META-ANALYSIS OF ENERGY USE IN CITIES

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I. OVERVIEW

Since 1973 and the energy crisis that raised the question of energy dependency, much research has examined the determinants of the energy demand. The Transportation sector in particular, was subject to investigation as one of the main contributor in term of energy consumption: transport-related fuel accounts for 30% of the world's energy consumption and this share is expected to grow at a rate of 1.5% per year until 2030 which would lead to a yearly increase of 1.7% in terms of transport-related CO_2 emissions (IEA 2008a). Yet contributing to 36% of the world final energy demand[2], the Building sector aroused less interest until recently (Ewing & Rong 2008, IEA 2008b).

The analysis of the role of economic determinants such as income and prices constitutes the core of the literature aiming at understanding, forecasting and sketching pathways to control the overall energy demand (see among others Dahl & Sterner (1991), Schmalensee & Stoker (1999) and Yatchew & No (2001) on the Transportation sector, and Alberini et al. (2011), Nesbakken (1999) and Reiss & White (2005) for a focus on the Residential sector). Yet, in the context of concerns about energy shortage and climate change, alternatives to energy price policies aiming at curbing the increasing energy demand, were also explored. Thus, the United-States urban growth pattern, relying on "low density development […] accompanied by a rapid increase in automobile ownership and vehicle miles traveled" (Bento et al. 2005) started to be questioned in the 90's: the relationship between urban form and mobility has been extensively studied over the past years, and special effort has been made to quantify the impact of urban form on travel behavior (Bento et al. 2005; Grazi et al. 2008; Newman & Kenworthy 1989). Yet, literature reviews reveal large variations in empirical estimations (Ewing & Cervero 2010; Stead & Marshall 2001), suggesting that questions about the relevance of the interaction mechanism between spatial organization and mobility remain to be answered.

This paper focuses on the spatial determinants of household energy consumption, and more precisely on the role of residential density[3] in the formation of household energy demand. Through an analysis of the literature – large on about the Transportation sector but relatively poor about the Residential sector, this article aims at providing an overall estimation of the relationship between urban form and mobility on the one hand, and between urban form and residential energy demand on the other. The methodology is based on meta-analyses i.e. empirical results found in the literature are

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[2] Primary energy is the energy used to support economic activities. It therefore refers to the source of energy and the type of technology employed for those purposes. Final energy is the energy used by households to heat dwellings and run appliances. The difference between the two measures the net energy losses due to inefficiency of energy production systems and distribution infrastructure network.

[3] Residential density refers to the ratio of the number of dwellings or individuals per area.

gathered to constitute a meta-sample that is treated statistically. By acknowledging the heterogeneity of studies in terms of data used or estimation methods employed, the objective of such a methodology is to identify potential systematic variations in estimation values quoted in studies and to provide a robust evaluation of the parameter of interest. Several research efforts relied on meta-analyses to investigate the role of determinants such as energy prices or income in the formation of the household transport and residential energy demands (see M. Espey (1998) and Goodwin et al. (2004) for the Transportation sector; J. A. Espey & M. Espey (2004) for the Residential sector). But to the best of our knowledge there is a gap in the literature of spatial determinants of transport and residential energy demand except for Ewing & Cervero (2010) and Leck (2006). This paper contributes to fill in this gap by conducting a meta-analysis of the effect of urban form on individual mobility on the one hand, and by providing a synthesis of previous research on the impact of spatial organization on residential energy demand on the other. Our study departs from previous work in a fourfold way: i) it enriches the number of comparable estimations of the impact of urban form on mobility from 10 in Ewing & Cervero (2010) to 50; ii) it provides additional information such as standard errors for the majority of meta-data allowing to provide robust weighted estimations; iii) it investigates the potential determinants of significance of urban form variables in explaining mobility; and iv) it offers an analysis of the global impact of urban form on households behavior as both the Transportation and the Residential sectors are considered.

The remainder of this paper is organized as follows. Section II presents the data used to conduct the meta-analysis of the effect of residential density on mobility whose results are revealed in section III. Section IV synthesizes the literature on the empirical estimation of the impact of population density on residential energy consumption, and section V offers concluding remarks.

