Assessing Social Equity in Distance Based Transit Fares Using a Model of Travel Behavior

ABSTRACT

The goal of this study is to develop and apply a new method for assessing social equity impacts of distance-based public transit fares. Shifting to a distance-based fare structure can disproportionately favor or penalize different subgroups of a population based on variations in settlement patterns, travel needs, and most importantly, transit use. According to federal law, such disparities must be evaluated by the transit agency, but the area-based techniques identified by the Federal Transit Authority for assessing discrimination fail to account for disparities in distances travelled by transit users. This means that transit agencies currently lack guidelines for assessing the social equity impacts of replacing flat fare with distance-based fare structures. Our solution is to incorporate a joint ordinal/continuous model of trip generation and distance travelled into a GIS Decision Support System. The system enables a transit planner to visualize and compare distance travelled and transit-cost maps for different population profiles and fare structures. We apply the method to a case study in the Wasatch Front, Utah, where the Utah Transit Authority is exploring a switch to a distance-based fare structure. The analysis reveals that overall distance-based fares benefit low-income, elderly, and non-white populations. However, the effect is geographically uneven, and may be negative for members of these groups living on the urban fringe.

RESEARCH HIGHLIGHTS

- A spatial econometric model of trip starts and distance travelled is used to assess differential impacts in distance based fares.
- Distance based fares are found to be socially progressive, in that they result in reduced fares for low-income and minority travelers, and increased fares for longer distance affluent riders.
- Pockets of Hispanic and non-white travelers exist in the cities surrounding Salt Lake City where transit fares are predicted to increase.
- The social sustainability of distance based fares are in large part driven by the spatial social structure of the region.

INTRODUCTION

Transport policy is inherently spatial. In the particular case of public transportation, building new transit infrastructure, changing the level of service, or modifying transit fares differentially impacts the spatial distributions of costs and benefits associated with this form of mobility. Despite its importance, few tools exist to aid researchers and planners in analyzing *social equity*, the fairness of cost/benefit distributions over space and across different population groups. Given the increasing importance placed on sustainability principles, it becomes salient to the transportation sector to balance environmental and economic concerns with those that are social, such as justice and equity. Without the proper tools, social equity analyses have been systematically underrepresented in transportation planning research and practice, or at least performed in an inconsistent, ad hoc manner from region to region (*1*).

This research aims to address this gap by developing a Geographic Information System-based Decision Support System (GIS-DSS) for evaluating the social equity impacts of transit fare policy. GIS-DSSs assist users with evaluating the costs and benefits of hypothetical solutions to inherently spatial problems and they are recommended by the Federal Transit Administration for analyzing the equity impacts of proposed changes in transit route and fare structures (*2*). The work has been performed in consultation with the Utah Transit Authority (UTA), a transit agency currently in the midst of reforming its transit fare strategy; the agency is considering a shift from a flat-rate fare to a distance-based fare structure.

The Utah Transit Authority is a large state-authorized transit operator in the United States. It services a population of 1.8 million people with a fleet of busses, vanpools, and light and commuter rail locomotives. Similar to many transit agencies in the United States, the UTA currently charges a "local-service" flat-rate fare for one- and two-way trips irrespective of distance travelled on the transit system. Following a steep decline in UTA revenues during the recent economic downturn, UTA is considering a distance-based fare structure in an effort to generate higher levels of ridership (for shorter distance travelers) and greater levels of fare-box revenue overall.

In the United States, before a fare structure can be modified, there is a legal requirement for most transit agencies to conduct a differential impacts analysis, with the specific goal of determining whether the planned changes will have a disparate impact on the basis of race, color, or national origin. The most recent guidelines put forward by the Federal Transit Authority in FTA Circular 4702.1B do not contain specific instructions for investigating a transition to distance-based fares. Rather, the guidelines focus on disparities with respect to purchasing of different forms of fare media (single tickets, monthly passes, discount fares, etc.). Moreover, the types of distributional analyses recommended by the FTA cannot be meaningfully extended to the case of distance-based fares because there is no suggested guideline for examining disparities in travel behavior, specifically distance travelled, the fundamental underlying behavior that may result in inequalities in distance-based fares paid by different demographic groups.

This research aims to improve our understanding of transit fares and social equity. We evaluate the equity implications of UTA moving from a flat-rate fare to a distance-based fare strategy through the development of a "Fare Equity Analyzer GIS" (FEAGIS), a spatial database tool that meets the strategic planning needs of UTA while providing a platform for social equity research. The GIS enables us to investigate the fairness in distributions of transit fare costs across multiple geographic scales and socio-economic dimensions. To achieve this goal, we estimate a state-of-the-art spatial econometric joint model of trip-generation and distance-travelled. The model is then incorporated into a GIS so that fare strategies may be assessed for equity concerns in compliance with federal regulations across the United States.

LITERATURE REVIEW

Research pertaining to socially sustainable transportation has evaluated the role of transportation in social exclusion, quality of life, and social equity (alternatively justice or fairness) at local and regional scales (*3; 4*). The notion of social equity in transportation is summarized by Sanchez (*5*) as the distribution of "benefits and burdens from transportation projects equally across all income levels and communities" (p. 8). It follows that socially equitable transportation is concerned with fairness in the distribution of transport investments, internal and external costs, and benefits (*6; 7*). The evaluation of costs may pertain to environmental justice (*8*), public health externalities (*9*), or to fiduciary expenses such as tax burdens (*10; 11*), tolls and congestion pricing (*12; 13*), and transit prices and fare structures (*14-16*).

The links between transportation and social justice have deep historic and political roots. In the United States, for instance, this history includes landmark Supreme Court decisions, bus boycotts, Freedom Riders, and the passage of federal legislation (e.g., (*5; 17*)), including the Civil Rights Act of 1964. Title VI of that Act prohibits federally-funded transit providers such as UTA from administering programs in ways that would subject individuals to discrimination based on their race, color, or national origin. President Clinton's 1994 Environmental Justice Executive Order similarly bars transit agencies from acting in ways that would have disproportionately high and adverse effects on low-income populations (*2*).

Equity can be examined from a variety of perspectives. Building on Litman's (*18*) theoretical structure, Bullard (*17*) identifies three types of equity: *horizontal equity*, which focuses on fairness between those of comparable wealth and ability, *vertical equity with regard to income and social class*, which looks at cost/benefit distributions between social and economic groups, and *vertical equity with regard to mobility need and ability*, which assesses "how well an individual's transportation needs are met compared with other in their community" (p. 26). Taylor (*19*) refines these concepts further, creating a three-by-three matrix that assesses three units of analysis (geographic, group, and individual) against three types of equity (market, opportunity, and outcome).

