Urban form and driving: Evidence from US cities

Preliminary and incomplete

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29 September 2015

Abstract: We estimate the effect of urban form on driving. We match
the best available travel survey for the US to spatially disaggregated
national maps that describe population density and demographics, sec-
toral employment and land cover, among other things. We develop a
novel approach to the sorting problem follows from an intuitive defini-
tion of sorting and an assumption of imperfect mobility. We address the
endogeneity problem by relying on measures of subterranean geology
as sources of quasi-random variation in urban form. The data suggest
that urban form has a small causal effect on individual driving. This
effect is small enough that it is unlikely to be cost effective to rely on
urban planning as a policy response to traffic congestion, automobile
related carbon emissions, or other automobile related pollution.

Key words: urban form, vehicle-kilometers traveled, congestion.

JEL classification: L91, R41

§Financial support from the Canadian Social Science and Humanities Research Council and from the Sustainable
Prosperity Network is gratefully acknowledged by both authors. This research could not have been conducted without
the help of our research assistants, Tanner Regan, Nicholas Gendron-Carrier, Prottoy Akbar and Rebecca Lindstrom.

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and with the University of Toronto Department of Economics. The financial support and hospitality of the Property and
Environment Research Center during part of the time that this research was conducted is gratefully acknowledged.
1. Introduction

We estimate the effect of urban form on driving. To conduct our analysis we exploit the best available travel survey data for the US and match them to spatially disaggregated national maps that describe, among other things, population density and demographics, sectoral employment, and land cover. Causal identification of the relationship between urban form and driving faces two primary obstacles, sorting and omitted variables. People with particular preferences for driving may sort into areas of particular density, and unobserved factors correlated with urban form may also affect driving behavior. We develop a novel approach to the sorting problem that follows from an intuitive definition of sorting and an assumption of imperfect residential mobility. To address the omitted variables problem we rely on a variety of measures of subterranean geology. These measures predict surface landscape and are plausible as sources of quasi-random variation in urban form.

We find that urban density has a small causal effect on individual driving. In most of our estimations ‘urban density’ is the density of residents and jobs within a 10 kilometers radius of where a driver lives. We find that the elasticity of vehicle kilometers traveled (vkt) with respect to this measure of density is between -7% and -10%. This result is not sensitive to the particular measure of density, but is sensitive to the scale at which we measure density. People and employment more than 10km from a driver’s residence do not have a measurable effect on driving behavior.

Using this elasticity, we calculate that relocating all residents in the bottom density decile to newly constructed developments with density at the current 90th percentile would reduce aggregate driving by about 2%. This effect is small enough to suggest that urban planning is unlikely to be a cost effective policy response to traffic congestion, automobile related carbon emissions or other automobile related pollution. A more formal evaluation of the welfare benefits and costs associated with increased density confirms this conclusion(?).

Our results are of interest for a number of reasons. First, traffic congestion is an important economic problem, and land use change is a widely proposed policy response to this problem. For example: in a State of Arizona Department of Transportation professional paper, Kuzmyak (2012) concludes that "greater adherence to smart growth principles of compact, mixed-land use,..., may result in important reductions in average trip lengths and VMT demand on local and regional roads"; the US Department of Transportation states that "[t]ransportation demand is reduced when
residential and commercial uses are planned to be within close proximity to each other...;¹ while the Brookings Institute asserts that to relieve traffic congestion "[w]e need to make places more efficient by joining up transportation with the housing, real estate, commercial, and industrial decisions it drives".² Our results provide a basis for evaluating such claims.

More generally, and as we discuss in more detail below, the hypothesis that changes in urban form can play an economically important role in moderating traffic congestion is the subject of a large literature in urban planning. To our knowledge, this literature is based almost entirely on cross-sectional associations, often in small samples describing small areas or relying on opaque indices to describe the built environment. That is, the current empirical literature does not provide a foundation that allows policy makers to use urban planning to affect driving with any confidence of achieving their desired outcome. We improve on the existing literature by providing plausibly causal estimates. We also exploit better data than has previously been available. This permits us to test different measures of urban form against each other and to investigate the scale at which urban form affects driving. Hence, we can provide some insight into which of the many correlated characteristics of urban form influence driving and which do not.

Urban planning also plays a prominent role in policy discussions of carbon abatement. The Fourth Assessment Report of the IPCC discusses land use as a potential policy to reduce the demand for automobile travel (e.g., section 5.5.1.1, on Climate Change (2007)), the more recent Fifth Assessment suggests that "[u]rban Densification in the USA over about 50 years could reduce fuel use by 9-16%" (table 8.3, on Climate Change (2014)), and California’s Senate Bill 375 (September 7, 2006) asserts that "it will be necessary to achieve significant additional greenhouse gas reductions from changed land use patterns and improved transportation". Because driving accounts for a large share of carbon emissions, our analysis helps to inform these sorts of policies by providing causal estimates of how particular changes to urban form affect driving behavior.

Finally, the value of US residential real estate alone is above 20 trillion dollars, while annual household expenditures on driving are on the order of a trillion dollars. Given the magnitude of the allocations involved, understanding how the spatial configuration of structures affects driving behavior is of intrinsic interest. More simply, much of the world’s population lives in cities and the

construction and operation of these cities is costly. Understanding how to better organize cities is clearly a policy question of the first order.

2. Literature

This relationship between urban form and driving is a core question in the urban planning literature and has received some attention from economists. Our paper falls squarely into the large literature concerned with this relationship.

Pushkarev and Zupan (1977) show a tight connection between modal choice for urban travel and residential density in the New York region, in what is perhaps the first modern study on the topic. They argue, unsurprisingly, that high residential densities are needed to sustain a high use of public transit. In a highly-cited paper, Cervero and Kockelman (1997) argue that residential density is only one force behind travel choice. In their analysis of about 1,000 households in 50 neighbourhoods of the San Francisco Bay area, they find that index numbers describing ‘diversity’ and ‘design’ are associated with modal choice. In a related study of about the same number of households in Southern California, Boarnet and Sarmiento (1998) fail to find evidence of a link between the number of trips taken by households and land use at their place of residence. Although the relationship between urban form and total travel distance (e.g., Bento, Cropper, Mobarak, and Vinha, 2005, Brownstone and Golob, 2009) and the journey to work (e.g., Gordon, Kumar, and Richardson, 1989, Giuliano and Small, 1993, Glaeser and Kahn, 2004) have been a primary focus of this literature, the literature has also investigated the relationship between urban form and other travel outcomes, including pedestrian trips and energy consumption (e.g., Brownstone and Golob, 2009, Glaeser and Kahn, 2008).

An early synthesis of this large literature by Ewing and Cervero (2001) examines the results of 73 published studies. A number of subsequent reviews of this literature have also appeared, among them Handy (2005), Cao, Mokhtarian, and Handy (2009), and Boarnet (2011). In their meta-analysis, Ewing and Cervero (2010) consider more than 200 studies and cite 25 surveys of the literature. Boarnet and Crane (2001a) and Boarnet and Crane (2001b), raise several concerns about the reliability of the cross-sectional research designs that pervade this literature. High among these concerns is the possibility that household location choice may depend on their to their predisposition to travel. This is precisely the problem of sorting which will be the focus of much our attention.
Differences in individual outcomes across locations are widely observed and determining whether these differences reflect causal effects of the location or the sorting of different types of people is a pervasive problem in economics. The justly famous ‘Moving To Opportunity’ induced a random assignment of poor households to move to nicer neighborhoods than they would otherwise have chosen. The effects of this move for teenage children on educational attainment and economic outcomes are small while the effects for children under the age of 13 appear to be large (Kling, Ludwig, and Katz (2005) and Chetty, Hendren, and Katz (2015)). The urban economics literature has devoted considerable effort to investigating the relationship between city size and wages. Combes, Duranton, and Gobillon (2008) find that about half of this effect is accounted for by basic demographic controls and unobserved individual traits and half is causal. Eid, Overman, Puga, and Turner (2008) find that all of the cross-sectional relationship between obesity and neighborhood characteristics can be accounted for by individual fixed effects. Dahl (2002) finds that cross-sectional estimates of the returns to education are biased up by the tendency of educated individuals to migrate to states where the returns to education are high. Currie and Walker (2011) find that automobile pollution has a causal effect on the health of residents in neighborhoods exposed to pollution and does not find evidence that this reflects the sorting of unhealthy residents into polluted neighborhoods.

Summing up, cross-sectional difference in outcomes are sometimes due to sorting of people on the basis of observable or unobservable characteristics, but are also sometimes due to causal effects of locations on people. This means that we can have no clear prior about the extent to which sorting determines the cross-sectional relationship between urban form and driving, although it certainly does not allow us to be confident that this bias will be small. In fact, we will conclude that cross-sectional relationship between urban form and driving. In addition to informing urban policy, this adds another piece to the complicated puzzle of how landscape does and does not cause behavior to change.

3. A simple model of urban form and driving

To illuminate the inference problems that our empirical investigation must overcome, we first present a simple model of equilibrium driving behavior.

Consider a location with unit area and population density $x$. A resident derives utility from travel according to the function, $T(.)$, from the consumption of housing, $h$, and other goods, $q$, \[ U = T(\cdot) + h + q \]
According to $U = T + C(h,q)$. Note that we here treat travel as a final good. This simplifying assumption allows us focus attention on the roles of idiosyncratic location and individual characteristics while avoiding the complexity that arises if transportation is an intermediate good that allows residents to go to work, go shopping, and enjoy leisure.

Subutility $T$ describes utility from travel. It increases in the number of trips, $n$, and decreases in travel distance, $y$. To formalize these relationships as simply and transparently as possible, we define the utility derived from travel, $T(n,y)$, as

$$T(n,y) = \theta \delta n - \tau y^2.$$  \hspace{1cm} (1)

In this definition, $\theta$ is a resident-specific term, $\delta$ is a location-specific term, and $\tau$ parameterizes the cost of travel.

In equation (1) the parameter $\theta$ reflects an idiosyncratic taste for trips and $\delta$ reflects place-specific benefits of trips. While these quantities seem abstract they describe phenomena that are likely to be important empirically. Some locations have better amenities than others and residents must travel to enjoy them: a neighborhood near a nice beach may generate more trips than a neighborhood near a dirty beach. Our model can capture this by assigning one location a higher value of $\delta$. It is similarly easy to think of examples illustrating different individual propensities to travel. Younger residents may travel more often than older residents, and residents with young children may take them to activities many times each day. More fundamentally, and beyond demographics, we also expect residents to differ in their preferences. Some will enjoy staying home while others will prefer going out. Our model can reflect this heterogeneity by assigning individuals different values of $\theta$.

