Are Flat Public Transportation Fares Regressive?: A Look at D.C.'s Metro Fare Structure

Author: Ziyu Fan

Boston College Electronic Thesis or Dissertation, 2020

Are Flat Public Transportation Fares Regressive?

A Look at D.C.'s Metro Fare Structure

Ziyu Fan

Senior Honors Thesis

Department of Economics

Boston College

May 4, 2020

Are Flat Public Transportation Fares Regressive? A Look at D.C.'s Metro Fare Structure

ECON4497 Honors Thesis

Ziyu Fan

Supervised by Professor Richard Sweeney

May 4, 2020

Abstract

Public transportation is found across almost all major cities and differ widely in structure. Notably, transportation agencies adopt different *fare* structures to suit the idiosyncratic needs of cities. In the United States, the two most common fare structures are: distance based fares, and flat fares. This study evaluates the fairness of these two structures through the lens of consumer surplus and how it varies across different levels of poverty under each structure. Using ridership and demographic data from Washington D.C.'s "Metro" network, price elasticities of demand across demographic groups are determined and then applied to estimate the results of a hypothetical switch in fare structure. The resulting changes in consumer surplus are then compared between stations with different levels of poverty to determine whether one structure is more regressive than the other. The results of this analysis suggest that flexible fares such as distance based fares are more equitable as they charge higher prices for high-income individuals, who are also more price inelastic.

1 Introduction

The purpose of this paper is to evaluate the equity implications that different public transportation fare structures have on low-income riders, with Washington D.C. as the empirical setting. It is well established that cities contain a disproportionally high amount of poverty; this is certainly the case in the United States and holds true for the majority of urban centers internationally. Not only do cities offer more opportunities for upwards mobility, the popularity of public transportation networks provides an affordable means of facilitating economic activity, especially for those with low income. However, public transportation structures are by no means homogeneous. Of course, public transportation networks differ in physical infrastructure, but more consequentially, they differ in fare structure as well. While there is no consensus on what the "optimal" fare structure looks like, comparisons can and should be made. In regards to fairness, or equity, the effects of these fare structures will be different for riders depending on their socioeconomic status. This warrants a closer look at the equity implications of different public transportation fares.

The equity implications are indeed ambiguous. To begin, equity is a broad term and can be defined in various ways. In this paper, I define equity in terms of the welfare gained through consumer surplus, or, the benefit received from paying a lower price than what one is willing to pay. A fare structure in which low-income individuals see a disproportionate reduction in their level of consumer surplus would be considered inequitable and regressive. So, how do different fare structures affect one's level of consumer surplus? The answer depends on two components: how responsive people are to price changes (price elasticity), and the average market price people pay under their respective fare structure. In the context of public transportation, the market price is the price set by the transportation agency. Different agencies adopt different pricing strategies but distance based fares and flat fares are by far the most common fare structures utilized. As the names suggest, one is an increasing function of distance traversed while the other is fixed. I therefore pose the question: are flat fares more regressive than distance based fares?

My research plan is as follows: I consider a hypothetical change from one fare structure to another, I then leverage the change in average prices across income levels to determine if consumer surplus decreases or increases for low income riders. While flat fares are common across public transit networks in the United States (e.g. New York, Boston, Chicago), it would be difficult to analyze a hypothetical change *to* a distance based structure as the process would require data how far passengers travel and where. Therefore, comparing a hypothetical fare structure change using an empirical setting that *already* implements distance based fares is more ideal. An obvious choice for an empirical setting is the Metrorail in Washington D.C., henceforth referred to as "the Metro". The Metro is an ideal setting for multiple reasons: 1) ridership and fare data exists at the Origin-Destination pair by time period of entry (OD-t) level; 2) the Metro experiences frequent price changes; and 3) the passenger cohort is demographically diverse. The combination of these three features allows me to measure the price elasticity of riders by demographic groups. I then use these elasticities to estimate how riders will adjust to a hypothetical change in fare structure and compare the changes in consumer surplus across different levels of poverty in D.C.. The results suggest that, under a flat fare structure, low-income riders experience a decrease in consumer surplus due to higher average prices, and is therefore more regressive than distance based structures. But why is this the case?

The answer lies in the fact that demographics vary spatially. Cities have uneven income distributions and are home to diverse population groups that are geographically distinct. A combination of the expansiveness and diversity of the constituency of public transportation networks leads to the conclusion that while public transportation is a public good, it is a good that differentially affects people. In fact, a common trend across cities is that the poor disproportionately depend on public transportation, with evidence suggesting that public transportation is the primary reason why the poor live in cities (Glaeser et al., 2006). Current poverty trends support this: cities with large public transportation networks such as New York (18.9%), Chicago (19.5%), and Washington D.C. (16.8%) all have poverty levels much higher than the US national average of 11.8% (US Census, 2020). While the poor's extensive usage of public transportation is greater, how much they use it *intensively* depends on the geographic distribution of income within a city. If, on average, the poor live closer to the central business district (CBD) than the rich, then it is reasonable to assume that they also travel shorter distances than the rich. Hence, under a distance based fare structure, the poor would pay less. The opposite would be the case if the poor live farther away from the CBD.

In addition to how income is distributed geographically, elasticity is also a determinant of consumer surplus. As mentioned earlier, one of the reasons why the Metro is an attractive empirical setting is that it allows us to calculate demand elasticity by demographic group. The elasticity of riders is important for two reasons. First, the elasticity determines the shape of the demand curve, so more inelastic riders will experience a different change in consumer surplus than riders that are more elastic. Second, elasticity is required for the construction of a hypothetical, revenue-neutral flat fare. In other words, it is the flat fare in which the counterfactual revenue (after adjusting for a demand reaction, which depends on elasticity) equals the de facto (distance based) revenue.

