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Causality Between Energy and Output in the Long-Run

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Abstract

Though there is a very large literature examining whether energy use Granger causes economic output or *vice versa* this literature is fairly inconclusive. Almost all existing studies use relatively short time series or panels with a relatively small time dimension. Additionally, many recent papers continue to use what seem to be misspecified models. We apply Granger causality and cointegration techniques to a Swedish time series data set on energy and economic growth spanning 150 years to test whether increases in energy use and energy quality have driven economic growth. We show that these techniques are very sensitive to variable definition, choice of additional variables in the model, and sample periods. All of the following appear to make a finding that energy causes growth more likely: using multivariate models, defining variables to better reflect their theoretical definition, using larger samples, and including appropriate structural breaks. However, it is also possible that the relationship between energy and growth has changed over time and that results from recent smaller samples reflect this. Energy prices have a significant causal impact on both energy use and output.

Keywords

Energy, macroeconomics, Granger causality, cointegration, causality, time series

JEL Classification

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1. Introduction

Does growth in energy availability and use cause economic growth? Or does economic growth drive increasing energy consumption? There is a very large literature investigating these questions but it is fairly inconclusive (Stern, 2011). In this paper, we investigate these questions by applying Granger causality and cointegration techniques to a dataset covering 150 years of Swedish economic history. This is the longest time series that has been used in the large literature on causality between energy and economic growth. We show that these techniques are very sensitive to variable definition, choice of additional variables besides energy and output, and sample periods used. All of the following appear to make a finding that energy causes growth more likely: using multivariate models, defining variables to better reflect their theoretical definition, using larger samples, and including appropriate structural breaks. However, it is also possible that the relationship between energy and growth has changed over time and that results from recent smaller samples reflect this. Also, energy prices have a significant causal impact on both energy use and output.

Granger causality and cointegration methods have been extensively used to test for causal relations between the time series of energy, GDP, and other variables from the late 1970's on (Kraft and Kraft, 1978; Ozturk, 2010). Early studies relied on Granger causality tests on unrestricted vector autoregressions (VAR) in levels of the variables, while more recent studies tend to use cointegration methods as the key variables are likely to be non-stationary and stochastically trending. Studies can also be distinguished by whether they use a bivariate or a multivariate framework.

The results of early studies that tested for Granger causality using a bivariate model were generally inconclusive (Stern, 1993). Where there were nominally significant results, they mostly indicated that causality runs from output to energy. However, results differed across time periods, the countries investigated etc. Most economists believe that capital, labor, and technological change play a significant role in determining output, yet early studies implicitly assumed that energy is the only input to production. If this is not true, it will lead to omitted variables bias and in the case of stochastically trending variables non-cointegration and hence spurious and often sample dependent regression results (Stern and Common, 2001). In addition, all the samples used were small, which have higher inherent sampling variability, leading Stanley *et al*. (2010) to argue that we should simply discard most small sample studies when reviewing an empirical literature. These factors may explain the very divergent nature of both the early literature and much of the more recent literature.

In order to address the first of these issues, Stern (1993) tested for Granger causality in a multivariate setting using a VAR model of GDP, capital, and labor inputs, and a Divisia index of energy use in place of energy use measured in heat units. When both the multivariate approach and the quality adjusted energy index were employed, he found that energy Granger caused GDP.

Yu and Jin (1992) conducted the first cointegration study of the energy-GDP relationship. Again, the results of subsequent research differ according to the regions, time frames, number of variables, and the definitions of inputs and outputs used. Stern (2000) estimated a cointegrating VAR for the variables included in Stern (1993). The analysis showed that there is a cointegrating relation between the four variables and that energy Granger causes GDP either unidirectionally or possibly through a mutually causative relationship. Warr and Ayres (2010) replicate this model for the U.S. using their measures of exergy and useful work in place of Stern's Divisia index of energy use. They find both short and long run causality from either exergy or useful work to GDP but not *vice versa*. Oh and Lee (2004) and Ghali and El-Sakka (2004) apply Stern's (1993, 2000) methodology to Korea and Canada, respectively, coming to exactly the same conclusions, extending the validity of Stern's results beyond the United States. Lee and Chang (2008) and Lee *et al*. (2008) use panel data cointegration methods to examine the relationship between energy, GDP, and capital in 16 Asian and 22 OECD countries over a three and four decade period respectively. Lee and Chang (2008) find a long-run causal relationship from energy to GDP in the group of Asian countries while Lee *et al*. (2008) find a bi-directional relationship in the OECD sample. Taken together, this body of work suggests that the inconclusive results of earlier work are possibly due to the omission of non-energy inputs. By contrast, in recent bivariate panel data studies, Joyeux and Ripple (2011) find causality flowing from income to energy consumption for 56 developed and developing economies, while Chontanawat *et al*. (2008) find causality from energy to GDP to be more prevalent in the developed OECD countries compared to the developing non-OECD countries in a panel of 100 countries.

Other researchers have estimated multivariate VAR models that also include energy prices. Hamilton (1983) and Burbridge and Harrison (1984) found that changes in oil prices Granger-cause changes in GNP and unemployment whereas oil prices are exogenous to the system. More recently, Blanchard and Gali (2008) used VAR models of GDP, oil prices, wages, and two other price indices, to argue that the effect of oil price shocks has reduced over time. Hamilton (2009a) deconstructs their arguments to show that past recessions would have been mild or have merely been slowdowns if oil prices had not risen. Furthermore, he argues that the large increase in the price of oil that climaxed in 2008 was a major factor in causing the 2008-2009 recession in the US. However, because it is hard to substitute other inputs for energy, the short-run elasticity of demand for oil and other forms of energy is low and the main short-run effects of oil prices are expected to be through reducing spending by consumers and firms on other goods, services, and inputs rather than through reducing the input of energy to production (Hamilton, 2009a; Edelstein and Killian, 2009). Therefore, models using oil prices in place of energy quantities may not provide much evidence regarding the effects of energy use itself on economic growth.

Using a panel vector error correction model (VECM) model of GDP, energy use and energy prices for 26 OECD countries (1978-2005), Costantini and Martini (2010) find that in the short-run energy prices cause GDP and energy use and that energy use and GDP are mutually causative. However, in the long run they find that GDP growth drives energy use and energy prices. Other researchers who model a cointegrating relation between GDP, energy, and energy prices for individual countries produce mixed results. For example, Glasure (2002) finds very similar results to Costantini and Martini (2010) for Korea, while Masih and Masih (1997) and Hondroyiannis *et al*. (2002) find mutual causation in the long run for Korea and Taiwan and Greece respectively. Following Stanley *et al*. (2010), we should probably put most weight on the largest sample study – that of Costantini and Martini (2010) - concluding that these models identify a demand function relationship where in the long run GDP growth drives energy use.

Until very recently, all papers in this literature examined annual time series of a few decades at most, which is a small sample size for time series analysis, though researchers have also used panel data to try to increase statistical power. Two recent papers use much longer time series.[1] Vaona (2012) tests for causality between Malanima's (2006) data on Italian energy use and GDP from 1861 to 2000 using the Toda and Yamamoto (1995) procedure, the

[1] The downside of using larger samples is that it potentially increases heterogeneity. The data generating process may change over time for long time series and vary across countries in the case of panel data. Though both Stern and Kander (2012) and Vaona (2012) allow for structural breaks in the deterministic time trend, other parameters may also change. Similarly, though panel data studies allow for country effects, other parameters may also vary across countries.

Johansen cointegration test, and Lütkepohl *et al*.'s (2004) cointegration test that allows for a shift in the mean of the process at an unknown time. Vaona disaggregates energy into renewable and non-renewable energy but only estimates bivariate VARs. The causality tests find mutual causation between non-renewable energy and GDP and from one measure of renewable energy to GDP. While the standard Johansen procedure does not find cointegration between GDP and non-renewable energy, the Lütkepohl *et al*. approach does find cointegration with a structural break in 1947.

Stern and Kander (2012) estimate a model using 150 years of energy, gross output, labor, and capital data for Sweden. The model has two equations – a nonlinear constant elasticity of substitution production function for the logarithm of gross output and an equation for the logarithm of the ratio of energy costs to non-energy costs. Two specifications are estimated – one assumes that the rate of technological change was constant over the 150-year period and the other allows the rate to differ in each 50-year period. Using Choi and Saikkonen's (2010) non-linear cointegration test they find that the latter model cointegrates but the former does not. This implies that there is a causal relationship between the variables, but the direction of causality is unknown. The current paper investigates this issue using the same data set.

