# Demographic Dynamics and Per Capita Environmental Impact: Using Panel Regressions and Household Decompositions to Examine Population and Transport

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This paper examines how demographic changes can help explain changes/differences in personal transport using both International Energy Agency country panel regressions and decompositions of U.S. household data. An environmental Kuznets curve for per capita road energy use was rejected; instead, the relationship between income and road energy was found to be monotonic. The ideas that more densely populated countries have less personal transport demands, the young drive more, and smaller households mean higher per capita driving were confirmed. The household decompositions indicated that changes in demand were more important than compositional changes; yet, during some periods the compositional change component was considerable.

**KEY WORDS:** environmental Kuznets Curve; OECD countries; population and environment; transport energy use.

## INTRODUCTION

The purpose of this paper is to examine how population dynamics have an impact on the environment through transport. Transport is a

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significant component of the environmental impact in developed countries, and population—particularly the household—is an important level of analysis. I use two data sets and two measures of per capita impact from transport: (i) OECD country-level data and per capita road energy use; and (ii) U.S. household-level data and miles driven per person. Energy use in transport and miles driven are, of course, highly related in developed countries.[1] They tend to vary only because fuel intensities of vehicle fleets vary. First, I examine how some demographic variables may influence per capita road energy use through panel regressions. Then, using techniques from the demography literature, I decompose household-level data to see the extent to which changes in household structure have contributed to changes in per person miles driven over various time intervals.

There has been much work on economic growth/development's effect on the environment. Some of the earliest of this work, like Grossman and Krueger (1995) and Selden and Song (1994), concentrated on explaining per capita emissions as a function of income. These studies and the many subsequent ones became known as the environmental Kuznets curve (EKC) literature since their focal point was to determine whether the pollution–income relationship behaved as an inverted-U (i.e., regressions that produce an income coefficient that is significant and positive and an income-squared coefficient that is significant and negative). Advances in the environment-development literature have generally involved (i) examining additional explanatory variables, like trade and structural change (e.g., Suri & Chapman, 1998), institutions (e.g., Torras & Boyce, 1998), or geography (e.g., climate and endogenous resource base in Neumayer, 2002); (ii) considering a longer and/or wider data set (e.g., List & Gallet, 1999, who used U.S. state level data; Stern & Common, 2001,who used U.S. state level data); or (iii) using more advanced econometric techniques (e.g., Schmalensee, Stoker & Judson 1998; Stern, 2002).

Most of the environment-development work focuses on aggregate energy use or emissions or concentrations of certain pollutants rather than on the environmental impact from *activities*. Some exceptions to this generalization are Judson, Schmalensee and Stoker (1999), who examined the dynamics of the share of total energy use for the residential, transport, and industry sectors; Hilton and Levinson (1998), who estimated EKCs for automotive lead emissions; Roca, Padilla, Farre and Galleto (2001), who used road energy use per capita as an explanatory variable in a nitrogen oxide EKC regression for Spain; and Ramos-Martin (2001), who examined trajectories of a measure of household energy use for Spain. Also, the environment-development literature tends to consider population only as a divisor (to convert to per capita measures, or, occasionally, as the numerator in population density).

This paper represents an advance on the literature because: (1) it focuses on an activity which is an important source of impact on the environment, namely, personal transport; and (2) it considers spatial and demographic factors that are highly related to that activity (and to other environmentally important activities too). Energy used in transport is a particularly important focus for environment-development studies since it is increasing in both developed and developing countries and is (given current technology) a carbon-intensive activity everywhere (as opposed to, for example, electricity generation, which can be more or less carbon-intensive depending on the energy source used, e.g., coal, natural gas, nuclear, hydro-electric).

Indicators of the spatial distribution of population are likely to be explainers of cross-country transport demand for surveys of the North American literature (see Badoe & Miller, 2000; Handy, 1992). The analysis presented here considers urbanization, population density, and primacy (the percentage of a country's urban population that resides in its largest city), as well as some interaction terms. At least in the developed world, highly urban and dense countries may require less personal transport. Also, countries in which the population is heavily concentrated in one urban area may require less transport than countries in which urban population is spread throughout. Some previous environment studies have included certain spatial factors, like urbanization or population density; however, these studies were not focused specifically on environmental impact from transport activity (rather, they considered aggregate pollution coming from many sources).