With respect to income distribution and travel behavior, my results show a negative relationship between distance traveled and income. Across the entirety of the Metro, stations with higher levels of poverty have riders who travel shorter distances than stations with low levels of poverty. Specifically, after accounting for between state variation, every 1% increase in poverty rate is associated with a 0.15 mile decrease in distance traveled. With respect to elasticities, my results show that those who travel far and earn below the median level of income (elasticity = -0.451) are roughly 4 times more elastic than those who travel shorter distances and earn above the median level of income (-0.102). With respect to consumer surplus, for every 1% increase in poverty rate, there is an associated $0.015 decrease in consumer surplus per rider per day. All results are statistically significant and tell a compelling story: since the poor travel shorter distances, they pay less under a distance based structure and receive more consumer surplus than they would under a flat fare structure. Thus the more equitable fare structure is one that charges riders with higher abilities to pay. Interestingly, the use of consumer surplus also allows us to compare economic efficiency where the more efficient structure is one with higher levels of overall surplus. In the next section, I provide an overview of relevant literature surrounding equity and public transportation fare structures which were useful in my analysis.

2 Literature Review

This analysis contributes to a limited library of literature on equity and public transportation fare structures. As referenced in the introduction, equity can be interpreted in multiple ways; specifically, vertical and horizontal equity. Vertical equity describes fairness across income groups: how much one pays is proportional to how much one earns. Horizontal equity describes fairness within demographic groups: those with similar socioeconomic statuses should pay similar amounts. The majority of research on equitable pricing in public transportation is highly theoretical. For example, Kaddoura et al. (2015) constructs an "agent-based" simulation model in which bus passengers are charged based on marginal costs and analyzes its effects on social welfare through internalizing negative externalities. Their results suggest that differential pricing indeed increases social welfare by reducing delays and that optimal pricing is one in which fares increase with distance traveled to account for the extended duration of crowding costs that long distance travelers impose. This exhibits an evaluation of horizontal equity where people are charged proportional to their level of usage.

But what determines public transportation usage? That is, how do demographics affect travel behavior? In their paper, Farber et al. (2014) presents a method to assess distanced based transit fares and how it affects social equity for people with different demographics. Their research takes place in the Wasatch Front, Utah where the public transportation agency is considering changing their flat fare structure. They combine a probit model where they estimate the probably of taking public transport across different demographics with a continuous model analyzing what and to what extent certain commuter characteristics affect the distance they travel. Their major findings suggest that being unemployed, a student, Hispanic, and low income all increase the likelihood of taking public transportation and travel shorter distances. Interestingly, they also find that individuals of high income, \$75,000 to \$100,000 also travel shorter distances compared to individuals with income in the \$50,000 to \$75,000 range, although still more than those who earn less than \$25,000. A possible explanation is that high income earners who fall in the above \$75,000 category substitute longer distance public transit with private alternatives.

Bandegani and Akbarzadeh (2016) offer a different approach by incorporating different demand elasticities by travel distance. They first determine demand elasticities using survey data from 300 commuters in the city of Isfahan, Iran which has a population of 1.7 million and 900,000 daily bus commuters. Next, they construct a hypothetical distance based structure in which fares increase as a function of the number of stations traversed to analyze the effects on horizontal equity. Horizontal equity here is measured by the ratio of fare revenue per mile (RPM) and system cost per mile (CPM). Thus, a RPM/CPM ratio of one would imply perfect equity. The results show that passengers who traverse more stations, i.e. longer distances, have RPM/CPM ratios less than one, meaning they are paying too little for the benefit they reap. Using this ratio, they were able to construct a Lorenz curve for both fare structures, thus enabling a comparison of Gini coefficients. Specifically, they find Gini coefficients of 0.38 and 0.17 for a DBF structure and flat fare structure, respectively. Thus, a distance based fare structure would improve vertical equity.

Brown (2018) contributes to this analysis by evaluating how different fare structures affect those who travel different distances and those who differ by income level. Her study exploits a travel survey in the county of Los Angeles and makes various comparisons between fare structures, using the per-mile fare paid by different riders as a metric of vertical equity. Her findings reinforce the findings of Glaeser et al. and show that "more than three-quarters

(77%) of respondents who rode transit on the survey day earned below the living wage"; again, highlighting the importance of public transportation for the poor. Moreover, low-income riders take significantly shorter trips (5.05 miles) than high-income riders (6.84 miles) leading to the conclusion that flat fares produce the least equitable outcomes as low-income riders pay 29% more per mile than higher-income riders.

My analysis combines the methods used in the previous two papers by measuring how elasticities vary across income and distance ranges. The intuition is that income and distance are likely to be large determinants of how one responds to a price change. It is not difficult to see that the adverse affects of a price hike is much less for someone of high-income than for someone of low-income, with the former experiencing a much smaller reduction in purchasing power than the latter.

Not all research supports the implementation of variable fares in the provision of equity and welfare. A recent paper on flat fares and equity in the County of Stockholm's public transportation network published by Rubensson et al. (2020) finds that while distance based fares provide more horizontal equity (similar pay across individuals of similar income and wealth), they are actually less *vertically* equitable compared to flat fares. Their findings are convincing in that the County of Stockholm switched between both distance based and flat fares throughout the duration of the study, hence allowing the researchers to empirically measure the resulting changes in equity. However, comparing Sweden's demographics with that of the US would be naïve indeed; there are systematic differences between Northern European countries and much of the world. Not only is the population racially homogeneous, the Organisation for Economic Co-operation and Development (OECD) estimates that, the poverty rate in the US is almost twice (1.91) as large as it is in Sweden, (OECD Data, 2019).

Despite the general indication that flat fares may be regressive, the ambiguity of implications across countries as well as the scarcity of empirical research within the US warrant a closer look at the equity outcomes. In this paper, I focus specifically on how flat fares and distance based fares generate different levels of welfare as measured by consumer surplus.

Using America's second largest public transit network as the empirical setting, I look at how poverty affects consumer surplus. Before I present the data and methodology, I first provide background information on the D.C. Metro pertinent to the analysis of this paper.

