Urban Density and Climate Change: A STIRPAT Analysis using City-level Data

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ABSTRACT
Two important, increasing trends for those concerned about climate change to consider are urbanization/the importance of cities and energy used in transport—particularly energy used to achieve personal mobility. While national urbanization levels are not a good indicator of urban transport demand, there is an established negative relationship between urban density and such demand. This paper uses a consistent, well-known population-based framework (the STIRPAT model) and three separate, but highly related, datasets of cities from developed and developing countries (with observations from 1990, 1995, and 2001) to examine the relationship among private transport energy consumption, population, income, urban density, and several variables (e.g., network size and prices) that describe the nature of the public and private transport systems of those cities. The paper confirms the now well-established result that urban density is negatively correlated with urban private transport energy consumption. In terms of policies, improving private vehicle fuel efficiency, in particular, and increasing fuel price as well as other ownership/operating costs for private transport could have a substantial impact on lowering transport energy consumption. On the other hand, there is no evidence that further lowering the cost to riders of public transport would lower private transport energy consumption. For cities in developing countries, demographic variables (population size and urban density) are particularly important in determining private transport energy consumption. Also, private transport energy consumption is considerably less price sensitive in those developing country cities compared to cities in the most developed countries.

Keywords: urban density; STIRPAT; transport energy demand; city-based data.

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1. Introduction and background

The level of world urbanization crossed the 50% mark in 2009; the United Nations expects that over the next 40 years, urban areas will absorb all of the projected 2.3 billion global population growth while urban areas will continue to draw in some rural population. In addition, most of the population growth expected in urban areas will be concentrated in less developed regions. At the same time, transport contributes more than one-fifth of global anthropogenic carbon dioxide emissions; furthermore, transport energy consumption is increasing in both developed and developing countries and is a carbon-intensive activity everywhere. To illustrate, for International Energy Agency (IEA) countries as a whole, carbon emissions from manufacturing industries and construction and from the residential sector (i.e., housing) both declined by around 20% from 1971-2007, but emissions from road transport more than doubled over that period (data from IEA).

While national urbanization levels are not a particularly good indicator of transport demand (Liddle and Lung 2010), several studies have shown a (negative) relationship between urban density and vehicle miles traveled or energy consumed in private transport, using city-based data (e.g., Newman and Kenworthy 1989; Kenworthy and Laube 1999; Romero-Lankao et al. 2009; Karathodorou et al. 2010; and Travisi et al. 2010). This paper uses the well-known STIRPAT model and three separate, but highly related, datasets of cities from developed and developing countries to examine the relationship among (aggregate) private transport energy consumption, population, income, urban density, and several variables (e.g., network size and prices) that describe the nature of the public and private transport systems of those cities. In doing so, the paper is similar to Romero-Lankao et al. (2009), but expands on that work by employing the three city-based transport datasets (indeed, the current paper is the only work we know of that considers all three of these related datasets), and by considering additional explanatory variables (largely taken from economics) that also can be considered policy variables.

A popular framework used to distinguish between population's and GDP's (or income's) impact on the environment is Dietz and Rosa's (1997) STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology). STIRPAT builds on IPAT/impact equation of Ehrlich and Holdren (1971):

$$I = P \times A \times T \tag{1}$$

Where I is environmental impact, P is population, A is affluence or consumption per capita, and T is technology or impact per unit of consumption. Dietz and Rosa (1997) addressed the criticism that the Ehrlich-Holdren/IPAT framework does not allow hypothesis testing by proposing a stochastic version of IPAT:

$$I = aP_i^b A_i^c T_i^d e_i \tag{2}$$

Where the subscript i denotes cross-sectional units (e.g., countries), the constant a and exponents b, c, and d are to be estimated, and e is the residual error term.

Since Equation 2 is linear in log form, the estimated exponents can be thought of as elasticities (i.e., they reflect how much a percentage change in an independent variable causes a percentage change in the dependent variable). In addition to determining whether population or GDP has a greater marginal impact on the environment, another important/popular hypothesis to test is whether population's elasticity is different from unity. That hypothesis is worth testing since, if population's elasticity is one, then population could be removed as an independent variable via division (in Equation 2), and so the dependent variable would be in per capita terms as is often the case in non-STIRPAT analyses (like those in the so-called Environmental Kuznets Curve or EKC literature). Also, the *T* term can now be treated more like an intensity of use variable and be modelled as a combination of log-linear factors.

2. Data and models

The STIRPAT model typically is employed with national level data. There are a few single-country studies using local level data, typically the US and typically county level (e.g., DeHart and Soule 2000; Squalli 2009; and Roberts 2011); the only other STIRPAT study we know of to use both city-based data and locally-based, cross-national data is Romero-Lankao et al. (2009).

The first of the three transport and cities datasets used here is Kenworthy et al. (1999). It contains data from 1960, 1970, 1980, and 1990, but economic data (GDP per capita and prices/costs) is available only for 1990. Cities from Asia, Australia, Europe, and North America (46 in total) are included (the specific cities used here from each of the three datasets are displayed in Appendix Table A-1). The Millennium Cities Database for Sustainable Transport (Kenworthy and Laube 2001) is by far the largest of the three, both in terms of the indicators collected and the cities covered. It contains 1995 data for 100 cities (which comprised a total population of over 400 million in 1995)—included is nearly every city with more than 2 million inhabitants that is located in an International Union for Public Transport (UITP) member country. There also are a substantial number of cities from developing countries, including ones from Africa, Middle East, and South America. Lastly, the Mobility in Cities Database (UITP 2005) contains 2001 data for 50 cities. The UITP aimed to have the Kenworthy and Laube (2001) and UITP (2005) databases as compatible as possible; however, fewer indicators are contained in UITP (2005), and some of the remaining indicators have slightly changed definitions. Furthermore, nearly all of the cities in UITP (2005) are European.

