Mapping transport policy scenarios

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ABSTRACT

Most statistical analyses do not report location-specific results, making it impossible for policymakers to use these studies to identify which locations will benefit most from policy interventions. We aim to fill this gap by focusing on the location-specific predictions from a discrete choice analysis of location and transport choices in New York City. We simulate transport policy and investment scenarios, and use GIS to map their predicted effects. Every scenario produces a highly-differentiated spatial pattern of response. It is not only *possible* to show how statistical results vary across a landscape, but it can be misleading *not* to do so.

KEYWORDS: GIS, New York City, discrete choice

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INTRODUCTION

“LOCATION, LOCATION, LOCATION!!!” scream the real estate ads, especially for fixer-uppers near the center of town. Location determines access to jobs, services, recreation, and transit. Location determines who neighbors are. Policies such as zoning changes or parking regulations are implemented according to location. City investments in infrastructure differ by location. Individual travel choices are inextricably linked to transport options at two locations – the trip origin and destination.

Research aiming to inform transport policy often uses statistical models estimated from survey data. Results of these models are usually expressed as though they were uniform across the city landscape, represented by a single coefficient or marginal effect estimate; the spatial heterogeneity that is central to much of on-the-ground urban transport policy is ignored.

This paper demonstrates that it is not only *possible* to express statistical results that vary across a city's landscape, but also that it can be misleading *not* to do so. New York City is used as a case study of the spatial dimensions of behavioral response to transport policy change. We estimate a joint discrete choice model of New Yorkers' choices of residential neighborhood, car ownership status, and commute transport mode, and link this model to a GIS database. This allows us to calculate location-specific results and simulate location-specific policy scenarios. Changes to policy that are implemented both uniformly across the city and differentially across city neighborhoods are simulated.

The discrete choice model estimated for the policy scenarios presented in this paper is quite complex, but GIS can be combined with much simpler statistical models. The main requirement to create a tool that can simulate location-specific scenarios is that the data must be spatially referenced so that the results can be displayed on a map. Because data used to analyze transportation choices is usually spatially referenced and many analysts already use GIS to highlight spatial heterogeneity in their data, providing location-specific results is often a relatively simple extension of existing work.

The paper begins with a brief description of discrete choice methodology and the data used in model estimation. Results are displayed both in a standard table of estimated coefficients and using maps – maps illustrating the discrete choice results by neighborhood are shown alongside maps of the underlying data. Then, seven scenarios of changes to the New York transport system are simulated and the predicted behavioral responses are mapped. The first four scenarios are of changes to the transport system implemented uniformly across the city. The following three scenarios are location-specific. The final section concludes the paper.

CONCEPTUAL BACKGROUND, DATA, AND METHODOLOGY

This paper uses a discrete choice analysis to gain insight into how New Yorkers make decisions simultaneously about where to live and how to travel. Discrete choice demand models are distinct from continuous choice demand models in that the dependent variable can take only discrete values. Random utility theory forms the basis for the multinomial logit discrete choice model estimated here (see Train (2002) or Ben-Akiva and Lerman (1985) for details on logit model theory).

The discrete choice model that is the base for the spatial analysis in this paper is similar to prior applications, including Lerman (1976), Train, (1980), Anas (1982), and Quigley (1985). One aspect that these older studies have in common with the present application is a compound choice set, meaning that each alternative in the choice set is composed of more than one sub-choice alternative. In the present analysis, each element of the compound choice set contains one commute mode alternative, one car ownership status alternative, and one residential location alternative as defined by a census tract. For example, one alternative is {walk to work, own zero cars, live in census tract 23}, and a separate alternative would be {walk to work, own one car, live in census tract 23}.

The main data source used to estimate the discrete choice model is the Regional Travel-Household Interview Survey (RT-HIS), conducted in the fall of 1997 and the spring of 1998 by NuStats International and jointly commissioned by the New York Metropolitan Transportation Council and the North Jersey Transportation Planning Authority. Households completed both a 24 hour travel diary on an assigned day and a lengthy telephone interview that collected information about their socioeconomic situation, their residential location choice, and their travel habits. Since the present analysis focuses on New York City proper, it uses survey responses from the 2,728 commuters living in New York City for whom there were not missing data.

The RT-HIS data set provides the individuals doing the choosing in the model – the dependent variables – as well as most of the independent variables used to explain the travel mode sub-choice and some of the independent variables used to explain the car ownership and residential location sub-choices. The rest of the independent variables come from a variety of other data sources including the US Decennial Censuses of 1990 and 2000, the 1997 Business Patterns Census, the New York State Insurance Department (2004), the New York City Department of City Planning (2004), and New York City Transit (2005).

Before discussing the location-specific scenario analysis, a few details of the model estimation methodology warrant mention. First, in the discrete choice estimation that underlies this paper, households were weighted by residential neighborhood, following the methodology described in Manski and Lerman (1977).

Second, in choice models that have compound choice sets such as this one, the number of alternatives in the choice set is this number of residential location alternatives multiplied by the number of car ownership status alternatives and commute mode choice alternatives. A full choice set for the present model would thus have more than 40,000 alternatives. To reduce the choice set to one that is computationally manageable, this paper follows McFadden (1978) by taking a random sample of 11 of the residential location sub-alternatives. The estimated choice set has 220 alternatives: 11 residential locations, 3 car ownership levels, and 7 commute modes.