3 D.C. Metro Background

The D.C. Metro, or Metrorail, was opened in 1976 and is the second largest public transportation network in general and the third largest heavy rail transit network in the United States, serving on average 700,000 commuters per weekday. The network is administered and funded by the Washington Metropolitan Area Transit Authority (WMATA) which also provides bus services within and around Washington D.C.. Over the years, the Metrorail has seen numerous expansions and is now a network of 91 stations with 118 miles of track across six lines. The network model follows what is known as a "spoke-hub distribution paradigm" in which various lines extend outward from a central hub in all directions, analogous to spokes on a wheel. This model allows the Metro to provide access to public transportation in communities within Washington D.C. as well as neighboring jurisdictions in Virginia and Maryland. **Figure 10** in the Appendix presents a map of the Metrorail as of 2019 (WMATA).

In order to access the Metrorail, passengers must tap in using their SmarTrip stored-value proximity cards; passengers must also tap out upon exiting a station. Fares are then calculated as a function of the distance between Origin and Destination stations upon exit and charged to the passenger. The fares have not remained constant throughout the history of the Metro. In fact, during its inaugural year, D.C. utilized a flat fare structure along its first line. However, that was quickly reformed in 1977 where a distance based fare structure comparable to a two-part tariff was introduced. Under such a structure, passengers are required to pay a fixed "baseline" fare and are additionally charged by the marginal mile. Since then, there have been 21 changes to both the baseline and marginal prices as well as the introduction of “distance tiers”. Distance tiers serve the purpose of categorizing the fare increase for the marginal mile. For example, trips in the first tier (3-6 miles) currently charge passengers \$0.326 per marginal mile, trips in the second tier (6+ miles) charge passengers \$0.288 per marginal mile.

The official WMATA annual budget reports assert that recent price changes are designed to support previously established “Fare Policy Principles”, which can be summarized by the following criterion (WMATA, 2013):

- Ensure and enhance customer satisfaction
- Simplify fare calculations
- Establish compliance with federal equity regulations
- Facilitate movement while optimizing revenue

While not entirely explicit, these guidelines suggest that price changes are not reactionary to ridership trends but rather forward looking and standardized. Therefore, this paper operates under the identifying assumption that the price changes are exogenous to ridership trends. Hence, we can exploit the price change as a natural experiment.

The distance used in the fare calculation formula is measured in “Composite Miles” which is the average of two different distance measurements: track distance or the length of the track that connects one station to another, and straight line distance which is the distance between two stations if a straight line is drawn between them on a map. The fares also vary depending on the time of day of travel. This temporal variation was introduced in 1988 to account for the surge in transit demand during rush hours. Specifically, time periods are divided by “peak hours” and “off-peak hours” each of which is subdivided into “AM” or “PM”, and “Midday” or “Evening”, respectively. Peak fares are in effect from 5:00 AM to 9:30 AM and 3:00 PM to 7:00 PM on weekdays while off peak fares are in effect during all other times including weekends. Fares during peak and off peak hours are also capped to maintain affordability for particularly long trips. For example, fares are capped at \$6.00 during peak hours and \$3.85 during off peak hours under the most recent fare scheme which was implemented in 2017.

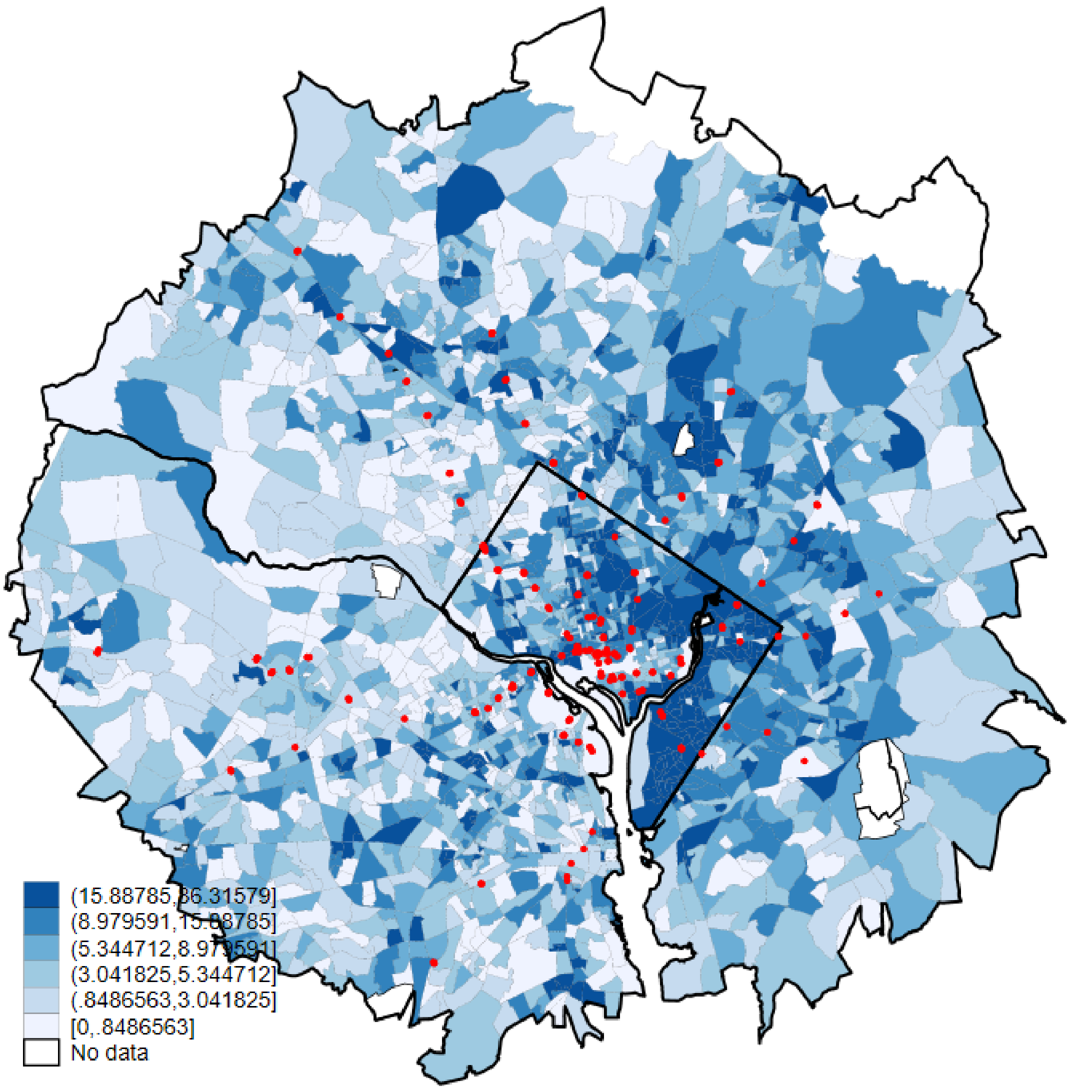
As previously mentioned, Washington D.C.'s demographics make it an ideal setting for this analysis. In addition to being one of most densely populated cities in the US, D.C. is also highly diverse along multiple measurements of demographics. This heterogeneity facilitates the analysis of how flat fares differentially affect commuter cohorts within D.C.. **Tables 17-19** in the Appendix present summary statistics of a selected set of demographic variables at the Census block group level for counties in D.C., Virginia, and Maryland that have access to a Metro station. Further characteristics of datasets and their construction will be discussed in the following section. Additionally, there are significant differences in terms of median household income and poverty rates between D.C. and its surrounding suburbs, with residents living in D.C. earning less and experiencing higher levels of poverty. **Figure 1** supports this claim by presenting the spatial distribution of poverty in D.C. and neighboring counties at the Census block group level, with red points representing Metro stations. Block groups with high levels of poverty are notably more concentrated within D.C. and towards the east. Such large levels of spatial income disparity makes it a matter of socioeconomic concern that transportation fare structures are fair and equitable in a city where large numbers of people depend on public transportation.

