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On the Exploration of Causal Relationships between Energy and the Economy

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On the exploration of causal relationships between energy and the economy

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ABSTRACT

The paper provides an overview of theoretical and methodological aspects of approaches used to test the interaction between energy use and economic development, and discusses the appropriateness of drawing policy conclusions on the basis of energy-economy Granger causality tests. Methodological issues, arising from the number and type of variables or the test methods used, are outlined. Problems associated with the use of bivariate models are illustrated by performing energy-economy causality tests for Germany and the US, using aggregate and sectoral data and three different econometric methods. The empirical examples presented illustrate that one should be cautious when drawing policy implications with the aid of bivariate causality tests on small sample sizes. Besides econometric problems, bivariate approaches may suffer from additional shortcomings, and the paper underlines the importance of using multivariate models, which accommodate several mechanisms and causality channels and provide a better representation of real-world interactions between energy use and economic growth.

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1. Introduction

The relationship between energy and the economy has undergone extensive investigation after the two oil crises of the 1970s, focusing mainly on the effect of energy prices on economic activity. In a recent paper, for example, Brown and Yücel (2002) provide a survey of the theory and evidence on the macroeconomic impact of energy prices. Compared to price effects, the relationship between energy consumption and economic growth was of somewhat less interest. Although the first relevant study dates back to the late 1970s (Kraft and Kraft, 1978), less evidence has been accumulated over the years, and it is only recently that this relationship has been the subject of an increasing number of studies. Most of these studies were primarily empirical, focusing on the concept of Granger causality.

Since the seminal paper by Granger (1969), the literature on Granger causality has grown considerably. Among applied studies, a significant amount of work has been devoted to addressing the above mentioned question of causality between energy consumption and economic development. Lee (2005; 2006) and Yoo (2006) provide extensive summary tables of results regarding Granger causality between economic growth and energy use or electricity use; Fatai et al. (2004) also provide an extensive (but not tabulated) literature review.

The results from research in this field worldwide are very mixed, with some studies finding unidirectional Granger causality from energy consumption to economic growth or vice versa, others confirming the 'neutrality hypothesis' (i.e. no causality in any direction), and other studies finding bidirectional causality. It is interesting to note that some results vary for the same countries and sample periods and despite the use of similar data sets, depending on the estimation methods that were applied (bivariate or multivariate models, employing different causality techniques). Although it has been attempted to provide economic interpretations for all these results, their diversity indicates clearly that such *ex post* conclusions have to be treated with caution.

Apart from risky economic interpretations of contradictory results, analysts often proceed with deriving implications for energy policy on the basis of their Granger causality tests. If unidirectional causality from energy to the economy is found, a usual conclusion is that limiting energy use (e.g. through energy conservation) would hamper economic growth. A result showing causality running from the economy to energy is said to imply that energy conservation measures may be implemented without putting economic development at risk. Bidirectional causality indicates mutual interdependence of energy and the economy so that in a forecast model both variables should be treated as endogenous. Finally, when the analysis seems to confirm the 'neutrality hypothesis', i.e. no causality between the two variables, the usual explanation is that the economy develops irrespective of energy consumption patterns and vice versa; in such a case economic growth will not affect energy use (probably because of counterbalancing effects), and policies aiming at energy savings may not be detrimental to economic development.

Some analysts point to further and more concrete policy implications. For example, Lee (2006) uses the results of his causality tests between primary energy consumption and GDP per capita to conclude that the United Kingdom, Germany and Sweden "may take greater responsibility to reduce their CO_2 emissions because such a reduction in energy consumption would not significantly affect economic growth". Conversely, in Canada, Belgium, the Netherlands and Switzerland "the enactment of the Kyoto Protocol will actually harm the economy" (pp. 1091–1092).

In this paper I will try to demonstrate why such conclusions have to be treated with care. First I will go through some theoretical and methodological considerations in sections 2 and 3 respectively. In section 4 I will apply three different modern methods to test for Granger causality between energy consumption (total and disaggregated in the main sectors: residential, industry, services and transport) and an appropriate economic variable in Germany and the United States. The methods comprise: i) a test based on a Vector Error Correction model, ii) a test based on an autoregressive distributed lag (ARDL) model and iii) the Toda-Yamamoto test. Section 5 summarizes and discusses the test results, and section 6 will conclude.

2. Theoretical considerations

Linkages between energy and the economy have been addressed in several ways, which largely reflect the theoretical background of each approach and the scope of each analysis[1]. Within the mainstream neoclassical theory of economic growth, for example, the focus has been on exploring the substitutability or complementarity between energy and other production factors as well as on the interaction between energy, technical progress and productivity using aggregate or sector-specific production functions (see e.g. Berndt, 1990) or general equilibrium approaches (e.g. Jorgenson and Wilcoxen, 1993; Kemfert and Welsch, 2000; Smulders and de Nooij, 2003). Even within this quite homogeneous theoretical framework, empirical findings give contradictory results as regards the impact of energy conservation policies on economic growth, the effect of high-quality energy on total productivity or the effect of technical progress on energy efficiency[2]. In the same context, but from a different perspective, Toman and Jemelkova (2003) examine the relationship of energy development (expressed as the availability, quality and use of energy resources) with economic development, focusing mainly on low-income countries. Reviewing available studies and trying to interpret findings with the aid of additional parameters such as the allocation of women's household time,

[1] See Stern (2004) for a review of theories and empirical findings on the relationship between economic growth and energy.

[2] For example, Smulders and de Nooij (2003) conclude that all energy conservation policies they studied reduce per capita income and some reduce economic output, while Kemfert and Welsch concluded that energy conservation may increase or decrease GDP depending on the policy to be implemented. Conversely, Berndt (1980) and Denison (1979) assumed that energy costs represent a very small fraction of GDP and hence energy does not affect income or economic growth.

electrification rates or the productivity of education, they conclude that energy development is an important component of broader development and underline the need for more in-depth analysis of this interaction.

Distancing themselves from neoclassical economic theory, ecological economists adopt a different viewpoint on the relationship between energy and the economy, emphasizing that there are limits to both technical progress and substitution possibilities between energy and other production factors (Stern, 2004). They treat economies as open thermodynamic subsystems (within a materially closed ecosystem), which extract low entropy materials and energy from the environment to create goods and high entropy wastes (Daly, 1997; Templet, 1999). In such a biophysical approach, the impact of energy use on economic growth is unquestionable (Cleveland et al., 1984).