Although we look at a range of travel outcomes, we are primarily interested in the total distance that a resident travels. Mechanically, travel distance depends on the number of trips and their length. However, because denser locations may allow trips to closer destinations, we assume that $y = n x^{-\zeta}$ where $\zeta$ measures the reduction in travel distance per trip that comes with greater population density.\(^3\) We sometimes refer to $\zeta$ as the ‘elasticity of accessibility’.

Solving for the resident’s optimal choice of travel distance, we have

$$y = \frac{\theta \delta x^\zeta}{2\tau}. \hspace{1cm} (2)$$

\(^3\)As accessibility improves residents face both more and closer options. Our formulation reflects this tradeoff, albeit in a simple, reduced-form manner. See Couture (2014) for micro-foundations.
Inspection of equation (2) reveals the following intuitive comparative statics. Driving by a resident increases with $\theta$ and $\delta$, decreases in denser locations and increases as travel costs decline.

In practice, we expect that the travel technology is congestible and that congestion depends on aggregate travel in the location. To capture this stylized fact in our model, suppose that travel costs are $\tau = (x\bar{y})^{\phi}$ where $\bar{y}$ is mean travel distance and $\phi$ measures the elasticity of travel cost per unit with respect to aggregate travel. We sometimes refer to $\phi$ as the ‘congestion elasticity’. From equation (2), it is easy to compute average travel distance as a function of the average taste for trips of local residents, $\bar{\theta}$.

Using equation (2), its analog for average travel distance, and the above definition of $\tau$, we have

$$y = \theta \left[ \frac{\delta x^{\zeta - \phi}}{2 \bar{\theta} \phi} \right]^{\frac{1}{1+\phi}} ,$$

and taking logs gives,

$$\log y = \frac{\log 2}{1 + \phi} - \frac{\phi - \zeta}{1 + \phi} \log x + \epsilon \quad \text{where} \quad \epsilon = \frac{1}{1 + \phi} \log \delta + 2 \log \theta - \frac{1}{1 + \phi} \log \bar{\theta} .$$

Finally, using equation 3 to eliminate travel distance from travel utility yields:

$$T(x) = \frac{\theta^{2} \delta x^{\frac{1}{1+\phi}}}{2^{\frac{1}{1+\phi}} \bar{\theta}^{\frac{\phi}{1+\phi}}} x^{\frac{\zeta}{1+\phi}} .$$

We draw four conclusions from equations (3)–(5). First, if the congestion elasticity, $\phi$, is larger than the accessibility elasticity, $\zeta$, travel distance declines with population density. Two forces are at play. Travel distance increases with population density because of improved accessibility. At the same time, the cost of travelling also increases because of rising congestion. It is only when the congestion elasticity dominates the accessibility elasticity that travel declines with population density.\(^4\)

Second, the effect of population density on equilibrium utility is ambiguous. If $\phi > \zeta(2 + \phi)$, the congestion effect is so strong that it reduces travel utility when population density increases. If instead $\phi < \zeta(2 + \phi)$, travel utility increases with population density. We note that it is only when $\zeta(2 + \phi) > \phi > \zeta$ that travel declines with population density and residents achieve a

\(^4\)By construction, individuals do not account for their impact on $\tau$. Thus, the equilibrium we describe here will not be optimal. There will be too much driving. It follows that, even if changes in urban form reduce congestion and increase utility, they do not remove the need for congestion pricing.

\(^5\)One could add a taste parameter in the travel utility by elevating the number of trips $n$ to some power in equation (1). This would lead to a more complicated expression for travel to decline with population density as the relationship between accessibility and congestion would be complicated by this taste parameter affecting the elasticity of the demand for travel.
higher travel utility. Hence, it is only in this intermediate situation that we can both predict a widely conjectured empirical relationship and satisfy a necessary condition to rationalize policies to increase population density.

Third, in the case where utility increases with population density, \( \zeta(2 + \phi) > \phi \), it is easy to see that \( \frac{\partial^2 T}{\partial \theta \partial x} > 0 \), so that residents with a greater propensity to make trips benefit more from higher population density than residents with a smaller \( \theta \). This single-crossing condition should lead to the sorting of residents with a greater propensity to make trips into denser locations. We, therefore expect a positive correlation between the propensity to make trips, \( \theta \), the mean propensity to make trips, \( \bar{\theta} \), and population density to be a feature of our data.\(^6\)

Equations (3) and (5) imply that \( \frac{\partial^2 T}{\partial \delta \partial x} > 0 \). That is, there are greater benefits to higher population density in locations with higher benefits from making trips. Accordingly, we should also expect a positive correlation between how beneficial trips are in a location \( \delta \) and population density.

Equation (4) describes a regression of driving on urban form. This regression, typically conducted with cross-sectional survey data, forms the basis of the large literature described in section 2. Because trip benefits, \( \delta \), and the propensities to make trips, \( \theta \) and \( \bar{\theta} \), are not observed, they enter the error term. Given their expected correlation with population density, the estimated coefficient of \( x \) is likely to be biased. The sorting of travellers and the endogeneity of density are the two main identification challenges we face in our empirical work below.\(^7\)

4. Econometric model

We would like to estimate the relationship between urban form and driving behavior. On the basis of the model articulated above, we are concerned that people sort into different landscapes on the basis of their propensity to drive and that urban form may be correlated with unobservable

\(^6\) As residents with a stronger propensity for making trips sort into denser locations, this creates more congestion and reduces utility. However, the indirect equilibrium effect in \( \bar{\theta} \) in equation (5) is dominated by the direct effect of individual propensities to make trips, \( \theta \).

\(^7\) We note that the direction of the bias that these unobserved variables cause is sensitive to the details of our model. It is easy to imagine variants of the model proposed here where these biases would work in the opposite direction. For example, if residents differ in their (dis-)taste for travel distance by adding an idiosyncratic preference parameter in the second term of T in equation (1). In this case, it is easy to understand that, at least under some parameter values, individuals with low distaste for travel distance will elect to live in locations with low population density where travel is not congested. In short, those who enjoy driving will locate in places where it is easy to drive. Under this alternative type of sorting, locations with high population density will host residents with a stronger distaste for travelling and thus a naive regression of travel distance on population density will overestimate the true effect of population density. Given our results, we are more concerned with the first bias.
location specific determinants of driving. We begin by considering the problem of sorting and then turn to the problem of omitted variables.

Each person is assigned to a geographic unit, usually a pixel, for which we construct measures of urban form, usually the sum of population and employment within 10 kilometers. Let \( i \) index people and \( j \) index residential locations. As we discuss below, these will usually be regular grid-cells approximately 1km square. We are interested in explaining how driving behavior \( y_{ij} \) varies with urban form. More specifically, we are interested in knowing how the driving behavior, \( y_{ij} \), of a randomly selected person changes when we change urban form in or around their residential location, \( j \).

Let \( x_{0j} \) denote the urban form variable of interest for geographic unit \( j \) at an initial period, usually around 1990 and let \( x_{1j} \) denote the urban form variable of interest usually around 2010, contemporaneous to \( y \). Define \( \Delta x_j = x_{1j} - x_{0j} \). We observe both contemporaneous and historical descriptions of urban form at each location, but we observe each driver only once.\(^8\)

Suppose that driving for each person is described by the following equation,

\[
y_{ij} = \theta_i + \beta x_j + \delta_j,
\]

(6)

so that observed driving for each person is determined by an individual specific intercept, \( \theta_i \), a location specific intercept, \( \delta_j \), and the urban form in person \( i \)'s location \( j, x_j \). The parameter of interest, \( \beta \), measures the effect of local urban form on distance travelled.

We note that this is a slightly simpler variant of the equilibrium driving equation (4) derived above. In a slight abuse of notation we treat all variables as logarithms, as in equation (4), without making the notation explicit. We adopt this practice throughout this section so that linear regression coefficients can be interpreted as elasticities. Equation (6) also renormalizes \( \theta_i \) and \( \delta_j \) to avoid carrying some constants. These minor differences aside, equation (6) shares an important feature with the theoretically founded equilibrium relationship of equation (4). In both equations, individual taste parameters and location specific effects enter only through the intercept. They do not lead to individual or neighborhood level difference in \( \beta \), the rate at which individuals change their behavior in response to density. This simplifies our econometric task considerably and we appeal to theoretical analysis above to justify this restriction. This assumption also finds some

\(^8\)To our knowledge, no large-scale panel data describing driving behavior has ever been constructed for the US. Our econometric methodology is partly a response to this deficit. See Houston, Boarnet, Ferguson, and Spears (2015) for a short panel of travelers in some neighborhoods of Los Angeles and a discussion of the difficulties associated with this exercise.
empirical support in our results: we perform our main regression on many different subsamples and do not find any measurable differences in $\beta$ across samples.

Given equation (6), our two main inference problems are that people do not choose their locations at random and that observed and unobserved attributes of urban form are correlated and may affect driving. More succinctly, we worry about unobserved individual characteristics and unobserved location attributes.\footnote{One may also consider that unobserved local attributes $\delta$ are simultaneously determined with individual attributes $\theta$. This is a variant of the selection problem.} We address each problem in turn.

