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ANALYSIS

Energy consumption, income, and carbon emissions in the United States

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A B S T R A C T

This paper investigates the effect of energy consumption and output on carbon emissions in the United States. Earlier research focused on testing the existence and/or shape of an environmental Kuznets curve without taking energy consumption into account. We investigate the Granger causality relationship between income, energy consumption, and carbon emissions, including labor and gross fixed capital formation in the model. We find that income does not Granger cause carbon emissions in the US in the long run, but energy use does. Hence, income growth by itself may not become a solution to environmental problems.

1. Introduction

Greenhouse gas emissions (GHG), especially carbon dioxide (CO_2) emissions, are considered to be the main causes of global warming. In order to prevent global warming several countries have signed the Kyoto Protocol and promised to decrease their emission levels. This in turn calls for a clear identification of the sources of CO_2 emissions (Hamilton and Turton, 2002). One line of research in ecological economics points out the link between environmental degradation and economic growth. The main focus of this line of research has been on the Environmental Kuznets Curve (EKC) hypothesis. The conjecture of the hypothesis is such that initially as per capita income rises environmental degradation intensifies, but in later levels of economic growth it tends to subside. Hence, economic growth may become a solution rather than a source of the problem (Rothman and de Bruyn, 1998). This may be interpreted as an increase in the demand for environmental quality as economies grow

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(Lantz and Feng, 2006). Indeed, Dinda and Coondoo (2006) argue that developed economies have to forgo income growth and developing countries have to restrain their growth ambitions to reduce carbon emissions.

To the extent of our knowledge, there are only a limited number of studies that examine the Granger causality link between economic growth and environmental degradation. Therefore, this study attempts to fill a void in the literature by providing new empirical evidence on the relationship among energy consumption, income and carbon emissions in a multivariate Granger causality setting. Both Granger causality analyses and earlier EKC studies may be sensitive to the stationarity of the series and subject to omitted variables bias. Therefore, the time series characteristics of the variables under investigation should be assessed before any estimation or hypothesis testing is done. Additionally, in order to identify the correct variables to overcome the omitted variables problem, it may be useful to adopt a formal framework that relies more on theory than on an ad hoc basis for choosing the explanatory variables in the study.

Furthermore, countries may have different economic characteristics that may yield different causality directions. Even countries at the same level of economic development may have differing economic dynamics through which inputs interact. Depending on the direction of causality, different policy options may be available to these countries. Hence, studying the Granger causality relationship between emissions and growth in individual countries in a multivariate framework may provide important insights to policy makers.

In this paper, we specifically consider the theory behind the emissions–growth nexus. We evaluate the relationship between real output and CO2 emissions in the US, while accounting for three variables; labor, investment in fixed capital, and energy consumption. We employ the relatively new time series technique known as the Toda–Yamamoto (TY) procedure (Toda and Yamamoto, 1995) to test for long run Granger causality. Additionally, we utilize innovation accounting methods known as *generalized* forecast error variance decompositions (VDC) and *generalized* impulse response (IR) functions. We find that income does not Granger cause CO_2 emissions in the long run. Growth in income does not appear to improve emission forecasts. Therefore economic growth may not become a solution to environmental problems by itself, as suggested by the EKC hypothesis. Furthermore, the US may not have to forgo economic growth to reduce carbon emissions, as suggested by Dinda and Coondoo (2006). As one could probably expect we find that energy consumption Granger causes CO_2 emissions, but not vice versa. The results may have important implications and may provide useful insights for other developed countries in light of Munasinghe (1999) who argues that developing countries may learn how to shape their environmental policies from the experiences of developed countries.

The remainder of the paper is organized as follows. Section 2 provides a brief summary of the empirical literature. In Section 3 we introduce the data definitions and discuss the time series properties of the variables. Sections 4 and 5 summarize and discuss the TY, and generalized VDC and IR results respectively. Section 6 concludes.

