The impact of urban form on vehicle fuel consumption in Mexican metropolitan areas

In this study we analyze the impact that two measures of the urban form – residential density and the land use diversity index – have on gasoline consumption in households located in metropolitan areas of Mexico. The econometric specification implemented is a modified two-part model that fits the distribution of gasoline consumption, while mitigating the endogeneity bias resulting from residential self-selection. The results from the instrumental variables specification, suggest that after controlling for household characteristics increasing residential density in the vicinity of the household location could increase gasoline consumption while increasing residential density at the metropolitan scale may reduce gasoline consumption. Interestingly, the land use diversity index does not seem to affect gasoline consumption. Put together, these findings are indicative of the potential risk of not taking advantage of high residential densities to, together with other strategies, reduce gasoline consumption in metropolitan areas in Mexico.

En este estudio analizamos el impacto que dos indicadores urbanísticos –la densidad residencial y el índice de diversidad del uso del suelo– tienen en el consumo de gasolina de familias ubicadas en las áreas metropolitanas de México. La especificación econométrica adoptada es un modelo de dos partes modificado con variables instrumentales que se ajusta a la distribución del consumo de gasolina, y mitiga el sesgo de endogeneidad resultante de la autoselección residencial. Los resultados señalan que, teniendo en cuenta las características del hogar, un aumento de la densidad residencial en las áreas próximas a la ubicación del hogar podría incrementar el consumo de gasolina, mientras que aumentar la densidad residencial a escala metropolitana podría reducir dicho consumo. Curiosamente, el índice de diversidad del uso del suelo no parece afectar al consumo de gasolina. En conjunto, estos resultados indican el riesgo potencial de no aprovechar las altas densidades residenciales para, junto con otras estrategias, reducir el consumo de gasolina en las áreas metropolitanas de México.

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Keywords: gasoline consumption, compact development, two-part model, travel behavior, residential density, land use diversity index.

Palabras clave: consumo de gasolina, desarrollo compacto, modelo en dos partes, comportamiento de viajes, densidad residencial, índice de diversidad del uso de suelo.

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1. INTRODUCTION

The scientific consensus maintains that climate change has already caused observable impacts in natural and human systems and that is expected to largely disrupt these if societies fail to drastically reduce anthropogenic greenhouse gas (GHG) emissions by 2030 (IPCC, 2014). Globally, according to WRI (2019), the transportation sector is the second largest source of GHG accounting for 16% of the total emissions with large differences across country income groups. For example, in the Americas, 28.8% of GHG emissions in Canada and the United States combined originate in the transportation sector, while for the Latin America and the Caribbean region this sector contributes with 14.6%. In Mexico, the focus of our study, the share of GHG emissions generated in this sector is 23.2%, which is closer to that from most developed countries in the continent. Based on the main channel of change, the measures from a policy portfolio to tackle emissions within the transportation sector could be broadly classified into technological and behavioral. Importantly, either group of measures has the potential to influence and reinforce changes through the other's channel. Among the technological measures, regions have experimented with the introduction of fuel economy standards for vehicles, low carbon fuel standards, green vehicle rebates, and renewable energy portfolios. Among the measures that are aimed to mainly target the behavior of consumers, standout carbon (or fuel) taxes and public transit subsidies that have been widely implemented throughout the globe. While being a less resorted measure among the latter group, driving restriction programs have been increasingly adopted in several metropolitan areas across the world during the last two decades, including cities from high-income countries.[1] As Beaudoin *et al.* (2018) point out, political and economic constraints may preclude the implementation of the most efficient policies to curb down emissions in the transportation sector. Nevertheless, a cost-effective transition towards low carbon economies will necessitate a policy menu indicating the comparative performance of alternative policies under different settings.

In this study we revisit the case of a policy that shares characteristics of both technological and behavioral interventions, as it is intended to reduce emissions from vehicle use through the modification of the built environment that affects people´s travel choices. By changing the spatial configuration of trip generators and attractors, this type of intervention has the potential to influence travel decisions in a number of dimensions such as frequency and length of trips, as well as the transport mode chosen. Specifically, we estimate the impact of two indicators of the built environment or urban form - residential density and land use diversity - on gasoline consumption of households located in Mexican metropolitan areas (MAs). Although our study restricts its analysis to a single country, we believe that the lessons that can be drawn from it can be extended to other low and middle-income countries. As they develop the transportation emissions from cities in this set of countries will continue to rise if no major technological and behavioral changes are introduced to affect how people move[2]. Additionally, policies that address transportation GHG emissions have not only the potential to contribute to the global climate crisis but also to bring about improvements in the quality of life at the local level, as some of the most health-threatening pollutants are majorly generated within the transportation sector (WHO, 2018; SEDEMA, 2018) and the most polluted cities are located outside the wealthiest countries.

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[1] Studies within the economic literature have questioned the effectiveness of driving restrictions to tackle both emissions overall and atmospheric concentrations of local pollutants. See Zhang *et al.* (2017) for a recent theoretical discussion of driving restrictions and an empirical application to the case of Bogota, Colombia.

[2] Among the group of least developed countries, transportation GHG emissions have grown from 0.8% to 2.5% as a share of the total generated between 1990 and 2016 (WRI, 2018).

Within the literature exploring the effects of characteristics of the built environment on travel behavior, the most salient difficulty in correctly estimating their impact is the potential bias that can result from residential self-selection or residential sorting. That is, it is not straightforward to discern whether observed differences in distances driven across individuals are shaped by density and abundance of services, or by the preferences of such individuals who in the first place chose residential locations according to their travel preferences. For instance, people who dislike driving could choose to live in an amenity-rich–and dense–area, which would allow them to move differently through the likes of walking or cycling. These types of areas serve as attractive factors for people who have similar anti-car preferences, while sprawled residential areas conversely may attract people for whom driving does not generate a large disutility. The causal identification of the effect is policy-relevant since as the example illustrates, the resulting travel behavior after an intervention depends on whether the modification of the urban form in fact has an effect on individuals who chose to reside in a car-oriented development. To isolate these drivers of the effect, some studies have turned to econometric tools that address residential sorting or self-selection such that a causal interpretation of the estimated effects estimated can be obtained.

Our study provides new evidence regarding the role of the built environment on travel behavior which has been the subject of an extended decades-long debate as recently documented in Stevens' (2017) meta analysis of the impact of residential density - the most researched indicator of the built environment associated to travel behavior. Based on estimates from almost forty studies, of which only about 25% addressed self-selection bias, Stevens (2017) concludes that the impact of residential density is rather small, especially in light of the complex political process involved in increasing it. However, as argued by Heres and Niemeier (2017), aside from properly modeling self-selection, one major avenue to improve upon the policy implications originated in this literature is to conduct studies in low and middle income countries where this type of intervention may still prove to be cost-effective as their cities grow and populations become wealthier.