To begin, suppose that individual specific intercepts are not observed, but are drawn from the real interval $\Theta$, and let the distribution of individual types at each location $j$ be determined by the well behaved density function $f(\theta|x,j)$ where,

$$E(\theta|x,j) = \alpha_0 + \alpha_1 x + \mu_j$$

and $E(x_j \mu_j) = 0$. That is, the assignment of types to location $j$ depends on urban form and on unobserved location specific characteristics. If $\beta > 0$, then we expect that drivers with a larger $\theta$ to sort into neighborhoods with a larger $x$ and conversely. As $\mu$ increases, residents derive more utility from trips for reasons unrelated to $x$.\footnote{If $\theta$ varies systematically with observable individual characteristics, $x_{ij}$, then we have, for example, that $E(\theta|x_{ij},x,j) = \alpha_0 + \alpha_1 x + \alpha_2 x_{ij} + \mu_j$. While we investigate this issue in our empirical work, we omit it here in the interests of clarity.}

Using both equation (7) and (6), we have that

$$E(y_{ij}|x_{ij},j) = (\alpha_0 + \alpha_1 x_j + \mu_j) + \beta x_j + \delta_j
= \alpha_0 + (\alpha_1 + \beta)x_j + \epsilon_j,$$

where $\epsilon = \mu + \delta$. Thus, if $\alpha_1 \neq 0$ or $E(\epsilon x_j) \neq 0$, ols estimates of $\beta$ will be biased.\footnote{Equation (8) describes a regression at the level of the residential unit $j$, rather than the individual. In fact, we observe individual level demographic information. To incorporate this information into our regressions, we conduct them at the individual level and generalize to allow $\mu_{ij}$ to vary systematically with observable individual characteristics.}

Our approach to this sorting problem relies on an assumption of imperfect mobility. We suppose that at $t = 0$ all agents match to locations according to $f$ as described above. At $t = 1$ a randomly selected fraction, $s_j$, of these residents relocates and is replaced by agents who sort on the basis of current conditions. With these assumptions in place, for a location where $x_{ij}^1 = x_{ij}^0 + \Delta x_j$, expected...
Equation (9) suggests two parametric tests of the importance of sorting. First, the difference between the coefficients of $x^0$ and $\Delta x$ is $\alpha_1$. This is the parameter that describes how individual tastes vary with urban form in equation (7). Therefore, we can reject the hypothesis that $\alpha_1 = 0$ by rejecting the hypothesis that $A_1 = A_3$. Second, if we observe $s$ then $\alpha_1$ is the coefficient of $s\Delta x$. Therefore, we can also reject the hypothesis that $\alpha_1 = 0$ by rejecting the hypothesis that coefficient of that $A_2 = 0$. Consolidating, sorting of individuals on the basis of their unobserved propensity to drive biases our estimates of $\beta$ if we can reject

$$H_{-\text{Sorting}}: A_1 = A_3 \text{ and } A_2 = 0.$$ (10)

We will report tests of this hypothesis with our estimates of equation (9). As we will see, the data do not reject this hypothesis, and therefore do not support the idea that sorting $\alpha_1 \neq 0$.

In fact, we will not observe $s_j$ directly. Instead, we observe characteristics that vary systematically with the mobility rate, e.g., driver age or mean housing tenure in the driver’s home cell. To understand how this allows similar tests, denote our mobility proxy by $\tilde{x}$ and suppose that mobility varies with $\tilde{x}$ according to $s = g(\tilde{x})$. Taking a first order approximation, we have

$$s = \gamma_0 + \gamma_1 \tilde{x},$$

where $\gamma_1 \neq 0$ is assumed. Substituting this expression for $s$ into (9) we see that the coefficient on $\tilde{x}\Delta x$ is $\alpha_1 \gamma_1$. Given our assumption that $\gamma_1 \neq 0$, rejecting $\alpha_1 \gamma_1 = 0$ allows us to reject $\alpha_1 = 0$. In our empirical work, we implement these two tests and the results suggest that $\alpha_1$ is very close zero.

This requires two comments. Identification rests on the assumption that as urban form changes, so do the characteristics of the marginal resident. Not only does this seem like a reasonable hypothesis, it also a common sense definition of ‘sorting’. While we express the intuition precisely and in particular functional forms, the underlying intuition seems unrestrictive. Second, as we have described it, sorting affects only residents moving to a location, not those moving away from it. More realistically, we might expect a non-random sample of people to move from a location, and in the case of an increase in density, they should value density less highly than the average
current resident, who in turn should value density less highly the average arrival. Generalizing our framework to describe this intuition precisely is straightforward and leads to an indistinguishable empirical strategy.

While the estimation described in equation (9) addresses the problem of sorting by unobserved individual characteristics, it does not address the possibility of omitted location variables correlated with urban form and driving, for example, if municipal snow removal is systematically worse in dense areas. To address this problem, we consider the system of equations,

\[ y_{ij} = \theta_i + \beta x_j + \delta_j, \]  
\[ x_j = \gamma_0 + \gamma_1 z_j + \eta_j. \]

In the context of this system, our omitted variables problem may be stated as \( E(x_j \delta_j) \neq 0 \). We resolve this problem by relying on instrumental variables estimation. As the system above suggests, this requires an instrument that predicts urban form but that does not otherwise affect driving, or more formally, that \( \gamma_1 \neq 0 \) and \( E(z \delta_j) = 0 \). In our empirical work, we rely on various measures of subterranean geology as instrumental variables. As we will see, these measures are important determinants of urban form and it is difficult to imagine other channels through which they could affect driving behavior than by affecting the urban form.

Although this is a standard instrumental variables estimation, in our context, it requires two comments. First, we should not expect our instrumental variables estimation to resolve the problem of sorting. To see this, let \( \tilde{x}_j = \gamma_0 + \gamma_1 z_j \) and rewrite equation (8) using (12) as,

\[
E(y_{ij}|x_j, j) = a_0 + (a_1 + \beta)(\tilde{x}_j + \eta_j) + \epsilon_j,
\]
\[
= a_0 + (a_1 + \beta)\tilde{x}_j + ((a_1 + \beta)\eta_j) + \epsilon_j.
\]

That is, as long as residents sort on the component of the urban form predicted by underground geology in the same way as they sort on the residual component, the instrumental variables regression does not lead to unbiased estimates of \( \beta \). Thus, instrumental variables estimation can solve the problem of unobserved local characteristics. It cannot solve the problem of unobserved individual characteristics.

In light of the intuition above, we would ideally implement our instrumental variables strategy in the context of equation (9) which explicitly accounts for sorting. In practice, our instruments are not able to predict changes in urban form, only levels. Thus, in spite of its theoretical appeal,
### Table 1: Descriptive statistics for NHTS households, MSA sample

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>5th percentile</th>
<th>95th percentile</th>
<th>Observations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vehicles km travelled (VKT)</td>
<td>37,022</td>
<td>29,826</td>
<td>4,459</td>
<td>87,906</td>
<td>99,875</td>
</tr>
<tr>
<td>log VKT</td>
<td>10.17</td>
<td>1.01</td>
<td>8.40</td>
<td>11.38</td>
<td>99,875</td>
</tr>
<tr>
<td>Annual VKT</td>
<td>33,014</td>
<td>29,766</td>
<td>3,645</td>
<td>82,620</td>
<td>93,602</td>
</tr>
<tr>
<td>Odometer VKT</td>
<td>33,123</td>
<td>24,647</td>
<td>6,388</td>
<td>74,483</td>
<td>71,742</td>
</tr>
<tr>
<td>Household daily VKT</td>
<td>73.2</td>
<td>66.8</td>
<td>6.5</td>
<td>208.1</td>
<td>83,313</td>
</tr>
<tr>
<td>Household travel minutes</td>
<td>98.7</td>
<td>70.0</td>
<td>17</td>
<td>234</td>
<td>83,313</td>
</tr>
<tr>
<td>Household daily speed</td>
<td>42.6</td>
<td>38.8</td>
<td>13.9</td>
<td>75.6</td>
<td>83,313</td>
</tr>
<tr>
<td>Dist. to work</td>
<td>22.5</td>
<td>34.4</td>
<td>1.6</td>
<td>61.6</td>
<td>95,532</td>
</tr>
<tr>
<td>Household income</td>
<td>71,257</td>
<td>48,575</td>
<td>12,500</td>
<td>150,000</td>
<td>99,875</td>
</tr>
<tr>
<td>Household age</td>
<td>53.5</td>
<td>18.3</td>
<td>23.7</td>
<td>81.0</td>
<td>99,875</td>
</tr>
<tr>
<td>Renters (%)</td>
<td>11.0</td>
<td>31.3</td>
<td>0</td>
<td>1</td>
<td>99,875</td>
</tr>
<tr>
<td>People within 10 km</td>
<td>1,072</td>
<td>1,559</td>
<td>44.9</td>
<td>3,222</td>
<td>99,875</td>
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<td>log people w. 10 km</td>
<td>6.30</td>
<td>1.31</td>
<td>3.81</td>
<td>8.08</td>
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<td>Population w. 10 km</td>
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<td>1,027</td>
<td>34.7</td>
<td>2211</td>
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<td>Share developed w. 10 km (%)</td>
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<td>5.61</td>
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<td>15.5</td>
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<td>People w. 1 km</td>
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<td>Share developed w. 1 km (%)</td>
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<td>8.21</td>
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<td>Local share high education (%)</td>
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<td>18.5</td>
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<td>Local mean income</td>
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<td>29,113</td>
<td>39,135</td>
<td>132,854</td>
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<td>2.44</td>
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<td>Local mobility rate (%)</td>
<td>34.5</td>
<td>6.63</td>
<td>22.8</td>
<td>44.2</td>
<td>99,875</td>
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</table>

**Notes:** Authors calculations for 2006-2011. Distances are measured in kilometers and monetary values in current American dollars. Household age is mean age for the adult members of the household. Household daily VKT, travel time, and speed are computed for all households with positive travel by summing all trips across the surveyed members of the household. Household speed is computed by dividing VKT by travel time for each household and averaging across households. 'People' refer to the sum of jobs and residents. All density are measured per square kilometer.

This strategy is beyond the reach of our data. With this said, the data strongly suggest that neither sorting nor omitted variables cause economically important biases in our estimates, so we can reasonably conjecture that allowing these two biases to interact would also be unimportant.

### 5. Data

Our analysis requires three main types of data; household (individual) level travel behavior, a description of urban form for each household, and finally, a description of subterranean geology. To implement our response to the sorting problem, we require panel data describing urban form, but only cross-sectional data describing drivers.

We also require a way of matching survey respondents to landscapes. To accomplish this, we
construct a regular grid of 990 meter cells covering the entire continental US. Each household is matched to the cell with centroid closest to the latitude and longitude of the household’s census block group. We will refer to this cell as an individual or household’s ‘home cell’, and in a slight abuse of language, describe cells as having an area of 1sq km. We convert all data describing urban form to this resolution as described below. With this data structure in place, we are able to construct urban form measures for each household on the basis of arbitrary geographies by averaging over the relevant sets of grid cells. In particular, we can examine the square kilometer surrounding each household by reporting the characteristics of its home cell, we can average over all cells within 10 kilometers of the home cell or over all cells lying in the same MSA.

Data on individual travel behavior come from the 2008-2009 National Household Transportation Surveys (NHTS). The NHTS survey reports several measures of total annual driving for each household or individual in a nationally representative sample of households. Our main dependent variable is household annual vehicle kilometers travelled (vkt) and is reported in the first row of table 1. This measure of household annual mileage is computed by the survey administrators, ‘bestmiles’, and is their preferred measure. In robustness checks, we consider four other measures of individual and household driving distance, stated annual vehicle kilometers traveled, a reported odometer measure of kilometers traveled, individual daily kilometers traveled on the survey day, and distance to work.