2. Granger Causality Testing

As is well known, correlation alone does not imply causation and so, without additional information, simple static regression analysis of observational data can only be used to estimate the partial correlations between variables or to compactly represent the joint probability distribution (Chen and Pearl, 2012). In this context, researchers must use theory to establish potential causal mechanisms (Heckman, 2008; Gerring, 2010), determine if variables are truly exogenous, and ensure that there are no confounding omitted variables. If, the classical regression conditions do hold true, then the static regression model can be interpreted causally. More sophisticated techniques including Granger causality testing, instrumental variables regression, and the potential outcomes framework (Ferraro and Hanauer, 2011) can be used to determine causal relationships under weaker conditions, though some assumptions are still needed.

Granger causality testing has been the most common approach to determining the causal validity of energy-output models. A variable x is said to Granger cause another variable y if past values of x help predict the current level of y given all other appropriate information.

This definition is based on the concept of causal ordering. Two variables may be contemporaneously correlated by chance but it is unlikely that the past values of *x* will be useful in predicting *y*, given all the past values of *y* and other relevant information, unless *x* does actually cause *y* in a philosophical sense. Similarly, if *y* in fact causes *x*, then given the past history of *y* it is unlikely that information on *x* will help predict *y*. However, where a third variable, *z*, drives both *x* and *y*, and is omitted from the conditioning information, *x* might still appear to drive *y* though there is no actual causal mechanism directly linking the variables. The simplest test of Granger causality requires estimating the bivariate VAR:

$$y_t = \beta_{1,0} + \sum_{i=1}^{p} \beta_{1,i} y_{t-i} + \sum_{j=1}^{p} \beta_{1,p+j} x_{t-j} + \varepsilon_{1t} \tag{1}$$

$$x_t = \beta_{2,0} + \sum_{i=1}^{p} \beta_{2,i} y_{t-i} + \sum_{j=1}^{p} \beta_{2,p+j} x_{t-j} + \varepsilon_{1t} \tag{2}$$

where *p* is the number of lags that adequately models the dynamic structure so that the coefficients of further lags of variables are not statistically significant and the error terms ε are white noise but may be correlated across equations. Deterministic time trends can also be added to the model. If the *p* parameters $\beta_{1,p+j}$ are jointly significant, then we can reject the null that *x* does not Granger cause *y*. Similarly, if the *p* parameters $\beta_{2,i}$ are jointly significant then the null that *y* does not Granger cause *x* can be rejected. There are several other variants of this Granger causality test including the Sims (1972) causality test and the Toda and Yamamoto (1995) procedure discussed below.

Sargent (1979) and Sims (1980) introduced the VAR modeling approach as a method of carrying out econometric analysis with a minimum of *a priori* assumptions about economic theory (Qin, 2011). The VAR model generalizes the model given by equations (1) and (2) to a multivariate setting. Though a VAR cannot, due to limits on degrees of freedom, include all variables that may be causally related to the principal variable under investigation, some attempt can be made to include as many as possible. Standard multivariate Granger causality tests are identical to that described above except that there are lags of additional variables in the regression. The advantage of multivariate Granger tests over bivariate Granger tests is that they can help avoid spurious correlations. This is through adding additional variables that may be responsible for causing *y* or whose effects might obscure the effect of *x* on *y* (Lütkepohl, 1982; Stern, 1993). There may also be indirect channels of causation from *x* to *y*, which VAR modeling could uncover. Tests can also be constructed to exclude the lags of variables from multiple equations (Sims, 1980).

Of course, failure to reject the null hypothesis that x does not cause y, does not necessarily mean that there is in fact no causality. A lack of sensitivity could be due to a misspecified lag length, insufficiently frequent observations (Granger, 1988), too small a sample (Wilde, 2012), omitted variables bias (Lütkepohl, 1982), or nonlinearity (Sugihara *et al*., 2012).

When some or all of the variables are non-stationary, a standard Granger causality test on a VAR in levels is invalid as the distribution of the test statistic is not the standard chi-square distribution (Ohanian, 1988; Toda and Phillips, 1993). This means that the significance levels reported in the early studies of the Granger-causality relationship between energy and GDP may be incorrect, as both variables are generally integrated series. If there is no cointegration between the variables then the causality test should be carried out on a VAR in differenced data, while if there is cointegration, standard chi-square distributions apply when the cointegrating restrictions are imposed (Toda and Yamamoto, 1995**)**. Toda and Yamamoto (1995) developed a modification of the standard Granger causality test on the variables in levels that is robust to the presence of unit roots. This method, described in detail below, adds additional lagged variables to the vector autoregression that are not restricted in the Granger causality test. Clarke and Mirza (2006) show that, despite the additional parameters, this approach shows little loss of power compared to the alternative of testing the restrictions on a VECM that imposes cointegrating restrictions. The latter can result in severe over-rejection of the null of non-causality due to the pre-testing for cointegration involved in its construction. Bauer and Maynard (2012) suggest an alternative approach where only one extra lag of the variable being tested for exclusion is added. This procedure is robust to a wide array of data generating processes including structural breaks in the explanatory variables but not to I(2) variables. They find that the reduction in parameters increases power across the data generating processes that they test in a Monte Carlo exercise.

Nonlinear Granger causality testing procedures exist, such as the frequently used Hiemstra and Jones (1994) approach. The latter has been applied to test for nonlinear causality between energy and output (Chiou-Wei *et al*., 2008) but is not applicable to non-stationary data and has several other shortcomings (Hassani *et al*., 2010). Chiou-Wei *et al*. (2008) difference their data in order to apply the test, but this throws away the information on the long-run relationship between the variables. Hassani *et al*. (2010) present a method based on singular spectrum analysis that they claim can cope with non-stationary series. Another kernel-based approach is developed by Sun (2008). However, these methods remain experimental or little used as yet and we do not use them in this paper.

3. Data

Some background on the Swedish economy will be useful for interpreting the data and the econometric results discussed below. Swedish industrialization and modern economic growth took off roughly around 1850 (Greasley *et al*., 2013), which is also the starting year for the analysis in this paper. Sweden went from being one of the poorest European economies in the early nineteenth century to one of the richest 150 years later.

Sweden is a small open economy and exports have constituted a great part of its economic success. Natural resources, such as the charcoal-based Swedish bar iron were the traditional export good and completely dominated Swedish exports until the mid-nineteenth century. The upswing in industrial growth in Western Europe in the 19th Century, led to an expansion in Swedish exports in three staple goods – bar iron, wood, and oats. In order to connect Sweden’s vast natural resources with the international market, state-sponsored railways were initiated and built starting in the 1850s. From the1890s, the focus shifted towards new enterprises, which were closely related to the so-called Second Industrial Revolution. This meant that scientific knowledge and more complex engineering skills replaced the earlier dependence on natural resources. The electrical motor became especially important and new companies such as ASEA (later ABB) were formed that combined engineering skills with the large supply of hydropower in Sweden (Schön, 2008).

Compared to many other industrialized nations, Sweden’s energy system was never very dominated by coal, but rather went from dependence on firewood in 1850 (roughly 75 per cent of energy according to Gales *et al*. 2007) to becoming relatively dependent on primary electricity. Sweden is well endowed with hydropower resources and great advances were made in the electricity infrastructure from the 1910s to the 1950s. The national electrical grid was integrated in the 1930s and the technology of high voltage transmission made it possible to supply industries with electricity at lower prices and with great regularity. In 2000, primary electricity constituted around 30 per cent of the energy consumed in the country, half of which came from nuclear energy and half from hydropower (Gales *et al*. 2007). Reliance on oil came only after the Second World War.

During the interwar period, when the rest of Europe was torn by world wars and depression, the Swedish economy fared relatively well. The post-war period saw rapid economic growth in all of Europe, and Sweden was no exception. In addition, this period also saw the cementation of the "Swedish Model" for the welfare state. The “Swedish Model” at this time was said to build on two main pillars: one the public responsibility for social security and the other regulation of labor and capital markets. As long as the export sectors grew, the model worked well. However, in the 1970s and early 1980s Sweden was hit by the oil crisis and faced subsequent problems with structural adjustment of the economy. Industries such as steel works, pulp and paper, shipbuilding, and mechanical engineering ran into crisis and the Swedish Model started to disintegrate. The labor and capital markets became deregulated and the expansion of public sector services came to an end. During the last decades of the twentieth century, Swedish economic policy converged to European norms and this facilitated the Swedish application for membership and final entrance into the European Union in 1995 (Schön, 2010).