By far the most popularly used datasets are the ones drawing on the 1990 and 1995 data (Romero-Lankao et al. 2009 employ Kenworthy and Laube 2001). Indeed, we know of only one published paper that depends on UITP (2005).[1]

Because of indicator availability, this study uses data from 167 cities (from 1990, 1995, and 2001). In Figure 1, the ratio of city GDP per capita to the associated country GDP per capita is plotted against that country GDP per capita for 160 of those cities.[2] There are two interesting observations. First, most of the cities have higher GDP per capita than their respective countries as a whole—the ratio of GDPs is below one for only 35 cities, and below 0.85 for only 14. Second, the relative economic importance of cities is stronger in countries with lower GDP per capita. That second point demonstrates the important migratory pull cities have in developing countries, and provides insight into why the vast majority (20 of 26) of megacities (cities with populations over 10 million) are located in less developed countries, and why the UN projects all future population growth (over the next 40 years) will be located in urban areas.

Figure 1

2.1 Variables analyzed

As a dependent variable, we focus on (aggregate) private transport energy consumption (measured in megajoules[3]) as opposed to total energy consumption (the dependent variable considered in Romero-Lankao et al. 2009); we do so because public transport is the main mobility alternative to private transport, and we aim, in part, to explain this choice. Since private

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[1] That paper, Albalate and Bel (2010), focuses on public transit provision in Europe.
[2] The city-states Hong Kong and Singapore and Taipei, Taiwan have been excluded from this figure, and from all other city-to-nation comparisons.
[3] A megajoule (MJ) is one million joules.

transport is much more energy intensive than public transport, a major way cities can lower their transport energy consumption is to shift mobility away from private to public modes. Indeed, for the cities studied here, the average ratio of private to public transport intensity (energy consumed divided by passenger kilometers driven/provided) is 4.4, and in all but 10 cities, private transport was at least 50% more energy intensive (the ratio was below one only for Glasgow in 1995).

In addition to GDP per capita and total population, we consider several intensity variables (the "T-type" variables from Equation 2). The main intensity variable used here is urban density—indeed, urban density is a primary motivation for the use of these datasets by all researchers. As mentioned above, the negative correlation between private transport use and urban density was established by Newman and Kenworthy (1989) and has been confirmed by several studies since then. Although there is still debate about the *causal* mechanism involved, we agree with Rickwood et al. (2008) that the most compelling explanation is that "… there is a positive feedback loop between transport and land use such that public transport friendly land use encourages less automobile travel and more public transport travel, which in turn encourages public transport friendly land use…" (Rickwood et al. 2008, p. 74).

The relationship between urban density of cities and some related national-level indicators may be surprising. For the sample used here, the correlation (ρ) between urban density and the corresponding national population density is only 0.35, and national urbanization levels are actually negatively correlated with urban density (ρ = -0.59). Figure 2 shows, for the data used here, the relationship between urban private transport energy use per capita (the dependent variable) and both urban density (the upper graph) and the corresponding national urbanization level (the lower graph). The upper graph displays the now well-known negative, nonlinear relationship between urban private transport and urban density (e.g., Newman and Kenworthy

1989; Kenworthy and Laube 1999); whereas, the bottom graph shows the weaker and, perhaps surprising, *positive* relationship between urban private transport and urbanization level. That higher levels of national urbanization are correlated with greater levels of urban private transport most likely reflects the positive correlation between urbanization and income ($\rho = 0.61$ for the countries represented in this study).

Figure 2

In their analysis of total energy from transport, Romero-Lankao et al. (2009) considered the percentage of public transportation use in cities. Rather than use that variable, we use a series of variables designed to infer the private vs. public transport choice. The first of those variables involves the costs of private and public transport: fuel price, the cost per passenger kilometer of private transport (which, in addition to fuel, includes maintenance, insurance, and taxes, among other costs), and the cost to the traveler of one public transport kilometer. As well as representing the economic choice facing city inhabitants, differences in these prices across cities represent the broader society values of public and private transport. One would expect higher fuel and private per kilometer costs to discourage private transport and thus lower private transport energy consumption; whereas, higher public per kilometer costs would discourage public transport and thus raise private energy consumption. The other choice-based variable relates to the public transport network coverage: the public transport seat kilometers of service offered per city inhabitant. The larger that indicator, the better the public transport alternative would be for achieving desired mobility, and thus, the lower private transport energy consumption should be.

The last independent variable considered is fuel efficiency. Fuel efficiency is clearly the key factor in the relationship between vehicle miles traveled (VMT) and transport fuel consumption. In the transport economics literature, fuel efficiency is often thought to be influenced by fuel price (e.g., Karathodorou et al. 2010). We include both fuel price and fuel efficiency for several reasons.

First, the fuel price indicator is only available for the 1995 dataset, whereas fuel efficiency can be estimated for all three datasets. Second, the measure of fuel efficiency used is based on travel and energy consumption within the urban borders averaged across several vehicle modes (passenger cars, motorcycles, and taxis). Thus, the measure of *effective* fuel efficiency for private urban travel may differ from the overall fuel efficiency of a country's vehicle fleet, and it is that second measure of efficiency that is most likely to have a strong association to fuel price. Indeed, the correlation between the fuel efficiency and fuel price measures used here is only 0.22.