In this article, gasoline consumption of households located in fifty-two Mexican MAs is characterized as a function of household socio-demographic attributes and neighborhood characteristics measuring urban form such as residential density and land use diversity. Our paper follows closely the methodology proposed in Heres-Del-Valle and Niemeier (2011) who estimated the impact of residential density, land use diversity and access to public transportation on the distances driven by California households in 2000. After controlling for household characteristics and addressing both the non-linearity in the dependent variable typical of travel surveys (i.e., several observations with no reported vehicle use) and self-selection, they find that the most important variable that impacts driving is residential density. They report that the marginal effect of increasing a household area's density by 10% is to lower the vehicle miles traveled by between 1.4% and 1.9%. However, according to the authors this impact albeit larger than estimated in previous literature, continues to be low when compared to other policy options such as increasing gasoline prices. Conversely, Ewing and Cervero (2017) argue that the elasticity of driving with respect to gasoline price is within the same range as that for residential density, thus apparently making them comparable in terms of their potential effectiveness. Nevertheless, it is worth noting that gasoline prices can be subjected to, and in fact have had, large variations in the short run in magnitudes that the urban form conversely would not be able to experience due to technological and political constraints.

Our study also joins the literature that had explored travel behavior in the Mexican context, where Galindo *et al.* (2006) show how the creation of new roadways may have improved traffic circulation in the short term but in the long term, the number of trips increased to a higher equilibrium compared to a scenario in which no road network expansion took place (i.e., induced demand). While according to Galindo *et al.* (2006) driving had also increased as income had, Crotte *et al.* (2011) finds as expected that transit ridership falls in Mexico City as income rises by a proportionate amount. In Mexico City the car fleet augmented twofold between 1990 and 2010 (Guerra, 2014), perhaps in part due to an unintended consequence of the driving ban program as documented by Davis (2008). Further evidence on the rise of private motorized travel in Mexico comes from Guerra (2014) who based on two waves of Mexico City's household travel survey reports that vehicle kilometers traveled increased by 33% between 1994 and 2007. The results from Guerra's *et al.* (2018) study exploiting a rich set of metropolitan measures of urban form, suggest that both these measures and transit supply at the metropolitan scale largely determines mode choice across urban areas in Mexico. As proposed in Bento *et al.* (2005), a strategy to isolate the effect of urban form measures form those of underlying travel preferences is to include measures at the MA level. The validity of the approach lies on the fact that it is unlikely that households would choose their location within a MA based on the aggregate urban form of the MA, and that the typical household would not choose to locate on a given MA based on its urban form. While this argument most likely holds, this approach dismisses the large heterogeneity that residential density and land use diversity presents within a given MA. Nevertheless, in our estimations we also include built environment measures at the MA level.

In sum, we consider the present study to contribute to the related literature and policy debate through the estimation of: 1) the impact of the built-environment on both the extensive and intensive margins of travel decisions (i.e., the discrete decision on whether to drive or not, and how much to drive); 2) such impact based on indicators of built-environment at both the MA-level and a finer spatial scale in the context of a middle-income country; 3) such impact from specifications with instrumental variables and indicators at the MA-level as means to correct for the residential self-selection bias. Our results suggest that medium-sized cities experiencing rapid growth have the potential to be intervened such that land use diversification favors travel patterns less dependent on private motorized transportation. However, relying uniquely on this type of policy bears the risk of allowing the forces that drive up gasoline consumption, such as rising incomes, to prevail.

In the remainder of this paper we describe the data used in the econometric analysis, present the econometric model to be estimated, discuss the main results and conclude.

2. DATA

The data used to estimate the model presented in the next section come from three sources from which we generated variables at the level of the household and the census tract where the household is located. [3] Specifically, first, household gasoline consumption and household characteristics come from the 2014 National Survey of Household Income and Expenditures (ENIGH, for its initials in Spanish). This survey has been running every two years since 2000 (plus 2005). With modifications to the methodology across the period implemented. This survey collects information regarding socio-demographic characteristics, along with quarterly information regarding households' earnings and expenditures. Its national reach includes all urbanized areas with more than 2,500 inhabitants and rural localities with fewer than 2,500 individuals. For our dependent variable we use the reported gasoline expenditures in households located in any of 52 MAs as defined by CONAPO (2016). We convert expenditures to liters of gasoline consumed in the household based on the average gasoline price during the 30 days before the interview took place as the survey asks for last month's expenditures. Our model controls for households characteristics included in the survey such as age of the household head, household head education, household income, number of household members older than 65, number of household members younger than 2, working household members, and whether a couple lives in the household.

Second, we consider two measures of the built environment as explanatory variables of interest. Residential density was obtained from the 2010 Population and Housing Census (P-Census) and calculated at the census tract level as the number of housing units divided by the census tract area. The number of housing units was also used in the calculation of the variable that represents the land use diversity that approaches 1 (0) as the neighborhood becomes more (less) diverse in their land use. Third, in order to generate this index we also collected data on the number of business units from four different sectors within the census tract from the 2014 Economic Census (E-Census). The sectors are manufacturing, trade, services, and a fourth set that this Census groups together for privacy concerns. The index is brought up from Salon (2015), which itself is a modification of Shannon's Diversity Index calculated as follows:

$$MIX = \left| \frac{\sum_{i=1}^{N} p_i \ln(p_i)}{\ln(N)} \right| \tag{1}$$

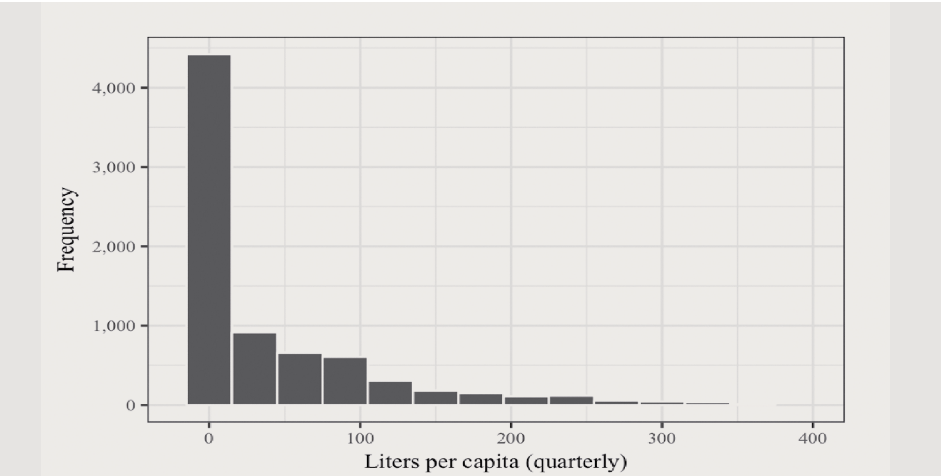
where p_i is the proportion in each of the five categories: housing and the four major economic groups previously mentioned.

