

ABSTRACT

In this paper, we develop comparable multilevel logistic regressions predicting whether a sample of 5.7 million workers commute by bicycle in the hundred largest urban areas in the US and Mexico. In both contexts, men in relatively poor households are likeliest to cycle. The similarities in cycling commuters generally stop with these two commonalities, however. The archetypal US bike commuter is a recent college graduate, lives by himself in a centrally located apartment in a moderate-to-high density city, like Portland, OR, and commutes to work in a relatively low-paying service sector job for a college graduate, perhaps at restaurant or not-for-profit. The archetypal Mexican bike commuter, by contrast, is in his mid-thirties, has only a few years of formal education, lives with a large family in a house in the suburbs of a large dense metropolitan area, like Mexico City, and commutes to a relatively low-paying agriculture, construction, or manufacturing job. Local context matters and the most effective public policies to promote urban cycling will almost certainly vary across national borders. For example, our analysis suggests that requiring showers and bicycle parking in new office developments will likely do a lot more to support US cyclists than Mexican ones. Last, we conclude that there is a need for studies that include comparable measures of cycling infrastructure, local built environments, and non-work trips in different national contexts.

RESEARCH AGENDA

1. Introduction

Demographics, Socio-Economic and Geographic factors have all been identified as factors impacting levels of cycling. We reviewed predictors for cycling identified for developing and developed countries. For the former, the literature in China and Latin America has found a weak connection between population density or certain other urban form measures and cycling rates. (Zhao, 2013. Cervero et. al., 2009) One possible explanation is a uniformly high level of densities and mix of uses. The significant factors, however, include proximity to transit, street density, bike infrastructure, etc. Moreover, demographics, particularly gender, are also found to impact cycling rates. (Trang et. al., 2012).

Contrary to the evidence above, studies on developed countries found a positive correlation between population density and cycling. (Parker et. al., 2011) What is similar is that being male also increases the likelihood of cycling, but the significance level varies depending on the study and location. (Pucher & Buehler, 2010) Studies alsoidentified a significant positive relationship between bike infrastructure and cycling rates. (Parker et. al., 2011). Moreover, the presence of sloping terrain has been well documented as a negative predictor of cycling. (Ma & Dill, 2015)

As existing research predominantly focuses on individual or similar geographies, it is not clear how broadly applicable these results are to other geographies. Our study attempts to fill this gap through a

large-scale metropolitan-level analysis covering two countries, the United States and Mexico, that despite their close proximity are significantly different along many vectors.

2. Data

The micro data for the US was obtained from the Census Bureau, chiefly from the American Community Survey (ACS) and Public Use Microdata Sample (PUMS) datasets. The Mexican micro data was obtained from the 2015 Mexican Intercensal Survey provided by the national statistics agency. Metropolitan areas are identified separately in each geography. We identified major cities and their surrounding suburbs in Mexico using the Mexican Population