Lastly, demographic factors, like age and household structure, are likely to be very important in explaining environmental impact. The first to consider households as the unit of analysis was MacKellar, Lutz, Prinz and Goujan (1995). More recently, O'Neill and Chen (2002) looked at how U.S. residential and transport energy use vary according to household demographic characteristics. Indeed, in developed and developing countries the size of the average household has fallen, and in many developed countries this has meant an increase in the number of households despite constant or declining total populations. Figure 1a shows that in the U.S. as the size of a household increases the average miles driven per person in that household falls. Figure 1b illustrates (data also from the U.S.) that young people tend to drive more (at least in small households). Prskawetz, Leiwen and O'Neil (2002) demonstrated that similar relationships exist for Austria.

One may expect a study on the effect of demographic factors on the environment to employ micro- or household-level data; however, such data are difficult to find for a large sample of countries. And since this is one of

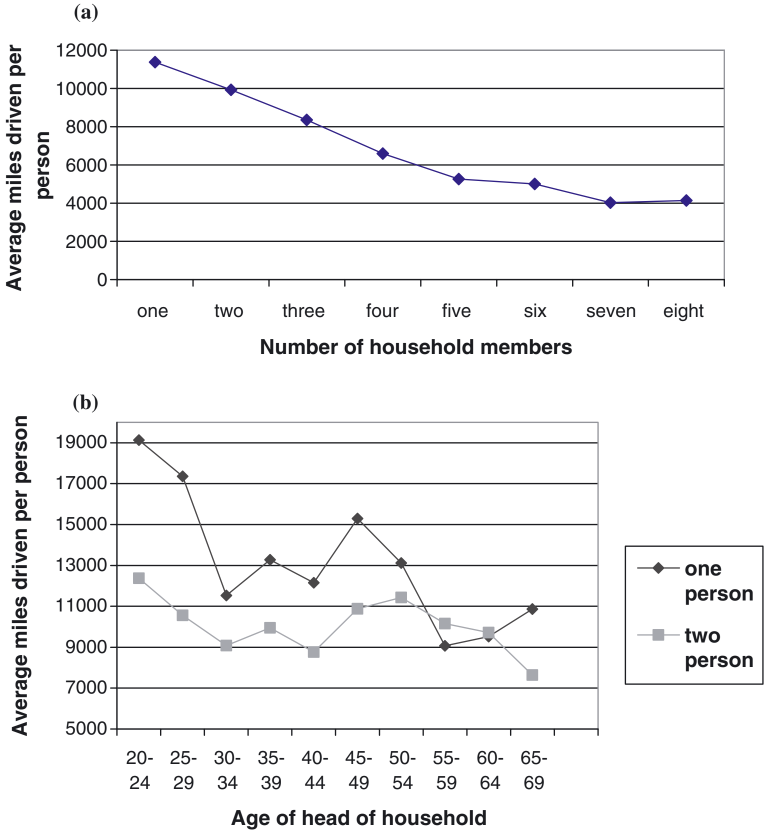


**FIGURE 1.** (a) Average miles driven per person by household size. Data for the U.S. in 1994 from the Residential Transportation Energy Consumption Survey 1994. (b) Average miles driven per person by age of head of household for households of one and two people. Data for the U.S. in 1990 from the Residential Transportation Energy Consumption Survey.

the first analyses to consider demography, a macro-level survey of a number of countries is useful. Yet, a decomposition of household data (done here for the U.S.) can indicate the extent to which demographic momentum rather than intrinsic changes in demand lead to environmental impact. Thus, investigations using both macro- and micro-level data are presented here. The following two sections involve the panel regression analysis. The second section covers the data set and methodology used, while the third section discusses the results. Figure 1a and 1b, showing the strong relationship between household characteristics and personal transport in the U.S., motivate the household decomposition analysis contained in the fourth section. In that section the data set, methodology, and results of this investigation are covered. The fifth section concludes the paper with summary and policy implications.

