The Effects of Land-use Policy on Commuting Distance and Road Related Adverse Health Outcomes

or

Aligning Transportation Policy with Residential Location Preference Among Tradeoffs

Center for Transportation, Environment, and Community Health
Final Report

by

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Research shows the use of roadway networks generate health risks thus, the amount of time people use these networks has direct implications for public health. Our research hypothesizes a credible link exists between commuting distance, land use policy, and health outcomes. To date, the primary means of investigating commuting distance has been regarding socio-economic status and the primary means of investigating land use policy has been regarding changes in travel behaviour. In both cases researchers have neglected the domain of public health linking to structural policy factors. Our research advances this topic by hypothesizing that minimum lot size policy directly affects commuting distance which, in turn, increases exposure to road related adverse health outcomes. We use econometric analysis on county/city level data to estimate the effects of commuting distance on emissions, accident rates, and cardiovascular disease, as well as, the effects of minimum lot size on work-trip length.</td></tr>
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The Effects of Land-use Policy on Commuting Distance and Road Related Adverse Health Outcomes
or
Aligning Transportation Policy with Residential Location Preference Among Tradeoffs

Christian Sprague[1] and H. Oliver Gao[2]

Abstract— **Integrating land use and transportation policy is widely understood as an efficient approach to meet sustainable transport objectives, yet impacts on residential location preference may limit policy effectiveness. Incorporating the effects on residential location preference is especially important for aligning policy decisions with policy goals. Using travel survey data, matched to block group characteristics, this study uncovers an important constraint: an integrated consumer-driven policy mix can influence households to either a more compact and accessible city or a more sprawled, revenue-generating city. We further estimate the effect of policy decisions on household exposure to road-traffic fatality and noise pollution, greenspace accessibility, and walkability and find significant differences in outcomes depending on the policy decision.**
Keywords: Residential location choice, Scenario discovery, Compact development, Accessibility, Fuel tax, Integrated transport policy

I. INTRODUCTION

Falling tax revenues, poor public transit accessibility, and high urban sprawl all reflect the performance of the U.S. land-use and transportation system (Winston 2013). Going forward, researchers suggest the need for an improved strategy to face the rising challenges of such issues. One solution is to evolve past the use of "single policy tools addressing single policy issues" and into an integrated policy mix that addresses a package of issues simultaneously. In comparison, a single-use policy strategy may accomplish one policy goal at the risk of contradicting another, while an integrated policy mix would unite the various land-use and transportation policies to become both internally consistent and consistent with consumer preferences and multisector government objectives (Santos, Behrendt and Teytelboym 2010).

Even though an integrated consumer-driven policy strategy could prove to be more equitable, sustainable, and economically beneficial, choosing appropriate policy measures will require weighing a set of potentially conflicting goals, such as CO_2 emissions, road-traffic safety, oil security, tax revenue, economic competitiveness, and consumer impact (Schäfer et al. 2009). Consequently, policy makers may wish to understand how combinations of land-use and transport policies effect land use and transportation consumer behavior and whether the policies complement or contradict each other. By gaining insight into the tradeoffs between policy mixes, planners and policy makers can more effectively align policy with preference to efficiently address the needs of the current land-use and transportation system.

This study uses the Atlanta Regional Commission (ARC) 2011 travel survey, matched to block group characteristics, to ask several questions. How do households change their residential location preference in response to simultaneous changes in MFT and public transit provision? How does this response influence changes in expected tax revenue, accessibility, and urban compactness? What do the underlying tradeoffs mean for an optimal integrated policy mix? We uncover a new finding: an integrated consumer-driven policy mix can achieve targeted increases in tax revenue, accessibility, and urban compactness at the expense of decreases in citywide performance.

By seeking to align policy with preference, we uncover and empirically address two gaps related to three veins of literature. One gap is the need to simulate the interaction effects of different policy mix configurations on residential location preferences. Second is the need to identify trade-offs between, and feasibility of, policy goals. One related vein of work incorporates household location choice within a greater urban modeling simulator to analyze policy decisions, see **(Figure 1)**. These land-use modeling systems encapsulate interdependencies between markets (i.e. land, housing, labor, etc.) and space to assist in land-use planning and growth management (Mackett 1993). There are two approaches that extend land use models to include travel demand: a four-step transport demand model (FSM) and an activity-based approach (ABA). These extended land-use transport integration (LUTI) models can simulate the effect of both land-use and transportation policy on travel behavior and locations choices. From the LUTI simulations planners evaluate changes in urban density, accessibility, and travel cost.

Our work circumvents a limiting factor for this class of modeling system: their computational complexity (Wagner and Wegener 2007; Waddell 2011). For example, (Weidner et al. 2010) found, "a 19-year run takes 3.5 days to complete and outputs consume 65 GB of disk space." This makes sensitivity analysis, robust decision making, scenario discovery, and policy mix optimization, which may require hundreds to millions of simulations, difficult (Wegener 2011; Waddell 2011). As a result, though theoretically grounded, the modeling system complexity makes robust identification of causal chains difficult (Lundqvist 2003).

To study the causal mechanisms between land use, transport, and travel behavior, the second vein of related research looks to empirical findings from different contexts. For example, researchers consider the impact of compact urban development (Ewing and Cervero 2010), gasoline tax (Levinson 2016), congestion tax (Brownstone 2008), or vehicle standards (Davis and Knittel 2016) on travel consumption. Here, researchers use residential location choice models to control for residential self-selection bias (Pinjari et al. 2007). Yet, while this method is appropriate for estimating the effect of transportation policy on travel behavior, it implicitly states that household location preference is outside the analytical scope. In contrast, our work directs research toward understanding the effects of land use-transportation policy on household location.

Less commonly, researchers use residential location choice models in studies on household location preference formation processes (Liao, Farber and Ewing 2015). This vein of work investigates the formation and malleability of household location preferences and location decisions, develops cognitive measures connecting to the built environment, and seeks to understand the processes by which households decide where to live (Handy 2017). While these studies are informative, they disconnect their implications from economic or physical policy (e.g. MFT and transit provision) and focus on soft policy measures (e.g. information tools and education campaigns).

We begin to address these gaps by carrying out a policy simulation that assesses the impact on residential location preference given a two-policy mix. The policy mix comprises a motor fuel tax and a level of public transit service provision. We then test the alignment of the policy tools with the policy goals by calculating the effect on tax revenue, accessibility, and urban compactness because of a change in location preference. We divide the modeling schema into two separate components. The first estimates a change in policy mix on a change in residential location choice. The second measures the impact on policy goals that result from a change in residential location preference. We use scenario discovery techniques to estimate how the policy mix affects location preference and leads to certain policy outcomes. This methodological framework can aid in aligning policy tools and consumer preference with the desired policy goals into an internally consistent, integrated land use-transport policy mix.

