

**Vehicles, Roads, and Road Use:  
Alternative Empirical Specifications**

Gregory K. Ingram and Zhi Liu <sup>\*</sup>

---

\* The authors are grateful to Esra Bennathan, David Canning, Marianne Fay, Reuben Gronau, Kenneth Gwilliam, David D. Li, and Lant Pritchett for discussions on the general topic and related empirical work, and to Michael Young and Alfred Young for research assistance.

## 1. Introduction

A previous paper used panel data from 50 countries and 35 urban areas to summarize trends in motorization and the provision of roads, and to examine the ratio of motor vehicles to roads in a production function framework at both the national and urban levels (Ingram and Liu, 1997). The countries and urban areas, which covered a wide range of income levels, exhibited strong regularities in cross section regressions across country and city characteristics. In particular, income was a strong determinant of both the level of vehicle ownership and road provision. Road provision was buoyant at the national level but not at the urban level, where congestion stimulated decentralized growth and urban road length increased mainly from the annexation of surrounding areas.

The current paper presents additional empirical results obtained using essentially the same national and urban data sets.<sup>1</sup> These new empirical analyses explore alternate specifications of the underlying relations between three dependent variables--vehicle ownership, road length, and the vehicle-road length ratio--and various independent variables. In particular, they investigate (i) whether income elasticities of motor vehicle ownership and road length vary or are essentially constant across a wide range of income, and (ii) how vehicle ownership and road provision respond to changes in income over time.

An income elasticity measures how responsive demand for a good or service is to a change in income, and income elasticities may vary across income levels. However, most empirical studies of motorization (including our previous paper) have estimated only constant income elasticities. Constant elasticities are usually estimated from regressions with a restricted functional form (typically a log-linear specification). One major weakness of a constant income elasticity is its limited predictive power for forecasting beyond the observed income range when the true elasticities vary with income. While constant elasticity estimates are often statistically very robust, their usefulness in forecasting depends on whether they are at least as robust as variable elasticity estimates. This paper reports estimates of variable elasticities and compares them with constant elasticities.

Our previous paper suggested differences between the cross-section and time series relations in the panel data, particularly in the urban data. Cross-section variation often results from long-run behavior, and time series variation from short-run behavior. Specifically, long-run income elasticities capture the change in demand when consumers are able to make an unconstrained behavioral adjustment in response to a change in income, and short-run income elasticities measure the demand change in a constrained situation. Empirically, long-run income elasticities can be estimated using cross-section data that cover a wide range of income levels, while short run elasticities require time series data. The empirical results presented in Ingram and Liu (1997) are essentially long-run estimates because they are obtained from cross-section analyses. While these long-run estimates provide a broad picture of growth patterns of motorization and road provision, in this paper we also compare them with short-run income elasticities.

---

<sup>1</sup> Based on additional data sources, we made minor corrections on the national data set and added two new observations to the urban data set. See Annex A for details and Appendix Tables 10 to 12 for the national data.

## 2. Technical Issues

Table 1 summarizes the key features of the earlier and current empirical analyses. The first two changes were to use less restrictive specifications in the regression equations so that the results were less constrained by the specification.

- First, the dependent variables used in the current study differ from those used earlier because they are not normalized. For example, vehicles are now used as the dependent variable rather than vehicles per thousand persons.
- Second, the earlier estimates all used constant elasticity (log-linear) model specifications. The current results present constant and variable elasticities by employing alternative functional specifications. In addition, both long run (cross sectional) and short run (first differences over time) elasticities were estimated.
- The third change is an attempt, in the urban analysis, to account for the impact of a city's historical spatial endowment on its motorization and road network expansion.

### Dependent Variables

In Ingram and Liu (1997), motor vehicle ownership was normalized with respect to population (vehicles per thousand persons), and the road network was normalized with respect to land area at the country level (kilometers of road length per square kilometer) and population at the urban level (meters of road length per person). When a dependent variable is normalized by an explanatory variable in the log-linear functional specification, the underlying assumption is that the normalizing variable (the denominator) has a constant scale effect on the dependent variable. This assumption is relaxed in the current study. The dependent variable is now the number of vehicles in the vehicle ownership models, and kilometers of road length in the road models. The variables (population or land area) that were used to normalize the dependent variables in the previous paper are now independent variables on the right hand side of the equation. Similar to the properties of the generalized Cobb-Douglas production function, the magnitude of the parameter estimate for each independent variable indicates the existence of any scale effect. The scale effect is constant if the estimated parameter is equal to one, increasing if greater than one, and decreasing if smaller than one.

### Estimating Variable Elasticities

In regression analysis, elasticities can be conveniently estimated using a log-log specification. However, the log-log specification normally used is log-linear and constrains the elasticities to be constant. It does not have the functional flexibility that is required for estimating the variable elasticities. Variable elasticities can be estimated by a more flexible functional form shown below:

**Table 1. Key Features of the Earlier and Current Empirical Analyses**

Feature	Ingram and Liu (1997)	The Current Paper
Dependent variable definition	<ul style="list-style-type: none"> <li>Number of vehicles per thousand population;</li> <li>Length of roads per unit area.</li> </ul>	<ul style="list-style-type: none"> <li>Total number of vehicles;</li> <li>Total length of roads.</li> </ul>
Functional Specification	<ul style="list-style-type: none"> <li>Log-log specification to estimate constant elasticities.</li> </ul>	<ul style="list-style-type: none"> <li>Log-linear specification to estimate constant elasticities;</li> <li>Quadratic log-log specification to estimate variable elasticities;</li> <li>First differencing the time series to control country or urban area specific effect (fixed effect).</li> </ul>
Urban development history	<ul style="list-style-type: none"> <li>No explicit treatment for historical spatial endowment.</li> </ul>	<ul style="list-style-type: none"> <li>Attempt to take historical spatial endowment into account.</li> </ul>

$$\log V = a + b_1 \log Y + b_2 (\log Y)^2 + \sum c_i \log X_i + \sum d_i (\log X_i)^2$$

where  $V$  is the dependent variable;  $Y$ , per capita income;  $X_i$ , other explanatory variables; and  $b_0$ ,  $b_1$ ,  $b_2$ ,  $c_i$  and  $d_i$ , parameters to be estimated. This is called a quadratic log-log equation because it includes independent variables in both linear and quadratic form. It allows non-linearity for all explanatory variables. With this specification, the income elasticity is

$$b_1 + 2 b_2 \log Y$$

and it varies with the level of income.<sup>2</sup> The results of log-linear and quadratic log-log regressions for vehicle ownership, road length, and the vehicle-road ratio at the national level (presented in Appendix Tables 1, 2, and 3) and at the urban level (presented in Appendix Tables 4 and 5) are discussed in the next section.

Non-linear effects can also be tested for by fitting piecewise linear equations. A piecewise linear equation provides flexibility for estimating different slopes for different value ranges of a given explanatory variable. For example, we are interested in knowing whether the income elasticities are different between low-income and high-income countries. We can fit a two-piece linear equation that takes the form:

---

<sup>2</sup> See Annex B for the procedure of deriving the elasticity formula from a quadratic log-log function.

$$\log V = a + b_1 \log Y + b_2 D (\log Y - \log Y^*)$$

where  $V$  is the dependent variable,  $Y$  is per capita income,  $Y^*$  is the benchmark income level that separates the countries into low-income and high-income groups, and  $D$  is a dummy variable that takes the value of zero for low-income countries and one for high-income countries. With this specification,  $b_1$  is the elasticity for the low-income group, and  $(b_1 + b_2)$  is the elasticity for high income groups. Results testing for non-linearity effects of income using piece-wise linear specifications for vehicle ownership, road length, and the vehicle-road ratio (presented in Appendix Tables 6 and 7) are also discussed in the next section. In these equations, we used \$5,500 (in 1987 constant US dollars) as the benchmark income level to separate developing countries from high-income countries.

### Controlling Fixed Effects

Both the national and urban data sets contain observations from a wide range of country income levels, but data are available at only two or three points in time, usually at the beginning of decades or when decennial censuses are taken. Ingram and Liu (1997) presented charts indicating that the cross-section and time-series relations among variables such as vehicle ownership and income are sometimes very similar, but sometimes differ dramatically--particularly for road length at the urban level. The cross-section regressions with the use of year dummy variables, reported in Ingram and Liu (1997), do not really exploit the panel nature of the data. In those regressions, the *levels* of income often explain much of the variations in the *levels* of the dependent variable. It is often interesting to know how *changes* in the dependent variable over a given period of time correspond to the *changes* of the explanatory variables over the same period of time. In addition, it is often desirable to control for country or urban fixed effects which may be associated with the level of the dependent variable. This can be done by estimating the first difference regressions in the functional form shown below:

$$\log V_2 - \log V_1 = b_0 + \sum b_i (\log X_{i2} - \log X_{i1}) \quad (i = 1, \dots, k);$$

where subscripts 1 and 2 denote two points in time;  $V_t$ , the dependent variable;  $X_{it}$ , the  $i$ th explanatory variable; and  $b_0$  and  $b_i$ , parameters. The first-difference regression results are shown in Appendix Table 8 for the national level and Appendix Table 9 for the urban level.

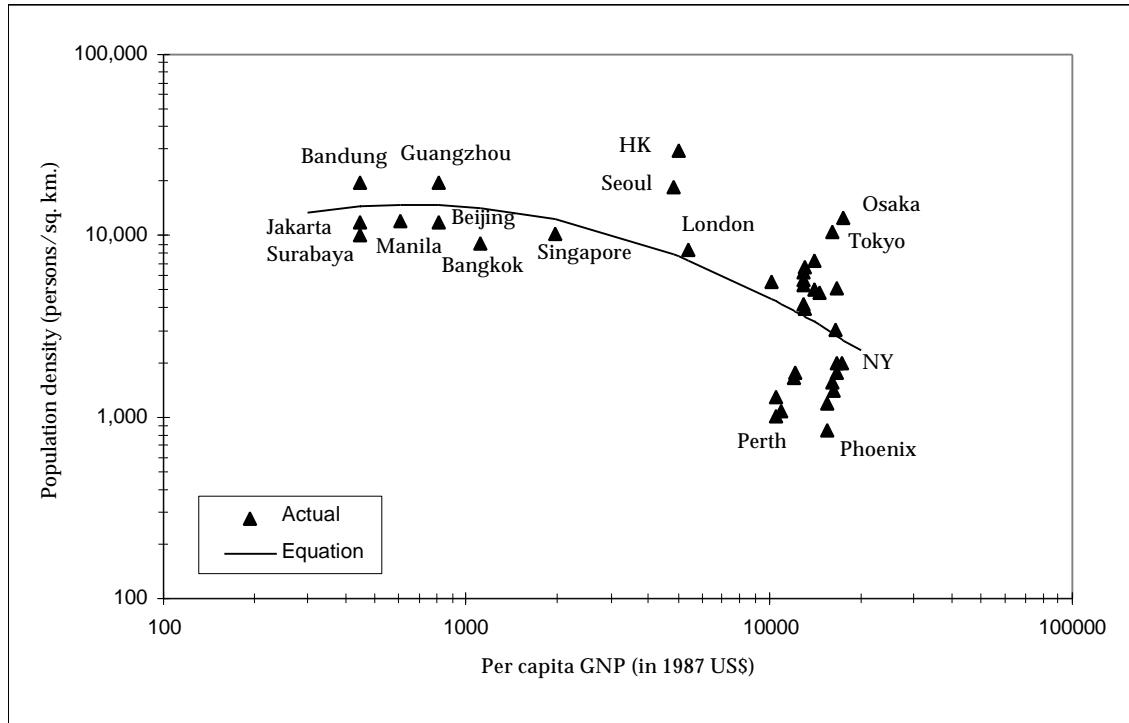
### Analyses with Urban Area Data

In Ingram and Liu (1997), income and population density were often used as explanatory variables in the same regression equation. As Figure 1 indicates, urban per capita income and population density are strongly and nonlinearly related. This cross-section correlation between income and population density at the urban level makes it difficult to interpret the coefficients of these two variables and their effects on urban area motorization when both are used as independent variables. In this study, we attempt to deal explicitly with this problem.