[3] Here we use the Área Geoestadística Básica (AGEB), which is a Mexican official unit used for statistical purposes and that is similar to the US Census tract.

Lastly, in the instrumental variables specifications (explained below) we exploit another set of variables from the 2010 Population and Housing Census calculated at the census tract level. These variables are the shares of the population who are: a) under 2 years old, b) over 60 years old; and c) percentage of households constituted by a couple.[4]

From Table 1 about 54% of the households in our sample reported no gasoline consumption, while the average quarterly consumption per capita in the whole sample was 46.7 liters (102.3 liters when excluding those households without consumption). Figure 1 shows the highly skewed distribution of quarterly gasoline consumption per capita across the households in our sample, even after removing households that consume more than 400 liters per capita (1% of the sample) not shown in the graph for the sake of clarity. This feature from the data will be addressed in the model specification described in the next section by estimating a two-part model that first estimates the probability of consuming gasoline, and then estimates the amount of gasoline consumed in households that do consume gasoline.

Figure 1. **DISTRIBUTION OF GASOLINE CONSUMPTION**



Source: Own elaboration based on CONAPO (2016) and INEGI (2014).

[4] For the sake of comparability between non-instrumented and instrumented estimates, the final sample in all models is restricted to households residing in census-tracts where these three variables were available from the 2010 Population and Housing Census. After this procedure and removing the bottom and upper 1% of households from the income per capita distribution in our initial sample, our final sample comprises data from households located in 52 MA out of the total of 59 MAs defined by CONAPO (2016). The seven MAs not represented in our sample include the five with the lowest MA population and two others that are within the bottom 25 percentile of the MA population distribution in 2010. These are in ascending order of their population (name of state in parentheses): Moroleón-Uriangato (Guanajuato), Acayucan (Veracruz), Teziutlán (Puebla), Rioverde-Ciudad Fernández (San Luis Potosí), Ocotlán (Jalisco), Tianguistengo (Estado de México), and Tula (Hidalgo).

The average household (HH) annual income per capita in our sample is $47,199 pesos (or about 3,629 USD based on the 2014 average exchange rate) with 16% of HH heads with at least a college degree. The average HH in our sample has at least one member under 2 years old but few have members older than 65 (mean 0.25). Couples live in most households (67%) and typically there is more than one income earner in the sampled HH (mean 1.6).

Table 1. **DESCRIPTIVE STATISTICS**

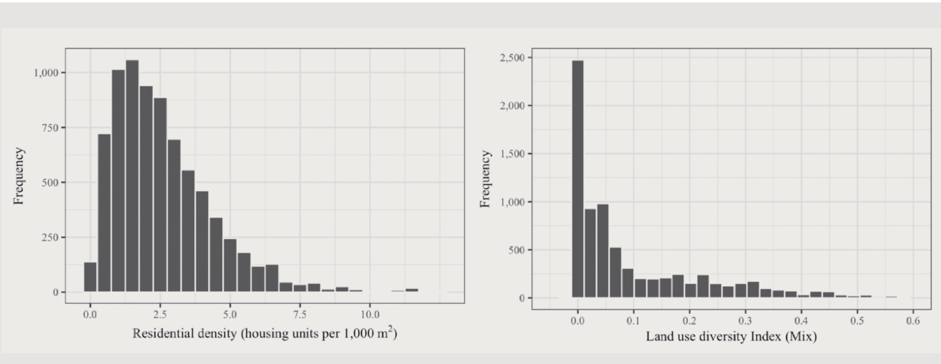
Variable	Variable ID	Mean (std.dev.)	Source
Indicator variable equal to 1 if the household consumed gasoline	consumed	0.46 (0.50)	ENIGH
Gasoline quarterly consumption per capita (liters)	gasoline	46.67 (88.21)	ENIGH
HH annual income per capita (in thousand pesos)	income	47.20 (47.75)	ENIGH
HH head age	age	48.03 (15.18)	ENIGH
HH head education (1= college degree or more, 0 otherwise)	school	0.16 (0.37)	ENIGH
HH members who receive an income	worker	1.62 (1.02)	ENIGH
HH members who are older than 65	age65	0.25 (0.55)	ENIGH
HH members who are under 2 years old	kids	1.19 (1.24)	ENIGH
Indicator variable equal to 1 if a couple inhabits the household	couple	0.67 (0.47)	ENIGH
Indicator variable equal to 1 the household lives in a large MA	zmlarge	0.77 (0.42)	P-Census
Household density in the HH's tract	density	2.61 (1.81)	P-Census
Diversity land use index in the HH's tract	mix	0.10 (0.13)	P-Census and E-Census
Household density in the HH's MA	density_ma	0.78 (0.80)	P-Census
Diversity land use index in the HH's MA	mix_ma	0.13 (0.12)	P-Census and E-Census
Percentage of households inhabited by a couple in the HH's tract	couples_ tract	0.79 (0.12)	P-Census
Percentage of population under 2 years old in the HH's tract	age2_tract	0.05 (0.02)	P-Census
Percentage of population older than 60 years old in the HH's tract	age60_tract	0.08 (0.05)	P-Census

Source: Own elaboration.

The two measures selected to characterize the built environment indicate that neighborhoods are poorly mixed in terms of land uses as the average *mix* is close to zero, while the average residential density at the census tract level in our sample is 2.6 housing units per 1,000 squared meters. Average residential density at the MA level is less than 1 unit per 1,000 squared meters (0.78), which in terms of population density[5] is relatively low compared to large European metropolitan areas but relatively high compared to cities in Canada and United States (OECD).

Figure 2 depicts the distribution of the two measures of built environment at the census tract level, which are highly skewed towards lower levels, more dramatically in the case of *mix*, even after removing the less than 1% of households in our sample that reside in census tracts with a land use diversity larger than 0.6. These same two measures are also used in the analysis but at the MA-level to potentially address self-selection as proposed in Bento *et al.* (2005).