2. Literature review

The EKC literature is abundant in studies that test for linear[3], as well as quadratic and cubic[4] relationships between per capita income and CO_2 emissions. These studies treat environmental degradation measure(s) as the dependent variable(s) and income as the independent variable and provide mixed results. Hill and Magnani (2002), Dinda (2004), Copeland and Taylor (2004), and Stern (2004) provide a good review of this extensive EKC research. The literature points out several problems in the empirical studies. The criticisms include econometric issues ranging from stationarity of the variables to omitted variables bias, as well as weak (or nonexistent) theoretical and conceptual frameworks that allow neither a feedback effect from environmental degradation to economic output nor the possibility of a longer lag effect (i.e., beyond one period).

The suspected dynamic link between CO_2 emissions and income suggests a time series approach, since the series in concern may influence each other with some lags. Furthermore, if CO_2 is emitted during the production process, then economic growth may follow CO_2 emissions rather than precede them. Hence, in order to assess the correct intertemporal link between emissions and economic growth, a flexible methodology is called for that allows testing which way the precedence may go and/or the relative importance of each variable in explaining the forecast variance of the other variable. To date, related studies have failed to fully consider these issues, the exceptions being Coondoo and Dinda (2002) and Dinda and Coondoo (2006) who, to some extent, do consider these issues.

Coondoo and Dinda (2002) and Dinda and Coondoo (2006) question the Granger causality between income and carbon dioxide emissions in groups of countries using panel data and maintain that the direction of causality is unclear. For instance, if there is unidirectional causality running from emissions to GDP then the relationship may be such that emissions occur during production and, as a result, income rises. On the other hand, if there is unidirectional causality running from income to emissions, then the relationship may be referred to as an Engel curve for an economic bad (see Coondoo and Dinda (2002) for a formal model and detailed explanations for causality relations). Upon existence of bidirectional causation, then the variables are directly affecting each other and there is a feedback effect (Dinda and Coondoo, 2006).

Note that although the main focus in the fight against global warming has been carbon emissions, there are several studies that examined an EKC-type relation between income and other environmental variables (sulfur emissions, nitrogen oxide, suspended particulate matter, deforestation, water

[3] See for example Shafik and Bandyopadhyay (1992), Shafik (1994), de Bruyn et al. (1998).

[4] These studies include de Bruyn et al. (1998), Heil and Selden (2001), Holtz-Eakin and Selden (1995), Moomaw and Unruh (1997), de Bruyn and Opschoor (1997), Roberts and Grimes (1997), Harbaugh et al. (2002), Friedl and Getzner (2003), Canas et al. (2003).

pollution, etc.) with mixed results as well.[5] Yet some other studies, Schipper et al. (1997), Greening et al. (1998), Liaskas et al. (2000), Roca and Alcantara (2001), Hamilton and Turton (2002), Lise (2006), and Stern (2002), for example, employ decomposition methods to study the link between energy use and emissions. Unruh and Moomaw (1998) argue that the relationship in concern has dynamic characteristics. They apply phase diagrams in their analysis of several countries, but again only find mixed results.

There are several studies that realize the problem of omitted variables bias and therefore include different explanatory variables ranging from macroeconomic variables such as prices, population, income distribution and trade balances to education, technology, and human development indicators.[6] The range of included variables is fairly wide and somewhat arbitrary. Richmond and Kaufmann (2006) include energy consumption into their analyses in order to overcome the omitted variables problem and seem to find a positive relation between income and energy consumption or emissions. Perman and Stern (2003) analyze the EKC relationship in a panel of 74 countries using sulfur emissions and point out that the data have stochastic trends. Hence, they argue that there may be a long run equilibrium relationship between the environmental degradation variable and income and thus an appropriate model should allow for cointegration. Their results do not support the EKC hypothesis. Furthermore, Bulte and van Soest (2001) point out the importance of selecting the appropriate dependent variable in the regressions.