Figure 1 shows that urban population densities vary widely in high income cities. This variation in population density in high income cities reflects the impact of historical paths of development on urban form. Cities that have experienced much of their population growth when auto ownership levels have been high have lower densities than older cities. Although average densities vary significantly across high income cities, the trends in urban

population density in high income cities are similar: population densities are falling in virtually all high income cities (Ingram, 1997). However, because buildings and lot sizes are durable, population density adjusts slowly and historical development patterns persist.

**Figure 1. Per Capita Income and Population Density, 37 World Cities**



The effect of historical paths of development on urban densities is represented by a new variable, the historical spatial endowment index, that measures the variation in per capita land area across cities that is not explained by income and population. Using the urban data set, per capita land area (the inverse of population density) is the dependent variable in the regression shown below (standard errors are in parentheses under the coefficient estimates). It is a function of population (P) and per capita income (Y).

$$\log A = 5.23 - 0.14 \log P - 2.08 \log Y + 0.16 (\log Y)^2 \quad R^2 = 0.41$$

$$(4.14) \quad (0.07) \quad (1.07) \quad (0.07)$$

This estimated equation is used to calculate the predicted amount of per capita land area for each of the cities included in the sample. The historical spatial endowment index is defined as the log of each city's actual per capita land area divided by its predicted per capita land area, and it is used in place of population density in the urban regressions in Appendix Tables 5 and 7..

The historical spatial endowment index measures the residual from the above equation and captures the variations in per capita land area which cannot be systematically explained by per capita income and population. These variations, to a great extent, represent the historical spatial endowment of the cities. Phoenix and Perth, for example, have very low population densities partly because they were largely developed after the advent of automobiles, and partly because their income levels are high. They have positive historical spatial endowment indices. In contrast, some high-income European cities were

shaped long before the advent of automobiles. These cities have income levels similar to Phoenix and Perth, but they have much higher population densities and negative historical spatial endowment indices. Theory suggests that the level of motorization across cities will be higher when the historical spatial endowment index is positive (densities are low). This hypothesis is supported by the statistically significant coefficients of this historic spatial endowment index variable in the equations presented in Appendix Tables 5 and 7..

### 3. Results

The regressions presented in Appendix Tables 1 through 9 produce elasticity estimates of vehicle ownership, road length and the vehicle-road ratio at the national and urban levels, with respect to per capita income, population, and population density. Our primary interest is in the comparison of three types of income elasticities: constant, variable, and first difference (short-run or fixed-effect controlled). The variable elasticities are calculated for the mean values of independent variables for low-income and high-income countries, and these mean values are shown in Annex A, Table A-1.

#### Vehicles

Table 2 summarizes the elasticity estimates from the national and urban vehicle ownership models. At the national level, all income elasticities are statistically significant, while population and population density elasticities are not always significant. The estimates obtained from the constant elasticity equations suggest that both the total motor vehicle fleet and the passenger car fleet expand roughly at the same rate as per capita income and population (elasticities are around 1). The commercial vehicle fleet expands at a lower rate than per capita income but at the same rate as population. Population density has a small but significant negative effect on total motor vehicle ownership and on the number of commercial vehicles. These results are consistent with the estimates obtained from the per capita (instead of total) vehicle ownership models presented in Ingram and Liu (1997) because population has a constant scale effect (its elasticity is about 1). Moreover, the first difference equations that control for country fixed-effects produce short-run income elasticity estimates of about 1.0 for total motor vehicles, passenger cars, and commercial vehicles. The first two are similar to the long-run elasticities, while the long-run elasticity for commercial vehicles (0.7) is lower than the short-run elasticity (1.1).

At the national level, the variable income elasticities are statistically significant and decrease with income. The variable elasticities for population and population density change little and are not always significant. At the urban level, the variable income elasticities are not significant. In addition to examining the statistical significance of the quadratic terms in the regressions to test for non-linearity, the R-square statistics also indicate the overall goodness of fit of the linear and nonlinear specifications. Table 2 indicates that the adjusted R-square statistics for the linear and nonlinear specifications are

**Table 2. Elasticities of Motor Vehicle Ownership with Respect to Per capita Income, Population, and Population Density**

Type of Elasticity Estimates	Elasticity Estimates			R-squared
	Per capita income	Population	Population density	
<b>National motor vehicle fleet</b>				
Constant	0.9 *	1.0 *	-0.1 *	0.94
Varying: at the mean of low-income group	1.3 *	0.9	-0.1 *	0.95
Varying: at the mean of high-income group	0.9 *	0.9	-0.1 *	0.95
First difference	1.0 *	0.5	n.a.	0.55
<b>National passenger cars</b>				
Constant	1.0 *	1.0 *	-0.1	0.93
Varying: at the mean of low-income group	1.5 *	0.8 *	-0.1 *	0.94
Varying: at the mean of high-income group	0.9 *	0.9 *	-0.2 *	0.94
First difference	1.1 *	0.3	n.a.	0.61
<b>National commercial vehicles</b>				
Constant	0.7 *	1.0 *	-0.2 *	0.88
Varying: at the mean of low-income group	1.0 *	1.2	-0.1	0.89
Varying: at the mean of high-income group	0.3 *	1.2	0.0	0.89
First difference	1.1 *	0.9	n.a.	0.26
<b>Urban motor vehicle fleet</b>				
Constant	0.7 - 0.8 *	0.8 - 1.0 *	-0.4 *	0.90
Varying: at the mean of low-income group	0.6	n.a.	n.a.	0.90
Varying: at the mean of high-income group	0.7	n.a.	n.a.	0.90
First difference	1.0 *	1.0 *	0.1	0.49

n.a. Not applicable.

\* Statistically significant at the 0.05 level.

virtually identical at both the national and urban level--suggesting that the two specifications fit the data equally well.

At the national level, the piecewise linear regression specification (Appendix Table 6, Eq. 1) produces a lower income elasticity estimate for high-income countries than for developing countries, and the effect is significant. Yet that equation's adjusted R-square statistic of 0.95 is also virtually identical to the 0.94 of the linear specification. At the urban level, the piecewise linear regression specification (Appendix Table 7, Eq. 1) is not significant, and its R-square is similar to the regular linear regression.

The conclusion of this analysis is that income elasticities of motor vehicle ownership at the national level are only weakly nonlinear, and population and population density elasticities are essentially linear. At the urban level income elasticities of motor vehicle ownership are linear. Overall, linearity is the most parsimonious specification consistent with the data.

These results for income elasticities are summarized graphically in figures 2a and 2b

which plot the relationship between per capita income and motor vehicles per thousand population using the constant and variable elasticity equations, respectively. The variable elasticity estimates appear to be heavily affected by the behavior pattern of the lowest income countries (below US\$1,000 per capita in 1987 constant US dollars). It is not clear, however, whether the higher income elasticities at the lower income level are an indication of different behavior (higher rates of capital accumulation), or merely the result of limited sample size (50 countries). Because the estimated quadratic log-log equations do not deviate much from the log-log equations at the national level (and not at all at the urban level), using constant elasticities to project motorization would not yield a substantially different result from using the variable elasticities.

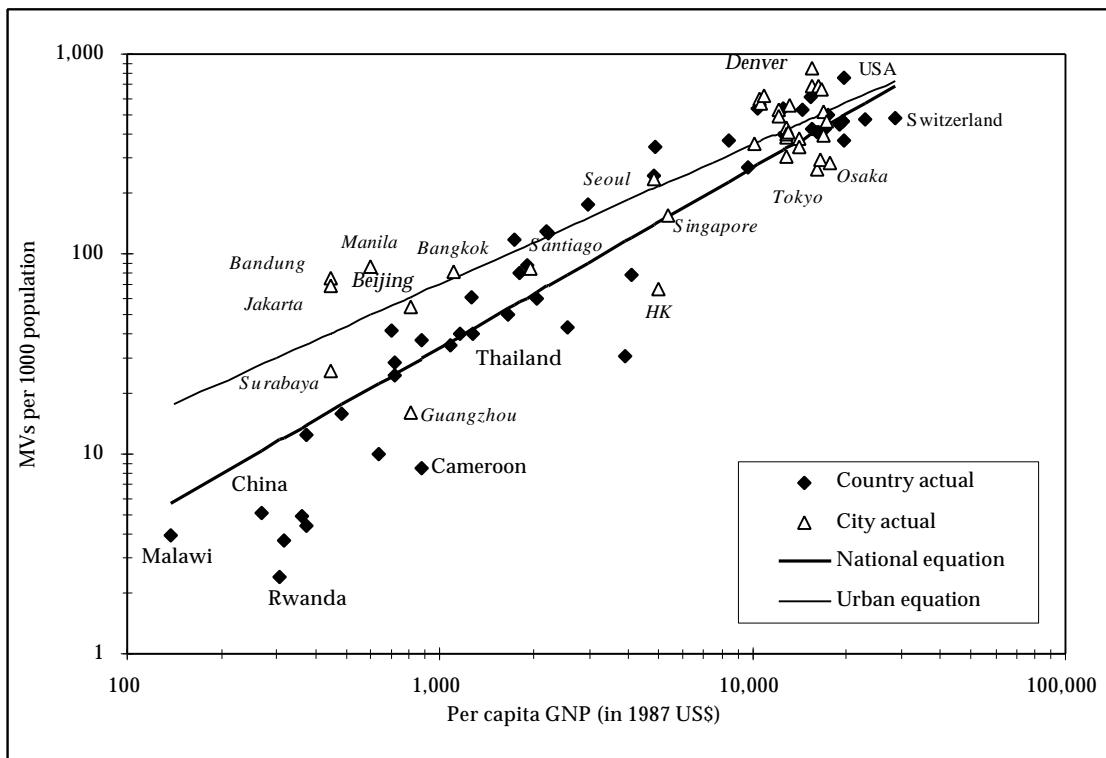
It is fair to conclude that although elasticity estimates vary depending on the functional specification, a good point estimate is approximately 1 for the elasticity of national fleet growth with respect to per capita income and population. These values mean that country motor vehicle fleets grow at roughly the same rate as country incomes.

At the urban level, the estimates of the income elasticity of vehicle ownership should be interpreted with caution because vehicle ownership interacts strongly with population density, and both are strongly affected by income. Income elasticity estimates are about 0.8 if population density is omitted from the vehicle ownership equations (see, for example, Appendix Table 4, Eq. 1b). When the historical spatial endowment index is considered, the estimate is about 0.7 (Appendix Table 5, Eq. 1a). A comparison of the two urban vehicle ownership equations in Appendix Table 5 (Eq. 1a and 1b) indicates that motor vehicle ownership is basically linear with income on the log-log scale. And the estimates from the piecewise regression (Appendix Table 7, Eq. 1) suggest that the income elasticity for low-income cities is not statistically different from that for high-income cities. Finally, similar to the national equations, the income elasticity estimates from the first-difference urban equations turns out to be about 1.0.

