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

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ABSTRACT
Demographic variables have tended to be ignored in many environment-development analyses. This paper examines how population changes (in aging, households, and urbanization/density) can help explain changes/differences in personal transport using both macro- and micro- level data. First, panel regressions are performed with IEA-OECD road sector energy use data (spanning 1960-2000) on spatial population measures, average household size, and age structure data. Then US household data is used to determine the extent to which compositional changes in the nature of households can explain changes in per capita driving.

An Environmental Kuznets Curve for per capita road energy use was rejected—the coefficients on the GDP squared terms were insignificant, and the implied turning points were well outside the sample range; instead, the relationship between wealth and road energy was found to be monotonic (log-linear). 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 basic result from the household decompositions was that changes in 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. The look at micro data 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 look at the macro data implies that spatial factors, like population density and urbanization (which also can be difficult to alter) are significant in influencing personal transport demand.

Disclaimer
The views expressed in this paper are the author's own views and do not necessarily represent those of the Max Plank Institute for Demographic Research.

Keywords: population and environment; transport energy use; environmental Kuznets Curve;

OECD countries.

1. Introduction

The purpose of this paper is to take a closer look at how population dynamics (in terms of spatial measures, households, and age structure) impact the environment through transport. Transport is a 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) US 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 impact 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 if 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 examining additional explanatory variables, like trade and structural change (e.g., Suri and Chapman, 1998), institutions (e.g., Torras and Boyce, 1998), or geography (e.g., climate and endogenous resource base in Neumayer, 2002); considering a

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[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.

longer and/or wider data set (e.g., Stern and Common, 2001 or List and Gallet, 1999, who used US state level data); or using more advanced econometric techniques (e.g., Schmalensee et al., 1998 and 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 *certain activities*. Some exceptions to this generalization are Judson et al., (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 et al., (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 important source of impact on the environment, namely, personal transport; and (2) it considers population-geography and demographic factors that are highly related to that activity (and 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 (see Handy, 1992 and Badoe and Miller, 2000 for surveys of the North American literature). 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 developed countries, 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 very important in explaining environmental impact. The first to consider households as the unit of analysis was MacKellar et al. (1995). More recently, O'Neill and Chen (2002) looked at how US residential and transport energy use vary according to household demographic characteristics. Meanwhile, Liu et al., (2003) argued that the increase in number of households, spurred in part by the decline in household size, has a negative impact on biodiversity. 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 1-a shows that in the US as the size of a household increases the average miles driven per person in that household falls. Figure 1-b illustrates (data also from the US) that young people tend to drive more (at least in small households). Prskawetz et al., (2002) demonstrated that similar relationships exist for Austria.

Figures 1-a & b

The following two sections involve the panel regression analysis. Section 2 covers the data set and methodology used, while Section 3 discusses the results. Figures 1-a and 1-b, showing the strong relationship between household characteristics and personal transport in the US, motivate the household decomposition analysis contained in Section 4. In that section the data set, methodology, and results of this investigation are covered. Section 5 concludes the paper with summary and policy implications.

2. 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 9 time periods, i.e., five-year intervals from 1960 to 2000. Total population, GDP (in 1995 US$ using purchasing power parity), and road energy use[3] (in tons of oil equivalent) data come from the IEA (a more detailed explanation of the data and sources is in the appendix). Urbanization, primacy, and the share of people in the 20-39 age cohort 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 square km) is from the International Road Federation.

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.[4] Since all of these countries are democracies, the willingness of people to accept a higher gasoline tax reflects their options to personal transport, a characteristic the spatial indicators are trying to capture. Yet, countries with higher prices may have more

[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] In the US, cars and small trucks consumed between 75-80 percent of fuel used on highways from 1980-2000 (data from *National Transportation Statistics 2002*, US Department of Transportation). Data from Schipper et al. (1997) suggests a similar ¾ : ¼ energy consumption breakdown between passenger cars and freight in other IEA countries.
[4] For example, the average pump-price of gasoline (in USD/liter) 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).

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 or 1965; thus, having a balanced panel means either not including information from the 1960s or not including two of the three developing countries. Second, there are a number of observations of average household size missing (the availability of this data for all the countries is shown in Appendix Table A). If a full, balanced panel containing average household size were used, the data set would be reduced to two cross-sections.

3. Panel regressions: results and discussion

The first model, results shown in Table 1, is essentially a test of an EKC for per capita road energy use. The level of per capita road energy use was regressed on the levels of per capita GDP (GDP) and per capita GDP squared (GDP^2), 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, sometimes, the average household size (avg_hh_size) in people per household. Again, there were also individual country and time dummies (a time trend was tried too, but it did not appreciably change the results). Even with five-year intervals there was evidence of serial correlation. To correct for this an AR 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—Durbin Watson statistics are very close to two.