## PANEL REGRESSIONS: DATA AND METHODOLOGY

I performed OLS, fixed effects regressions with time dummies on OECD panel data.[2] The reported standard errors are White heteroskedasticity consistent. The panel data covers 23 countries (including Korea, Mexico, and Turkey) with observations over five time periods, i.e., 10-year intervals from 1960 to 2000.[3] Total population, GDP (in 1995 USD using purchasing power parity), and road energy use [4] (in tons of oil equivalent) data all come from the International Energy Agency (a more detailed explanation of all the data and sources is in Appendix 1). Urbanization, primacy, and the share of people in the 20–39 age group come from the UN and Eurostat. Average household size comes from the UN and the individual country's national statistics offices. Lastly, the area of each country (in km$^2$) is from the International Road Federation. The model to be estimated is:

$$E_{it} = \alpha_i + \gamma_t + \beta_1(Y_{it}) + \beta_2(Y_{it})^2 + \beta_3(Z_{it}) + \varepsilon_{it} \qquad (1)$$

where $E$ is energy use per capita, $Y$ is GDP per capita, $Z$ is a vector of geographic and demographic variables, $\varepsilon$ is a random error term, the $\alpha_i$'s are country specific intercepts, and the $\gamma_t$'s are time specific intercepts. Subscripts $i$ and $t$ represent the countries and years, respectively. The geographic and demographic terms in the vector $Z$ are: urbanization (urban), primacy, and share of people aged 20–39 (pc_y20_39) all in decimal terms; the level of population density (pop_den) in people per square km; and the average household size (avg_hh_size) in people per household.

The choice not to include gasoline price was a difficult one. Gasoline price may affect both use (i.e., miles driven) and efficiency (i.e., gas mileage). However, price also is endogenous: the main reason gasoline price differs among OECD countries is that the tax on gasoline differs.[5] Since all of these countries are democracies, the willingness of people to accept a higher gasoline tax reflects their attitudes to personal transport, a characteristic the spatial indicators are trying to capture. Yet, countries with higher prices may have more efficient vehicle fleets. In fact, when examining a sub-sample of OECD countries at two points in time (1991 and 1997), a measure of gasoline price was (negatively) correlated with both kilometers driven per capita and liters of fuel consumed per kilometer driven. However, the correlation coefficient for distance per capita was one-and-one-half to two times larger (in absolute magnitude) than the coefficient for efficiency—implying the spatial indicators may indeed account for the more important impact of price.

The data set is complete with two exceptions. First, the IEA does not report energy data for Korea and Mexico in 1960; thus, having a balanced panel means either not including information from the 1960 or not including two of the three developing countries. Second, there are a number of observations of average household size missing. If a full, balanced panel containing average household size were used, the data set would be reduced to two cross-sections.

## PANEL REGRESSIONS: RESULTS AND DISCUSSION

The idea that per capita road energy use will eventually decline with income (i.e., an EKC) was rejected. Indeed, when a ''classical'' EKC

**TABLE 1**

**Dependent Variable is the Level of Per Capita Road Energy Use. OLS Estimation with Fixed and Time Effects; 1960–2000 Panel**

| | Regression | |
|---|---|---|
| | I-1 | I-2 |
| GDP | 2.69E-05* | 8.41* |
| | (3.37) | (7.37) |
| GDP$^2$ | −9.51E-11 | −0.39* |
| | (0.53) | (6.27) |
| Adj. $R^2$ | 0.97 | 0.96 |
| D–W | 1.88 | 2.06 |
| Cross-sections | 23 | 23 |
| Obs | 113 | 113 |
| Turning point | 141,000 | 48,150 |

*Notes*: Absolute *t*-values in parentheses; heteroscedasticity-robust standard errors; turning points are in real 1995 PPP U.S. dollars; levels of statistical significance indicated by asterisks: * 99%, ** 95%, *** 90%. In Regression I-2 all terms, including the dependent variable, are in natural logs.

regression (excluding the *Z* vector terms in Equation (1)) was run (Regression I-1 in Table 1), the estimated turning point was $141,000 (although the per capita GDP squared term had a *t*-statistic well under one). When the same regression was run with all terms in logs (Regression I-2 in Table 1), the estimated turning point was nearly $48,000 (in this specification both GDP terms had statistically significant coefficients); yet the highest per capita GDP in the sample is under $33,000 (the U.S. in 2000). Thus, the finding of an EKC in logs reflects that eventually per capita road energy use increases at a declining rate, rather than that it actually begins to decline at high income levels. An EKC was rejected too when the vector *Z* terms were included—the coefficient on the GDP squared term was statistically insignificant, and the implied turning point was well outside the sample range (results not shown).

The rejection of an EKC relationship is not surprising, particularly since the data suggests a more or less monotonic association between income and road energy use. Figure 2 is a plot of per capita road energy use and per capita GDP for the complete data set on a log scale.