In a four country study, de Bruyn et al. (1998) argue that the EKC relationship discovered in panel data may not hold for individual countries. As also noted by Dinda (2004) and Stern (2004), time series investigation in addition to panel data methods may shed more light on how pollution may be associated with development. According to de Bruyn et al. (1998) the formal way to take into account the stochastic influences between the series is to first check the stationarity properties of all series, then determine if they are cointegrated or not. Once a cointegrating relationship is identified, it can be safely concluded that there is Granger causality between the series and that they are not neutral with respect to each other. Stern (2000) for example examines the relationship between income, energy use, labor, and capital stock in the US for the period 1948–1994 using cointegration and vector error correction modelling. He concludes that there is mutual causality between energy consumption and GDP in the US. However, he does not specifically consider the relationship between income and emissions in his study. Furthermore, cointegration tests may be sensitive to lag selection and omitted variables and they themselves may be subject to biases. In order to avoid pre-test bias we utilize a procedure introduced by Toda and Yamamoto (1995).

In addition to the econometric issues highlighted above, we focus on the United States because of the important role that it plays in world energy markets. First, according to the Statistical Abstract of the United States (2006), GHG emissions in the US rose nearly 17 percent between 1990 and 2000 before leveling off in 2001 and 2002. Second, over that same time period, the US accounted for around 23 to 24 percent of the world's total carbon dioxide emissions from consumption of fossil fuels. Third, the US share of total world energy production has fallen slightly from 20 percent in 1990 to 18 percent and 17 percent in the years 2000 and 2003, respectively. Fourth, over the same time frame, the US share of total world energy consumption has remained fairly constant at around 24 percent. These, facts confirm that the US is a significant consumer, as well as producer, of energy in the world economy. However, they also indicate the historical rate of increase in GHG emissions has stabilized in recent years, even in light of the continued longer term growth in the US economy. Clearly, any policy that alters the energy use patterns in the US will have significant ramifications in the world energy markets. The Economic Report of the President (2006) notes that "Policies that reduce U.S. vulnerability to (energy) supply disruptions, encourage energy efficiency, and protect the environment can… be beneficial supplements to markets. Policymakers can design these policies to be more effective and less costly by harnessing the power of economic incentives and aiming to minimize distortion of normal market forces." (p. 257). Clearly, it is important to better understand the relationships that exist among US economic growth, energy use, and GHG emissions before effective polices can be developed.

Although it may be applied for any arbitrary level of integration, the TY procedure requires knowledge about the highest order of integration in the variables. In the next section, we therefore discuss the unit root test results to determine the integration order of all series used in the analysis.

3. Data and time series properties

We utilize annual data on real GDP (*Y*) and gross fixed capital formation (*K*) (both in constant 2000 US$), total labor force (*L*), energy use (*E*) (kt of oil equivalent), and CO_2 emissions (*C*) (kt) for the period 1960–2004. All data are from World Development Indicators and are in natural logarithms. Note that capital stock data are not available. Therefore, we control for investment in fixed capital which may be a reliable proxy for "changes" in capital stock, assuming a constant depreciation rate.

Friedl and Getzner (2003) argue that the Kyoto Protocol calls for a reduction in the percentage of emissions and they suggest the use of total rather than per capita emissions. Furthermore, in a single country study, dividing by population number only scales the variable down. Unit root test results are also needed to properly specify and estimate VARs in generalized variance decompositions, we utilize five different unit root tests. These tests are: augmented Dickey and Fuller (1979) (ADF), Phillips and Perron (1988) (PP), Elliott et al. (1996)

[5] Among these are Selden and Song (1994), Shafik and Bandyopadhyay (1992), Grossman and Krueger (1995), Suri and Chapman (1998), Bradford et al. (2000), Rothman (1998), Kaufmann et al. (1998), Koop and Tole (1999), List and Gallet (1999), Hettige et al. (2000), Zaim and Taskin (2000), Panayotou (2000), Stern (2005), and Khanna (2002).

[6] These include de Bruyn et al. (1998), Torras and Boyce (1998), Agras and Chapman (1999), Heerink et al. (2001), Andreoni and Levinson (2001), Hamilton and Turton (2002), Frankel and Rose (2002), Jha and Murthy (2003), Friedl and Getzner (2003), Hill and Magnani (2002), Lantz and Feng (2006).