Finally, a note about our choice to estimate a multinomial logit model rather than a nested logit model. The nested logit model relaxes a major assumption of the multinomial logit – the assumption of Independence of Irrelevant Alternatives (Train (2003) provides an excellent explanation of this econometric issue). Whenever a compound choice set is modeled with a multinomial logit, there is reason to suspect that this assumption is violated and the model results may therefore be biased. In addition to estimating the multinomial logit model presented here, we also estimated nested logit versions of this model and compared them statistically. In all cases, the multinomial logit model results were not significantly different from the nested logit model results.

Further details about both the data set used here and the estimation methodology are available in Salon (2006).

[TABLE 1 ABOUT HERE]

Table 1 provides the estimated coefficients from the discrete choice model. The model includes variables that are thought to affect New Yorkers' decisions about which neighborhood to live in, whether to own a car, and how to travel around the city. Economic theory guides the choice of variables to include in the model to explain each of these choices. Although the choices of location, car ownership, and commute mode are estimated as a single compound choice, Table 1 is separated into three variable sections that correspond to the three sub-choices to aid in comprehension. The remainder of this section provides an overview of the rationale for inclusion of variables in the model.

As in all models of demand, the variables included should represent the income of the individual making the choice, the prices of each alternative, and the prices of the substitutes and complements for each alternative. These prices need not be confined to be money prices alone; time prices can and should be included as well.

To model the choice of transportation mode for a particular trip, then, variables to use in the estimation include the time and money prices of traveling by each mode, the income of the traveler, and perhaps some measure of the relative qualities of service offered by each mode alternative. As expected, the variables in Table 1 corresponding to commute time and cost all have negative effects on the utility of the mode.

In modeling the choice of car ownership status, important variables include the price of owning the car, the income of the potential car owner, the availability of alternative transport modes in his or her residential location, and the access that is afforded by these alternative modes to important destinations. Because the models here do not aim to explain the choice between different vehicle types, but rather the choice of whether or not to own a car, the quality of the car does not enter into the decision. Table 1 shows that car ownership is a more appealing alternative for households with higher incomes, more household members, and who live farther from midtown Manhattan. Higher retail density, population density, and subway availability all reduce the attractiveness of car ownership.

To model the choice of residential location, key variables include the price of a dwelling both in the chosen location and in alternative locations, the income of the potential resident, the access afforded by the chosen and alternative locations to important destinations, and other measures of the quality of the neighborhood. These measures of neighborhood quality could include attributes of the people who already live there such as their race, income, and whether they own their homes. Most people prefer to live in neighborhoods where they “fit in”, and fitting in means matching the racial makeup of the area and having a similar economic status as the neighbors. Researchers have hypothesized that neighborhoods with higher percentages of home owning households are better cared for, and therefore are more desirable residential neighborhoods. Table 1 shows that households choose to live in neighborhoods with lower rent-to-income ratios (given household income), higher median incomes and population densities, and where they are similar in terms of race, income, and housing tenure.

GETTING TO LOCATION-SPECIFIC RESULTS

The model results include not only the estimated coefficients for the utility function shown in Table 1, but also estimates for each individual of the probability that each alternative is chosen. These probabilities can be averaged by neighborhood to create maps that illustrate the spatial heterogeneity of the model results. All of the maps in this paper that illustrate model predicted probabilities are those probabilities that are conditional on residential neighborhood choice.

The simulation methodology used in the scenarios is straightforward. First, the predicted probabilities of car use for commuting from the model are saved. Second, we alter the data to reflect each scenario. Third, the new predicted probabilities are calculated using the original model's coefficients and the altered data set. Finally, the change in the probabilities predicted by the model is calculated for each individual and expressed as an absolute percentage point change. These percentage point changes in the probabilities of car commuting are then averaged over neighborhoods and these values are displayed on the scenario maps.

Note that the maps illustrate percentage point changes and not percent changes. This makes interpretation straightforward because it is not dependent on the initial commute mode shares. The mapped percentage point changes should be interpreted as the neighborhood-level changes in market share for the relevant commute mode.

A note about neighborhood identification

There is no single correct way to identify the boundaries of neighborhoods for use in statistical analysis, partially because the concept of "neighborhood" is actually different depending on who is conceptualizing it and why. Even if the researcher has a clear concept of neighborhood for her application, drawing boundaries is not straightforward. Many analysts simply use census tract boundaries. For our location-specific scenario analysis, however, census tracts cannot be used because many were simply not sampled in the survey.

The 51 neighborhoods used here are actually contiguous groups of census tracts identified to have similar attributes through cluster analysis. The attributes used in the cluster analysis were the geographic coordinates of the tract plus the principal components extracted from the following ten variables: median income, median house value, rent per room, percent homeowners, percent white, subway lines, cars per housing unit, population density, employment density, and retail establishment density. For more detail on the neighborhood boundary identification process, see Salon, 2006.

WHEN IS LOCATION-SPECIFIC ANALYSIS USEFUL?

There are three important conditions that must hold in order for location-specific analysis to be both useful and defensible. First and foremost, there must be a desire to understand the location-specific implications of policy. There are at least two reasons this could be important – to highlight differential incidence of a policy to understand equity implications or to implement policies only in locations where they are most likely to be effective. Second, each location must have enough sampled individuals in the dataset that the results are likely to be robust. Finally, location-specific model predictions must be tested and shown to match the actual data with reasonable accuracy.