Various examinations of equity have been reported in the international literature, with the objective of assessing mainly vertical equity by comparing service availability to needs. In Melbourne, Australia, Currie (*20*) combined information about the distribution of transit stops and number of trips per week to create a supply-side service index. On the other hand, deprivation and a transport index (constructed using variables such as number of adults without cars and number of persons with disabilities) were used to measure social transport needs. The approach developed by Currie is useful to identify need-gaps, that is, areas with high needs and limited or non-existent transit services, which in the case of Melbourne were found to be mostly in the periphery of the city. Bocarejo and Oviedo (*21*) also adopted a geographical perspective for their study of a Bus Rapid Transit line in Bogotá, Colombia. These authors considered the percentage of time and income that travelers needed to spend to reach employment locations using the system. Whereas the approach of Currie considered only the ability to enter the transit system, Bocarejo and Oviedo were also concerned with the ability to reach destinations. The results of the analysis for Bogotá indicate that purchasing power and location can combine to influence the redistributive effects of a project. Furthermore, the case study illustrates a situation where fare policy can have a greater equity impact than the expansion of the network.

In the US, the mandate to comply with Title VI has also prompted studies of equity. For instance, Nuworsoo, Golub, and Deakin (*22*) analyzed a series of fare proposals for Alameda-Contra Costa Transit District in California, using disaggregated analysis of fares that considered the attributes of trip-makers (e.g. income, age, race), as well as their travel behavior. More recently, Hickey et al. (*23*) argued for the

use of quantitative approaches to assess equity, and illustrated the use of travel statistics and statistical methods for evaluating the impact of restructuring transit fares. A notable limitation noted for New York City Transit is the assumption that "elasticities in fare class and cross-elasticities between fare classes are independent of geography and demographics" (p. 82). The adequacy of this assumption is suspect. In the specific case of the US there is substantial evidence of spatial segregation along socio-economic and demographic dimensions (e.g., *24; 25*). Not surprisingly, this has an effect on transport equity. Haas et al. (*26*), for instance, documented the trade-offs facing households in metropolitan areas in the US in terms of housing and transportation costs. The average percentage of income spent in transportation by low income households (<$20K) was a staggering 56% in 2000, at the end of a historic economic growth period, and before the economic recessions of the next decade. By contrast, the average percentage of income spent in transportation was only 18%, 13% and 8% for the top three income classes ($50K to $75K, $75K to $100K, and $100K to $250K, respectively). In this fashion, while transit systems may not intentionally discriminate against low-income and minority populations, flat-rate fare prices may, nevertheless, have disparate impacts on low-income and minority households by virtue of the higher rates of transit usage and the tendency for shorter trips exhibited by members of these households, compared to members of the general population (*5; 27*). These differences in usage can lead to situations where minority and low-income riders are effectively subsidizing other riders who use transit only for commute purposes and/or travel longer distances.

Of several fare structures, the literature on distance-based fares is not extensive, since much of the material seems to focus rather on optimizing fare structures for enhancing revenues (*28-32*). However, of the various schemes analyzed by Nuworsoo, Golub, and Deakin (*22*) for Alameda-Contra Costa Transit District patrons, flat fares were found to most negatively impact vulnerable populations (youth, low-income, and minority travelers) due to their more frequent use of transit and transfer patterns. This finding is consistent with earlier works by Ballou & Mohan (*33*), Cervero (*27*), and Deakin and Harvey (*34*). Implementing a distance-based fare system presents UTA the opportunity to take affirmative steps to alleviate disparate effects. The case for distance-based fares however is not clear-cut. Distance-based fares might exacerbate concerns over spatial mismatch, a situation arising from large spatial separations between low-income and minority households and suitable locations of employment or other locations of participation (*5*) . To the extent that spatial mismatch exists, distance-based fares may result in increased out-of-pocket travel expenses for those low-income households engaged in long-distance travel routines. Furthermore, increasing fares for long-distance transit riders may result in increased use of less sustainable modes of transportation, namely the automobile. Such a change could lead to increased greenhouse gas emissions, lower air-quality, more traffic accidents and increased traffic congestion. Spatial disparities in the social benefits of distance-based fares must therefore be accurately calculated in order to facilitate a comparison with economic and environmental costs. The system presented in this paper aims to facilitate the analysis of the social equity dimension of sustainability based on detailed analysis of socio-economic, demographic, and geographical factors.

RESEARCH METHOD

Data

The research primarily relies on data from the Utah Household Travel Survey (UHTS) conducted in the spring of 2012. The one-day trip survey recorded 101,404 trips taken by 27,046 individuals living in 9,155 households across the state of Utah. The survey, being partially funded by Metropolitan Planning

Organizations along the Wasatch Front, oversampled the urbanized regions of the state in which UTA operates. This provides a spatially dense sample of 6,238 households and 16,071 individuals considered to be within the operating district of the transit authority.

The UHTS collected information about individual trips, the trip-makers, and households. Descriptive characteristics of the dataset can be found in Table 1. The table indicates social disparities in transit trip generation and distance travelled. Note that the table only includes factors that directly relate to social equity concerns in the Wasatch Front but additional control variables are used in the multivariate model below. We present the percentage of respondents in each factor level that reported a transit trip and the mean trip generation rate and mean total distance travelled among transit riders.

The summary transit ridership statistics tell a consistent story of higher ridership but shorter distances travelled among individuals of lower socioeconomic status. Interestingly, contrasting the pattern seen for trip distances, there is very little variation in numbers of trips generated per transit rider. Looking at socioeconomic status, compared to individuals in high-income households, individuals in households earning less than $35,000 per year were more than twice as likely to ride transit, but had average distances of nearly half the length. Hispanics and non-white respondents are 70% more likely to ride transit in comparison to non-Hispanics and whites, but whites travelled about 45% greater distances on transit than their non-white counterparts. In terms of employment status, students who are employed for more than 25 hours per week have the highest penetration rates of transit use, but fully employed transit riders travelled 40-65% longer distances compared to others. In all of these cases, distance-based fares would seem to be favorable to lower socioeconomic groups given their increased uptake of transit ridership (in terms of mode-share) but decreased use of long-distance services.

The same benefit of distance-based fares can by posited to exist along other socioeconomic dimensions. Those without driver licenses were about 6 times more likely to ride transit than licensed respondents, but licensed transit riders traveled 80% longer distances. 27.3% of those living in carless households reported using transit, taking 2.26 transit trips per day with a mean total distance travelled of only 11.94 miles per day. This is all in comparison to 1.87% of two-car households, averaging 1.89 trips per day but travelling 38.14 miles. Related to car-ownership are the factors of neighborhood and residence types. Those living in apartment buildings and in mixed-use urban areas reported much higher rates of transit use, but with much shorter distances travelled.