Lastly, fuel efficiency, like many of the independent variables, can be thought of as a policy variable/lever that can be adjusted via national vehicle fuel efficiency standards. Fuel price, of course, can be and is affected by taxes. The cost of private transport travel can be further affected by vehicle registration, parking, and road-use tolls; whereas, public transport can be encouraged by ticket subsidies and/or frequent traveler discounts and investment in network coverage. Urban density also can be influenced through various policies, but probably less directly and arguably less effectively so than the previous variables. Table 1 lists the variables used, their definitions and units, and their coverage in the three datasets.

Table 1

We do not consider any geography-based dummy variables, in part, because the urban density variable appears to play that role very well. Figure 3 displays the average urban density for each of four geographic/cultural groups: Asia; Europe; Australia, Canada, and the US; and a rest of world group. Figure 3 also shows the 99% confidence bounds for those averages (the error bars).

Figure 3

Not surprisingly, Australian, Canadian, and US cities have by far the lowest average urban density—the very cities for which Newman and Kenworthy (1989) coined the term auto-dependent. European cities have average urban densities considerably higher than those auto-dependent cities, and Asian cities have average urban densities considerably higher than the European ones. Also, for those three groups, their averages are all highly significantly different from one another. The rest of world cities (mostly drawn from developing countries) have an average urban density between Europe's and Asia's. However, that average is not statistically different from Europe's (not very surprising given the diversity in the rest of world group).

Table 2 displays some descriptive statistics (means and standard deviations) for each of the variables considered and for each dataset used. Table 2 also splits the 1995 dataset into cities from developed and from less developed countries for reasons that will be made clear below.

Table 2

3. Results and discussion

In part because the indicators covered and the definitions of similar indicators differed from dataset to dataset, and because the coverage of cities changed considerably, a series of Chow tests confirmed that the datasets should not be pooled, but rather analyzed individually as cross-sections.[4] (OLS with White-corrected standard errors was employed on the three cross-

[4] In principle one could construct, from the three datasets, a balanced panel of 14 cities. However, 10 of those cities would be from Western Europe, and none could be considered located in a developing country. Furthermore, several of the variables determined significant here either do not have coverage for each year or have their definitions change in the various datasets. Indeed, a balanced panel consisting of all three time observations could only include GDP per capita, population, and urban density as explanatory variables; hence, such a panel analysis was not performed.

sections.) Thus, Table 3 displays the regression results for the three datasets/cross-sections. The variance inflation factors (VIF) are shown (both average and maximum) for the regressions that exclude insignificant variables.

Table 3

The elasticities for population, GDP per capita, and urban density are statistically significant—typically highly so (except for GDP per capita in Regression II), usually large, and always have the expected sign. The elasticity for population is always greater than that for GDP per capita (their 95% confidence intervals overlap only marginally and only in regression VII), but the population elasticity is only significantly different from one (at the 95% confidence level) for Regression IV. (Appendix Table A-2 displays the 95% confidence intervals for GDP per capita and population for each regression shown in Tables 3 and 4.) The elasticity for the variable measuring the user costs of the public transport alternative is never significant; however, the elasticity for the variable measuring the size of the public transport network is significant and negative (as expected), but is always smaller than the other statistically significant elasticities.

When fuel price was added to the regressions (V and VI), the elasticity for fuel efficiency fell (in absolute terms), implying that fuel price does indeed affect effective urban fuel efficiency (in addition to fleet efficiency). Urban density had its lowest elasticity estimates in Regressions VII and VIII—the regressions on the mostly European city sample. That result is not surprising for a Europe dominated sample, given the rather tight distribution of urban densities among European cities (demonstrated in Figure 3). The elasticities for GDP per capita, fuel efficiency, and the measure of the total private transport cost per kilometer (in absolute terms for those second and third variables) were all the highest in the regressions on the most recent, predominately European city sample.

Thus, the regressions displayed in Table 3, using a consistent modeling framework, across three different city-based datasets, confirm the finding that greater urban density is associated with lower private transport energy consumption. In terms of policy, the regressions also confirm that measures to improve fuel efficiency (e.g., standards) would lead to a substantial lowering of private transport energy consumption. In addition, at least in Europe, increasing the total costs of private vehicle ownership and operation (e.g., registration fees, parking fees, and road tolls) could lead to a similar (nearly one-to-one) drop in private transport energy consumption.

3.1 Importance of income/development level: further investigation into the 1995 dataset

Researchers often want to know whether the elasticity for a variable, like affluence, changes with development. That question of nonlinear relationships is often addressed by including a GDP per capita squared term in regressions (e.g., as done in the EKC literature) and testing whether the coefficient for that squared term is negative and statistically significant. Furthermore, when the coefficient for the GDP term is positive and the GDP squared term negative, the implied turning point—the level of GDP at which the relationship between income and the dependent variable (environmental impact) changes from positive to negative—can be calculated by differentiating the estimated equation with respect to GDP per capita, setting equal to zero, and solving.

Romero-Lankao et al. (2009) included such a squared term in their regressions, and the elasticity for that term is sometimes negative and significant. However, the implied turning points are approximately at 5-7 times the sample average GDP per capita, or at a level of 2-3 times the highest GDP per capita in the sample—i.e., well out of the sample range.[5] Such a finding is to be expected for an essentially normal consumer good like transport. Indeed, Liddle

[5] The turning points had to be estimated since Romero-Lankao et al. (2009) do not report such statistics.

(2004) similarly rejected an EKC for road energy use per capita using national-level OECD country data (again, the implied turning-point was well outside the sample range).