II. THE METHOD: ESTIMATING THE IMPACT OF DENSITY ON INDIVIDUALS TRAVEL BEHAVIOR

The rich literature on individual transportation determinants offers more than 200 empirical studies including spatial aspects. One characteristic of this literature is its twofold heterogeneity, on the one hand in the spatial variables used, and on the other hand in the forms of the specification used to model mobility. The diversity of spatial organization explains the variety of spatial variables found in the studies as no standardized variable does exist to measure urban form. Yet, population density is largely used: i) first, from a theoretical standpoint, as recalled in Grazi et al. (2008), Fujita (1989) suggested a negative relationship between commuting distance and residential density as workers choose their location by making a trade-off between generalized commuting costs and housing prices; ii) second, residential density provides a reliable proxy known to capture aspects of urban structure that induce mobility mechanisms (Niemeier & Rutherford 1994; Schimek 1996b). The heterogeneity in demand functions used to model transport demand results from the complexity of spatial economic theory and especially regarding energy consumption that prevents one for providing a standardized analytic relationship which links spatial organization to mobility. In order to ensure comparability among studies, this paper focuses on residential density as a variable capturing urban form, whose impact on mobility is measured through the elasticity of mobility on residential density. Thus previous elasticity is the parameter of interest or effect size of this meta-analysis. The demand of mobility is measured either in terms of energy consumed or in distance traveled. Given the nature of the studies found in the literature and their available statistical information (directly provided or obtained by request from authors), our final database results in 50 observations from 24 different studies providing estimates of the effect size, related standard error when available, characteristics of the estimation method and characteristics of data used. Selected studies are described in *TABLE 1*. In the remaining of this paper, the term of *primary* refers to elements of selected studies listed in *TABLE 1* while *meta-* refers to specific elements of this paper. The effect size, denoted as e, is the elasticity of residential density (d) on mobility (M).

When the estimate of elasticity was not directly available in studies, it was evaluated at the mean point of the primary sample: the estimated coefficient of the impact of density on mobility provided by the study was combined with mean values of dependant variable *M* and/or independent variable *d* available to us from the statistical summary of the study or directly from authors upon request or from alternative data sets. Evaluating elasticity at the sample mean point is only an approximation of mean values of individual elasticity as non linearity often exists in models estimated (Train 1986, p.42). Yet, as Ewing & Cervero (2010) mentioned, the error introduced by this approximation mainly concerns discrete choice models, which are not predominant in our meta-sample. Furthermore, we included a dummy variable stating whether the estimated effect size was computed at the sample mean or directly provided by the study, in order to capture the potential systematic bias due to the approximation conducted. Studies using categories of population density as explanatory variables rather than a continuous population density variable were treated as follows: first estimations of elasticity of population density on mobility were computed for each adjacent couple of categories at the mean point of the primary sample; second, the resulting estimates were weighted according to the distribution of the observations by categories of density in order to compute a single mean elasticity estimate. A couple of studies found insignificant estimates of the impact of population density on mobility: in that case, the hypothesis that population density has no effect on mobility failed to be rejected and we computed effect size as 0 accordingly. Standard errors were collected or computed when possible. Descriptive statistics of our resulting meta-dataset are given in *TABLE 2*.

Mean estimate of population density elasticity on mobility is -0.16 in the meta-dataset. 82% of the observations of our meta-sample are significant at a level of 10% or lower level. Estimates of the effect size range from -0.60 to 0.04, and from -0.60 to -0.02 when excluding the single positive estimate 0.04 and insignificant ones. Standard errors are known for 64% of the meta-observations and sample sizes vary from 31 to 95360. Regarding model characteristics, independent equations were used in 64% of the selected studies while 26% of estimations were controlled for selection-effect mechanisms. Estimations are largely conducted at the vehicle or the individual or the household level, and rarely on longitudinal data. The imbalance in geographical areas considered is noteworthy as 54% of the meta-sample relies on US data. The next section investigates further systematic variations in estimations.

III. SYSTEMATIC HETEROGENEITY IN EFFECT SIZE: META-ANALYSIS RESULTS

III.A. Homogeneity test

The hypothesis that estimate variation is only due to sample error - that is to say the hypothesis of homogeneity in estimates - was tested first before investigating further sources of systematic heterogeneity. e_i refers to the effect size of meta-observation *i*, and v_i to the related standard error. The weighted mean effect size $\overline{e_w}$ and its related standard error $\overline{v_w}$ were computed as defined in equations (1) and (2) :

$$\overline{e_w} = \frac{\sum_{i=1}^{36} \frac{e_i}{v_i^2}}{\sum_{i=1}^{36} \frac{1}{v_i^2}} \qquad e_i \in \mathbb{R} \;\; ; v_i \in \mathbb{R}^{+*} \qquad (1)$$

$$\overline{v_w} = \sqrt{\frac{1}{\sum_{i=1}^{36} \frac{1}{v_i^2}}} \qquad v_i \in \mathbb{R}^{+*} \qquad (2)$$

Computed values and the Q-statistic used to test homogeneity (Brons 2006) are presented in *TABLE 3*. The weighted mean elasticity computed on the 36 significant estimates of the meta-dataset is -0.12 with a standard error of 0.00094. Whereas main studies in transportation or the urban planning sector compute the unweighted mean, or alternatively the mean weighted by sample size (Ewing & Cervero 2010), this paper uses the reverse of the estimate variance as weight. Thus it allows to provide more robust mean results (Hedges & Olkin 1985). Furthermore, the relevance of computing the weighted mean value to estimate the effect size required the hypothesis of homogeneity across estimates, a hypothesis which has been rarely tested in previous transportation meta-analysis literature. In our case, the hypothesis of homogeneity is rejected at 1%: hence the weighted mean value is insufficient to provide a robust estimate of elasticity of mobility on population density and should be combined with further investigation aiming at identifying sources of heterogeneity in estimates.