The data we use is identical to that used by Stern and Kander (2012) where a full description can be found. The energy data comes from Kander (2002) and the other data from the Swedish historical national accounts (Krantz and Schön, 2007). The variables considered in our models and tests are: Gross output (GRO), GDP, capital (K), labor (L), heat content of primary energy (HE), Divisia index of primary energy (DE),[2] the Divisia energy price index deflated by the GDP deflator (PE), and the oil price in Swedish Krona deflated by the GDP deflator (PO). The reason for looking at the price of oil is that it is more exogenous than the energy price index. However, the series only starts in 1885. We transform all variables into logarithms. We use the Divisia energy index to take into account the increased productivity of energy over time due to the shift from coal and biomass to oil, natural gas, and primary electricity (Stern and Kander, 2012).

[2] The heat content of primary energy is simply the total joules of the various forms of energy used in the economy before combustion of some fossil fuel and biomass to produce secondary electricity. Most electricity is primary (from nuclear, hydropower etc.) in Sweden. Divisia indexation computes a “volume index” of energy input taking into account shifts between fuels with different productivities or “quality” as reflected in their prices (see Stern, 2010).

The quality of the data, especially of the energy quantity data, is better for more recent decades. Therefore, we carry out unit root and causality tests for 1900-2000 and 1950-2000 sub-periods as well as for the full 150-year period.

Figure 1 presents the time paths of the key quantity variables. As all the variables are strongly trending they are highly correlated. Fluctuations and changes in the trend slope also appear to be correlated. Figure 2 compares the growth rates of the Divisia energy index (which is less volatile than heat units of energy series) and GDP. The two series are strongly correlated in the mid 20th Century. In the 19th Century the energy series is much less volatile than the GDP series and the reverse is true in the late 20th Century. The reason for this is that the 19th Century data are dominated by renewable energy and the way that this data was constructed from the original sources did not put a focus on annual fluctuations (Stern and Kander, 2012). The decline in energy's cost share as the 20th Century progressed might explain the change in relative volatilities over the course of the century.

The simple correlation between the rates of change in Figure 2 is 0.49, which is highly statistically significant ($t = 6.89$). The correlation between the rates of change is suggestive of a functional relationship but the direction of causation and the role of other variables are not indicated.

Figure 3 shows the two price series - the real price of oil and the Divisia energy price index deflated by the GDP deflator. Oil is relatively expensive compared to the average energy carrier and its price is also much more volatile. In particular, the 1st and 2nd World Wars generated massive price spikes and a smaller spike follows the oil crisis of the 1970s. These two series are strongly correlated ($r = 0.56$). The direction of causation between these two series is pretty certain – oil prices are one component of the energy price index and are largely driven by global oil prices and exogenous disruptions such as the World Wars.

4. Econometric Methods

4.1. Unit Root Tests

First we test for unit roots assuming that are no structural breaks using the Phillips and Perron (1988) test (PP), which has a null of a unit root and the Kwiatkowski *et al*. (1992) test (KPSS), which has a null of stationarity. For the variables in log levels we estimate the following regression:

$$y_t = \alpha + \beta t + \gamma y_{t-1} + \varepsilon_t \tag{3}$$

where y is the log of the variable of interest. The null hypothesis is that y_t contains a unit root and so $\gamma = 1$. The PP test is a modified t-statistic for $\gamma = 1$. The alternative hypothesis is that y_t is trend stationary with slope β. For the first differences we estimate:

$$\Delta y_t = \alpha + \gamma \Delta y_{t-1} + u_t \tag{4}$$

so that the alternative hypothesis is levels stationarity. We use the default four lags to compute the standard errors used in the PP test statistic by the RATS procedure unitroot.src.

We also test for unit roots assuming the presence of structural breaks. We assume both that the timing of the structural breaks is known – the breakpoints used by Stern and Kander (2012) - using Park and Sung's (1994) unit root test and that the timing is unknown, *a priori*, using the tests developed by Lee and Strazicich (2003, 2004). We use the latter only on the full 1850-2000 sample. Park and Sung's (1994) tests modify (3) and (4) to allow for breaks in the intercept and trend and to create test statistics that are invariant to the location of the breakpoints. Park and Sung (1994) provide the distribution of these test statistics for one or two breakpoints. Like Lee and Strazicich's test, Park and Sung's test allows for a structural break under the null hypothesis. For the log levels the alternative hypothesis we use is trend stationarity with breaks - Lee and Strazicich's "break" model – while for the first differences of logs the alternative is levels stationarity with breaks - Lee and Strazicich's "crash" model. We used the RATS procedure lsunit.src to compute the Lee and Strazicich tests and we wrote the code for the Park and Sung test ourselves in RATS.

4.2. Granger Causality Tests

For all VAR models, including the cointegration models discussed in the next subsection, we select the optimal lag length, p, using the Akaike Information Criterion considering a maximum of four lags (Schwert, 1989). We use the Toda and Yamamoto (1995) procedure for testing for causality in the possible presence of unit roots and non-cointegration. We add additional lags of all variables to account for possible unit roots in the time series and compute the Wald test statistic for excluding only the first p lags of the variable of interest from the relevant equation. The model we estimate is:

$$y_t = \sum_{j=0}^{n}\left(\gamma_j \Delta t_{jt} + \delta_j t_{jt}\right) + \sum_{i=1}^{p}\Pi_i y_{t-i} + \sum_{i=1}^{d}\Pi_{i+p} y_{t-p-i} + \varepsilon_t \tag{5}$$

where d is the maximal order of integration in the data and n is the number of structural breaks in the data. y_t is the vector of m variables modeled in the VAR in year t and ε_t is the corresponding vector of disturbances. γ_j and δ_j are m x 1 vectors and the Π_i are m x m matrices of regression coefficients. There are n-1 structural breaks. t_0 is a simple linear time trend and, therefore its first difference, Δt_0, is a constant term. For $j > 0, \Delta t_j$ is equal to zero up to and including the year of the structural break and unity after it. This means that the slope of the time trend in period j is $\sum_{k=0}^{j}\delta_k$ and similarly for the level of the intercept in period j. This formulation of the trend and intercept components is intended to allow for a linear time trend in the long-run relationship if the model is cointegrated, as well as drift terms in the short run dynamics while allowing both to undergo structural change. This trend is intended to model a possible unobserved technology trend. It is not intended to allow for a shift in the mean of the series and, therefore, it differs from the formulation of the deterministic components in Joyeux (2007).

Though parameter estimates are identical whether the system is estimated using OLS or a seemingly unrelated regression estimator (SUR), following Toda and Yamamoto (1995) and Clarke and Mirza (2006) we test the restrictions on the system of equations as a whole rather than using the traditional F-test on a single equation. To test whether variable y^j causes variable y^k, where the superscripts indicate individual variables in the vector y, we need to test that $\Pi_1^{kj} = \Pi_2^{kj} = ... = \Pi_p^{kj} = 0$, where Π_i^{kj} is the element of the matrix Π_i in the kth row and jth column. We stack the matrices in (5) into a single matrix $\Pi = vec\left[\Pi_1, \Pi_2, ..., \Pi_{p+d}\right]$. Then define R as a selector matrix so that $R\Pi = vec\left[\Pi_1^{kj}, \Pi_2^{kj}, ..., \Pi_p^{kj}\right]$. The null hypothesis can now be expressed as $R\Pi = 0$ and the Wald test statistic is:

$$W = \hat{\Pi}' R' \left[R \hat{V} R' \right]^{-1} R \hat{\Pi} \quad (6)$$

where hats indicate estimated parameters and $\hat{V}$ is the estimated covariance matrix of Π using the standard formula for seemingly unrelated regressions with one iteration of GLS. The test statistic is distributed asymptotically as chi-square with p degrees of freedom.