Table 1 – Unit root test results

		ADF	DF–GLS	PP	KPSS	NP–Z_α
		Levels				
Intercept	E	−2.731098b (1)	−0.162362 (1)	−2.819083^c	0.749215^a	0.04045 (1)
	Y	−1.058000 (0)	0.868984 (1)	−1.491761	0.862668^a	1.07840 (1)
	K	−0.177985 (2)	0.939354 (2)	−0.330651	0.824998^a	1.58676 (2)
	L	−4.192965^a (0)	−0.176397 (2)	−2.932573^b	0.853073^a	−2.94174 (2)
	C	−2.399953 (0)	0.395812 (0)	−2.399953	0.698537^b	1.17402 (0)
Intercept and Trend	E	−2.912064 (1)	−1.870799 (1)	−2.146167	0.155093^b	−5.21091 (1)
	Y	−4.351313^a (1)	−3.270009^b (1)	−2.850431	0.120982^c	−17.0668^c (1)
	K	−4.054434^b (1)	−3.931006^a (1)	−2.308994	0.115085	−29.5546^a (1)
	L	−0.852005 (2)	−1.263034 (2)	−0.289238	0.208703^b	−16.8571^c (2)
	C	−2.170725 (0)	−1.459040 (0)	−2.170725	0.134121^c	−2.48030 (0)
		First differences				
Intercept	E	−3.770567^a (0)	−3.774035^a (0)	−3.855424^a	0.384125^c	−16.3417^a (0)
	Y	−5.036230^a (1)	−5.078096^a (1)	−4.978818^a	0.258792	−31.6638^a (1)
	K	−5.385670^a (1)	−5.046048^a (1)	−4.650502^a	0.163126	−44.3620^a (1)
	L	−1.710558 (1)	−1.349016 (1)	−3.991342^a	0.555753^b	−4.39372 (1)
	C	−4.432539^a (0)	−4.374997^a (0)	−4.432539^a	0.296809	−17.7572^a (0)
Intercept and Trend	E	−4.189435^b (0)	−4.108802^a (0)	−4.179712^b	0.131532^c	−16.6439^c (0)
	Y	−5.050595^a (1)	−5.071135^a (1)	−5.226421^a	0.140144^c	−35.9054^a (1)
	K	−5.312616^a (1)	−5.371358^a (1)	−4.157442^b	0.162760^b	−43.3918^a (1)
	L	−2.332940 (1)	−2.388664 (1)	−5.127334^a	0.083628	−7.89475 (1)
	C	−4.663640^a (0)	−4.604496^a (0)	−4.707414^a	0.141266^c	−17.5944^b (0)

All variables in natural logs, lag lengths are determined via SIC and are in parentheses. Superscripts a, b, and c indicate significance at 1, 5, and 10% respectively.

Dickey–Fuller GLS detrended (DF–GLS) and Point Optimal (ERS–SPO), Kwiatkowski et al. (1992) (KPSS), and Ng and Perron's (2001) MZ_α (NP)[7] The results of the stationarity/unit root tests are reported in Table 1.

According to Table 1, the integration orders of K, E, Y, C, and L do not appear to be exceeding 1.[8] Having determined the highest integration order $d=1$, we proceed with the TY procedure.

4. Diagnostics and granger causality test results

Sims et al. (1990) show that inferences based on level VARs are valid, but their procedure requires pre-testing for cointegration and cannot be applied to mixed integration orders. The TY procedure, on the other hand, is especially appealing because it does not depend on the cointegration properties of the system. The TY procedure tests for long run Granger causality but does not require pre-testing for cointegration, thus enabling feedback effects through several lags. TY tests can be applied for any arbitrary level of integration on the part of the variables. Furthermore, the TY procedure involves a vector autoregression (VAR) in levels; hence there is no loss of information due to differencing.