The upper part of table 1 reports descriptive statistics for each of these measures of driving from the NHTS. The three measures of total household driving have sample means of 37,022, 33,014 and 33,123 kilometers over slightly different samples of households. Except where noted otherwise, we restrict attention to households and individuals who live in MSAs. Aggregating individual vkt and travel time at the household level implies that households travel 73.2 kilometers in 98.7 minutes at an average speed of 42.6 kilometers per hour. Individual distance to work is 22.5 kilometers. This is an average across households. Dividing aggregate vkt by aggregate travel time implies a speed of 44.5 kilometers per hour. Couture, Duranton, and Turner (2014) report a mean speed per trip of 38.5 kilometers per hour. The differences between those numbers are due to the fact that shorter trips are slower. Averaging across trip gives them a greater weight than averaging total travel across households. In turn, a household average will also weight shorter trips more does the ratio of aggregate distance to aggregate travel time.

---

13 Our initial NHTS sample contains 150,147 households of whom we can locate 149,638 on our grid. We have a positive measure of vehicle kilometer traveled for 136,530 households. After restricting our sample to those for which we have a full set of household and individual characteristics, we are left with 126,203 households, 99,875 of whom live in an MSA as defined by their 1999 definitions.
14 This is purely for expositional convenience. It allows us to include MSA indicator variables in our regressions without changing our sample.
15 This is an average across households. Dividing aggregate vkt by aggregate travel time implies a speed of 44.5 kilometers per hour. Couture, Duranton, and Turner (2014) report a mean speed per trip of 38.5 kilometers per hour. The differences between those numbers are due to the fact that shorter trips are slower. Averaging across trip gives them a greater weight than averaging total travel across households. In turn, a household average will also weight shorter trips more does the ratio of aggregate distance to aggregate travel time.
kilometers. These values reflect the sample of household members who filled out a travel diary reporting positive travel and those who reported driving to work. Because households often consist of more than one member, each NHTS survey describes more individuals than households.

The NHTS survey reports household and individual demographics. These demographic variables provide a description of household race, size, income, educational attainment, and homeownership status. Table 1 provides descriptive statistics for these demographic characteristics. Mean household income is $71,257 and the average over households of the average age of household adults is 53.5 years. We also note that nearly 90% of households in our sample are homeowners.

Urban form data are more complicated. To measure the share of developed land cover, we rely on the 1992, 2002 and 2006 National Land Cover Data (NLCD). While the NLCD reports many land cover classifications, we sum the urban classes in each year to measure the share of urban cover in each of grid cells. Table 1 reports descriptive statistics for our sample. For an average survey respondent, 5.0% of their home cell is in urban cover in 2008.

To assign 2000 census data to our grid cells, we distribute block group data to our grid cells using an area weighting on the basis of geocoded map of 2000 census block groups. We perform a similar exercise for 1990 and 2010. With this correspondence between block groups and grid cells in place, we are able to assign any block group variable reported in the 1990, 2000 or 2010 census and in the American Community Survey (ACS) to our grid. All urban form variables involving demographic characteristics are computed on this basis. Table 1 reports that for an average survey respondent, the average residential density within a radial distance of 10 kilometers of their home cell is 755 per square kilometer, that the share of residents with some college living in their home cell is 32.8% and that the mean household income in their home grid cell is $78,073. Note that all densities for rings around a survey respondent’s home are normalized by the number of grid cells for which we have population and employment information. This prevents us from underestimating density for households who live by the sea, a lake, or uninhabitable terrain.

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18Sources for these data are: Missouri Census Data Center (1990), Missouri Census Data Center (2000), Missouri Census Data Center (2010) and National Historical Geographic Information System (2010).
19This figure is about 10% higher than the income reported by surveyed households. Income for survey respondents is from the NHTS while mean local income is from the ACS which uses a variety of sources and for which under-reporting might be less of an issue.
Using ACS and census tabulations, we also measure a number of other local characteristics such as an average length of tenure of 10.3 years and a local five-year mobility rate of 34.5% averaged over the last three censuses.

Employment data are based on zipcode business patterns. These data report both aggregate and sectoral employment by zipcode. We assign these data to our grid on the basis of zipcode maps using the same procedure that we use for census data.\textsuperscript{20} We use zipcode business patterns for the years closest to the NHATS survey years, and to reduce measurement errors, average over the nominal year of the survey and the preceding year. For much of our analysis, we rely on the total number of people living or working within 10 kilometers of each survey respondent. This involves summing the count of population with the count of employment. We call this measure ‘people’. Table 1 reports that for an average household survey respondent, the density of residents and jobs is 1,072 per square kilometer within 10 kilometers of their address, and that 1,513 people lived or worked in the home cell of an average survey respondent.

In addition to these data we also use the PRISM gridded climate data (PRISM Climate Group at Oregon State University, 2012\textsuperscript{a,b}) to measure temperature and precipitation in each grid cell.


Finally, in some of our results we investigate the relationship between road density and driving. To describe the US road network, we rely on the 2007 National Highway Planning Network map (Federal Highway Administration, 2005). This map is part of the federal government’s efforts to track roads that it helps to maintain or build. It all interstate highways and most state highways and arterial roads in urbanized areas. To construct measures of road density, for each grid cell containing a survey respondent, we construct disks of radius 5, 10 and 25 kilometers centered on this cell. For each such disk, we then calculate kilometers of each type of road network in that disk.

6. Results

To proceed with our investigation we must choose among the competing measures of driving available in the NHTS and from the many measures of urban form in our data. We must also choose the scale at which to compute urban form variables, e.g., home cell, 10 kilometers radius or MSA. Finally, we must confront the inference problems described in section 3.

We proceed in steps. First, we present OLS results showing the relationship between our preferred measures of driving and urban form, household vkt and the density of people within 10 kilometers. Second, we verify that these relationships are robust to different measures of driving and to the scale at which we calculate the urban form variable. Third, we consider the problems of sorting and endogeneity. Finally, we investigate other measures of urban form.

A OLS estimations

Table 2 reports the results of OLS regressions of driving on urban form in US MSAs. Our unit of observation is a household described by the 2008 NHTS. In every column, our dependent variable is the log of household vkt, reported in the second row of table 1. In all specifications, our measure of urban form is the density of residents and employment within 10 kilometers of the respondent household’s address, also as described by table 1.

In column 1, we regress log annual household vkt on the log number of jobs and residents within a 10 kilometers radius, i.e., ‘people’ within 10 kilometers to estimate an elasticity of -8.7%. Households in locations with a 10% higher density of residents and jobs drive 0.87% less and a one standard deviation increase in density within 10 kilometers is associated with a 0.11 standard deviation decrease in vkt. At the sample mean, this represents about 3,300 kilometers annually. Moving from the bottom density decile to the top density decile is associated with a 26% reduction
Table 2: Driving and density, baseline OLS estimations

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<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
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<td>(0.033)</td>
<td>(0.014)</td>
<td>(0.015)</td>
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</tr>
</tbody>
</table>

R^2                      | 0.01         | 0.36         | 0.01         | 0.05         | 0.37         | 0.02         | 0.37         | 0.36         |

Notes: The dependent variables is log household VKT in all columns. All regressions include a constant including 275 MSA fixed effects in columns 6 and 7 and 837 county fixed effects in column 8. Robust standard errors in parentheses, clustered by MSA in columns 3-7, and by county in column 8. a, b, c: significant at 1%, 5%, 10%.
in vkt or about 9,500 kilometers annually. We note that these magnitudes are relevant to most of the tables presented below because the coefficient on density does not vary much across specifications.

In column 2, we add household characteristics to our specification and estimate a slightly larger effect of 10-kilometer density on household vkt with an elasticity of -9.8%. White and asian households drive slightly more by about 2%. We also find that female households drive less. The coefficient of -0.26 implies that a single female is predicted to drive 23% less on average than a single male. Large households also drive more but not proportionately so. The coefficients on log household size and the indicator for one-person households show that two-person households will drive about 30% more than one-person households. We also observe that vkt is concave in age. At age 20, an extra year of age is associated with 2% more driving. Then, vkt peaks around the age of 45 before declining. The elasticity of vkt with respect to income is large at around 26%. vkt increases with education (which is coded 1 to 5) for low levels of educational achievement and then decreases for the most educated households. Because the coefficients on households’ characteristics are stable across specifications, we do not report or discuss them for subsequent tables.

In column 3, we consider geographic characteristics. Relative to column 1, the coefficient on 10-kilometer people density is mostly unchanged. The results of this column indicate that vkt is higher where temperature is on average higher and varies less over the year. We find no significant effect of precipitation or its variation over the year. In other specifications we often find that vkt is higher in places with less precipitation and more variation over the year.

In column 4, we consider neighborhood socio-economic characteristics. We find that driving declines with the share of university educated workers and increases with average local income. Because richer neighbourhoods are also on average denser, the coefficient on density also increases marginally in magnitude relative to the one estimated in column 1. In column 5, we consider all the controls together and estimate an elasticity of vkt with respect to the density of jobs and residents within 10 kilometers of -9.1%. Relative to column 4, we note that the magnitudes of neighbourhood characteristics drop sharply and loses significance. This is unsurprising. Richer and more educated households tend to live in richer and more educated neighbourhoods and the resulting co-linearity makes it difficult to separately estimate the effects of household and neighborhood income.

In column 6, we return to the specification of column 1 but also include a fixed effect for each Metropolitan Statistical Area (MSA). Estimating the elasticity of vkt with respect to density within
MSAs yields a coefficient larger in magnitude relative to column 1. This is because richer and more educated households that drive more disproportionately locate in denser MSAs. Consistent with this, including all the household, geographic, and neighbourhood characteristics in column 7 gives a coefficient on density close to that of column 5 and, in spite of the extra fixed-effects, does not improve the fit of the regression. This specification is our benchmark OLS specification. Finally, column 8 introduces a fixed effect for each of the 837 counties where metropolitan households are located. At -0.075, the coefficient on local density is marginally lower but statistically indistinguishable from our preferred coefficient in column 7 or from the coefficient obtained in column 1, the simplest estimation.

Our choice of explanatory variables in table 2 controls for obvious determinants of household travel, like household demographics or the geography of where they live. We also include controls for the neighborhood socio-economic characteristics in spite of the fact they are may be correlated with urban form and capture some of its effect. Given our concern about the sorting of household on the basis of unobserved tastes for driving, we prefer the larger set of control variables. As it turns out, once we control for basic household demographics, including further controls does not measurably affect the coefficient of urban form.