We ran an EKC-type regression on the 1995 sample (the only sample with enough cities located in developing countries to possibly make such an exercise worthwhile), by adding a GDP per capita squared term to model VI in Table 3; in doing so, the additionally considered variables (beyond those included in the regressions reported by Romero-Lankao et al. 2009) meant an EKC relationship was rejected even more strongly. The elasticity for the GDP per capita squared term, while negative, was not significant (p-value = 0.19), and the implied turning point was 69 times the sample average or at a level of over one million USD per capita (regression not shown).

Yet, after splitting the 1995 sample into cities in OECD/developed/rich countries[6] and cities in less developed countries, a Chow test suggested that many of the estimated elasticities in Regressions III-VI (in Table 3) may be significantly different depending on development level. Thus, the sample was split in two, and the regressions run again. Those regression results are shown in Table 4.

Table 4

The top half of Table 4 displays the results of the regressions run with cities from OECD or the most developed countries. Those results are not too different from the previous regressions shown in Table 3. In comparing Regression III to Regression IX, the biggest difference is that, when only rich cities are considered, the elasticity for the variable measuring total private transport costs per kilometer is now significant and fairly large. Also, the elasticity for the variable measuring the user costs of the public transport alternative is (marginally) significant,

[6] The cities located in non-OECD countries that were considered to be in rich/developed countries were: Hong Kong, Singapore, Taipei, and Tel Aviv.

but, surprisingly, negative. Regressions X and XI again imply that fuel efficiency and fuel costs are associated since the elasticity for fuel efficiency is substantially smaller (in absolute terms) when fuel costs are considered.

The bottom half of Table 4 shows the results for the cities located in less developed countries. The elasticity for population is substantially larger than in any of the other regressions and (for Regressions XIII and XV) statistically significantly greater than one (at the 95% confidence level). Also, the elasticity for urban density is larger (in absolute terms) than in any of the other regressions. Thus, it appears cities in developing countries differ importantly along demographic lines in terms of the drivers of private transport energy consumption.

The only other variable that had a significant elasticity is fuel price (in Regression XV), although its impact on energy consumption is only about half of that found in developed, richer cities (shown in Regressions X and XI). Because only the very rich may own cars in developing country cities, perhaps it is not surprising that the elasticity for fuel price should be smaller (in absolute terms), since those relatively richer drivers may be less (fuel) price sensitive.

In general, it is not clear whether cities in developing countries truly have fewer policy levers at their disposal to lower private transport energy consumption, or whether because their transport systems are less developed, the impact of certain policy levers cannot be accurately assessed (the smaller sample size could be a factor in finding fewer variables with significant elasticities, too).

4. Conclusions

The paper confirmed the now well-established result that urban density is negatively correlated with urban private transport energy use; it did so by analyzing three separate, but related datasets (with observations from 1990, 1995, and 2001) using a consistent modeling framework and as consistent variables as the three datasets would allow. Also, population was found to have a greater elasticity with respect to energy consumption than GDP per capita (their 95% confidence intervals virtually never overlap). Variables representing effective private transport fuel efficiency, fuel price, and public transport network size were typically statistically significant and had the expected signs. However, some differences in estimated elasticities were uncovered between cities located in more developed and less developed countries.

Interestingly, judging by the data collected in the sets analyzed here, urban density in Europe, while still significantly higher than most of the rest of the developed world, is declining (dropping by nearly 40% from 1960 to 2001 for the 11 cities for which there is data over this period). At the same time, European countries are experiencing population aging, and an association between a higher proportion of population in advanced age groups and a decline in transport energy/carbon emissions has been established by studies examining micro-level data and macro-level, cross-national data (e.g., Prskawetz et al. 2004 and Liddle 2011, respectively). Thus, in European cities at least, that trend of more sparse population density could partly offset the decline private transport that would be associated with the well established trend of aging/older populations.[7]

In terms of policies, improving private vehicle fuel efficiency, in particular, and increasing fuel price could have a substantial impact on lowering transport energy consumption. Furthermore, in developed country cities, increasing the entire costs of private transport (e.g., registration, parking, and road tolls) could lower energy consumption substantially as well. On the other hand, there is no evidence that further lowering the cost to riders of public transport would lower private transport energy consumption. And the elasticity for the public transport

[7] That the transport impacts from changes in urban density uncovered here may run counter to transport impacts from population aging was suggested by an anonymous reviewer.

network per capita is significant and negative, but typically considerably smaller than the elasticities for the other variables. For developing country cities, which did have a much smaller sample size, the only policy variable/lever (other than urban density, which is already quite high in those cities) that could be recommended is increasing the fuel price; the elasticity for fuel price is negative and significant, but significantly smaller in absolute terms than that for developed country cities (i.e., private transport energy consumption is less price sensitive in developing country cities than in developed country cities).

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Table 1. Variables analyzed in the study.