III.B. Systematic heterogeneity in significance.

This sub-section analyses the study's heterogeneity in significance among study by first exploring the question of publication bias and second, by investigating for potential significance explanatory variables of significance in studies. When conducting statistical processing on estimations provided by the literature, a crucial question arises, i.e. the potential existence of a publication bias. Such a bias may be motivated for two reasons: i)first, a tendency of academic journals to publish papers with "statistically significant" results (Long & Lang 1992); ii)second a tendency of researchers to adjust their specification choices according to expected estimation results (Card & Krueger 1995). Despite the high percentage, i.e. 86%, of our meta-data significance, an underlying publication bias would prevent us from concluding about an effective impact of population density on mobility.

Under the hypothesis of a non nil density elasticity of transport demand, the precision of empirical elasticity estimates should increase with sample size: more specifically, "the absolute value of the t-ratio of the estimate should vary proportionally with the square root of the number of degrees of freedom" (Card & Krueger 1995).

FIGURE 1displays the t-ratio according to the square root of the number of degrees of freedom, excluding meta-observations including some missing values. The results of the OLS regression of the absolute t-ratio on the square root of the degrees of freedom are shown in *TABLE 4*. FIGURE 1 shows an upward-sloping pattern between absolute t-ratio and sample size, as expected from the hypothesis of non nil density elasticity of transport. Moreover, the OLS regression results in *TABLE 4* confirm this expected relationship as we found a significant positive coefficient of 0.035 between the t-ratio and the square root of the number of degrees of freedom. Hence, our meta-dataset does not provide strong evidence of publication bias and the assumption of an impact of residential density on mobility is not rejected.

In order to investigate further into the heterogeneity in the significance found in studies, we built a discrete model predicting the population density significance in explaining transport demand as a function of the study's characteristics that provides this estimate. The dependant variable, *y*, takes the value of 1 for significant estimates and the value of 0 otherwise. *y* is modeled using a binary logit model. Most of the explanatory variables are dummies. Given the relatively small number of meta-observations (50), some of the binary variables are very unevenly distributed toward one of their alternative and consequently had to be excluded in order to avoid bias in the logit model estimation. Odd ratios of independent variables are shown in *TABLE 5*. Here three variables seem to play a role in the significance probability of the role of residential density on the formation of the transport demand. First, the measurement of population density at infra-MSA level increases the ratio of the probability that significance is observed on the probability that insignificance by almost 185: this result strongly indicates that main spatial mechanisms at stake in the formation of the transport demand happen at infra-MSA level. Second, estimations relying on disaggregated studies, such as studies conducted at the household, the individual or the private vehicle levels, are slightly more likely to result in a significant effect size than estimations run on aggregated levels (city or state level): the odd ratio observed arises of 0.005 when considering disaggregated data. Besides the question of the relevant scale of performing an analysis of the impact of density on mobility, previous results clearly indicate that downscaled data for population density measurements - and to a lesser extent mobility measurements - are more suitable to capture mechanisms at stake. Thus, if price and income elasticity of mobility can equally been estimated at aggregated or disaggregated levels (M. Espey 1998), our results suggest that future work should focus on a disaggregated level when analyzing the impact of spatial organization on transport demand. Finally, the odd ratio of significance increases by 0.005 when controlling for private vehicle characteristics.

III.C. Systematic heterogeneity in effect size estimate.

This section explores the sources of systematic variations in effect size by estimating the expected value of the population density elasticity of mobility as a function of the studies' characteristics. Two types of models were tested: i) Ordinary Least Square (OLS), Weighted Least Square (WLS) and Tobit regression models, assuming that all variation in effect size beyond sampling error is systematic (Type 1); and ii) fixed and random effect regression models allowing for explicit within study correlation beyond systematic variations and sample error (Type 2). The Tobit models allow for the inclusion of nil meta-observations which were excluded from estimations of other models in order to avoid a downward bias due to insignificant effect size. The five models tested are summarized in *TABLE 6*, whereas the results of the estimations are displayed in *TABLE 8*. The key model parameters are noted as follows: e_i stands for the effect size estimate of meta-observation *i*, $\mathbf{x_i}$ is the related vector of explanatory variables, $\underline{\boldsymbol{\beta}_i}$ is the vector of coefficients to be estimated, ε_i is the error term. *s* refers to the study number (some studies provide several estimates of effect size), μ_s to the in-studies fixed effect, and δ_{is} to the in-study random effect of meta-observation *i*.