According to Stern (2004), 'a fully worked out alternative model of the growth process [compared to neoclassical theory] does not seem to exist' (p. 36). Empirical findings, on the other hand, are not unanimous in their results. Therefore, a commonly accepted conclusion is that the discussion on the interactions of energy with the economy remains open for different interpretations within diverse theoretical and modeling frameworks, which however have to be consistent and supported empirically. In this context, the structure of each economy and its stage of development may also be crucial for determining the energy-economy interaction. For example, in comparison to causality findings in rich industrialized countries, the interpretation of casual relationships may be very different in the developing world, often characterized by low energy use per capita and per unit of GDP, poor infrastructure, energy supply shortages and the use of fuels (such as biomass) that are not sufficiently accounted for in official statistics[3].

3. Methodological issues

Apart from theoretical considerations, there are a number of methodological issues arising from the various applications of Granger causality tests. These relate to the number of variables examined, the actual test method and the appropriateness of energy and economic variables used.

3.1. Number of variables

To test for Granger causality in a time series analysis framework, most of the studies so far have used bivariate models that contain an energy variable and an economic variable describing income, economic activity or employment. Some trivariate approaches have also been employed, using a model that includes energy, income and prices (Asafu-Adjaye, 2000; Glasure, 2002; Masih and Masih, 1997; 1998) or panel models of several countries including energy, GDP and capital stock (Lee, 2005) or energy per capita, GDP

[3] Analysts dealing with low-income countries often outline the country-specific policy implications of their causality test results (see e.g. Wolde-Rafael 2006, Yoo 2006).

per capita and a time fixed effect to capture price variation as well as other time-related impacts such as technical progress (Judson et al., 1999). A few studies utilize a multivariate approach: Ghali and El-Sakka (2004), Oh and Lee (2004) and Stern (1993; 2000) apply a model of GDP, energy use, capital and labor inputs.

The use of several variables can help avoid econometric problems caused by a potential omitted variable bias (Lütkepohl, 1982) and offers multiple causality channels which, under a bivariate approach, may remain hidden or can lead to spurious correlations and thereby to erroneous conclusions. The latter argument is explained in detail by Stern (1993): Changes in energy use are often countered by the substitution of other factors of production (capital, labor) for energy. In a bivariate model the individual effects of production factors on GDP might cancel each other out so that no causality would appear from energy to GDP. In a multivariate framework, these effects would be revealed and causality from energy to GDP might become evident. Hence the ability of bivariate approaches to describe energy-economy interactions may be limited and their results should be dealt with cautiously.

3.2. Test method

As regards the causality test method, older approaches utilized techniques such as the standard Granger (1969) or the Sims (1972) method. It was later shown, however, that the use of non-stationary data in causality tests can yield spurious causality results (Park and Phillips, 1989; Stock and Watson, 1989). Hence most causality studies since the late 1980s employ unit root tests to examine the stationarity properties of variables, perform cointegration analysis, mostly following the Johansen (1988; 1991) procedure, and formulate a Vector Error Correction (VEC) model in order to capture both long-run and short-run sources of causality between the variables. An alternative method is that of Hsiao (1981), presupposing the use of unit root and cointegration tests but applying the standard Granger test rather than a VEC model, in cases when no cointegration is found; Yoo (2006) has applied this method among others.

As unit root and cointegration tests are known to have low power and size properties in small samples (Cheung and Lai, 1993; Harris and Sollis, 2003), there has been an increasing use of methods which do not require that the variables be pre-tested for stationarity and cointegration. Such methods are the autoregressive distributed lag (ARDL) approach due to Pesaran and Shin (1999) and the Dolado-Lütkepohl and Toda-Yamamoto methods, which involve a modified Wald test in an augmented vector autoregressive model (Dolado and Lütkepohl, 1996; Toda and Yamamoto, 1995). Hypothesis tests can be carried out with these methods irrespective of whether the variables involved are stationary or not and regardless of the existence of a cointegrating relationship among them. Altinay and Karagol (2005), Lee (2006) and Wolde-Rafael (2006) are among those who have applied one or more of these methods.

In principle, the selection of causality test method should not affect the results as long as the time series properties of variables are accounted for appropriately. However, asymptotically equivalent methods do not necessarily demonstrate similar properties in small samples of 25-35 observations, which is the actual sample size in most causality studies. In this respect, Pesaran and Shin (1999) have shown that the ARDL model is more rigorous in small samples than cointegration methods; and Zapata and Rambaldi (1997) have demonstrated that the modified Wald tests employed by the Toda-Yamamoto and Dolado-Lütkepohl methods have lower power than the Johansen-based VEC approach in bivariate and trivariate models with sample size of 50 or less. One has to keep in mind these findings when comparing and interpreting the outcome of diverse causality tests.

3.3. Type of variables

Diverse variables have been used in causality studies to describe the energy-economy interaction. The most common variables are primary energy consumption and real GDP but, depending on data availability, specific energy forms have been examined separately (e.g. industrial, residential and transportation energy consumption, or coal, oil and electricity consumption). Apart from real GDP, economic variables such as real GDP per capita, industrial output or employment have been employed. Stern (1993; 2000) has proposed a quality-adjusted index of energy as an alternative way to aggregate energy instead of just adding up the consumption figures of all energy forms, and Oh and Lee (2004) followed the same approach.

It is evidently necessary to select appropriate pairs of energy and economic variables (and the corresponding additional variables in multivariate models) in order to ensure that causality test results will be meaningful. In this respect one can observe in several causality studies that the pairs of variables are not matching. To give some examples, tests are sometimes carried out between total energy consumption and GDP per capita; or between total energy consumption and industrial output; or between industrial energy use and total GDP; or between coal consumption and GDP per capita. Since the energy and economy variables in such cases do not cover the same area of economic activity or are sometimes expressed in different units (e.g. aggregate energy vs. per capita income), it is questionable whether profound policy implications can be deduced from their results.

4. Causality tests in Germany and the United States

In this section three widely used tests of Granger causality will be employed for Germany and the US, two developed economies with readily available energy and economic data and for which past causality studies have led to diverse results[4]. In the light of the

[4] See Lee (2006) for an overview of tests for these countries, while Thoma (2004) and Stern (2000) provide a more detailed overview of US studies.

methodological issues raised in the previous section, all tests will be carried out with bivariate energy-economy models so as to explore the robustness of using such models with aggregate variables in causality tests. Aggregate and sectoral energy-economy interactions will be explored. Two types of aggregate energy data are used, total primary and total final energy consumption; the latter variable does not account for primary energy inputs used for the production of final energy forms (e.g. coal input for electricity generation). Energy variables of individual sectors (residential, industrial, commercial and transport) refer to final energy consumption. All energy data are expressed in million tonnes of oil equivalent (Mtoe). Economic variables are GDP, personal disposable income and the value added of industry and services, all expressed in real terms (Euros at 2000 prices for Germany, US$ at 2000 prices for the US). For the transport sector, which covers both passenger and freight transport, GDP was selected as the most appropriate economic variable. Table 1 shows the pairs of variables used in the causality tests.