Variable name	Definition	Units	Coverage
Private transport energy consumption	Energy consumed for fuel for private passenger transport within the metropolitan area (includes cars, motorcycles, taxis, and share taxis)	MJ	1990, 1995, & 2001 a
GDP p.cap.	Metropolitan gross domestic product per capita	2001 USD per person	1990, 1995, & 2001
Population	Population in metropolitan area	persons	1990, 1995, & 2001
Urban density	Ratio between the population and the urbanized surface area of the metropolitan area (i.e., does not include sea, lakes, rivers, etc.)	Persons per hectare	1990, 1995, & 2001
Fuel efficiency	Private passenger vehicle kilometres travelled divided by private passenger transport energy use	VKm/MJ	1990, 1995, & 2001 a
Pub. cost p. Pass. km	Cost of one public transport passenger kilometre for the traveller (ticket revenue plus fines paid by fare-evaders divided by public transport passenger kilometres travelled)	2001 USD	1990, 1995, & 2001
Prvt. Cost p. Pass. Km	Cost of one private motorised passenger kilometre for the traveller/motorist (includes fuel, maintenance, insurance, taxes, parking, tolls, and depreciation)	2001 USD	1995 & 2001
Fuel price	Average (weighted by distance travelled) price of fuel for private cars and motorcycles	2001 USD/MJ	1995
Pub. Seat km p. Cap.	Summed over all public transport vehicles: the distance travelled times the number of seats/places offered in the vehicle, divided by the number of inhabitants	Seat/place km per person	1995 & 2001 b

a: It is not clear whether the 1990 cross-section includes taxis and share taxis.
b: The 1995 cross-section considers only seats; the 2001 cross-section counts seats and standing passengers, assuming the capacity of four standing passengers per square metre of vehicle passenger space.

Table 2. The means and standard deviations (in parentheses) for the variables considered for each dataset/cross-section.

	1990		**1995**		**2001**
		All	**OECD/developed**	**Less developed**	
Private transport energy consumption	1.6E+11 (1.9E+11)	7.7E+10 (1.2E+11)	9.2E+10 (1.4E+11)	4.7E+10 (6.2E+10)	3.6E+10 (5.5E+10)
GDP p.cap.	31,706 (14,323)	24,856 (17,284)	34,301 (12,345)	4,568 (3,133)	22,882 (9,101)
Population (mil.)	4.9 (6.0)	4.7 (5.5)	3.6 (5.2)	6.9 (5.5)	2.8 (3.4)
Urban density	61.6 (75.5)	75.7 (74.3)	52.6 (52.8)	125.2 (88.2)	54.7 (41.5)
Fuel efficiency	0.204 (0.036)	0.296 (0.103)	0.278 (0.059)	0.335 (0.154)	0.301 (0.029)
Pub. cost p. Pass. km	0.10 (0.04)	0.10 (0.06)	0.12 (0.06)	0.03 (0.02)	0.08 (0.04)
Prvt. Cost p. Pass. Km		0.32 (0.15)	0.37 (0.12)	0.19 (0.11)	0.36 (0.09)
Fuel price		0.024 (0.015)	0.026 (0.011)	0.020 (0.020)	
Pub. Seat km p. Cap.		3,507 (2,281)	3,614 (2,299)	3,276 (2,224)	8,602 (4,802)

Table 3. OLS Regression results. Private transport energy consumption dependent variable.

Cross-section	1990		1995				2001	
Regression	**I**	**II**	**III**	**IV**	**V**	**VI**	**VII**	**VIII**
GDP p.cap.	0.310**	0.162*	0.483***	0.407***	0.466***	0.461***	0.679***	0.699***
	(0.143)	(0.091)	(0.086)	(0.048)	(0.077)	(0.048)	(0.118)	(0.096)
Population	1.035***	1.025***	1.065***	1.096***	1.063***	1.063***	0.992***	0.997***
	(0.055)	(0.048)	(0.051)	(0.042)	(0.041)	(0.041)	(0.038)	(0.035)
Urban	-0.513***	-0.523***	-0.525***	-0.561***	-0.533***	-0.534***	-0.273**	-0.293***
density	(0.066)	(0.067)	(0.078)	(0.053)	(0.060)	(0.055)	(0.106)	(0.092)
Fuel	-0.866**	-0.915**	-0.717***	-0.723***	-0.567***	-0.566***	-1.226***	-1.260***
efficiency	(0.330)	(0.347)	(0.171)	(0.147)	(0.133)	(0.132)	(0.378)	(0.369)
Pub. cost p.	-0.266		-0.0142		-0.00736		0.0337	
Pass. km	(0.170)		(0.069)		(0.070)		(0.082)	
Prvt. Cost p.			-0.145				-0.888***	-0.863***
Pass. Km			(0.164)				(0.186)	(0.181)
Fuel price					-0.163**	-0.162**		
					(0.070)	(0.068)		
Pub. Seat km			-0.144***	-0.148***	-0.107**	-0.107**	-0.141**	-0.153**
p. Cap.			(0.055)	(0.047)	(0.047)	(0.048)	(0.065)	(0.060)
Adj. R^2	0.93	0.93	0.94	0.93	0.94	0.94	0.95	0.96
VIF (avg./max)		1.3/1.4		2.0/2.7		2.3/2.7		2.1/3.6
N	35	35	84	85	84	84	46	47

Notes: White heteroscedasticity-consistent standard errors in parentheses. Statistical significance is indicated by: *** p <0.01, ** p <0.05, and * p<0.10.

Table 4. OLS Regression results with the 1995 cross-section split according to income/development level. Private transport energy consumption dependent variable.