B Robustness to measure of driving and urban form

In table 3 we assess the stability of the results of table 2 as we vary our dependent variable. In each column of this table we estimate a specification similar to that of column 7 of table 2, with controls for households demographics, neighbourhood socio-economic characteristics, and geography as well as a full set of MSA fixed effects. In column 1, we replace our preferred measure of vkt with a stated measure of vkt. We find a density elasticity of -11% instead of -8.2%. Measuring vkt through odometer readings by households in column 2, we estimate a density elasticity of -9.5%. Using a measure of daily vkt for individual drivers aggregated at the household level in column

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21 In alternative specifications we also used the distance to the CBD as explanatory variable. Adding it in log to the specification of column 7 makes the coefficient on density marginally smaller in absolute value at -0.074. The elasticity of vkt with respect to distance to the CBD is small at 0.015.

22 We experimented with many characteristics and included all those that are ‘often’ significant in the preliminary regressions we estimated. For instance, we include an indicator variables for households that are white or asian. As can be seen in table 2 below, this variable is often significant but the magnitude of its effects is small. We grouped white and asian households because differences between them were minimal. Similarly we grouped all other minorities together because the differences between them were also minimal.
Table 3: Robustness of baseline OLS estimations to measures of travel

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<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
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</tr>
</thead>
<tbody>
<tr>
<td>stated odometer ind. day</td>
<td>km</td>
<td>km</td>
<td>km</td>
<td>dist. to work</td>
<td>km</td>
<td>km</td>
<td>minutes</td>
<td>speed</td>
</tr>
<tr>
<td>log people 10 km</td>
<td>-0.11(^a)</td>
<td>-0.095(^a)</td>
<td>-0.13(^a)</td>
<td>-0.18(^a)</td>
<td>-0.026(^a)</td>
<td>-0.11(^a)</td>
<td>0.004(^a)</td>
<td>-0.15(^a)</td>
</tr>
<tr>
<td>(0.0054)</td>
<td>(0.0055)</td>
<td>(0.0066)</td>
<td>(0.0097)</td>
<td>(0.0036)</td>
<td>(0.0040)</td>
<td>(0.0020)</td>
<td>(0.0061)</td>
<td></td>
</tr>
</tbody>
</table>

Controls:
Demographics | Y | Y | Y | Y | Y | Y | Y | Y |
Geography | Y | Y | Y | Y | Y | Y | Y | Y |
Local socio-econ. | Y | Y | Y | Y | Y | Y | Y | Y |
MSA fixed effects | Y | Y | Y | Y | Y | Y | Y | Y |

\( R^2 \) | 0.42 | 0.43 | 0.18 | 0.11 | 0.12 | 0.14 | 0.33 | 0.10 |
Observations | 93,602 | 71,742 | 83,313 | 86,387 | 85,996 | 82,849 | 83,313 | 83,313 |

Notes: All regressions include 275 MSA fixed effects. Robust standard errors clustered by MSAs in parentheses. \(^a\), \(^b\), \(^c\): significant at 1%, 5%, 10%. The dependent variables and explanatory variables of interest are in log in all columns except for the number of trips in column 7. Demographic controls include a white/Asian indicator, log income, log household size, a single indicator, age, age squared, gender, education, and education squared. Geographic controls include average precipitation and its standard deviation, and average temperature and its standard deviation. Local socio-economic controls include the share of residents with higher education and its square and log local income.

3, the elasticity is again slightly larger at -13%. Using instead, distance to work in column 4 yields an even larger elasticity of -18%.

These elasticities for alternative measures of kilometers traveled are estimated on slightly different samples of households. Restricting attention to the about 37,000 households for whom we observe our preferred measure of travel and the four alternatives from columns 1-4 of table 3, we estimate the following elasticities: -9.2% for our preferred measures of travel, -12% for stated miles, -11% for odometer miles, -14% for daily travel, and -18% for distance to work. The differences from the corresponding elasticities reported in tables 2 and 3 are small.

We find some differences across different measures of kilometers traveled but note that these differences are small and that these measures are conceptually distinct. For instance, daily \( VKT \) is measured at the individual level whereas odometer \( VKT \) is measured for vehicles regardless of the number of household members who travel. Distance to work is more sensitive to local density. This is not surprising because commutes often take place when congestion is at its worst. Importantly, commutes represent 27% of household \( VKT \) and the density elasticity is -18% for commute distance. Hence, commutes account for \((0.27 \times 0.18)/0.092 \approx 53\%\) of the density elasticity of -9.2% that we estimate for all travel.
Table 4: Robustness of baseline OLS estimations to measure of density

<table>
<thead>
<tr>
<th>Sample restriction</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Urban form:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>people</td>
<td>population</td>
<td>emp.</td>
<td>land cover</td>
<td>people</td>
<td>people</td>
<td>people</td>
<td>people</td>
</tr>
<tr>
<td>1 km</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>-0.067&lt;sup&gt;a&lt;/sup&gt;</td>
<td></td>
<td>-0.083&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.065&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.055&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.080&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.078&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.081&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.067&lt;sup&gt;a&lt;/sup&gt;</td>
</tr>
<tr>
<td>(0.0036)</td>
<td></td>
<td>(0.0052)</td>
<td>(0.0046)</td>
<td>(0.0033)</td>
<td>(0.0045)</td>
<td>(0.0035)</td>
<td>(0.0046)</td>
<td>(0.0050)</td>
</tr>
<tr>
<td>Controls:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Demographics</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Geography</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Local socio-econ.</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>MSA fixed effects</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>R&lt;sup&gt;2&lt;/sup&gt;</td>
<td>0.37</td>
<td>0.37</td>
<td>0.37</td>
<td>0.36</td>
<td>0.37</td>
<td>0.37</td>
<td>0.38</td>
<td>0.34</td>
</tr>
<tr>
<td>Observations</td>
<td>99,875</td>
<td>99,875</td>
<td>99,870</td>
<td>99,423</td>
<td>94,970</td>
<td>74,864</td>
<td>26,328</td>
<td>90,662</td>
</tr>
</tbody>
</table>

Notes: All regressions include 275 MSA fixed effects. Robust standard errors clustered by MSAs in parentheses. <sup>a</sup>, <sup>b</sup>, <sup>c</sup>: significant at 1%, 5%, 10%. The dependent variables and explanatory variables of interest are in log in all columns. Demographic controls include a white/asian indicator, log income, log household size, a single indicator, age, age squared, gender, education, and education squared. Geographic controls include average precipitation and its standard deviation, and average temperature and its standard deviation. Local socio-economic controls include the share of residents with higher education and its square and log local income.

In column 5, our dependent variable is a measure of travel time that corresponds to the kilometers traveled in column 3. For this measure of travel time, we estimate an elasticity of -2.6%, much lower than for travel distance. In column 6, we turn to travel speed as dependent variable and estimate an elasticity of -11%. Although residents in denser locations travel fewer kilometers, their travel time is only marginally lower because travel is slower. In column 7, we use the number of trips as dependent variable and estimate a small positive density elasticity of 1.4%. Finally, in column 8, we estimate an elasticity of mean trip distance to 10 kilometer density of -15%. This shows that the lower vkt of residents in denser locations is exclusively explained by shorter trips not by fewer trips. If anything, residents of denser locations tend to travel more often.

In table 4, we assess the stability of the results of table 2 as we vary our explanatory variable of interest. In column 1, we use the density of people in a respondent’s home cell to measure urban form instead of a 10 kilometer radius. Relative to the -8.2% elasticity we estimate with 10-kilometer density, the estimate here is modestly lower at -6.7%. Columns 2 and 3 use the number of residents

<sup>23</sup>Although our approach is very different from that developed in Couture et al. (2014), they estimate a comparable elasticity of travel speed with respect to population of -13% across the largest 100 US MSAs.
and the number of jobs within a 10 kilometer radius respectively and estimate comparable elasticities. We estimate a smaller elasticity in column 4 when using the share of developed land within a 10 kilometer radius as measure of urban form. Consistent with the presence of mild measurement error, we tend to estimate moderately lower elasticities when we use arguably worse measures of urban form such as the physical footprint of development instead of actual measures of density and extremely local measures instead of measures that capture the density encountered by residents in most of their travel. Recall that mean trip distance is slightly below 13 kilometers in our data. We return to these measures below when consider several measures of urban form in the same regression.

In columns 5 to 8, we consider various sample restrictions to confirm that our results are not driven by a small subgroup of locations or drivers. In column 5, we estimate again our preferred OLS estimation of column 7 of table 2 without the New York MSA. Although New York is often acknowledged to be a major outlier for urban transportation, the elasticity of VKT with respect to density is unchanged when excluding it. In results not reported here, we also estimate the same specification for only the New York MSA and obtain an elasticity of -14%. In column 6, we eliminate all observations in the top density quartile and still estimate an elasticity of -7.8%. In column 7, we consider only the non-MSA residents who are excluded from most of our specifications and estimate an elasticity of -8.1%. Finally, in column 8, we eliminate the 10% of households with the highest VKT. Collectively, these households are responsible for more than 20% of aggregate VKT. As these high VKT households are disproportionately located in low density areas, we are bound to estimate a lower elasticity of VKT with respect to density. We do but the interesting feature is that the effect is fairly modest. We still estimate an elasticity of -6.7%.

Overall, these results suggest that our findings are broadly consistent across a variety of measures of driving and landscape, but that particular measures of driving may be more or less sensitive to urban form.

C Sorting

We now turn attention to the possibility that households and individuals in dense areas are different from those in less dense areas, and that it is the difference in people rather than the difference in urban form that causes the difference in driving behavior across neighborhoods.
To the extent that the prior investigations of urban form and driving consider the possibility of such sorting on unobservables, it does so in the context of (Heckman) selection models estimated without an exclusion restriction. That is, they resolve the problem of sorting on unobservables entirely by functional form restrictions. In the interests of completeness, appendix table 11 reports the results of a series of such regressions. When we include demographic, neighborhood, and geographic controls, the resulting estimate of the elasticity of \( vkt \) with respect to the density of jobs and residents within 10 kilometers is \(-9.1\%\). Comparing this to our benchmark estimate is column 7 of table 2 shows that this change of functional form is not important.