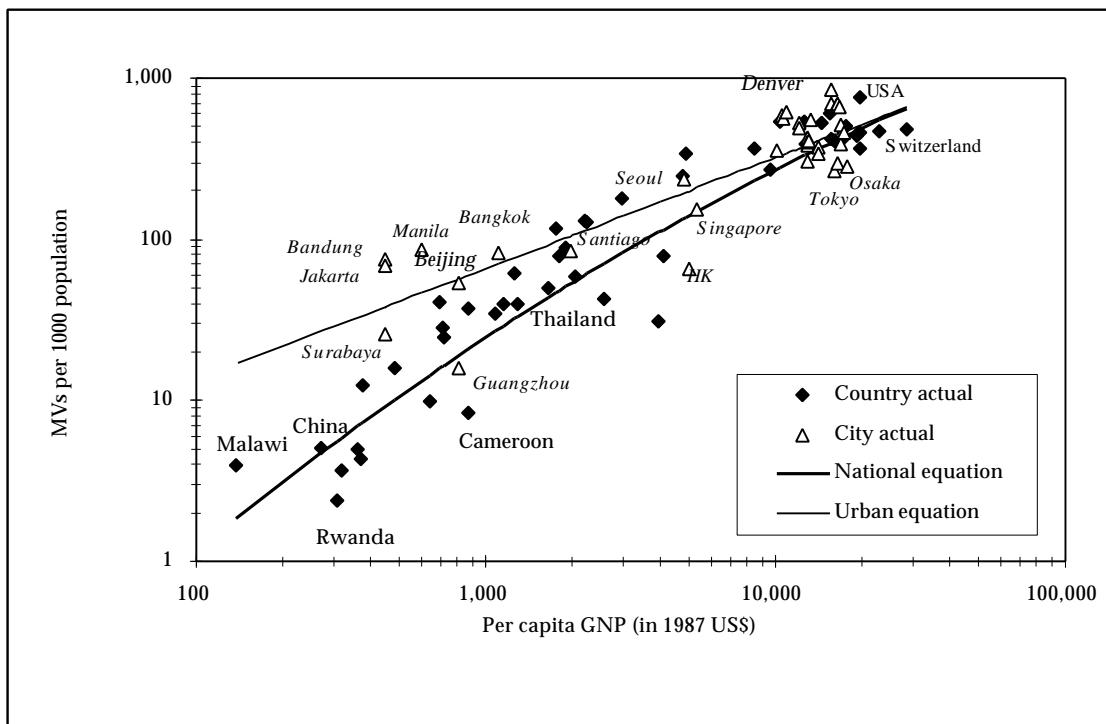
It should be noted that the per capita incomes used in the urban area data set are actually country income data. It is known that the urban and national difference in per capita income is much greater in developing countries than in high income countries. This implies that the true range of urban income levels for the urban sample is narrower than that suggested by the income data used. Therefore, the true income elasticities for urban areas may be greater than the current estimates. The use of country income data in urban equations may affect the cross-section estimates more than the first-difference estimates, because changes in urban incomes would be quite similar to changes in country incomes over a short period of time.

### Roads

Because roadways complement motorization, the growth of the road network is likely to be associated systematically with changes in the same economic variables that affect the growth of the motor vehicle fleet. Empirical analyses by Ingram and Liu (1997) at the national level found that income per capita is a major determinant of road length, and that road provision is quite responsive to demand. While total road networks expand more



**Figure 2a. Per Capita Income and Motor Vehicle Ownership**



**Figure 2b. Per Capita Income and Motor Vehicle Ownership: Alternative Specification for National Equation**

slowly than income, paved road networks expand at the same rate as income. At the urban level, per capita road length is positively associated with per capita income across world cities but changes little over time.

The empirical results from the current analyses are summarized in Table 3. At the national level, income elasticities of road length are 0.5 for total roads and 1.0 for paved roads. The variable income elasticity estimates are statistically insignificant even at the 0.10 level for both total roads and paved roads, suggesting that the income elasticity of road length is constant. The piecewise regression analysis produces a statistically significant non-linear relation for total road length, but not for paved road length (Appendix Table 6, Eq. 2 and 3). Both total road length and paved road length are unit elastic with population, and the variable population elasticities are not significant, indicating that the constant elasticity specification for population is consistent with the data. Again, population demonstrates a constant scale relation with road length because its elasticities are 1. These estimates are based on the cross-sectional variation in panel data, but fixed effect estimates based on first differences over time in the same panel data produced generally similar results for income. The first difference results differ for population: The population elasticity is insignificant for total roads (value of 0.4) and significant and larger for paved roads (value of 1.3) compared to the cross section results..

**Table 3. Elasticities of Road Length with Respect to Per Capita Income, Population, and Population Density**

Type of Elasticity Estimates	Elasticity Estimates			R-squared
	Per capita income	Population	Population density	
<b>National: length of total road</b>				
Constant	0.5 *	1.0 *	-0.3 *	0.89
Varying: at the mean of low-income group	0.6	1.1	-0.3	0.90
Varying: at the mean of high-income group	0.5	1.1	-0.3	0.90
First difference	0.5	0.4	n.a.	0.30
<b>National: length of paved road</b>				
Constant	1.0 *	1.0 *	0.0	0.86
Varying: at the mean of low-income group	0.8	1.3	-0.1 *	0.87
Varying: at the mean of high-income group	1.0	1.2	-0.2 *	0.87
First difference	0.8 *	1.3 *	n.a.	0.32
<b>Urban: length of urban road</b>				
Constant	0.7 *	0.8 *	-0.8 *	0.92
Varying: at the mean of low-income group	0.6 *	n.a.	n.a.	0.93
Varying: at the mean of high-income group	1.2 *	n.a.	n.a.	0.93
First difference	0.1 *	0.5 *	-0.4 *	0.18

n.a. Not applicable.

\* Statistically significant at the 0.05 level.

The elasticity of population density for the total road equation is negative and statistically significant, suggesting that holding total population equal, lower population density (or higher per capita--and national--land area) is associated with longer total road length. The total road network in a country usually expands to connect all population distributed across the country. Therefore, a larger area requires more extensive road network to serve. In contrast, there is a weak relationship between population density and the total length of paved roads. This is because roads are paved for facilitating high volume of motorized traffic, instead of improving connectivity to human settlements and economic activities. Empirical analyses by Canning (1998) also provided similar findings.

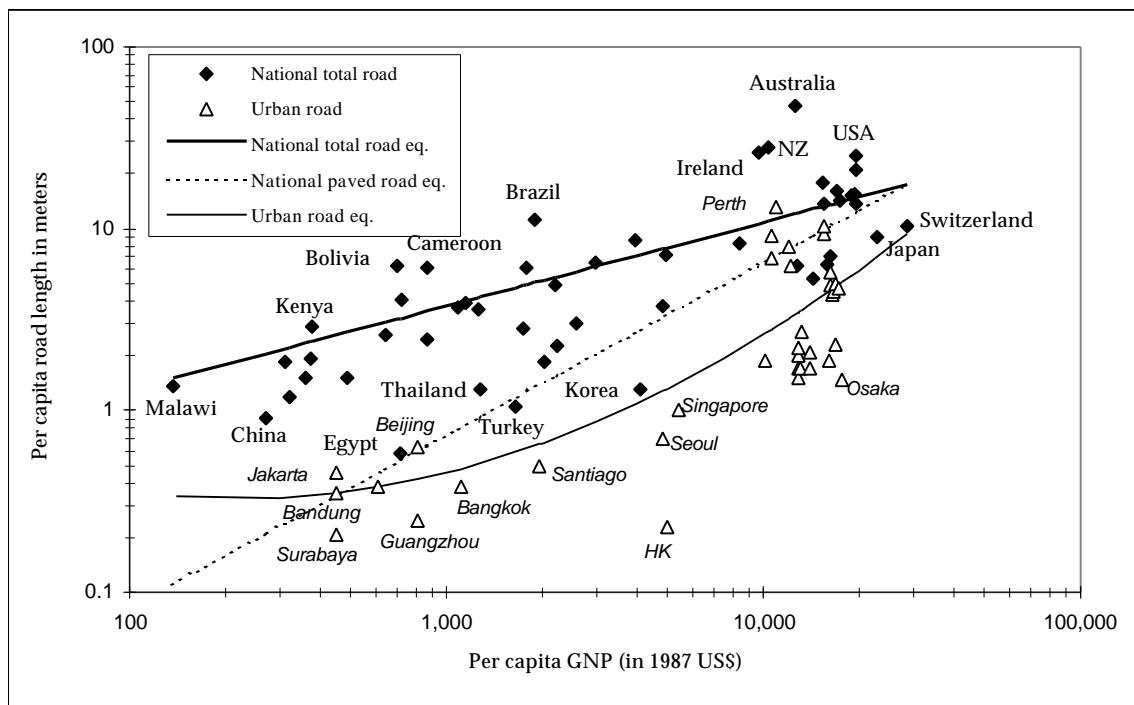
Road provision at the urban level differs greatly from that at the national level. The urban results shown in Table 3 are based on panel data from 36 cities in both developing and developed countries, and the elasticities take into account the strong negative correlation between per capita income and population density at the urban level. (The results are from equations using the historical spatial endowment index, Appendix tables 5 and 7.) As the results indicate, urban road length has a population elasticity of 0.8, suggesting a decreasing scale effect. The elasticity of urban road length with per capita income is non-constant (increasing with income), and its elasticity with population density (negative) is much stronger than at the national level. Another major difference with the urban results is the relatively large differences between the long run (cross section) and

short run (first difference) elasticity estimates--particularly for the elasticity of road provision with respect to income. Urban road length increases over time very slowly with income. The first difference elasticities of population and population density are also smaller than the cross section estimates. The cross section data and equation estimates of the relation between road length and income are summarized in Figure 3.

The strong non-linear relationship between urban road length and per capita income reflects the non-linear relationship between per capita income and per capita land area shown in Figure 1. Much of this cross section non-linearity stems from the growth of high income cities during the automobile age, discussed earlier.

In addition, as incomes rise in urban areas, population densities often decline in built up areas as both employment and residences decentralize. Some urban population growth occurs through expansion of the urban perimeter by annexation of surrounding municipalities. Municipalities that are annexed are usually already developed and have road networks. Therefore, most of the increases in urban road length stem from annexation and not from constructing new roads in built-up areas (Ingram and Liu, 1997). In fact, relatively little new road length is being constructed in the existing urban areas, presumably because the cost of new rights of way is high in both economic and political terms. Urban growth often takes place in the periphery where land costs are lower, more open space can be found, and less-congested roads are available. The strong implication of urban territory annexations is that urban areas provide road capacity by spreading development over space and not by increasing the density of roads in existing built up areas. Even with annexation as a source of new road capacity, however, urban road length is increasing much more slowly than the number of urban vehicles.

**Figure 3. Per Capita Income and Per Capita Road Length**



### Ratio of Vehicles to Roads

Our previous paper used the ratio of vehicles to roads as a proxy for road traffic per unit of road length and examined its variation at the national and urban levels in a production function framework. Similar to the production of manufactured goods with factor inputs of labor and machinery, road transport services are produced by a combination of vehicles and roads, and the ratio of vehicles to roads should vary with their relative prices. We hypothesized that the ratio of vehicles to total roads should increase with income at the national level because the prices of vehicles (as traded goods) should not vary with income, whereas the cost of roads (as nontraded goods) should increase with country income level. But the relationship between the vehicle-road ratio and income may not increase with income at the urban level when congestion is present because the value of commuter travel time (a component of vehicle service cost) increases with income--and travel time would increase as congestion worsened. The results from the simple models based on the above reasoning had substantial power to explain the variation in vehicle-road ratios at the national level.

In the current analyses, we test the non-linearity between income and the vehicle-road ratio at the national and urban levels. The results are summarized in Table 4. At the national level, the income elasticity of the vehicle-road ratio based on the constant elasticity specification is roughly 0.4 for total roads, and essentially zero for paved roads.<sup>3</sup>

---

<sup>3</sup> Because the log of vehicle-road ratio can be decomposed into the log of vehicles minus the log of road length, the relationship between vehicle-road ratio and income can be approximately inferred from the income elasticity estimates of motor vehicle fleet minus those of road length.