Table 1

The results confirm the ideas that more dense countries have less personal transport demands and the young drive more. Urbanization and primacy were typically not significant. The time dummies (not shown) were all significant and typically mirrored a trend rather than indicated events like the energy crises. The idea that per capita road energy use will eventually decline with wealth (i.e., an EKC) was rejected—both the coefficients on the GDP squared terms were (in all but one case) statistically insignificant, and the implied turning points were well outside the sample range. This finding is not surprising, particularly given the way the data looks. 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 figure indicates a more or less monotonic relationship.

Figure 2

Indeed, when a classical EKC regression (with only GDP terms as independent variables) was run (Regression I-5 in Table 1) in levels, 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-6), 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 US 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 actually begins to decline at high income levels.

Hence 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 with Schipper et al.'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 results for what was argued above as the better specified, semi-log model are shown in Table 2. Again the most important expected results were confirmed: the relationship between wealth and road energy use is monotonic, although the increase in driving slows at higher levels of income; dense populations demand less personal transport; smaller households mean higher per capita road energy use; and younger people rely more on personal transport. Also, the time dummies were all statistically significant and increasing. Under Model II, urbanization was typically significant, and implied, as expected, that highly urbanized societies have lower demands for personal transport.

Table 2

The main casualty of loosing 50 data points in order to eliminate the serial correlation problems was the average household size variable. In Regression II-4, its coefficient was somewhat lower (than in Regression II-3) and was only significant at an 80 percent 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 1-a for the US (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-4. In part at least, because nearly all the countries used are of similar levels of development (at least in recent years[5]),

[5] In 2000 only Turkey and Mexico have per capita GDPs below $13,500.

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-4 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-5, 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 the other variables were similar as before (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 US data that follows.

It was somewhat surprising that primacy was typically insignificant.[6] This result may stem from the fact that some countries with excellent public transport networks like Belgium and the Netherlands have primacy rates similar to the US 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 was 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 vis-a-vis income. To explore this issue, standardized coefficients were calculated for the regressions of the semi-log model (Model II) with the highest Durbin-Watson statistics. The standardized coefficients, reported in

[6] However, removing primacy did not appreciably change the coefficients of the other variables in the regressions shown in Table 2.

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 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 (I believe) unique to this paper, had at least as much explanatory power as per capita GDP in Regression II-5.

Table 3

Finding variables (in the case here, demographic ones) with considerable explanatory power compared to income provides a contrast to Neumayer (2002), who considered natural factors in his examination of carbon dioxide emissions. Although Neumayer discovered variables measuring climate, natural resource base endowment, and land area impacted by human activity 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 (i.e., these variables could only be expected to explain a fraction of total emissions). 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.

4. Household decomposition: data, methodology, and results

Both Figure 1-a and the results from some of the previous regressions demonstrate that micro-level changes in population (in household sizes, age structure) can impact per capita transport indicators at a more macro-level. In this section I examine the extent to which changes in households 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). US 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 and Canudas, 2002) is:

$$\dot{\bar{v}} = \bar{\dot{v}} + Cov(v, w') \tag{1}$$

Where a dot indicates a derivative, a bar an average, and an accent an intensity of change or relative derivative. Thus, the first right-hand-side term, $\bar{\dot{v}}$, represents the direct change or the demand component, while the second right-hand-side term, $Cov(v, w')$, 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:

$$\bar{v} = \sum_{i=1}^{9} \left(d_i \frac{N_i}{\sum_{i=1}^{9} N_i} \right) \tag{2}$$

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.

Table 4

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.[7] Regardless of the time interval, per capita miles driven increased for data taken as the whole of the US. 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.

5. Conclusions and policy implications

This paper has examined population and transport, specifically household and spatial dynamics, 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). From the panel regressions, an Environmental Kuznets Curve 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 wealth 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 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.

[7] Because Equation 1 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 US$ 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 square km) 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 cohort came from Eurostat's New Cronos 2001 database for the European countries. 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

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/

Table A:
The availability of average household size for each of the countries used in the panel regressions

Country	Periods that average household size is available
Australia	All 9 periods
Austria	60, 70, 80, 90, 95, 2000
Belgium	60, 65, 70, 80, 90, 2000
Canada	All 9 periods
Denmark	60, 65, 70, 80, 85, 90, 95, 2000
Finland	60, 70, 75, 80, 85, 90, 95, 2000
France	60, 70, 75, 80, 90, 2000
Greece	60, 70, 80, 90, 95, 2000
Ireland	60, 65, 70, 80, 90, 2000
Italy	60, 70, 80, 90, 2000
Japan	All 9 periods
Korea*	All 7 periods (not 1960 & 1965)
Mexico*	70, 80, 90, 95, 2000
Netherlands	All 9 periods
New Zealand	All 9 periods
Norway	60, 70, 80, 90, 2000
Portugal	60, 80, 90, 2000
Spain	60, 70, 80, 90, 2000
Sweden	All 9 periods
Switzerland	60, 70, 80, 90
Turkey	60, 65, 70, 75, 80, 85, 90
United Kingdom	All 9 periods
United States	All 9 periods

* Korea and Mexico do not have energy data for 1960 and 1965.

