The Systemic, Long-run Relation among Gasoline Demand, Gasoline Price, Income, and Vehicle Ownership in OECD Countries: Evidence from Panel Cointegration and Causality Modeling

Liddle, Brantley

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Brantley Liddle
Victoria University
Level 13, 300 Flinders St.
Melbourne, VIC 8001
Australia
btliddle@alum.mit.edu

ABSTRACT

This paper analyzes gasoline consumption per capita, income (GDP per capita), gasoline price, and car ownership per capita for a panel of OECD countries by employing panel unit root and cointegration testing, panel Dynamic and Fully Modified OLS estimations, and panel Granger-causality tests. The four variables are determined to be panel $I(1)$ and cointegrated. Estimated long-run and short-run income elasticities are smaller than what typically had been found previously. Lastly, gasoline consumption is Granger-caused by gasoline price, but not by car ownership or income; whereas, car ownership is Granger-caused by income and at the margin by gasoline consumption, but not by gasoline price.

Keywords: gasoline demand elasticities; OECD countries; panel unit roots; panel cointegration; panel Dynamic OLS and Fully Modified OLS estimation; panel Granger-causality testing.

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1. Introduction

This paper examines a panel of 14 OECD countries to determine cointegration and the direction of causality among gasoline consumption per capita, gasoline price, income (GDP per capita), and car ownership per capita, and to estimate the short-run and long-run elasticities. Those four variables are found to be cointegrated, i.e., have a long-run relationship, and to be mutually causal. The long-run inter-relationship finding, combined with relatively price inelastic estimations and the causality analysis result that income impacts fuel consumption primarily by increasing car ownership, suggests that the use of a number of policy levers, like increased fuel efficiency standards, are needed to lower transport's carbon emissions.

Accordingly, this paper tests in a panel setting a model that Liddle (2009) found mutually causal and cointegrated for the US using data from 1946 to 2006. Liddle (2009) found that gasoline demand is influenced by gasoline price, income, and the vehicle stock (which also is influenced by income and gasoline price). Besides expanding Liddle's (2009) analysis to a panel of 14 OECD countries, we calculate short- and long-run elasticities.

While there has been a great deal of work devoted to estimating the price and income elasticities of gasoline demand,[1] only recently have studies paid attention to the stationarity properties of the data and tested for cointegration among the variables. Yet, highly trending, stock-based variables like income (GDP per capita), energy consumption, and vehicle stock are likely nonstationary—i.e., their mean, variance, and/or covariance with other variables change over time. When ordinary least squares (OLS) is performed on nonstationary variables, measures like R-squared and t-statistics are unreliable, and there is a serious risk of the estimated relationships being spurious. No gasoline demand study, to our knowledge,

[1] As an ongoing project, Dahl has found 190 new studies since her initial 1991 review that deal with energy demand; for her most recent draft see: http:// dahl.mines.edu/demand.pdf.

has used time-series cross-section data and tested for *panel* unit roots (or stationarity) and for *panel* cointegration (i.e., a long-run relationship among nonstationary variables).

Dahl and Sterner (1991) contributed an early survey of many estimates of transport elasticities. Graham and Glaister (2002) provided an update; but of the studies cited, only four involved cointegration, and all were focused on single countries. Likewise, the few (eight) studies since the Graham and Glaister review that employed/tested for cointegration also have focused on single countries. However, according to Mark and Sul (2000), single-country cointegration estimates (of OECD countries) often display so much variability that they are difficult to interpret; thus, combining cross-sectional and time-series information of similar countries in the form of a panel provides much more precise estimates of the cointegration vector and direction of causality.

2. Data and methods

The data is a balanced panel of 14 OECD countries spanning 1978[2]-2005. The variable names, descriptions, and sources are listed in Table 1 below. As discussed in Pock (2010), the share of diesel cars in the passenger car fleet has increased substantially in several European countries (notably so in Austria, Belgium, France, and Spain where diesels comprise nearly half the passenger car fleet).[3] Thus, we restrict the panel to those OECD countries where diesel cars have had low penetration rates as of 2005 (less than 15% of passenger cars), and where they have had a fairly constant rate of penetration since the early 1990s (around 20% in Netherlands), and to countries for which the vehicle data can be adjusted to include gasoline cars only (United Kingdom).[4]

[2] The first year for which the IEA's price data is available.