Figure 2. **DISTRIBUTION OF BUILT ENVIRONMENT MEASURES**



Source: Own elaboration based on CONAPO (2016), INEGI (2010), INEGI (2014) and INEGI (2014b).

Finally, we consider a set of variables describing neighborhood socio-demographic characteristics that may influence residential choice but not travel decisions. From Table 1, 79% of households are inhabited by a couple, and in a typical census-tract 5% of its population is under 2 years old while 8% is older than 60.

[5] Based on the average household size in our sample (3.7), the average population density at the metropolitan area scale would be 2,886 inhabitants per square kilometer. This density is within the range of that of Donosti-San Sebastian (Spain), Frankfurt (Germany), and Toulouse (France). Mexico City, the most dense city in Mexico, is slightly less denser than Paris (France) but less dense than Barcelona (Spain). Within Latin American cities, the average density of Mexican MAs is only 15% that of Santiago (Chile) and 60% that of Bogota (Colombia). New York City in the United States is half as dense as the average MA in Mexico (OECD, 2020).

3. **MODEL**

Two characteristics of the data commonly available to estimate the impact of built environment on travel make ordinary least squares not suitable for reaching consistent estimates. First, the large mass of zeroes reported for gasoline consumption (or driving) by households requires specification of non-linear models that address this characteristic of the distribution of the dependent variable. Selection models, latent variable models and two-part models have been proposed to correct for this feature of the data (Cameron and Trivedi, 2005). Second, residential self-selection which has been identified as a key obstacle on the pursue of estimates with causal interpretation has been addressed mainly through the implementation of simultaneous equations models, selection models, joint choice models, attitudinal surveys, including aggregate measures of the built environment and instrumental variables (see Brownstone, 2008; Mohktarian and Cao, 2008 for a discussion of these).

Compared to other approaches, two-part models (2PM) offer a few advantages over other methods that deal with distributions that include a large mass of actual zeroes and censored data. Notably among these, the two outcomes (in our case whether to consume gasoline or not and how much gasoline to consume) can be modeled as separate processes, while the validity of the estimations relies on fewer distributional assumptions and exclusion restrictions, and observations with zero gasoline consumption are not treated as latent (Heres-Del-Valle and Niemeier, 2011; Dow and Norton, 2003, Vance and Hedel, 2007; Vance and Hedel, 2008).

Equation (2) shows the structure of the 2PM in which the first part consists of estimating the probability of using a vehicle *(y>0)* while the second part estimates the usage level *(y)* among those who drive in both cases conditional on a set of characteristics *x*.

$$E[y|x] = \Pr(y > 0|x) \times E[y|y > 0, x] \tag{2}$$

In this study we estimate the first part of the model with a probit model that assumes that the cumulative density function describing $Pr(y>0|x)$ is normally distributed. Although in several applications the second part has been modeled with the outcome variable log transformed, Mullahy (1998) shows that transforming back the predictions to levels can be subjected to bias and therefore proposes to model directly the levels of *y* through an exponential mean model as in equation (3):

$$E[y|y > 0, x] = \exp(x\beta) \tag{3}$$

After assuming the normal cumulative density function in part 1, and substituting (3) in (2), the expected value of *y* given *x* under the full M2PM would be:

$$E[y|x] = \Phi(x\alpha)\exp(x\beta) \tag{4}$$

where α and β are respectively the vectors of coefficients estimated in the probit and the exponential mean models and Φ is the cumulative density function of the standard normal. Marginal effects of the variable x_j would be the partial derivative of *E[y|x]* with respect to x_j as follows:

$$\frac{\partial E[y|x]}{\partial x_j} = \beta_j \Phi(x\alpha)\exp(x\beta) + \alpha_j \phi(x\alpha)\exp(x\beta) \qquad (5)$$

where φ is the derivative of Φ or the standard normal density. Similarly, the elasticity of gasoline consumption with respect to a variable x_j is calculated as follows:

$$\frac{\partial E[y|x]}{\partial x_j} \times \frac{x_j}{E[y|x]} = \beta_j + \alpha_j \frac{\phi(x\alpha)}{\Phi(x\alpha)} \qquad (6)$$

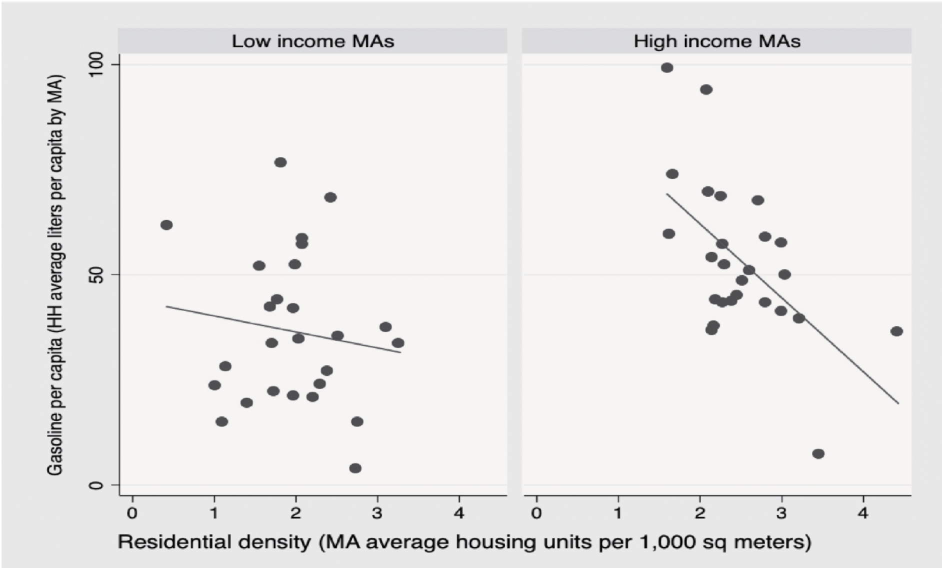
Particular interest in our econometric model lies on the effects of *density* and *land use diversity (mix)* on gasoline consumption controlling for observable household and neighborhood characteristics. Due to the potential bias arising from unobservable characteristics correlated with both the explanatory variables of interest and the outcome variable we propose a model with instrumental variables. An omitted variable bias in this setting originates from the impossibility to observe households' travel mode preferences. In other words, although we observe in which type of neighborhood and how many liters of gasoline per capita are consumed in each household, we do not observe to what extent a given household chose its residential location based on its travel preferences. As the latter are correlated with both the residential location (and thus residential density and land use diversity) and to gasoline consumption, estimates from an econometric model that does not address this endogeneity will be biased and inconsistent.