TABLE 1 Transit Ridership, Trip Generations, and Distance Travelled for Select Personal and Household Characteristics

	Ridership Percentage	Trips	Distance Travelled (miles)
Household Income <0.014,0.002>			
No Answer	1.91	1.73	20.09
Under $35,000	5.17	1.94	13.25
$35,000 - $49,999	2.94	1.88	19.14
$50,000 - $99,999	2.24	1.85	20.56
$100,000 or more	2.17	1.86	24.51
Hispanic <0.038,0.348>			
Yes	4.38	1.89	17.39
No	2.60	1.88	19.60
Prefer not to answer	3.02	1.64	5.34
Race <0.000,0.018>			
White or Caucasian	2.50	1.89	19.93
All other	4.61	1.77	14.25
Age <0.110,0.944 >			
18-24 years old	6.87	1.82	17.47
25-34 years old	4.07	1.88	17.51
35-44 years old	3.37	1.84	24.19
45-54 years old	3.49	1.87	19.73
55-64 years old	3.13	1.88	17.82
>65 years old	1.59	2.08	13.91
Employment <0.000,0.000>			
Employed full-time	4.58	1.84	22.43
Employed part-time	3.05	1.84	13.61
Student, not employed or employed less than 25 hrs/week	6.88	1.76	15.96
Student, employed 25+ hrs/week	10.79	1.91	14.61
All Other	1.36	2.00	13.88
Education <0.017,0.005>			
High school or less	3.73	1.85	13.08
Some College/Vocational/Associates	3.40	1.87	18.56
Bachelors	2.90	1.80	19.34
Grad/Post Grad	5.26	1.95	21.88
Licensed <0.000,0.000>			
Yes	3.14	1.86	20.39
No	13.67	1.96	11.34
Limited Mobility <0.012,0.290>			
Yes	7.05	2.09	14.99

No	3.51	1.86	19.16
Prefer not to answer	6.90	2.00	20.75
Number of vehicles <0.000,0.000>			
Zero vehicle household	27.34	2.26	7.42
1 vehicle household	5.40	1.78	14.04
2 vehicle household	1.87	1.89	23.70
3+ vehicle household	1.99	1.81	23.21
Home Ownership <0.000,0.000>			
Rent	5.56	1.86	11.66
Own	2.17	1.87	22.77
Other	0.77	2.00	17.61
Number of years (Residence) <0.158,0.000>			
less than 1 year	4.44	1.97	16.23
1 to 5 years	2.58	1.88	19.21
more than 5 years	2.42	1.83	19.96
Place Type (Self-reported) <0.000,0.000>			
City, downtown with a mix of offices, apartments and shops	7.44	1.72	7.41
City, residential neighborhood	2.82	1.94	13.72
Suburban neighborhood, with a mix of houses, shops and businesses	3.15	1.91	22.28
Suburban neighborhood, with houses only	2.09	1.83	22.95
Other	1.61	1.78	34.41
Residence Type <0.000,0.000>			
Single-family house (detached house)	2.17	1.88	22.82
Building with 4 or more apartments or condos	6.17	1.92	11.38
Other	3.34	1.74	13.89

Ridership Percentage is the percentage of respondents that reported a public transit trip. **Trips** is the average number of trips reported amongst those who took transit. **Distance Travelled** is the average number of miles travelled on transit by those who took transit. ANOVA results in format ***<A,B>*** where **A** is the p-value of the F-test associated with ridership and **B**, is the p-value of the F-test associated with distance travelled.

Next, we turn to investigate locational factors that may influence transit use: distance to the CBD, and distance to the nearest bus stop, Trax (light-rail) stop, and Front Runner (commuter rail) station. Table 2 shows two clear patterns. First, respondents with residences closer to the CBD and various public transit facilities are more likely to ride transit. Second, amongst transit riders, living farther away from the CBD and transit facilities is associated with longer distances travelled.

The descriptive analysis of transit ridership and distance travelled reveals a common pattern across a multitude of socioeconomic factors. It is important to realize that these descriptive results are uncontrolled; effects of one factor, like income, may be correlated with another, such as employment status. For this reason, a multivariate approach to modeling trip generations and distances travelled is applied next. This will help determine the independent impact of each dimension explored above.

TABLE 2: Distance to CBD and Transit Facilities Amongst Transit Riders and Non-Riders

	CBD	Bus Stop	Trax Stop	FrontRunner
Mean Distance for Non Transit Riders	21.06	0.50	13.73	15.97
Mean Distance for Transit Riders	15.47	0.37	9.57	10.75
Ratio (Row 1/Row 2)	1.36	1.47	1.43	1.49
Correlation with Distance Travelled	0.46	0.22	0.39	0.24

Joint Ordinal/Continuous Model

In this section we put forward the derivation of an ordinal/continuous model that will be used to simultaneously estimate the joint decision of how many transit trips to take (discrete-ordered), and how far to travel by transit in a day (continuous). Probability functions for each dependent variable and a correlation structure between the random components affecting each decision process will be accounted for. This procedure controls for the selection bias associated with only observing transit travel distance for those respondents that selected to travel by transit for 1 or more trips on the survey day. Ignoring the ordinal selection process is likely to result in biased estimates of regression coefficients in the continuous, distance-travelled function (*35*).

In order to derive the model, let us begin by considering that an individual incurs some cost in deciding to make a transit trip. Defining cost as a generalized negative utility sensitive to socio-demographic characteristics of individuals, we can specify a function as:

$$C^* = \beta x + \varepsilon \tag{1}$$

where, C^* indicates total disutility of trips generated, x is the vector of explanatory variables, β is the vector of corresponding coefficients, and ε is the unobserved error term. Considering the number of transit trips to make as an ordered decision, it is possible to define the probability of taking successive numbers of trips, T, based on generalized cost as:

$$\begin{array}{llll} T = 3+ & \text{if} & C^* \leq \mu_3 & \& \ \Pr(T = 3+) = \Phi(\mu_3 - \beta x) \\ T = 2 & \text{if} & \mu_3 < C^* \leq \mu_2 & \& \ \Pr(T = 2) = \Phi(\mu_2 - \beta x) - \Phi(\mu_3 - \beta x) \\ T = 1 & \text{if} & \mu_2 < C^* \leq \mu_1 & \& \ \Pr(T = 1) = \Phi(\mu_1 - \beta x) - \Phi(\mu_2 - \beta x) \\ T = 0 & \text{if} & C^* > \mu_1 & \& \ \Pr(T = 0) = 1 - \Phi(\mu_1 - \beta x) = \Phi(\beta x - \mu_1) \end{array} \tag{2}$$

where μ_k are latent threshold values of generalized cost. Equation (2) follows directly from the ordered-probit specification provided by McKelvey and Zavoina(*36*).