The rest of this paper is as follows. Section (II) describes the methodology for the empirical analysis. Section (III) describes data sources and variable construction. Section (IV) presents empirical results. Section (V) discusses implications for policy. Finally, Section (VI) concludes.

II. METHODS

We break the methodology into three stages (1) estimate a residential location choice model; (2) simulate a change in policy mix causing a change in residential location preference; (3) and conduct a trade-off analysis on updated policy goals.

A. Estimate a residential location choice model

We follow McFadden (1978). The utility of a household i in a location j is given as,

$$U_{i,j} = V_{i,j}(\mathbf{z}_j, \mathbf{x}_{i,j}) + \varepsilon_{i,j} \tag{1}$$

where $\mathbf{z}_j$ is a vector of location j attributes, and $\mathbf{x}_{i,j}$ is a vector of location j attributes interacted with household i characteristics. To determine the probability of household i choosing location j, the error term of the indirect utility function is assumed to be independently, identically distributed extreme value giving the multinomial logistic equation,

$$P_{i,j} = \frac{e^{V_{i,j}}}{\sum_k e^{V_{i,k}}}. \tag{2}$$

The utility function is linear in the unknown parameters giving the systematic portion of the utility as,

$$V_{i,j} = \mathbf{z}_j \boldsymbol{\beta} + \mathbf{x}_{i,j} \boldsymbol{\gamma}, \tag{3}$$

where $\mathbf{z}_j$ is a vector of zonal attributes and $\mathbf{x}_{i,j}$ is a vector of zonal-household interaction attributes. The policy tools can enter the systematic portion of the utility in both terms. For example, a public transit policy may affect both a location attribute (e.g. accessibility) and a household interaction attribute (e.g. ridership).

B. Simulate a change in policy mix causing a change in residential location preference

Next, to simulate the change in residential location preference from a change in policy mix, we incorporate in **Equation 2**,

$$P^k_{i,j} = \frac{e^{V^k_{i,j}}}{\sum_k e^{V^k_{i,k}}}, \tag{4}$$

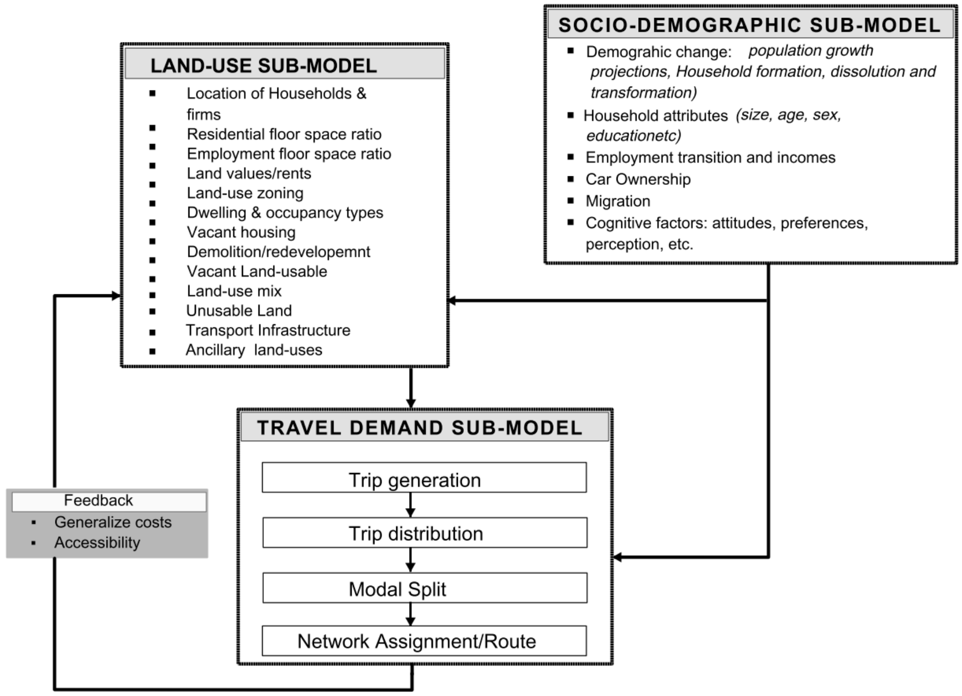

Fig. 1: General structure of LUTI model, source: (Acheampong and Silva 2015)

where k is the policy mix scenario. Note that $P^0_{i,j}$ represents the predicted probabilities of the baseline scenario. The systematic portion of the utility then becomes,

$$V^k_{i,j} = \mathbf{z}_j(k)\boldsymbol{\beta} + \mathbf{x}_{i,j}(k)\boldsymbol{\gamma}, \tag{5}$$

which represents the effect of a policy mix k on the location and household interaction attributes.

In this paper, we generate 6,216 policy mix scenarios. Each scenario is comprised of our policy mix. The first policy tool, a change in gasoline tax, is taken over a range of 84 possible values. In 2010, the Georgia MFT was set to $\$0.168$. We choose scenario values by sampling over a MFT range of $(\$0.0, \$2.00)$ incremented by $\$0.025$.

The second policy tool is a change in public transit accessibility. We generate these data by altering the total number of bus runs per hour for each route. In this paper, we consider 6 route-frequency arrangements. For each route-frequency arrangement, f, the route-frequency pattern, α, is given as $\{\alpha \in (1, 20) : \alpha \in \mathbb{Z}\}$ for a total of $6 \times 20 = 120$ arrangement patterns, however, only 74 of these are unique. The 84 representative MFT levels, in combination with the 74 route-frequency arrangements, generate the 6,216 policy mix scenarios.

C. Conduct a cross-scale scenario analysis on updated policy goals.

Next, we compare the outcomes for policy mix k against the baseline policy mix to measure the change in household location preference. Following (Train 2009), we take the mean of the predicted probabilities across individuals for each location j and each policy mix k. This represents the weight, w_j, for the total population demand for each zonal location j under a policy mix. The weighted mean of the policy goal metric m is given as,

$$\mathbb{E}_w[m^k_c] = \frac{\sum_c w^k_j m^k_j}{\sum_c w^k_j}, c \in J \tag{6}$$

where c is a subset of the J locations. In this paper, the subset c is defined on four levels of aggregation: block, census tract, county, and metro-area.

Last, we classify each simulation outcome. We classify according to a success-failure criteria defined by the number of successful policy goals achieved by the policy mix. Thus, given the three primary policy goals of interest there are a total of seven classification formulations - 1 for satisfying the trilemma (meeting all three objectives), 3 for satisfying a dilemma (meeting two out of three objectives), and 3 for satisfying a lemma (meeting one out of three objectives). We consider the policy objective met when the simulated scenario performs better than the baseline scenario. In this paper, we strictly report results that meet all three objectives. For example, a scenario that produces a percentage increase in urban compactness, accessibility, and increase in MFT revenue.