In the next section we contrast estimates from a set of models that ignore self-selection to those from models in which self-selection is addressed either through instrumental variables, built-environment measures at the MA-level (which presumably would not affect residential location choice) or both. In the set of instrumental variables specifications, residential density variable and land use diversity index will be instrumented through a series of neighborhood level characteristics that are expected to influence residential choice but not travel mode choice directly. In sum, to address both the large number of zeroes in the sample and self-selection in the following section we implement a two-part model with instrumental variables (2PM with IV) as proposed in Vance and Hedel (2007) and Heres-Del-Valle and Niemeier (2011). As in the latter we adopt the modified version of the 2PM (M2PM) suggested in Mullahy (1998).

4. RESULTS AND DISCUSSION

Previous sections stressed the importance of correctly identifying the impact of built-environment measures on gasoline consumption in Mexican MAs. As a preamble to the discussion of results from econometric estimations of the models presented in section 3, we first present the relationship between aggregate MA-level measures of household gasoline consumption per capita and the two variables in our analysis representing the built environment. Figures 3 and 4 show these relationships for two subsets of the 52 MAs, separated by the median MA-level average household income per capita.

Figure 3. **RELATIONSHIP BETWEEN GASOLINE CONSUMPTION AND RESIDENTIAL DENSITY, BY MA**

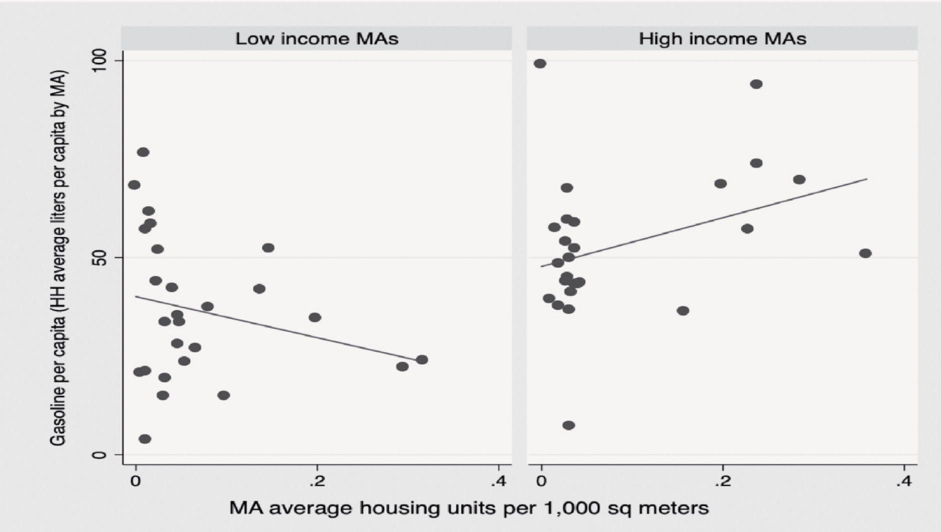


Source: Own elaboration based on CONAPO (2016), INEGI (2010), INEGI (2014) and INEGI (2014b).

Figure 3 suggests a negative association between gasoline consumption and residential density, more clearly in the case of higher income MAs where the downward sloping line seems to closely fit the data points. The interpretation is that households in MAs with higher average census-tract residential density, consume, in average, less gasoline per capita. Oppositely, a higher average land use diversity index does not seem to be associated with reductions in gasoline consumption. Strikingly, the value of this measure for most MAs is close to zero. This feature of the MA-level sample limits the interpretation of the fitted line in the right panel of Figure 4, which would otherwise suggest a positive correlation between gasoline consumption and land use diversity.

In the following we report results from three different specifications for both the modified two-part model (M2PM) and the M2PM with instrumental variables (IVM2PM) exploiting the household-level data. The specifications further differ in the built environment measures included: 1) only residential density at the census tract-level, 2) only land use diversity index at the census tract-level, 3) both residential density and land use diversity index at the census tract-level, 4) both residential density and land use diversity index at both the census tract-level and MA-level.[6]

Figure 4. **RELATIONSHIP BETWEEN GASOLINE CONSUMPTION AND LAND USE DIVERSITY, BY MA**



Source: Own elaboration based on CONAPO (2016), INEGI (2010), INEGI (2014) and INEGI (2014b).

4.1. **Modified Two-Part Model (M2PM): Parts 1 and 2**

Table 2 shows results for the first part of the M2PM. Interestingly, in line with what Figures 3 and 4 suggested, residential density (both at the census-tract and MA-levels) is negatively associated with the probability of consuming gasoline. Land use diversity at the census-tract level maintains the opposite relationship with the probability of consuming gasoline in two out of the three specifications in which this variable is included. Nevertheless, the specification that also includes MA-level measures of the built environment as a means to address self-selection indicates that while land use diversity within the census-tract may reduce the probability of consuming gasoline, land-use diversity in the MA may increase it. Common across specifications are the positive statistically significant associations between the probability of consuming gasoline with all control variables except for the number of el-

[6] All models presented in this section were also estimated for subsets of the sample. Results are qualitatively the same whether we run separate regressions by income quartile, MA size, and MA growth rate. Results are also robust to the inclusion of an interaction between density and mix. Results from these robustness checks are not shown here for brevity but are available from the authors upon request.

derly household members. The signs of these coefficients seem sensible as income, age and education of household head, and the number of household members that work and children would increase the probability of driving to different attractors. On the other hand, as more elderly people inhabit the household, the less likely the household will spend any money on gasoline.

Table 2. **PART 1 OF MODIFIED TWO PART MODEL M2PM (probit)**

Variable	Dependent variable is consumed			
	(1)	(2)	(3)	(4)
density	-0.0509*** (0.00874)		-0.0510*** (0.00874)	-0.0303** (0.00938)
mix		0.318** (0.116)	0.323** (0.116)	-0.416* (0.172)
density_ma				-0.142*** (0.0212)
mix_ma				1.153*** (0.192)
income	0.0103*** (0.000464)	0.0102*** (0.000462)	0.0103*** (0.000464)	0.0104*** (0.000466)
age	0.00835*** (0.00139)	0.00797*** (0.00139)	0.00826*** (0.00139)	0.00874*** (0.00139)
school	0.531*** (0.0478)	0.522*** (0.0476)	0.529*** (0.0478)	0.551*** (0.0481)
workers	0.0751*** (0.0158)	0.0736*** (0.0158)	0.0748*** (0.0158)	0.0787*** (0.0159)
age65	-0.0796* (0.0367)	-0.0750* (0.0366)	-0.0814* (0.0367)	-0.0705 (0.0368)
kids	0.0667*** (0.0143)	0.0682*** (0.0142)	0.0665*** (0.0143)	0.0644*** (0.0143)
couple	0.690*** (0.0356)	0.697*** (0.0356)	0.694*** (0.0357)	0.704*** (0.0358)
zmlarge	0.156*** (0.0371)	0.0957** (0.0367)	0.140*** (0.0375)	0.135*** (0.0381)
constant	-1.701*** (0.0864)	-1.803*** (0.0853)	-1.718*** (0.0866)	-1.778*** (0.0875)
N	7708	7708	7708	7708
Pseudo R^2	0.145	0.142	0.146	0.153

Standard errors in parentheses. * ρ<0.1; ** ρ<0.05; *** ρ<0.01
Source: Own elaboration based on CONAPO (2016), INEGI (2010), INEGI (2014) and INEGI (2014b).