[3] However, diesel car stock data is not available for the lengths of time necessary to perform panel cointegration modeling.

[4] The countries considered are Australia, Canada, Denmark, Finland, Greece, Ireland, Japan, Netherlands, Norway, New Zealand, Sweden, Switzerland, United Kingdom, and United States.

In addition to the petrol vs. diesel issue, the quality of car ownership data varies considerably across OECD countries. For the non-European countries data from the International Road Federation (IRF) and World Bank (which sources its vehicle data from the IRF) was used. For five European countries (Denmark, Greece, Netherlands, Sweden, and United Kingdom) Eurostat vehicle data covered the entire study period; for the other four European countries the IRF/World Bank data was used until 1988/89, at which time the Eurostat data began. In the instances in which two data sources were used, the data appeared to combine more or less smoothly (i.e., year-to-year growth rates were similar).

Table 1

Even though diesel vehicles are more fuel efficient, the systemic relationship among mobility demand, vehicle stock, income, and fuel price for diesel is likely to be similar to that for gasoline (elasticity magnitudes would be different, but the signs and causal relationships among the variables are likely to be the same). Also, since diesel engines emit more carbon per liter of fuel burnt than gasoline engines, a complete switch to diesel vehicles will only slow down road carbon emissions marginally. Thus, similar policy prescriptions to reduce such emissions should apply to both vehicle classes.

The following relationship is tested for cointegration and estimated:

$$\ln Gas_{it} = \alpha_i + \beta_t + \gamma_1 \ln Price_{it} + \gamma_2 \ln Income_{it} + \gamma_3 \ln Car_{it} + \varepsilon_{it} \tag{1}$$

Where subscripts *i* and *t* denote the *i*th cross-section and *t*th time period. The constants α and β are the country or cross-section and time fixed effects, respectively, and ε is the error term.

2.1 Pre-testing methods

The first step is to determine whether all the variables are integrated of the same order.[5] A number of panel unit root tests have been developed to determine the order of integration of panel variables. The earlier tests allow for heterogeneous unit root processes among cross-sections, but assumed that the cross-sections were independent.[6] Yet, for variables like GPD per capita, cross-sectional dependence is possible to likely for panels of similar countries because of, for example, regional and macroeconomic linkages. More recently, panel unit root tests—so-called second-generation tests—have been developed that relax this independence assumption (e.g., Pesaran 2007). All four tests considered here assume the null hypothesis of nonstationarity.

If all the variables are integrated of the same order, the next step is to test for cointegration. Engle and Granger (1987) pointed out that a linear combination of two or more nonstationary series may be stationary. If such a stationary linear combination exists, the nonstationary series are said to be cointegrated. The stationary linear combination is called the cointegrating equation and may be interpreted as a long-run equilibrium relationship among the variables.

The Pedroni (1999, 2004) heterogeneous panel cointegration test is an extension to panel data of the Engle-Granger framework. We focus on the two statistics—the panel-ADF-statistic and the group-ADF-statistic—that Pedroni (1999) demonstrated have the best small-sample (time dimension less than 40-50) properties of all the statistics, and thus, provide the strongest single evidence of cointegration. The Westerlund (2007) second-generation panel cointegration test is robust to cross-sectional correlation. We focus on the group-τ and panel-

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[5] A variable is said to be integrated of order d, written $I(d)$, if it must be differenced d times to be made stationary. Thus, a stationary variable is integrated of order zero—$I(0)$—and a variable that must be differenced once to become stationary is integrated of order one—$I(1)$.

[6] The so-called first-generation tests considered here are: IPS (from Im, Pesaran and Shin 2003), ADF-Fisher (from Maddala and Wu 1999), and Fisher-PP (from Choi 2001).

τ statistics since, according to Westerlund (2007), those statistics have the highest power and are the most robust to cross-sectional correlation (i.e., dependence). Both the Pedroni and Westerlund tests assume a null hypothesis of no cointegration.