After classification, we predict the impact of the policy tools on each set of policy success-criteria formulations using a binary logistic regression model following (Quinn et al. 2018).

III. DATA

The primary data source comes from the Atlanta Regional Commission (ARC) 2011 travel survey. The 2011 regional travel survey includes socio-economic and demographic information for 10,278 households, 25,810 persons, and 21,270 vehicles in the ten-county metropolitan area. The ARC survey data contains 2011 geocoded home, work, and school locations. The surveyors took a stratified sample across each of the subgroups within a divided survey universe. The surveyors then chose a random sample within each subgroup. They conducted the survey from November 2010 to October 2011.

Besides the travel survey, we use 15 other data sets associated with the Atlanta area. **(Table I)** provides a list of variables and their data sources. All spatially explicit calculations use the 2010 Census TIGER/Line shapefile at the block or block group level. There are 2,565 block groups in the study area.

We use these data sources to generate a rich set of variables we include in either the model specification or the post-estimation simulation, discussed in Section II. We classify the variables into three groups: policy tools, policy goals, and controls. Policy tools are the variables of interest within the model specification, discussed in Section III-B. Policy goals are the variables of interest to be measures post-estimation, discussed in Section III-C.

A. Estimation sample

The geographic area of study is the Atlanta Metropolitan Area, as defined by the Atlanta Regional Commission, which comprises the 10-county area of Cherokee, Clayton, Cobb, DeKalb, Douglas, Fayette, Fulton, Gwinnett, Henry and Rockdale counties, including the city of Atlanta, 2,565 block groups. We focus on households with at least one worker as some variables of interest depend on an employment origin-destination, such as commute travel cost, road traffic fatality exposure, average commute distance, tax revenue. After removing households without at least one commuter, the sample size becomes 6,023 households.

Regarding large sample sizes, we follow the recommendation of Nerella and Bhat (2007) - who suggest, "that a fourth of the full choice set is a desirable target." Thus, we select a sample of $2,565/4 \approx 640$, translating to 1 observed location choice and 639 alternatives. We use a random sampling scheme for the selection of alternatives on all 6,023 households; giving $n = 6,023 \times 640 = 3,854,720$ observations.

B. Policy Tools

The two policy tools of interest are public transit provision and motor fuel tax (MFT). In this paper, we use a Time-of-Day-Based transit accessibility measure, see (Polzin, Pendyala and Navari 2007) for a detailed description. This measure incorporates both spatial and temporal dimensions and also incorporates supply and demand data into the temporal dimension. We calculate accessibility for each block group in the study area. This measure considers service availability for a 24-hour cycle, zonal coverage by route, travel demand, and transit service availability.

For each scenario, we adjust the route-frequency arrangement. We intend to capture a breadth of dynamics associated with altering access in suburban and urban areas or shifts in the total transit system. For bus route r at hour of day t, the bus route-frequency arrangement f is modified by parameter α, as:

Increment the route-frequency

$$f_{1_{r,t,\alpha}} = f_{r,t} + \alpha \tag{7}$$

Decrement the route-frequency:

$$f_{2_{r,t,\alpha}} = \begin{cases} \text{if } f_{r,t} - \alpha > 0, & \text{then } f_{r,t} - \alpha \\ \text{otherwise}, & 0 \end{cases} \tag{8}$$

Enforce a ceiling function on route-frequency

$$f_{3_{r,t,\alpha}} = \begin{cases} \text{if } f_{r,t} > \alpha, & \text{then } \alpha \\ \text{otherwise}, & f_{r,t} \end{cases} \tag{9}$$

We reassign route-frequency to threshold, α, given the current route-frequency is above α.

Enforce a floor function on route-frequency:

$$f_{4_{r,t,\alpha}} = \begin{cases} \text{if } f_{r,t} < \alpha, & \text{then } \alpha \\ \text{otherwise}, & f_{r,t} \end{cases} \tag{10}$$

We reassign route-frequency to threshold, α, given the current route-frequency is below α.

Set the maximum allowed route-frequency:

$$f_{5_{r,t,\alpha}} = \begin{cases} \text{if } f_{r,t} > \alpha, & \text{then } \max \\ \text{otherwise}, & f_{r,t} \end{cases} \tag{11}$$

We reassign route-frequency to maximum route-frequency given the current route-frequency is above to threshold, α.

Set the minimum allowed route-frequency:

$$f_{6_{r,t,\alpha}} = \begin{cases} \text{if } f_{r,t} < \alpha, & \text{then } 0 \\ \text{otherwise}, & f_{r,t} \end{cases} \tag{12}$$

We reassign route-frequency to a zero route-frequency

TABLE I: Data source descriptions for aggregate variables

Variable	Data Source
Policy Instrument	
Public transit accessibility	ACS, MARTA, CCT, & GCT
Total household commute travel cost	ATS & OSM
Policy Outcome	
Tax revenue	ATS
Public transit operation cost	ACS & MARTA
Commute VMT	OSRM & OSM
Paratransit accessibility	ARC Research & Analytics Division
Greenspace accessibility	ARC Community Development Division
Noise pollution exposure	Bureau of Transportation Statistics
Walkability index score	EPA
Road traffic fatality exposure	NHTSA-FARS & OSRM
Control Variables	
Zonal Land-Use Structure	
Land-use mix	ARC LandPro2010
Fraction of residential land area	
Fraction of single family housing	
Logarithm of number of households in zone	ACS
Household density	
Zonal Real Estate	
Average sale price	Zillow
# of houses purchased in 2010-2011	Zillow
# of single-family units available in 2010-2011	
Average lot size (sqft)	
Median housing value	ACS
Zonal Transportation Network	
Street block density (# of block per square km, 10^{-2})	OSM
Bicycle infrastructure access	ARC Trans. Access Mobility Division
Walkability index score	EPA
Zonal Socio-Economics and Demographics	
Absolute difference in household income from zonal median	ACS & ATS
Absolute difference in household size from zonal average	
Zonal % same race as head of household	
# schools with score (> 7)	GreatSchools
# of homicides within past 10 years	Socrata
Commute-related	
Total household commute drive time	OSRM & OSM
Absolute difference in household commute distance from zonal average	OSRM, OSM, & LEHD-LODES7

Note: ACS: American Community Survey 2010 5-year estimates; ATS: Atlanta Travel Survey; EPA: U.S. Environmental Protection Agency; MARTA: Metropolitan Atlanta Rapid Transit Authority; CCT: Cobb Community Transit; GCT: Gwinnett County Transit; NHTSA: National Highway Traffic Safety Administration; OSM: OpenStreet Map; FARS: Fatality Analysis Reporting System; OSRM: Open Source Routing Machine given the current route-frequency is below to threshold, α.