OECD/ most developed countries			
Regression	**IX**	**X**	**XI**
GDP p.cap.	0.362***	0.240***	0.220***
	(0.081)	(0.083)	(0.065)
Population	0.976***	0.999***	1.000***
	(0.029)	(0.028)	(0.027)
Urban density	-0.375***	-0.428***	-0.428***
	(0.060)	(0.053)	(0.052)
Fuel efficiency	-0.870***	-0.383**	-0.373**
	(0.148)	(0.1177)	(0.175)
Pub. cost p. Pass. km	-0.141*	-0.037	
	(0.071)	(0.081)	
Prvt. Cost p. Pass. Km	-0.470***		
	(0.131)		
Fuel price		-0.399***	-0.411***
		(0.095)	(0.094)
Pub. Seat km p. Cap.	-0.144***	-0.125***	-0.126***
	(0.036)	(0.035)	(0.034)
Adj. R^2	0.98	0.98	0.98
VIF (avg./max)	1.9/3.4		2.2/4.3
N	58	58	58

Less developed countries				
Regression	**XII**	**XIII**	**XIV**	**XV**
GDP p.cap.	0.563***	0.539***	0.603***	0.632***
	(0.171)	(0.106)	(0.141)	(0.117)
Population	1.207***	1.335***	1.188***	1.219***
	(0.167)	(0.140)	(0.151)	(0.118)
Urban density	-0.606**	-0.758***	-0.600**	-0.679***
	(0.253)	(0.187)	(0.210)	(0.164)
Fuel efficiency	-0.342		-0.136	
	(0.321)		(0.299)	
Pub. cost p. Pass. km	0.068		0.051	
	(0.104)		(0.102)	
Prvt. Cost p. Pass. Km	-0.116			
	(0.212)			
Fuel price			-0.242*	-0.224**
			(0.121)	(0.090)
Pub. Seat km p. Cap.	-0.061		0.053	
	(0.141)		(0.163)	
Adj. R^2	0.84	0.85	0.85	0.87
VIF (avg./max)		2.4/3.2		2.2/3.0
N	27	28	27	27

Notes: White heteroscedasticity-consistent standard errors in parentheses. Statistical significance is indicated by: *** p <0.01, ** p <0.05, and * p<0.10.

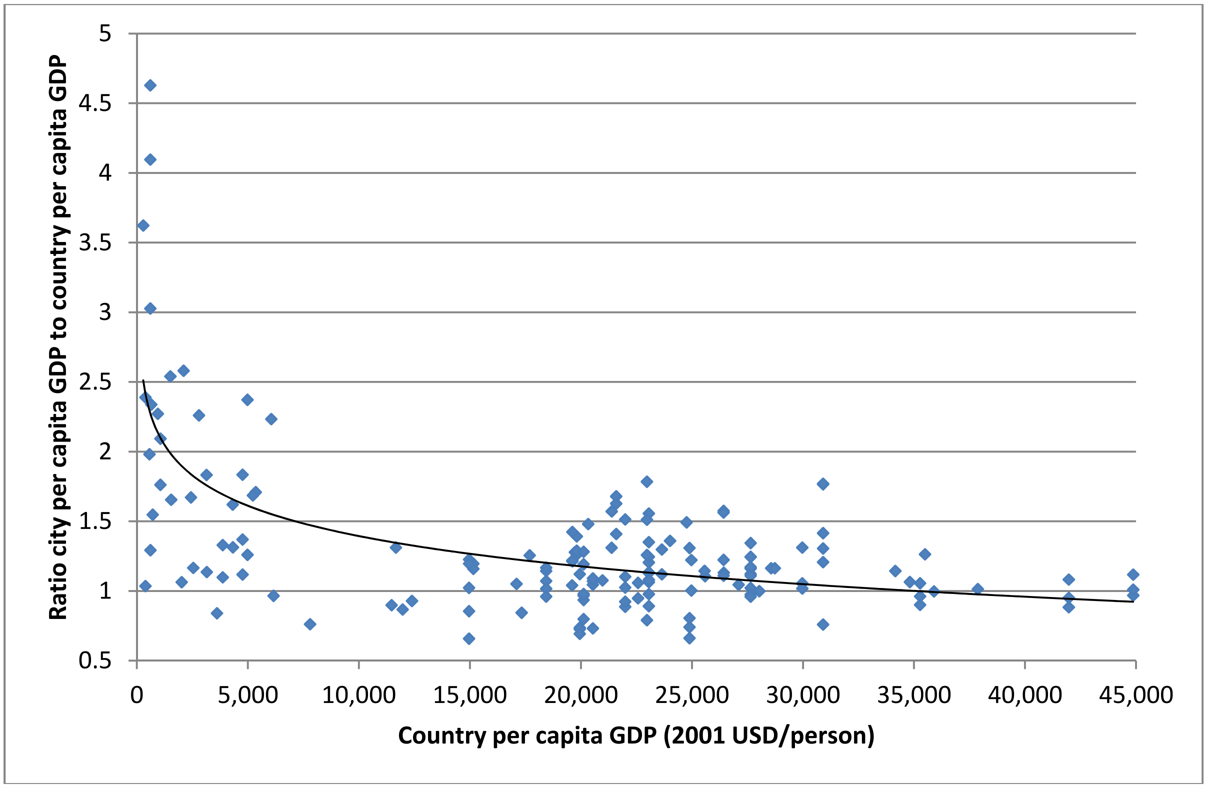

Figure 1. The economic importance of cities. The ratio of city per capita GDP to the corresponding country per capita GDP is plotted against that corresponding country per capita GDP for 160 world cities. Logarithmic trend line also shown.