4.3. Cointegration Modeling

Finally, we test for cointegration using the Johansen procedure allowing for both deterministic trends and deterministic trends with structural breaks using the methodology of Johansen *et al*. (2000). The purpose of this analysis is to see if there is a difference between linear cointegration analysis and the Stern and Kander's (2012) non-linear cointegration analysis as well as to test for the direction of causality in the cointegration framework.[3] We estimated the VECM models using E-Views implementing the structural breaks and associated cointegration tests using code provided by David Giles.[4]

5. Results

5.1. Unit Root Tests

Table 1 presents the results of the Phillips-Perron (PP) and Park and Sung (PS) unit root tests, Table 2 the Lee and Strazicich (LS) unit root tests, and Table 3 the KPSS unit root tests. Looking first at the PP tests on the log levels, the null of a unit root cannot be rejected for any series when for either the complete period 1850-2000 or either of the sub-periods.[5] However,

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[3] Testing for causality using a t-test on the adjustment parameters is not a formally appropriate test (Clarke and Mirza, 2006) but one that is widely used in the literature. First, the cointegration test is a pre-screening procedure. If cointegration is found between two variables then there must be Granger causality in at least one direction between them (Engle and Granger, 1987). Second, the correct causality test should jointly restrict the long-run coefficient of the variable in question, the adjustment parameter, and the associated first differences in the appropriate equation. Despite this, we report these tests for some cointegrated models with this strong "health warning".

[4] The files - relating to the "Cointegrated at the hips" blogpost - are available at: http://davegiles.blogspot.com.au/p/code.html.

[5] This contrasts with the finding of International Monetary Fund (2011, 91-92) that real oil prices from 1875 to 2010 are I(0). Our Swedish price series appears much less volatile in the

we can reject the unit root null for all the differenced series except for capital in the two sub-periods. Allowing for structural breaks in 1900 and 1950 (PS tests) does not change this picture substantially. Neither does allowing endogenous selection of the breakpoints (LS tests, Table 2). Capital appears to be a possibly I(2) series and the other series I(1).

The KPSS test (Table 3) easily rejects the null of trend stationarity for all the variables in log levels in all time periods. For the first differences of the variables, we cannot reject the null of levels stationarity for any variable for the full sample or the 1900-2000 subsample. However, levels stationarity can be rejected for several variables in the 1950-2000 period. Therefore the Toda-Yamamoto test appears to need up to two extra lags.

The endogenous breakpoints (Table 2) differ across variables and the levels and first difference specifications. We also found that the number of lags included in the procedure affected the choice of breakpoint. We also carried out LS tests with a single structural break (Lee and Strazicich, 2004) and three structural breaks. These resulted in a different selection of breakpoints that also varied across variables. Looking at Table 2, the obvious break in the energy quantity series following the oil price shock in the early 1970s only shows up in the first differences for DE and PE as well as for GDP and K. In levels these series have breaks in the early- or mid- 1960s, which are not at all visible in the data (Figure 1). Given the disagreement across these tests we use exogenous breakpoints – the 1900 and 1950 breakpoints used by Stern and Kander (2012) and 1916 (First World War) and 1973 (Oil Crisis) breakpoints, which are apparent in the energy series.

5.2. Toda-Yamamoto Causality Tests

We start by estimating and testing the simple bivariate model for GDP and the heat content of primary energy. Each equation also includes a constant and a simple linear time trend as a proxy for technological change. We find (first two columns of Table 4) that GDP causes energy use but not *vice versa* in each sub-period. When we replace the heat content of energy with the Divisia index we find that there is causality from energy to GDP in the full sample ($p=0.015$) and causality from GDP to energy in the 1950-2000 subsample but no causality in either direction for the 1900-2000 sub-period. This shows the sensitivity of bivariate tests to the definition of variables.

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short-run than their US dollar real oil price series. On the other hand, Hamilton (2009b) argues that real oil prices follow a random walk with no drift.

Next, we estimate a multivariate VAR for GDP, capital, labor, and Divisia energy. This shows causality from energy to GDP for the full period (p=0.031) and for 1900 to 2000 (p=0.037). But for the 1950-2000 period GDP causes energy (p=0.000). When GDP is replaced with gross output, energy causes output in the full period and output causes energy in the 1950-2000 period at the 10% significance level while there is no causation in either direction in the 1900-2000 subsample. So these multivariate results are also somewhat ambiguous.

The final two columns of the table allow for a trend break in 1900 and 1950. This mostly does not change the results. However, it does reduce the significance of energy in the full period in all three models with the Divisia energy index and dramatically reduces the significance of GDP in the full period in the first model.

Table 5 shows the results of estimating VARs including GDP and the quantity and price of energy. The Divisia price index Granger causes energy use in all samples. GDP causes energy use in the 1950-2000 subsample but the significance level is much lower in the full sample and the 1900-2000 subsample. So there is only tentatively a demand function relationship in these data in the full sample. The Divisia price index Granger causes GDP in the full period and in the 1900-2000 sub-period. The quantity of energy has no significant effect on GDP. In the full sample, the Divisia price index is, however, endogenous with respect to energy quantity (p=0.019) and GDP (p=0.053) but this relationship does not hold in the sub-samples though GDP causes prices in the 1950-2000 subsample (p=0.072).

Next, we replace the price of energy by the price of oil and the Divisia energy quantity index by the heat equivalent of energy. The price of oil is clearly exogenous as we would expect. The other main differences are that GDP causes energy in all samples and price does not cause energy use in the 1950-2000 subsample. There is also more evidence of causation from energy to GDP.

When a trend with structural breaks is used the results are very similar. The main difference is that now GDP causes Divisia energy in each sample so that there is stronger support for the demand function interpretation.

We also added capital and labor to these latter models to produce a composite of the Table 4 and Table 5 models. The results were very similar to the models in Table 5. The price of energy plays the dominant role in the models and capital and labor are mostly insignificant.

We also estimated all the models with structural breaks in 1916 and 1973 instead of 1900 and 1950. The results were similar with generally lower significance levels.

5.3. Linear Cointegration Analysis

We estimate vector error correction models for capital, labor, energy, and output measuring energy using either heat units or the Divisia index and output using GDP or gross output. We also estimate models with and without linear trends in the cointegration space and with and without structural breaks. Finally, some models include the Divisia energy price index and others do not. We assume that all variables are I(1). The results of the Johansen trace statistic tests for the number of cointegrating vectors are presented in Tables 6-11 and coefficient estimates for some of the models that passed the cointegration tests are presented in Tables 12 and 13.

The models in both Tables 6 and 7 are estimated for two specifications of the deterministic components: under the assumption of an unrestricted constant term in the VAR but no linear trends in the cointegrating relation (denoted as case 3 in Juselius, 2006, p.100) and under the assumption that there is a linear trend in the cointegration space (denoted as case 4 in Juselius, 2006). In tables 8 to 11 we allow for structural breaks in the intercept and in the linear trend of the cointegration relation and so we only estimate the models that allow for linear trends (the case 4 model). Each model uses 2 lags in the levels as suggested by the Akaike information criterion.

As seen in Table 6, the null hypothesis of no cointegration cannot be rejected at the 5% significance level in any model for either the full sample or the two subsamples. However, for the model with the Divisia index of energy and gross output allowing for a trend in the cointegration relation, we come very close to rejection of the null of non-cointegration at 5% levels in the full sample (the trace statistic of 62.7 is very close to the critical value of 62.99). At the 10% significance level the null of non-cointegration can be rejected while the hypothesis of at most one cointegrating relation cannot be rejected. Of course, more than one false rejection at the 10% level would be expected when 24 tests are carried out.

The models in Table 7 are the same as in Table 6 except that the price of energy is included alongside the other four variables. In the full sample, we can formally reject the null of zero cointegrating vectors for two of the eight models at the 10% level, while several of the models are very close to being significant at the 10 % level. Taking the low power of the

Johansen test into account, this could suggest at least one cointegration relation. In the 1950-2000 subsample, we can reject the null of non-cointegration at either the 5% or 10% level for all models with a trend in the cointegration space despite the expected low power of the test in a sample of this size.

We also test for cointegration in the presence of a trend that is allowed to change slope every 50th year. Johansen *et al*. (2000) derive the formulae for simulating the asymptotic distribution in the presence of structural breaks. We use the critical values that correspond to the model that Johansen *et al*. (2000) call the $H_l(r)$ test, which means that we assume a structural change in both the unrestricted constant and the slope of the trend in the cointegration relation. The distribution of the critical values depends on the proportion of the way through the sample that the break occurs. The new critical values were calculated using the code described and supplied by Giles and Godwin (2011). Table 8 presents the trace test statistics and the critical values for this test with structural breaks in 1900 and 1950 for the model without energy prices. Adding structural breaks every 50th year does not increase the rate of rejection of the null hypothesis of non-cointegration. On the contrary, the null hypothesis of no cointegration cannot be rejected in any model. In Table 9 we add energy prices to this model but the results stay the same: the null hypothesis of zero cointegration relations cannot be rejected.