As in table 2, the existing literature also controls for observable individual characteristics. Intuitively, if such controls change the estimate of the coefficient of interest, then we worry that other unobserved variables might also be important. We see in table 2 that this does not occur. Oster (2015) refines this intuition and points out that observed control variables do not generally inform us about the importance of unobserved controls unless the observed controls improve the \( R^2 \) of the regression. In addition, Oster (2015) provides a parametric test for bias caused by sorting on unobservables. This test leads to a test statistic, \( \delta \), reported for columns 2-5 of table 2. Loosely, \( \delta \) measures how much more sensitive the estimate of the coefficient of interest must be to unobservable than observable controls before we would lose the ability to distinguish the coefficient of interest from zero at conventional levels of confidence. If the unobservable and observable controls are the same in their ability to influence the coefficient of interest then \( |\delta| = 1 \). As \( |\delta| \) increases, unobservables must be progressively more ‘unlike’ the observables in order to affect the coefficient of interest. Comparing column 1 with columns 2-5 of table 2, we see that the addition of control variables never affects the coefficient of interest, but affects the \( R^2 \) only in columns 2 and 5. The values of \( \delta \) change accordingly. Only in columns 2 and 5 do we estimate large values for \( \delta \). Thus, columns 2 and 5 suggest that unobserved controls must satisfy an implausible condition in order to bias our estimates while columns 3 and 4 are uninformative about this issue.

Our primary strategy for addressing the possibility of sorting, however, revolves around variants of equation (9). Consistent with the discussion of section 3, we proxy for the mobility rate in a given neighborhood with the mean tenure of a resident in the survey respondent’s home cell.\(^\text{24}\) We multiply by minus one so that increases in our proxy correspond to increases in mobility.

\(^{24}\)Our information on residential tenure comes from the ACS block group data (National Historical Geographic Information System, 2010). We impute this variable to grid cells as described in section 5.
Table 5: Selection and mobility using information about local mobility measured through the tenure length of local residents

<table>
<thead>
<tr>
<th>Period</th>
<th>Household sample</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
</tr>
</thead>
<tbody>
<tr>
<td>90 to 10</td>
<td>All</td>
<td>-0.080</td>
<td>-0.075</td>
<td>-0.046</td>
<td>-0.084</td>
<td>-0.069</td>
<td>-0.080</td>
<td>-0.076</td>
<td>-0.075</td>
</tr>
<tr>
<td>90 to 10</td>
<td>All</td>
<td>(0.0052)</td>
<td>(0.0055)</td>
<td>(0.014)</td>
<td>(0.0073)</td>
<td>(0.0060)</td>
<td>(0.0072)</td>
<td>(0.0055)</td>
<td>(0.0048)</td>
</tr>
<tr>
<td>90 to 10</td>
<td>All</td>
<td>-0.12€</td>
<td>-0.063</td>
<td>-0.030</td>
<td>-0.061</td>
<td>-0.056</td>
<td>-0.033</td>
<td>-0.014</td>
<td>-0.18€</td>
</tr>
<tr>
<td>90 to 10</td>
<td>All</td>
<td>(0.025)</td>
<td>(0.029)</td>
<td>(0.033)</td>
<td>(0.054)</td>
<td>(0.060)</td>
<td>(0.035)</td>
<td>(0.043)</td>
<td>(0.054)</td>
</tr>
<tr>
<td>90 to 10</td>
<td>Big Δ</td>
<td>0.0077€</td>
<td>-0.0033</td>
<td>-0.00059</td>
<td>0.0014</td>
<td>-0.0048</td>
<td>0.0023</td>
<td>-0.00014</td>
<td>-0.012€</td>
</tr>
<tr>
<td>90 to 10</td>
<td>Small Δ</td>
<td>(0.0034)</td>
<td>(0.0036)</td>
<td>(0.0038)</td>
<td>(0.0067)</td>
<td>(0.0072)</td>
<td>(0.0044)</td>
<td>(0.0057)</td>
<td>(0.0062)</td>
</tr>
<tr>
<td>90 to 10</td>
<td>&lt;50</td>
<td>-0.0099€</td>
<td>-0.040</td>
<td>-0.0056</td>
<td>-0.016€</td>
<td>-0.010€</td>
<td>-0.010€</td>
<td>-0.0083€</td>
<td>-0.18€</td>
</tr>
<tr>
<td>90 to 10</td>
<td>All</td>
<td>(0.0029)</td>
<td>(0.013)</td>
<td>(0.0043)</td>
<td>(0.0044)</td>
<td>(0.0033)</td>
<td>(0.0027)</td>
<td>(0.0029)</td>
<td>(0.0011)</td>
</tr>
<tr>
<td>00 to 10</td>
<td>All</td>
<td>0.0026€</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>00 to 10</td>
<td>All</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: The dependent variable is log household VKT in all columns. Mobility is measured as - average tenure length in of residents of the same blockgroup. All regressions are estimated with OLS and include 275 MSA fixed effects with demographic controls (a white/asian indicator, log income, log household size, a single indicator, age, age squared, gender, education, and education squared), geographic controls (average precipitation and its standard deviation, and average temperature and its standard deviation) and local socio-economic controls (the share of residents with higher education and its square and log local income). Robust standard errors clustered by MSA in parentheses. a, b, c: significant at 1%, 5%, 10%.

Equation (9) offers two parametric tests of sorting, summarized by $H_{\sim \text{Sorting}}$ (10). One of these tests involves the coefficient of the interaction of a mobility proxy with the change in urban form, and the second involves the difference between the coefficients of the level and of the change in the measure of urban form.

All of the specifications in table 5 contain these three terms. In addition to the controls from our preferred specification in column 7(?) of table 2; household, neighbourhood and geographic characteristics, and msa fixed effects, column 1 also controls for the 1990 level of the density of people within 10 kilometers, the change in this measure between 1990 and 2010, and the interaction of the change in density with minus one times mean tenure. In order to address the possibility that driving behavior varies with tenure, column 2 also controls for the level of the mobility proxy. This specification closely approximates equation (9) and is our preferred specification. Column 3 also controls for the mobility rate interacted with the initial level of density. Column 4 restricts attention to bottom and top quartile of density growth in a 10 kilometer radius (excluding the top
and bottom percentiles). Column 5 considers the complementary sample of households located in locations at the second and third quartile of density change. Column 6 restricts attention to survey respondents with household age below 50. Columns 7 and 8 consider the ten year periods from 1990 to 2000 and from 2000 to 2010.

In every case, we find that the coefficient on initial density and that on the change in density are close. Except for columns 1 and 8, the coefficient on the change in density is less than a standard deviation apart from the coefficient on density. According to equation (9), the difference between these two coefficients is $\alpha_1$, our measure of selection. Hence, we cannot reject that $\alpha_1$ is zero. In equation (9), $\alpha_1$ is also directly measured with the coefficient on the interaction between mobility and the change in density. This coefficient is a precisely estimated zero in all columns except for columns 1 and 8. Even in these two columns, we can reject values of $\alpha_1$ smaller than $-0.025$ or larger than $0.015$. The bottom row of table 5 presents p-values for an F-test of $H_{\sim \text{Sorting}}$. In no case are we able to reject this hypothesis at ordinary levels of confidence.

We note that, in the same spirit as equation (9), we can also compare the coefficient on initial density in high-mobility locations (column 4) and low-mobility locations (column 5). In addition, we can even compare the coefficient obtained when estimating our preferred specification on a sample of more mobile residents (those below 50 as in column 6) to the overall sample in column 2. In both cases, the differences are close to zero and the coefficients are precisely estimated.

More generally and in light of the hypothesis tests developed in section 3, the findings of table 5 suggests that as the landscape changes, the driving behavior of the people who arrive is like that of the people who leave.

In the remainder of this section, we report a number of robustness tests for this result. First, appendix table 12 replicates our preferred estimation from column 2 of table 5 under various sample restrictions, with a purely residential population based measure of density, and using alternative dependent variables. These results are consistent with our findings so far. Excluding high-density locations or high-vkt households makes no difference. Focusing more narrowly on more mobile households in locations facing greater changes in population or on less mobile households in more stable locations yields elasticities of vkt with respect to density that are of the same magnitude. Using only population instead of population and employment to measure density makes no difference. We also confirm the results of table 3. That is, the elasticity of daily vkt is slightly larger than the annual measure, the elasticity of travel time is close to zero, and this
Table 6: Sorting on age OLS estimations

<table>
<thead>
<tr>
<th>Household sample</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
</tr>
</thead>
<tbody>
<tr>
<td>log people 10 km 1990</td>
<td>-0.082&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.085&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.086&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.074&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.087&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.080&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.087&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.073&lt;sup&gt;a&lt;/sup&gt;</td>
</tr>
<tr>
<td>(0.0053)</td>
<td>(0.0063)</td>
<td>(0.0073)</td>
<td>(0.0053)</td>
<td>(0.0068)</td>
<td>(0.0068)</td>
<td>(0.0086)</td>
<td>(0.0076)</td>
<td></td>
</tr>
<tr>
<td>(\Delta_{90-10}) log people 10 km</td>
<td>-0.071&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.068&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.080&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.058&lt;sup&gt;b&lt;/sup&gt;</td>
<td>-0.091&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.093</td>
<td>-0.092&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.13</td>
</tr>
<tr>
<td>(0.013)</td>
<td>(0.019)</td>
<td>(0.022)</td>
<td>(0.025)</td>
<td>(0.019)</td>
<td>(0.057)</td>
<td>(0.027)</td>
<td>(0.096)</td>
<td></td>
</tr>
</tbody>
</table>

Controls:

Demographics: Y Y Y Y Y Y Y Y
Geography: Y Y Y Y Y Y Y Y
Local socio-econ.: Y Y Y Y Y Y Y Y
Decade indicators: N Y N N N N N N
Decade \(\times\) log people: N Y N N N N N N
Decade \(\times\) \(\Delta\) log people: N Y N N N N N N

\(R^2\) | 0.37 | 0.37 | 0.26 | 0.26 | 0.36 | 0.37 | 0.25 | 0.27 |
Observations | 99,875 | 99,875 | 39,253 | 40,421 | 46,942 | 48,939 | 18,710 | 19,980 |
Number of MSA | 275 | 275 | 274 | 274 | 263 | 272 | 247 | 257 |

Notes: All regressions include MSA fixed effects. Robust standard errors clustered by MSA in parentheses. \(a\), \(b\), \(c\): significant at 1%, 5%, 10%. The dependent variables and explanatory variables of interest are in log in all columns. Demographic controls include a white/asian indicator, log income, log household size, a single indicator, age, age squared, gender, education, and education squared. Geographic controls include average precipitation and its standard deviation, and average temperature and its standard deviation. Local socio-economic controls include the share of residents with higher education and its square and log local income. When decade effects are introduced, households in their 40s are used as reference. See table 7 for the detailed results of column 2.

difference is still explained by the difference in travel speed.