Furthermore, Zapata and Rambaldi (1997) show that there is no need to know the cointegration properties of the system to apply TY. Hence, there is no need to conduct potentially biased cointegration tests.

The TY procedure is a modified Wald test that is to test restrictions on the parameters of the VAR(k) model. The statistic follows an asymptotic χ^2 distribution with k degrees of freedom ($\chi^2(k)$). The procedure requires augmenting the VAR(k) in levels (where k is the optimum lag length) with d. If the resulting VAR($k+d$) passes some diagnostic tests, then a Wald test is conducted on the first k parameters. If the first k parameters are found to be statistically significant, then we reject the null hypothesis of non-causality.

Having identified d as 1, we evaluate several lag length criteria to determine the optimum lag length, k. The

Table 2 – Diagnostic test results

Equation	Adj. R^2	B–G test	J–B test	ARCH LM	White test	Ramsey RESET
E	0.9866	9.4985^c	1.6120	0.3536	21.328^c	0.2721
Y	0.9970	11.933^b	2.0438	0.5927	18.435	2.3956
K	0.9860	18.134^a	0.2288	0.0811	21.548^c	10.421^a
L	0.9995	9.2567^c	1.3969	0.1006	10.981	12.050^a
C	0.9727	12.832^b	1.6576	0.2720	20.634^c	0.3893

The first column gives the adjusted R^2. The rest of the entries are the relevant test statistics. B–G test null is no serial correlation. J–B test null is normality. ARCH LM null is no ARCH up to the selected lag. Lag lengths are selected by AIC and are in parentheses. White test is with cross terms and null is no heteroscedasticity. Ramsey RESET test null is no specification errors and is conducted for one fitted term using LR. Superscripts a, b, and c represent significance at the 1, 5, and 10% respectively.

[7] See Maddala and Kim (1998) for a review of ADF, PP, KPSS, and DF–GLS; and Ng and Perron (2001) for more on NP.

[8] All series are stationary in second differences. Results are available from the authors upon request.

Table 3 – Granger causality test results

Dependent variable	E	Y	K	L	C
E	–	0.3486	0.7621	0.0926	0.8652
Y	2.0840	–	0.6506	0.3908	0.0381
K	1.9551	3.1408[c]	–	1.4891	0.0377
L	0.2137	0.9121	1.3563	–	0.3848
C	4.0536[b]	0.3674	0.0391	0.3328	–

Superscripts a, b, and c represent significance at the 1, 5, and 10% respectively. Significance implies that the column variable Granger causes the row variable.

likelihood ratio, Schwarz and Hannan–Quinn criteria point to an optimum lag length of 1. Hence, we estimate a VAR(2) in levels and report a variety of diagnostic results for all equations in Table 2. The estimated VAR(2) system is as below:

$$V_t = \alpha_v + \beta_1 V_{t-1} + \beta_2 V_{t-2} + \varepsilon_{vt} \quad (1)$$

where $V_t=(Y_t,E_t,K_t,L_t,C_t)'$, α_v is a (5×1) vector of constants, β_1 and β_2 are (5×5) coefficient matrices, and ε_{vt} denotes white noise residuals.

Note from the first column of Table 2 that the adjusted R^2's are rather high and show only slightly lower than the unadjusted R^2's. Therefore, the explanatory power of these equations cannot be attributed to using too many explanatory variables relative to the sample size. Although, the Breusch–Godfrey (BG) test statistics appear to be significant, the correlograms of residuals and squared residuals do not indicate any serial correlation problem. Neither the Jarque–Bera (JB) tests for normality nor the Lagrange multiplier test for autoregressive conditional heteroscedasticity (ARCH LM) reveal any problems with the equations. White tests do not imply heteroscedasticity at 5% significance level for any of the equations. There is some evidence of parameter instability as indicated by Ramsey RESET tests for the *K* and *L* equations. However, CUSUM and CUSUM of squares tests could not verify a stability violation. Furthermore, the Chow breakpoint tests indicate that the equations are robust with respect to a possible break in 1973 due to the oil crisis. The VAR is stable with all roots within the unit circle.[9] Hence, these diagnostic tests allow us to confidently apply the Wald test for Granger causality. The test statistics are computed on β_1 of Eq. (1) for each variable and are summarized in Table 3.