Type-2 models are based on the hypothesis of in-study dependence - fixed dependence in the fixed effect model and random dependence in the random effect model – while Type 1 models do not allow for in-study correlation. Yet, the absence of in-study dependence fails to be rejected in the fixed effects model as the related F-test gives a p-value of 0.1682. Moreover, the in-study variance is found to be nil in the random-effect model. Both previous results indicate that the hypothesis of within-study correlation does not hold on the meta-dataset considered and all estimated models are thus likely to be relevant in capturing systematic heterogeneity in the elasticity value of mobility on residential density.

Results displayed in *TABLE 8* reveal a significant role of the geographical characteristics of datasets used. First, the region related to the dataset used by the empirical study has an impact on the quantification of the relation between mobility and population density: i) the effect size estimated in the United States appear to be significantly stronger than in other regions as the elasticity of mobility on residential density is higher in absolute - from 0.243 to 0.404 higher when estimated on US data; ii) elasticity results from a worldwide dataset are also higher in absolute value – from 0.223 to 0.367 higher – than other study results. Second, the type of area considered also matters in the systematic heterogeneity of the effect size. Indeed estimations run on urban-only data produce lower absolute elasticity - from 0.085 to 0.260 lower - than estimations including rural areas. This result points out the fact that the impact of population density on distance traveled and related energy consumption is comparatively higher in rural areas than in urban areas.

Data characteristics used for the estimation of the effect size also matter in the estimation. Thus disaggregated data are thus found to generate smaller evaluations of the impact of population density on mobility that aggregated data - absolute elasticities decrease from 0.389 to 0.474 when estimated at the households, the individual or the private vehicles levels. Moreover, the scale at which population density is measured also affects the estimation results: the relation between the residential density and mobility is found to be much stronger - from 0.382 to 0.520 - when population density is measured at an infra Metropolitan Statistical Area (MSA) scale than at a higher scale. Yet datasets often provide coherent results between the scale of the observation unit and the scale at which density is measured – only 4 studies account for disaggregated observation unit and density captured at a level of the MSA or above. Thus, when combining both effects, results in *TABLE 8* indicates that estimations run on data at disaggregated level of observation unit and density are likely to produce variations in effect size from -0.046 to 0.007.

The choice of control variables to be included in the specification is also found to influence the value of the effect size estimate. On the one hand, controlling for transport infrastructures induces higher absolute estimates than in specification that do not allow for such control. This result points out that higher residential density may affect transport infrastructure in a way that tends to increase mobility demand - when controlling for infrastructure, this effect is excluded from the effect size estimate which induces a stronger impact of density on mobility demand from 0.152 to 0.223. On the other hand, including vehicle characteristics (mainly number of vehicles) in the specification produces lower absolute elasticity of mobility on population density. This confirms the hypothesis that higher population density affects vehicle characteristics in the way that it decreases transport demand and related energy consumption. The elasticity of mobility on residential density, when including this mechanism, is found to be significantly higher in absolute value than estimated elasticity while controlling for private vehicle characteristics. The difference ranges from 0.094 to 0.132.

Models and specification characteristics are not found to significantly change the estimate of the elasticity of mobility on population density, except when the meta-data are weighted by the inverse of their variance. Moreover, no significant difference is found when the self-selection mechanism is accounted for or not, except in the Tobit model: in the latter, the result does not confirm the expectation that not accounting for a self-selection mechanism induces an overestimation of the impact of population density on the mobility demand.

Finally, no significant difference is found between effect size estimations run on data measuring mobility by distance traveled (*DT*) or by related-energy consumption (*E*). Yet, both variables are linked through energy efficiency γ (energy consumed by distance traveled). Thus related elasticity of distance traveled (e_{DT}), of energy consumption (e_E) and of energy efficiency (e_γ) on population density are also connected as described in equations (3) and (4).

$$E = TD \cdot \gamma \qquad (3)$$

$$e_E = e_{TD} + e_\gamma \qquad (4)$$

Some studies point out the negative value of e_γ, reflecting an increase of private vehicle energy efficiency of with higher residential density (Fang 2008), while others do not find a significant effect of population density on vehicle energy efficiency (Karathodorou et al. 2010). Regarding our analysis, the absence of a significant impact of the unit measure of mobility is coherent with the latter hypothesis, thus confirming the negligible impact of density on vehicle efficiency when analyzing mobility demand.

IV. ANALYTICAL REMARKS ON THE IMPACT OF DENSITY ON RESIDENTIAL ENERGY CONSUMPTION

The sections above revealed that much work questioning the interplay between spatial organization and transport demand and associated emissions fueled the international debate on urban form. Yet, little attention has been drawn to the fact that the location of activities and associated urban spatial structure of the economy refers to two sectors: the Transportation sector and its counterpart the Building sector. Consequently, effective quantitative assessment of the potential of planning policies in curbing energy demand should investigate the impact of urban form on both sectors. Through a review of empirical studies of the literature, this section aims at offering some qualitative insights into the potential effect of spatial policies on the Building sector in terms of energy savings.