2.2 Estimation/analysis methods

If the variables are shown to be cointegrated, then Pedroni's (2000 and 2001) panel FMOLS and DOLS estimators correct for endogeneity and residual autocorrelation and produce asymptotically unbiased normally distributed estimates of the long-run elasticities. FMOLS is a nonparametric approach in which an initial estimation calculates the serial correlation and endogeneity correction terms; DOLS is a parametric approach in which lead and lagged difference terms of the independent variables correct for serial correlation and endogeneity.[7] However, DOLS may be superior to FMOLS for small samples (and, perhaps, for large ones too), in part, because DOLS does not require an initial estimation for the nonparametric correction (Kao and Chiang 2000).

The short-run elasticities are estimated from an OLS regression with all variables in first differences. The regression includes a lagged error correction term (ECT) that is the residuals from the long-run cointegration relationship (Equation 1) estimated in OLS, and is interpreted as the speed to which the system adjusts towards its long-run trends when subjected to a shock.

Lastly, if a set of variables are determined to be cointegrated, then statistical techniques from Granger (1980) can be used to reveal the causal direction (so called Granger-causality)[8] among/between pairs of variables. Since it is most interesting to uncover

[7] There is no agreed upon convention for determining the optimal number of leads and lags in the applied literature, but many follow the lead (as we do) of Mark and Sul (2003) and set them at two each.

[8] *Y* is said to be "Granger-caused" by *x* if *x* helps in the prediction of *y*. Thus, Granger causality measures precedence and information content but does not by itself prove causality (that *y* is the effect or result of *x*), any more than any statistical test can prove causality.

causality as it relates to gasoline consumption and car ownership, we focus the causality analysis on the following two equations from a Vector Error Correction Model (VECM):

$$\Delta Gas_{it} = \alpha_{1i} + \sum_{k=1}^{l_1} \beta_{1ik} \Delta Gas_{it-k} + \sum_{k=1}^{l_1} \gamma_{1ik} \Delta Price_{it-k} + \sum_{k=1}^{l_1} \lambda_{1ik} \Delta\ Income_{it-k} + \sum_{k=i}^{l_1} \theta_{1ik} \Delta Car_{it-k} + \eta_{1i} ECT_{it-1} + u_{1it} \quad (2)$$

$$\Delta Car_{it} = \alpha_{2i} + \sum_{k=1}^{l_2} \beta_{2ik} \Delta Gas_{it-k} + \sum_{k=1}^{l_2} \gamma_{2ik} \Delta Price_{it-k} + \sum_{k=1}^{l_2} \lambda_{2ik} \Delta\ Income_{it-k} + \sum_{k=i}^{l_2} \theta_{2ik} \Delta Car_{it-k} + \eta_{2i} ECT_{it-1} + u_{2it} \quad (3)$$

Where all variables are in natural logarithms, Δ is the difference operator, *ECT* is the error-correction term, the *l*'s are the number of lagged difference terms, the α 's are cross-section specific constants, and the *u*'s are the error terms. Short-run causality is tested with a Wald test on the sum of the lags of an explanatory variable,[9] and long-run causality is tested by a t-test on the ECT.

3. Pre-testing results

Table 2 displays the panel unit root test results. The tests provide very strong evidence that all four variables analyzed here are panel *I*(1) or nonstationary in levels but stationary in first differences, and thus, OLS regressions with the variables in levels would be inefficient and likely spurious. The null hypothesis of nonstationarity in levels is rarely rejected—and never unanimously rejected; whereas, the null hypothesis of nonstationarity in first differences is rejected by each test at the highest level of significance.

Table 3 shows the results of the panel cointegration tests. There is evidence that, as Liddle (2009) found for the US, the four variables are panel cointegrated for OECD countries, too; this is so because only one of the four statistics fails to reject the null of no cointegration.

Tables 2 & 3

[9] For example, if the Wald test statistic for the γ 's in Equation 2 is significantly different from zero, then price is said to Granger-cause gas consumption.

4. Main results and discussion

The long-run and short-run elasticity estimates are displayed in Table 4. The FMOLS long-run estimations suggest that gasoline consumption is highly income and price inelastic (the elasticity for income is insignificant), and that gasoline demand is caused primarily through vehicle ownership. The long-run elasticities estimated via DOLS are all statistically significant, and all have the expected signs. The (absolute) magnitudes of the income and price elasticities are considerably larger from DOLS than from FMOLS, whereas the DOLS car ownership elasticity is considerably smaller than the FMOLS one. Yet, the DOLS estimations, like the FMOLS ones, suggest price inelasticity (all elasticities are significantly less than unity in absolute terms).