Second, appendix table 13 presents a series of regressions that are identical to those of table 5, except that we proxy for the renter (vs. homeowner) status of the survey respondent. These results are qualitatively similar to those of table 5 except that the interaction terms are marginally larger and are estimated somewhat less precisely. In spite of this, these results suggest the same conclusion as does table 5. That is, as the landscape changes, the driving behavior of arrivals is like that of those who leave.

We next use age as a proxy for mobility. However, given that the relationship between age and residential mobility is unlikely to be linear, we use a vector of decadal age dummies to describe the age of drivers. Then, consistent with the intuition developed in equation (9), we interact these indicators with changes in landscape. We include these interactions in regressions that also contain the 1990 level of urban form and changes in urban form. Table 6 reports these results. Column 1 includes only the level and change of people within 10 kilometers of a survey respondent’s home.
Table 7: Detailed results for column 2 of table 5

<table>
<thead>
<tr>
<th>Age</th>
<th>20-29</th>
<th>30-39</th>
<th>40-49 (ref.)</th>
<th>50-59</th>
<th>60-69</th>
<th>&gt;70</th>
</tr>
</thead>
<tbody>
<tr>
<td>Decade indicators</td>
<td>-0.057</td>
<td>0.087</td>
<td>0</td>
<td>0.034</td>
<td>-0.22&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.13</td>
</tr>
<tr>
<td></td>
<td>(0.098)</td>
<td>(0.10)</td>
<td></td>
<td>(0.075)</td>
<td>(0.082)</td>
<td>(0.087)</td>
</tr>
<tr>
<td>Decade × log people 10 km 1990</td>
<td>0.0033</td>
<td>-0.0073</td>
<td>0</td>
<td>-0.0039</td>
<td>0.014&lt;sup&gt;b&lt;/sup&gt;</td>
<td>0.0035</td>
</tr>
<tr>
<td></td>
<td>(0.0079)</td>
<td>(0.0085)</td>
<td></td>
<td>(0.0060)</td>
<td>(0.0068)</td>
<td>(0.0067)</td>
</tr>
<tr>
<td>Decade × Δ&lt;sub&gt;90-10&lt;/sub&gt; log people 10 km</td>
<td>-0.010</td>
<td>-0.0097</td>
<td>0</td>
<td>0.027</td>
<td>0.022</td>
<td>-0.053</td>
</tr>
<tr>
<td></td>
<td>(0.022)</td>
<td>(0.020)</td>
<td></td>
<td>(0.020)</td>
<td>(0.028)</td>
<td>(0.036)</td>
</tr>
</tbody>
</table>

Notes: This table reports the coefficients on decades of age, interactions between decades of age and log 1990 people density, and interactions between decades of age and log density changes between 1990 and 2010.

cell, along with an extensive set of control variables. Column 2 includes the interaction terms. Columns 3-8 repeat column 1 on a variety of subsamples. The results of this table are striking. In every specification the coefficient of the level and change in urban form are indistinguishable. Moreover, the coefficients do not vary across specifications. This is consistent with α<sub>1</sub> = 0 in equation (9).

Table 7 reports the interaction terms for column 2 of table 6. On the basis of equation 9 the coefficients of the last set of interaction terms, the interaction of decade of life with change in urban form, should give us the value of α<sub>1</sub> for that subgroup. We see that these coefficients are all small relative to the effect of density on driving and are indistinguishable from zero. We note that the table includes a complete set of interaction as controls. We are concerned that driving behavior may vary by age or that relationship between driving and density was different in places with different initial demographics.

We have now completed five distinct tests of the role of sorting. In our OLS results we control for observable characteristics. We find these controls have only a tiny effect on our estimates of the effect of density on driving and the more formal test of Oster (2015) indicates that unobservables are unlikely to bias our estimates. We also develop a parametric test for the role of sorting and implement it using three different proxies for the mobility rate of residents. In each case, we find little support for the idea that sorting is an important determinant of the relationship between density and driving. Finally, we report the result of Heckman type selection corrections. These estimates also suggest that the relationship between urban form and driving does not reflect sorting of individuals across places on the basis of their propensity to drive.
Table 8: IV regressions

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<td></td>
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<td>Y</td>
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</tbody>
</table>

Notes: All regressions TSLS regressions with a constant. Controls are demographic controls (a white/asian indicator, log income, log household size, a single indicator, age, age squared, gender, education, and education squared), geographic controls (average precipitation and its standard deviation, and average temperature and its standard deviation) and local socio-economic controls (the share of residents with higher education and its square and log local income). <sup>a</sup>, <sup>b</sup>, <sup>c</sup>: significant at 1%, 5%, 10%. Robust standard errors clustered by county in parentheses. Clustering is by county to have a sufficient number of clusters to compute robust covariance matrices more reliably than when clustering by MSA. The dependent variables and explanatory variables of interest are in log in all columns.

D Endogeneity

Table 8 reports the results of a series of instrumental variables estimations. These regressions are all variants of equation 11 in which we rely on permutations of three instruments. These instruments measure the share of the 10 kilometer disk surrounding a respondent’s home cell that overlays an aquifer that can provide residential water. This variable is well known to predict urban form (Burchfield, Overman, Puga, and Turner, 2006). In addition, we construct variables measuring a respondent’s exposure to earthquakes and landslides. These variables have a remarkably strong ability to predict surface employment and residential density, and it is not easy to see how they might influence driving through any other channel. In column 1 we present an instrumental variables regression using our aquifers instrument but do not include other controls. In the second column we add MSA indicators and the same long list of controls that we use in column 7 of table 2. In the subsequent columns we experiment with the different instruments and with permutations of instruments. The coefficient of density is stable across specifications. In every case our instruments are not weak according to conventional tests, and in regressions including
more than one instrument, we comfortably pass over-id tests.

Most importantly, coefficient estimates are statistically indistinguishable from those in our table of OLS estimations. This suggests that omitted variables correlated with driving and urban form are not causing economically important bias in our estimates of the relationship between urban form and driving.

E Other landscape variables

On the basis of our work so far, it appears that neither sorting nor omitted variables cause bias in OLS estimates. Given this, we now turn to an investigation of the effects of different measures and spatial scales of urban form on driving using OLS regressions.

Tables 9 and 10 report these results.

7. Conclusion and policy implications

1. Doubling the density of people causes about a 10% reduction in household annual vkt. This is very robust. 'Mixed-use' matters too.

2. How big is this effect? Consider moving 10% of people living in least dense places to new neighborhoods at 90th percentile of density. This increase sample mean density of people (10k) from 869 to 1081 $\Rightarrow$ about a 2% decrease in driving. This is very small(?). Four million internally displaced people in Iraq out of population of 33 million is about 12%. This calculation is based on NHTS population distribution. This is incorrect w/o sampling weights. Calculate distribution of population across landscape from census instead?

3. What should we do?

   • Absent regulation, cites are probably "too big".
   • but regulation restricting entry is probably harmful.
   • this can only happen if regulated cities are too small (consider Palo Alto or NYC).
   • relaxing building restrictions is probably good. If there is too much driving, it is better

4. Even if increasing density is welfare improving, it does not solve the problem of congestion.
Table 9: Driving and urban form, extended OLS estimations

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<td>-0.082*</td>
<td>-0.085*</td>
<td>-0.090*</td>
<td>-0.088*</td>
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R²  | 0.37 | 0.37 | 0.37 | 0.37 | 0.37 | 0.37 | 0.37 | 0.37 |
Number of MSA | 275 | 275 | 275 | 275 | 275 | 275 | 275 | 275 |

Notes: The dependent variable is log household VKT in all columns. All regressions are OLS regressions with MSA fixed effects. Controls are demographic controls (a white/Asian indicator, log income, log household size, a single indicator, age, age squared, sex, education, and education squared), geographic controls (average precipitation and its standard deviation, and average temperature and its standard deviation) and local socio-economic controls (the share of residents with higher education and its square and log local income). Robust standard errors clustered by MSA in parentheses. *a, b, c*: significant at 1%, 5%, 10%.
Table 10: Driving and the local composition of economic activity, OLS estimations

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<th>Measure of activity</th>
<th>(1) log emp.</th>
<th>(2) log emp.</th>
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<th>(8) share emp.</th>
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<td>-0.083(^a)</td>
<td>-0.073(^a)</td>
<td>-0.069(^a)</td>
<td>-0.060(^a)</td>
<td>-0.064(^a)</td>
<td>-0.065(^a)</td>
<td>-0.076(^a)</td>
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<td>(0.0066)</td>
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<td>(0.0050)</td>
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<td>(0.0057)</td>
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<td>-0.013(^b)</td>
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<td>Consumer services</td>
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<td>-0.048(^a)</td>
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<td></td>
<td>(0.0025)</td>
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<td>(0.016)</td>
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R\(^2\) 0.37 0.37 0.37 0.37 0.37 0.36 0.37 0.37
Number of MSA 275 275 275 275 275 275 275 275

Notes: The dependent variable is log household VKT in all columns. All regressions are OLS regressions with MSA fixed effects. Controls are demographic controls (a white/asian indicator, log income, log household size, a single indicator, age, age squared, gender, education, and education squared), geographic controls (average precipitation and its standard deviation, and average temperature and its standard deviation) and local socio-economic controls (the share of residents with higher education and its square and log local income). Robust standard errors clustered by MSA in parentheses. \(^a\), \(^b\), \(^c\): significant at 1%, 5%, 10%.

References


Environmental Systems Research Institute. 1998a. Esri data and maps 1998: Discs 3&4 - block group boundaries. This map data was included with an ArcGIS 7 License.

Environmental Systems Research Institute. 1998b. Esri data and maps 1998: Disc 2 - zip code tabulation areas. This map data was included with an ArcGIS 7 License.

Environmental Systems Research Institute. 2004. Esri data and maps 2004: United states disc - block group boundaries. This map data was included with an ArcGIS 9 Licence.