The results presented in Table 3 indicate evidence of unidirectional Granger causality running from energy consumption to carbon emissions in the US. It is noteworthy to mention that there is no causality (in any direction) between carbon emissions and income, and between energy consumption and income. Indeed, income level does not seem to improve forecasts of environmental degradation. Hence, income growth may not be a solution to environmental problems by itself. This contradicts the findings of Dinda and Coondoo (2006), who employ bi-variate analysis and find bidirectional causality between emissions and income for North America. Our results are also inline with Soytas and Sari (2003) who find no cointegrating relation between energy consumption and GDP in the US.[10]

Accounting for investment in fixed capital, labor, and energy consumption, these results do not indicate a strong link between environmental degradation and economic growth, but confirm causal relation between energy consumption and emissions. Hence, our results do not support the EKC hypothesis in the case of the US.

5. Generalized impulse response and variance decompositions

Although only energy consumption appears to Granger cause carbon emissions, examining the impacts of innovations in all variables in the system on carbon emissions may provide useful insights about the short run. To that respect we employ generalized impulse response and generalized variance decompositions of Koop et al. (1996) and Pesaran and Shin (1998). Note that unlike the standard approach, the generalized approach is not sensitive to the ordering of variables in the VAR system. The generalized VDC and IR overcome the orthogonality problem inherent in traditional out-of-sample Granger causality tests. Impulse responses show how a variable responds to a shock in the other variable initially and whether the affect of the shock persists or dies out quickly. Forecast error variance decompositions point out what proportion of the variation in a variable can be explained by the changes in another variable in the same VAR system. The generalized impulse responses of emissions to one standard deviation innovations in energy consumption, labor, fixed capital formation, and income are graphed in Fig. 1.[11]

It is clear from an examination of Fig. 1 that carbon emissions do not respond at all to changes in *L*, whereas shocks to *E*, *K*, and *Y* have positive and significant initial impacts on *C*. However, not only is the initial impact of *E* slightly higher than the others, but it also appears to last slightly longer than those of *K* and *Y*. Hence, providing some support for the Granger causality test results.

The generalized variance decompositions are summarized in Table 4.

The generalized VDC results are consistent with the TY results. The initial impact of energy consumption on forecast error variance of emissions is approximately 72 percent, which is higher than any other variable in the system. In all horizons, the impact of energy on emissions is the highest. The results based on the energy consumption equation indicate that emissions account for more than 61 percent of the variance in energy consumption at the shorter horizons and more than 47 percent in the longer horizons. Both results

9 Correlograms of residuals and squared residuals, CUSUM and CUSUM of squares, Chow breakpoint and roots of VAR are available from the authors upon request.

10 Our results also differ from Stern (2000) in that we were not able to identify Granger causality relationship between energy use and income in any direction in the US.

11 All variables respond significantly positively to innovations in each other, except for labor. All impulse response graphs are available from the authors upon request.

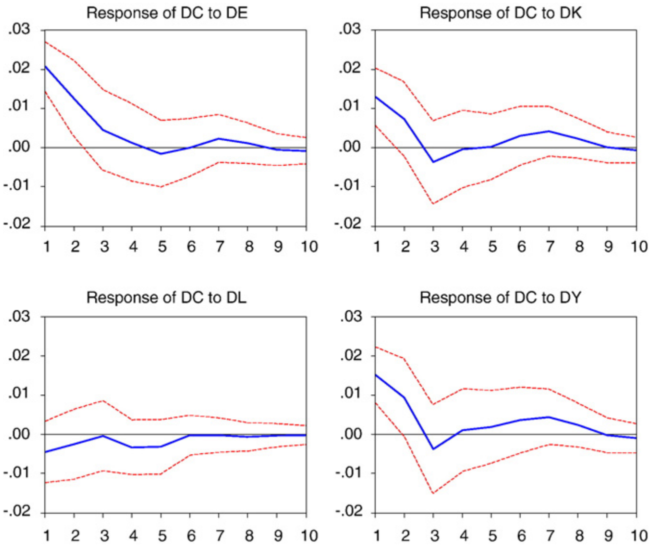

Fig. 1 – Generalized impulse responses of carbon dioxide to one standard deviation innovations in *E*, *K*, *L*, and *Y*. *D* denotes the first difference operator.