Still, allowing for a structural break in the trend every 50th year is arbitrary. In Table 10 we conduct a similar analysis with the four variables from the production function framework but allow for structural breaks in 1916 and 1973 instead of 1900 and 1950. As seen from the table, the null hypothesis of no cointegration can now be rejected at the 10 % level in the model in which Divisia energy and gross output were used together with capital and labor. This finding indicates that both the definition of variables and the choice of structural breaks in the cointegration relation can have an important effect on the results. In Table 11 we add energy prices to the analysis in Table 10. We are now able to reject the null of no cointegration in all the models, but the test still only suggests at most one cointegration relation. In conclusion, the Johansen test for cointegration in a multivariate setting in a linear model only picks up a long-run cointegrating relationship between the variables in cases where the structural breaks in the long-run relations are carefully chosen and the variables carefully defined.

In Tables 12 and 13 we report estimates of the cointegrating vector, β, and the adjustment parameters, α, for the models where we find cointegration in Tables 7 and 11. In Table 7 we found one cointegrating vector at at least the 10% significance level for each model we tested for the 1950 to 2000 period. We found cointegration at at least the 10% significance level for all models in Table 11, which cover the entire 1850-2000 period allowing for two structural breaks. We rejected non-cointegration in further isolated cases but do not report further results for those models, which might simply be cases of Type 1 error. We normalized the estimates of the cointegrating vectors on the energy variable and do not report the constant term or any of the trend terms for the model with structural breaks.

Capital is not significant in any of the long-run relationships in Table 12 but energy prices are highly significant in each, and labor, output, and the trend term are highly significant for the first two models. Output, energy, prices, and the time trend have the expected signs. If we interpret the labor variable as a proxy for population then the output variable can be interpreted as the effect of income per capita, while the labor variable is the effect of increasing population while reducing income per capita. Therefore, the effect of population alone is the sum of these two elasticities. For the first two models income per capita has a greater than unit elasticity while the implied elasticity of population is rather small but positive. The elasticity of demand with respect to prices is very inelastic (0.28 to 0.38). Energy use declines autonomously at a rate of 1.4% to 1.8% per annum. The models for Divisia energy show much lower but less precisely estimated income per capita elasticity and a close to unit implied population elasticity. The elasticity of energy demand with respect to prices is less inelastic (0.64 to 0.73) and the autonomous rate of reduction of energy use is lower too.

The adjustment parameter, α, is highly significant and negative for energy as expected in each model in Table 12, implying that energy is endogenous. Output has a significant adjustment parameter at the 5 or 10% level in the first three models but not in the fourth. Only one other variable in one model – the energy price in the third model has an adjustment parameter that is significant at the 10% level. These causality test results conform well to our findings using the Toda-Yamamoto test in Tables 4 and 5.

The results in Table 13 are much harder to interpret, probably because most variables are now endogenous. Capital is only significant in the third model, while prices are only significant in the first. Population now has a net negative effect on energy use, which is not intuitive, while the income elasticity varies from 0.59 to 0.81. In the first two models all variables apart from capital are endogenous. In the final two models the adjustment coefficient for output is also insignificant. The results for the final model results are similar to the causality tests for the most similar model in Table 5 except that here energy prices do not cause energy use.

6. Discussion and Conclusions

Review of the literature on the time series analysis of energy and economic growth shows that multivariate models that include capital and perhaps labor inputs and/or improved measures of the energy input tend to find causality from energy to GDP. Results are more mixed for bivariate models. Models with oil prices, energy, and output tend to find that in the long-run GDP growth drives energy use while energy prices are exogenous at least in the short-run.

As we would expect, most of the Swedish time series variables investigated are strongly trending and all have stochastic trends. As a result there are strong correlations among them, which do not necessarily say anything about causality.

A simple bivariate energy and GDP VAR model found causation from GDP to energy but this was reversed in the full sample period when we used a Divisia index of energy. But we found causality from GDP to energy in the 1950-2000 subsample and no causality in the 1900-2000 subsample. A multivariate model that included capital and labor inputs also showed causality from energy to GDP in the 1850-2000 and 1900-2000 samples but from GDP to energy in the 1950-2000 sample. These results for the most recent period are intriguing because Stern and Kander (2012) find that the contribution of energy to economic growth was much greater in the 19th and early 20th Centuries than in the late 20th Century. As the cost share of energy fell its relative contribution to production fell too.

The only other long-term study of energy-growth causality (Vaona, 2012) found mutual causation between non-renewable energy and GDP and from one measure of renewable energy to GDP using bivariate models. Non-cointegration between GDP and renewable energy could only be rejected when a structural break was allowed.

Our VAR models of GDP, energy quantity, and energy prices mostly find that energy prices, and particularly oil prices, are exogenous, that prices have a more significant impact on GDP than energy quantities, and that GDP and energy prices drive energy use. But the significance of the effect of energy prices on GDP was also attenuated in the 1950-2000 period.

We find that the Granger causality technique is very sensitive to variable definition, choice of additional variables in the model, and sample periods. Better results can be obtained by using multivariate models, defining variables to better reflect their theoretical definition, and by using larger samples. A lot fewer significant relationships were found in the 1950-2000 sample than in the two longer samples. Of course, it is hard to know if that is due to the smaller sample size or to changes in the nature of the relationship over time. It is likely that IV and other causal techniques also are subject to similar vagaries of specification.

We also estimated VECM models using the Johansen procedure allowing for both simple linear trends and time trends with structural breaks in the long-run relations. We found that a model that both includes energy prices in addition to output and the three factors of production and has structural breaks in 1916 and 1973 allows us to find at least one cointegrating vector. We also found cointegration for the 1950-2000 subsample for models with energy prices and a simple linear trend. Directions of causality in the long-run relations of the VECM models quite closely matched those found with the Granger causality tests. The long-run relationship seems to identify an energy demand model. However, VECMs that do not include energy prices and have no structural breaks or structural breaks at other times only find cointegration for a few specifications, which could simply be explained by type 1 error.

This is in contrast to the findings of Stern and Kander (2012) who estimate a static non-linear production function model. They found that when arbitrary structural breaks in the time trend every fifty years that represent a varying rate of technological change are allowed, the null of cointegration could not be rejected by the Choi and Saikkonen (2010) non-linear cointegration test. But when a constant rate of technological change was assumed the null was rejected. This suggests that the long-run relationship between energy and output is in fact non-linear due to the low elasticity of substitution between energy and other inputs. Perhaps including energy prices in the model is a proxy for the changes in cost shares in the non-linear model.

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Table 1. Phillips and Perron and Park and Sung Unit Root Tests

Variable Form	Log Levels	First Differences of Logs	Log Levels	First Differences of Logs
H0	Unit Root	Unit Root	Unit Root	Unit Root
H1	Trend Stationary	Levels Stationary	Trend Stationary	Levels Stationary
1850-2000 No Structural Breaks			**1850-2000 with Structural Breaks in 1900 and 1950**	
GRO	-2.03	**-13.15**	-3.18	**-13.86**
GDP	-2.15	**-12.26**	-2.72	**-12.36**
K	-1.19	**-3.52**	0.24	-3.08
L	-0.87	**-9.89**	-3.15	**-11.87**
HE	-2.50	**-15.71**	-4.08	**-15.96**
DE	-1.83	**-12.59**	-2.60	**-11.99**
PE	-2.52	**-13.23**	-4.00	**-13.85**
PO	-2.55	**-7.40**	-2.66	**-8.26**
1900-2000 No Structural Breaks			**1900-2000 with Structural Break in 1950**	
GRO	-1.93	**-9.16**	0.15	**-7.66**
GDP	-1.60	**-8.80**	0.10	**-7.08**
K	-0.73	-2.27	0.30	-1.70
L	-0.85	**-6.91**	-0.05	**-7.59**
HE	-2.17	**-12.92**	-1.81	**-11.59**
DE	-0.48	**-10.63**	-0.94	**-8.65**
PE	-1.45	**-10.18**	-2.02	**-7.79**
PO	-2.39	**-6.93**	-2.28	**-7.47**
1950-2000				
GRO	-0.99	**-4.48**		
GDP	-1.14	**-3.75**		
K	-0.02	-1.02		
L	-1.90	**-3.60**		
HE	-1.28	**-7.32**		
DE	-1.10	**-6.75**		
PE	-1.67	**-4.53**		
PO	-2.65	**-5.22**		

Notes: For definition of variables see the main text. For the price of oil the first observation is for 1885. Values significant at the 5% level are in bold. For the trend stationarity tests the critical value for the Phillips-Perron test at the 5% level is -3.45. For the Park and Sung test the critical values are -4.15 for one structural break and -4.75 for two structural breaks. For the levels stationarity tests the critical value for Phillips-Perron is -2.89 while for the Park and Sung tests they are -3.33 and -3.72.