The second model used is a semi-log one, where the dependent variable (energy use per capita) remains in levels, and the per capita GDP term is in natural logarithms (there is no per capita GDP squared term). That a measure of automobile use would increase with the log of income agrees

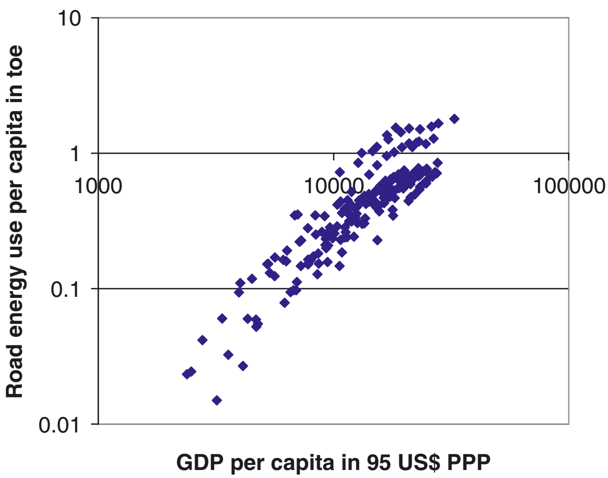


**FIGURE 2.** GDP per capita (in 95 USD PPP) and road energy use per capita in tons oil equivalent (toe) for the entire data set is log scale.

with Schipper, Unander, Murtishow and Ting's (2001) characterization of IEA country data. They argue the observed increase of vehicle kilometers along with higher GDP in IEA countries is caused mainly by increased automobile ownership rather than greater use per car; thus, one would expect a saturation point and the more or less linear pattern to flatten. The spatial and demographic explanatory variables remain as percentages (urbanization, primacy, and age structure) or averages (population density and household size) in this second equation. The second model is shown below (variable definitions as before):

$$E_{it} = \alpha_i + \gamma_t + \beta_4\, ln(Y_{it}) + \beta_5(Z_{it}) + \varepsilon_{it} \tag{2}$$

The results for what was argued above as the better specified, semi-log model are shown in Table 2. The most important expected results were confirmed: the relationship between income and road energy use is monotonic, although the increase in driving slows at higher levels of

**TABLE 2**

**Dependent Variable is the Level of Per Capita Road Energy Use. OLS Estimation with Fixed and Time Effects; 1960-2000 Panel**

| | Regression | | |
|---|---|---|---|
| | II-1 | II-2 | II-3 |
| Ln(GDP) | 0.25* | 0.21* | 0.18* |
| | (4.59) | (3.77) | (2.86) |
| Pop_den | −0.00093** | −0.0013** | −0.0015* |
| | (2.15) | (2.45) | (2.83) |
| Urban | −0.47* | −0.40* | −0.34*** |
| | (2.90) | (2.55) | (1.85) |
| Pc_Y20_39 | 1.16* | 1.07* | |
| | (2.74) | (2.59) | |
| Avg_hh_size | | −0.065 | −0.10** |
| | | (1.27) | (1.98) |
| Adj. $R^2$ | 0.96 | 0.96 | 0.97 |
| $R^2$ w/o country dummies | 0.46 | 0.49 | 0.51 |
| D–W | 1.88 | 1.92 | 1.89 |
| Cross-sections | 23 | 23 | 23 |
| Obs | 113 | 110 | 110 |

*Notes*: Absolute *t*-values in parentheses; heteroscedasticity-robust standard errors; levels of statistical significance indicated by asterisks: * 99%, ** 95%, *** 90%.

income; dense populations demand less personal transport; smaller households mean higher per capita road energy use; and younger people rely more on personal transport. The time dummies (not shown) were all significant and typically mirrored a trend rather than indicated events like the energy crisis. Urbanization was typically significant, and implied, as expected, that highly urbanized societies have lower demands for personal transport.

As alluded to in Footnote 3, when 5-year intervals were used, both age structure and average household size ''appeared'' significant on the basis of *t*-statistics, but there was evidence of serial correlation. When 10-year intervals were used, serial correlation was no longer present. However, the move from 5- to 10-year intervals entailed the loss of 50 data points. The main casualty appears to have been the average household size variable, which is seen in Regression II-2, to be only significant at an 80% level. Given both the theoretical appeal that large households provide economies of scale for transport and the strong association between household size and per person miles driven illustrated in Figure 1a for the U.S. (and knowing a similarly strong relationship exits in Austria as well), it is hard to believe changes in household size are insignificant in explaining variations in transport over time. Of course, that household size matters dynamically is one explanation for the results of Regression II-2. In part at least, because nearly all the countries used are of similar levels of development (at least in recent years[6]), the household size variable varies much more over time than cross-sectionally, and it was these very temporal data points that were reduced to address the serial correlation issue.