From each scenario, we define the percent change in transit operations provision (cost) for scenario k as,

$$\text{TOP}_k \propto D_k = \sum_r l_r \left(\frac{b_r^k - b_r^0}{b_r^0} \right), \tag{13}$$

where b is the total number of bus runs per day for each route r with a corresponding route length, l. It is more intuitive to represent **Equation (13)** by distributing l_r and the summation term. The weighted summation for each component represents the total distance traveled per day by the bus network. Thus, giving the percent change in total distance traveled per day, D. We assume that the percentage change in total distance traveled is proportionally equivalent to the percentage change in transit operations provision, TOP.

For the gasoline tax, we calculate the total household commute travel cost for household h in zone j, given as:

$$TC_{h,j} = \frac{\sum_i \text{OSRM}_h(j,i)}{\left(\frac{\sum_v m_h(v)}{V} \right)} (p) \tag{14}$$

where i is work location for each household commuter, OSRM is a function call to the API which retrieves the shortest path route distance in miles, m_v is the miles-per-gallon for each used vehicle in household h, V is the total number of vehicles in use, and p is dollars-per-gallon.

C. Policy goals

The three primary policy goals of interest are: MFT revenue, public transit accessibility, and urban density. Secondary outcomes of interest are: greenspace accessibility, noise pollution exposure, walkability index score, and road-traffic fatality exposure. We measure each policy goal at the aggregate level.

We assume the percentage change in tax revenue to be proportional to the percentage change in total travel cost. Giving, for scenario k,

$$TR_k = \frac{\sum_h \sum_j P_h^k(j) TC_{h,j}^k - \sum_h \sum_j P_h^0(j) TC_{h,j}^0}{\sum_h \sum_j P_h^0(j) TC_{h,j}^0} \tag{15}$$

where $P(\cdot)$ is the probability of household h choosing location j and the superscript 0 indicates the baseline scenario.

Similarly, we define the take the expectation of public transit accessibility for scenario k as,

$$\mathbb{E}(A_k) = \left(\frac{1}{H} \right) \sum_h \sum_j P_h^k(j) \cdot a_h^k(j) \tag{16}$$

where a is the public transit accessibility for h household living in location j. $P(\cdot)$ is the probability of the household selecting location j. We then sum over each household location giving the expected household public transit accessibility. Finally, we take the average of the expected household public transit accessibility for all households. From this we calculate the percentage change in accessibility from the baseline scenario a^0.

We calculate urban density, road-traffic fatality exposure, noise pollution exposure, greenspace access and walkability index score synonymously to **Equation (16)**.

IV. RESULTS

A. Household location choice model estimates

(Table II) presents the results for the residential location choice model. Overall, our results are consistent with the literature regarding factors that influence residential location (Lee and Waddell 2010; Bhat and Guo 2007; Pinjari et al. 2011). First, we focus on the two policy tools of interest. As mentioned, the MFT enters the indirect utility function through household commuting costs. We find that households are less attracted to zones that increase their commute costs and even more so for households in the bottom income quantile. The increase in sensitivity to residential location from the bottom income quantile is consistent with the literature suggesting that gasoline tax is a regressive policy (Levinson 2016). Next, we focus on the second policy tool coefficient, public transit accessibility. We find that the interaction effect between household income and accessibility for the bottom three quantiles is negative. Here, the reference level is the highest income quantile and the progression of increasingly negative coefficients, relative to the reference level, shows accessibility correlates with higher household income location preferences. As expected, we find households who commute via public transit to prefer zones with public transit access. This is consistent with the residential self-selection hypothesis that suggests households consider mode preference when choosing a residence (Boarnet 2011; Ewing and Cervero 2010). Plausibly, households who do not commute via public transit are auto-dependent and therefore can live further away from the main roadways traversed by public transit.

Next, we discuss the zonal control variables, starting with zonal land-use structure. The log of the total number of households is positive, showing households are more likely to locate in zones with a larger number of housing units. Households with containing either seniors or children are less likely to live in areas with high housing density. On average, households are more likely to prefer larger lots (average lot size) and households that prefer single family housing are likely to self-select into zones dominated by single family housing units. Intuitively, the remaining households prefer not to live in such zones. The land-use mix coefficient is negative, suggesting that households prefer a low-diversity (i.e. homogeneous) land-use pattern. Pinjari et al. (2007) suggests that this

TABLE II: **Multinomial logistic regression results**

Variable	Parameter	t-stat
Policy Instrument		
Public transit accessibility		
Interacted with first income quartile	-2.394	-4.921
Interacted with second income quartile	-2.120	-6.593
Interacted with third income quartile	-1.044	-2.658
Interacted with household public transit use	1.348	7.656
Total household commute travel cost $(\times 10^{-1})$	-0.825	-5.338
Interacted with first income quartile	-1.098	-6.287
Control Variables		
Zonal Land-Use Structure		
Land-use mix	-0.544	-4.676
Fraction of residential land area	-0.578	-3.783
Fraction of single family housing $(\times 10^{-1})$	-1.077	-6.116
Interacted with household in single family housing	1.510	10.543
Logarithm of number of households in zone	1.120	34.299
Household density interacted with presence of senior in household $(\times 10^{-1})$	-1.098	-3.456
Household density interacted with presence of child in household $(\times 10^{-1})$	-1.679	-5.618
Zonal Real Estate		
Average sale price to income ratio $(\times 10^{-1})$	-0.496	-7.216
Average sale price to income ratio squared $(\times 10^{-1})$	-0.001	4.407
# of houses purchased (2010-2011, $\times 10^{-1}$)	-0.275	-5.109
Interacted with homeowner	0.373	6.779
Average lot size (Sq. Ft., $\times 10^{-3}$)	0.050	4.613
Median housing value $(\times 10^{-5})$	-0.105	-7.113
Zonal Transportation Network		
Street block density (km^2, $\times 10^{-3}$)	0.469	8.614
Interacted with # of vehicles per licenses in household	-0.892	-10.680
Bicycle infrastructure within 15 km $(\times 10^{-2})$	0.418	4.617
Interacted with household bicycle use	0.417	4.617
Walkability index score $(\times 10^{-1})$	-0.518	-8.871
Zonal Socio-Economics and Demographics		
Absolute difference in household income from zonal median $(\times 10^{-5})$	-1.483	-22.905
Absolute difference in household size from zonal average	-0.519	-12.731
Zonal % same race as head of household	2.396	37.848
# schools with score (> 7) interacted with presence of child in household	0.118	8.410
# of homicides within past 10 years	-0.261	-2.904
Commute-related		
Total household commute drive time $(\times 10^{-1})$	-0.815	-29.084
Absolute difference in household commute length from zonal average $(\times 10^{-1})$	0.14	6.462