Table 2. Lee and Strazicich Unit Root Tests

Variable Form	Log Levels			First Differences of Logs		
H0	Unit Root			Unit Root		
H1	Trend Stationary, "Break"			Levels Stationary, "Crash"		
	Test Statistic	Breakpoint 1	Breakpoint 2	Test Statistic	Breakpoint 1	Breakpoint 2
GRO	-3.97	1882	1961	**-6.26**	1890	1945
GDP	-4.16	1882	1961	**-5.44**	1904	1970
K	-4.12	1925	1962	-3.61	1934	1974
L	-3.55	1885	1936	**-5.61**	1890	1942
HE	-5.14	1948	1978	**-5.45**	1923	1980
DE	-3.60	1912	1959	**-6.22**	1945	1973
PE	-4.86	1912	1965	**-5.75**	1928	1973
PO	-4.76	1910	1950	**-5.90**	1921	1941

Notes: For definition of variables see the main text. For the price of oil the first observation is for 1885. Values significant at the 5% level are in bold. Exact critical values for the trend stationarity test depend on the location of the breakpoints and vary from -5.59 to -5.74. For the levels stationarity test the critical value is -3.84.

Table 3. KPSS Unit Root Tests

Variable	Log Levels		Log First Differences	
	H0: Levels Stationary	H0: Trend Stationary	H0: Levels Stationary	H0: Trend Stationary
1850-2000				
GRO	**3.10**	**0.58**	0.23	0.08
GDP	**3.11**	**0.50**	0.15	0.09
K	**3.09**	**0.37**	0.19	**0.18**
L	**3.08**	**0.46**	0.39	0.06
HE	**3.04**	**0.37**	0.08	0.08
DE	**3.02**	**0.59**	0.41	**0.26**
PE	**2.65**	**0.26**	0.09	0.09
PO	**0.73**	**0.17**	0.07	0.04
1900-2000				
GRO	**2.12**	**0.22**	0.09	0.09
GDP	**2.12**	**0.21**	0.12	0.11
K	**2.12**	**0.28**	0.31	**0.31**
L	**2.01**	**0.45**	0.31	0.06
HE	**2.06**	**0.21**	0.10	0.10
DE	**2.09**	**0.25**	0.30	**0.21**
PE	**1.64**	**0.26**	0.17	0.07
PO	**0.63**	**0.19**	0.06	0.06
1950-2000				
GRO	**1.09**	**0.27**	**0.53**	0.10
GDP	**1.08**	**0.27**	**0.48**	0.10
K	**1.09**	**0.29**	**0.97**	0.10
L	**0.83**	**0.20**	0.12	0.05
HE	**0.91**	**0.26**	**0.59**	0.07
DE	**0.93**	**0.28**	**0.82**	0.08
PE	0.26	**0.22**	0.35	0.07
PO	**0.75**	**0.19**	0.33	0.08

Notes: For definition of parameters and variables see the main text. Values significant at the 5% level are in bold. For the price of oil the first observation is for 1885.

Table 4. Causality Tests: Production Function Models

		Simple Time Trend		Time Trend with Structural Breaks	
Model	**Period**	**Energy -> GDP**	**GDP -> Energy**	**Energy -> GDP**	**GDP -> Energy**
Bivariate GDP & HE	1850-2000	0.0123 (0.994)	8.8298 (0.012)	0.0341 (0.853)	0.6819 (0.409)
	1900-2000	1.7882 (0.181)	10.341 (0.001)	1.8056 (0.179)	9.0543 (0.003)
	1950-2000	0.3247 (0.850)	14.343 (0.001)		
Bivariate GDP & DE	1850-2000	5.8844 (0.015)	0.5195 (0.471)	6.3337 (0.042)	3.0376 (0.219)
	1900-2000	1.4505 (0.228)	0.2129 (0.644)	4.6809 (0.096)	0.9316 (0.394)
	1950-2000	0.2742 (0.872)	10.1098 (0.006)		
Multivariate GDP, DE, K, L	1850-2000	6.9394 (0.031)	1.4469 (0.485)	5.3801 (0.068)	2.8490 (0.241)
	1900-2000	6.5671 (0.037)	0.9707 (0.615)	4.3018 (0.116)	0.9894 (0.372)
	1950-2000	2.0888 (0.719)	19.5444 (0.000)		
Multivariate GRO, DE, K, L	1850-2000	6.6914 (0.035)	0.9950 (0.498)	5.7733 (0.056)	0.4030 (0.668)
	1900-2000	3.0552 (0.217)	2.2524 (0.325)	2.8161 (0.245)	1.4682 (0.480)
	1950-2000	9.7121 (0.045)	18.1519 (0.001)		

Notes: All variables are in log levels and all equations include a constant and a time trend as specified. Statistics are chi-square statistics for excluding the first p lags of the variable listed first in the equation of the variable listed second. Significance levels in parentheses. Structural breaks are in the trend and intercept in 1900 and 1950.

Table 5. Causality Tests: Demand Function Models

Model	Period	Energy -> GDP	Price -> GDP	GDP -> Energy	Price -> Energy	GDP -> Price	Energy -> Price
GDP, DE, PE, Simple Trend	1850-2000	1.2242 (0.542)	29.131 (0.000)	4.5628 (0.102)	12.775 (0.002)	5.8744 (0.053)	7.9718 (0.019)
	1900-2000	6.5279 (0.163)	26.418 (0.000)	6.3804 (0.172)	31.402 (0.000)	3.699 (0.448)	6.2954 (0.178)
	1950-2000	0.5031 (0.777)	2.4693 (0.290)	11.458 (0.003)	13.787 (0.001)	5.2602 (0.072)	1.5143 (0.469)
GDP, HE, PO, Simple Trend	1850-2000	2.4696 (0.116)	10.465 (0.001)	5.8271 (0.016)	7.5631 (0.006)	0.0148 (0.903)	0.2500 (0.617)
	1900-2000	3.3500 (0.187)	7.5522 (0.023)	5.7254 (0.057)	7.4194 (0.024)	1.1222 (0.571)	2.5951 (0.273)
	1950-2000	3.3911 (0.066)	2.6685 (0.102)	11.187 (0.001)	1.5898 (0.207)	0.0008 (0.977)	0.0730 (0.787)
GDP, DE, PE, Trend with 2 Structural Breaks (1900, 1950)	1850-2000	2.4803 (0.289)	28.691 (0.000)	9.2418 (0.010)	11.133 (0.004)	4.7681 (0.092)	5.5780 (0.061)
	1900-2000	7.7194 (0.102)	28.025 (0.000)	15.590 (0.004)	31.645 (0.000)	5.785 (0.216)	9.2770 (0.055)
GDP, HE, PO, Trend with 2 Structural Breaks (1900, 1950)	1850-2000	2.1269 (0.145)	9.5089 (0.002)	7.0704 (0.008)	8.5365 (0.003)	0.0228 (0.880)	0.0450 (0.832)
	1900-2000	2.6338 (0.268)	5.9331 (0.051)	7.3232 (0.026)	10.641 (0.005)	0.3808 (0.827)	0.7989 (0.671)

Notes: All variables are in log levels and all equations include a constant and a linear time trend. The test statistics are F statistics with p-values given in parentheses