Only few empirical studies dealing with building energy consumption include an analysis of spatial determinants. Larivière & Lafrance (1999) focus on the commercial and residential electricity consumption of 45 cities in Quebec: using data from 1991, they reveal a significant negative impact of population density on the cities' electricity demand - related approximated elasticity at -0.07 through the author's calculation. Similar results have been obtained by Holden & Norland (2005): conducting a disaggregated study on 591 individuals in Oslo (Norway), they find on the one hand a significant, and on the other negative, impact of residential density (measured as the number of housing per surface) on residential energy use. Ewing & Rong (2008) also contribute to validating the hypothesis considering urban form as a significant spatial determinant of the residential energy demand. By using a spatial index computed with population density and alternative urban structure variables, their article relies on a combination of two multivariate regressions in order to assess the significant and negative impact of urban organization on residential energy consumption. They identify a twofold impact mechanism of urban form on energy use: i) through housing characteristics - evaluated as the main causal pathway as it induces an approximated elasticity of -0.36; and ii) through the heat island effect – that induces an approximated elasticity of -0.03. Finally, Kaza (2010) indicates that when controlling for housing characteristics, "reported neighborhood density does not seem to have any impact on energy use". *TABLE 7* synthesized the characteristics and results of studies reviewed.

V. CONCLUSION

This paper focuses on the spatial determinants of household energy consumption, and more specifically on the role of residential density in the formation of household energy demand. By exploring the existing literature through meta-analyses and qualitative analyses, it extracts significant insights into the impact of spatial organization on both the Transportation and Residential sectors.

Regarding the Transportation sector, 50 comparable estimations of the impact of urban form on mobility as well as main related standard errors are provided, which allows for completing previous literature reviews. Potential determinants of the significance of urban form variables on explaining mobility are investigated and systematic heterogeneity in the impact of density on transport demand is estimated. In terms of the results, our meta-dataset provides a mean value of the density elasticity of mobility of -0.16 and a weighted mean value of -0.12. While no evidence in publication bias is found in the selected studies, the analysis of their significance clearly indicates that future empirical research should favor downscaled data for both mobility and population density measurements as they are shown to be more suitable in capturing mechanisms at stake. Besides the debate about the relevant scale of analysis, the causal impact pathway between urban form and transport demand is specified - the characteristics of the vehicles (mainly the number of vehicles) are found to play a significant role, contrary to vehicle energy efficiency which density is not found to affect significantly. Finally, highlighting geographical features when estimating the interaction between spatial organization and mobility has two useful policy implications. First it is important to be cautious when generalizing estimation results on different regions because geographical area has been shown to significantly affect the extent of the impact of urban form on transport demand - our dataset reveals a stronger impact in the United-States - and to promote geographical diversity in future estimation work could help to refine this result. Second, the comparative higher effect of density in rural versus urban areas suggests that future planning policies consider the high potential of transport demand reduction in rural areas.

First, insights into the Residential sector reveal that beside the Transportation sector, the Residential sector may also play a key role in energy management through urban planning -residential density elasticity of energy consumption ranges roughly from -0.07 to -0.39 when accounting for the impact of density on housing characteristics.

Building on existing literature, this paper leads to the conclusion of the importance of keeping questioning urban planning in the debate on energy management: it outlined the significant and negative impact of population density on residential energy consumption and paved the way for future estimation work on diverse geographical areas including rural areas and offering an integrated approach for both Transportation and Building sectors.

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LIST OF TABLES AND FIGURES

TABLE 1 – Empirical studies that estimate the impact of residential density on mobility and that were included in the meta-analysis