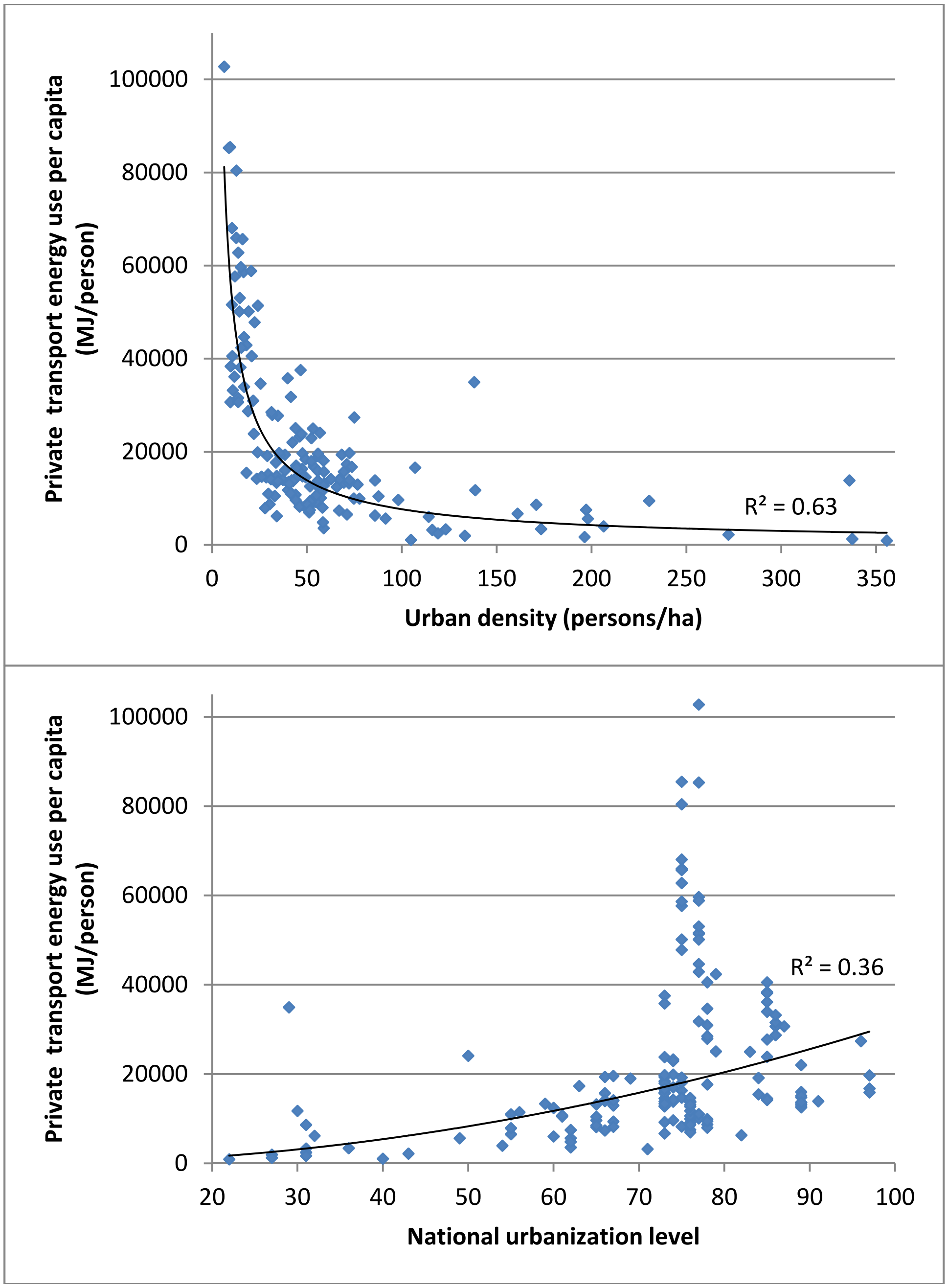

Figure 2. The relationships between urban private transport energy use per capita for 160 world cities and both urban density (upper graph) and the corresponding national urbanization level (lower graph). Power-based trend lines and corresponding R-squared values shown.