Distance travelled, on the other hand, can be considered as a continuous random variable. Considering total distance travelled, D, as a logarithmic function (ensuring non-negativity of distance), this can be specified as:

$$\ln(D) = \gamma y + \eta \tag{3}$$

where, y is the vector of explanatory variables, γ is the vector of corresponding coefficients, and η is the unobserved error term. If the number of trips generated is classified as 0, 1, 2, and 3+ and corresponding distances travelled are 0, D_1, D_2, and D_3, the joint probabilities of trip generation and corresponding distance travelled can be specified as:

$$\begin{aligned}
&\Pr(T = 3+ \ \& \ D = D_3) = \mathrm{JointPr}(C^* \leq \mu_3 + \ \& \ D = D_3)\\
&\Pr(T = 2 \ \& \ D = D_2) = \mathrm{Joint}\Pr(C^* \leq \mu_2 \ \& \ D = D_2) - \ \mathrm{JointPr}(C^* \leq \mu_3 \& \ D = D_3)\\
&\Pr(T = 1 \ \& \ D = D_1) = \mathrm{Joint}\Pr(C^* \leq \mu_1 \ \& \ D = D_1) - \ \mathrm{JointPr}(C^* \leq \mu_2 \ \& \ D = D_2)\\
&\Pr(T = 0 \ \& \ D = 0) = 1 - \mathrm{JointPr}(C^* > \mu_1)
\end{aligned} \tag{4}$$

Consider the specifications for the error terms. We assume that ε is normally distributed with zero mean and unit variance and the random error of continuous distance, η is normally distributed with zero mean and variance, σ^2. Correlations between unobserved factors of these two decisions are addressed by positing that ε and η are bivariate normal distributed with covariance matrix $\Sigma = \begin{bmatrix} 1 & \rho\sigma \\ \rho\sigma & \sigma \end{bmatrix}$. Probabilities of individual orders of trip making are defined in equation (2). In order to ensure that the model never predicts a negative distance value, we assumed that distance follows a log-normal distribution.

In order to estimate the parameters, β, γ, and σ, the joint probabilities are derived considering the correlation between the two types of decisions specified in equation (4). So, the joint likelihood (L) for any one observation becomes:

$$\begin{aligned}
L = {} & I(T = 3+)\left\{\left[\frac{1}{\sigma D_3}\phi\left(\frac{\ln(D_3)-\gamma y}{\sigma}\right)\Phi\left(\frac{u_3-\beta x-\rho\left(\frac{(\ln(D_3)-\gamma y)}{\sigma}\right)}{\sqrt{1-\rho^2}}\right)\right]\right\} + I(T = \\
& 2)\left\{\left[\frac{1}{\sigma D_2}\phi\left(\frac{\ln(D_2)-\gamma y}{\sigma}\right)\Phi\left(\frac{u_2-\beta x-\rho\left(\frac{(\ln(D_2)-\gamma y)}{\sigma}\right)}{\sqrt{1-\rho^2}}\right)\right] - \left[\frac{1}{\sigma D_3}\phi\left(\frac{\ln(D_3)-\gamma y}{\sigma}\right)\Phi\left(\frac{u_3-\beta x-\rho\left(\frac{(\ln(D_3)-\gamma y)}{\sigma}\right)}{\sqrt{1-\rho^2}}\right)\right]\right\} + \\
& I(T = 1)\left\{\left[\frac{1}{\sigma D_1}\phi\left(\frac{\ln(D_1)-\gamma y}{\sigma}\right)\Phi\left(\frac{u_1-\beta x-\rho\left(\frac{(\ln(D_1)-\gamma y)}{\sigma}\right)}{\sqrt{1-\rho^2}}\right)\right] - \left[\frac{1}{\sigma D_2}\phi\left(\frac{\ln(D_2)-\gamma y}{\sigma}\right)\Phi\left(\frac{u_2-\beta x-\rho\left(\frac{(\ln(D_2)-\gamma y)}{\sigma}\right)}{\sqrt{1-\rho^2}}\right)\right]\right\} + \\
& I(T = 0)\{\Phi(\beta x - \mu_1)\}
\end{aligned} \tag{5}$$

where $I(\cdot)$ is an indicator function, ρ is the correlation between the two random error terms, and subscripts of D indicate total distances travelled for corresponding numbers of trips generated.

Now for N observations, the log-likelihood (LL) of the sample becomes:

$$LL = \sum_{i=1}^{N} \ln(L) \tag{6}$$

The log-likelihood function is estimated and maximized with code written in MATLAB. The standard errors of the parameters are calculated using the inverse Hessian procedure. The goodness of fit of the models is estimated using an adjusted likelihood ratio test:

$$\bar{\rho}^2 = 1 - \frac{LL^* - k}{LL_R} \tag{7}$$

where LL^* is the log-likelihood at convergence, LL_R is the log-likelihood of the restricted constants-only model, and k indicates the number of parameters in the fully specified model minus the number of parameters in the restricted model. Application of the model is very straight forward. The correlation parameter ρ does not enter into the individual probability functions of the ordered probit and hazard models. It only enters into the joint probability function to derive a likelihood function that eliminates estimation bias. Hence, the model can be used to forecast trip generation frequency and total distance travelled by applying equations 2 and 3 directly to estimated regression coefficients and known

characteristics of individuals, x and y. Importantly, we do not need to simulate the correlated residuals in order to make these forecasts.

RESULTS

The results of the joint ordinal-continuous regression model appear in Table 3. A selection of variables describing personal and household characteristics was used to calibrate the model. Factors of particular relevance to social equality (low income, elderly, low education, employment status, race, and others) were spatially expanded using distance to the CBD and a polynomial function of the household spatial coordinates (denoting longitude and latitude with u, v respectively) following Casetti (*37*) and a slew of recent transportation studies (*38-40*). The expansion method captures spatial non-stationarity that may exist in the relationships between dependent and independent variables without resorting to semi- and non-parametric techniques, such as Geographically Weighted Regression (*41*).

Stepwise selection on each non-joint model was used to inform the selection of variables that appear in the joint specification. Many variables that attain significance in the non-joint models no longer add explanatory power in the joint specification, evidence that the introduction of the correlated residuals produce more efficient estimators. Variables that retain significance at the $\alpha = 0.3$ level were kept in the model. The final model specification depends on 55 independent variables plus 5 parameters that are used to specify the thresholds of the ordinal model ($\mu_1 - \mu_3$), the variance of residuals (σ), and the correlation used to specify the bivariate normal residuals (ρ). The model obtains an adequate fit as characterized by a significant test of the likelihood ratio, a McFadden's $\bar{\rho}^2$ of 0.114, and a pseudo-r^2 of distance travelled of 0.58.

Interpretation of the regression coefficients follow from the normal ways to interpret ordinal probit and OLS regression coefficients for the trip generation and distance travelled models respectively. In the ordered probit case, negative coefficients indicate lower generalized costs of taking transit, and therefore higher propensity to make more trips. According to the results, factors most strongly associated with taking more trips include: being 18-24 years old, living in a household with retirees for household heads, being a student that is employed for more than 25 hours per week, being highly educated, living in a zero-vehicle household, living in larger households, and living in a suburban neighborhood that maintains a high mix of land uses (self-reported). Variables that decrease the propensity to take transit include: being younger than 18, being self-employed, being female, living in households with 2 or more vehicles, living in households that are neither rented nor owned, living in households with many children's bicycles, and living in households that are farther away from long-distance commuter rail (presumably because the commuter-rail only serviced a small fraction of suburbs at the time of the data collection.