**Table 4. Elasticities of the Vehicle-Road Ratio with Respect to Per Capita Income, Population, and Population Density**

Type of Elasticity Estimates	Elasticity Estimates			R-squared
	Per capita income	Population	Population density	
<b>National vehicles/total road km</b>				
Constant	0.4 *	0.0	0.2 *	0.66
Varying: at the mean of low-income group <sup>(1)</sup>	0.8 *	0.0 *	0.4	0.73
Varying: at the mean of high-income group	0.3 *	0.1 *	0.5	0.73
First difference	0.4	0.3	n.a.	0.18
<b>National vehicles/paved road km</b>				
Constant	0.0	0.0	-0.1 *	0.20
Varying: at the mean of low-income group	0.4 *	0.0 *	-0.1	0.33
Varying: at the mean of high-income group	-0.2 *	0.1 *	-0.1	0.33
First difference	0.2	-0.9	n.a.	0.01
<b>Urban vehicles/road km</b>				
Constant	-0.03	0.1	0.6 *	0.40
Varying: at the mean of low-income group	0.1 *	n.a.	n.a.	0.42
Varying: at the mean of high-income group	-0.5 *	n.a.	n.a.	0.42
First difference	0.9	0.5	0.5	0.28

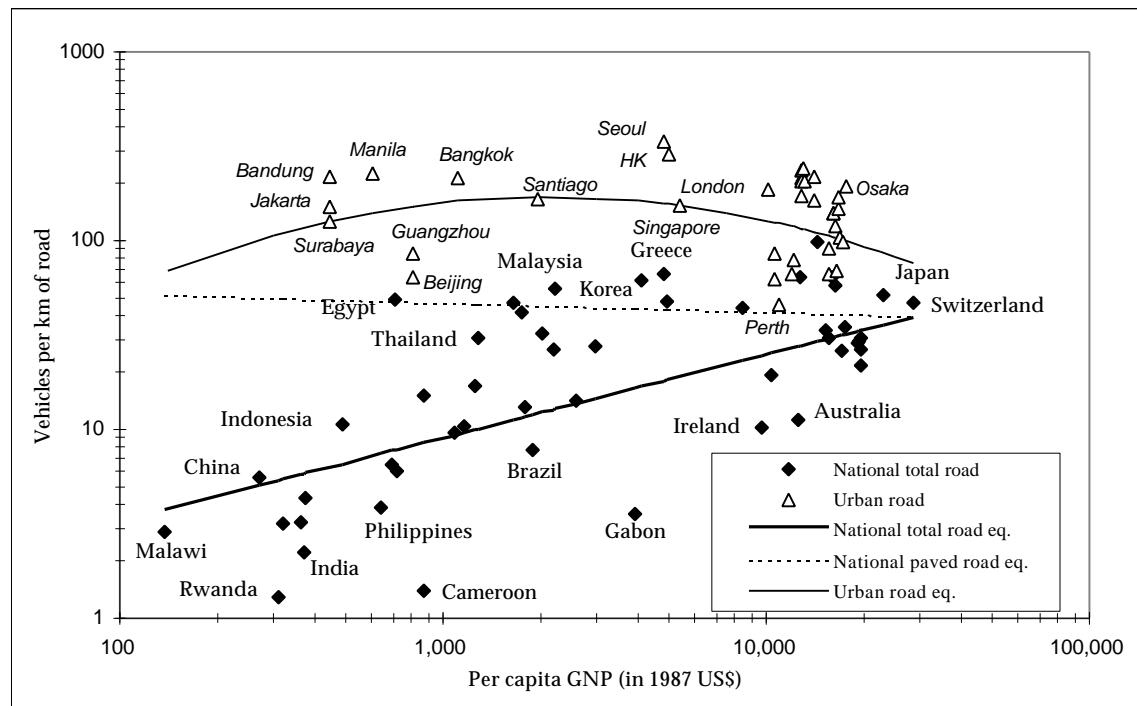
n.a. Not applicable.

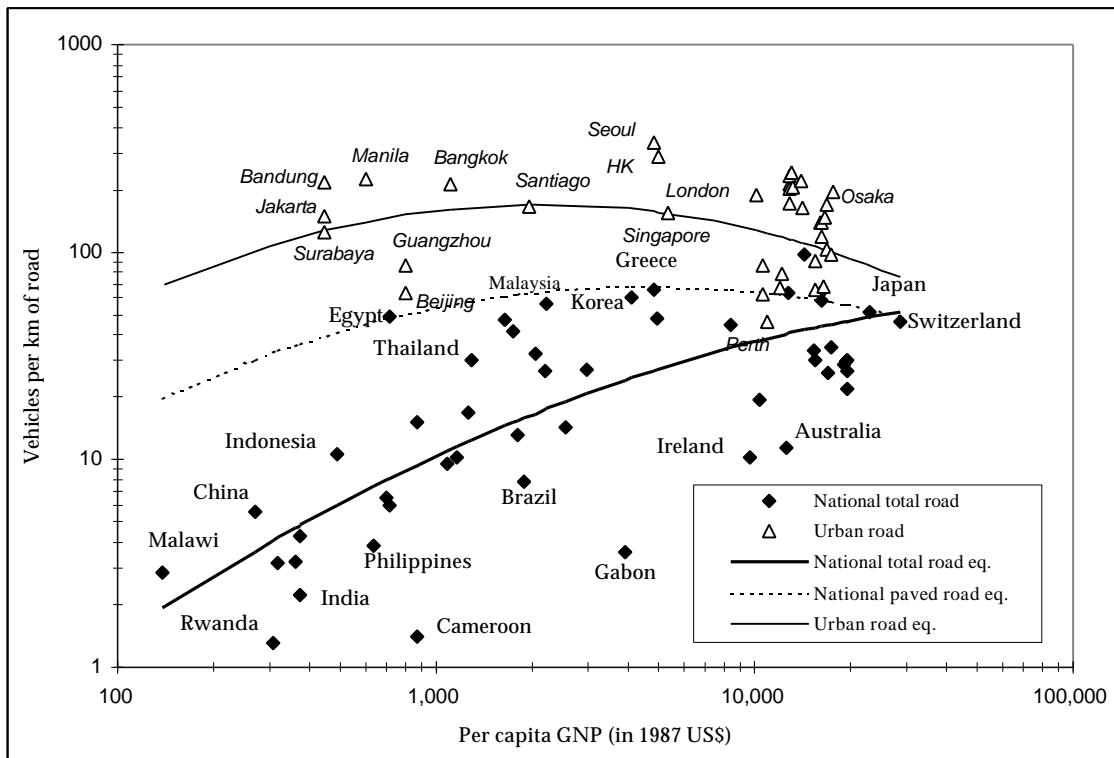
\* Statistically significant at the 0.05 level.

(1) The mean of per capita income for each income group is taken from Appendix 1, Table A-1.

The relation between the vehicle-total road ratio and income is reasonably similar in cross section and (fixed effect) time series specifications. The relations between the vehicle-paved road ratio and income differ for the cross section and first difference estimates, but both are not significantly different from zero. However, the quadratic log-log regression produces relatively significant non-linear results for both total and paved roads, and these non-linear relations are also confirmed by the piecewise regression analysis. In addition, the R-square statistic is notably higher for the nonlinear specifications--suggesting that the vehicle-road income elasticities are nonlinear.

The relation between the vehicle-road ratio and population is insignificantly different from zero in both the constant elasticity and first difference specifications at both the national and urban level. This is consistent with the constant scale effect of population in the vehicle ownership and road length equations. But the relation is significant, although numerically small, in the nonlinear specifications which indicates that population growth slightly increases the vehicle-road ratio at the national level. Population density is significant only in the constant elasticity specifications, where it is positive for the ratio of vehicles to total national roads and to urban roads, but negative for paved roads. This indicates that higher population densities increase the overall vehicle-road ratio, but also stimulate improvements in road quality via paving.

**Figure 4a. Per capita Income and Vehicle-to-Road Ratio****Figure 4b. Per capita Income and Vehicle-to-Road Ratio: Alternative Specifications for National Equations**



The estimated linear and non-linear relations between the vehicle-road ratio and income are illustrated in Figures 4a and 4b for the purpose of comparison. As Figure 4b shows, the ratio of vehicles to total roads is an increasing function of income (though at a decreasing rate) across the wide range of country income levels. This is consistent with our argument that the vehicle-road ratio should increase with income on the national total road network. The non-linear equation for the ratio of vehicles to paved roads suggests that across countries the ratio increases with country per capita income up to about US\$5,000 (in 1987 US dollars) and then declines. This income level is close to the benchmark (US\$5,500) that separates countries into low-income and high-income groups. Caution should apply to the non-linear relation for the ratio on paved roads, however, because we do not know how many vehicle trips are actually made on the paved roads and on the unpaved roads. That the ratio of vehicles to paved roads is independent of income should not be ruled out, as the analysis with the constant elasticity specification indicates that both the motor vehicle fleet and paved road length expand roughly at the same rate as income.

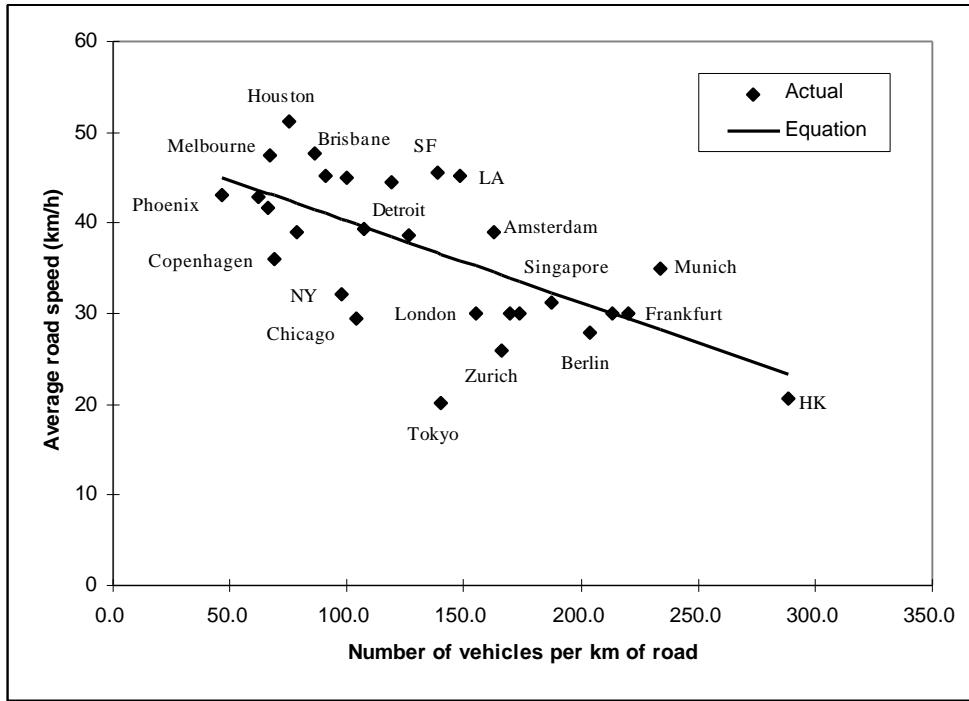
At the urban level, because of the linearity in vehicle ownership and the non-linearity in road provision (see Tables 2 and 3), it is not surprising that the vehicle-road ratio exhibits a strong non-linear relation with income. As per capita income grows, the vehicle-road ratio first increases up to an income level of about US\$2,000 (in 1987 US dollars), then decreases.

This non-linear relation can be explained by the presence of road congestion in urban areas. Although the vehicle-road ratio is an imperfect indicator of the level of road congestion, it is nonetheless a reasonably good proxy. As the statistics shown in Table A-1 of Annex A indicate, on average the number of motor vehicles per kilometer of total roads at the urban level is more than ten times higher than at the national level for developing countries, and five times higher for high-income countries. Moreover, the data for 29 world cities shown in Figure 5 indicate that the vehicle-road ratio at the urban level is highly correlated with average road speeds. The figure reveals a clear negative relationship between the vehicle-road ratio and average road speed, which is generally similar to the empirical relationship between speed and the volume-capacity ratio commonly used in urban transport planning. As a proxy for the traffic level on the road network, the vehicle-road ratio is expected to increase with the relative prices of vehicles to roads at low vehicle-road ratios (such as on national total road networks). Most of the national road networks have fewer than 50 motor vehicles per kilometer of road length, so congestion on national roads is not a common problem even in high income countries. But when congestion occurs in urban areas, speeds fall and travel time cost increases, thus economically justifying more roads.