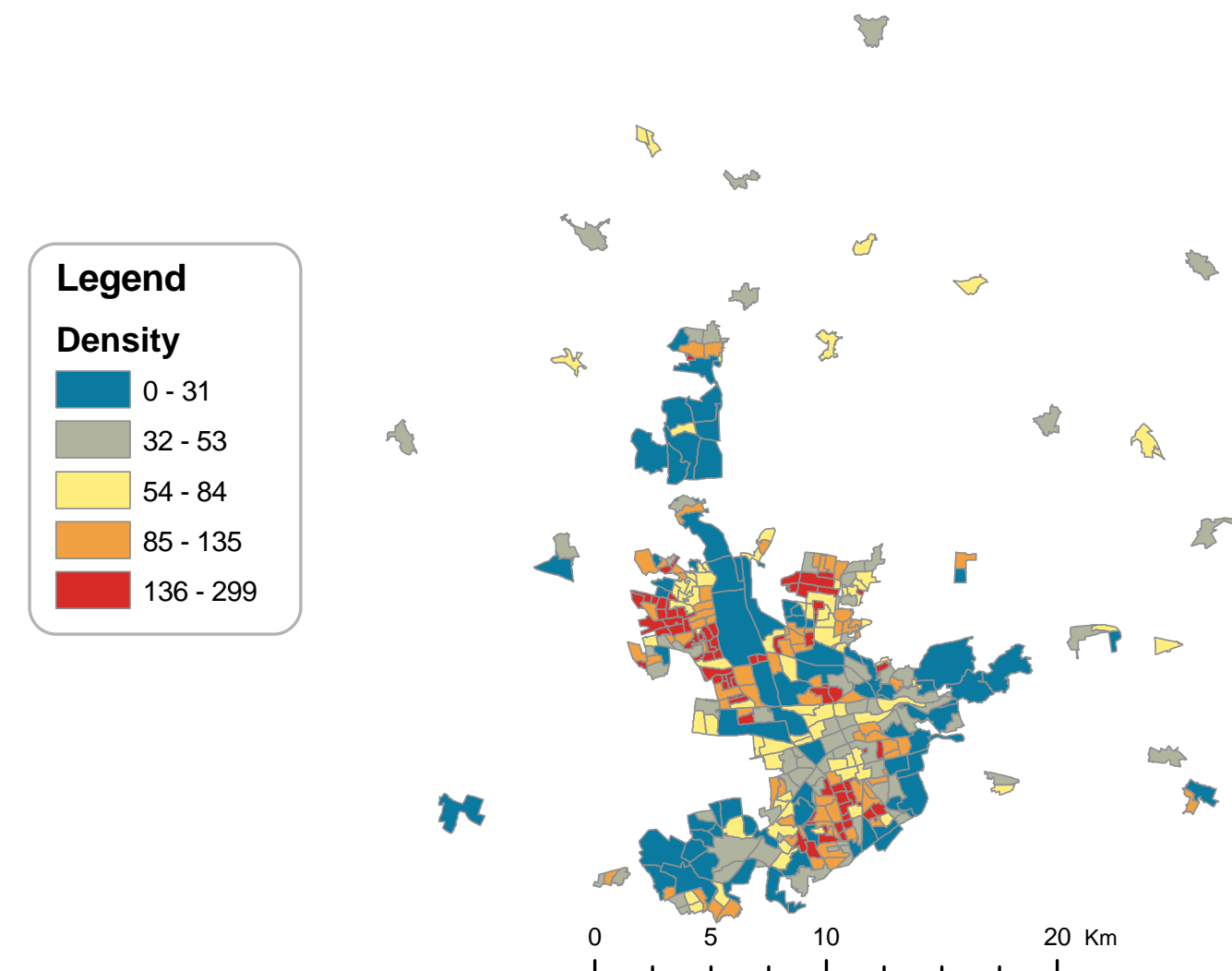


Figure 1:Population per hectare by Census tract (Ageb) in Querétaro, Mexico

Council's National Urban System, and utilized the Metropolitan Statistical Area (MSA) for the US. Data is primarily from the US 2010 Census and the 2009 Economic Census of Mexico, complemented by other sources such as the NOAA climate data.

3. Methods

We modeled the factors and their associations with cycling using multi-level logistic regression. The response is binary (cycling/ non-cycling); the explanatory variables include individual, household, and urban form factors. We chose only several urban form indicators due to the sample size of metropolitan areas (100 for each country), with the help of Principal Component Analysis.

We included random intercepts by metropolitan area and random slopes for different housing types by metropolitan area to model relationships at different levels. Written formally the probability of commuter cycling to work in urban area is equal to equation 1 below:

$$y_{ij} = \frac{e^{\beta_0 + \beta X_{ij} + \mu_i X_{ij} + \mu_{i0}}}{1 + e^{\beta_0 + \beta X_{ij} + \mu_i X_{ij} + \mu_{i0}}}$$

(eq. 1)

Where:

- $\beta_0$  is a fixed constant.
- $\beta$  is a vector of fixed parameter estimates for all predictors  $i$  included in the model.
- $X_{ij}$  is the data value of  $i$  for each commuter  $j$ .
- $\mu_i$  is the zero-centered, normally distributed random parameter for the subset of parameters  $\beta$  that vary by urban area (housing type, income, and car ownership).
- $\mu_{i0}$  is the zero-centered, normally distributed random constant for each urban area.

RESULTS & DISCUSSION

1. Who cycles to work more in the US and Mexico?

We found that men consistently cycle more than women in both countries, with the gender gap larger in Mexico than in the U.S. While the elderly had low likelihood of cycling in both countries, in Mexico the middle-aged were the most likely to cycle, creating an inverted-U relationship, while in the U.S. cycling consistently declined with age. In Mexico, cycling consistently declined with education, while in the U.S. those with at least a bachelor’s degree were most likely to cycle. Finally, in the U.S. service industry workers were most likely to cycle, while in Mexico agricultural workers were the most likely to cycle. This too may reflect urban form, with agricultural jobs more likely to be located in peripheral areas of a metropolitan area, and service jobs often concentrated in the core and in key hubs.

2. Where do workers cycle more in the US and Mexico?

We found population density strongly associated with cycling in different ways in the two countries. In the U.S., cycling is most likely to be a commuting mode where density is medium. By contrast, the suburbs and densest areas most favor bike commuting in Mexico. Apart from densities, road structure is a significant indicator in the U.S. and precipitation is one in Mexico. Our analysis of local urban form through the proxy of housing suggest cycling is a more suburban phenomenon in Mexico and a more urban one in the U.S.