In the case of the model estimated here, all but five of the neighborhoods include at least 10 observations, and most of them have at least 20 observations. For a single neighborhood in a sparse area of this dataset, then, the results of the scenario analyses presented in this paper are not reliable. However, as will become clear, the spatial pattern of results does seem to be robust. To demonstrate this point, we use GIS to compare the model prediction in each neighborhood to the underlying data, starting with a comparison of commute mode choices and continuing by comparing car ownership choices.

[FIGURE 1 ABOUT HERE]

Figure 1 illustrates the actual and predicted percent of commuters in each neighborhood in NYC who commute by car. The map on the left side of Figure 1 shows the spatial distribution of car commuting as reported by respondents to the RT-HIS. The map on the right side of Figure 1 shows the probability of commuting by car in each neighborhood of New York as predicted by the model. The spatial pattern of the predicted percent of commuters using cars from the model is quite close to that in the underlying RT-HIS data. This provides evidence that the discrete choice model results are valid not only in aggregate, but also when they are spatially disaggregated to the neighborhood level.

[FIGURE 2 ABOUT HERE]

Much of the interpretation of the location-specific results in the scenarios that follow is related to access to New York’s subway system. Figure 2 provides a map of subway lines in New York for reference.

SIMULATIONS OF UNIFORM CHANGES ACROSS LOCATIONS

Even changes in the transportation-land use system that are not location-specific illicit behavioral responses that are far from uniform across a cityscape. Here, we explore four scenarios of spatially-uniform changes in the transportation system, mapping behavioral responses by neighborhood to show the extent of this spatial heterogeneity.

There are actually two types of “spatially-uniform” scenarios one might envision – uniform percent changes in variables of interest and uniform absolute changes in variables of interest. Half of the scenarios discussed here are of each type. Though none of these scenarios represent policy proposals that are currently being considered, it is instructive to explore the model predictions for spatially-uniform "policies" before attempting to model more complex real-world policies (in the next section).

A 25% increase in car travel cost versus a 25% increase in car travel time

The first two scenarios are a 25 percent increase in the cost of commuting by car and a 25 percent increase in the commute time by car. This level of cost increase has more than become a reality over the past few years, as gasoline prices have approximately doubled. The commute time increase also reflects reality as traffic congestion increases over time in New York due to increased decentralization of jobs and residences. Decentralization causes increased traffic congestion for two reasons. First, people have physically greater distances to travel. Second, public transportation systems are less effective at providing access in decentralized land use settings, forcing more people to rely on cars for commuting.

When the travel cost for the car mode is increased by 25 percent, our analysis predicts that the mode share of cars for commuting will fall by 3.2 percent overall. When the travel time for the car mode is increased by 25 percent, our analysis predicts that the mode share of cars for commuting will fall overall by 2.2 percent overall. As illustrated in Figure 3, however, location-specific responses to both of these scenarios are far from uniform.

[FIGURE 3 ABOUT HERE]

Commuters living farther from the central business district (CBD) are more likely to switch away from commuting by car in response to percent changes in the cost of car commuting. The reason for this is twofold. First, car commuters living farther from the CBD have higher travel costs than those living closer to the CBD. This means that the percent change in car travel cost will be a larger absolute change in car travel cost for commuters living farther from the CBD. The second reason for this difference is that car commuters living farther from the CBD are likely to be less constrained in their mode choice than car commuters living closer to the CBD. If someone living close to the CBD in New York City is commuting regularly by car – where transit is inexpensive and convenient – she likely faces a hard constraint that practically forces her to do so. For example, she might be a doctor and have a schedule that requires her to work long hours and to commute at times when transit is infrequent. Or perhaps she must pick up her child at a daycare center that is on a different transit line than the one she would take to get to work. Relatively small changes in travel cost are not likely to affect the decisions of these commuters. A car commuter living farther from the CBD may be choosing to drive simply because it is marginally more convenient, and may therefore be more sensitive to increases in car commute cost.

As car commute time rises, commuters living farthest from Manhattan's business district switch away from their cars and toward transit commuting. In this scenario, the explanation for the spatial pattern is not that car commuters living farther from the CBD initially have higher travel times. They do not. The spatial heterogeneity here is entirely explained by the difference in constraints that car commuters in different areas of the city face.

$1 increase in car commute cost

This third scenario is a $1 absolute change in the cost of commuting by car for all locations. It is hard to envision a policy that would actually make this happen, but it is useful to compare this scenario with that of a 25 percent increase in car commute costs. Here, everyone is impacted equally regardless of their initial level of car commute cost. The average predicted response to this increase in car commute cost is a 5.5 percentage point decrease in car use for commuting. As is clear from Figure 4, however, commuters in locations that are farther from the CBD are predicted to be much more sensitive to this change than the average.

[FIGURE 4 ABOUT HERE]

A doubling of transit headways

The final spatially-uniform change simulated here is a doubling of transit headways. This means that buses and trains would arrive at half their current frequency, doubling transit waiting times. With transit ridership as high as it is in New York City, this is not a likely future scenario for the city. Unfortunately, it is representative of a national trend that we have been seeing over the past few decades as transit has been losing market share to the private auto, sometimes forcing transit operators to reduce service levels. It is therefore interesting to look at the effect such a change might have on the commute mode decisions of New Yorkers.

Transit headways in the data used for this model vary by time of day, but not by location. Doubling them should therefore be thought of as an absolute rather than a relative change to the transport system. The average predicted effect of this scenario is to reduce transit market share by 5.3 percentage points, increase car market share by 3.4 percentage points, and increase walk market share by 1.6 percentage points.