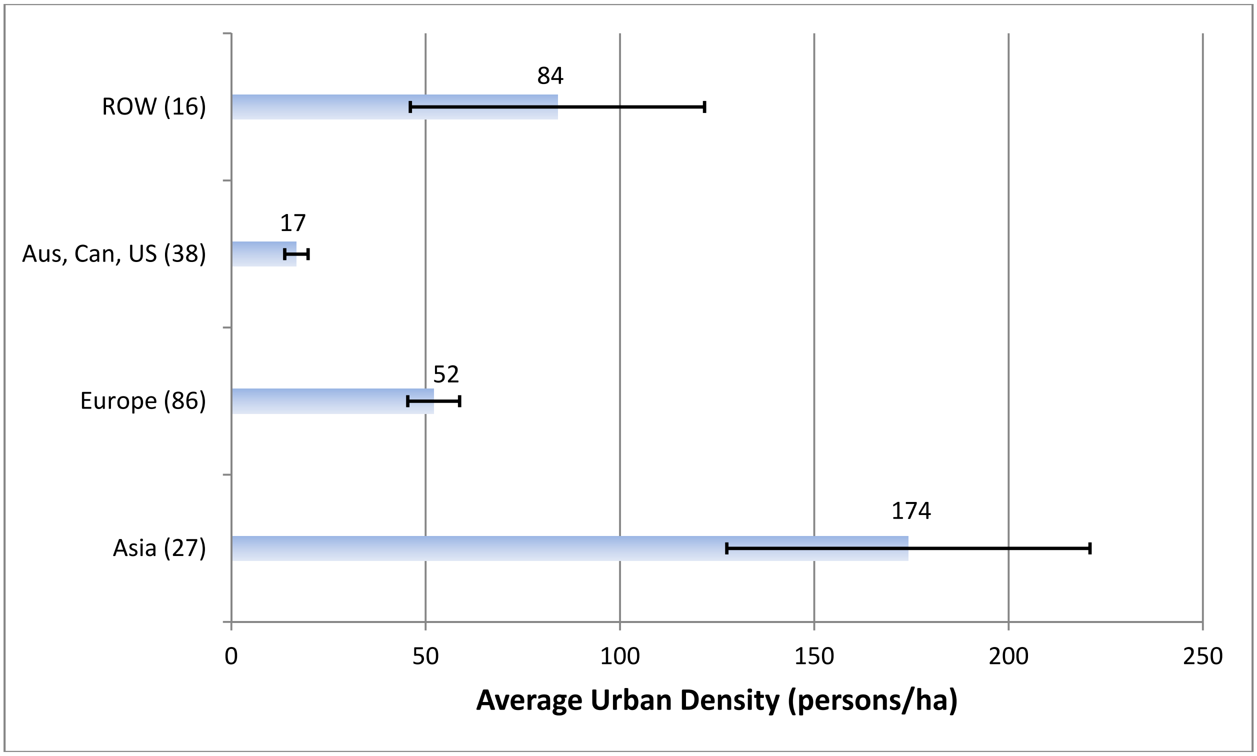

Figure 3. The average urban density by geographic/cultural group for the 167 cities considered in the study. In addition to the average density, the figure displays each groups' 99% confidence bounds (the error bars). Thus, the difference between any two groups' average is statistically significant (at the 0.01 level) if one group's upper error bound is outside another group's lower error bound. The Australia, Canada, and US (Aus, Can, US) group also contains Wellington, NZ (from 1995). The rest of world (ROW) group contains cities from Africa (6), Middle East (4), and South America (6). All but two ROW observations are from 1995.

Appendix Table A-1. Cities included in each dataset/cross-section.

1990 (35 total)		1995 (85 total)			2001 (47 total)	
Boston	Amsterdam	Atlanta	Amsterdam	Brisbane	Amsterdam	Stockholm
Chicago	Brussels	Calgary	Athens	Melbourne	Athens	Stuttgart
Denver	Copenhagen	Chicago	Barcelona	Perth	Barcelona	Turin
Detroit	Frankfurt	Denver	Berlin	Sydney	Berlin	Valencia
Houston	Hamburg	Houston	Berne	Wellington	Bern	Vienna
Los Angeles	London	Los Angeles	Bologna		Bilbao	Warsaw
New York	Munich	Montreal	Brussels	Bogota	Bologna	Zurich
Phoenix	Paris	New York	Budapest	Cairo	Brussels	
San Francisco	Stockholm	Ottawa	Copenhagen	Cape Town	Budapest	Chicago
Toronto	Vienna	Phoenix	Dusseldorf	Curitiba	Copenhagen	Dubai
Washington	Zurich	San Diego	Frankfurt	Dakar	Geneva	Honk Kong
		San Francisco	Geneva	Harare	Ghent	Melbourne
Bangkok	Adelaide	Toronto	Glasgow	Johannesburg	Glasgow	Sao Paulo
Hong Kong	Brisbane	Vancouver	Graz	Mexico City	Graz	Singapore
Jakarta	Melbourne	Washington	Hamburg	Rio de Janeiro	Hamburg	
Kuala Lumpur	Perth		Helsinki	Riyadh	Helsinki	
Manila	Sydney	Bangkok	Krakow	Sao Paulo	Krakow	
Seoul		Beijing	London	Tehran	Lille	
Singapore		Chennai	Lyon	Tel Aviv	Lisbon	
Tokyo		Guangzhou	Madrid	Tunis	London	
		Ho Chi Minh City	Manchester		Lyons	
		Hong Kong	Marseille		Madrid	
		Jakarta	Milan		Manchester	
		Kuala Lumpur	Munich		Marseilles	
		Manila	Nantes		Moscow	
		Mumbai	Newcastle		Munich	
		Osaka	Oslo		Nantes	
		Sapporo	Paris		Newcastle	
		Seoul	Prague		Oslo	
		Shanghai	Rome		Paris	
		Singapore	Stockholm		Prague	
		Taipei	Stuttgart		Rome	
		Tokyo	Vienna		Rotterdam	
			Zurich		Seville	

Note: Cities are listed in alphabetical order within the following regional groupings: North America (Canada and US), Asia, Europe, and Oceania/other, except for the 2001 cross-section in which only two groupings are used: Europe and other.

Appendix Table A-2. 95% confidence intervals for GDP per capita and population for each regression.

Regression	**Cross-section**	**GDP per capita**	**Population**
I	1990	[0.019 0.602]	[0.923 1.147]
II	1990	[-0.023 0.348]	[0.926 1.124]
III	1995	[0.311 0.655]	[0.963 1.166]
IV	1995	[0.311 0.503]	[**1.013 1.180**]
V	1995	[0.313 0.619]	[0.980 1.145]
VI	1995	[0.366 0.556]	[0.982 1.145]
VII	2001	[0.441 $\boxed{\mathbf{0.917}}$]	[$\boxed{\mathbf{0.916}}$ 1.069]
VIII	2001	[0.505 0.893]	[0.925 1.069]
IX	1995, OECD/most developed	[0.200 0.524]	[0.918 1.035]
X	1995, OECD/most developed	[0.072 0.407]	[0.943 1.054]
XI	1995, OECD/most developed	[0.089 0.351]	[0.946 1.054]
XII	1995, less developed	[0.117 0.876]	[0.906 1.613]
XIII	1995, less developed	[0.249 0.682]	[**1.096 1.673**]
XIV	1995, less developed	[0.192 0.874]	[0.915 1.559]
XV	1995, less developed	[0.305 0.825]	[**1.024 1.508**]

Notes: Interval bounds with overlap between GDP per capita and population are in bold and boxed; population intervals that exclude 1.0 are in bold.