4 Data and Methodology

4.1 Data

This section describes the data used in my analysis and how it was constructed. My analysis relies on the use of two "analytical" datasets which are constructed from ridership and demographic data. I first describe the ridership data. Rather than relying on the use of travel survey, this paper utilizes ridership data collected before and after a network wide

Figure 1: Poverty in D.C.



Geographical distribution of poverty (measured in percentages) across is shown at the Census block group level. State boundaries are included to separate Virginia to the Southwest and Maryland to the Northeast of D.C., with red points indicating Metro stations.

fare change to determine elasticities and predict travel behavior. The ridership data comes from the WMATA and reports the average *weekday* ridership between all possible Origin-Destination (OD) station pairs in the month of May for both 2012 and 2013. For each OD pair, ridership is further specified by 4 time periods of entry, as discussed in the previous section. During this time period, the D.C. Metro had only 86 stations, resulting in a total of 28,911 OD pair by time period (OD-t) observations. A unique OD-t identifier was then created for merging purposes.

It is important to note that on July 1st, 2012, a fare change was introduced in which base fares and fares across all distance tiers/time periods were increased. Because the WMATA does not provide historical fares by OD station pair, the fares had to be constructed. Fare is calculated as a function of distance, so given the Composite Distance between any OD-t pair, one can calculate the fare for any year through following the fare schedule. I obtained data on Composite Distance per OD pair from the WMATA API developers' site and subsequently merged it with the ridership data using the unique OD-t identifier to calculate the peak and off-peak fares before and after the fare change. These fares were then confirmed by cross-checking with the Metro website's "fare calculator" feature and added to the dataset. **Tables 1** and **2** present the fares for both years. Note that under the old fare schedule, off-peak fares were not charged incrementally by distance but have fixed rates within a distance tier. To summarize, each observation in the ridership dataset reports the ridership, distance in Composite Miles, fare, as well as the time period and year of a trip between an OD pair.

Table 1: Peak Fare

Date	Baseline	3-6 Miles	6+ Miles	Max Fare
08/01/2010	\$1.95	\$0.299	\$0.265	\$5.00
07/01/2012	\$2.10	\$0.316	\$0.280	\$5.75

Table 2: Off-Peak Fare

Date	Baseline	7-10 Miles	10+ Miles	3-6 Miles	6+ Miles	Max Fare
08/01/2010	\$1.60	\$2.15	\$2.75			\$2.75
07/01/2012	\$1.70			\$0.237	\$0.210	\$3.50

Next, I describe the demographic data which was separately obtained through the NHGIS (National Historical Geographic Information System) data library of IPUMS (Integrated Public Use Microdata Series). Not only does NHGIS compile demographics data, it also produces geographic shapefiles used for GIS purposes. The measurements compiled by NHGIS were collected by the US Census Bureau and are from its 2011-2015 ACS (American Community Survey) 5-year estimates dataset, with observations measured at the Census block group level. Block groups are comprised of Census blocks, which are the smallest geographical area for which the Census Bureau collects demographic data, and have populations of 600 to 3000 people. Being smaller than Census tracts, block groups allow for more precise depictions of the spatial distribution of demographics such as income and poverty rate in areas surrounding Metro stations. Looking solely at D.C. block groups is not sufficient, however, as the Metro extends well into surrounding counties in both Virginia and Maryland. In fact, Metro stations provide transportation access to Prince George's County Montgomery County in Maryland; and Arlington County, the City of Alexandria, Fairfax County, the City of Fairfax, and the City of Falls Church in Virginia. Block groups in these regions were then appended to the D.C. demographic data. The specific measurements reported in the dataset include but are not restricted to: median household income, median age, education attainment, race, and poverty rate.

