (indirectly, through a causal impact on employment) and natural gas consumption (directly) were found to Granger cause GDP.

6. Concluding remarks

The outcomes of this paper lead to the conclusion that for oil consumption and natural gas usage the growth hypothesis is the best one in the short–run. However, in the long–run the conservation hypothesis was found to be the best for both oil consumption and natural gas usage. The main conclusion arising from these two facts is that changes in the level of oil and natural gas usage had only a transient impact on the pace of the growth of the Polish economy in recent years. The absence of any long–run impact of the usage of these fuels on Polish GDP is most probably caused by the economy moving from energy intensive activities towards services in the last decade.

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