Study	# of estimates	Data type	Data period	Observation unit	Geographical area	Model type	Mobility unit	Infra-MSA residential density	Standard Error	Sample size	Effect size
Albalate & Bel (2009)	2	CS	2001	A.	Europe	IE/SURE	DT	No	No	45	0
Bento et al. (2005)	1	CS	1990	DisA.	US	2-step DC	DT	No	No	8297	0
Brownstone & Golob (2009)	2	CS	2001	DisA.	US California	SEM	DT & EU	Yes	Yes	2079	-0.14 / -0.12
Cervero & Murakami (2010)	2	CS	2003	A.	US	SEM	DT	No	No	370	-0.60 / -0.38
(C. A. Dahl 1978)	2	P	1954-1973	A.	Europe	IE	EU	No	No	55	0
Emrath & Liu (2008)	2	CS	2001	DisA.	US	IE	DT & EU	Yes	Yes	20356	-0.53 / -0.52
Fang (2008)	2	CS	2001	DisA.	US California	SURE	DT	Yes	Yes	2299	-0.05 / -0.04
Frank et al. (2010)	1	CS	2001	DisA.	US Atlanta	IE	EU	Yes	No	10184	-0.15
Glaeser & Kahn (2010)	5	CS	2001	DisA.	US	IE	EU	Yes	Yes, No	11728	[-0.11; -0.04]
Grazi et al. (2008)	4	CS	1998	DisA.	The Netherlands	IE	DT	Yes	Yes	25991	[-0.39; -0.13]
Giuliano & Narayan (2003)	2	CS	1995	DisA.	US	IE	DT	Yes	Yes	95360	-0.37 / -0.26
Guo & Gandavarapu (2010)	1	CS	2001	DisA.	US Wisconsin	SURE	DT	Yes	Yes	4974	0.04
Heres-Del-Valle & Niemeier (2011)	4	CS	2001	DisA.	US California	2-step DC	DT	Yes	Yes	7666	[-0.19; -0.16]
Holden & Norland (2005)	1	CS	2003	DisA.	Norway	IE	EU	Yes	No	650	0
Karathodorou et al. (2010)	4	CS	1999	A.	World	IE/SURE	DT & EU	No	Yes	84	[-0.35;-0.23]
Levinson & Kumar (1997)	1	CS	1990	DisA.	US	IE	DT	Yes	Yes	8651	-0.42
Liddle (2004)	3	P	1960-2003	A.	OECD	IE	EU	No	Yes	113	[-0.05; -0.04]
Schimek (1996a)	1	P	1988-1992	A.	US	IE	EU	No	Yes	255	-0.02
Shim et al. (2006)	1	CS	1999	A.	Korea	IE	EU	No	Yes	61	-0.12
Su (2010)	2	P	2001	A.	World	Other	DT	No	Yes, No	1700	-0.33 / -0.13
Su (2011)	2	CS	1982-2003	DisA.	US	IE	EU	No	Yes, No	5756	-0.06 / 0
van de Coevering & Schwanen (2006)	1	CS	1990	A.	Europe, Canada and US	IE	DT	No	Yes	31	-0.52
Zegras (2010)	2	CS	2001	DisA.	Santiago	IE/2-step DC	DT	Yes	No	4103	-0.04 / 0
Zhou & Kockelman (2008)	2	CS	1998	DisA.	US Texas	IE	DT	Yes	Yes, No	776	-0.22 / 0
Number of selected studies: 24											

# of estimates: Number of estimates provided by a study.
Data type: CS = cross-section data, P = panel data.
Observation unit: Unit of observation of the study; DisA = disaggregated (vehicle, individual or household level), A = aggregated (Metropolitan Statistical Area or states or country level).
Model type: IE = independent equations, SUR= seemingly unrelated regressions, SEM = structural equations model, 2-step DC = 2-step discrete-continuous model.
Mobility unit: Unit used to measure mobility in the study; EU = Energy Used, DT = Distance Traveled.
Infra-MSA residential density: Indicates if residential density is measured at infra-MSA level versus studies where residential density is measured at MSA, states or country level.

TABLE 2 - Descriptive statistics

Variables	% in the meta-sample	Mean	Std. Dev.	Min.	Max.
Elasticity of mobility on residential density		-0.16	0.17	-0.60	0.04
Significant estimate	82%				
Standard error available	64%				
Samples size		7767	14527	31	95360
Model and specification characteristics					
Method					
Independant Equation	64%				
Seemingly Unrelated Regressions	12%				
Structural Equations Model	8%				
2-step discrete-continuous model	12%				
Other					
Selection effect accounted for[#]	26%				
Data characteristics					
Cross-section data	84%				
Disaggregated observation unit	64%				
Categories of Density	18%				
Mobility measured in Distance Traveled	60%				
Private vehicle mobility	80%				
Infra-MSA population density	56%				
MSA population density	32%				
Geographical characteristics					
United-States	54%				
Europe	18%				
World*	20%				
Infra-national area	72%				
Urban area	54%				
Control variables					
Transport infrastructure characteristics	40%				
Energy prices	28%				
Private vehicle characteristics	32%				
Other					
Author's computation**	54%				

Number of observations in the meta-dataset: n=50

*Refers to studies that account for observations disseminated around the world.
**Author's computation: author's computation of elasticity from collected information.
#Selection effect refers to the individual choice of location driven by preferences for high or low density location, preferences that also affect their mobility behavior. The initial hypothesis of unidirectional impact of the density location on travel demand fails: selection effect induces a bilateral causal mechanism between both variables.