The ridership and demographic data were then merged to construct the analytical dataset at the OD-t level (with 28,911 observations). Distance from the centroid of every block group to the coordinates of every Origin station in a given OD-t pair was calculated and those within two miles of a station were selected. The reasoning is that riders can be characterized by the demographics of the Origin station of a given trip. All block groups within a two mile radius of an Origin station are therefore linked to that station and represent the demographics of that station. A radius of 2 miles was chosen since it is small enough to be specific and large enough to account for those who take some other mode of transport to the Metro. For every OD-t pair, average demographic measurements were then constructed as a weighted average of the block groups linked to its respective Origin station, with the weights determined by taking the inverse of the distance between the two entities. Inverse distance weighting achieves the effect that block groups farther away from stations are weighted less than those nearby. Importantly, each OD-t observation now has ridership, fare, and income data, which can then be used to calculate price elasticity by income levels. **Table 3** presents the summary statistics of variables averaged at the OD-t level. I note that the poverty rate shown here is in fact very close to the average national poverty rate in the US.

Table 3: Summary Statistics (Station Level)

	mean	sd	p25	p50	p75
Total Pop. (1000s)	110.95	49.25	72.15	98.70	139.64
Total HH. (1000s)	48.11	25.15	28.26	39.88	61.94
OD Station Dist.	9.13	5.24	4.95	8.57	12.56
Med. Age	36.27	2.50	34.24	35.82	38.14
Med. HH Inc. (1000s)	92.86	26.74	71.57	93.24	107.30
White Share	50.37	24.76	34.22	57.82	70.94
Black Share	34.28	29.07	11.28	25.30	49.09
Asian Share	7.09	5.41	2.89	6.75	9.41
Other Share	5.10	5.06	2.19	3.65	5.43
Not-Hisp. Share	87.89	7.23	85.88	89.37	92.40
Hisp. Share	12.11	7.23	7.60	10.63	14.12
Non-White Share	49.63	24.76	29.06	42.18	65.78
Poveraty Rate	11.04	5.46	6.75	11.33	13.38
HH Inc. Below $50k Share	30.43	11.62	20.77	29.92	35.18
HH Inc. $50k-$100k Share	27.02	4.97	23.32	25.73	29.90
HH Inc. $100k-$150k Share	18.37	4.15	16.34	18.40	21.34
HH Inc. Above $150k Share	24.18	11.32	14.44	26.46	29.83
HH Pub. Assist. Share	2.41	2.20	0.97	1.68	2.92
HS Diplo. Share	13.64	9.45	6.40	10.07	19.00
BA Share	25.42	7.76	20.64	28.82	30.51
Metro Users Share	21.09	5.20	18.26	22.45	24.52
Observations	28911				

Observations at the OD Station Pair by entry period level. Measurements are inverse distance weighted. "Other" race share includes American Indian, Pacific Islander, and other race categories.

While the analysis of elasticity relies on a dataset at the OD-t level, the analysis of consumer surplus and poverty is done at the Origin station level (86 observations) and does not require fare data. Demographic data do not vary across time periods nor do they vary across Destination stations, but ridership does. Hence, the second analytical dataset reports the average of demographic variables (note: equivalent to values at the OD-t level) and a weighted average of Composite Miles, with weights determined by ridership (weighting by ridership accounts for higher and lower ridership between certain OD pairs), at the Origin station level. In this dataset, each observation represents a Metro station and reports the average poverty rate (and other demographic variables) of block groups within two miles of that station, the average distance people travel from that station, and the county and state.

4.2 Motivational Results

Before I present the methodology, I put forth some correlations suggested by the data to motivate the primary empirical exercise. **Figure 2** presents a scatter plot of distance and poverty rate at the station level, overlaid by a simple linear fit model. **Table 4** shows the corresponding results of a simple regression model with distance as the dependent variable and poverty rate as the explanatory variable.