The peak and decline of the vehicle-road ratio for national paved roads is likely to be related to an increasing demand for higher quality roads, and possibly for vehicle speed, as incomes increase. Paving roads is an obvious means of improving road quality, which reduces vehicle operating costs. Speeds are typically higher on paved roads than on unpaved roads, and the demand for speed (lower travel times) increases with income and the value of time.

Finally, there is a big difference between the cross section and first difference

income elasticities of the vehicle-road ratio at the urban level. The vehicle-road ratio is increasing over time (first difference results) nearly in step with income, whereas the cross



**Figure 5. Vehicle-Road ratio and Average Road Speeds in Urban Areas**

Source: generated from data provided in Newman and Kenworthy (1989).

section income elasticity is much smaller. The increase in the urban vehicle-road ratio, and associated urban congestion, is emerging as the key issue in urban transportation.

Finally, it is interesting to see whether a saturation level for the vehicle-road ratio exists at the urban level, where the road network is often congested. The saturation level for the vehicle-road ratio is defined as the possible maximum vehicle-road ratio among any combinations of income level, population, population density, gasoline prices, etc.. It can be estimated by searching across alternative assumed saturation levels in regressions specified in the form of an S-shaped logistic function. The regression with the highest R-square gives the saturation level under a “business as usual” scenario.<sup>4</sup> These logistic regressions have the following functional form:

$$V/R = S / (1 + e^{b_0 + b_1 Y + b_2 P + b_3 D + b_4 G}),$$

where  $V/R$  is the vehicle-road ratio;  $S$ , the saturation level;  $Y$ , per capita GNP;  $P$ , population;  $D$ , population density;  $G$ , gasoline prices; and  $b_0, \dots, b_4$ , parameters.

The saturation level for the vehicle-road ratio at the urban level is estimated to be 550 vehicles per kilometer of road. The maximum value in the sample, 425, is found in Paris. It is interesting to note that Paris is often considered to be one of the more successful world cities in effectively controlling the use of motor vehicles. In contrast, no saturation level is found from the national level data for both total road and paved road networks. The result is not surprising as the national road networks are rarely congested.

#### 4. Concluding Remarks

This paper explores alternative specifications for the relations of vehicle ownership, road length, and the vehicle-road ratio with various independent variables at the national and urban level. It examines three issues: dependent variable definition, equation specification, and urban historical spatial endowments. We first summarize the results of these efforts and then comment on the overall implications of the findings.

**Dependent variable definition.** The analysis here compared the results of normalized (e.g., vehicles per thousand persons) and non-normalized (e.g., vehicles) dependent variables in regression equations to explain vehicle ownership and road length. For vehicle equations at the national and urban level, the normalized and non-normalized results were very similar because the elasticity of population with vehicle ownership is approximately 1, and population has a constant scale effect on vehicle ownership. The road length regressions at the national level produced similar results with normalized (road length per square kilometer) and non-normalized (road length) dependent variables. This was not true at the urban level where the normalized dependent variable had been road length per capita. In the urban road length equation, population had an elasticity of around 0.8, and because it differed from 1, the non-normalized equation elasticities differed from the

---

<sup>4</sup> Searching over a single parameter value to maximize  $R^2$  produces a maximum likelihood estimate of the parameter value.

normalized equation elasticities. The general lesson from this exercise is that normalized dependent variables should not be used without testing for their validity. Non-normalized variables are generally preferable.

**Equation specifications.** The first question addressed was whether the elasticities of the various dependent variables were constant or varying with respect to the main independent variables--income, population, and population density. The results of this exercise are summarized in Table 5. The results of main interest pertain to the income elasticities, where the most notable feature is the contrast between the national level and urban level results. The income elasticity of vehicle ownership is weakly variable at the

**Table 5. Summary of Elasticity Results--Constant versus Variable**

Dependent variable	National			Urban
	Income	Population	Pop. density	Income
Vehicles	variable?	constant	constant	constant
Road length	constant	constant	constant	variable
Vehicle-road ratio	variable	variable	constant	variable

national level but constant at the urban level. The road length results are the reverse. And the vehicle-road ratios show evidence of variability at both the national and urban levels.

The second question addressed regarding equation specifications involved comparing cross section (long run) elasticities with time series or first difference (short run) elasticities. The estimated elasticities resulting from the two different specifications are summarized in Table 6. There are only modest differences between the time series and cross section income elasticities at the national level, but beyond that many differences emerge. The most striking differences between the time series and cross section elasticities emerge among the income elasticities for road length and the vehicle-road ratio at the urban level. These results offer stark evidence that road provision is lagging in urban areas while the size of urban vehicle fleets continues to grow. The consequence is that the urban vehicle-road ratios are growing nearly as rapidly as income. Because vehicle use does not grow as rapidly as vehicle ownership, congestion may not be growing as fast as the number of vehicles, but it is clearly increasing with income.

**Table 6. Comparison of Time Series (T.S.) and Cross Section (C.S) elasticities**

**Urban spatial endowments.** The strong relation between income and population density at the urban level had produced unstable results in earlier regressions. Several of the urban equations reported on here use the deviation in area per capita (the inverse of density) from a predicted level for each city to summarize the effect of the durability of urban development patterns. This variable, termed an urban historical endowment index, worked well in the equations.

**Implications.** Many implications flow from the empirical results presented here. Most notably is the increase in urban congestion over time reflected in the remarkably rapid increase in the urban vehicle-road ratio with income over time. The magnitude of these trends is so large that it is alarming. Economic growth appears to be producing urban gridlock and promoting low density urban development.

During recent decades, urban areas have coped with congestion by spreading their activities over larger areas and adding road space by annexation. Decentralized urban development is most evident in high income countries, such as the U.S. and Australia, where land costs at the periphery of urban areas are relatively low. Yet over a 20 year period in the global sample of 35 cities analyzed here, average population densities declined in 25 and the urban area increased in 30, so urban area expansion with decentralization is a common pattern of urban growth. Cities with high densities typically face high relative land prices at the periphery, and their expansion will occur at higher densities than in cities that face low land prices. This suggests that urban areas will not converge to similar levels of population density and congestion. Population densities and congestion in a particular city will be related to relative land prices at the urban periphery, to urban income levels, and to the city's historical endowment of buildings, street layout, block sizes, and related physical infrastructure.

Congestion appears to have a strong impact on urban development patterns, as cities decentralize and spread their development into surrounding areas in order to increase the supply of urban roads and moderate congestion. This phenomenon deserves more attention and analysis. If firms and households move in ways that foster low density development at the periphery of urban areas in order to reduce congestion, they may also do so in order to avoid congestion tolls. How urban development will react to congestion tolls is an open question.

It is noteworthy that at a fixed point in time, the vehicle road ratio across cities has its peak in cities with relatively low incomes. These cities have few motor vehicles, but even fewer roads, and they can be highly congested. Bangkok is a famous example of this. Among high income cities, population density and vehicle-road ratios vary over a surprisingly large range. These cities also vary widely in the availability and use of transit systems, and it is likely that the older, denser, and more congested cities have more extensive and higher quality transit systems than the newer, low density, and less congested cities. More empirical work needs to be done relating vehicle ownership and use to transit availability in urban areas.

Although the urban results are somewhat alarming, the national results indicate that the vehicle-road ratio at the national level--particularly on paved roads--is relatively low and

is not rising very rapidly. It shows remarkable stability across country income levels. This contrast between the national and urban results reinforces the view that urban decentralization is likely to continue to be the major mode of adjustment to urban congestion.

## Annex A. The Data Sets

The national and urban data sets used in the current paper are essentially the same as those used in Ingram and Liu (1997). The primary data sources are explained in the Appendix of Ingram and Liu (1997, p. 35). The national data are from 50 countries with full data for 1970, 1980, and 1990. The urban data include 35 cities with data in two years (mostly in 1960 and 1980). The summary statistics for developing and high-income countries at both national and urban levels for the year of 1980 are shown in Table A-1 below. Data for 1980 are used for the comparison because it is the only common year for the national and urban data sets.

When we carried out the empirical analyses presented in the current paper, a database of world infrastructure stocks for 1950-1995 compiled by Canning (1998) became available to us. Canning (1998) identified inconsistencies in the definition of paved road among countries and adjusted the official paved road data to fit a more consistent definition. Based on the Canning data, we made a few corrections to our national paved road length data. We also used the corrected data to re-estimate the paved road regressions presented in Ingram and Liu (1997) and found that the minor data corrections did not alter the empirical findings summarized there. The national data used in the current analyses are presented in Appendix Tables 10, 11, and 12.

**Table A-1. Sample Summary Averages, 1980**

Item	Developing economies		High income economies <sup>a</sup>	
	National (31 countries)	Urban (9 cities)	National (19 countries)	Urban (26 cities)
Per capita GNP in 1987 US\$ <sup>b</sup>	546	1,589	14,247	15,037
Population per sq. km.	86	14,982	125	3,989
Motor vehicles/1000 persons	41	60	379	482
Auto share of fleet	60%	61%	86%	82%
Kilometers of road per sq. km.	0.2	5.9	1.2	10.9
Percent of roads paved	34%	n.a.	77%	n.a.
Meters of road per capita	3.7	0.5	16.5	4.5
Meters of paved road per capita	1.0	n.a.	11.2	n.a.
Motor vehicles per km. of road	12	142	31	152
Motor vehicles per paved km.	41	n.a.	41	n.a.

n.a. Not available.

a. In 1980 high-income countries had a GNP per capita over \$4,800; see World Bank (1992).

b. Average weighted by population.

The earlier urban data set presented in Appendix Table 3 of Ingram and Liu (1997) includes 35 cities, each with observations at two points in time. In the current urban cross-section analyses (see Appendix Tables 5 and 7 of the current paper), two cities (Beijing and Santiago), both with only one year observation, were added to the data set. The data for Beijing and Santiago are shown in Table A-2.

**Table A-2. Data for Beijing and Santiago**

	Beijing, 1994	Santiago, 1990
Urban population ('000)	5,748	4,768
Urban land area (km <sup>2</sup> )	485	467
Per capita GNP in 1987 US\$	807	1,960
Population density (persons/km <sup>2</sup> )	11,860	10,201
Total motor vehicles per 1,000 persons	54	84
Passenger cars per 1,000 persons	46	67
Road network density (km/km <sup>2</sup> )	7.47	5.10
Per capita road length (m)	0.63	0.50
Motor vehicles per km of road	86	168

Source: Data for Beijing are primarily from Li (1996); and for Santiago, from Kain and Liu (1994).

## Annex B. Deriving the Elasticity from a Quadratic Log-log Equation

Regression estimated:

$$\log Y = \log a + b_1 \log X + b_2 (\log X)^2 \quad (1)$$

Transforming:

$$\log Y = \log a + \log X (b_1 + b_2 \log X) \quad (2)$$

$$e^{\log Y} = e^{\log a} e^{\log X (b_1 + b_2 \log X)} \quad (3)$$

$$Y = a X^{(b_1 + b_2 \log X)} \quad (4)$$

Taking derivatives of (2):

$$\begin{aligned} dY/Y &= (b_1/X) dX + \{(2 b_2 \log X)/X\} dX \\ &= (b_1 + 2 b_2 \log X) dX/X \end{aligned} \quad (5)$$

Elasticity:

$$E = (dY/dX) (X/Y) = b_1 + 2 b_2 \log X \quad (6)$$

## References

- American Automobile Manufacturers Association (1996). World Motor Vehicle Data. Washington, D.C.
- Canning, David (1998). "A Database of World Infrastructure Stocks 1950-1995." Policy Research Working Paper 1929. Washington, D.C.: World Bank.
- Ingram, Gregory K. (1996). "Urban Development: What Have We Learned?" Policy Research Working Paper 1841. Washington, D.C.: World Bank.
- Ingram, Gregory K., and Zhi Liu (1997). "Motorization and the Provision of Roads in Countries and Cities." Policy Research Working Paper 1842. Washington, D.C.: World Bank.
- International Road Federation (various years). World Road Statistics.
- Kain, John F., and Zhi Liu (1994). "Efficiency and Locational Consequences of Government Transport Policies and Spending in Chile." Harvard Project on Urbanization in Chile, Harvard University.
- Li, Yaming (1996). "Urban Transport Statistics," Annex in Stephen Stares and Zhi Liu (eds.), China's Urban Transport Strategy: Proceedings of a Symposium in Beijing, November 8-10, 1995, World Bank Discussion Paper No. 352.
- Newman, Peter, and Jeffrey Kenworthy (1989). Cities and Automobile Dependence. Gower Publishing Company Limited.
- World Bank (1992). World Development Report 1992: Development and the Environment. Oxford University Press.
- World Bank (1994). World Development Report 1994: Infrastructure for Development. Oxford University Press.