Figure 5 illustrates the predicted location-specific impact of a doubling of transit headways. In the previous scenarios, the simulated change affected the car mode. Because transit is the main substitute for the car, maps illustrating only the changes in car commuting are shown in this paper. Illustrating the change in transit commuting would simply be the same maps with the labels having the opposite signs. Here, however, the simulated change directly affects transit, and both the car and walking are close substitutes for transit, depending on which part of New York you look at. To fully depict the change in behavior, then, we need to display three maps that represent the changes in transit use, car use, and walking for commuting.

As depicted in the left-most map in Figure 5, the increase in car commuting in the lower half of Manhattan is small despite the fact that this same area is where the largest decrease in transit commuting takes place (see the center map in Figure 5). The reason for this becomes clear by looking at the right-most map in Figure 5, which shows a large increase in the percent of commuters who arrive at work on foot in the lower half of Manhattan.

SIMULATIONS OF LOCATION-SPECIFIC SCENARIOS

Looking at spatially-uniform changes in the transportation-land use system is appealing for its methodological simplicity as well as the relatively straightforward interpretation of its results. However, many important changes to the transportation-land use system in the real world are location-specific. This section of the paper identifies and simulates two such changes for New York, both of which are scheduled for implementation in the near future.

Congestion pricing in New York City

New York recently completed its PlaNYC, a sustainability plan for the city from 2007-2030. Following in London’s footsteps, the transport piece of the plan includes implementation of congestion charging for Manhattan below 86th Street. Under the plan, this means that every car entering this area between 6 am and 6 pm will pay an $8 charge, and every car making a trip that originates in the area will pay $4. Politically, this plan may or may not be implemented as proposed; the policy scenario simulated here is as originally proposed by the Mayor.

[FIGURE 6 ABOUT HERE]

Our analysis predicts that this policy will reduce aggregate car market share for the commute trip by 7 percentage points for impacted New York residents. As has been the case throughout the scenarios explored in this paper, this response is far from uniform. In Figure 6, we map the response according to both the home and work locations of the commuters. In the map on the right, individual mode choices are assigned to work locations rather than home locations. The darker neighborhoods indicate a larger change in the probability of commuting by car for commuters who work in that neighborhood. It is clear that those people who work in the area of the city affected directly by the charge change their behavior substantially.

Interestingly, however, the spatial pattern of response to the charge is much less clear when mapped by home location. The model predicts that those who will be most sensitive to this new policy are those who do not have easy subway access. To see this, refer back to the spatial layout of the subway from Figure 2. The rationale for this is again that people who already have easy subway access are using the subway for their commute into Manhattan unless they have a constraint that forces them to drive. These people do not have the flexibility to change their behavior in response to the congestion charge. Those who drive because the subway is somewhat inconvenient for them, however, may find it more “convenient” to drive or take a bus to the subway than to pay the congestion charge to drive downtown.

The building of the Second Avenue subway

The final scenario we model is the building of the much-discussed Second Avenue subway line. Since the 1920's, New York City planners have been talking about building an additional north-south subway line in Manhattan that runs along Second Avenue. This project has been started and stopped a number of times; the most recent groundbreaking ceremony was held in April, 2007.

[FIGURE 7 ABOUT HERE]

Figure 7 illustrates the change in the predicted transit commute mode share by home neighborhood that would result from the building of the Second Avenue subway. Although the overall predicted increase in transit market share for commuting is only 0.9 percentage points, the spatial distribution of this effect is far from uniform. Predictably, the largest change occurs in the area of Manhattan close to Second Avenue (the light gray line on the east side of Manhattan on the map). The reason that changes in transit commute mode are predicted outside of this area at all is that there are many work locations in this area, and transit use for commuting is partially influenced (in both the discrete choice model and in reality) by transit availability near work.

POLICY IMPLICATIONS

Many (if not most) urban transport policies and infrastructure investments today are aimed at least partly at reducing traffic congestion. Those commuters who switch away from driving make the policy effective at achieving this goal, and are represented in the darker shaded neighborhoods of Figures 3 through 7. In the case of policy options that require enforcement (Figures 3 through 6), it is in these policy-sensitive neighborhoods that enforcement will be most cost-effective – assuming the cost of enforcement is not differentiated by neighborhood. In the case of infrastructure investments (Figure 7), it is the residents of these darker-shaded neighborhoods who benefit most from the new infrastructure – by using it!

For the transport policy scenarios depicted in Figures 3 through 6, the maps in this paper show graphically who “pays” by switching commute modes and who pays by paying more – in either money or time – to stick with their original mode choice. Those in the second category are the residents of the lighter-shaded neighborhoods in the maps. Economic theory tells us that those people who choose to switch their transport mode are likely to be "paying" less in utility terms than those people who pay the extra money or time and do not change their choices. Thus, those whose behavior is *least sensitive* to the policy changes are those who are both *paying a high price* for the policy and *not contributing* to achieving its goals.

When considering demand-reducing policies, city decision makers should be particularly concerned about the residents of these lighter-shaded neighborhoods and look for policies that minimize their number. If they are poor, the concern is that the policy is having the perverse effect of further stressing an already disadvantaged community. If they are wealthy, the concern is that they might use their political clout to fight against a policy that is good for the city as a whole, but disproportionately impacts their community.

CONCLUSION

To adequately address many transport policy questions, it is crucial to look at location-specific patterns of behavior in addition to aggregate model results. Local policies such as zoning changes or parking regulations are often implemented to different degrees across city neighborhoods. City investments in infrastructure are almost never spatially uniform. Even policies implemented uniformly across a city will alter behavior differently in different neighborhoods. Unfortunately, statistical results are usually presented as if people in all locations experience and react identically to changes in the transport-land use system.