Equations for discrete approximations used in the decomposition analysis

The formula to decompose the change in an average (Equation 1) was derived using calculus; however, the data is discrete; thus, the following approximations (also from Vaupel and 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 4 gives the approximation of the value at the mid-point (time $y + h/2$). Equation 3 yields the relative derivative, or intensity of change at the mid-point, and Equation 5 provides the estimate of the derivative. These equations assume exponential growth/change between the two data points.

$$v'(x, y + h/2) \approx \frac{\ln\left[\frac{v(x, y+h)}{v(x, y)}\right]}{h} \tag{3}$$

$$v(x, y + h/2) \approx \left[v(x, y)\, v(x, y + h)\right]^{1/2} \tag{4}$$

$$\dot{v}(x, y + h/2) \approx v'(x, y + h/2)\, v(x, y + h/2) \tag{5}$$

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	I-3	I-4	I-5	I-6
GDP	3.07E-05*	3.14E-05*	3.09E-05*	2.80E-05*	2.69E-05*	8.41*
	(5.03)	(4.22)	(4.53)	(3.61)	(3.37)	(7.37)
GDP^2	-1.91E-10	-1.75E-10	-2.02E-10	-1.34E-10	-9.51E-11	-0.39*
	(1.19)	(0.95)	(1.11)	(0.69)	(0.53)	(6.27)
Pop_den	-0.00047	-0.00059	-0.00086**	-0.00079***		
	(1.60)	(1.60)	(2.44)	(1.83)		
Urban	-0.036	-0.061	-0.024	-0.036		
	(0.36)	(0.48)	(0.20)	(0.27)		
Primacy	-0.15	-0.10	-0.23	-0.13		
	(1.00)	(0.50)	(1.18)	(0.63)		
Pc_Y20_39	0.95*	1.14*	0.91*	1.11*		
	(4.41)	(3.45)	(3.43)	(3.43)		
Avg_hh_size			-0.049	-0.037		
			(1.59)	(0.88)		
Adj. R^2	0.97	0.7	0.98	0.97	0.97	0.96
D-W	0.82	1.91	0.99	1.98	1.88	2.06
Turning point	87,700	89,700	76,500	104,00	141,000	48,150
Panel	5 yr	10 yr	5 yr	10 yr	10 yr	10 yr
Cross-sections	23	23	23	23	23	23
Obs	203	113	160	110	113	113

Notes: Absolute *t*-values in parentheses; heteroscedasticity-robust standard errors; turning points are in real 1995 PPP US dollars; levels of statistical significance indicated by asterisks: * 99 percent, ** 95 percent, *** 90 percent. In Regression I-6 all terms, including the dependent variable, are in natural logs.

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	II-4	II-5
Ln(GDP)	0.24*	0.25*	0.24*	0.21*	0.18*
	(5.48)	(4.59)	(5.40)	(3.77)	(2.86)
Pop_den	-0.00077**	-0.00093**	-0.0013*	-0.0013**	-0.0015*
	(2.22)	(2.15)	(3.08)	(2.45)	(2.83)
Urban	-0.42*	-0.47*	-0.42*	-0.40*	-0.34***
	(3.28)	(2.90)	(2.87)	(2.55)	(1.85)
Primacy	-0.021	0.025	-0.14	-0.035	-0.25
	(0.11)	(0.10)	(0.55)	(0.13)	(0.90)
Pc_Y20_39	0.99*	1.16*	0.84**	1.07*	
	(3.72)	(2.74)	(2.47)	(2.59)	
Avg_hh_size			-0.080**	-0.065	-0.10**
			(2.26)	(1.27)	(1.98)
Adj. R^2	0.97	0.96	0.97	0.96	0.97
R^2 w/o country dummies	0.46	0.46	0.54	0.49	0.51
D-W	0.80	1.88	0.91	1.92	1.89
Panel	5 yr	10 yr	5 yr	10 yr	10 yr
Cross-sections	23	23	23	23	23
Obs	203	113	160	110	110

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

Table 3: Standardized coefficients for selected regressions from Table 2 (dependent variable is the level of per capita road energy use).

Regression	II-2	II-4	II-5
Ln(GDP)	0.40*	0.33*	0.28*
Pop_den	-0.31**	-0.44**	-0.51*
Urban	-0.21*	-0.18*	-0.15***
Pc_y20_39	0.083*	0.076*	
Avg_hh_size		-0.15	-0.24**

Note: Levels of statistical significance indicated by asterisks: * 99 percent, ** 95 percent, *** 90 percent.