**Appendix Table 1. Test of Non-Linearity between Income and Motor Vehicle Ownership  
(50 countries for 1970, 1980, and 1990)**

Explanatory Variable	OLS Estimates and (Standard Error)					
	Log of total motor vehicles		Log of passenger cars		Log of commercial vehicles	
	Eq. 1a	Eq. 1b	Eq. 2a	Eq. 2b	Eq. 3a	Eq. 3b
Constant	-11.75 (0.93)**	-26.23 (3.99)**	-13.40 (1.17)**	-38.15 (4.73)**	-9.93 (1.19)**	-17.96 (5.28)**
Log of real GNP per capita	0.92 (0.05)**	2.01 (0.42)**	1.04 (0.06)**	2.63 (0.49)**	0.66 (0.07)**	2.22 (0.55)**
Square of log of real GNP per capita		-0.06 (0.03)**		-0.09 (0.03)**		-0.10 (0.03)**
Log of population	1.02 (0.03)**	1.62 (0.44)**	1.01 (0.04)**	2.63 (0.52)**	0.99 (0.04)**	0.46 (0.58)
Square of log of population		-0.02 (0.01)		-0.05 (0.02)**		0.02 (0.02)
Log of per capita land area	0.09 (0.03)**	0.46 (0.13)**	0.08 (0.04)*	0.58 (0.15)**	0.17 (0.04)**	0.24 (0.17)
Square of log of per capita land area		-0.06 (0.02)**		-0.08 (0.02)**		-0.02 (0.03)
Share of urban population (%)	1.29 (0.30)**	0.74 (0.93)	1.33 (0.37)**	-0.45 (1.05)	1.19 (0.38)**	2.43 (1.23)**
Square of the share of urban population (%)		0.27 (0.80)		1.21 (0.95)		-1.37 (1.06)
Log of gasoline prices	0.07 (0.12)	2.54 (0.96)**	0.15 (0.15)	2.58 (1.14)**	-0.14 (0.15)	2.96 (1.27)**
Square of log of gasoline prices		-0.33 (0.12)**		-0.33 (0.15)**		-0.40 (0.16)**
Year dummy for 1980	0.18 (0.10)*	0.14 (0.09)	0.23 (0.12)*	0.18 (0.10)*	0.10 (0.13)	0.04 (0.12)
Year dummy for 1990	0.36 (0.10)**	0.31 (0.10)**	0.44 (0.13)**	0.40 (0.11)**	0.30 (0.13)**	0.22 (0.12)*
Adj. R-squared	0.94	0.95	0.93	0.94	0.88	0.89
F-statistic	338	249	248	207	148	104

Note: (\*\*) Significant at the 0.05 level; and (\*) significant at the 0.10 level.

**Appendix Table 2. Test of Non-Linearity between Income and Road Length  
(50 countries for 1970, 1980, and 1990)**

Explanatory Variable	OLS Estimates and (Standard Error)			
	Log of total road length		Log of paved road length	
	Eq. 1a	Eq. 1b	Eq. 2a	Eq. 2b
Constant	-10.10 (0.71)**	-1.90 (4.03)	-14.68 (1.04)**	-2.37 (5.93)
Log of real GNP per capita	0.55 (0.05)**	0.60 (0.45)	0.95 (0.07)**	0.27 (0.66)
Square of log of real GNP per capita		-0.003 (0.03)		0.04 (0.04)
Log of population	0.98 (0.03)**	0.02 (0.49)	1.05 (0.05)**	-0.18 (0.71)
Square of log of population		0.03 (0.01)**		0.04 (0.02)*
Log of per capita land area	0.31 (0.03)**	0.40 (0.14)**	-0.01 (0.05)	0.48 (0.21)**
Square of log of per capita land area		-0.01 (0.02)		-0.07 (0.03)**
Share of urban population (%)	0.04 (0.30)	-2.18 (1.03)	0.04 (0.44)	1.16 (1.52)
Square of the share of urban population (%)		2.19 (0.89)		-0.62 (1.31)
Year dummy for 1980	-0.005 (0.10)	0.004 (0.10)	0.02 (0.15)	0.02 (0.14)
Year dummy for 1990	-0.02 (0.10)	-0.01 (0.10)	0.02 (0.15)	0.002 (0.15)
Adj. R-squared	0.89	0.90	0.86	0.87
F-statistic	197	126	151	95

Note: (\*\*) Significant at the 0.05 level; and (\*) significant at the 0.10 level.

**Appendix Table 3. Test of Non-Linearity between Income and Vehicle-Road Ratio (50 countries for 1970, 1980, and 1990)**

Explanatory Variable	OLS Estimates and (Standard Error)			
	Log of motor vehicles per km of total road		Log of motor vehicles per km of paved road	
	Eq. 1a	Eq. 1b	Eq. 2a	Eq. 2b
Constant	0.41 (1.24)	-21.28 (5.27)**	2.45 (1.29)*	-24.38 (5.68)**
Log of real GNP per capita	0.43 (0.07)**	1.68 (0.55)**	-0.04 (0.07)	1.69 (0.59)**
Square of log of real GNP per capita		-0.07 (0.03)**		-0.10 (0.04)**
Log of population	-0.01 (0.05)	1.52 (0.58)**	-0.02 (0.05)	1.82 (0.63)**
Square of log of population		-0.04 (0.02)**		-0.05 (0.02)**
Log of per capita land area	-0.26 (0.05)**	0.03 (0.17)	0.11 (0.05)**	-0.02 (0.18)
Square of log of per capita land area		-0.05 (0.02)**		0.01 (0.03)
Share of urban population (%)	1.36 (0.40)**	2.64 (1.23)**	1.22 (0.41)**	-0.35 (1.33)
Square of the share of urban population (%)		-1.58 (1.06)		0.81 (1.14)
Log of gasoline prices	-0.33 (0.16)**	1.36 (1.27)	0.16 (0.17)	2.71 (1.37)**
Square of log of gasoline prices		-0.22 (0.16)		-0.34 (0.18)*
Year dummy for 1980	0.16 (0.13)	0.11 (0.12)	0.17 (0.14)	0.13 (0.13)
Year dummy for 1990	0.35 (0.13)**	0.29 (0.12)**	0.35 (0.14)**	0.32 (0.13)**
Adj. R-squared	0.66	0.73	0.20	0.33
F-statistic	42	34	6	7

Note: (\*\*) Significant at the 0.05 level; and (\*) significant at the 0.10 level.

**Appendix Table 4. Regressions of Motor vehicle Ownership, Road Length, and Vehicle-Road Ratio (35 world cities, each in two different years)**

Explanatory Variable	OLS Estimates and (Standard Error)							
	Log of total motor vehicles		Log of passenger cars		Log of commercial vehicles		Log of road km	Log of V/R
	Eq. 1a	Eq. 1b	Eq. 2a	Eq. 2b	Eq. 3a	Eq. 3b	Eq. 4	Eq. 5
Constant	1.56 (0.64)**	1.50 (0.72)**	1.50 (0.85)**	1.42 (0.95)*	0.50 (0.93)	0.45 (0.96)	0.11 (0.61)	1.45 (0.82)**
Log of population	1.00 (0.06)**	0.90 (0.06)**	1.00 (0.07)**	0.87 (0.07)**	0.96 (0.08)**	0.90 (0.07)**	0.92 (0.05)**	0.08 (0.07)**
Log of real GNP per capita	0.52 (0.08)**	0.82 (0.05)**	0.50 (0.11)**	0.90 (0.06)**	0.39 (0.12)**	0.59 (0.07)**	0.32 (0.08)**	0.20 (0.11)**
Log of per capita land area	0.44 (0.10)**		0.58 (0.14)**		0.29 (0.15)**		0.89 (0.10)**	-0.45 (0.13)**
Log of gasoline prices	-0.06 (0.17)	-0.63 (0.11)**	-0.04 (0.23)	-0.80 (0.15)**	0.13 (0.25)	-0.26 (0.15)**	-0.04 (0.16)	-0.02 (0.22)
Dummy for ending year	0.32 (0.10)**	0.25 (0.11)**	0.42 (0.13)**	0.32 (0.14)**	0.20 (0.13)	0.15 (0.14)	-0.17 (0.09)**	0.50 (0.12)**
Adj. R-squared	0.91	0.89	0.86	0.86	0.77	0.77	0.91	0.44

Note: (\*\*) Significant at the 0.05 level; and (\*) significant at the 0.10 level.

**Appendix Table 5. Test of Variable Income Elasticities of Motor Vehicle Fleet, Road Length, Vehicle-Road Ratio (34 world cities with 2 observations, and 2 cities with one observation)**

Explanatory Variable	OLS Estimates and (Standard Errors)					
	Log of total number of motor vehicles		Log of total road length		Log of vehicle- road ratio	
	Eq. 1a	Eq. 1b	Eq. 2a	Eq. 2b	Eq. 3a	Eq. 3b
Constant	0.64 (0.76)	1.73 (2.74)	-3.14 (0.71)**	3.79 (2.38)	3.78 (0.95)**	-2.06 (3.34)
Log of population	0.92 (0.05)**	0.92 (0.06)**	0.80 (0.05)**	0.84 (0.05)**	0.12 (0.07)**	0.09 (0.07)
Log of real GNP per capita	0.69 (0.05)**	0.33 (0.84)	0.72 (0.05)**	-1.50 (0.73)**	-0.03 (0.06)	1.84 (1.03)*
Square of log of real GNP per capita		0.02 (0.05)		0.14 (0.05)**		-0.12 (0.06)**
Log of actual per capita land area over estimated <sup>a</sup>	0.37 (0.09)**	0.39 (0.11)**	0.83 (0.09)**	0.96 (0.09)**	-0.46 (0.12)**	-0.58 (0.13)**
Log of gasoline prices	-0.21 (0.15)	-0.16 (0.19)	-0.22 (0.14)	0.10 (0.17)	0.01 (0.19)	-0.26 (0.23)
Year dummy <sup>b</sup>	0.02 (0.01)**	0.02 (0.01)**	0.00 (0.005)	-0.01 (0.01)	0.02 (0.01)**	0.03 (0.01)**
Adj. R-squared	0.90	0.90	0.92	0.93	0.40	0.42

Note: (\*\*) Significant at the 0.05 level; and (\*) Significant at the 0.10 level.

(a) Estimated per capita land area is obtained from the following regression:

$$\log A = 5.23 - 0.14 \log P - 2.08 \log Y + 0.16 (\log Y)^2 \quad R^2 = 0.41$$

where A is per capita land area, P is population, and Y is per capita GNP.

(b) Zero for all initial year observations, and the actual number of years between the initial and ending year for all ending-year observations.