This paper has provided examples of the use of GIS together with a discrete choice model of travel behavior in New York City to perform location-specific scenario analyses and display the results in easy-to-digest maps. These maps provide convincing empirical evidence that even if a transport system change is implemented uniformly across New York, there can be big differences between neighborhoods in the behavioral response to that change. If a system change is not uniform across the city, the response will almost certainly differ by location.

Understanding this spatial heterogeneity in the behavioral response is important to policy makers and planners because it gives them insight into which communities will be impacted most by policies and which will gain most from public investments. This is crucial both to clearly see equity implications of policies, and to identify communities that might use their political clout to block policy implementation. Once a policy is implemented, spatial analyses such as this one can also allow for better targeting of policy enforcement.

Although this paper focuses on spatial patterns in discrete choice model results, heterogeneity in model results may exist and be important for policy makers along other dimensions such as income, gender, or household type. In all cases, because the real world is not homogeneous, travel behavior analyses are more useful when analysts take the time to highlight relevant heterogeneity in the results.

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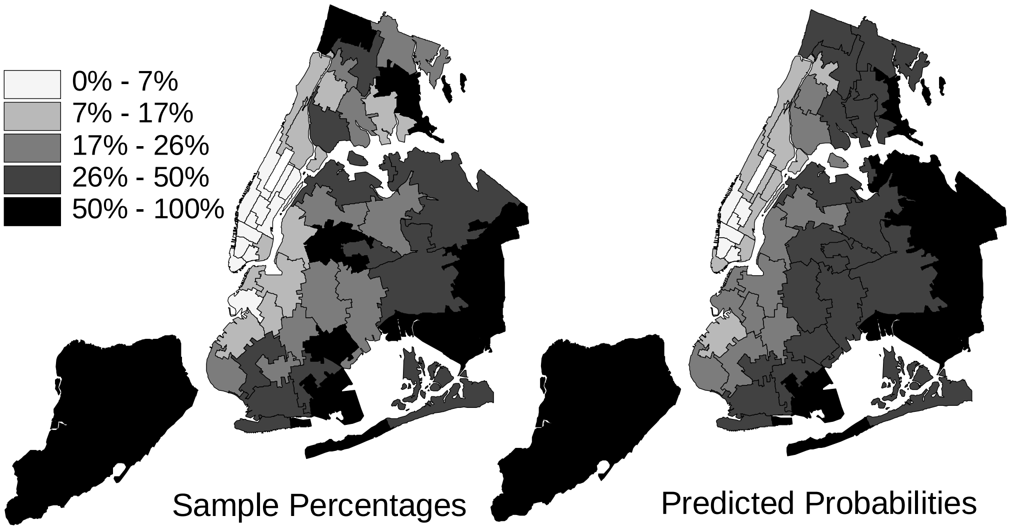
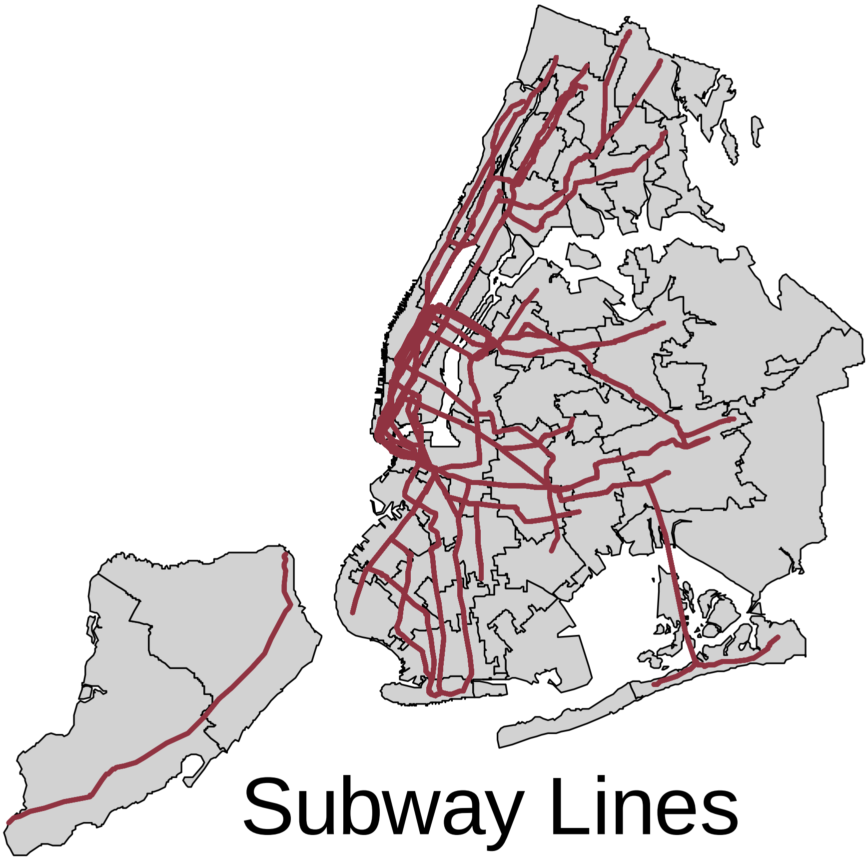
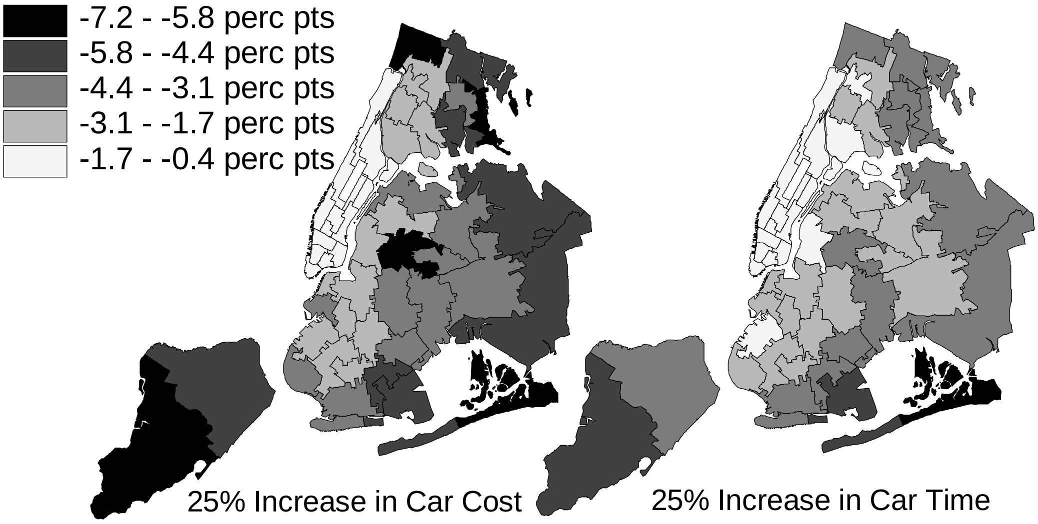
Table 1: Multinomial Logit Model of the Joint Choice of Residential Location, Car Ownership Status, and Commute Mode