TABLE 3: Results of the Joint Ordinal/Continuous Model for Public Transit Trip Generation and Distance Travelled

Ordered Model Estimates			**Continuous Model Estimates**		
	B	**p-value**		**B**	**p-value**
Age less than 17 years	0.9052	0.0000	Constant	-3.9564	0.0000
Age 18-24 years	-0.1468	0.0607	Two transit trips	1.1045	0.0000
Age over 65 * u^2	1.4356	0.0193	Three transit trips	1.5018	0.0000
Age over 65 * v^2	0.8022	0.0167	Age over 65	-0.2700	0.1709
Mobility Limitation * v	-0.3858	0.0956	No children or retirees	-0.1596	0.0821
Household w/ retirees	-0.3449	0.0004	Student, em. < 25 hrs/week	-0.2771	0.1868
Self employed	0.9011	0.0000	Unemployed/retired	-0.2670	0.0483
Student, emp. 25+ hrs/week	-0.4158	0.0000	High school or less * D_CBD	-0.0072	0.0619
Unemployed/retired * u^2	-1.1084	0.2099	Hispanic - Refusal	-0.5133	0.0464
Unemployed/retired * u	1.8918	0.0003	Race: non-white * D_CBD	0.0199	0.0052
Grad. or post-grad. degree	-0.3251	0.0000	Race: non-white * v	-0.4355	0.1926
Female	0.1842	0.0001	Zero vehicles * D_CBD	-0.0132	0.0275
Hispanic	1.1440	0.0446	Income < $25K * uv	-0.8834	0.0818
Hispanic * v	-1.2459	0.0902	Income $75-$100K	-0.4831	0.0001
Hispanic * v^2	-2.4449	0.0011	4 people	0.1759	0.1779
No driver's license	-1.3931	0.0000	3+ workers	0.2371	0.0917
No driver's license * v	1.4272	0.0016	3+ children's bikes	0.2400	0.1706
Zero vehicle household	-0.7612	0.0000	5+ years in current res.	0.1163	0.1723
2 vehicle household	0.3455	0.0000	City, residential neigh.	-0.1825	0.0500
3+ vehicle household	0.5623	0.0000	Distance to CBD	0.0522	0.0000
Income < $25K * uv	-0.5827	0.1106	Distance to bus stop	0.1788	0.0003
Income – Refusal	0.1421	0.1002	v	17.4178	0.0000
Household rents * D_CBD	0.0087	0.0001	v^2	-15.0180	0.0000
Household rents * uv	-1.1271	0.0004	**Joint Model Parameter Estimates**		
Household Tenure - Other	0.6485	0.1282		**B**	**p-value**
Household Tenure - Refusal	0.8261	0.0700	μ_1	-1.3672	0.0000
3+ workers	-0.1580	0.0740	μ_2	-1.5167	0.0000
3+ children's bikes	0.2259	0.0186	μ_3	-2.4753	0.0000
6+ people	-0.2206	0.0076	ρ	-0.1883	0.0625
Suburban mixed neighborhood	-0.1226	0.0211	σ	0.8322	0.0000
Distance to Commuter Rail	0.0024	0.2466			
u^2	0.4476	0.0410			
Log-Likelihood: -3701.04; p(χ^2)<0.0000; McFadden's Adj. $\bar{\rho}^2$: 0.1144; pseudo-r^2=0.5782; n=16071					

Many coefficients were insignificant on their own, but became significant in the presence of one of the spatial expansion terms. Significant spatially expanded factors include: being aged older than 65, having a mobility limitation, being unemployed or retired, being Hispanic, not having a driver's license, being low-income and living in a rented house. These factors are all salient to the equitable distributions of transit costs; understanding their spatial heterogeneous effects on trip generation and distance travelled is an important precursor to assessing the equity of distance-based fares. While it is possible to view maps of these coefficient surfaces, for the sake of brevity, visual analysis of results will be reserved for distances travelled and fares.

The continuous portion of the model contains 20 independent variables. The dependent variable is ln(distance) and most of the variables are binary indicators of factor levels. Thus for a binary variable, a change from 0 to 1 indicates a $100*\beta$ percent change in distance travelled. In other words, individuals that take 2 and 3 transit trips respectively travel 110% and 150% farther than those that only take 1 trip. Other non-expanded factors that predict increased distance travelled include: living in a larger household with multiple workers, having lived in one's residence for 5 or more years, and living farther away from the central business district and nearest bus stop. Non-expanded factors that are associated with less distance travelled include: being older than 65, living in a household without children or retirees, being a student with limited or no outside employment, being unemployed or retired, living in a high income household, and living in a residential city neighborhood (self-reported). The factors that are significant when expanded include: low education, non-white race, zero vehicle households and low income. As before, the spatially expanded coefficients are difficult to interpret directly, but in Figure 1 we illustrate their impact on distance travelled using maps.

Before continuing, it is necessary to define the reference case respondent in the distance-travelled model. This is the profile of the respondent for which all dummy variables are set to zero. The reference individual is a white, non-Hispanic male, aged 35-44. He is employed full time with a bachelor degree, lives in a house with 1 car, 2 adults and no children, and has a household income between $50,000 and$75,000 per year, which he earns as the sole worker in the family. He has a driver's license and no bicycles. He owns a single-detached house in an urban but residential neighborhood that he has lived in for less than year. Given such a profile, the map in Figure 1A provides an indication of the distance such a person would travel by transit given 2 daily trips. Estimated distances travelled increase with distance to the CBD and bus lines. Figure 1B is for individuals who have high-school or less education living in zero-vehicle households with incomes below $25,000 per year. Figure 1C is for unemployed, elderly individuals with incomes less than $25,000. And Figure 1D is for non-white individuals who elected not to identify their Hispanic status. While the general spatial patterns of estimated distances travelled are similar, important differences do exist. For example, distances for low-income and elderly individuals are shorter than for the more mobile reference category, both in the core of the city, as well in the peripheral suburban towns. Distances for the non-White category have short distances in the center of the city, but estimated distances are actually larger than those for the reference category in the southward direction. These spatial patterns while interesting in their own right, can be made more directly useful by converting figures into estimated distance-based transit costs, and comparing distance-based fares to the current static fares charged by UTA.