As one would expect, the short-run elasticities are smaller (in absolute terms) than the long-run estimates (except for income estimated from FMOLS), and the short-run elasticity for car ownership on gasoline demand is very small. Gasoline is very price inelastic in the short run.

Table 4

4.1 Causality results

Table 5 shows the results of the panel Granger causality tests for gasoline consumption and car ownership. There is evidence of long-run Granger-causality (the ECT term is statistically significant): gasoline price, income, and car ownership Granger-cause gasoline consumption in the long-run. In the short-run, gasoline consumption is Granger-caused by gasoline price, but not by car ownership or income; and, also in the short-run, car ownership is Granger-caused by income and at the margin by gasoline consumption (perhaps a proxy for mobility demand), but is not Granger-caused by gasoline price. Thus, in the short-run, income influences gasoline consumption primarily through increasing car ownership. All these results are very plausible short-run results since people can always garage a car, and gas price is more likely to sway prospective buyers toward particular fuel efficiency characteristics than toward postponing the purchase.

Table 5

4.2 Comparisons with previous findings

From Dahl's updated, ongoing survey of demand elasticity (see Footnote 1 for the web address), estimates of gasoline demand price elasticity ranged from -0.46 to 0.25, with a mean of -0.13 in the short-run, and from -2.47 to 0.88, with a mean of -0.61 in the long-run. Graham and Glaister (2002) summarized their survey as: (i) the long-run price elasticities for the OECD ranged from -0.75 to -1.35; (ii) the short-run price elasticities tended to be 2.5 to 3.5 times lower in magnitude than the long-run effects (around -0.3); and (iii) the long-run income elasticity of fuel demand fell between 1.1 to 1.3, whereas, the short-run income elasticity ranged from 0.35 to 0.55. A more recent meta-analysis by Brons et al. (2007) found mean short-run and long-run price elasticities of gasoline demand of -0.36 and -0.81, respectively.

In comparison with Graham and Glaister (2002) and Brons et al. (2007), both the long-run and short-run price elasticities computed here are lower than the ranges they mentioned, and the differences between the long-run and short-run effects are narrower here. The long-run income elasticity estimated here is lower than the range Graham and Glaister found as well. Given that the income elasticity computed here is based on developed countries only and on more recent data, perhaps the lower value represents nearing saturation. Graham and Glaister noted that studies using cointegration often produced far lower price elasticities. Also, Brons et al. remarked that cross-section studies reported higher absolute elasticity estimates than time-series studies.

The finding of lower elasticity (absolute) values is not, however, an entirely new result. Small and Van Dender (2006) found both the short-run and long-run price elasticities of fuel consumption were lower (by a third to a quarter) when estimated from a 1997-2001 panel of US states than when estimated from their full sample that spanned 1966-2001. Hughes et al. (2008) found that the short-run price elasticity of gasoline demand is considerably more inelastic today than in pervious decades, estimating (from US monthly data) that it fell from a range of -0.21 to -0.34 over 1975 to 1980 to a range of -0.034 to -0.077 over 2001 to 2006. Liddle (2009) determined (using US annual data) that the short-run price elasticity of gasoline was statistically significantly lower (by a factor of more than three) over 1991-2006 than over 1978-1990. Also, Pock (2010), who focused on Europe and considered diesel as well, found gasoline was (i) highly price inelastic in the short-run (estimating elasticities even lower than those estimated here, depending on regression method used), and (ii) price inelastic in the long-run (estimating elasticities that fell between the FMOLS and DOLS estimations shown in Table 4, again depending on method). Lastly, Bonilla and Foxon (2009) determined that the demand for *fuel economy* was price inelastic for both gasoline and diesel in the UK.