**Appendix Table 6. Piecewise Regressions of Motor Vehicles, Road Length, and Vehicle-Road Ratio (50 countries for 1970, 1980, and 1990)**

Explanatory Variable	OLS Estimates and (Standard Error)				
	log of total MVs Eq. 1	log of total road length Eq. 2	log of paved road length Eq. 3	log of V/R (total road) Eq. 4	log of V/R (paved) Eq. 5
Constant	-12.43 (0.99)**	-11.21 (0.97)**	-13.40 (1.51)**	-1.22 (1.27)	0.97 (1.34)
log of population	1.02 (0.03)**	1.01 (0.03)**	1.02 (0.05)**	0.02 (0.04)	0.00 (0.04)
log of real GNP per capita	1.01 (0.07)**	0.36 (0.07)**	0.85 (0.11)**	0.66 (0.09)**	0.16 (0.10)*
log of real GNP per capita (>\$5,500) minus log (5,500)	-0.36 (0.16)**	0.36 (0.16)**	0.24 (0.24)	-0.72 (0.20)**	-0.60 (0.22)**
log of per capita land area	0.08 (0.03)**	0.37 (0.03)**	-0.01 (0.05)	-0.28 (0.04)**	0.09 (0.05)**
Share of urban population	1.11 (0.30)**	0.04 (0.30)	0.11 (0.46)**	1.07 (0.39)**	1.01 (0.41)**
log of gasoline prices	0.10 (0.12)	0.44 (0.11)**	-0.02 (0.18)	-0.34 (0.15)**	0.12 (0.16)
Year dummy for 1980	0.18 (0.10)**	0.02 (0.09)	0.03 (0.15)	0.16 (0.12)	0.16 (0.13)
Year dummy for 1990	0.38 (0.10)**	0.01 (0.10)	0.02 (0.15)	0.37 (0.13)**	0.35 (0.13)**
Adj. R-squared	0.95	0.91	0.87	0.71	0.29

Note: (\*\*) Significant at the 0.05 level; and (\*) Significant at the 0.10 level.

**Appendix Table 7. Piecewise Regressions of Motor Vehicles, Road Length, and Vehicle-Road Ratio (34 cities with 2 observations, and 2 cities with 1 observation)**

Explanatory Variable	OLS Estimates and (Standard Error)		
	Log of total MVs Eq. 1	Log of road length Eq. 2	log of vehicle-road ratio Eq. 3
Constant	0.67 (0.77)	-3.00 (0.70)**	3.67 (0.96)
Log of population	0.92 (0.05)**	0.81 (0.05)**	0.12 (0.07)*
Log of real GNP per capita	0.65 (0.11)**	0.57 (0.10)**	0.08 (0.13)
Log of real GNP per capita (>\$5,500) minus log (5,500)	0.11 (0.30)	0.48 (0.27)**	-0.36 (0.37)
Log of actual per capita land area over estimated <sup>a</sup>	0.39 (0.11)**	0.91 (0.10)**	-0.53 (0.13)**
Log of gasoline prices	-0.16 (0.20)	-0.01 (0.18)	-0.15 (0.25)
Year dummy <sup>b</sup>	0.02 (0.01)	-0.01 (0.01)	0.03 (0.01)**
Adj. R-squared	0.91	0.93	0.45

Note: (\*\*) Significant at the 0.05 level; and (\*) Significant at the 0.10 level.

(a) Estimated per capita land area is obtained from the following regression:

$$\log A = 5.23 - 0.14 \log P - 2.08 \log Y + 0.16 (\log Y)^2 \quad R^2 = 0.41$$

where A is per capita land area, P is population, and Y is per capita GNP.

(b) Zero for all initial year observations, and the actual number of years between the initial and ending year for all ending-year observations.

**Appendix Table 8. First Difference Regressions of Motor Vehicles, Road Length, and Vehicle-Road Ratio (50 countries for 1970-90)**

Explanatory Variable	OLS Estimates and (Standard Error)						
	dl total MVs		dl com. vehicles	dl total road length	dl paved road length	dl V/R (total road)	dl V/R (paved)
	Eq. 1	Eq. 2	Eq. 3	Eq. 4	Eq. 5	Eq. 6	Eq. 7
Constant	1.34 (0.76)*	1.92 (0.84)**	0.77 (1.21)	1.79 (0.75)**	-0.36 (0.99)	-0.29 (0.94)	1.71 (1.13)
dl population	0.47 (0.41)	0.32 (0.45)	0.92 (0.65)	0.37 (0.40)	1.34 (0.53)**	0.29 (0.51)	-0.86 (0.61)
dl real GNP per capita	0.98 (0.21)**	1.12 (0.23)**	1.12 (0.34)**	0.48 (0.21)**	0.82 (0.27)**	0.36 (0.27)	0.16 (0.31)
log of per capita land area at initial year	-0.02 (0.05)	-0.02 (0.05)	0.02 (0.08)	-0.04 (0.05)	-0.03 (0.06)	0.02 (0.06)	0.01 (0.07)
d share of urban population	2.10 (1.07)**	3.36 (1.19)**	0.09 (1.71)	0.10 (1.06)	1.04 (1.40)	1.44 (1.34)	1.06 (1.59)
dl total rail km	-0.005 (0.02)	0.01 (0.02)	-0.01 (0.03)	0.01 (0.02)	0.03 (0.02)	-0.01 (0.02)	-0.03 (0.03)
log of gasoline prices	-0.21 (0.15)	-0.35 (0.16)**	-0.17 (0.24)	-0.38 (0.15)**	0.08 (0.19)	0.12 (0.18)	-0.29 (0.22)
d percent road paved							1.05 (0.47)**
Adj. R-squared	0.55	0.61	0.26	0.30	0.32	0.18	0.01

Note: "dl" stands for log difference, and "d" for first difference;

(\*\*) Significant at the 0.05 level; and (\*) Significant at the 0.10 level.

**Appendix Table 9. First Difference Regressions of Motor Vehicles, Road Length, and Vehicle-Road Ratio (35 world cities, each in two different years)**

Explanatory Variable	OLS Estimates and (Standard Error)									
	dl total MVs		dl psgr. cars		dl com. vehicles		dl road length		dl veh.-road ratio	
	Eq. 1	Eq. 1b	Eq. 2a	Eq. 2b	Eq. 3a	Eq. 3b	Eq. 4a	Eq. 4b	Eq. 5a	Eq. 5b
Constant	-0.80 (0.54)	-0.76 (0.54)	-0.68 (0.67)	-0.73 (0.67)	1.35 (0.81)*	1.37 (0.80)*	-0.03 (0.42)	-0.10 (0.44)	-0.77 (0.66)	-0.66 (0.68)
dl population	0.97 (0.24)**	0.95 (0.28)**	0.68 (0.30)**	0.73 (0.34)**	0.84 (0.13)**	0.84 (0.13)**	0.46 (0.19)**	0.30 (0.22)	0.50 (0.30)*	0.65 (0.35)*
dl real GNP per capita	1.01 (0.26)**	1.03 (0.29)**	1.88 (0.32)**	1.83 (0.36)**	0.53 (0.12)**	0.53 (0.12)**	0.10 (0.20)	0.20 (0.23)	0.92 (0.32)**	0.83 (0.36)**
dl per capita land area	-0.05 (0.23)		0.03 (0.29)		0.14 (0.12)		0.42 (0.18)**		-0.46 (0.28)*	
log of per capita land area at initial year		0.01 (0.08)		-0.03 (0.10)		0.16 (0.12)		0.09 (0.06)		-0.08 (0.10)
log of gasoline prices	0.23 (0.13)*	0.22 (0.13)*	0.12 (0.17)	0.12 (0.16)	-0.22 (0.20)	-0.22 (0.20)	0.03 (0.10)	0.10 (0.10)	0.19 (0.16)	0.12 (0.16)
Adj. R-squared	0.49	0.49	0.56	0.56	0.61	0.61	0.18	0.09	0.28	0.23

Note: "dl" stands for log-difference; (\*\*) Significant at the 0.05 level; and (\*) Significant at the 0.10 level.

Appendix Table 10. National Data, 50 Countries, 1970

Country	Per capita GNP (in 1987 US\$)	Land Area ('000 sq km)	Land Total pop. ('000)	Urban pop. ('000)	Total motor vehicles ('000)	Psg. cars ('000)	Road length ('000 km)	Paved roads ('000 km)	Railway routes (km)
Algeria	2,049	2,382	13,746	5,430	251	143	76.0	33.0	3,933
Argentina	3,403	2,737	23,962	18,786	2,318	1,440	201.1	33.4	39,905
Australia	9,514	7,644	12,535	10,680	4,870	3,899	884.7	185.8	43,380
Austria	9,992	83	7,467	3,860	1,575	1,197	94.8	94.8	6,506
Belgium	9,829	30	9,656	9,106	2,302	2,060	92.1	75.1	4,263
Bolivia	736	1,084	4,212	1,718	77	19	25.6	0.9	3,524
Brazil	1,132	8,457	95,847	53,483	3,000	1,595	1,130.0	38.9	31,847
Cameroon	558	465	6,612	1,342	35	20	46.6	0.9	925
Canada	9,946	9,221	21,324	16,142	8,340	6,602	830.3	186.9	70,784
Chile	1,435	749	9,494	7,139	328	176	64.5	7.4	8,281
China	89	9,291	818,315	142,387	488	50	636.7	47.0	47,500
Colombia	777	1,039	21,360	12,218	343	239	49.5	6.0	3,436
Cote d'Ivoire	889	318	5,515	1,511	89	56	35.0	1.3	656
Denmark	14,055	42	4,929	3,928	1,471	1,079	61.5	57.6	2,890
Ecuador	652	277	5,970	2,358	180	27	20.6	2.9	990
Egypt	310	995	35,285	14,890	270	131	23.6	10.1	4,234
Finland	11,121	305	4,606	2,317	997	712	72.4	23.2	5,841
France	11,214	550	50,772	36,048	14,370	12,900	785.2	691.0	36,532
Gabon	4,215	258	504	129	13	6	6.0	0.2	0
Germany	9,919	350	77,709	61,856	15,663	14,673	440.9	317.4	33,010
Greece	3,159	129	8,793	4,616	344	227	35.1	17.4	2,571
India	240	2,973	554,911	109,872	1,092	627	972.3	324.8	59,997
Indonesia	204	1,812	120,280	20,568	359	239	84.3	21.1	6,640
Ireland	5,766	69	2,954	1,527	440	394	86.7	71.6	2,190
Italy	8,649	294	53,822	34,608	11,115	10,181	285.0	262.2	20,212
Japan	11,554	377	104,331	74,284	17,826	8,832	1,013.6	152.0	27,104
Kenya	235	569	11,498	1,184	114	96	41.5	4.8	6,933
Malawi	123	94	4,518	271	18	9	10.7	1.1	566
Malaysia	961	329	10,853	3,636	312	238	22.6	14.8	2,160
Mauritius	874	2	826	347	11	6	1.8	1.6	0
Mexico	1,334	1,909	50,455	29,768	1,825	1,234	72.3	42.7	24,468
Morocco	560	446	15,310	5,282	306	223	45.9	21.1	1,796
Netherlands	11,461	34	13,032	11,221	2,913	2,258	79.9	78.6	3,148
New Zealand	8,776	268	2,820	2,287	1,080	891	93.8	41.9	4,847
Nigeria	326	911	55,070	11,014	98	57	89.0	15.2	3,504
Norway	10,766	307	3,877	2,536	835	694	72.3	21.7	4,292
Pakistan	207	771	65,706	16,361	146	93	31.7	17.5	8,564
Philippines	487	298	37,540	12,388	510	279	75.7	13.5	1,052
Portugal	2,552	92	9,044	2,342	553	510	41.8	32.4	3,563
Rwanda	279	25	3,728	119	6	3	6.5	0.1	0
South Africa	2,304	1,221	22,458	10,735	1,973	1,545	185.5	33.1	21,391
South Korea	608	99	31,923	12,993	180	61	40.2	3.6	4,007
Spain	5,174	500	33,779	22,294	3,125	2,378	139.4	94.7	16,592
Sweden	14,451	412	8,043	6,523	2,690	2,289	98.0	38.6	12,203
Switzerland	22,415	40	6,187	3,372	1,524	1,383	59.2	59.2	5,010
Thailand	493	511	35,745	4,754	376	185	16.3	10.0	2,160
Tunisia	687	155	5,127	2,282	104	66	17.9	9.1	1,523
Turkey	823	770	35,321	13,563	298	138	59.5	19.0	7,985
United Kingdom	8,523	242	55,632	49,234	13,330	11,666	334.1	324.2	18,969
United States	13,893	9,573	205,051	150,918	109,305	88,840	6,003.0	2,668.9	331,174

Source: (1) Country GNP, land area, population, and urban population are from World Bank's World Development Indicators Database; (2) Total motor vehicles and passenger cars are from International Road Federation (various years); (3) Length of total roads and paved roads are from International Road Federation (various years), World Bank (1994), and Canning (1998); and (4) Railroad route length data are from World Bank (1994) or provided by Louis Thompson.