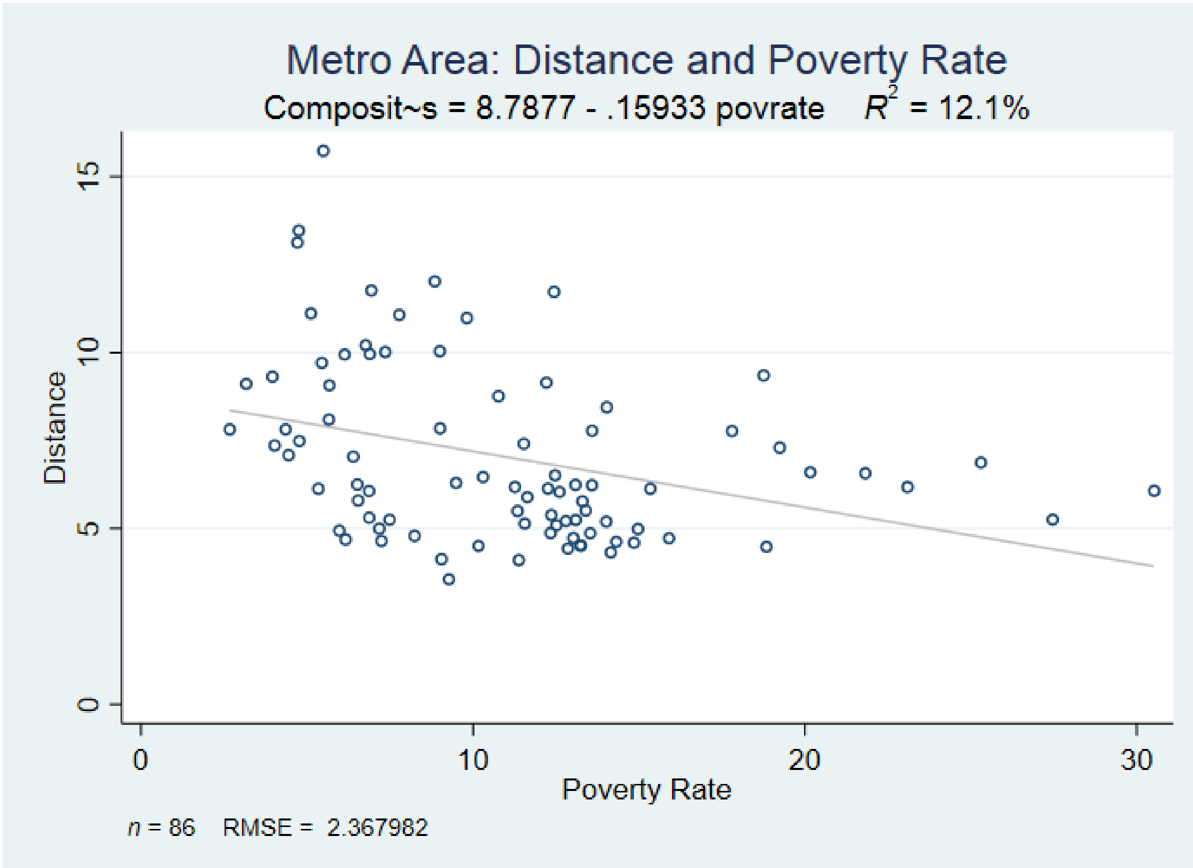
Table 4: Distance and Poverty Rate

	(1)	(2)	(3)
Poverty Rate	-0.159***	-0.345***	-0.150**
	(0.0468)	(0.0512)	(0.0619)
Non-White Share		0.0648***	0.0284**
		(0.0113)	(0.0125)
Regression Type	OLS	OLS	FE
Controls	N	Y	Y
State FE	N	N	Y

Robust tandard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

I then add a racial diversity control variable and state fixed effects to the baseline model. In all cases, the coefficient is significant and negative, implying that stations with higher levels of poverty also have riders who travel shorter distances. Once the model controls for non-White share, the coefficients on poverty rate become larger in magnitude; the coefficient in model (3) implies that for every 1% increase in poverty rate, the distance traveled decreases

Figure 2: Distance and Poverty Rate

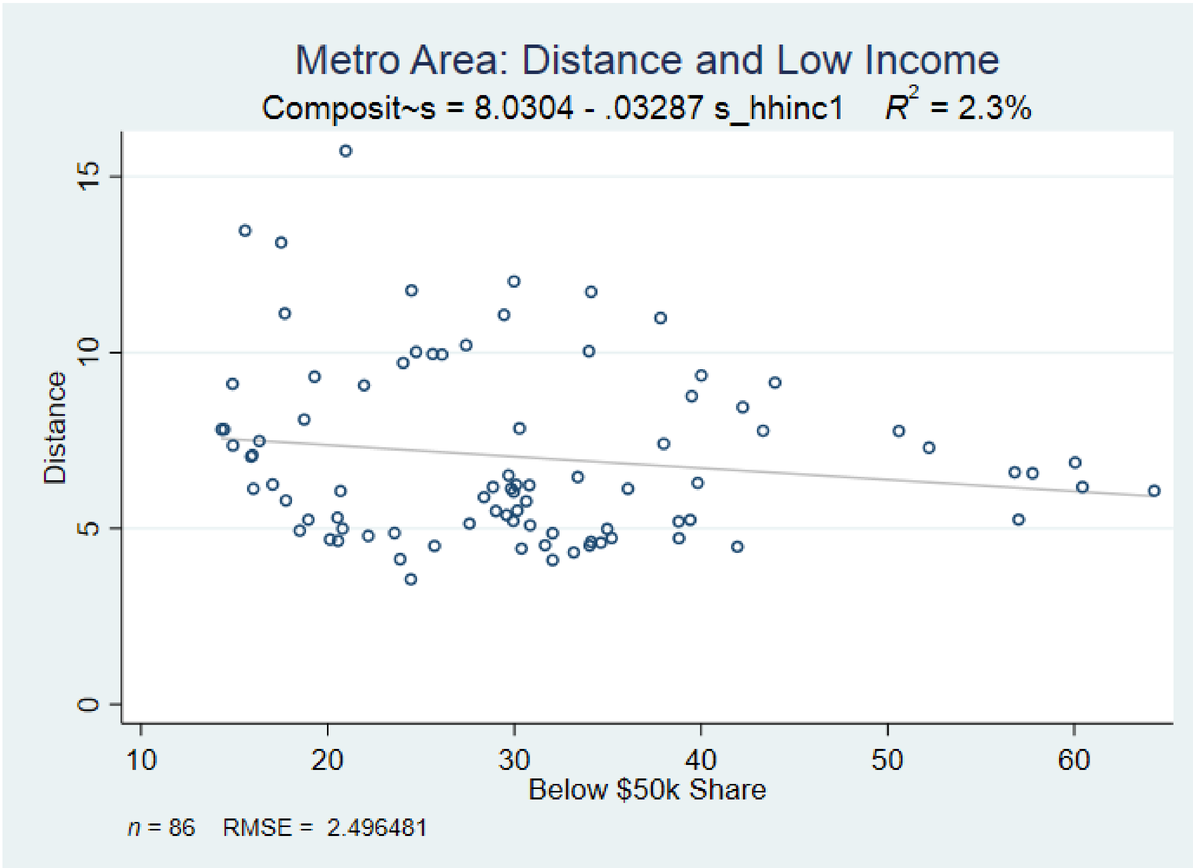


Correlation between the average distance riders travel and poverty rate.
Observations at the station level.

by 0.15 miles. Note, the coefficients of non-White share are positive, suggesting that stations with higher non-White proportions have riders who also travel farther. I repeat the same with "low-income" rate as defined by the share of people with annual income less than $50,000. **Figure 3** and **Table 5** tell a similar story, while the coefficient in model (1) is insignificant, they become significant once controls and state fixed effects are introduced.

Figures 15-17 in the Appendix repeat the same exercise except across the whole spectrum of income range shares. The results show that as the income range rises, the correlation between distance traveled and the share of individuals that fall within that income range becomes more positive. However, for the "ultra" high-income, the relationship is less clear and is in alignment with the findings of Farber et al. (2014). It is likely that in addition

Figure 3: Distance and Low Income Share



Correlations are between the average distance riders travel and the share of individuals whose annual income below $50,000. Observations at the station level.