Table 6. Johansen Test for Cointegration, No Structural Breaks

		Unrestricted constant				Unrestricted constant & linear trend in cointegration space			
Variables	**# CI vectors under H0**	**Trace stat**	**5 % Crit. Val**	**10 % Crit. Val.**	**Conclusion**	**Trace stat**	**5 % Crit. Val.**	**10 % Crit. Val.**	**Conclusion**
1850-2000									
GRO, HE, K, L	0	37.43	47.21	44.49	H0	47.98	62.99	60.08	H0
	≤ 1	18.98	29.80	27.06	H0	26.09	42.92	39.75	H0
GDP, HE, K, L	0	33.02	47.21	44.49	H0	43.95	62.99	60.08	H0
	≤ 1	16.20	29.39	27.06	H0	24.73	42.92	39.75	H0
GRO, DE, K, L	0	41.04	47.21	44.49	H0	62.70	62.99	60.08	Reject H0 @ 10%
	≤ 1	18.69	29.79	27.06	H0	29.76	42.44	39.75	H0
GDP, DE, K, L	0	39.29	47.21	44.49	H0	55.93	62.99	60.08	H0
	≤ 1	20.03	29.79	27.06	H0	32.56	42.92	39.75	H0
1900-2000									
GRO, HE, K, L	0	34.73	47.21	44.49	H0	43.55	62.99	60.08	H0
	≤ 1	14.90	29.80	27.06	H0	20.89	42.92	39.75	H0
GDP, HE, K, L	0	32.37	47.21	44.49	H0	41.56	62.99	60.08	H0
	≤ 1	17.05	29.39	27.06	H0	21.38	42.92	39.75	H0
GRO, DE, K, L	0	38.79	47.21	44.49	H0	54.18	62.99	60.08	H0
	≤ 1	17.28	29.79	27.06	H0	29.38	42.44	39.75	H0
GDP, DE, K, L	0	31.21	47.21	44.49	H0	48.98	62.99	60.08	H0
	≤ 1	15.98	29.79	27.06	H0	25.99	42.92	39.75	H0
1950-2000									
GRO, HE, K, L	0	31.49	62.99	60.08	H0	47.44	62.99	60.08	H0
	≤ 1	17.60	42.92	39.75	H0	27.48	42.92	39.75	H0
GDP, HE, K, L	0	32.91	62.99	60.08	H0	53.54	62.99	60.08	H0
	≤ 1	18.79	42.92	39.75	H0	27.73	42.92	39.75	H0
GRO, DE, K, L	0	30.39	62.99	60.08	H0	48.03	62.99	60.08	H0
	≤ 1	16.24	42.44	39.75	H0	27.85	42.44	39.75	H0
GDP, DE, K, L	0	31.06	62.99	60.08	H0	50.06	62.99	60.08	H0
	≤ 1	17.16	42.92	39.75	H0	27.93	42.92	39.75	H0

Table 7. Johansen Test for Cointegration, No Structural Breaks, Energy Price Included

		Unrestricted constant				Unrestricted constant & linear trend in cointegration space			
Variables	**# CI vectors under H0**	**Trace stat**	**5% Crit. Val**	**10% Crit. Val.**	**Conc-lusion**	**Trace stat**	**5% Crit. Val.**	**10% Crit. Val.**	**Conc-lusion**
1850-2000									
GRO, HE, K, L, PE	0	68.34	69.81	65.81	Reject H0 @ 10%	83.7	88.8	84.38	H0
	≤ 1	39.46	47.85	44.49	H0	50.04	63.88	60.08	H0
GDP, HE, K, L, PE	0	63.90	69.81	65.81	H0	81.65	88.8	84.38	H0
	≤ 1	34.16	47.85	44.49	H0	50.75	63.88	60.08	H0
GRO, DE, K, L, PE	0	61.88	69.81	65.81	H0	81.65	88.8	84.38	H0
	≤ 1	29.90	47.85	44.49	H0	43.93	63.88	60.08	H0
GDP, DE, K, L, PE	0	66.77	69.81	65.81	Reject H0 @ 10%	83.72	88.8	84.38	H0
	≤ 1	31.94	47.85	44.49	H0	47.57	63.88	60.08	H0
1900-2000									
GRO, HE, K, L, PE	0	65.63	69.81	65.81	Reject H0 @ 10%	76.13	88.8	84.38	H0
	≤ 1	33.65	47.85	44.49	H0	43.65	63.88	60.08	H0
GDP, HE, K, L, PE	0	66.73	69.81	65.81	Reject H0 @ 10%	80.44	88.8	84.38	H0
	≤ 1	33.64	47.85	44.49	H0	46.68	63.88	60.08	H0
GRO, DE, K, L, PE	0	59.49	69.81	65.81	H0	80.96	88.8	84.38	H0
	≤ 1	31.27	47.85	44.49	H0	46.75	63.88	60.08	H0
GDP, DE, K, L, PE	0	61.08	69.81	65.81	H0	82.38	88.8	84.38	H0
	≤ 1	31.90	47.85	44.49	H0	48.64	63.88	60.08	H0
1950-2000									
GRO, HE, K, L, PE	0	65.21	69.81	65.81	H0	86.40	88.8	84.38	Reject H0 @ 10%
	≤ 1	38.30	47.85	44.49	H0	53.88	63.88	60.08	H0
GDP, HE, K, L, PE	0	63.82	69.81	65.81	H0	87.59	88.8	84.38	Reject H0 @ 10%
	≤ 1	37.17	47.85	44.49	H0	54.80	63.88	60.08	H0
GRO, DE, K, L, PE	0	67.20	69.81	65.81	H0	93.08	88.8	84.38	Reject H0 @ 5%
	≤ 1	33.91	47.85	44.49	H0	59.34	63.88	60.08	H0
GDP, DE, K, L, PE	0	65.30	69.81	65.81	Reject H0 @ 10%	91.26	88.8	84.38	Reject H0 @ 5%
	≤ 1	32.90	47.85	44.49	H0	58.81	63.88	60.08	H0

Table 8. Johansen Test for Cointegration, Structural Breaks in 1900 and 1950					
Model	**# CI vectors under H0**	**Trace statistic**	**5% Crit. Val**	**10% Crit. Val.**	**Conclusion**
GRO, HE, K, L	0	75.52	105.44	100.64	H0
	≤ 1	42.17	75.26	71.17	H0
GDP, HE, K, L	0	71.07	105.44	100.64	H0
	≤ 1	42.22	75.26	71.17	H0
GRO, DE, K, L	0	82.71	105.44	100.64	H0
	≤ 1	44.7	75.26	71.17	H0
GDP, DE, K, L	0	76.99	105.44	100.64	H0
	≤ 1	45.12	75.26	71.17	H0

Note: Models with changing intercept and broken linear trend in the cointegration space (HLr) and structural breaks in 1900 and 1950 (v1=0.33, v2=0.66).

Table 9. Johansen Test for Cointegration, Structural Breaks in 1900 and 1950, Energy Prices Included					
Model	**# CI vectors under H0**	**Trace statistic**	**5 % critical value**	**10 % critical value**	**Conclusion**
GRO, HE, K, L, PE	0	111.37	139.37	133.9	H0
	≤ 1	76.26	105.44	100.64	H0
GDP, HE, K, L, PE	0	115.53	139.37	133.9	H0
	≤ 1	79.44	105.44	100.64	H0
GRO, DE, K, L, PE	0	108.1	139.37	133.9	H0
	≤ 1	71.71	105.44	100.64	H0
GDP, DE, K, L, PE	0	116.52	139.37	133.9	H0
	≤ 1	77.3	105.44	100.64	H0

Note: Models with changing intercept and broken linear trend in the cointegration space (HLr) and structural breaks in 1900 and 1950 (v1=0.33, v2=0.66).

Table 10. Johansen Test for Cointegration, Structural Breaks in 1916 and 1973

Model	**# CI vectors under H0**	**Trace statistic**	**5 % critical value**	**10 % critical value**	**Conclusion**
GRO, HE, K, L	0	89.92	102.6	97.8	H0
	≤ 1	54.05	72.96	68.7	H0
	≤ 2	24.84	48.64	43.7	H0
GDP, HE, K, L	0	95.44	102.6	97.8	H0
	≤ 1	53.63	72.96	68.7	H0
	≤ 2	20.19	48.64	43.7	H0
GRO, DE, K, L	0	101.49	102.6	97.8	Reject H0 @ 10%
	≤ 1	61.23	72.96	68.7	H0
	≤ 2	25.5	48.64	43.7	H0
GDP, DE, K, L	0	93.81	102.6	97.8	H0
	≤ 1	54.27	72.96	68.7	H0
	≤ 2	20.02	48.64	43.7	H0

Note: Models with changing intercept and broken linear trend in the cointegration space (HLr) and structural breaks in 1916, 1973 (v1=0.44, v2=0.82).

Table 11. Johansen Test for Cointegration, Structural Breaks in 1916 and 1973, Energy Prices Included

Model	# CI vectors under H0	Trace statistic	5 % critical value	10 % critical value	Conclusion
GRO, HE, K, L, PE	0	143.96	136.2	130.74	Reject H0 @ 5%
	≤ 1	92.09	102.6	97.8	H0
	≤ 2	54.79	72.96	68.7	H0
GDP, HE, K, L, PE	0	145.13	136.2	130.74	Reject H0 @ 5%
	≤ 1	96.81	102.6	97.8	H0
	≤ 2	58.21	72.96	68.7	H0
GRO, DE, K, L, PE	0	133.22	136.2	130.74	Reject H0 @ 10%
	≤ 1	83.04	102.6	97.8	H0
	≤ 2	46.98	72.96	68.7	H0
GDP, DE, K, L, PE	0	140.75	136.2	130.74	Reject H0 @ 5%
	≤ 1	92.01	102.6	97.8	H0
	≤ 2	55.16	72.96	68.7	H0

Note: Models with changing intercept and broken linear trend in the cointegration space (HLr) and structural breaks in 1916, 1973 (v1=0.44, v2=0.82).