Table 1: The pairs of energy and economic variables that were used in the tests.

Energy variable	*Economic variable*
Primary energy consumption, total	Real GDP
Final energy consumption, total	Real GDP
Final energy consumption, residential	Real disposable income
Final energy consumption, industry	Real value added, industry
Final energy consumption, services	Real value added, services
Final energy consumption, transport	Real GDP

4.1. Data

For Germany, energy data come from the International Energy Agency (IEA, 2002; 2005) and cover the period 1971-2003. Economic data were taken from the Federal Statistical Office of Germany[5] and, except for GDP that was provided in real terms, were turned into constant prices by using the GDP deflator. All data refer to the whole of the country throughout the sample period, i.e. include both the former West and East Germany for the pre-1991 period.

US energy data were extracted from the 2004 Annual Energy Review published by the US Energy Information Administration (EIA, 2005) and extends from 1949 to 2004. The corresponding macroeconomic data come from the US Bureau of Economic Analysis[6]. Where data in real terms were not directly available, nominal values were deflated into

[5] Data are available on the World Wide Web at http://www.destatis.de/e_home.htm.
[6] Data are available on the World Wide Web at http://www.bea.gov.

constant US$(2000) terms by using the sector-specific price deflators provided by the same source[7]. Figures 1 and 2 show the data used for each country.

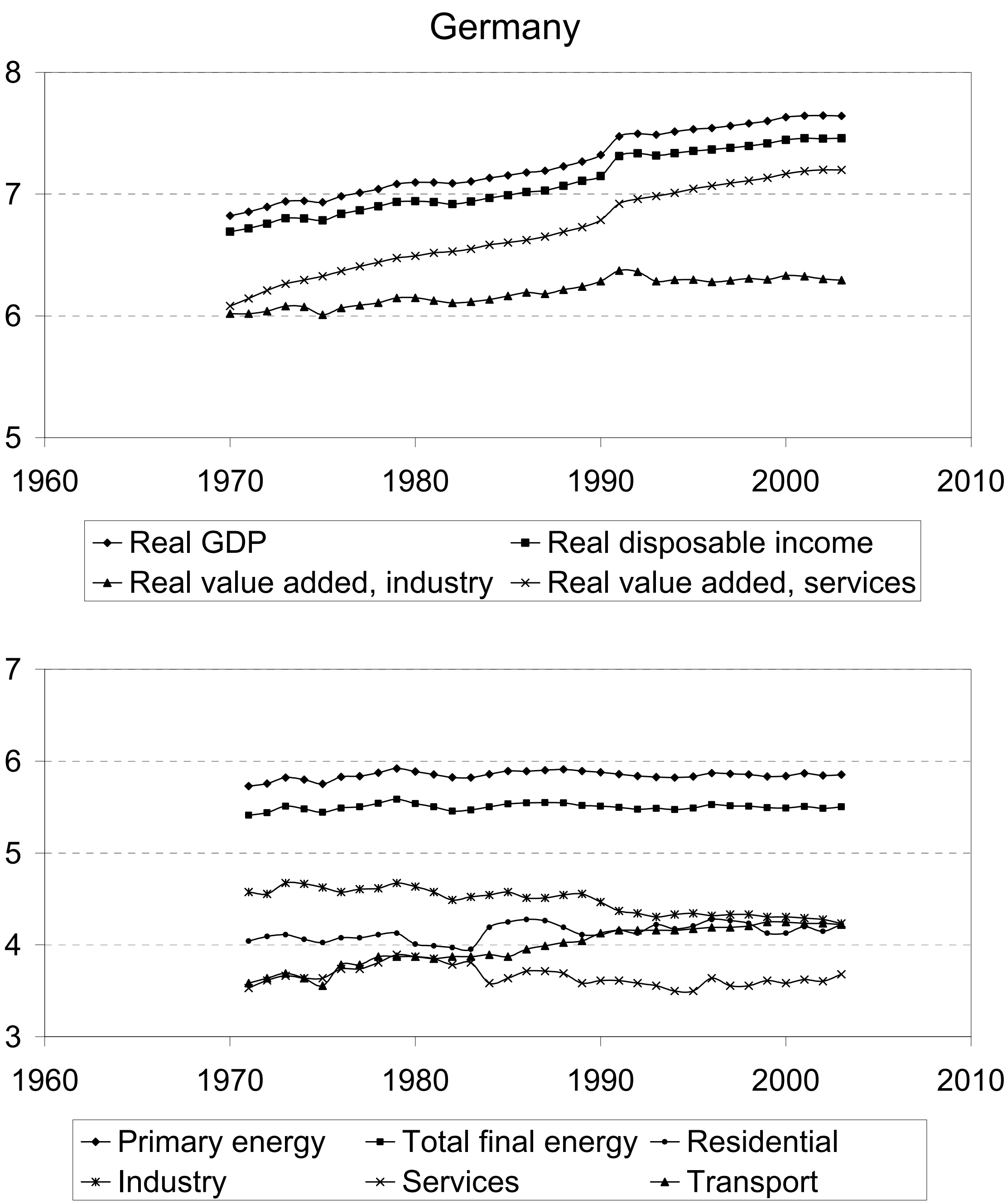
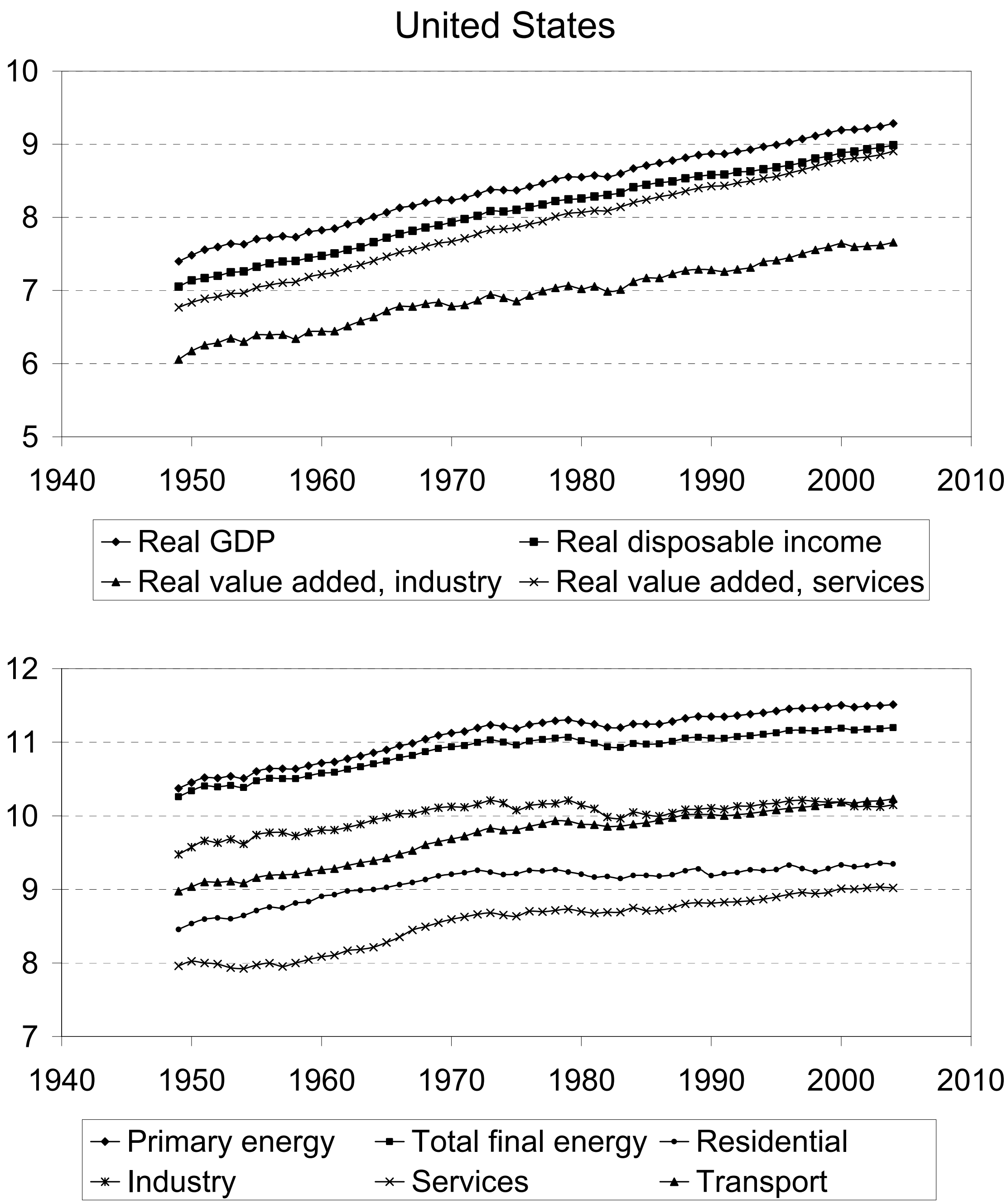