based on energy and emissions equations support the previously reported causal relationship between emissions and energy consumption.

6. Conclusions and policy implications

This paper investigated the temporal linkages among energy consumption, income, and carbon emissions in the US. By employing the TY procedure, generalized impulse response and variance decompositions in a multivariate setting, including labor and investment in fixed capital, we were able to find evidence against the existence of an EKC-type relationship in the US. Our results suggest that in the long run the main (statistical) cause of CO_2 emissions in the US is energy consumption. There does not seem to be a trade off between emission reduction and income growth in the US. Hence, the US does not need to accept a reduction in income levels to reduce emissions, as suggested by Dinda and Coondoo (2006). The relevant emission reduction policy variable is energy consumption. Reducing energy consumption will decrease carbon emissions. Since there does not appear to be a causal relation between energy use and income, US may consider reducing energy consumption as a serious environmental policy that does not harm long run growth prospects. Alternatively, policies considering the composition of energy use and technological changes may also be applied to mitigate environmental pressure. Alternative policies such as decreasing energy intensity, increasing energy efficiency in renewable energy use, increasing the utilization of cleaner energy sources (wind, solar, natural gas) may mitigate the pressure on the environment and gain some time until technological developments enable a full switch from fossil fuels to cleaner energy sources. Overall, our results are consistent with US policies geared toward reducing growth of energy consumption as the most effective and immediate way to mitigate the speed of environmental degradation.

Depending on the nature and relative importance of energy sources in an economy, the results may change from country to country. Furthermore, the technological improvements may allow economies to increase the utilization rate of environment friendly sources. Hence, the relationship between income, energy use, and emissions may change through time. However, as Cleveland et al. (2000) note, the existence of limits to substitution, that is, the imperfect substitutability of energy sources, coupled with the oil supply declining earlier than expected may make coal the next best (but more polluting) alternative and therefore limit the switch to higher quality energy sources. Energy use will therefore remain to be an important source of GHG emissions.

This paper employs aggregate energy consumption. Disaggregate energy consumption according to sources and/or industries may provide more insight regarding the link between output and environmental degradation. Furthermore, our model does not directly account for technical

Table 4 – Generalized variance decompositions results

Dependent variable	Horizon	DE	DK	DL	DY	DC
DC	0	0.72111	0.28423	0.03457	0.38743	1.00000
	1	0.69649	0.26460	0.03242	0.37904	0.77481
	2	0.58162	0.22701	0.02637	0.31968	0.62854
	5	0.51750	0.20853	0.04174	0.29746	0.56864
	10	0.51028	0.22225	0.04134	0.31137	0.55939
DY	0	0.44467	0.87886	0.00428	1.00000	0.38743
	1	0.49721	0.79442	0.01248	0.90563	0.39733
	2	0.44888	0.72438	0.01284	0.83436	0.37846
	5	0.43657	0.69758	0.02036	0.79966	0.35461
	10	0.43484	0.69774	0.02041	0.79953	0.35368
DE	0	1.00000	0.34759	0.00015	0.44467	0.72111
	1	0.92441	0.26925	0.01149	0.37228	0.61242
	2	0.82226	0.25085	0.01052	0.33533	0.53669
	5	0.72911	0.23986	0.01996	0.33149	0.48684
	10	0.71762	0.25354	0.01982	0.34519	0.47875

D denotes the first difference operator.

change, but nevertheless includes labor and fixed capital investment which may be reflecting the changes in relative shares of factors of production.

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