Table 12. Parameter Estimates for Models in Table 7, 1950-2000

Variables	HE	GRO	K	L	PE	Trend
β	1.000	-1.12	-0.07	0.83	0.38	0.014
		(-5.37)	(-0.38)	(2.98)	(6.16)	(4.01)
α	-1.34	-0.20	0.01	-0.03	0.41	
	(-5.93)	(-2.23)	(0.52)	(-0.55)	(1.42)	
Variables	HE	GDP	K	L	PE	Trend
β	1.000	-1.09	-0.17	0.88	0.28	0.018
		(-5.00)	(-0.93)	(2.87)	(3.97)	(4.60)
α	-1.25	-0.14	0.002	-0.035	0.42	
	(-6.25)	(-1.77)	(0.13)	(-0.63)	(1.61)	
Variables	DE	GRO	K	L	PE	Trend
β	1.000	-0.45	-0.23	-0.57	0.73	0.007
		(-1.47)	(-0.83)	(-1.39)	(7.81)	(1.28)
α	-0.44	-0.11	-0.02	-0.02	-0.31	
	(-3.28)	(-1.85)	(-1.34)	(-0.61)	(-1.74)	
Variables	DE	GDP	K	L	PE	Trend
β	1.00	-0.41	-0.37	-0.43	0.64	0.010
		(-1.45)	(-1.54)	(-1.08)	(7.12)	(1.98)
α	-0.51	-0.04	-0.02	-0.03	-0.28	
	(-3.7)	(-0.59)	(-1.23)	(-0.62)	(-1.42)	

t-statistics in parentheses

Table 13. Parameter Estimates for Models in Table 11, 1850-2000

Variables	HE	GRO	K	L	PE
β	1.000	-0.59	0.16	1.62	0.18
		(-3.71)	(0.10)	(4.72)	(2.34)
α	-0.39	-0.18	-0.00	-0.07	0.29
	(-4.88)	(-3.32)	(-0.44)	(-2.94)	(2.26)
Variables	HE	GDP	K	L	PE
β	1.000	-0.76	0.22	1.97	-0.06
		(-3.45)	(1.70)	(5.00)	(-0.63)
α	-0.35	-0.16	-0.01	-0.07	0.29
	(-4.73)	(-4.06)	(-1.31)	(-3.89)	(2.54)
Variables	DE	GRO	K	L	PE
β	1.000	-0.78	-0.15	1.16	-0.01
		(-6.89)	(-2.06)	(4.80)	(-0.13)
α	-0.33	0.06	-0.01	-0.10	0.86
	(-4.12)	(-0.79)	(-0.86)	(-3.27)	(5.03)
Variables	DE	GDP	K	L	PE
β	1.00	-0.81	-0.13	1.65	-0.00
		(-4.76)	(-1.30)	(5.44)	(-0.20)
α	-0.26	-0.07	-0.01	-0.09	0.60
	(-4.00)	(-1.40)	(-0.86)	(-3.83)	(4.36)

t-statistics in parentheses

Figure 1. Quantity Variables: Sweden 1850-2000

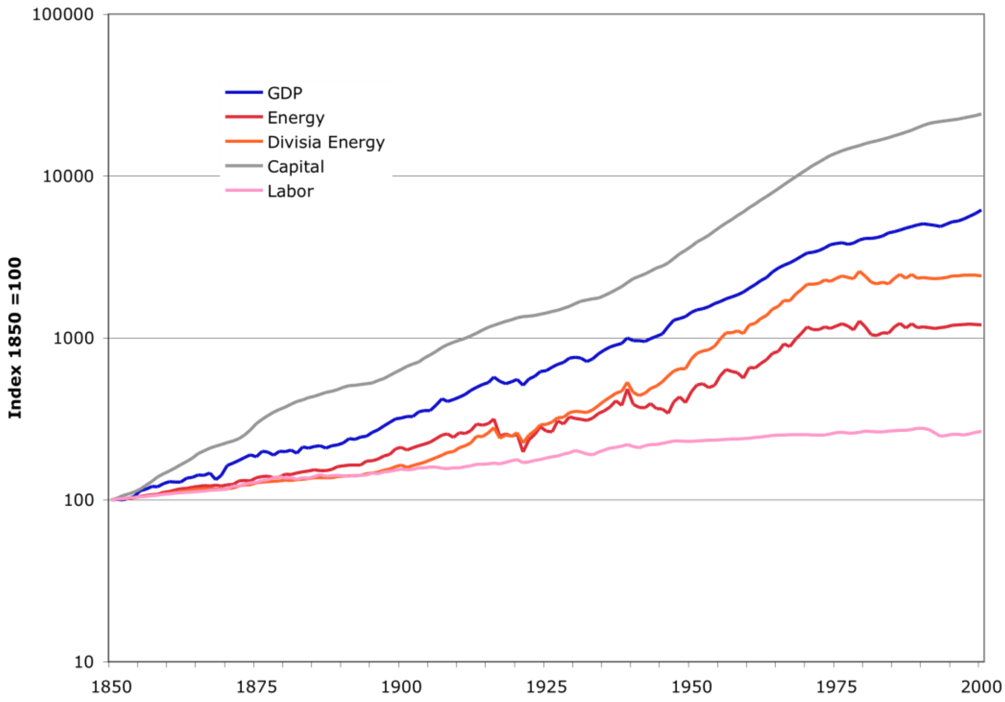

Figure 2. Growth Rates of GDP and Divisia Index of Energy Use

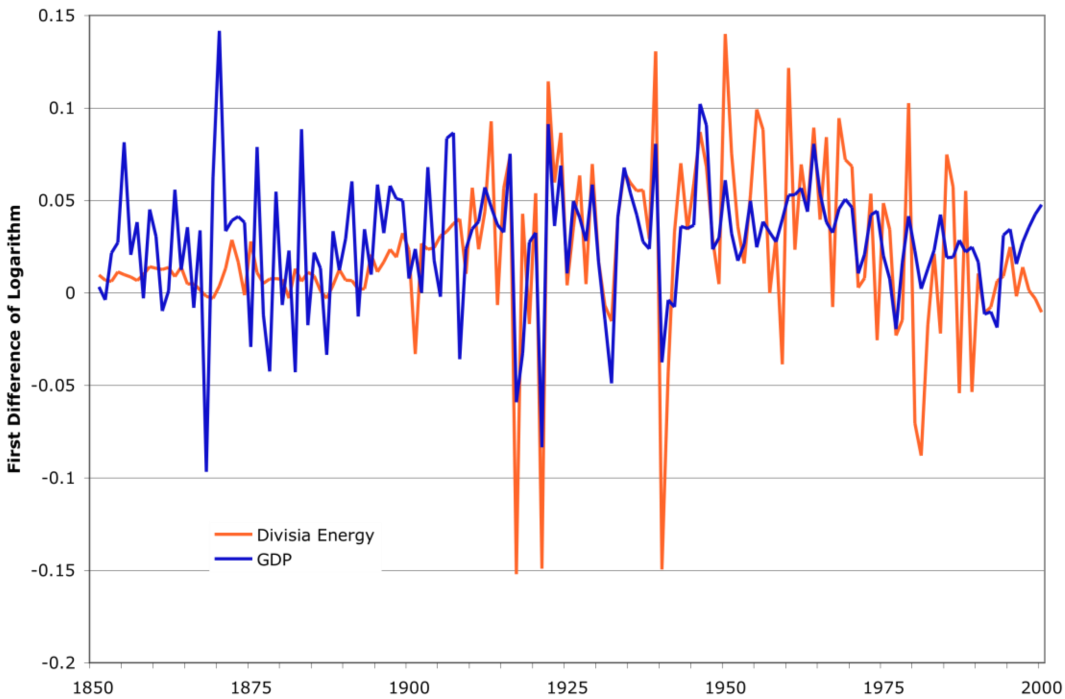

Figure 3. Energy Prices