



The long-run causal relationship between transport energy consumption and GDP: Evidence from heterogeneous panel methods robust to cross-sectional dependence



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HIGHLIGHTS

- 107 countries (over 1971–2009) analyzed in three income-based balanced panels.
- Methods employed address both heterogeneity and cross-sectional dependence.
- GDP per capita causes transport energy consumption per capita in the long run.
- The sign of the long-run relationship was highly uniform (positive) across countries.
- Neither the direction nor the sign of long-run causality is a function of income level.

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ABSTRACT

This paper employs panel methods that address/mitigate heterogeneity and cross-sectional dependence to determine the direction and sign of long-run causality between transport energy consumption per capita and real GDP per capita. Granger-causality was determined to run from GDP to energy.

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1. Introduction

There is a large and still growing literature that examines the Granger-causality relationship between aggregations of energy/electricity consumption and real GDP (see the reviews by Payne, 2010a,b). This paper contributes to this literature by studying what we believe is the largest panel to date—107 countries, spanning 1971–2009—and by employing panel methods that stress both heterogeneity and cross-sectional dependence to analyze both the sign and direction of long-run causality between transport energy consumption per capita and real GDP per capita. Transport is an

important energy aggregation since transport energy consumption is growing in developed and developing countries, and transport energy use tends to be carbon intensive (everywhere). Indeed, transport contributes more than one-fifth of global anthropogenic carbon dioxide emissions. Yet, most panel causality studies have not considered transport energy consumption (exceptions are Costantini and Martini, 2010; Liddle, 2012).

It is well recognized that averaging across countries (i.e. panel analysis) produces plausible estimates even when individual country estimates can be difficult to interpret/nonsensical (e.g., Boyd and Smith, 2002; Mark and Sul, 2003). However, variables like GDP per capita and energy consumption are expected to be cross-sectionally correlated; that is so, for example, because of regional and macroeconomic linkages that manifest themselves through (i) common global shocks, like the oil crises in the 1970s; (ii) shared institutions like the World Trade Organization or International

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Table 1

Cross-sectional dependence: Absolute value mean correlation coefficients and Pesaran (2004) CD test.

Panels	Transport energy	Δ transport energy	GDP	Δ GDP
High income	0.72 (125.3 [*])	0.22 (27.4 [*])	0.85 (102.3 [*])	0.32 (47.9 [*])
Middle income	0.58 (80.8 [*])	0.15 (8.2 [*])	0.60 (87.5 [*])	0.20 (21.1 [*])
Low income	0.46 (10.7 [*])	0.12 (0.8)	0.54 (15.1 [*])	0.17 (9.1 [*])

Notes: Absolute value mean correlation coefficients shown. The CD-test statistic is in parentheses. The null hypothesis is cross-sectional independence. Δ = first difference.

^{*} Statistical significance <0.001.

Monetary Fund; or (iii) local spillover effects between countries or regions. When the errors of panel regressions are cross-sectionally correlated, standard estimation methods can produce inconsistent parameter estimates and incorrect inferences (Kapetanios et al., 2011). Furthermore, it seems likely that the dynamics for most aggregate country level data are heterogeneous; yet, if one mistakenly assumes that they are homogeneous (when the true coefficients of a dynamic panel are indeed heterogeneous), then all of the panel parameter estimates will be inconsistent (Pesaran and Smith, 1995). Hence, we focus on panel long-run causality using the methods suggested by Canning and Pedroni (2008)—their approach allows for a high degree of heterogeneity in long-run causality, unlike the more conventional pooled approach to vector error correction modeling (VECM), which assumes the long-run relationship is the same for all members of the panel. The only other energy–GDP causality studies to use the Canning and Pedroni approach were Narayan et al. (2010) and Narayan and Popp (2012). This paper builds on the work of Narayan et al. (2010) and Narayan and Popp (2012) in several ways: we consider a different energy variable, transport; we group countries into panels based on income; and to determine the sign of the causal direction, we use a heterogeneous panel estimator that is robust to cross-sectional dependence.¹

2. Data, pre-testing methods and results, and causality direction and sign methods

We analyze International Energy Agency data of 107 countries, spanning 1971–2009, which we group into three income-based balanced panels (consisting of 40 high-income, 39 middle-income, and 28 low-income countries).² Transport energy consumption per capita is in ktoe and covers all transport activity (regardless of the economic sector to which it contributes). Real GDP per capita data are PPP adjusted and are in 2000 US dollars. Both variables are converted to natural logs. Table 1 displays the results of the Pesaran (2004) CD test, which indicate that the null hypothesis of cross-sectional independence is rejected for both variables and for each panel. However, when first differences are taken, cross-sectional dependence is mitigated since the mean correlation coefficients are substantially lower (and for the case of transport energy and the low income panel, independence cannot be rejected).