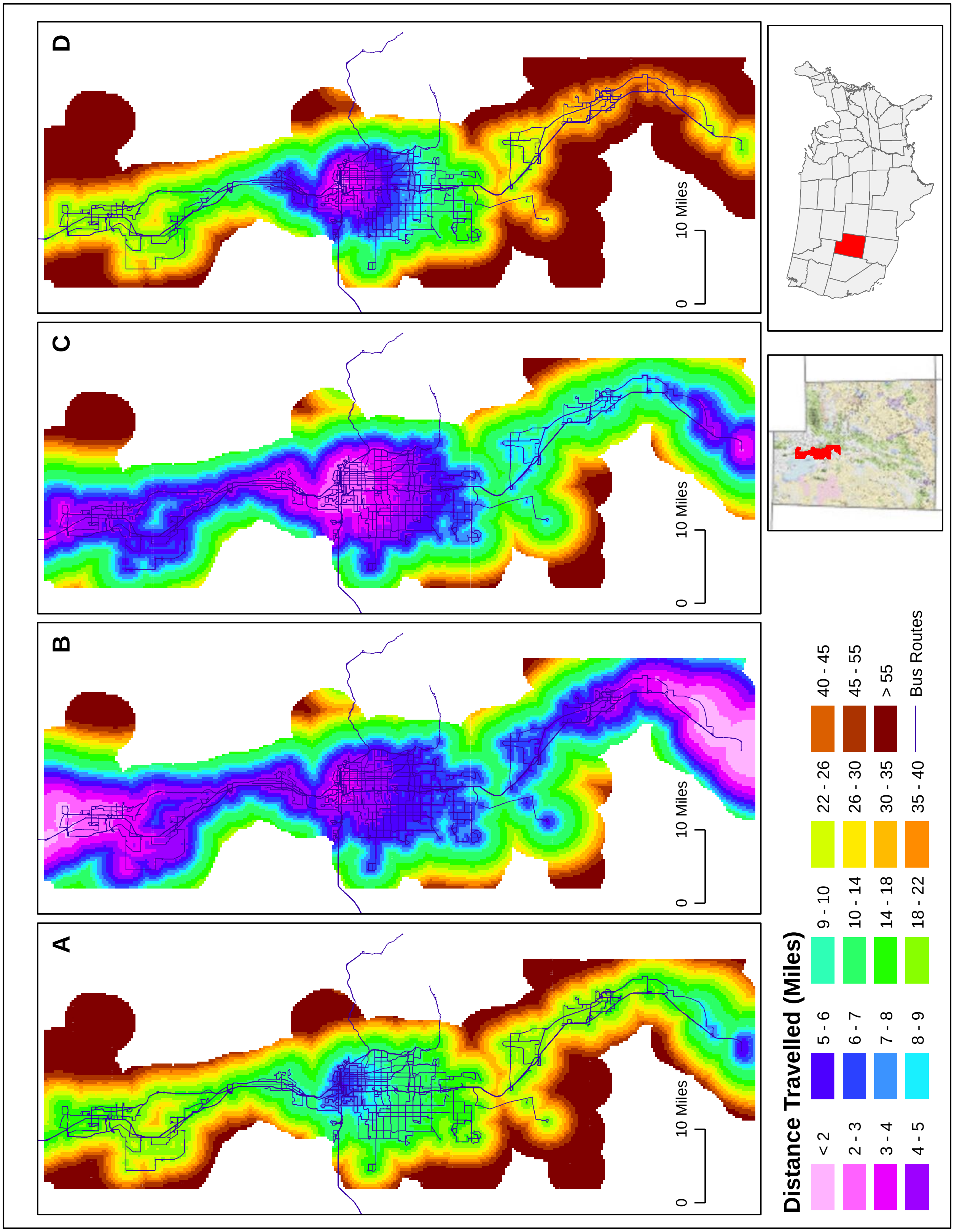

FIGURE 1 Expected Distances Travelled by Public Transit for Socioeconomic Profiles A) Reference Group, B) Low Income and Education, C) Low Income/Elderly D) Non-White

Distance-based fares are commonly structured around a nominal fee per trip plus a distance-based component. Based on the 787 transit trips observed in our dataset, we can generate revenue-neutral pricing schemes where the overall revenue collected under the distance-based fare structure equals the amount collected using flat fares. Assuming, for now, no price elasticity in ridership, revenue neutral fare structures must be solutions to the following equation:

$$2.5T = aT + bD$$

where 2.5 is the fare per trip under the flat-fare pricing structure, T is the total number of linked trips taken, a is the new fee per trip and b is the fare per mile of travel. Given T and D from our survey, we find that all revenue neutral distance-based fares are defined by the line:

$$b = 0.2377 - 0.0951a$$

For example, if the nominal fee per trip was $1, then the fare per mile should be set to about 14 cents. Intuitively, based on our knowledge of travel behavior (i.e.: trip generation and distances travelled) fare structures with a high fixed price and low distance-based price (with flat-fares being an extreme of this type) will disproportionately favor long distance, predominantly wealthier riders. Without loss of generality, for the remainder of the analysis we will continue to work with a fare of 50 cents plus 19 cents per mile travelled.

Under this fare scenario, we can calculate the average flat and distance-based fares for individuals based on the summary trip-making statistics found in Table 1 (see Table 4). According to these averages, it is quite apparent that distance-based fares progressively provide price-reductions to those who need it most, and ask those in higher socioeconomic positions to pay more for their travel. These findings are robust with respect to the use of a single distance based fare in the comparison since they rely on the underlying trends in distance travelled. However, despite the overall equity impact of distance-based fares being quite positive, our model can be used to calculate the expected change in fares paid by individuals of a specific demographic profile, differentiated by residential location. Such fares can be found in Figure 2 for the profiles A-D as described above. In these surfaces, green colors denote cost savings, reds denote cost increases, and the bright blue shade denotes cost-parity, where the expected transit fare is about equal under the two fare structures. The reader will see that many areas within the region, for these four profiles, lie within the cost-parity ring, indicating an expected cost saving for most inhabitants. This is especially true for the low-income and elderly subgroups (maps B and C), but less so for the wealthier reference profile in map A and the non-white profile in map D. For the latter, the model estimates cost increases for many living outside the central urbanized area of Salt Lake County. Such spatial disparities are masked by the spatial averaging taking place in Table 4, which is precisely why an approach based on a model is preferred to one based on descriptive statistics.

Figure 3 provides a closer look at the cost increases for non-white and Hispanic individuals. On top of identifying areas of cost increase, we overlay the top 20% of census tracts in terms of non-white and Hispanic populations. We include the high Hispanic tracts under the assumption that many survey respondents who refused to identify their Hispanic status, are in fact of Hispanic ethnicity. The overlay clearly identifies tracts in Provo (to the south), Ogden (to the north), and in the region between Magna and West Jordan (to the west) where non-white and Hispanic transit users may experience cost-increases as a result of shifting to distance-based fares. It should be mentioned that, according to the trip survey data, fares for Hispanic respondents on average declined by 9%, and by 55% amongst those who refused to state their status. Clearly, this very large decline is a function of the very short trips taken by the refusal group, who on average travel only 5.3 miles each day.