Appendix Table 11. National Data, 50 Countries, 1980

Country	Per capita GNP (in 1987 US\$)	Land		Total		Psgr. cars ('000)	Road length ('000 km)	Paved roads ('000 km)	Railway routes (km)
		Area ('000 sq km)	Total pop. ('000)	Urban pop. ('000)	motor vehicles ('000)				
Algeria	2,598	2,382	18,740	8,133	839	492	72.1	38.9	3,907
Argentina	3,866	2,737	28,114	23,307	4,329	3,005	213.9	52.2	34,077
Australia	11,274	7,644	14,569	12,500	7,410	5,801	810.9	243.8	39,463
Austria	14,050	83	7,549	4,137	2,458	2,247	106.3	106.3	6,482
Belgium	13,065	30	9,852	9,399	3,477	3,315	126.8	119.2	3,978
Bolivia	822	1,084	5,355	2,437	104	32	39.7	1.4	3,328
Brazil	1,979	8,457	121,286	80,291	10,160	8,005	1,399.4	79.4	28,671
Cameroon	854	465	8,655	2,718	67	50	62.4	2.5	1,168
Canada	13,174	9,221	24,594	18,618	13,212	10,256	928.3	206.6	67,066
Chile	1,512	749	11,143	9,048	672	449	79.9	9.8	6,302
China	134	9,291	981,235	192,322	1,681	238	883.3	158.0	49,940
Colombia	1,086	1,039	26,525	16,949	365	322	79.9	12.0	3,403
Cote d'Ivoire	1,156	318	8,194	2,852	224	146	41.3	3.1	680
Denmark	16,473	42	5,123	4,288	1,798	1,398	68.9	68.9	2,461
Ecuador	1,161	277	7,961	3,742	276	65	33.0	4.3	965
Egypt	510	995	43,749	19,162	472	326	23.1	8.0	4,667
Finland	14,822	305	4,780	2,858	1,384	1,226	75.0	36.0	6,096
France	14,630	550	53,880	39,494	21,780	18,400	803.0	730.7	34,382
Gabon	4,753	258	806	289	24	15	7.1	0.5	224
Germany	12,911	350	78,304	64,679	24,769	23,192	471.4	466.7	28,517
Greece	4,599	129	9,643	5,564	1,297	863	37.1	25.3	2,461
India	262	2,973	688,856	159,126	1,729	949	1,491.9	644.2	61,240
Indonesia	324	1,812	150,958	33,513	1,200	640	142.3	56.5	6,637
Ireland	7,525	69	3,401	1,881	803	734	92.3	86.9	1,987
Italy	11,854	294	56,434	37,585	19,115	17,686	297.2	287.9	16,133
Japan	16,065	377	116,807	89,007	37,874	26,133	1,113.4	511.0	22,235
Kenya	359	569	16,560	2,666	142	114	51.5	8.7	4,531
Malawi	155	94	6,183	563	29	12	10.8	1.9	782
Malaysia	1,618	329	13,763	5,780	882	714	32.4	19.0	2,082
Mauritius	1,240	2	966	410	42	26	1.8	1.6	0
Mexico	1,853	1,909	67,056	44,458	6,026	4,241	212.6	72.3	20,058
Morocco	745	446	19,382	7,947	651	430	57.6	25.4	1,756
Netherlands	14,074	34	14,144	12,503	4,858	4,552	93.9	93.3	2,880
New Zealand	9,731	268	3,113	2,596	1,568	1,303	93.4	47.7	4,449
Nigeria	378	911	72,024	19,519	346	215	108.0	30.0	3,523
Norway	15,709	307	4,086	2,881	1,398	1,233	81.7	46.6	4,242
Pakistan	249	771	85,299	23,969	195	138	87.1	26.0	8,815
Philippines	679	298	48,317	18,119	859	466	151.9	21.3	1,059
Portugal	3,648	92	9,766	2,871	1,457	1,269	51.9	44.8	3,588
Rwanda	344	25	5,163	243	13	5	10.7	0.4	0
South Africa	2,444	1,221	29,529	14,031	3,601	2,333	183.6	46.4	20,499
South Korea	1,894	99	38,124	21,693	528	249	47.0	15.6	3,135
Spain	6,574	499	37,542	27,331	8,962	7,557	237.9	150.8	15,728
Sweden	16,790	412	8,310	6,906	3,377	2,883	129.0	94.9	12,010
Switzerland	24,957	40	6,319	3,602	2,522	2,247	64.0	64.0	5,041
Thailand	715	511	46,718	7,942	612	410	67.7	23.6	3,735
Tunisia	1,130	155	6,384	3,281	241	125	23.8	12.3	2,013
Turkey	1,177	770	44,438	19,464	1,374	742	232.9	35.7	8,193
United Kingdom	10,172	242	56,330	50,021	16,918	15,619	352.5	339.8	18,028
United States	16,608	9,573	227,757	167,857	155,890	118,459	6,365.6	3,226.0	288,073

Source: (1) Country GNP, land area, population, and urban population are from World Bank's World Development Indicators Database; (2) Total motor vehicles and passenger cars are from International Road Federation (various years); (3) Length of total roads and paved roads are from International Road Federation (various years), World Bank (1994), and Canning (1998); and (4) Railroad route length data are from World Bank (1994) or provided by Louis Thompson.

Appendix Table 12. National Data, 50 Countries, 1990

Country	Per capita GNP (in 1987 US\$)	Land Area ('000 sq km)	Total pop. ('000)	Urban pop. ('000)	Total motor vehicles ('000)	Psgr. cars ('000)	Road length ('000 km)	Paved roads ('000 km)	Railway routes (km)	Year 1997 gasoline price (US (cents/l.)
Algeria	2,563	2,382	24,935	12,891	1,069	725	75.7	45.0	4,653	32
Argentina	2,965	2,737	32,377	28,006	5,776	4,284	215.4	61.4	35,754	100
Australia	12,611	7,644	16,888	14,372	9,052	7,442	810.3	288.7	40,478	59
Austria	17,011	83	7,705	4,269	3,253	2,991	107.2	107.2	6,875	106
Belgium	15,543	30	9,951	9,603	4,197	3,875	137.9	131.8	3,568	113
Bolivia	695	1,084	6,627	3,698	272	109	41.6	1.8	3,462	57
Brazil	1,897	8,457	148,477	110,764	13,000	10,598	1,670.1	139.7	22,123	83
Cameroon	870	465	11,526	4,645	98	63	70.1	3.6	1,104	62
Canada	15,317	9,221	27,791	21,288	16,805	12,622	825.7	289.0	93,544	48
Chile	1,794	749	13,154	10,957	1,048	711	79.6	11.0	7,998	59
China	269	9,291	1,135,160	297,412	5,717	1,622	1,028.3	822.6	53,378	25
Colombia	1,156	1,039	33,322	23,325	1,330	1,100	129.1	15.4	3,239	45
Cote d'Ivoire	719	318	11,974	4,837	293	191	49.0	4.2	650	74
Denmark	19,666	42	5,140	4,359	1,892	1,604	71.1	71.1	3,272	111
Ecuador	1,080	277	10,264	5,625	359	166	37.6	6.3	965	39
Egypt	713	995	53,214	23,361	1,513	1,054	45.9	17.0	5,110	29
Finland	19,048	305	4,986	3,061	2,197	1,940	76.4	46.6	5,054	119
France	17,404	550	56,718	41,234	28,290	23,550	805.6	741.2	34,593	111
Gabon	3,928	258	957	437	30	19	8.3	0.6	683	60
Germany	16,000	349	79,365	67,698	32,174	30,695	501.0	496.0	41,828	101
Greece	4,806	129	10,238	6,409	2,512	1,738	38.1	34.3	2,784	91
India	372	2,973	844,847	215,436	6,161	2,736	1,970.0	960.0	75,333	59
Indonesia	487	1,812	178,096	54,497	2,806	1,294	283.5	125.1	6,964	29
Ireland	9,653	69	3,503	1,993	945	803	92.3	86.8	2,464	105
Italy	14,391	294	57,023	38,034	29,727	27,300	303.9	303.9	25,858	113
Japan	22,890	377	123,537	95,371	57,702	43,853	1,120.0	771.4	23,962	97
Kenya	375	569	23,354	5,512	291	240	67.2	12.5	2,652	64
South Korea	4,098	99	42,869	31,637	3,395	2,075	56.7	40.5	4,340	94
Malawi	138	94	9,367	1,105	37	19	12.9	2.3	782	65
Malaysia	2,233	329	17,671	8,800	2,253	1,846	54.0	37.8	2,222	44
Mauritius	2,039	2	1,057	428	63	46	1.9	1.7	0	78
Mexico	1,742	1,909	84,511	61,355	9,916	6,893	237.1	82.0	26,334	38
Morocco	873	446	24,334	11,218	897	670	59.5	29.1	1,901	81
Netherlands	16,244	34	14,952	13,262	6,055	5,509	104.6	103.1	3,138	113
New Zealand	10,401	268	3,360	2,849	1,800	1,498	93.1	52.8	4,029	66
Nigeria	318	911	96,154	33,846	467	273	112.9	31.3	3,557	13
Norway	19,539	307	4,241	3,066	1,943	1,612	88.9	62.2	4,168	132
Pakistan	361	771	112,897	36,127	904	715	168.9	51.0	12,624	45
Philippines	639	298	60,779	29,660	604	455	160.6	23.1	478	42
Portugal	4,919	92	9,868	3,306	3,365	2,552	70.2	60.3	3,598	105
Rwanda	308	25	6,986	391	17	7	13.2	0.8	0	72
South Africa	2,193	1,221	37,959	18,236	4,901	3,600	185.8	55.4	23,507	48
Spain	8,444	499	39,272	29,611	14,396	11,996	332.0	239.9	19,089	82
Sweden	19,423	412	8,559	7,113	3,945	3,601	133.7	118.4	12,000	117
Switzerland	28,501	40	6,834	4,066	3,297	2,994	71.1	71.1	5,020	85
Thailand	1,283	511	55,223	10,327	2,198	1,222	200.3	39.9	3,940	37
Tunisia	1,262	155	8,069	4,430	494	320	29.2	15.2	2,270	65
Turkey	1,648	770	56,098	34,164	2,785	1,885	367.4	47.5	8,695	67
United Kingdom	12,766	242	57,411	51,153	22,603	20,807	356.5	356.5	16,629	105
United States	19,567	9,573	249,924	187,943	188,798	143,550	6,243.2	3,633.5	205,000	36

Source: (1) Country GNP, land area, population, and urban population are from World Bank's World Development Indicators Database; (2) Total motor vehicles and passenger cars are from International Road Federation (various years); (3) Length of total roads and paved roads are from International Road Federation (various years), World Bank (1994), and Canning (1998); (4) Railroad route length data are from World Bank (1994) or provided by Louis Thompson; and (5) Gasoline prices are from the World Bank's fuel prices database.