Note: All independent variables are significant at the 5% significance level

TABLE III: Logit estimations of policy mix on single policy formulations

1	↑ *MFT Revenue*		↑ *Accessibility*		↑ *Urban Density*	
Variable	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat
Constant	-4.381	-9.714	1.673	3.285	1.625	11.431
TOP	6.239	10.495	466.715	6.551	-6.856	-21.245
MFT	-3.327	-9.417	1.354	6.712	0.337	15.016
TOP * MFT	-0.728	-4.817	8.935	3.200	0.068	4.183
Total $Y = 1$	272		3031		4844	
L	-115.742		-54.830		-600.655	
L_{null}	-1117.07		-4306.695		-3280.921	
$R^2_{McFadden}$	0.896		0.987		0.817	

Note: The dependent variable is classified a success if we observe a percentage increase from the baseline simulation. All variables are in terms of a percentage change from the baseline. TOP: Transit Operations Provision; MFT: Motor Fuel Tax.

finding may be a structural artifact of both zoning policies and zone definition strategies.

Third, we discuss zonal real estate variables. Here, we find evidence that households living in a single family detached housing prefer zones with a high number of single-family housing sales. The coefficient for the zonal average sale price to income ratio and its squared term is negative - implying that households prefer relative affordability. Similarly, we find households to prefer zones with low median housing values and a low number of housing sales. The latter finding could imply a disutility from locating in rapidly developing zones or zones with a high neighborhood turnover rate.

Next, we focus on the five remaining zonal transportation network variables. Overall, we find that households prefer zones are driveable but not walkable or bikeable. These findings are consistent given Atlanta's urban form - auto dependent, low density, and a large land area. We find that households with high vehicle availability (a high vehicle to license ratio) are more attracted to zones with low street density. This is most likely capturing an attraction to suburban areas. Reasonably, we observe households that commute on a bicycle to prefer zones with high bicycle accessibility.

Next to last, zonal socio-economic and demographic variables. We find that households prefer homogenized zones in which they align with the median household income and median household size. Households prefer zones with similar ethnic groups and low crime, and households with children prefer zones with high quality schools.

Finally, households have an aversion to zones that increase commute time. Interestingly, we find a positive effect for households whose average commute distance deviates from the zonal average commute distance. This implies that it is not absolute zonal characteristics that attract households of a certain commute-preference profile, but it is the household who desires zones with relatively low commuting costs.

B. Simulation results

1) Policy Tool Tradeoffs: In this section, we review the results from the tradeoff analysis. **(Table III)** reports the binary logistic regression model estimates. These are the effects of the policy mix on the single-policy success-criteria formulation. As mentioned, we classify a policy goal as a success if the simulation scenario performs better than the baseline scenario. Both policy tool and policy goal variables are in terms of a percentage change from the baseline scenario. We find that increases in transit operations correlate with higher MFT revenue, accessibility, and urban sprawl. Increases in MFT see a lower MFT revenue but with higher accessibility and urban compactness. Finally, increases in both policies interact to reduce MFT revenue and increase accessibility and urban density.

Both policy effects on MFT revenue are similar in relative magnitude. This implies that one policy could offset the change in the other. When considering public transit accessibility, however, the MFT level has less influence on changes in household location preference compared to changes in the provision of transit operations. The same holds for changes in urban density. We consider that 272 out of the total $6,216$ simulations satisfy the increase in MFT revenue, roughly 4% of the simulated solution space. Approximately 49% of the simulation solutions successfully increase accessibility and 78% increase urban density. Comparing these percentages, we find a wider variation amongst policy mix configurations that encourage households to prefer more accessible or more compact locations.

Second, we report the estimated effect of the policy mix on the two-policy success-criteria formulation; see **(Table IV)**. In the first column, we find increases in transit operations corresponds with a joint increase in MFT revenue and accessibility, and increases in MFT correspond with a joint decrease. From their interaction term, we observe that transit operations must increase as MFT grows large to stay in the solution space. However, the counteracting effect of transit operation occurs at a diminishing rate. We report the diminishing effectiveness of increases in transit operation in **(Figure 2)**. The top right corner is a scenario that maximizes MFT revenue and accessibility. Here, we see a maximum increase in transit provision. However, the maximum allowable MFT remains far below the modeled range, approximately only a $0.15 increase.

In the second column, we find that MFT revenue and urban density decline with an increase in MFT. Both the transit operations and the interaction term coefficients are not distinguishable from zero. This means that adjusting transit operations is not a useful policy tool in influencing households towards a compact, MFT revenue generating city. We contrast this with the single policy case where increases in transit operations significantly reduce urban density and increases in MFT revenue. This contradiction neutralizes transit provision as a useful policy tool.

The third column finds that provisional changes in transit operations have no joint effect on accessibility and urban density. **(Table III)** reports that the effects of transit operations on accessibility and on urban density are significant with opposing coefficient signs. These factors contribute to a counterbalancing effect in the joint two-policy success-criteria formulation. **(Figure 3)** displays this counterbalancing effect by plotting solutions of the joint accessibility and urban density two-policy success-criteria formulation annotated by the policy mix. The figure shows that increases in transit operations leads to higher levels of accessibility but also reduces urban density. Thus, the MFT must also increase to simultaneously cause an increase in urban density to counteract this effect. We find complementary evidence reported by the significant and positive coefficient of the interaction effect in **(Table IV)**. This implies that policymakers should use caution when increasing transit operations without a corresponding increase in MFT as this may cause urban sprawl.

Just as in the single policy case, we find that the magnitude of the policy tool coefficients on joint increase in MFT revenue and accessibility are similar. However, when looking at a joint increase in MFT revenue and urban density, the MFT level is larger. Out of the 6,216 simulations: 241 (3.8%) jointly increase MFT revenue and accessibility, 15 (0.2%) jointly increase MFT revenue and urban density, 1,676 (27.0%) jointly increase accessibility and urban density. This implies a greater flexibility for policy mix configurations that influence households toward a compact, accessible city with MFT revenue losses.

Third, we consider a three policy success-criteria formulation. Here, we classify a policy goal as a success for a joint increase in tax revenue, accessibility, and urban density. For this classification, we did not observe any policy mix to satisfy these criteria at the regional scale.