The Bai and Carrion-i-Silvestre (2009) panel unit root test accounts for cross-sectional dependence (captured through common factors) and allows for multiple, cross-section specific endogenous breaks (in both the level and trend). For both variables, the test results identified no break points for the majority of countries;

most of the countries with an identified break point had only one break. The test results—which are reported in Table 2 of the working paper version (available from the authors or via the SSRN, <http://ssrn.com/abstract=2337274>)—provide strong evidence that both panel variables are $I(1)$ nonstationary panels.

The Westerlund and Edgerton (2008) panel cointegration test allows for both structural breaks and cross-sectional dependence (as above, cross-sectional dependence is captured through common factors). Those results reject the null hypothesis of no cointegration for all three (income) panels and both endogenous structural break assumptions (results shown in Table 3 of the working paper version, which is available from the authors or via the SSRN, <http://ssrn.com/abstract=2337274>).

2.1. Heterogeneous panel causality direction and sign methods

Since in each country all of the series are individually nonstationary, but the series pairs together are cointegrated, these series pairs can be represented and estimated (for each country) in a dynamic error correction model (ECM):

$$\Delta ten_{it} = c_{1i} + \lambda_{1i} e_{it-1} + \sum_{j=1}^{K_1^1} \varphi_{11ij} \Delta gdp_{i,t-j} + \sum_{j=1}^{K_1^1} \varphi_{12ij} \Delta ten_{i,t-j} + \varepsilon_{1it} \quad (1)$$

$$\Delta gdp_{it} = c_{2i} + \lambda_{2i} e_{it-1} + \sum_{j=1}^{K_2^2} \varphi_{21ij} \Delta gdp_{i,t-j} + \sum_{j=1}^{K_2^2} \varphi_{22ij} \Delta ten_{i,t-j} + \varepsilon_{2it} \quad (2)$$

where ten is transport energy per capita, gdp is real GDP per capita, K is a country-specific lag length, the subscripts i and t denote country i and the t th time period, respectively, Δ is the first difference operator, and e_{it-1} is the one period lag of the residuals from the long-run cointegrated relationship ($ten_{it} = a_i + b_t + \beta_i gdp_{it} + e_{it}$), which is estimated using fully modified ordinary least squares.

Canning and Pedroni (2008) propose that cross-sectional dependence is addressed (in the construction of the panel statistics) via subtracting out common time effects (i.e., the b_t term). Indeed, Pedroni (2000) argued that “...in many cases cross-sectional dependence does not play as large a role as one might anticipate once common time dummies have been included”.³ We note that the inclusion of first differenced terms in Eqs. (1) and (2) should at least mitigate cross-sectional dependence since, as demonstrated in Table 1, our data display relatively low mean correlation coefficients once the difference operator is applied. (Indeed, in Footnote 9 we report diagnostic tests that confirm that cross-sectional dependence has been mitigated/addressed in the causality tests).

A t -test on the point estimate for λ_{1i} (from Eq. (1)) would be a test on long-run Granger-causality from gdp to ten , and accordingly, a t -test on the point estimate for λ_{2i} (from Eq. (2)) would be a test on long-run Granger-causality from ten to gdp . At the high level of data aggregation considered here, we might expect to find bi-directional causality (with a positive sign) since transport energy is both an input to production (e.g., freight, commercial airlines) and a form of consumption (e.g., personal transport in low fuel efficiency vehicles and leisure travel).

¹ The only other energy–GDP studies to estimate elasticities robust to cross-sectional correlation were Belke et al. (2011) and Liddle (2013).

² The country make-up of the three panels is listed in the Appendix of the working paper version, which is available from the authors or via the SSRN: <http://ssrn.com/abstract=2337274>.

³ Addressing cross-sectional dependence in causality testing is an active area of econometric research. For example, both Konya (2006) and Dumitrescu and Hurlin (2012) recommend using bootstrapped critical values; however, those two approaches are appropriate for non-cointegrated variables only. Furthermore, modifying Pedroni's RATS code to allow for bootstrapping was not possible.

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