TABLE 3 – Unweighted and weighted mean effect size, related standard error and homogeneity-test statistic

Unweighted mean effect size *(# of obs.)*	-0.16 *(50)*
Weighted mean effect size $\overline{e_w}$ *(# of obs.)*	-0.12 *(36)*
Standard error $\overline{v}_w$	9.1E-04
Homogeneity test-statistic*	2897***

*Follows a χ^2(n-1) distribution (n being the number of effect size) under the hypothesis of homogeneity. In our case, n=36 significant elasticity estimates and the critical value at 1% is 67 - the hypothesis of homogeneity is rejected at the 1% level.

FIGURE 1 - Relation of estimated absolute t-ratios to sample size

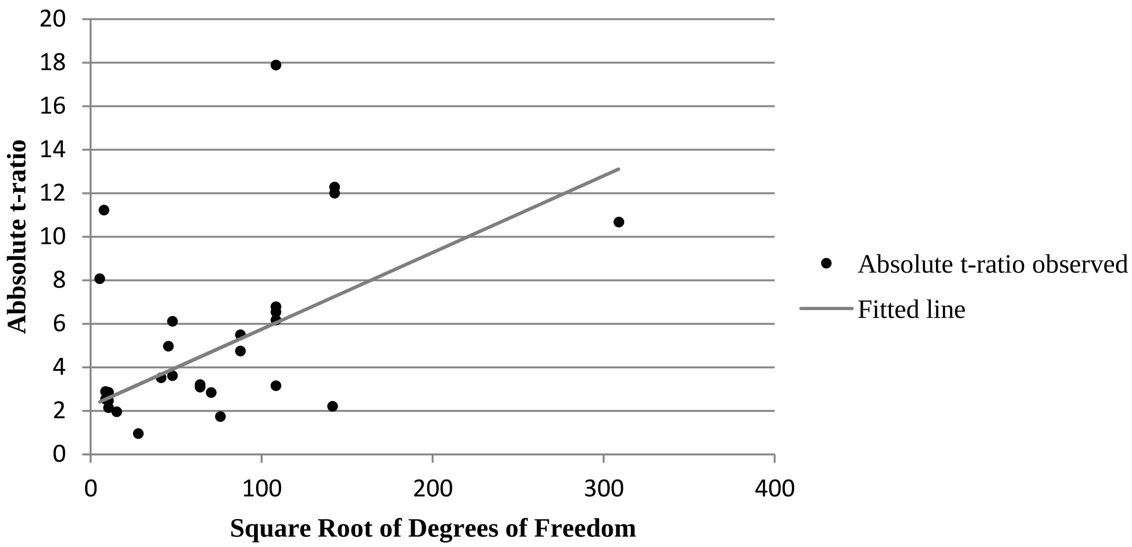

TABLE 4 - Descriptive regression model of the absolute t-ratio on the square root of the degrees of freedom

	Mean	St. Dev.	Coefficient	Standard Error
Square root of Degrees of Freedom	64	62	0.035***	0.0102155
Intercept			2.22**	0.9046844
R-squared			0.27	
Adj. R-squared			0.25	
Number of meta-observations			34	

: significant at 5%; *: significant at 1%.

TABLE 5 - Binary logit model estimates of significance of the effect of residential density on mobility

Explanatory variables	Odd ratio	Standard error	P>z
Model and specification characteristics			
Independent Equation Model	1.241	2.424	0.912
Selection effect accounted for	16.517	35.761	0.195
Data characteristics			
Panel data	2.375	7.130	0.773
Disaggregated observation unit	**0.005***	**0.016**	**0.072**
Mobility measured in energy	0.248	0.520	0.507
Private vehicle mobility	0.577	1.109	0.775
Infra-MSA population density	**184.916****	**388.586**	**0.013**
Geographical characteristics			
United-States	28.886	70.102	0.166
Control variables			
Transport infrastructure	1.176	2.010	0.925
Private vehicle characteristics	**0.005****	**0.010**	**0.015**
Number of observations of the meta-dataset		50	
Log likelihood		-1.3862948	

*: significant at 1%; **: significant at 5%.

TABLE 6 - Specification of the five models estimated

	Models	Specification forms
Type 1	OLS with robust standard errors WLS	$e_i = \boldsymbol{\beta}_\mathbf{i}'\mathbf{x}_\mathbf{i} + \varepsilon_i$
	Tobit with robust standard errors	$\begin{cases} e_i = e_i^* & if\ e_i^* < 0 \\ e_i = 0 & if\ e_i^* > 0 \\ e_i^* = \boldsymbol{\beta}_\mathbf{i}'\mathbf{x}_\mathbf{i} + \varepsilon_i \end{cases}$
Type 2	Fixed effects model	$e_{is} = \boldsymbol{\beta}_\mathbf{i}'\mathbf{x}_\mathbf{i} + \mu_s + \varepsilon_i$
	Random effects model	$e_{is} = \boldsymbol{\beta}_\mathbf{i}'\mathbf{x}_\mathbf{i} + \delta_{is} + \varepsilon_i$