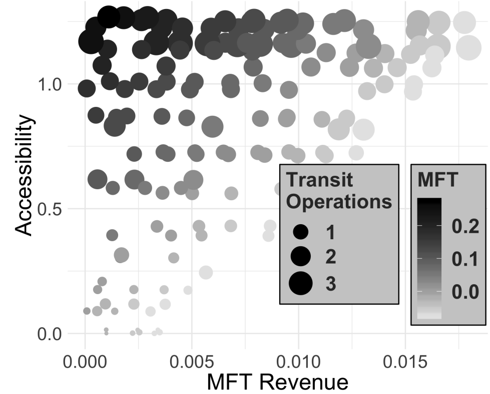

Fig. 2: Satisfying Solutions for Joint MFT Revenue and Accessibility Formulation Note: Solutions of the joint MFT revenue and accessibility two-policy success-criteria formulation annotated by the policy mix. MFT is in terms of dollars. Transit Operations is in terms of percent increase $(\times 10^{-2})$ in operations provision. See **Equation (13)** for details on Transit Operations.

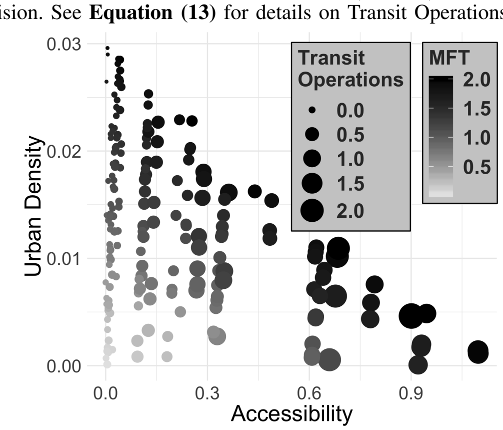

Fig. 3: Satisfying Solutions for Joint Accessibility and Urban Density Formulation Note: Solutions of the joint accessibility and urban density two-policy success-criteria formulation annotated by the policy mix. MFT is in terms of dollars. Transit Operations is in terms of percent increase $(\times 10^{-2})$ in operations provision. See **Equation (13)** for details on Transit Operations.

C. *Consequences of Aggregation*

(Table V) reports binary logistic regression model estimates of the policy mix on the trilemma policy success-criteria formulation at the block, tract, and county scales[1]. As mentioned, we classify a policy goal a success if the simulation scenario performs better than the baseline scenario. We preform the analysis across four levels of scale, the block, tract, county, and metro area.

[1]All blocks, tracts, and counties that contain no successes are excluded from the estimation

TABLE IV: Logit estimations of policy mix on dilemma policy formulations

	↑ *MFT Revenue* ↑ *Accessibility*		↑ *MFT Revenue* ↑ *Urban Density*		↑ *Accessibility* ↑ *Urban Density*	
Variable	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat
Constant	-4.443	-10.037	-6.889	-6.257	-1.869	-30.722
TOP	6.133	10.359	-0.032	-0.030	-0.081	-1.441
MFT	-2.103	-7.497	-2.386	-3.787	0.065	16.562
TOP * MFT	-1.166	-6.437	0.104	0.170	0.029	7.802
Total $Y = 1$	241		15		1676	
L	-112.602		-57.383		-3353.355	
L_{null}	-1019.537		-105.384		-3623.227	
$R^2_{McFadden}$	0.890		0.455		0.075	

Note: The dependent variable is classified a success if we observe a percentage increase from the baseline simulation. All variables are in terms of a percentage change from the baseline. TOP: Transit Operations Provision; MFT: Motor Fuel Tax.

We find that increases in transit operations is on average associated to meeting the solution criteria. Specifically, a 100% increase in the transit operations cost is associated with a block being exp(0.176) = 1.192438 times more likely to meet the trilemma criteria. Similarly, a one dollar increase in the motor fuel tax is associated with a block being exp(0.453) = 1.57 times more likely to meet the trilemma criteria. The marginal effect is not directly interpretable for the interaction term. Together, these findings suggest the success criteria is satisfied by both an increase in MFT and TOP. However, as we aggregate from block to tract and tract to county we find that the effect of motor fuel tax on success inverts and the interaction term becomes less significant. These findings imply a heterogenous and nonlinear effect of the MFT across the census blocks.

To further investigate this phenomena, we include plots at each level of scale which displays the proportion of successes for each area over the 6,216 scenarios. From Figure (4), we again find significant heterogeneity. The majority of high success blocks ($> 50\%$) are located within suburban communities along the major corridors of the Atlanta metro area. The rural areas which do not have public transit access are unable to achieve any level of success. While the downtown Atlanta area did achieve a moderate level of success, we find it less than the surrounding suburban communities. This supports evidence from Table (V), where we find that an increase in MFT is associated with a higher probability of success. Together these evidence suggest a path that simultaneously satisfies an increase in density, increase in MFT revenue, and increases transit accessibility should seek to drive households to suburban centers.

A well known issue among demographers in the modifiable areal unit problem (MAUP). Simply the MAUP is statistical bias that occurs when aggregating data within spatial boundaries. We visualize the consequences of the MAUP in Figure (5) and Figure (6). Here we find diminishing levels of success for the aggregated areal units. At the regional level we found zero successful simulations. This implies that the trilemma deterministically exists at the level of the metro area but is stochastic at the level of an individual block. In other words, a policymaker can successfully achieve increases in MFT revenue, density, and access for certain blocks but cannot at the metro level.

Returning to **(Table V)**, we also find effects of the MAUP within the scenario discover procedure. Recall, the MFT inverts sign and increases in magnitude across aggregation. This results suggests that decreases in MFT is associated with higher probabilities of success. This is a consequence of Arrow's impossibility theorem which states that in the presence of aggregation, certain units - in this case census blocks - will disproportionately influence the aggregated outcome.

V. IMPLICATIONS FOR POLICY

In this section, we discuss the significance of our results for policy. First, transportation policy mix significantly influences residential location preferences. Second, residential location preferences significantly affect changes in MFT revenue, public transit accessibility, and urban density. Third, we cannot find a regional solution satisfying all three policy goals. These findings suggest that households update their location preference to counter-act the disutility resulting from increases in MFT and/or changes in transit provision. As a result, policymakers seeking to align policy with preference can only satisfy two out of the three policy objectives regionally. To help guide this policy decision, we suggest choosing acceptable levels of loss for both primary and secondary policy goals. Once defined, we recommend selecting one of two policy pathways that properly align

TABLE V: Logit estimations of policy mix on trilemma policy formulation across scale

	Block		Tract		County	
Variable	Parameter	z-test	Parameter	z-test	Parameter	z-test
Constant	-3.249***	-61.483	-4.425***	-67.659	-6.042***	-8.433
TOP	0.176***	103.004	1.921***	308.210	0.407***	2.783
MFT	0.453***	271.282	-0.290***	-48.897	-12.519***	-4.750
TOP * MFT	0.080***	55.944	-0.011**	-2.227	1.853	1.482
Obs.	7,061,376		2,119,656		30,080	

Note: The dependent variable is classified a success if we observe a percentage increase from the baseline simulation. All variables are in terms of a percentage change from the baseline. TOP: Transit Operations Provision; MFT: Motor Fuel Tax.

the policy mix with residential location preferences and policy goals.