Figure 1: Macroeconomic and energy data of Germany. All values shown are natural logarithms of original data.

[7] Results for the US that will be presented in section 4 do not change if, instead of sector-specific deflators, the GDP deflator is used across all sectors.



<u>Figure 2</u>: Macroeconomic and energy data of the United States. All values shown are natural logarithms of original data.

4.2. Test methods

As mentioned above, for each country and pair of variables three models were constructed, reflecting three different methods to test for Granger causality: a vector error correction (VEC) model, an autoregressive distributed lag (ARDL) model and a vector autoregressive (VAR) model with augmented lag order to allow for the implementation of the Toda-Yamamoto test. The three models are well known in applied econometrics and are therefore very briefly described in the following paragraphs.

<u>a) VEC model</u>

The VEC modeling procedure involves: i) testing the stationarity properties of the variables through unit root tests, including structural breaks if appropriate, ii) performing cointegration analysis if variables are found to be non-stationary and iii) formulating a VEC model for the examination of short-run and long-run interactions as well as Granger causality between variables.

As regards the stationarity tests, it seems appropriate to account for structural breaks in the data series. As shown by Perron (1989), tests that do not account for structural breaks may falsely fail to reject the unit root null hypothesis when the data generating process is trend-stationary with a one-time break. Figure 1 indicates that it is reasonable to assume one exogenous structural break for each country: in the year 1991 in Germany due to the re-unification of the country that led to significant economic restructuring in the former East Germany; and in 1973 for the US due to the oil price shock. Therefore, the test proposed by Perron (1989), and more specifically Perron's model C, was applied for the unit root tests in order to capture both a one-time change in level (more evident in Germany) and a change in the slope (more clearly observed in the US):

$$y_t = \hat{\mu} + \hat{\theta} DU_t + \hat{\beta} t + \gamma DT_t + \hat{d} D(TB)_t + \hat{a} y_{t-1} + \sum_{i=1}^{k} \hat{c}_t \Delta y_{t-i} + \hat{e}_t \qquad (1)$$

where y is the test variable, DU is a dummy variable having the value of 0 until the year of the structural break and 1 from the following year onwards, DT is a dummy taking the value of t for each year after the break and the value of 0 for all previous years, $D(TB)$ is another dummy taking the value of 1 one year after the break and 0 in all other years and $\hat{e}_t$ is an $(0, \sigma^2)$ innovation series. The lagged differences of y are added in order to eliminate possible nuisance-parameter dependencies in the limit distributions of the test statistics caused by temporal dependence in the disturbances (Zivot and Andrews, 1992). The number of lags k is determined by a test of the significance of coefficients $\hat{c}_t$. Perron started with a maximum of $k=8$, but in our case due to the limited sample size such a high lag order would decrease the power of the test too much, therefore maximum lag orders of 4 and 6 were used for Germany and the US respectively.

If variables are found to exhibit non-stationary properties, models should not be estimated with variables in their level form but in first differences. The obvious problem of such a solution, i.e. the loss of information on any long-run relationships between variables, can be resolved with the use of cointegration analysis initiated by Engle and Granger (1987), Phillips and Durlauf (1986) and others. This involves, within a Vector Autoregression (VAR), checking whether a linear combination of non-stationary variables is stationary, which would imply that there exists a long-run equilibrium relationship between the variables. In this study cointegration analysis was carried out with the widely used Johansen (1988; 1991) system approach.