Another explanation for household size's disappointing *t*-statistic in Regression II-2 is that age structure and household size are highly correlated (very young and very old adults tend to have the smallest households). This possibility was explored in Regression II-3, where the Pc_Y20_39 term was left out. Indeed, in this regression the coefficient of household size was both large (and again expectedly negative) and statistically significant, while as before the other variables were similar (both in value and significance). Lastly, it is possible that average household size is too crude a measure (for example, young, small households are different from old, small households), something that is partially addressed in the micro-level analysis of U.S. data that follows.

Primacy was insignificant[7] (and is therefore omitted from the tables), probably because some countries with excellent public transport networks like Belgium and the Netherlands have primacy rates similar to the U.S. and Canada. The importance of the spatial variables (population density, urbanization, and primacy) may be better captured through an interaction term than the linear sum in the regression models. A few interaction terms were tried; however, the results did not seem appreciably different (e.g., the stability of the other variables as well as the interaction term with respect to the different samples were similar as shown in Table 2).

Because many of the independent variables used have very different units and magnitudes, it is difficult to tell how much these various spatial and demographic terms add to the explanation of per capita road energy use as compared to income. To explore this issue, standardized coefficients were calculated for the regressions of the semi-log model (Model II). The standardized coefficients, reported in Table 3, indicate by how many standard deviations the explained variable changes for a one standard deviation increase in one of the explanatory variables. (The table includes also the coefficient of variation for each variable.) For example, in Regression II-3, a one standard deviation change in average household size caused per capita road energy use to change by one-quarter of its standard deviation in the opposite direction. The table illustrates that some of the spatial variables, particularly population density, often left out of these types of analyses, had considerable explanatory power compared to income. Also, average household size, a variable unique to this paper, had at least as much explanatory power as per capita GDP in Regression II-3.

Finding variables (in the case here, demographic ones) with considerable explanatory power as compared to income provides a contrast to Neumayer (2002), who considered factors such as temperature and energy resource endowment in his examination of carbon dioxide emissions. Although Neumayer discovered variables measuring climate, natural

**TABLE 3**

**Standardized Coefficients for Selected Regressions from Table 2 (Dependent Variable is the Level of Per Capita Road Energy Use)**

| | Regression | | | |
|---|---|---|---|---|
| | II-1 | II-2 | II-3 | Coeff. Variation |
| Ln(GDP) | 0.40* | 0.33* | 0.28* | 0.0653 |
| Pop_den | −0.31** | −0.44** | −0.51* | 0.967 |
| Urban | −0.21* | −0.18* | −0.15*** | 0.237 |
| Pc_y20_39 | 0.083* | 0.076* | | 0.0872 |
| Avg_hh_size | | −0.15 | −0.24** | 0.268 |

*Note*: Levels of statistical significance indicated by asterisks: * 99%, ** 95%, *** 90%. Coefficient of variation is the standard deviation divided by the mean.

resource base endowment, and land area on which human activity had an impact all were significant, his calculations of standardized coefficients were much higher for income (six to 60 times higher). One reason for this difference between the results presented here and Neumayer's is that Neumayer looked at a very aggregate environmental measure (total carbon emissions) and non-income explanatory variables that are related to a particular source of emissions (so, these variables could only be expected to explain a fraction of total emissions, i.e., those attributable to that particular source). Thus, in his case it was not surprising that income, also a comprehensive indicator, would be relatively more important. By contrast, the dependent variable (transport) and the non-income, independent variables (spatial intensity, age structure, and household size) used here are at levels of aggregation where their expected interaction would be direct.

## HOUSEHOLD DECOMPOSITION: DATA, METHODOLOGY, AND RESULTS

Both Figure 1a and the results from some of the previous regressions demonstrate that micro-level changes in population (in household sizes, age structure) can have an impact on per capita transport indicators at a more macro-level. In this section I examine the extent to which changes in household structure contribute to changes in aggregated per capita miles driven. In general, demand for individual transport has increased, yet at the same time households have become smaller. Since there are economies of scale for mobility at the household level, changes in per capita miles driven could be caused by both of the above trends. Thus, I employ a method from the demography literature (described below) to decompose changes in per capita miles driven according to changes in driving demand and household characteristics (i.e., household size). U.S. household level data come from the Residential Transportation Energy Consumption Survey (various years).