TABLE 4 Average Fare Change for Different Population Groups

	Transit Trips	Distance Travelled (miles)	Flat Fare[a] ($)	Distance-Based Fare[b] ($)	Percentage Change
Household Income					
No Answer	1.73	20.09	4.33	4.68	8.3%
Under $35,000	1.94	13.25	4.85	3.49	-28.1%
$35,000 - $49,999	1.88	19.14	4.70	4.58	-2.6%
$50,000 - $99,999	1.85	20.56	4.63	4.83	4.5%
$100,000 or more	1.86	24.51	4.65	5.59	20.1%
Hispanic					
Yes	1.89	17.39	4.73	4.25	-10.1%
No	1.88	19.6	4.70	4.66	-0.8%
Prefer not to answer	1.64	5.34	4.10	1.83	-55.3%
Race					
White or Caucasian	1.89	19.93	4.73	4.73	0.1%
All other	1.77	14.25	4.43	3.59	-18.8%
Age					
18-24 years old	1.82	17.47	4.55	4.23	-7.0%
25-34 years old	1.88	17.51	4.70	4.27	-9.2%
35-44 years old	1.84	24.19	4.60	5.52	19.9%
45-54 years old	1.87	19.73	4.68	4.68	0.2%
55-64 years old	1.88	17.82	4.70	4.33	-8.0%
>65 years old	2.08	13.91	5.20	3.68	-29.2%
Employment					
Employed full-time	1.84	22.43	4.60	5.18	12.6%
Employed part-time	1.84	13.61	4.60	3.51	-23.8%
Student, not employed or employed less than 25 hrs/week	1.76	15.96	4.40	3.91	-11.1%
Student, employed 25+ hrs/week	1.91	14.61	4.78	3.73	-21.9%
All Other	2.00	13.88	5.00	3.64	-27.3%
Education					
High school or less	1.85	13.08	4.63	3.41	-26.3%
Some College/Vocational/Associates	1.87	18.56	4.68	4.46	-4.6%
Bachelors	1.80	19.34	4.50	4.57	1.7%
Grad/Post Grad	1.95	21.88	4.88	5.13	5.3%

[a] Flat fares are based on a price of $2.50 per trip.
[b] Distance-based fares are based on a price of 50 cents per trip plus 19 cents per mile of travel.

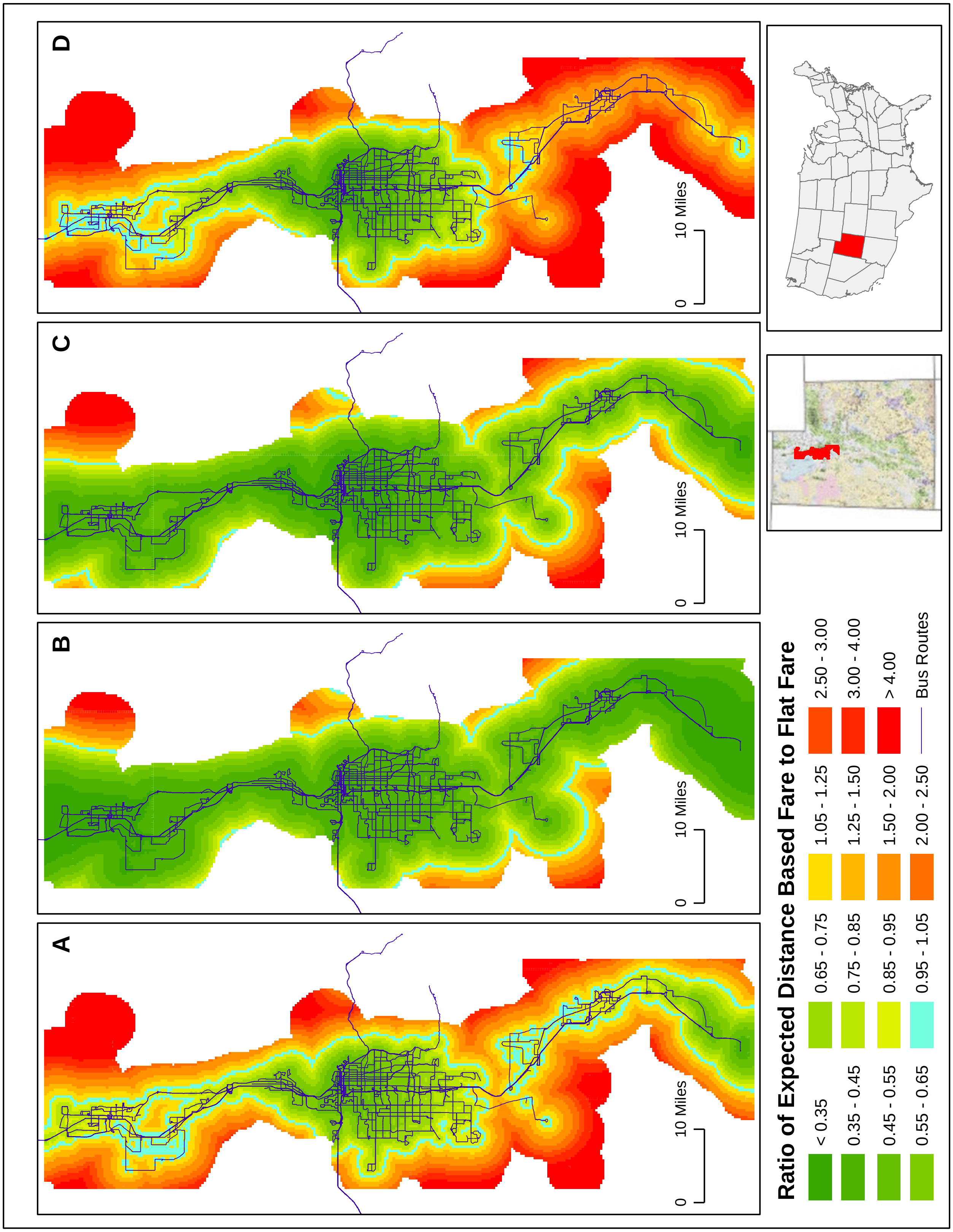

FIGURE 2: Expected Change in Fare for Travelers Taking 2 Transit Trips in a Day A) Reference Group, B) Low Income+Education, C) Low Income/Elderly D) Non-White