Once the cointegrating relationships (if any) have been determined, the next step is to estimate a VEC model, i.e. with the variables in first differences and including the long-run relationships as error-correction terms in the system. In our case the VEC equations take the form:

$$\Delta e_t = \alpha_{01} + \alpha_{11}\, \Delta e_{t-1} + \alpha_{21}\, \Delta y_{t-1} + \alpha_{31}(e_{t-1} + b\, y_{t-1} + c) + u_{1t} \tag{2}$$

$$\Delta y_t = \alpha_{02} + \alpha_{12}\, \Delta e_{t-1} + \alpha_{22}\, \Delta y_{t-1} + \alpha_{32}(e_{t-1} + b\, y_{t-1} + c) + u_{2t} \tag{3}$$

where *e* and *y* denote the natural logarithms of the corresponding energy and economic variable respectively. The term in parenthesis is the error correction term, whose parameters have been estimated in the cointegration analysis. Residual terms u_{1t} and u_{2t} are independently and normally distributed with zero mean and constant variance. For each model, dummy variables were used to account for the structural breaks mentioned above.

Having equations (2) and (3) as a reference, Granger causality can be examined in three ways:

i) By observing the significance of the lagged differences of the variables in the above mentioned equations through a joint Wald or F-test; this is a measure of short-run (or weak Granger) causality.

ii) By reviewing the significance of the error-correction term in the above equations as a measure of long-run causality; the t-statistic of coefficients α_{31} and α_{32} is sufficient for this purpose.

iii) By testing the joint significance of the error-correction term and the lagged variables in each VEC variable through a joint Wald or F-test, sometimes mentioned as a measure of 'strong Granger causality' (Oh and Lee, 2004).

b) ARDL model

Autoregressive distributed lag (ARDL) models were commonplace in energy analysis until the 1980s. Then the introduction of unit root and cointegration methods, which found that some regressions may be spurious if the time series properties of variables are not examined, almost dismissed the ARDL model as inappropriate. The 'revival' of ARDL methods came in the late 1990s with the aid of work by Pesaran, Shin and Smith (see e.g. Pesaran et al., 2001), and recently many analysts have used it for Granger causality tests.

The ARDL approach involves testing whether a long-run relationship exists among the variables involved in a model. For this purpose, a bounds testing approach has been developed (Pesaran et al., 2001). In accordance with that method, the energy-economy system is initially modeled with the following equation:

$$\Delta e_t = \beta_0 + \sum_{\mathrm{i}=1}^{\mathrm{m}} \beta_{1i}\, \Delta e_{t-i} + \sum_{j=0}^{n} \beta_{2j}\, \Delta y_{t-j} + \beta_3\, e_{t-1} + \beta_4\, y_{t-1} + \varepsilon_t \tag{4}$$

where symbols denote the corresponding variables explained in the previous section and ε_t is assumed to be a white noise error process.

The null hypothesis of 'no long-run relationship' is tested with the aid of an F-test of the joint significance of the lagged level coefficients of eq. (4):

H_0: $\beta_3 = \beta_4 = 0$ against H_1: $\beta_3 \neq 0, \beta_4 \neq 0$

Pesaran et al. (2001) have proved that the distribution of this F-statistic is non-standard irrespective of whether the regressors are I(0) or I(1), and have tabulated the appropriate critical values. Depending on the number of regressors and on whether an intercept and/or a time trend is included in the equation, a pair of critical values is provided, which constitute an upper and a lower bound respectively. If the F-statistic is greater than the upper bound, the null hypothesis is clearly rejected and a long-run relationship exists among the test variables. If the F-statistic is smaller than the lower bound, then the null cannot be rejected and estimation can continue assuming no long-run relationship. If the statistic falls between the two bounds, then the result is inconclusive; it is only at this stage that the analyst may need to conduct unit root tests in order to proceed (Pesaran and Pesaran, 1997).

The long-run relationship test is equivalent to the cointegration test summarized in the previous section. If such a relationship is found in eq. (4) according to the bounds test described above, this would imply long-run causality from income to energy. Short-run causality in the same direction can be tested through a standard Wald or F-test for the joint significance of coefficients β_2. To test causality from energy to income, one has to formulate an equation similar to eq. (4) but using *y* as the dependent variable and *e* as the exogenous one and employ the same tests as outlined above.

c) The Toda-Yamamoto approach

Toda and Yamamoto (1995) have developed a simple procedure that involves testing for Granger non-causality in level VARs irrespective of whether the variables are integrated, cointegrated or not. For this purpose, a VAR is estimated not with its 'true' lag order *k* but with lag order of (*k*+*d*), where *d* is the maximal potential order of integration of the variables. Then, Granger causality is tested by performing hypothesis tests in the VAR ignoring the additional lags *k+1, ..., k+d*. Toda and Yamamoto proved that in such a case linear and nonlinear restrictions can be tested using standard asymptotic theory. This method, which like the ARDL technique avoids the low-power unit root and cointegration pre-tests, has recently been applied in several causality studies.

4.3. Results[8]

a) VEC model

Table 2 reports the results of Perron's unit root test for all economic and energy variables. The unit root hypothesis is rejected at the 5% level only for total final energy use in Germany, and at the 10% level for primary energy in Germany and industrial value added in both countries. Further investigation of unit root hypotheses in the first differences of variables (not presented here for the sake of brevity) shows that the differenced variables are stationary; therefore, with the exceptions stated above, all other economic and energy variables are found to be I(1) (integrated of order 1).

Results from the cointegration analysis are presented in Table 3. In Germany, a cointegrating relationship is found for all energy-economy pairs except transportation. This implies the existence of long-term causality, whose direction is not yet clear however. Conversely, the cointegration hypothesis within such a bivariate model is clearly rejected in the US for all sectors. Results remain unchanged even if a small-sample correction such as the one of Cheung and Lai (1993) is applied to the critical values.

[8] The estimated models that correspond to the three causality test methods have passed diagnostic tests for serial correlation and normality of residuals. In cases where residual heteroskedasticity was found, heteroskedasticity-consistent standard errors were estimated and used for the hypothesis tests presented in this section.

Table 2: Perron unit root test results.