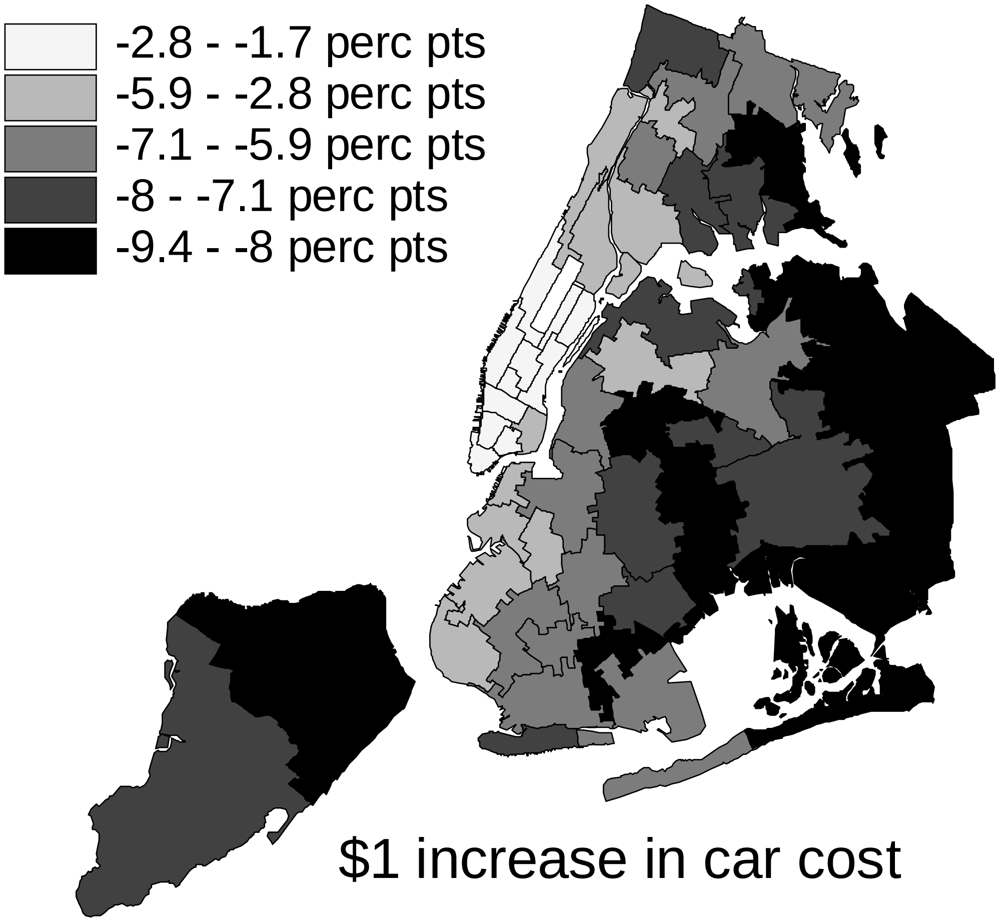
Commute Cost Variables	**Coefficient**	**S.E.**	**Coefficient**	**S.E.**
	Lower Income		**Higher Income**	
Commute cost not including parking costs	-0.468***	0.031	-0.414***	0.035
Parking cost at work	-0.024*	0.014	-0.026*	0.014
Walking time	-2.238***	0.131	-2.501***	0.185
Waiting time	-3.736**	1.447	-6.159***	1.900
Riding time	-1.477***	0.110	-1.735***	0.167
Not Segregated By Income				
Subway lines at home for bus alternative	-0.249***	0.064		
Subway lines at home for subway alternative	-0.096*	0.051		
Subway lines at home for auto alternative	-0.112*	0.058		
Subway lines at work for bus alternative	-0.217***	0.049		
Subway lines at work for subway alternative	0.230***	0.044		
Subway lines at work for auto alternative	-0.026	0.047		
Car Ownership Status Variables	**Lower Income**		**Higher Income**	
Car insurance cost	-0.582***	0.081	-0.373***	0.133
Income for one car alternative	0.528***	0.097	0.123***	0.039
Income for two-or-more car alternative	1.002***	0.105	0.152***	0.046
Subway lines at home for one car alternative	-0.117**	0.048	-0.004	0.054
Subway lines at home for two-or-more car alt.	-0.005	0.059	0.006	0.072
Dist. to midtown Manhattan for one car alt.	0.038**	0.018	0.169***	0.029
Dist. to midtown Manhattan for two-or-more cars			0.152***	0.028
Retail density at home for one car alternative	-1.111	1.027	0.429	0.588
Retail density at home for two-or-more car alt.	-4.902**	2.379	-3.099**	1.360
Population density at home for one car alt.			-0.070***	0.019
Population density at home for two-or-more cars	-0.275***	0.023	-0.125***	0.027
Not Segregated By Income				
Household size for one car alternative	0.153***	0.041		
Household size for two-or-more car alternative	0.514***	0.042		
Residential Location Variables	**Lower Income**		**Higher Income**	
Rent per income per household size	-0.050	0.100	-2.014**	0.779
Neighborhood percent owner-occupied	-1.425***	0.237	-1.413***	0.321
Neighborhood population density	0.120***	0.009	0.176***	0.016
Neighborhood dist. from midtown Manhattan	0.043***	0.016	-0.062**	0.029
Neighborhood retail density	-1.776***	0.587	-0.352	0.476
Neighborhood subway line availability	0.223***	0.058	0.140**	0.062
Neighborhood median income	-0.036	0.029	0.220***	0.035
Not Segregated By Income				
Neighborhood percent white if non-white HH	-2.337***	0.160		
Neighborhood percent non-white if white HH	-2.838***	0.138		
Neighborhood dist. from midtown for HH w/kids	0.051***	0.016		
Neighborhood subway line avail. for HH w/kids	-0.115***	0.043		
Neighborhood percent owner-occ. for homeowners	2.913***	0.209		
Plus 59 Alternative Specific Constants				
Observations = 2728	**Alternatives = 220**		**Psuedo R^2 = 0.29**	