The random intercepts capture unobserved differences among the geographies. For example, Portland-Vancouver-Hillsboro has the highest cycling probability in the US and San Francisco del Rincón in Mexico. The random slopes of housing types are greater in less cycled areas (e.g. Philadelphia-Camden-Wilmington) and smaller in the most cycled areas (e.g. Portland-Vancouver-Hillsboro). This implies a greater impact of local form in less cycled places.



3. Discussion: policy insights

Taken together, our findings provide several insights for public policy. First, understanding contextual differences is critical to the development of policy to increase cycling. As an example, suburban cycling corridors along major arterials may be particularly effective at improving cyclists’ experiences in Mexican urban areas but not in US ones. Even within countries, we find substantial differences. For example, living in an apartment building is much more strongly associated with cycling in the Philadelphia region than in the Portland region.

Second, the largescale differences in urban form that help shape car and transit use (Bento et al., 2005; Giuliano and Dargay, 2006; Guerra et al., 2018) are only weakly and inconsistently associated with cycling. As such, cycling policies may be substantially more effective at municipal or sub-municipal levels of governance as opposed to metropolitan ones. That said, investing in more and higher capacity roadway may reduce aggregate cycling rates at the margin. In Mexico, a simulated 10% increase in roadway per capita results in an 5% decrease in cycling to work. In the US, a 10% increase in the share of arterial roads corresponds with an estimated 7% reduction in cycling rates.

Last, three major limitations of this study present opportunities for future research into the how the predictors of cycling vary by context and which policies are likely to be more effective in a Mexican urban context than a US one. First, we have no consistent measures of cycling infrastructure across urban areas in the US and Mexico. Second, the data used in this study have limited spatial resolution. Third and finally, our study provides no insight into similarities and differences in recreational and non-work utilitarian cycling in the US and Mexico.

Reference (selected)

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Table 1: Multi-level logistic regression results for the U.S. and Mexico

	Dependent Variable: Cycling (0/1)			
	US	Mexico	US (New York excluded)	Mexico (Mexico City excluded)
Male	0.936*** (0.015)	1.807*** (0.012)	0.938*** (0.016)	1.972*** (0.014)
Age	-0.723*** (0.042)	0.212*** (0.015)	-0.751*** (0.044)	0.261*** (0.016)
Age^2	0.402*** (0.044)	-0.214*** (0.015)	0.429*** (0.046)	-0.251*** (0.016)
Log household income	-0.153*** (0.007)	-0.104*** (0.003)	-0.170*** (0.007)	-0.096*** (0.003)
Education: secondary	-0.144*** (0.046)	-0.296*** (0.007)	-0.104*** (0.049)	-0.309*** (0.008)
Education: high school	-0.507*** (0.040)	-0.787*** (0.010)	-0.443*** (0.044)	-0.837*** (0.011)
Education: BA plus	0.027 (0.040)	-1.894*** (0.017)	0.095** (0.044)	-2.089*** (0.020)
Multi-family housing	0.441*** (0.062)	0.114*** (0.030)	0.430*** (0.063)	0.117*** (0.030)
Apartment	0.776*** (0.043)	-0.262*** (0.045)	0.747*** (0.043)	-0.258*** (0.046)
Other housing types	0.008 (0.091)	-0.066** (0.032)	0.003 (0.092)	-0.040 (0.037)
Manufacturing occupation	-0.017 (0.113)	-0.100*** (0.010)	-0.026 (0.115)	-0.104*** (0.011)
Service occupation	0.393*** (0.112)	-0.997*** (0.011)	0.403*** (0.114)	-0.946*** (0.012)
Jobs-population imbalance Gini (0-1)	-0.043 (0.060)	0.063 (0.094)	-0.033 (0.062)	0.065 (0.108)
Population per hectare	2.447*** (0.434)	-1.689** (0.860)	1.441*** (0.320)	-1.430** (0.671)
Population per hectare^2	-2.343*** (0.460)	1.916* (1.138)	-0.968*** (0.335)	1.404* (0.741)
Road length per capita (km)	0.031 (0.064)	-0.120 (0.094)	0.055 (0.064)	-0.108 (0.089)
Share of arterial (0-1)	-12.188*** (3.160)	1.263 (2.216)	-11.928*** (3.132)	1.176 (2.224)
Share of highway (0-1)	-1.703 (1.647)	-2.213 (3.466)	-1.296 (1.643)	-2.419 (3.477)
Annual degrees below 65F	-0.060 (0.061)	-0.133* (0.079)	-0.097 (0.065)	-0.143 (0.090)
Annual precipitation (mm)	0.118* (0.063)	-0.196** (0.095)	0.132** (0.065)	-0.229** (0.108)
Rail transit length per capita (km)	0.008 (0.074)	-0.277 (0.241)	0.005 (0.068)	-0.187 (0.170)
Constant	-4.925*** (0.363)	-3.535*** (0.448)	-5.064*** (0.358)	-3.705*** (0.398)
Observations	3,303,944	2357157	2,989,714	1,822,524
Log Likelihood	-120,801.400	-387,116.100	-110,270.200	-307,557.700
Akaike Inf. Crit.	241,666.800	774,296.300	220,604.300	615,179.300
Bayesian Inf. Crit.	242,083.100	774,701.800	221,017.500	615,576.600