Variable	*k*	*μ*	t_μ	*θ*	t_θ	*β*	t_β	*γ*	t_γ	*d*	t_d	*α*	t_α
Germany													
Real GDP	1	3.180	2.592	0.108	1.824	0.010	2.654	-0.002	-1.230	0.074	2.532	0.537	-2.578
Real disposable income	1	3.591	3.230	0.105	1.803	0.010	3.259	-0.001	-0.827	0.083	2.832	0.466	-3.216
Real value added, industry	1	4.777	3.891	0.209	2.256	0.009	3.903	-0.008	-2.414	0.064	2.115	0.205	-3.887 *
Real value added, services	0	1.766	3.818	0.112	3.542	0.008	3.268	-0.003	-2.806	0.062	4.024	0.719	-3.720
Primary energy consumption	1	4.395	4.024	0.009	0.146	0.004	2.342	-0.003	-1.089	0.018	0.580	0.241	-4.004 *
Final energy consumption, total	1	4.140	4.419	-0.015	-0.253	0.002	1.591	-0.001	-0.428	0.008	0.296	0.244	-4.402 **
Final energy consumption, residential	1	2.275	3.138	0.087	0.531	0.005	1.453	-0.004	-0.624	0.006	0.073	0.432	-3.140
Final energy consumption, industry	0	3.154	3.692	-0.107	-1.122	-0.006	-3.094	0.001	0.225	-0.020	-0.411	0.324	-3.675
Final energy consumption, services	0	1.398	2.776	-0.303	-1.911	-0.004	-1.439	0.011	1.895	0.054	0.726	0.636	-2.669
Final energy consumption, transport	0	2.474	3.582	0.276	2.038	0.017	3.396	-0.011	-2.214	0.015	0.285	0.312	-3.552
United States													
Real GDP	1	3.275	3.837	0.070	2.446	0.017	3.804	-0.003	-2.975	-0.025	-1.158	0.561	-3.799
Real disposable income	6	2.985	3.279	0.159	3.433	0.019	3.527	-0.006	-4.006	-0.048	-3.266	0.572	-3.249
Real value added, industry	4	4.672	4.250	0.090	1.908	0.027	4.300	-0.006	-3.016	-0.004	-0.088	0.230	-4.229 *
Real value added, services	1	2.891	3.446	0.092	2.963	0.019	3.489	-0.004	-3.411	-0.023	-1.403	0.574	-3.403
Primary energy consumption	1	2.786	2.937	0.145	2.397	0.010	3.134	-0.007	-3.018	-0.022	-0.847	0.732	-2.917
Final energy consumption, total	1	2.905	3.063	0.134	2.278	0.009	3.190	-0.007	-2.943	-0.017	-0.631	0.718	-3.044
Final energy consumption, residential	0	3.446	3.519	0.203	2.504	0.012	3.088	-0.010	-2.881	-0.012	-0.368	0.599	-3.471
Final energy consumption, industry	0	3.090	3.324	0.115	1.711	0.008	2.854	-0.007	-2.458	0.014	0.325	0.679	-3.286
Final energy consumption, services	0	1.084	2.382	0.077	1.865	0.007	3.355	-0.005	-3.210	-0.028	-0.935	0.861	-2.383
Final energy consumption, transport	1	1.650	2.512	0.108	2.301	0.007	2.988	-0.005	-3.049	-0.047	-2.194	0.816	-2.499

Notes: Regression formula is $y_t = \hat{\mu} + \hat{\theta} DU_t + \hat{\beta} t + \hat{d} D(TB)_t + \hat{a} y_{t-1} + \sum_{i=1}^{k} \hat{c}_t \Delta y_{t-i} + \hat{e}_t$. See explanations under eq. (1) in the text. Sample size is 30-33 for Germany and 50-54 for the US, therefore the λ values for structural breaks in years 1991 (Germany) and 1973 (US) are approximately 0.65 for Germany and 0.4 for the US. *t*-statistics are reported for the hypotheses that the corresponding parameter is zero, except for α where t_α refers to the hypothesis $\alpha=1$. The critical values of t_α, taken from Table VI.B of Perron (1989) at the 5% and 10% level, are –4.21 and –3.89 for Germany and –4.23 and –3.95 for the US respectively. * and ** denote rejection of the unit root hypothesis at 10% and 5% level respectively.

\Long- and short-run causality tests for the same pairs of variables are shown in Table 4. Apart from long-run effects discussed in the previous paragraph, few short-run causality effects can be found in Germany. Granger causality, indicated by the existence of jointly significant short- and long-run effects, is found to run from income to energy in all cases where a cointegrating relationship was found, i.e. all energy-economy pairs except transportation. Energy seems to be Granger-causing income in the industrial and services sectors only, so that in these two sectors bidirectional causality is found. In the US, where long-run causality was rejected by the cointegration tests, short-run causality is found to run from energy to income in the services sector and from income to energy in transportation.

Table 3: Results of the Johansen cointegration analysis.

VEC Model	*Lag order*	*Rank, r*	*Eigenvalue*	*Max. Eigenvalue statistic*	*Trace test statistic*
Germany					
Primary Energy & GDP	1	0	0.336	12.704 *	14.352 *
		≤1	0.052	1.647	1.647
Total Final Energy & GDP	1	0	0.439	17.906 **	19.534 **
		≤1	0.051	1.628	1.628
Residential Energy & Disp. Income	3	0	0.743	39.383 **	40.234 **
		≤1	0.029	0.851	0.851
Industrial Energy & Value Added	1	0	0.483	20.421 **	22.205 **
		≤1	0.056	1.784	1.784
Services Energy & Value Added	1	0	0.412	16.482 **	18.545 **
		≤1	0.064	2.062	2.062
Transportation Energy & GDP	1	0	0.145	4.867	6.600
		≤1	0.054	1.733	1.733
United States					
Primary Energy & GDP	1	0	0.126	6.974	6.987
		≤1	0.000	0.013	0.013
Total Final Energy & GDP	1	0	0.085	4.820	4.823
		≤1	0.000	0.003	0.003
Residential Energy & Disp. Income	1	0	0.157	9.207	11.856
		≤1	0.048	2.649	2.649
Industrial Energy & Value Added	1	0	0.113	6.491	6.503
		≤1	0.000	0.012	0.012
Services Energy & Value Added	1	0	0.040	2.202	3.648
		≤1	0.026	1.446	1.446
Transportation Energy & GDP	1	0	0.076	4.262	4.286
		≤1	0.000	0.024	0.024

Notes: Rank *r* expresses the number of cointegrating equations according to each tested hypothesis. Lag length of underlying VARs was selected on the basis of the Schwarz criterion. In all models an unrestricted intercept was included. Critical values were taken from MacKinnon et al. (1999). * and ** denote rejection of the corresponding hypothesis at 10% and 5% level respectively.

Table 4: VECM-based Granger causality tests.