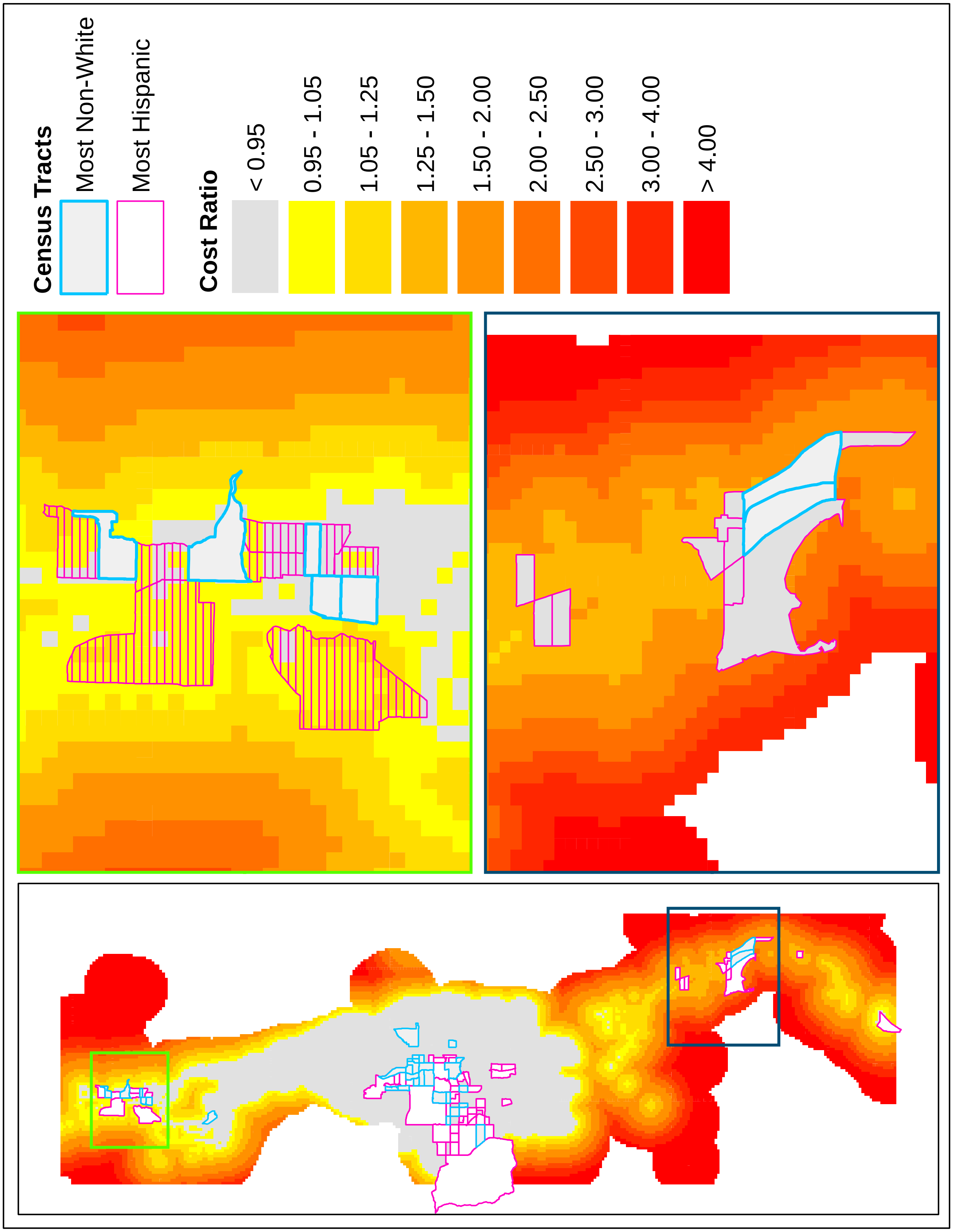

FIGURE 3 Fare Increases for Non-White and Hispanic Travelers Overlaid with Non-White and Hispanic Census Tracts

CONCLUSIONS

The tabular and graphical results presented above constitute the skeleton of a screening mechanism for identifying inequalities inherent in transit pricing structures. For two of the most transit dependent populations, low income households and the elderly, we find that given their expected trip-making rates and distances, the distance-based fare we analyzed is expected to lower their costs for public transit. The screening mechanism however identified locations, far away from the central business district, where fares charged to non-white (and potentially Hispanic) travelers may increase. These screened locations, however, were few compared to the dense concentration of non-white and Hispanic census tracts near the center of the city, where fares are more likely to decrease. In order to better understand the potential impact distance-based fares may have on this population, we recommend that a follow-up study of transit use be carried out in a number of suburban, minority and low-income neighborhoods. Such neighborhoods can be identified through continued exploration of transit fare maps for different socio-demographic profiles.

The work conducted has some limitations. The kernel of the research relies on an accurate behavioral model of trip generations and distances travelled and we must provide several caveats concerning the data and model specification. First, the Utah Household Travel Survey provides only a limited one-day snapshot of travel for each responding household. There is arguably much intrapersonal variation in transit use throughout the week, and this is lost by not capturing longer term travel patterns. Second, the trip records are geocoded at trip-ends, but detailed routing information is not captured by the web-based survey instrument. This means that actual distances travelled along the transit network are not known and must be imputed based on shortest paths or otherwise approximated using common-sense. The error associated with these imputations may have a limited impact on estimated costs. Third, the trip generation and distance models were calibrated without a price variable, implicitly assuming that travelers are not sensitive to price. We did not explore the impact of fares on ridership because the goal of our study is to derive a transferable methodology that satisfies Title VI obligations. While price elasticity is an important aspect of a revenue-based study of fares, and likely has ramifications on social equity from the perspective of captive and discretionary ridership, it is not a requirement of Title VI analyses, and therefore remains the subject of potential future research. Fourth, we have only explored a single type of distance based fare structure in this research, one that begins with a fixed cost per trip and increases linearly with distance. It may be fruitful to explore non-linear or discontinuous price functions, or fare structures with different price functions on different routes. Finally, we caution that with the growing trend of decentralized poverty across the United States, a follow-up social equity analysis of distance-based fares would benefit from the incorporation of estimated and projected population characteristics.

The research identifies a potential conflict between policies designed to promote equity and those intended to increase discretionary ridership (and decrease automobile emissions). For example, increasing fares for long distance discretionary riders travelling from suburban light-rail stations to the central business district may have a negative impact on ridership, despite being economically more efficient through cost-recapturing. At the same time, reducing fares for short distance trips that are currently too expensive compared to private automobile travel may attract new riders. A full cost-benefit analysis sensitive to heterogeneous price elasticity is recommended for future research.

Furthermore, while the findings related to spatiality and transit use discovered in this research are valid, the ability to transfer results to other regions with different spatial demographic patters is limited. The research findings are dependent on the current spatial distributions of population segments and travel patterns. The equity benefits of distance-based fares are primarily derived from residential clustering of

low-income and minority groups in more compact urban areas near the center of the city. Demographic trends, such as inner-city gentrification and suburban aging-in-place, may impose increased travel demands on low-income and elderly riders, nullifying future equity gains made by a transition to distance-based fares.

The technique developed to explore distance-based fares in this paper is novel. It is part of a growing body of research that specifically focuses on the societal implications of travel through the innovative adaptation of data and methods originally designed for travel behavior modeling. It combines state-of-the-art econometric models of travel behavior with spatial analysis and GIS. The next step of the work is to package the above demonstrated functionality into a GIS decision support system. Using an intuitive graphical user interface, this system will enable transit planners at UTA to visualize and compare distance travelled and transit-cost maps for different socio-demographic profiles and fare structures.

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