A change in a weighted average can be decomposed into the sum of the average change of the variable of interest and the covariance between the variable of interest and the intensity of change of the weighting function. For a population-weighted average, the intensity of change of the weighting function is the growth rate of a specific population. This decomposition method in equation form (from Vaupel & Canudas, 2002) is:

$$\dot{\bar{v}} = \bar{\dot{v}} + \mathrm{Cov}(v, w') \tag{3}$$

where a dot indicates a derivative, a bar an average, and an accent an intensity of change or relative derivative (which is defined by Vaupel, 1992, as a derivative divided by the function or the derivative of the natural log of a function). Thus, the first right-hand side term, $\bar{\dot{v}}$, represents the direct change in the variable of interest, typically a behavioral change, while the second right-hand side term, $\mathrm{Cov}(v, w')$, represents the indirect change or the compositional effect. For the purposes here the variable of interest, *v*, is the per capita miles driven, and the weighting function, *w*, is the number of households of a particular size. Hence, the average per capita miles driven, $\bar{v}$, for the population is:

$$\bar{v} = \sum_{i=1}^{9}\left(d_i \frac{N_i}{\sum_{i=1}^{9} N_i}\right) \tag{4}$$

where $d_i$ is the average miles driven per person in household size *i* (*i* ranging from 1 to 9 persons) and $N_i$ is the number of households of size *i*.

The results of the decomposition over various overlapping time periods are displayed in Table 4. The table shows, at the mid-point of the time period, the shares of the direct and compositional change, as well as the total change.[8] Regardless of the time interval, per capita miles driven

**TABLE 4**

**Decomposition of Change in US Per Capita Miles Driven Across Time According to Change in Driving Demand (Behavior) and Household Characteristics (Composition)**

| | 1983–1985 | 1985–1988 | 1988–1991 | 1991–1994 | 1983–1991 | 1983–1994 |
|---|---|---|---|---|---|---|
| Behavior share | 0.73 | 0.83 | 0.998 | 1.02 | 0.81 | 0.89 |
| Composition share | 0.27 | 0.17 | 0.002 | –0.02 | 0.19 | 0.11 |
| Total change | 247 | 242 | 42.3 | 282 | 168 | 199 |

*Note*: Decompositions are based on households of nine members and smaller.

increased for data taken as the whole of the U.S. The behavior, or demand, component of driving was always the most important. However, the compositional, or household size, component varied from relatively important, in 1983–1985, 1985–1988, and 1983-1991, to insignificant in 1988–1991 and 1991–1994 (where it was actually negative, implying households became larger). If the decomposition were performed regionally (e.g., New England, Mid-Atlantic, Pacific), the variance (both regionally and across time) of the size and direction of the compositional effect would be more pronounced.

## CONCLUSIONS AND POLICY IMPLICATIONS

This paper has examined population and transport, specifically household size and spatial distribution, using two different indicators of environmental impact, data sets, and methods. The primary contributions of this research are two-fold. The first, and perhaps most significant contribution, is the inclusion, and consequential finding of importance, of demographic variables in an analysis of environment in *developed* countries. The second important and rather unique aspect of the work is that the variables used are disaggregated: both the explained variable (transport) and the explanatory ones (demographic characteristics that are highly, theoretically related to transport). This sets this paper apart from previous analysis relating highly aggregated environmental impacts (e.g., energy consumption) to equally aggregated demographic variables (e.g., total population). From the panel regressions, an EKC for per capita road energy use was rejected—both the coefficients on the GDP squared terms were insignificant and the implied turning points were well outside the sample range; instead, the relationship between income and road energy use was found to be monotonic, although the increase in driving slows at higher levels of income. The results presented here did confirm the ideas that more densely populated countries have lower personal transport demands, the young drive more, and smaller households mean higher per capita driving. The basic result from the decompositions was that changes in transport demand were more important than compositional changes; however, during some periods the compositional change component was considerable.