The findings are important for two reasons: First; they are particularly relevant for land use-transportation policymakers. Household preferences do support concurrent increases in MFT revenue, transit accessibility, and urban density but not at a metro level of analysis. Policymakers must define the order of importance for their policy goals and the acceptable level of loss at the aggregate for the sake of improving targeted areas. Our simulations illustrate the importance of these decisions being made at the appropriate scale, that is, the finer the better.

First, policymakers who find it desirable to generate MFT revenue and transit accessibility should choose a policy strategy that influences the household to prefer locations that raise their total travel cost. To increase expected total travel cost, the policy mix should incentivize suburban desirability. An expansion of transit accessibility can contribute to suburban desirability (i.e. urban sprawl) in two ways. (1) Expanding transit provision in suburban areas influences those who prefer locations with high accessibility to consider locations further outside the city. (2) Extending transit provision in urban areas repels transit-avoidant households further outside the city. In our study, we find that a greater population comprises the latter group. Therefore, we suggest extending urban transit provision.

Additionally, we find a reduction in MFT contributes to suburban desirability. Although a reduction in MFT will reduce the amount of revenue per gallon, the increase in total gallons consumed will more than offset these losses leading to an expected increase in MFT revenue. Further, a reduction in MFT will disproportionately benefit lower income households. As a result, to align the goal of raising MFT revenue and accessibility with the policy mix, incentivizes should lead households to contribute to urban sprawl. Unfortunately, greater urban sprawl to associate with increased road-traffic fatalities and worsened walkability scores per capita. Although, suburban living associates with reductions in noise pollution exposure and increases in greenspace accessibility.

Second, policymakers wishing to develop a compact, accessible city face falling MFT revenues. These policymakers should expand suburban transit accessibility and raise the MFT. This policy mix will (1) acclimate suburban households to transit use and (2) incentivize moving to urban locations to reduce travel cost. However, this may lead households who prefer highly accessible zones to move to less dense housing - i.e. high income and transit dependent households. Although, from our results, we expect the tradeoff to be net-positive. Compact, accessible cities help reduce road-traffic fatalities and encourage walkable locations but also lead to reduced access to greenspace and greater exposure to noise pollution.

Policymakers who find it desirable to generate MFT revenue and urban density should reduce MFT and public transit provision. This incentivizes households who commute on public transit towards auto-dependency and attract transit avoidant households to more dense locations. However, our results emphasize that policymakers should avoid this path. Very few solutions can satisfy the policy goal constraints, and the narrow set of solutions implies a high risk of failure. Further, this policy agenda has the worst performance on secondary policy goals, increasing road-traffic fatalities and noise pollution exposure and sometimes leading to reductions in greenspace accessibility and walkability.

VI. CONCLUSION

By aligning policy with preference, planners can avoid the risk of mismatching policy tools and policy goals. This paper seeks to align policy with preference by uncovering the influence of residential location preference on motor fuel tax revenue, public transit accessibility, and urban compactness. We discover that policy changes provoke a reaction in residential location preferences, which leads to contradictions between policy tools and these three policy goals. Aware of these tradeoffs, an integrated policy mix suggests using motor fuel tax and

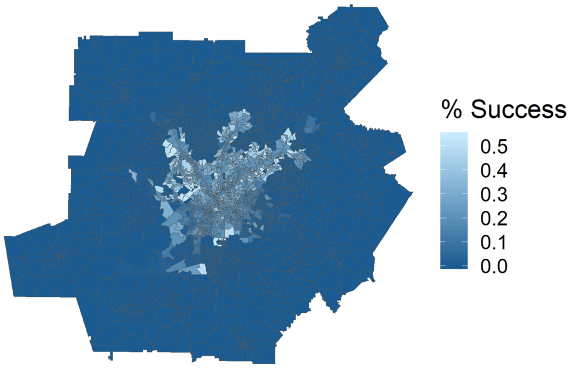

Fig. 4: Percentage of Satisfying Solutions at Block Level

Note: For example, a 50% success rate implies that block j satisfied the success conditions for 0.5*6,216 = 3,108 scenarios.

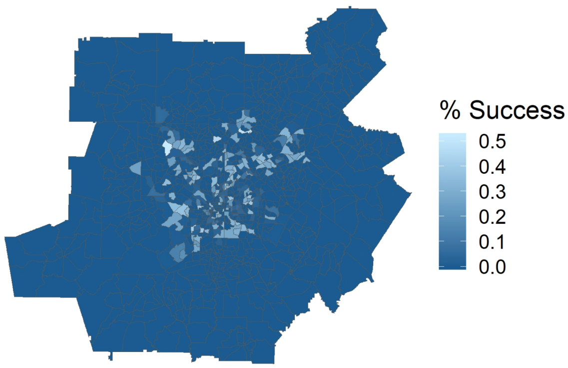

Fig. 5: Percentage of Satisfying Solutions aggregated to Census Tract

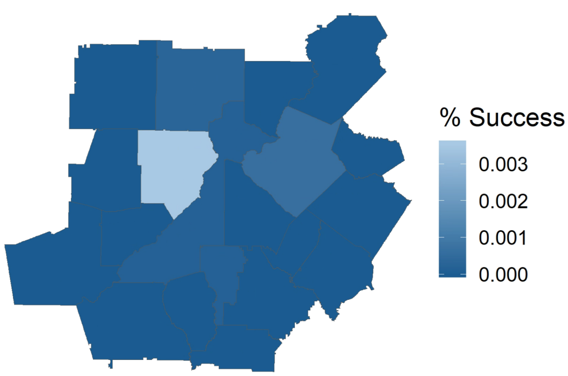

Fig. 6: Percentage of Satisfying Solutions aggregated to County Tract

public transit policy to influence households to either a more compact, accessible city or a more sprawled, revenue-generating city. There is an intuition for each of these scenarios: cities with low urban density expect a higher travel cost per capita raising the expected tax revenue and a more compact city can achieve a higher rate of accessibility at a lower operation cost relative to its less dense counterpart.

The findings are important for two reasons: First; they are particularly relevant for land use-transportation policymakers. Household preferences do not support concurrent increases in MFT revenue, transit accessibility, and urban density. Policymakers must define the order of importance for their policy goals and the acceptable level of loss for each outcome. Our simulations illustrate the importance of these decisions ranging from small matters - amenities and comfort - to more significant matters - health and well-being.

Second, the findings contribute to an expanded research agenda, one that combines location and travel (Boarnet 2011). By comparing residential location preference, MFT, transit accessibility, and urban density within a single framework, we place the interactions between urban policies at the forefront of analysis. Studying the interactions within policy bundles and their corresponding interactions with households promises to enhance our understanding of the greater urban policy context.

AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows: study conception and design, data collection, analysis and interpretation of results: Sprague, C. Editorial and draft manuscript preparation: Gao, H.O. All authors reviewed the results and approved the final version of the manuscript.

REFERENCES

[1] R. A. Acheampong and E. Silva. “Land use–transport interaction modeling: A review of the literature and future research directions”. *Journal of Transport and Land Use* (2015), pp. 11–38. DOI: 10.5198/jtlu.2015.806.

[2] C. Bhat and J. Y. Guo. “A comprehensive analysis of built environment characteristics on household residential choice and auto ownership levels”. *Transportation Research Part B: Methodological* 41.5 (2007), pp. 506–526. ISSN: 01912615. DOI: 10.1016/j.trb.2005.12.005.

[3] M. Boarnet. “A broader context for land use and travel behavior, and a research agenda”. *Journal of the American Planning Association* 77.3 (2011), pp. 197–213. ISSN: 01944363. DOI: 10.1201/9781315152431.

[4] D. Brownstone. “Key relationships between the built environment and VMT”. *Transportation Research Board* 7 (2008).

[5] L. Davis and C. Knittel. “Are Fuel Economy Standards Regressive?” *NBER WORKING PAPER SERIES* December (2016). URL: http://www.nber.org/papers/w22925.

[6] R. Ewing and R. Cervero. “Travel and the built environment”. *Journal of the American Planning Association* 76.3 (2010), pp. 265–294. ISSN: 01944363. DOI: 10.1080/01944361003766766.

[7] S. Handy. “Thoughts on the Meaning of Mark Stevens’s Meta-Analysis”. *Journal of the American Planning Association* 83.1 (2017), pp. 26–28. ISSN: 01944363. DOI: 10.1080/01944363.2016.1246379. URL: https://www.tandfonline.com/doi/full/10.1080/01944363.2016.1246379.

[8] B. Lee and P. Waddell. “Residential mobility and location choice: a nested logit model with sampling of alternatives”. *Transportation* 37 (2010), pp. 587–601. DOI: 10.1007/s11116-010-9270-4.

[9] A. Levinson. “Energy Efficiency Standards Are More Regressive Than Energy Taxes: Theory and Evidence”. *NBER Working Paper* (2016). DOI: 10.3386/w22956. URL: http://www.nber.org/papers/w22956.pdf.

[10] F. H. Liao, S. Farber and R. Ewing. “Compact development and preference heterogeneity in residential location choice behaviour: A latent class analysis”. *Urban Studies* 52.2 (2015), pp. 314–337. ISSN: 1360063X. DOI: 10.1177/0042098014527138.

[11] L. Lundqvist. “Land-Use and Travel Behaviour. A Survey of Some Analysis and Policy Perspectives”. *Ejtir* 3.3 (2003), pp. 299–313. URL: http://www.ejtir.tudelft.nl/issues/2003{_}03/pdf/2003{_}03{_}04.pdf.

[12] R. L. Mackett. “Structure of linkages between transport and land use”. *Transportation Research Part B: Methodological* 27.3 (1993), pp. 189–206.

[13] D. McFadden. “Modeling the Choice of Residential Location”. 515.2 (1978), pp. 2003–2003. ISSN: 0361-1981. URL: http://pfwww.kek.jp/acr2002pdf/part{_}b/pf02b256.pdf.

[14] S. Nerella and C. R. Bhat. “Numerical Analysis of Effect of Sampling of Alternatives in Discrete Choice Models”. *Transportation Research Record: Journal of the Transportation Research Board* 1894.1 (2007), pp. 11–19. ISSN: 0361-1981. DOI: 10.3141/1894-02.

[15] A. R. Pinjari et al. “Modeling residential sorting effects to understand the impact of the built environment on commute mode choice”. *Transportation* 34.5 (2007), pp. 557–573. ISSN: 00494488. DOI: 10.1007/s11116-007-9127-7.

[16] A. R. Pinjari et al. “Modeling the choice continuum: An integrated model of residential location, auto ownership, bicycle ownership, and commute tour mode choice decisions”. *Transportation* 38.6 (2011), pp. 933–958. ISSN: 00494488. DOI: 10.1007/s11116-011-9360-y.

[17] S. E. Polzin, R. M. Pendyala and S. Navari. “Development of Time-of-Day–Based Transit Accessibility Analysis Tool”. *Transportation Research Record: Journal of the Transportation Research Board* 1799.1 (2007), pp. 35–41. ISSN: 0361-1981. DOI: 10.3141/1799-05.

[18] J. D. Quinn et al. “Exploring how changing monsoonal dynamics and human pressures challenge multireservoir management for flood protection, hydropower production, and agricultural water supply”. *Water Resources Research* 54.7 (2018), pp. 4638–4662.

[19] G. Santos, H. Behrendt and A. Teytelboym. “Part II: Policy instruments for sustainable road transport”. *Research in Transportation Economics* 28.1 (2010), pp. 46–91. ISSN: 07398859. DOI: 10.1016/j.retrec.2010.03.002. URL: http://dx.doi.org/10.1016/j.retrec.2010.03.002.

[20] A. Schäfer et al. *Transportation in a climate-constrained world*. MIT press, 2009, pp. 251–252.

[21] P. Waddell. “Integrated land use and transportation planning and modelling: Addressing challenges in research and practice”. *Transport Reviews* 31.2

(2011), pp. 209–229. ISSN: 01441647. DOI: 10.1080/01441647.2010.525671.

[22] P. Wagner and M. Wegener. “Urban Land Use, Transport and Environment Models: Experiences with an Intergrated Microscopic Approach”. *The Planning Review* 43.170 (2007), pp. 45–56. ISSN: 0251-3625. DOI: 10.1080/02513625.2007.10556988. URL: http://www.spiekermann-wegener.de/pub/pdf/PWMW{_}ILUMASS.pdf{\%}0Ahttp://www.tandfonline.com/doi/abs/10.1080/02513625.2007.10556988.

[23] M. Wegener. “From macro to micro-how much micro is too much?” *Transport Reviews* 31.2 (2011), pp. 161–177. ISSN: 01441647. DOI: 10.1080/01441647.2010.532883.

[24] T. Weidner et al. “Sensitivity Testing with the Oregon Statewide Integrated Model”. *Transportation Research Record: Journal of the Transportation Research Board* 2133.1 (2010), pp. 109–122. ISSN: 0361-1981. DOI: 10.3141/2133-12.

[25] C. Winston. “On the performance of the US transportation system: Caution ahead”. *Journal of Economic Literature* 51.3 (2013), pp. 773–824.