Table 3. **PART 2 OF MODIFIED TWO PART MODEL M2PM (exponential conditional mean model)**

Variable	Dependent variable is gasoline consumed			
	(1)	(2)	(3)	(4)
density	-0.017* (0.009)		-0.017* (0.009)	-0.003 (0.01)
mix		0.062 (0.118)	0.055 (0.117)	0.066 (0.176)
density_ma				-0.077*** (0.021)
mix_ma				-0.013 (0.169)
income	0.005*** (0.000)	0.005*** (0.000)	0.005*** (0.000)	0.005*** (0.000)
age	-0.005*** (0.001)	-0.005*** (0.001)	-0.005*** (0.001)	-0.005*** (0.001)
school	0.23*** (0.037)	0.229*** (0.037)	0.23*** (0.037)	0.232*** (0.037)
workers	-0.074*** (0.013)	-0.076*** (0.014)	-0.074*** (0.013)	-0.073*** (0.013)
age65	-0.077* (0.035)	-0.075* (0.035)	-0.077* (0.035)	-0.074* (0.035)
kids	-0.224*** (0.014)	-0.223*** (0.014)	-0.225*** (0.014)	-0.222*** (0.014)
couple	-0.181*** (0.036)	-0.178*** (0.035)	-0.18*** (0.036)	-0.177*** (0.036)
zmlarge	0.068* (0.04)	0.053 (0.039)	0.064 (0.039)	0.072* (0.039)
constant	4.895*** (0.081)	4.859*** (0.078)	4.893*** (0.081)	4.881*** (0.083)
N	3,513	3,513	3,513	3,513

Standard errors in parentheses. * ρ<0.1; ** ρ<0.05; *** ρ<0.01

Source: Own elaboration based on CONAPO (2016), INEGI (2010), INEGI (2014) and INEGI (2014b).

Table 3 shows the estimates for the second part of the model in which the two built environment variables at the census-tract level have coefficients that are not statistically significant suggesting that even though these may impact the decision on whether to drive or not, they do not influence how much driving people do once they drive. Although this is true for census-tract level variables, the last column shows that a higher MA-residential density is associated with lower gasoline expenditures. Among the coefficients for control variables, results indicate that wealthier and more educated households spend more on gasoline. Conversely, negatively associated with the amount of gasoline consumed are the age of the household head and the number of children under 2 years old, both of which can be rooted in safety concerns. Somewhat surprisingly, the coefficient for number of workers in the household suggests that households constituted by more workers tend to spend less in gasoline. This finding, however, may be indicative of a feature of household composition not captured by our set of variables. For instance, two otherwise comparable households based on dimensions other than number of workers, may experience different economies of scale of gasoline consumption: a household with two workers that car-pool together to work will consume less gasoline per capita than a household with one worker that commutes by car from the same origin and destination as the household with two workers.

4.2. Modified Two-Part Model with Instrumental Variables (IVM2PM): Parts 1 and 2

A major concern from the previous estimations is that they may be subjected to an omitted variable bias problem due to residential self-selection. To address this concern Tables 4 and 5 present results from the first and second parts of the M2PM with instrumental variables. The instruments which are believed to not directly affect gasoline consumption in a given household are the shares of population in the census tract where the household lives who are under 2 years old, over 60 years old, and the percentage of households within the census-tract where a couple lives. These socio-demographic characteristics of census-tracts may play a role in the choice of residential location but are unlikely to determine travel decisions of a given household. As a counter-example, suppose we instead included the census-tract unemployment rate. Since this could be related in some instances to crime rates, and people may make travel decisions partially influenced by crime rates (Appleyard and Ferrell, 2017), then that variable would not be a good candidate for an instrument. In terms of the relevance and validity of the instruments, that is whether these are related to the endogenous regressors (residential density and land use diversity at the census tract level). Results from respective tests in Table 4 for the probability model indicate that instruments are neither relevant nor valid in specifications that only include *mix*. Conversely, instruments seem to comply with the two requirements in specifications that include *density*, with the exception of the last specification including *density* and *mix* at the MA level. Results for the instrumented second part of the model in Table 5 indicate that the set of instruments are both relevant and valid whenever *density* is included. These tests taken together cast doubt on the potential use of estimates for the variable *mix*.

Table 4. **PART 1 OF INSTRUMENTAL VARIABLES MODIFIED TWO PART MODEL IV2PM (probit)**

Variable	Dependent Variable is gasoline consumed			
	(1)	(2)	(3)	(4)
density	0.149*** (0.0427)		0.154*** (0.0435)	0.0792* (0.0375)
mix		0.0362 (0.411)	-0.259 (0.434)	0.421 (0.483)
density_ma				-0.231*** (0.0372)
mix_ma				0.458 (0.420)
income	0.0104*** (0.000475)	0.0103*** (0.000463)	0.0104*** (0.000478)	0.0103*** (0.000472)
age	0.00746*** (0.00145)	0.00806*** (0.00140)	0.00755*** (0.00146)	0.00840*** (0.00142)
school	0.517*** (0.0495)	0.522*** (0.0477)	0.518*** (0.0497)	0.536*** (0.0489)
workers	0.0698*** (0.0165)	0.0737*** (0.0158)	0.0697*** (0.0165)	0.0756*** (0.0161)
age65	-0.0549 (0.0384)	-0.0739* (0.0367)	-0.0541 (0.0386)	-0.0652 (0.0376)
kids	0.0770*** (0.0149)	0.0683*** (0.0143)	0.0774*** (0.0150)	0.0703*** (0.0146)
couple	0.716*** (0.0373)	0.694*** (0.0358)	0.715*** (0.0375)	0.726*** (0.0369)
zmlarge	-0.0217 (0.0533)	0.109** (0.0413)	-0.0129 (0.0552)	0.0704 (0.0442)
constant	-2.076*** (0.119)	-1.788*** (0.0874)	-2.073*** (0.119)	-1.935*** (0.106)
CLR (IVs relevance)	13.18 [0.003]	0.00 [0.945]	13.45 [0.002]	5.23 [0.076]
Hansen J-stat (IVs validity)	1.76 [0.414]	14.98 [0.001]	1.42 [0.233]	13.60 [0.000]
N	7708	7708	7708	7708

Standard errors in parentheses. * $\rho<0.1$; ** $\rho<0.05$; *** $\rho<0.01$. The null hypothesis under the conditional likelihood ratio (CLR) test is that the coefficients of the instruments are all zero in the equation of the endogeneous variable regressed on all assumed exogenous variables. The null hypothesis under the Hansen J test is that the instruments are uncorrelated with the error term and thus correctly excluded from the main equation. P-values for these tests are shown in brackets.