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.

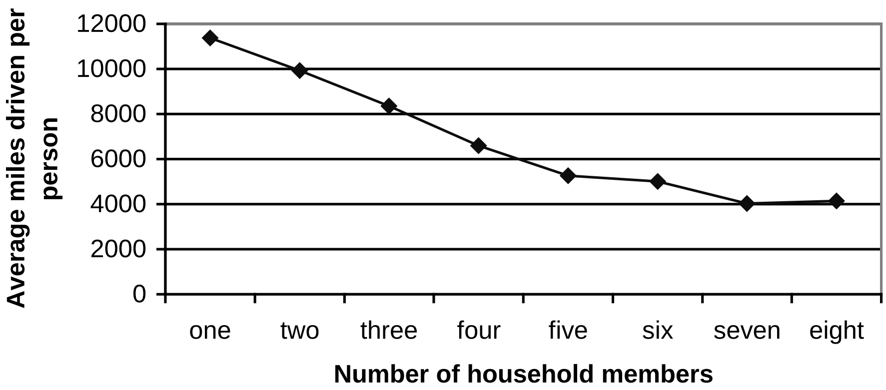

Figure 1-a: Average miles driven per person by household size. Data for the US in 1994 from the Residential Transportation Energy Consumption Survey 1994.

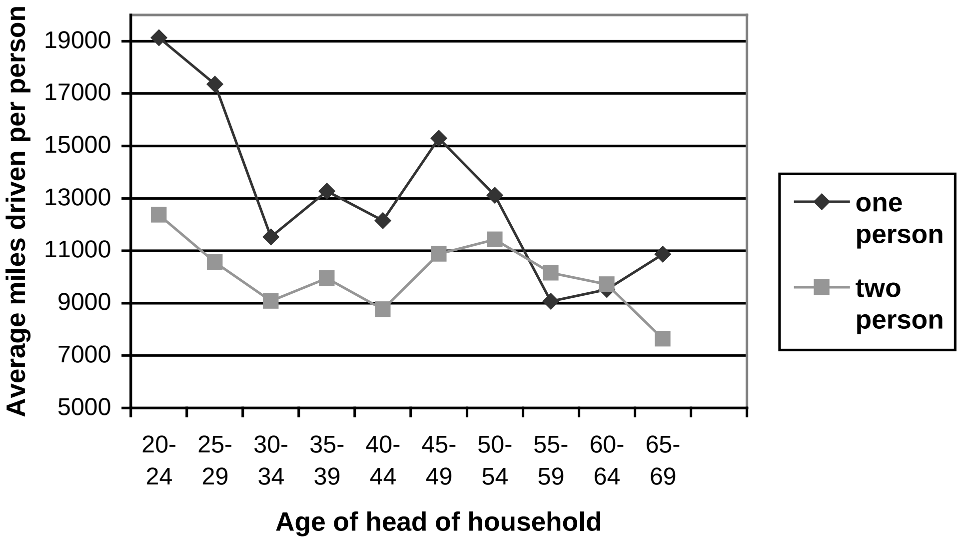

Figure 1-b: Average miles driven per person by age of head of household for households of one and two people. Data for the US in 1990 from the Residential Transportation Energy Consumption Survey.

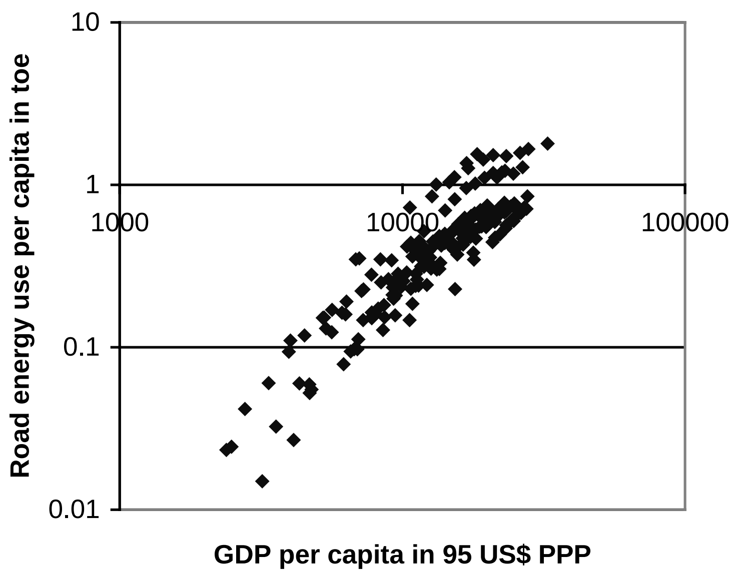

Figure 2: GDP per capita (in 95 US$ PPP) and road energy use per capita (toe) for the entire data set in log scale.