0% - 7%
7% - 17%
17% - 26%
26% - 50%
50% - 100%
Sample Percentages
Predicted Probabilities

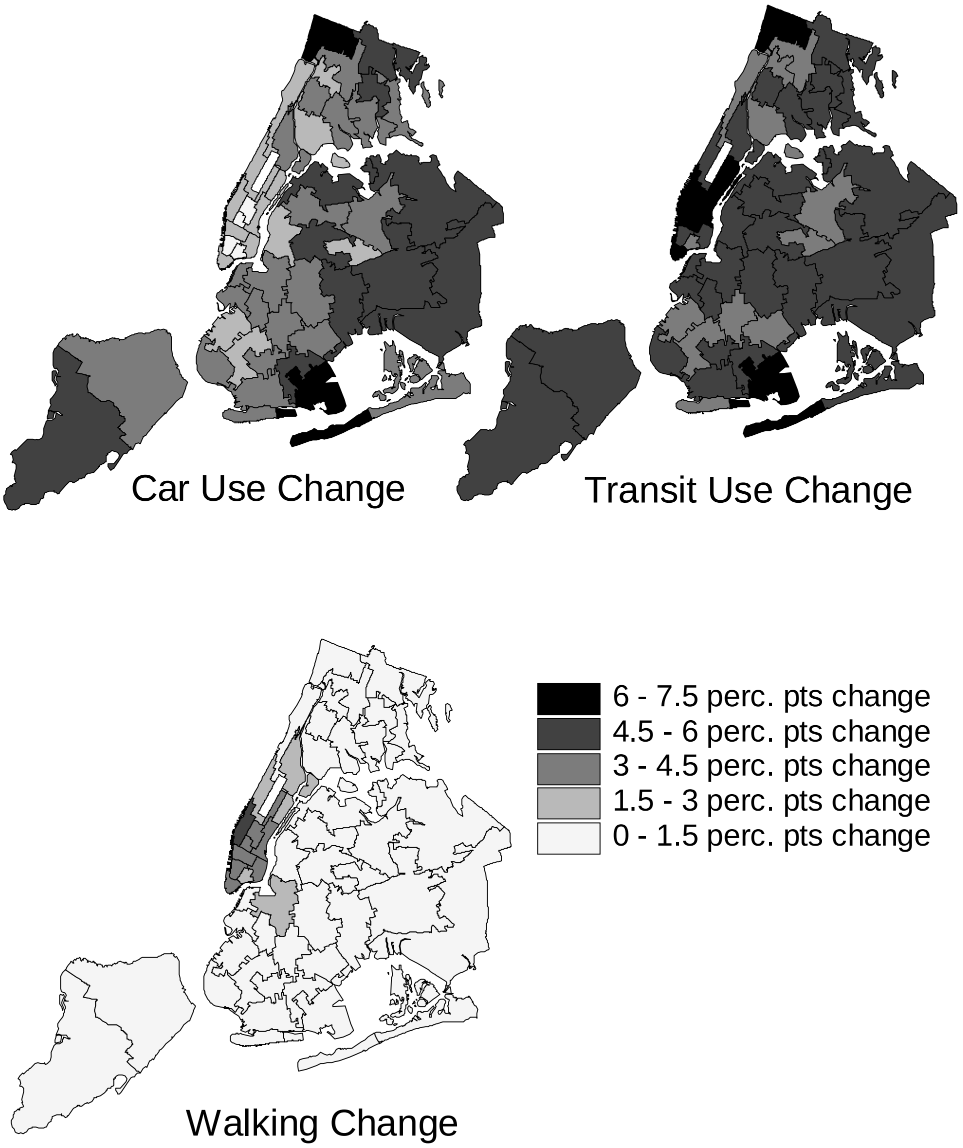


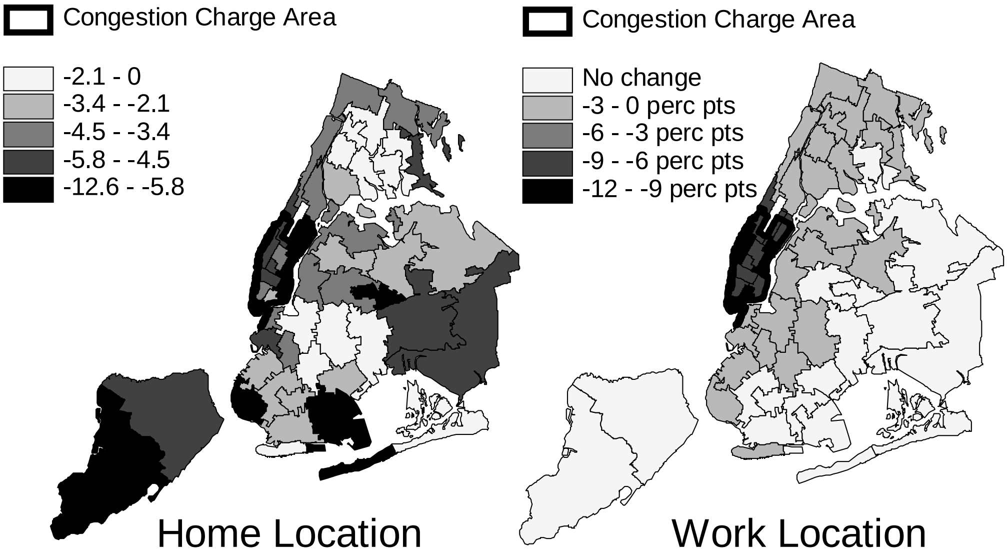
Subway Lines

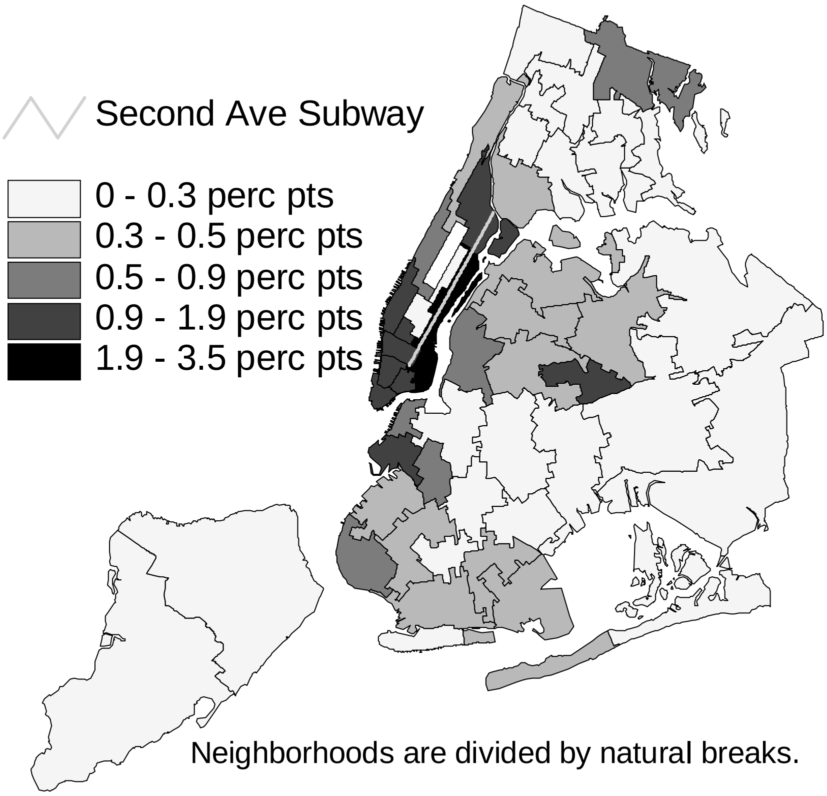

-7.2 - -5.8 perc pts
-5.8 - -4.4 perc pts
-4.4 - -3.1 perc pts
-3.1 - -1.7 perc pts
-1.7 - -0.4 perc pts
25% Increase in Car Cost
25% Increase in Car Time



$1 increase in car cost


Car Use Change
Transit Use Change
Walking Change
6 - 7.5 perc. pts change
4.5 - 6 perc. pts change
3 - 4.5 perc. pts change
1.5 - 3 perc. pts change
0 - 1.5 perc. pts change


Congestion Charge Area
-2.1 - 0
-3.4 - -2.1
-4.5 - -3.4
-5.8 - -4.5
-12.6 - -5.8
Home Location
Congestion Charge Area
No change
-3 - 0 perc pts
-6 - -3 perc pts
-9 - -6 perc pts
-12 - -9 perc pts
Work Location



Neighborhoods are divided by natural breaks.