Variables		Short-run effects (F-statistic) Δe_t	Δy_t	ECT effect (t-statistic)	Joint short- and long-run effects (F-statistic) ECT & Δe_t	ECT & Δy_t
Germany						
Primary Energy & GDP						
	Δe_t	-	0.519	-3.014 **	-	4.099 **
	Δy_t	0.154	-	-0.351	0.097	-
Total Final Energy & GDP						
	Δe_t	-	0.612	-4.452 **	-	10.816 **
	Δy_t	0.306	-	-0.367	0.172	-
Residential Energy & Disp. Income						
	Δe_t	-	4.196 **	-3.355 **	-	4.463 **
	Δy_t	1.947	-	2.774 **	2.010	-
Industrial Energy & Value Added						
	Δe_t	-	3.898 *	-4.530 **	-	10.386 **
	Δy_t	2.337	-	-2.001 *	2.619 *	-
Services Energy & Value Added						
	Δe_t	-	2.358	-2.600 **	-	4.387 **
	Δy_t	0.489	-	-3.474 **	6.587 **	-
Transportation Energy & GDP						
	Δe_t	-	0.134			
	Δy_t	1.482	-			
United States						
Primary Energy & GDP						
	Δe_t	-	1.085			
	Δy_t	0.076	-			
Total Final Energy & GDP						
	Δe_t	-	0.860			
	Δy_t	0.199	-			
Residential Energy & Disp. Income						
	Δe_t	-	0.538			
	Δy_t	3.015	-			
Industrial Energy & Value Added						
	Δe_t	-	0.002			
	Δy_t	0.199	-			
Services Energy & Value Added						
	Δe_t	-	0.000			
	Δy_t	7.439 **				
Transportation Energy & GDP						
	Δe_t	-	4.904 **			
	Δy_t	1.396	-			

Note: * and ** denote rejection of the corresponding non-causality hypothesis at 10% and 5% level respectively.

b) ARDL model

Table 5 shows the results of tests for the existence of long- and short-run relationships according to the ARDL approach. In Germany, jointly significant long- and short-run causality from income to energy use is found for the industrial sector only. Long-run causality from income to energy is also found for total primary and final energy consumption, while in the services sector short-run causality is found from income to

Table 5: ARDL-based Granger causality tests.

Dependent variable	*"Exogenous" variable*	*Lag order*	*F-statistic* long-term	*F-statistic* short-term
Germany				
Primary energy consumption	Real GDP	(1,1)	4.436 *	0.487
Real GDP	Primary energy consumption	(1,1)	0.619	0.014
Final energy, total	Real GDP	(1,1)	10.433 **	0.578
Real GDP	Final energy, total	(1,1)	0.657	0.118
Final energy, residential	Real disposable income	(1,1)	2.413	0.145
Real disposable income	Final energy, residential	(2,1)	1.801	0.454
Final energy, industry	Real value added, industry	(3,3)	10.380 **	3.615 **
Real value added, industry	Final energy, industry	(1,1)	2.805	1.028
Final energy, services	Real value added, services	(1,1)	3.701	3.165 *
Real value added, services	Final energy, services	(1,1)	7.052 **	0.296
Final energy, transport	Real GDP	(1,1)	0.473	0.046
Real GDP	Final energy, transport	(2,1)	1.072	0.002
United States				
Primary energy consumption	Real GDP	(1,1)	0.163	0.121
Real GDP	Primary energy consumption	(1,1)	0.054	0.004
Final energy, total	Real GDP	(1,2)	0.275	1.912
Real GDP	Final energy, total	(1,1)	0.009	0.027
Final energy, residential	Real disposable income	(1,1)	3.541	0.038
Real disposable income	Final energy, residential	(1,1)	1.505	1.889
Final energy, industry	Real value added, industry	(1,1)	2.131	0.003
Real value added, industry	Final energy, industry	(1,1)	1.086	0.976
Final energy, services	Real value added, services	(1,2)	1.300	2.247
Real value added, services	Final energy, services	(1,1)	0.746	6.091 **
Final energy, transport	Real GDP	(1,1)	1.051	5.463 **
Real GDP	Final energy, transport	(1,1)	0.458	1.252

Notes: Lag length was selected on the basis of the Schwarz criterion. Long-term causality is determined through the bounds test procedure (Pesaran and Shin 1999), with critical values those of Pesaran and Pesaran (1997) for equations with one exogenous variable, an intercept and no time trend: at 95% level: 4.934, 5.764; at 90% level: 4.042, 4.788. The F-statistic for the short-run causality test follows a standard distribution with the usual critical values. * and ** denote significance at 10% and 5% level respectively.

energy and long-run causality from energy to income. Residential and transportation sectors exhibit no relationship between energy and income. In the US the only cases where some form of (short-run) causality is detected is from energy to income in services and from income to energy in transportation.

c) Toda-Yamamoto model

According to this approach, the hypothesis of non-causality is rejected in three cases only (see Table 6). Thus causal relationships are found to run from income to energy in the German services sector and from energy to income in the US services, as well as from income to energy in US transportation.

Table 6: Causality test results using the Toda-Yamamoto approach.

Variables	*'True' lag order*	*F-statistic* $E \leftarrow Y$	$E \rightarrow Y$
Germany			
Primary Energy & GDP	1	0.224	0.133
Total Final Energy & GDP	1	0.708	0.008
Residential Energy & Disp. Income	1	0.001	0.742
Industrial Energy & Value Added	1	0.103	0.438
Services Energy & Value Added	1	4.205 *	0.630
Transportation Energy & GDP	1	0.107	0.422
United States			
Primary Energy & GDP	1	0.205	1.050
Total Final Energy & GDP	1	0.812	0.010
Residential Energy & Disp. Income	2	1.200	1.308
Industrial Energy & Value Added	1	0.009	1.504
Services Energy & Value Added	1	0.009	6.155 **
Transportation Energy & GDP	2	3.273 **	0.649

Note: A→B denotes causality running from variable A to variable B. * and ** denote rejection of the corresponding non-causality hypothesis at 10% and 5% level respectively.

5. Discussion

It was in the early 1980s that Kouris (1981), commenting on the use of energy demand elasticities, emphasized the need for the applied economist not to rely too much on econometric methods and to employ judgment as well. This statement seems to be also appropriate for the causality issues discussed here. If, for example, energy use is found to Granger cause GDP, a usual interpretation for developed economies is that energy conservation (or CO_2 mitigation) measures may be detrimental to economic growth. However, there are different ways to implement energy cuts: energy taxes, fiscal incentives for energy-saving equipment, and energy efficiency regulations with or without permit trade are among possible measures. Each one of these policies may have considerably different effects as regards sectoral economic growth[9], and potentially very different welfare impacts. Although one cannot expect simple bivariate models to address such complicated issues, it is necessary to keep in mind and refer to these limitations when drawing policy related conclusions[10].