Source: Own elaboration based on CONAPO (2016), INEGI (2010), INEGI (2014) and INEGI (2014b).

Table 5. **PART 2 OF INSTRUMENTAL VARIABLES MODIFIED TWO PART MODEL IV2PM (exponential conditional mean model)**

Variable	Dependent variable is gasoline consumed			
	(1)	(2)	(3)	(4)
density	0.134*** (0.036)		0.137*** (0.036)	0.153*** (0.039)
mix		-0.201 (0.473)	-0.297 (0.538)	0.534 (0.542)
density_ma				-0.25*** (0.055)
mix_ma				-0.367 (0.469)
income	0.005*** (0.000)	0.005*** (0.000)	0.005*** (0.000)	0.005*** (0.000)
age	-0.006*** (0.001)	-0.005*** (0.001)	-0.005 (0.001)***	-0.005*** (0.001)
school	0.229*** (0.04)	0.23*** (0.037)	0.23*** (0.04)	0.237*** (0.039)
workers	-0.091*** (0.015)	-0.075*** (0.013)	-0.09*** (0.015)	-0.082*** (0.015)
age65	-0.055 (0.038)	-0.072* (0.035)	-0.048 (0.041)	-0.05 (0.039)
kids	-0.211*** (0.016)	-0.221*** (0.014)	-0.21*** (0.016)	-0.206*** (0.015)
couple	-0.154*** (0.039)	-0.183*** (0.036)	-0.155*** (0.04)	-0.147*** (0.039)
zmlarge	-0.048 (0.052)	0.07 (0.047)	-0.031 (0.058)	-0.002 (0.046)
constant	4.594*** (0.111)	4.87*** (0.083)	4.595*** (0.112)	4.595*** (0.108)
CLR (IVs relevance)	26.84 [0.000]	0.66 [0.418]	27.22 [0.000]	22.22 [0.000]
Hansen J-stat (IVs validity)	0.55 [0.759]	26.51 [0.000]	0.09 [0.763]	2.39 [0.122]
N	3,513	3,513	3,513	3,513

Standard errors in parentheses. * $\rho<0.1$; ** $\rho<0.05$; *** $\rho<0.01$. The null hypothesis under the conditional likelihood ratio (CLR) test is that the coefficients of the instruments are all zero in the equation of the endogeneous variable regressed on all assumed exogenous variables. The null hypothesis under the Hansen J test is that the instruments are uncorrelated with the error term and thus correctly excluded from the main equation. P-values for these tests are shown in brackets.

Source: Own elaboration based on CONAPO (2016), INEGI (2010), INEGI (2014) and INEGI (2014b).

In terms of the signs and statistical significance of variables, Tables 4 and 5 show that those for household level characteristics remain as in the non-instrumented specification for both parts of the model. However, the coefficients for residential density at the census-tract level are reversed in all specifications, suggesting, contrary to the leading hypothesis, that higher residential densities may induce more gasoline consumption. Land use diversity is not statistically significant in any of the instrumented specifications for both the first and second parts of the model. In the specifications that instrument for census-tract level built environment variables while also incorporating these same variables at the MA-level, the impact of MA-residential density remains negative as in the non-instrumented specifications.

Table 6. **MARGINAL EFFECTS OF M2PM AND IV2PM (density and mix at the census tract level)**

	M2PM				IVM2PM			
	Estimate	Std. Err.	[95% Conf.	Interval]	Estimate	Std. Err.	[95% Conf.	Interval]
Marginal effects								
density	-2.285	0.449	-3.339	-1.606	9.991	1.877	6.93	14.29
mix	12.549	6.008	0.533	25.352	-19.291	26.232	-69.848	29.472
income	0.508	0.026	0.451	0.559	0.513	0.026	0.459	0.564
age	0.089	0.062	-0.013	0.215	0.039	0.069	-0.083	0.181
school	29.284	2.605	23.899	34.378	28.47	2.848	22.791	34.708
workers	-0.369	0.706	-1.763	0.966	-1.123	0.777	-2.869	0.287
age65	-5.549	1.755	-9.38	-1.894	-3.519	1.999	-7.346	0.427
kids	-6.29	0.679	-7.646	-5.059	-5.295	0.773	-6.631	-3.732
couple	16.036	1.477	13.383	19.369	17.232	1.57	14.367	20.246
zmlarge	6.739	1.679	3.035	9.829	-1.57	2.984	-7.733	3.513
Elasticities								
density	-0.158	0.031	-0.232	-0.112	0.703	0.142	0.475	1.02
mix	0.034	0.016	0.001	0.068	-0.053	0.073	-0.192	0.083
income	0.638	0.029	0.573	0.692	0.653	0.03	0.582	0.702

Standard errors and confidence intervals obtained through 299 bootstrap repetitions.
Source: Own elaboration based on CONAPO (2016), INEGI (2010), INEGI (2014) and INEGI (2014b).

4.3. **M2PM and IV2PM: Full effect**

Finally, the full marginal effects of the impact of each built environment variable on the amount of gasoline consumed under the specifications with both *density* and *mix* are presented in Tables 6 and 7. The full marginal effect given by equation (5) above represents the expected change in gasoline consumption from a marginal variation in the variable of interest, that is, it predicts the overall change, independently on whether this occurs at the extensive or intensive margins of the decision. Although the calculation of full marginal effects is straightforward from the coefficients estimated in the two parts of the model (equation 5), obtaining standard errors is not. We implemented a bootstrap routine over 299 repetitions to estimate standard errors and a 95% confidence interval for each marginal effect and elasticities for income and all built environment measures.