Appendix A. Robustness checks

Table 11: Heckman selection models (one-step MLE)

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<th>(1)</th>
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</thead>
<tbody>
<tr>
<td>log people 10 km</td>
<td>-0.050(^a)</td>
<td>-0.091(^a)</td>
<td>-0.098(^a)</td>
<td>-0.091(^a)</td>
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<td>(0.0025)</td>
<td>(0.0023)</td>
<td>(0.0020)</td>
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</table>

Controls:
Demographics     Y Y Y Y
Geography         N N Y Y
Local socio-econ. N N N Y
Observations      118,802,636 118,802 99,875 99,875

Notes: Results reported for the main regression using log household VKT as dependent variable. The selection equation regards selection into driving in columns 1 and 2 and selection into density in columns 3 and 4. Standard errors in parentheses. \(^a\), \(^b\), \(^c\): significant at 1%, 5%, 10%. Demographic controls include a white/Asian indicator, log income, log household size, a single indicator, age, age squared, gender, education, and education squared. Geographic controls include average precipitation and its standard deviation and average temperature and its standard deviation. Local socio-economic controls include the share of residents with higher education and its square and log local income.
Table 12: Robustness of selection estimations using local tenure length to measure mobility

<table>
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<th>(5)</th>
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<th>(7)</th>
<th>(8)</th>
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</thead>
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<tr>
<td></td>
<td>No high den.</td>
<td>No high</td>
<td>Big Δ</td>
<td>Small Δ</td>
<td>population</td>
<td>ind. day</td>
<td>ind. day</td>
<td>speed</td>
</tr>
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<td>0.00072</td>
<td>-0.15&lt;sup&gt;a&lt;/sup&gt;</td>
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<td></td>
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<td>(0.45)</td>
<td>(0.026)</td>
<td>(0.041)</td>
<td>(0.031)</td>
<td>(0.023)</td>
</tr>
<tr>
<td>Mobility × Δ log density</td>
<td>-0.00041</td>
<td>-0.00049</td>
<td>0.012&lt;sup&gt;c&lt;/sup&gt;</td>
<td>-0.0048</td>
<td>-0.0053</td>
<td>-0.019&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.0050</td>
<td>-0.013&lt;sup&gt;a&lt;/sup&gt;</td>
</tr>
<tr>
<td></td>
<td>(0.0038)</td>
<td>(0.0037)</td>
<td>(0.0068)</td>
<td>(0.040)</td>
<td>(0.0035)</td>
<td>(0.0047)</td>
<td>(0.0034)</td>
<td>(0.0030)</td>
</tr>
<tr>
<td>R²</td>
<td>0.37</td>
<td>0.34</td>
<td>0.25</td>
<td>0.27</td>
<td>0.37</td>
<td>0.18</td>
<td>0.12</td>
<td>0.14</td>
</tr>
<tr>
<td>Observations</td>
<td>74,864</td>
<td>90,662</td>
<td>18,711</td>
<td>19,979</td>
<td>99,875</td>
<td>83,313</td>
<td>85,996</td>
<td>82,849</td>
</tr>
<tr>
<td>Number of MSA</td>
<td>275</td>
<td>275</td>
<td>248</td>
<td>252</td>
<td>275</td>
<td>275</td>
<td>275</td>
<td>275</td>
</tr>
</tbody>
</table>

Notes: All regressions include 275 MSA fixed effects. Robust standard errors clustered by MSA in parentheses. <sup>a</sup>, <sup>b</sup>, <sup>c</sup>: significant at 1%, 5%, 10%. The dependent variable and explanatory variables of interest are in log in all columns. Demographic controls include a white/asian indicator, log income, log household size, a single indicator, age, age squared, gender, education, and education squared. Geographic controls include average precipitation and its standard deviation, and average temperature and its standard deviation. Local socio-economic controls include the share of residents with higher education and its square and log local income.

Table 13: Selection and mobility using information about the renter/homeowner status of the households

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Period</td>
<td>90 to 10</td>
<td>90 to 10</td>
<td>90 to 10</td>
<td>90 to 10</td>
<td>10 to 00</td>
<td>90 to 10</td>
<td>10 to 00</td>
<td></td>
</tr>
<tr>
<td>Household sample</td>
<td>All</td>
<td>All</td>
<td>All</td>
<td>Big Δ</td>
<td>Small Δ</td>
<td>&lt;50</td>
<td>All</td>
<td>All</td>
</tr>
<tr>
<td>Initial log people 10 km</td>
<td>-0.081&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.080&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.082&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.085&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.078&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.084&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.080&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.079&lt;sup&gt;a&lt;/sup&gt;</td>
</tr>
<tr>
<td></td>
<td>(0.0053)</td>
<td>(0.0052)</td>
<td>(0.0051)</td>
<td>(0.0067)</td>
<td>(0.0067)</td>
<td>(0.0072)</td>
<td>(0.0052)</td>
<td>(0.0049)</td>
</tr>
<tr>
<td>Δ log people 10 km</td>
<td>-0.057&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.071&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.074&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.089&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.081</td>
<td>-0.083&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.053&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.13&lt;sup&gt;a&lt;/sup&gt;</td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.012)</td>
<td>(0.012)</td>
<td>(0.018)</td>
<td>(0.018)</td>
<td>(0.022)</td>
<td>(0.017)</td>
<td>(0.023)</td>
</tr>
<tr>
<td>Renter × Δ log people</td>
<td>-0.20&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.013</td>
<td>0.040</td>
<td>-0.010</td>
<td>-0.087</td>
<td>0.040</td>
<td>0.033</td>
<td>0.0077</td>
</tr>
<tr>
<td></td>
<td>(0.030)</td>
<td>(0.036)</td>
<td>(0.038)</td>
<td>(0.046)</td>
<td>(0.16)</td>
<td>(0.035)</td>
<td>(0.050)</td>
<td>(0.072)</td>
</tr>
<tr>
<td>Renter</td>
<td>-0.15&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.33&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.14&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.12&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.14&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.15&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-0.15&lt;sup&gt;a&lt;/sup&gt;</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.094)</td>
<td>(0.020)</td>
<td>(0.040)</td>
<td>(0.018)</td>
<td>(0.011)</td>
<td>(0.014)</td>
<td></td>
</tr>
<tr>
<td>Renter × log people</td>
<td>0.015&lt;sup&gt;b&lt;/sup&gt;</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0073)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>0.37</td>
<td>0.37</td>
<td>0.37</td>
<td>0.36</td>
<td>0.37</td>
<td>0.26</td>
<td>0.37</td>
<td>0.37</td>
</tr>
<tr>
<td>Observations</td>
<td>99,875</td>
<td>99,875</td>
<td>99,875</td>
<td>46,942</td>
<td>48,939</td>
<td>39,253</td>
<td>99,875</td>
<td>99,875</td>
</tr>
<tr>
<td>Number of MSA</td>
<td>275</td>
<td>275</td>
<td>275</td>
<td>263</td>
<td>267</td>
<td>274</td>
<td>275</td>
<td>275</td>
</tr>
</tbody>
</table>

Notes: The dependent variables is log household VKT in all columns. All regressions are estimated with OLS and include 275 MSA fixed effects with demographic controls (a white/asian indicator, log income, log household size, a single indicator, age, age squared, gender, education, and education squared), geographic controls (average precipitation and its standard deviation, and average temperature and its standard deviation) and local socio-economic controls (the share of residents with higher education and its square and log local income). Robust standard errors clustered by MSA in parentheses. <sup>a</sup>, <sup>b</sup>, <sup>c</sup>: significant at 1%, 5%, 10%.
Table 14: Robustness checks for sorting on demographics OLS estimations

<table>
<thead>
<tr>
<th>Period</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Household sample</td>
<td>00 to 10</td>
<td>00 to 10</td>
<td>00 to 10</td>
<td>90 to 10</td>
<td>90 to 10</td>
<td>90 to 10</td>
<td>90 to 10</td>
<td>90 to 10</td>
</tr>
<tr>
<td>Dependent var.:</td>
<td>an. km</td>
<td>an. km</td>
<td>an. km</td>
<td>stated km</td>
<td>odometer</td>
<td>ind. day</td>
<td>km</td>
<td>an. km</td>
</tr>
<tr>
<td>Density:</td>
<td>ppl 10 km ppl 10 km ppl 10 km ppl 10 km ppl 10 km ppl 10 km ppl 10 km ppl 1 km nlcd 10 km</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Initial log density</td>
<td>-0.082&lt;sup&gt;a&lt;/sup&gt; (0.0053)</td>
<td>-0.087&lt;sup&gt;a&lt;/sup&gt; (0.0072)</td>
<td>-0.075&lt;sup&gt;a&lt;/sup&gt; (0.0054)</td>
<td>-0.12&lt;sup&gt;a&lt;/sup&gt; (0.0075)</td>
<td>-0.094&lt;sup&gt;a&lt;/sup&gt; (0.0060)</td>
<td>-0.14&lt;sup&gt;a&lt;/sup&gt; (0.0083)</td>
<td>-0.053&lt;sup&gt;a&lt;/sup&gt; (0.0037)</td>
<td>-0.040&lt;sup&gt;a&lt;/sup&gt; (0.0046)</td>
</tr>
<tr>
<td>Δ log density</td>
<td>-0.050&lt;sup&gt;a&lt;/sup&gt; (0.017)</td>
<td>-0.049&lt;sup&gt;c&lt;/sup&gt; (0.028)</td>
<td>-0.036 (0.035)</td>
<td>-0.066&lt;sup&gt;a&lt;/sup&gt; (0.024)</td>
<td>-0.077&lt;sup&gt;a&lt;/sup&gt; (0.024)</td>
<td>-0.066&lt;sup&gt;b&lt;/sup&gt; (0.029)</td>
<td>-0.047&lt;sup&gt;a&lt;/sup&gt; (0.0060)</td>
<td>-0.039&lt;sup&gt;a&lt;/sup&gt; (0.0069)</td>
</tr>
<tr>
<td>Past Δ density</td>
<td>-0.037 (0.028)</td>
<td>-0.015 (0.039)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Controls:
- **Demographics**: Y Y Y Y Y Y Y Y
- **Geography**: Y Y Y Y Y Y Y Y
- **Local socio-econ.**: Y Y Y Y Y Y Y Y
- **Decade indicators**: N N N Y Y Y Y Y
- **Decade × log people**: N N N Y Y Y Y Y
- **Decade × Δ log people**: N N N Y Y Y Y Y

| R² | 0.37 | 0.26 | 0.26 | 0.42 | 0.43 | 0.09 | 0.37 | 0.37 |
| Observations | 99,875 | 39,253 | 40,421 | 93,602 | 71,742 | 121,808 | 99,874 | 99,423 |
| Number of MSA | 275 | 274 | 274 | 275 | 275 | 275 | 275 | 275 |

Notes: All regressions include 275 MSA fixed effects. Robust standard errors clustered by MSA in parentheses. <sup>a</sup>, <sup>b</sup>, <sup>c</sup>: significant at 1%, 5%, 10%. The dependent variables and explanatory variables of interest are in log in all columns. Demographic controls include a white/asian indicator, log income, log household size, a single indicator, age, age squared, gender, education, and education squared. Geographic controls include average precipitation and its standard deviation, and average temperature and its standard deviation. Local socio-economic controls include the share of residents with higher education and its square and log local income. When decade effects are introduced, households in their 40s are used as reference.