TABLE 7 – Review of empirical studies on the impact of urban form on building energy use

Studies	**Region**	**Observation unit**	**Impact evaluated**	**Impact estimated**	**Approx. elasticity** [4]	**Method**
(Larivière & Lafrance 1999)	Quebec, Canada	Cities	Population density on residential, commercial and miscellaneous electricity consumption.	Significant/ Negative	-0.07	RA*
(Holden & Norland 2005)	Oslo, Norway	Individual	Housing density on residential energy consumption.	Significant/ Negative	-0.07	RA*
(Ewing & Rong 2008)	United States	Household	Urban form index on residential energy consumption through housing characteristics and heat island effect.	Significant/ Negative	-0.39	RA*
(Kaza 2010)	United States	Household	Population density on residential energy consumption at constant housing characteristics.	Non significant	0	QDA**

*RA: Regression analysis
**QDA: Qualitative data analysis

[4] Roughly computed through own calculation based on the information provided in the articles.

TABLE 8 – Results of regressions models estimations of the elasticity of mobility on residential density

			Type 1						Type 2	
	OLS robust SE		WLS		Tobit robust SE		Fixed effects		Random effects	
Variables	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Model and specification characteristics										
Independant Equations	-0.070	0.241	0.161	0.125	-0.036	0.103	(dropped)		-0.070	0.145
Seemingly Unrelated Regressions	0.053	0.241	**0.238***	0.111	0.073	0.088	-0.017	0.052	0.053	0.143
Structural Equations Model	0.074	0.201	**0.203***	0.112	0.089	0.089	(dropped)		0.074	0.122
Selection effect accounted for	-0.056	0.091	-0.044	0.027	-0.088	0.056	**-0.123****	0.052	-0.056	0.048
Non log-log specification	-0.084	0.109	**-0.149***	0.081	-0.080	0.052	-0.089	0.074	-0.084	0.061
Data characteristics										
Panel data	0.080	0.264	**0.334****	0.105	0.129	0.121	(dropped)		0.080	0.143
Disaggregated observation unit	**0.474****	0.148	0.403	0.332	**0.389*****	0.059	(dropped)		**0.474*****	0.097
Class of Density	-0.007	0.193	-0.632	0.494	**-0.272****	0.082	(dropped)		-0.007	0.123
Mobility measured in energy	0.002	0.058	-0.015	0.011	0.006	0.032	-0.016	0.052	0.002	0.037
Private vehicle mobility	0.007	0.131	0.409	0.751	**0.132***	0.065	(dropped)		0.007	0.090
Infra-MSA population density	**-0.520***	0.275	-0.144	0.238	**-0.382****	0.134	-0.075	0.074	**-0.520****	0.157
MSA population density	-0.399	0.246	-0.069	0.238	**-0.304****	0.131	(dropped)		**-0.399****	0.137
Meta-sample size	-5.06E-07	2.79E-06	8.86E-06	1.27E-05	**2.66E-06***	1.45E-06	-1.12E-06	1.27E-06	-5.06E-07	1.84E-06
Geographical characteristics										
United-States	**-0.243***	0.129	**-0.404***	0.223	**-0.238*****	0.067	(dropped)		**-0.243****	0.077
Europe	-0.236	0.222	0.371	1.026	0.088	0.094	(dropped)		-0.236	0.170
World	**-0.223***	0.107	**-0.367*****	0.079	**-0.243*****	0.065	(dropped)		**-0.223*****	0.060
Infra-national area	0.098	0.090	0.023	0.022	0.045	0.028	0.024	0.060	**0.098***	0.059
Urban area	**0.154***	0.084	-0.032	0.175	**0.085***	0.043	**0.260****	0.091	**0.154****	0.057
Control variables										
Transport infrastructure	**-0.152***	0.079	0.105	0.217	-0.043	0.039	**-0.223****	0.074	**-0.152****	0.058
Energy prices	0.213	0.134	(dropped)		**0.179****	0.056	(dropped)		**0.213****	0.093
Private vehicle characteristics	0.094	0.084	0.153	0.139	**0.132****	0.047	**0.132****	0.054	**0.094****	0.045
Other										
Author's computation	0.071	0.173	0.062	0.150	**0.102***	0.057	(dropped)		0.071	0.120
Contante	0.047	0.409	-0.507	1.083	-0.129	0.195	-0.124	0.076	0.047	0.223
AIC/BIC	-73.9/-35.1		-263.1/-236.6		-59.0/-13.2		-152.3/-133.7		-152.3/-133.7	
Number of Observations / Degrees of	40/23		35/17		50/24		40/11		40/11	
R-squared	0.882		0.995							
Additional information					10 right-censored		F-test that all u_i=0		Null within-study	
							F(18,11)=1.77		δ_{is} SD*	0.000
							(p-value=0.1682)		ε_i SD*	0.054

*SD: Standard Deviation