Getting back to the empirical results presented in the previous section, Table 7 summarizes the findings of the three test methods as regards Granger causality between energy and the economy in Germany and the US. For the reasons mentioned above, it is not important to compare these results with those of other studies since they should not be regarded as appropriate causality checks. It is interesting, however, to note that all three methods yield the same results for the US (with a sample size of about 55), whereas they do not for Germany (with 30-33 observations): the VEC and Toda-Yamamoto models generally diverge in their results and agree only in the case of transportation, while the ARDL method sometimes agrees with the VECM and sometimes with the Toda-Yamamoto model. This discrepancy has to be attributed to the small number of observations for Germany. Keeping in mind the discussion about the robustness of the three methods in small samples (see section 3.2), it seems to be advisable to follow the ARDL results in this case.

The summary provided by Table 7 gives rise to several remarks with regard to the robustness and economic meaningfulness of bivariate causality tests:

- It is hard to believe that transportation energy use evolves independently of GDP in Germany, despite the non-causality found by all three methods. It is more probable that there are additional causality channels in this relationship that could only be addressed by a multivariate model including e.g. fuel prices, technical progress (induced by fuel prices or other regulations such as the EU-wide voluntary commitment of the automotive industry to reduce new-car CO_2 emissions) and the share of diesel-fueled cars that are more fuel efficient.

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[9] See e.g. Kemfert and Welsch (2000), where a carbon tax increases or reduces GDP depending on the way that tax revenues are recycled within the economy.

[10] For example, Altinay and Karagol (2005), who find causality running from electricity consumption to income in Turkey, admit that "The two variables, in fact, cannot be directly related, because both of them are probably determined by some other factors".

Table 7: Summary of Granger causality tests.

	Primary energy consumption	Final energy consumption				
		Total	Residential	Industrial	Services	Transport
Germany (period: 1971-2003)						
VECM	E ← Y	E ← Y	E ← Y	E ↔ Y	E ↔ Y	E — Y
ARDL	E ← Y	E ← Y	E — Y	E ← Y	E ↔ Y	E — Y
Toda-Yamamoto	E — Y	E — Y	E — Y	E — Y	E ← Y	E — Y
United States (period: 1949-2004)						
VECM	E — Y	E — Y	E — Y	E — Y	E → Y	E ← Y
ARDL	E — Y	E — Y	E — Y	E — Y	E → Y	E ← Y
Toda-Yamamoto	E — Y	E — Y	E — Y	E — Y	E → Y	E ← Y

Note: A→B denotes causality running from variable A to variable B; ↔ denotes bidirectional causality; — shows no causality.

- Observing the US results, one finds 'neutrality' between total energy and GDP. However, causality from energy to income is found in the services sector, and from income to energy in transportation. In line with policy recommendations appearing in some causality studies one could argue that, if the US need to curtail energy use and CO_2 emissions, they should avoid imposing energy conservation measures on the services sectors, as these would affect economic activity; conversely, no matter what measures are implemented in the residential and industrial sectors, the economic performance of industries and the private household income will remain unaffected. It would be difficult, however, to accept that such a finding makes economic sense.
- The above comments become more important if one uses the results of one test method in a small sample to draw conclusions: in Germany, total energy use is unrelated to GDP if one follows the Toda-Yamamoto method, while there is causality from GDP to energy according to the two other methods used here. Bidirectional causality between industrial energy and economic activity comes out from the VEC model, only to become 'neutrality' if one uses the Toda-Yamamoto method. The foundation for providing economic interpretations to such results seems to be quite shaky in this case.
- On the other hand, and irrespective of the small-sample robustness of the tests, these results give useful hints about econometric estimation with such models (see e.g. Lee, 2006). For example, in cases where bivariate causality is detected in a VEC model, this is a clear indication that both variables should be treated as endogenous in this bivariate model context. Unidirectional causality e.g. from income to energy shows that forecasts of energy consumption can be performed by assuming income to be exogenous in this system, so that an analyst may obtain data from an independent macroeconomic forecast and apply these to calculate future energy use.

Finally, results highlight the importance of sector-specific analyses. It has to be reminded that all authoritative forecasts of energy use and CO_2 emissions are conducted at least at the sectoral level – and more often than not they address individual sub-sectors as well. As noted by Judson et al. (1999), each sector has its own dynamics so that sectoral composition of GDP changes over the years. Moreover, each sector utilizes a different fuel mix and can experience different rates of technical progress, depending on the technologies used. Energy consumption is affected by all these variations, and the impact is different for each country because of different GDP structure and different mix of energy sources available to each country. For these reasons, an analysis at the aggregate level, like the application of bivariate total energy-GDP models, can conceal sectoral particularities and may mislead policy discussions.

6. Conclusions

It is widely accepted that there is still much empirical work to do on examining the relationship between energy and the economy (in terms of productivity, employment, financial stability or GDP growth), while at the same time the theoretical foundations may not be firm as they are often challenged by empirical findings. After providing a brief overview of theoretical aspects, this paper has attempted to discuss the appropriateness of drawing policy-oriented conclusions on the basis of Granger causality tests in bivariate energy-economy models. Methodological issues arising from the number and type of variables or the test methods used have been outlined. In order to illustrate how conflicting results one can obtain by applying different methods in small samples with bivariate models, I tested for the existence of causality between appropriate energy-economy variable pairs in Germany and the US, using aggregate and sectoral data and three different modern econometric methods. Results of the three methods were in agreement for the US but in large disparity for Germany. This problem has to be associated with the small sample size of German data and the well-known loss of power of these tests in small samples. This is one reason to remain skeptical about policy conclusions and recommendations when they are drawn on the basis of causality tests conducted with one method in a small sample – and indeed many of the causality studies that have been published involve samples of not more than 40 observations per country.

A more fundamental reason for skepticism is associated with the use of bivariate models as such: apart from omitted variable bias, channels of causality may be hidden when only two variables are used. The problem may become more pronounced if unmatching variables are used (e.g. total energy use and GDP per capita, or electricity consumption per capita and industrial output). It is true that, particularly in developing countries, few data sets are available for a sufficiently long period of time in order to enable a meaningful time series analysis. Energy prices are hardly available, so that the consumer price index is sometimes used as a price variable instead. While all this makes sense, one should nonetheless be cautious when interpreting the findings. Differences in causality results shown in Table 7, depending on the method used or the level of aggregation, illustrate some of the problems one has to keep in mind.

Although complexity is not necessarily a virtue, it only seems appropriate to use multivariate models in order to test energy-economy linkages within an empirical time series context. Other modeling frameworks such as partial or general equilibrium approaches may be even more suitable platforms for such analyses, provided that data requirements can be met without sacrificing the robustness of these models. Furthermore, the use of a quality-adjusted energy index (Cleveland et al., 2000), along with similarly adjusted capital and labor indices if applicable (Berndt, 1990) has to be seriously considered, particularly if the analysis focuses on energy intensity or efficiency.

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