Table 6 shows marginal effects for both non-instrumented and instrumented specifications that only include built environment measures at the census tract level. Magnitudes and significance levels of all but the built environment variables are comparable across the M2PM and the IVM2PM. However, in terms of elasticities, that for *density* switches from -0.16 in the M2PM to 0.7 in the IVM2PM, while the one for *mix*, albeit not statistically significant, becomes negative in the instrumented specification. This latter result could be due to a lack of variability of the index, which as shown in Figure 2 is highly skewed towards zero and may therefore not be a complete measure of land use diversity.

The results from the instrumented specifications should be interpreted as local average treatment effects. For instance, in the case of residential density, this effect would be applicable to households that chose their residential location based on the set of the assumed exogenous variables, including the share of the population in the census tract that is younger than 2 years old, the share that is older than 60 years old, and the percentage of households inhabited by couples. To the extent that the local average treatment effect estimated by the IVM2PM applies to the entire sample, policy makers should be cautious when increasing residential density in census tracts without promoting other strategies that could directly reduce gasoline consumption as residential density could result in driving increases. The channel through which this counterintuitive result arises remains to be investigated, however, one potential explanation could be that some denser neighborhoods may lack amenities and services such as retail malls, large parks, university campuses and business districts that given their nature require large spaces and thus may result in more driving from households located in denser census-tracts.

Table 7 shows marginal effects for both non-instrumented and instrumented specifications including measures of built environment at the MA level in addition to those at the census tract level. The main difference compared to results from Table 7 is that although residential density at the census tract level remains positive in the instrumented specification, higher MA residential densities seem to reduce travel. This finding may point to the same channel proposed above by which denser neighborhoods may be mostly occupied by housing. However, denser metropolitan areas may perform better at condensing trip generators and attractors within a metropolitan area even if households must travel across neighborhoods to satisfy their travel needs. The negative impact of denser MAs and positive impact of denser neighborhoods on gasoline consumption seems particularly reasonable for metropolitan areas that have several clusters of trip attractors such that households have options to reach their destinations, even when not necessarily located within their census tract.

Table 7. **MARGINAL EFFECTS OF M2PM AND IV2PM (density and mix at the census tract and MA levels)**

	Full ZM				IVFullZM			
	Estimate	Std. Err.	[95% Conf.	Interval]	Estimate	Std. Err.	[95% Conf.	Interval]
Marginal effects								
density	-1.091	0.482	-2.179	-0.341	7.991	1.722	5.066	11.799
mix	-10.925	8.711	-27.412	6.082	32.364	25.94	-15.023	83.894
dnsity_ma	-7.455	0.979	-9.423	-5.755	-16.203	2.071	-20.618	-12.846
mix_ma	36.602	8.857	18.864	53.038	0.994	22.271	-37.687	43.189
income	0.51	0.025	0.452	0.56	0.502	0.025	0.448	0.55
age	0.112	0.061	-0.003	0.241	0.091	0.064	-0.038	0.219
school	29.969	2.622	24.814	34.542	28.767	2.705	23.075	33.629
workers	-0.19	0.704	-1.504	1.188	-0.612	0.718	-2.185	0.558
age65	-5.029	1.762	-8.826	-1.331	-3.846	1.881	-7.393	-0.255
kids	-6.233	0.684	-7.557	-4.998	-5.248	0.728	-6.55	-3.777
couple	16.35	1.475	13.743	19.468	17.369	1.478	14.966	20.805
zmlarge	6.801	1.68	3.24	10.013	2.102	2.132	-2.345	6.146
Elasticities								
density	-0.076	0.034	-0.153	-0.023	0.577	0.135	0.35	0.896
mix	-0.03	0.024	-0.074	0.017	0.091	0.074	-0.047	0.237
density_ma	-0.156	0.02	-0.194	-0.12	-0.35	0.051	-0.471	-0.272
mix_ma	0.128	0.031	0.065	0.187	0.004	0.081	-0.139	0.158
income	0.645	0.029	0.579	0.692	0.657	0.029	0.587	0.707

Standard errors and confidence intervals obtained through 299 bootstrap repetitions.

Source: Own elaboration based on CONAPO (2016), INEGI (2010), INEGI (2014) and INEGI (2014b).

Importantly, in line with previous literature (Galindo *et* al., 2006; Crotte *et al.*, 2011), the size of the elasticity of driving with respect to income across all specifications in Tables 6 and 7 is relatively large. The estimate of about 0.65 implies that a doubling of per capita income would in average increase gasoline consumption per capita by 65%. This also highly policy-relevant finding suggests that without any other interventions, gasoline consumption in Mexican MAs will rise at more than half the pace income will.

5. CONCLUSIONS

Societies aiming to become less dependent on carbon will necessarily curb emissions from the transportation sector through policies that affect the carbon intensity of travel, the amount of travel or both. In this study we estimated the impact of modifying the urban form on the probability and amount of gasoline consumption in households located in Mexican metropolitan areas. Through a modified two-part model we found that all else equal, doubling residential density at the neighborhood level would result in 7% less gasoline consumed but 57% *more* gasoline consumed when this variable is instrumented to address self-selection bias. Conversely, and in line with previous literature, our results indicate that increasing residential density at the metropolitan area scale can reduce between 15% and 35% gasoline consumption upon a two-fold increase in residential density. This type of counterfactual (i.e., doubling residential density) may seem highly ambitious in MAs with an already high residential density, but less so in MAs with low residential densities or in their early phases of urban development.

Land use diversity, our other measure of the built environment included in the analysis and presumably more feasible to modify in already built areas, does not seem to affect gasoline consumption. It remains unclear whether this result points to an actual lack of influence on gasoline consumption from this characteristic or to the lack of variability of an index highly skewed towards zero, which could itself originate from a measure that does not fully capture land use diversity.

It is important to note that we cannot discern whether the estimated changes on gasoline consumption upon changes on the explanatory variables are the result of changes in the number of trips, the length of trips, or the fuel–efficiency of the vehicles driven. It is likely that modifications to the built environment would affect all these dimensions of travel. This is particularly important in the context of multidimensional evaluation of alternative policies aimed to tackle multiple externalities from the transportation sector such as road accidents, local and global pollution, and travel time delays.

Although our mixed results on the impact of the built environment suggest avenues for changes on the design and renewal of metropolitan areas that could result in fuel consumption reductions, rising incomes may counteract this effect as the elasticity of gasoline consumption with respect to this variable was found to be relatively large. Further investigations are required to explore the channels through which fuel consumption may be affected by residential density, land use diversity and other measures of the urban form in the context of low and middle-income countries where motorization rates continue to rise and thus transportation GHG emissions reductions will be limited in spite of technological developments.

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