5. Policy implications and conclusions

This paper analyzed per capita gasoline consumption, income (GDP per capita), gasoline price, and car ownership per capita for a panel of OECD countries by employing panel cointegration modeling and panel DOLS and FMOLS estimations. That gasoline consumption, income, gasoline price, and car ownership are found here to have a long-run, cointegrated relationship in OECD countries means that these variables cannot be easily disentangled in the short-run. The elasticities computed here (particularly price) are lower (in absolute terms) than those reported in many previous studies—however, the lower values are in line with a recent argument that gasoline consumption has become less price sensitive in recent time (for example, Hughes et al. 2008). Those lower elasticities imply that adjustments to price (i.e., fuel taxes) alone are likely to have limited impact; instead, using a number of policy levers is necessary to reduce transport fuel consumption (and thus, carbon emissions). The combination of price inelasticity and the causality finding that higher income leads to greater car ownership rates suggests the value of fuel efficiency standards on vehicles—echoing the recommendations of Bonilla and Foxon (2009) and Liddle (2009), who studied the UK and US, respectively.

The panel cointegration approach used here has the advantages of (i) treating the variables systemically in one equation, distinguishing directly between short-run and long-run impacts without changing the dependent variable, and (ii) exploiting a substantial number of data points, while, at the same time, accounting for the time-series (i.e., unit root) properties of those variables. Furthermore, besides addressing both transport's systemic relationship (among gasoline demand, vehicle stock, income, and gasoline price) and the likely stationarity properties of stock and stock-related variables, using panels of similar countries delivers a more precise understanding of general, macro-level relationships.

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Table 1 Variable descriptions and sources

Name	Description	Source
Gas	Motor gasoline consumption per capita (tons/person)	International Energy Agency
Income	Real GDP per capita (2000 USD using PPP/person)	Ibid
Price	Real gasoline pump-price (in 2000 USD/liter using PPP)	Ibid
Car	Car ownership per 1000 people	World Bank, International Road Federation, Eurostat

Note: All variables in natural log form.

Table 2. Results for panel unit root tests

	Individual intercepts				Individual intercepts and trends			
Variable	IPS	ADF-Fisher	PP-Fisher	Pesaran Z-stat	IPS	ADF-Fisher	PP-Fisher	Pesaran Z-stat
	Variables in levels							
Gas	-1.8*	47*	31	-1.7*	-0.1	38	36	1.3
Income	5.9	4.4	6.7	-0.5	-2.6**	57***	25	-0.5
Price	-0.5	28	29	-0.8	2.5	16	16	1.2
Car	0.8	26	25	-0.4	-1.8*	43*	20	1.1
	Variables in first differences							
Gas	-7.3***	108***	133***	-3.8***	-7.0***	102***	116***	-3.8***
Income	-7.8***	115***	94***	-5.1***	-6.3***		71***	-3.7***
Price	-11.2***	163***	164***	-5.8***	-9.5***	128***	145***	-5.3***
Car	-9.1***	136***	144***	-4.9***	-7.6***	107***	111***	-3.7***

Note: Statistical significance is indicated by: *** p <0.001, ** p <0.01, and * p<0.05.

Table 3. Results for panel cointegration tests for gas consumption, gas price, income, and car ownership

Pedroni test statistics	
Panel ADF-statistic	-1.68*
Group ADF-statistic	-2.21*
Westerlund test statistics [a]	
Panel τ	-2.6*
Group τ	-1.5

Notes: Statistical significance is indicated by: * p<0.05.
[a] P-values are robust to cross sectional correlation via bootstrapping.

Table 4. Long-run panel elasticities from FMOLS and DOLS and short-run panel elasticities from OLS. Dependent variable is gasoline consumption per capita.

	Long-run		Short-run	
	FMOLS	DOLS		OLS
Income	0.197	0.344	Δ Income	0.283
	(0.23)	(26.79)		(4.29)
Gasoline price	-0.194	-0.429	Δ Gasoline price	-0.155
	(-6.58)	(-27.86)		(-7.17)
Car ownership	0.674	0.273	Δ Car ownership	0.116
	(17.53)	(26.17)		(3.02)
			ECT_{t-1}	-0.153
				(-7.00)

Notes: T-statistics are distributed as *N* (0,1) and shown in parentheses. Models include both cross-section and time dummies.

Table 5. Panel Granger causality tests

	Sources of causation (independent variables)				
	Short-run				Long-run
Dependent variable	Δ Gas	Δ Price	Δ Income	Δ Car	ECT
Δ Gas [2]		13.3**	3.6	1.7	-6.0****
Δ Car [1]	3.2*	0.1	19.7****		0.5

Notes: Statistical significance is indicated by: **** p <0.001, *** p <0.01, ** p<0.05, and * p<0.10. Optimal lag length is in brackets.