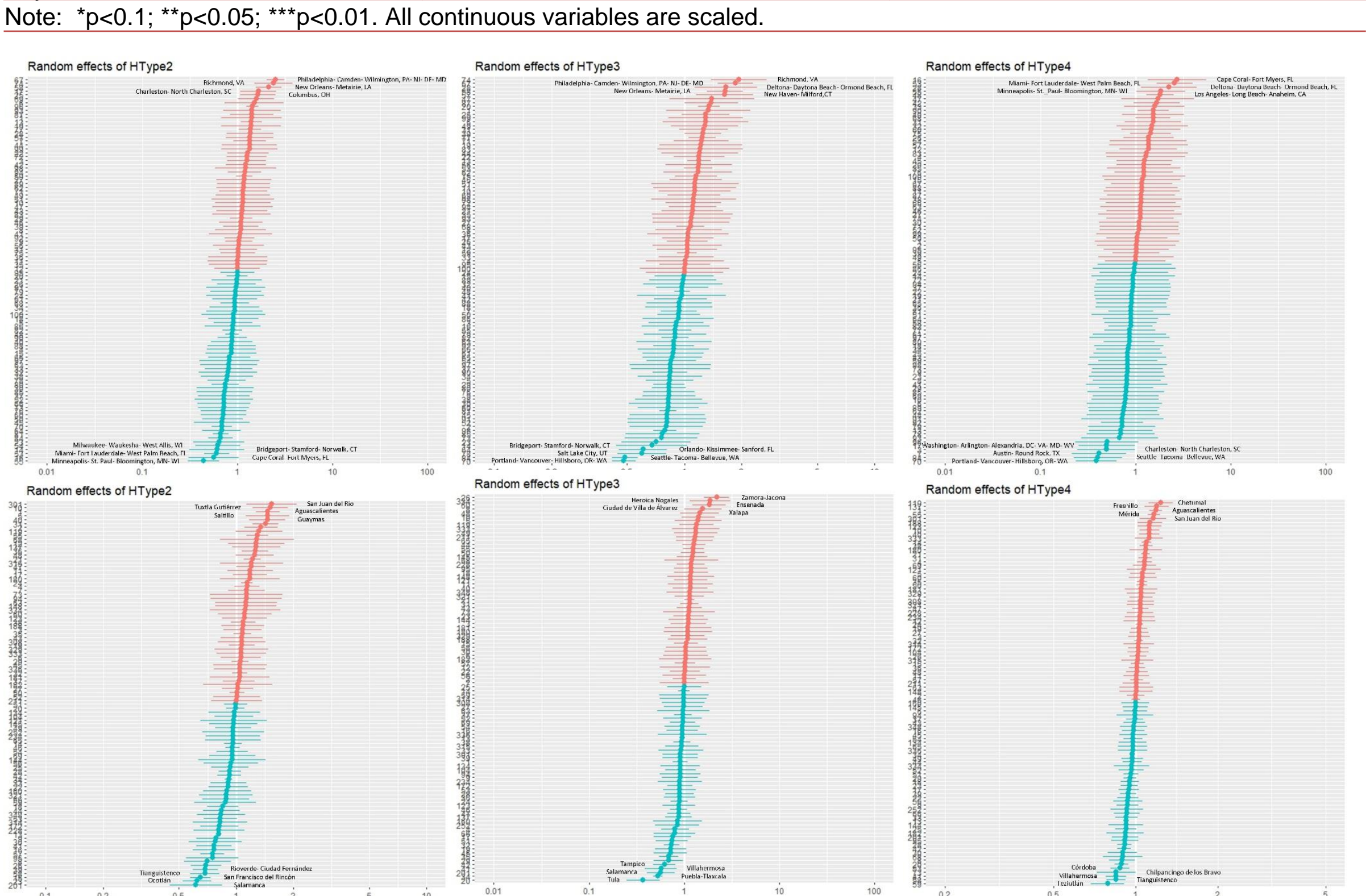


Figure 2: Random Slopes for housing types by metropolitan area. (Top: the U.S. Bottom: Mexico. Labels: names of metropolitan areas.)