A few policy implications can be drawn from these analyses. First, the decomposition analysis implies that there is much potential for policy to affect transport behavior since the compositional component of change—more difficult for policy to alter—is smaller than the behavioral or demand component. However, the panel regressions imply that spatial factors, like population density and urbanization—which also can be difficult to alter—are significant in influencing personal transport demand.

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## NOTES

1. Energy consumption per capita and distance driven per capita are, indeed, very highly correlated for the countries in this study. The change in the variable of interest reflects the different structure of the two data sets.
2. Hausman tests indicated that a random effects specification may be inconsistent; furthermore, the data set used is more comprehensive than a "sample" of OECD countries, and the unbalanced nature of the data may pose a greater problem for a random effects estimation.
3. Using 5-year intervals produced evidence of serial correlation. To correct for this an autoregressive term was tried, but the Durbin–Watson statistics were only around 1.5, and the regression results were less stable. However, using data occurring at 10-year intervals appears to have solved the serial correlation problems.
4. In the U.S., cars and small trucks consumed between 75 and 80% of fuel used on highways from 1980 to 2000 (data from *National Transportation Statistics 2002*, U.S. Department of Transportation). Data from Schipper, Scholl and Price (1997) suggests a similar 3/4:1/4 energy consumption breakdown between passenger cars and freight in other IEA countries.
5. For example, the average pump-price of gasoline (in USD/l) for the largest eight economies in the OECD was 0.93, during March 2003; the standard deviation was 0.32, and the range [0.42, 1.23]. However, excluding taxes the average price, standard deviation, and range were 0.34, 0.04, and [0.29, 0.42], respectively (data from the IEA).
6. In 2000 only Turkey and Mexico have per capita GDPs below $13,500.
7. However, removing primacy did not appreciably change the coefficients of the other variables in the regressions shown in Table 2.
8. Because Equation (3) was derived using calculus and the data used in the decomposition are discrete, I use the approximations contained in the appendix. Thus, the values in the table are approximations of the instantaneous change calculated at the mid-point.

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## APPENDIX: DATA SOURCES, DEFINITIONS, AND EQUATIONS

### *Panel Data*

Population, GDP (in 95 USD using PPPs), and energy use in the road sector (in tons of oil equivalent) came from the International Energy Agency's Energy Balances of OECD Countries CD-ROM (2002 edition). Energy in road includes all fuels used in road vehicles (including military) as well as agricultural and industrial highway use, but excludes motor gasoline used in stationary engines, and diesel oil for use in tractors that are not for highway use. The IEA does not have energy data for Korea and Mexico until 1971.

Area (in $km^2$) came from International Road Federation *World Road Statistics*.

Urbanization and primacy data came from the United Nation *World Urbanization Prospects: The 2001 Revision*.

The percentage of the population in the 20–39 age group came from Eurostat's New Cronos 2001 database for the European countries (which can be accessed via the internet). For all other countries this population share came from the UN *Demographic Yearbook* and the UN *World Population Prospects: The 2000 Revision*.

Average household size came from the UN *Demographic Yearbook* (various years) and the individual country's national statistics offices. These offices can be accessed from: http://unstats.un.org/unsd/methods/inter-natlinks/sd_natstat.htm.

### *US Household Data*

*Residential Transportation Energy Consumption Survey: Consumption Patterns of Household Vehicles (1994, 1991, 1988, 1985, and 1983).* US Department of Energy's Energy Information Administration. http://www.eia.doe.gov/emeu/rtecs/.

### *Equations for Discrete Approximations Used in the Decomposition Analysis*

The formula to decompose the change in an average (Equation (3)) was derived using calculus; however, the data is discrete; thus, the following approximations (also from Vaupel & Canudus, 2002) were used to estimate values at the mid-point of two data points. If data is available for time $y$ and $y+h$, then Equation (A2) gives the approximation of the value at the mid-point (time $y+h/2$). Equation (A1) yields the relative derivative, or intensity of change at the mid-point, and Equation (A3) provides the estimate of the derivative. These equations assume exponential growth/change between the two data points.

$$v'(x, y+h/2) \approx \frac{ln\left[\frac{v(x,y+h)}{v(x,y)}\right]}{h} \qquad (A1)$$

$$v(x, y+h/2) \approx [v(x,y)v(x,y+h)]^{1/2} \qquad (A2)$$

$$\dot{v}(x, y+h/2) \approx v'(x, y+h/2)v(x, y+h/2) \qquad (A3)$$