Table 5: Distance and Low Income Share

	(1)	(2)	(3)
Below $50k Share	-0.0329	-0.220***	-0.111***
	(0.0231)	(0.0358)	(0.0380)
Non-White Share		0.104***	0.0496***
		(0.0168)	(0.0170)
Regression Type	OLS	OLS	FE
Controls	N	Y	Y
State FE	N	N	Y

Robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

to higher poverty rates, city centers also contain levels of ultra-high-income individuals. In sum, these figures provide compelling evidence that the poor are more likely to travel shorter distances, and therefore pay lower distance based prices. This may not be the case under a flat fare.

4.3 Methodology

To evaluate the degree to which the above assertion is true, I breakdown my analysis into three components: 1) identify demand elasticities while allowing travel behavior to vary across levels of income and distance traveled; 2) construct a revenue-neutral flat fare; 3) compare the change in consumer surplus across different poverty levels. In regards to the first component, I first introduce the baseline Ordinary Least Squares (OLS) regression for OD pair i, time period t, and year y to estimate price elasticity:

$$\log(riders_{ity}) = \beta_0 + \beta_1 \log(fare_{ity}) + \epsilon_{ity} \tag{1}$$

Given that variables are in logs, β_1 represents the demand elasticity (measured as the percentage change in ridership given a one percentage change in fares). However, there are obvious endogeneity concerns since the model very clearly omits confounding variables along all three dimensions, i, t, and y that could bias the result. This warrants the addition of fixed effects. A natural place to begin is with the inclusion of year and OD-t fixed effects which will control for time invariant attributes across OD-t pairs as well as time varying attributes across years. However, the model could be more specified by including OD-t and OD-year fixed effects instead:

$$\log(riders_{ity}) = \beta_0 + \beta_1 \log(fare_{ity}) + \delta_{it} + \phi_{iy} + \epsilon_{ity} \tag{2}$$

where δ_{it} and ϕ_{iy} represent OD-t and OD-year fixed effects, respectively. The intuition for including OD-year fixed effects is that the previous model does not take into account the existence of four time periods per OD pair, treating them as independent observations instead. OD-year fixed effects therefore specify the model to look *within* each OD pair and tries to identify how ridership changes as a function of the price change. In **Table 6**, I present the results of the various model specifications applied to the ridership analytical dataset (OD-t level). The table presents large and significant coefficients for less specified models (1) and

Table 6: Elasticity Specifications

	(1)	(2)	(3)	(4)	(5)
logfare	-1.075***	-2.084***	-0.189***	-0.0846***	-0.213***
	(0.0326)	(0.0449)	(0.0212)	(0.0281)	(0.0237)
Regression Type	OLS	FE	FE	FE	FE
Year FE	N	Y	Y	N	N
Time FE	N	Y	N	N	N
OD-time FE	N	N	Y	Y	Y
Year-Time FE	N	N	N	Y	N
OD-year FE	N	N	N	N	Y

Standard errors are clustered at OD pair level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(2) which do not control for trends across OD pairs. I note that the coefficients decrease dramatically with the inclusion of OD-t fixed effects in the latter models. This confirms the suspicion of OVB in the baseline models, specifically highlighting positive biases across OD-t pairs. One possible explanation is that there are biases across just OD pairs: higher ridership between far away OD pairs may be positively correlated with fares as well as ridership, resulting in a positive bias. Variation across time period similarly explains a positive bias: it is likely that there is higher ridership during peak hours which also cost more. I therefore adopt the most specified model, (5), as the primary estimating model. The results of which indicate that on average, a one percent increase in fare prices results in a 0.21 percent decrease in ridership.

Price elasticities are likely to vary depending on one's socioeconomic conditions as well as the price of the good, ergo I allow the estimates from the preferred specification to vary across income and distance groups. First, I allow the estimates to vary across these variables separately. **Tables 20-21** in the Appendix show how price elasticities vary as one rises in the distance and income distributions by quartiles independently. In reality, distance and income levels are likely to interactively affect price elasticity. I therefore allow elasticity to vary across income and distance groups *together*, with the groups determined by the median poverty rate. Hence, we have four elasticity groups, as shown in **Table 7**. The coefficient in

Table 7: Elasticity by Median Earnings
by Distance Below and Above Median

	Inc. below	Inc. above
Dist. below	-0.190***	-0.102***
	(0.0361)	(0.0388)
Dist. above	-0.451***	-0.138*
	(0.0629)	(0.0559)

Standard errors clustered at the OD pair level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

upper left quadrant reports the elasticity for riders who travel less than the median distance and earn less than the median level of income. The coefficient in the bottom right quadrant represents the case for high income and long distance riders. All elasticities are significant at the 1% level except for high income and long distance riders (significant at the 10% level). They suggest that the people who earn less and travel far are more elastic than those who earn more and travel shorter distances. I repeat the same exercise but by income and distance *quartiles* in **Table 22** in the Appendix. While the elasticities are more heterogeneous, they are less statistically precise. Each OD-t pair in my dataset will now have one of the four elasticities as given by **Table 6**.

Using these elasticities, I calculate the effect of a change to a flat fare and how it affects consumer surplus. Identification of an appropriate flat fare is the second component of my analysis and can be summarized as an optimization problem. The goal is to identify a flat fare that minimizes the difference between counterfactual revenue and the de facto revenue. Since I want to isolate the comparison to just flat fares and distance based fares, I identify the fare that minimizes the revenue difference at each entry time period to control for time varying fares. In this optimization exercise, I first calculate the counterfactual ridership for each OD-t under a flat fare:

$$cfriders = riders \times (1 + (percd \times elast))$$

where

$$percd = (fare_{flat} - fare_{distance})/fare_{distance}$$

Then, at each time period, I calculate the de facto revenue and the counterfactual revenue:

$$rev = \sum_{i=1}^{28911} ridership \times fare_{distance}$$

$$cfrev = \sum_{i=1}^{28911} cfriders \times fare_{flat}$$

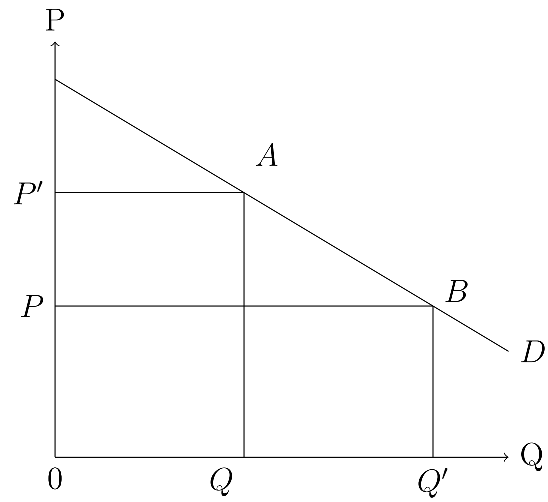
I then implemented an algorithm that looped through a range of possible $fare_{flat}$ values until $cfrev - rev$ is close enough to zero. I note that fares are rounded to three decimal places and therefore cannot perfectly minimize the difference.

The calculation of consumer surplus involves knowing the price under each fare structure as well as the riders' demand function (i.e. willingness to pay) and is the final component in my analysis. The sum of the differences between each rider's willingness to pay and the fare price (which is given), i.e. the area between the inverse demand curve and price, represents the level of consumer surplus per station. Since the data reports average *weekday* ridership, the resulting measurement is consumer surplus per weekday. **Figure 4** illustrates this concept where the region $P'ABP$ represents the change in surplus between two price levels. By construction, each OD-t observation has: two prices, the respective level of ridership under those prices, and the price elasticity. Together, these variables allow me to calculate the surplus under each fare structure. Assuming constant elasticity across quantity demanded, the riders face a nonlinear "isoelastic" demand curve, given by exponentiating the elasticity model:

$$\log(Q) = a + elast \log(P) \implies Q(P) = aP^{elast}$$

where $Q = ridership$, $a = constant$ as given by the estimating equation, and $P = fare$. Integrating demand as a function of price ($Q(P)$) from $fare_{distance}$ to $fare_{flat}$ yields the same

Figure 4: Consumer Surplus



area under the inverse demand function $(P(Q))$ as depicted in **Figure 4** and therefore gives the change the consumer surplus between the two fare structures for each OD-t observation, per weekday:

$$\Delta CS = CS_{flat} - CS_{distance} = \int_{P}^{P'} aP^{elast} dP$$

where $P = fare_{distance}$ and $P' = fare_{flat}$. At each OD-t observation, if the flat fare is higher than the distance based fare, then change in consumer surplus would be negative; the opposite is true when flat fare is lower than the distance based fare.

Estimating the effect poverty has on the change in consumer surplus is done at the (Origin) station level. That is, I take the total change in surplus for all OD-t pairs and compute the aggregate for each station. I then regress the change in consumer surplus, ΔCS, on the average poverty rate for station i using the following fixed effect model:

$$\Delta CS_i = \beta_0 + \beta_1 povrate_i + \beta_2 controls_i + \alpha + \epsilon_i \tag{3}$$

The vector of controls include: Black share, Asian share, "Other" race share, Bachelor's Degree holders share, and Metro riders share. I also include state fixed effects to reduce additional biases in the model. The sign of β_1 is crucial to the outcome of the analysis.

A positive coefficient would imply that under a flat fare structure, riders from more impoverished stations are likely to experience a net increase in consumer surplus. A negative coefficient would imply that lower income riders are likely to experience a net decrease in their level of consumer surplus.

5 Results

5.1 Naive Approaches

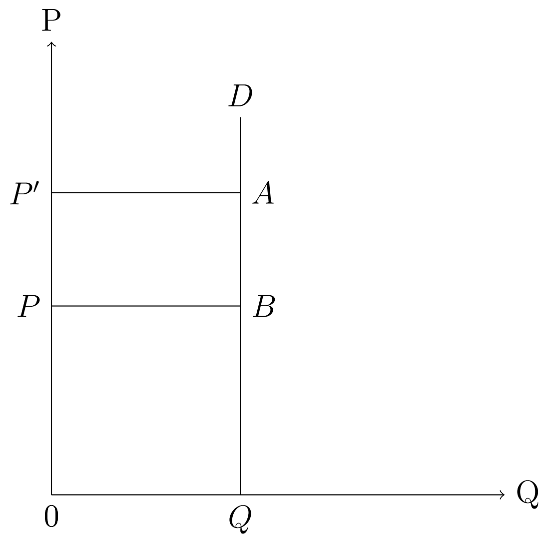
Before I present the results using the full elastic (i.e. multiple elasticities) specification, I put forth two "naive" approaches: 1) assume no behavioral response (i.e. no change in ridership) from a flat fare, and 2) assume a single elasticity across all demographic groups. I then compare those with the full elastic approach to highlight the contribution of elasticity and ridership responsiveness. In the first naive approach, the calculation of the flat fare does not depend on a counterfactual level of ridership but instead takes the de facto ridership in 2012 as constant. The average fare is given by :

$$fare_{inelastic} = \frac{\sum_{i=1}^{28911}(fare_i \times ridership_i)}{\sum_{i=1}^{28911}(ridership_i)}$$

at each time period and is then applied to each OD-t pair. The assumption of zero demand elasticity, or perfect inelasticity, also generates a vertical demand function as illustrated in **Figure 5**. In this naive scenario, the change in surplus from price change is equal in magnitude and opposite in sign to the total change in *expenditure* by the consumers. If flat fares are greater than distance base fares, then net change in expenditure is positive and net change in surplus is negative.

The second naive approach allows for complexity in the model by taking demand reaction into account but applies a single elasticity to the sample. The elasticity is given by the coefficient (-0.213) in model (5) shown in **Table 6**. Identifying the flat fare in this scenario

Figure 5: Consumer Surplus with Inelastic Demand

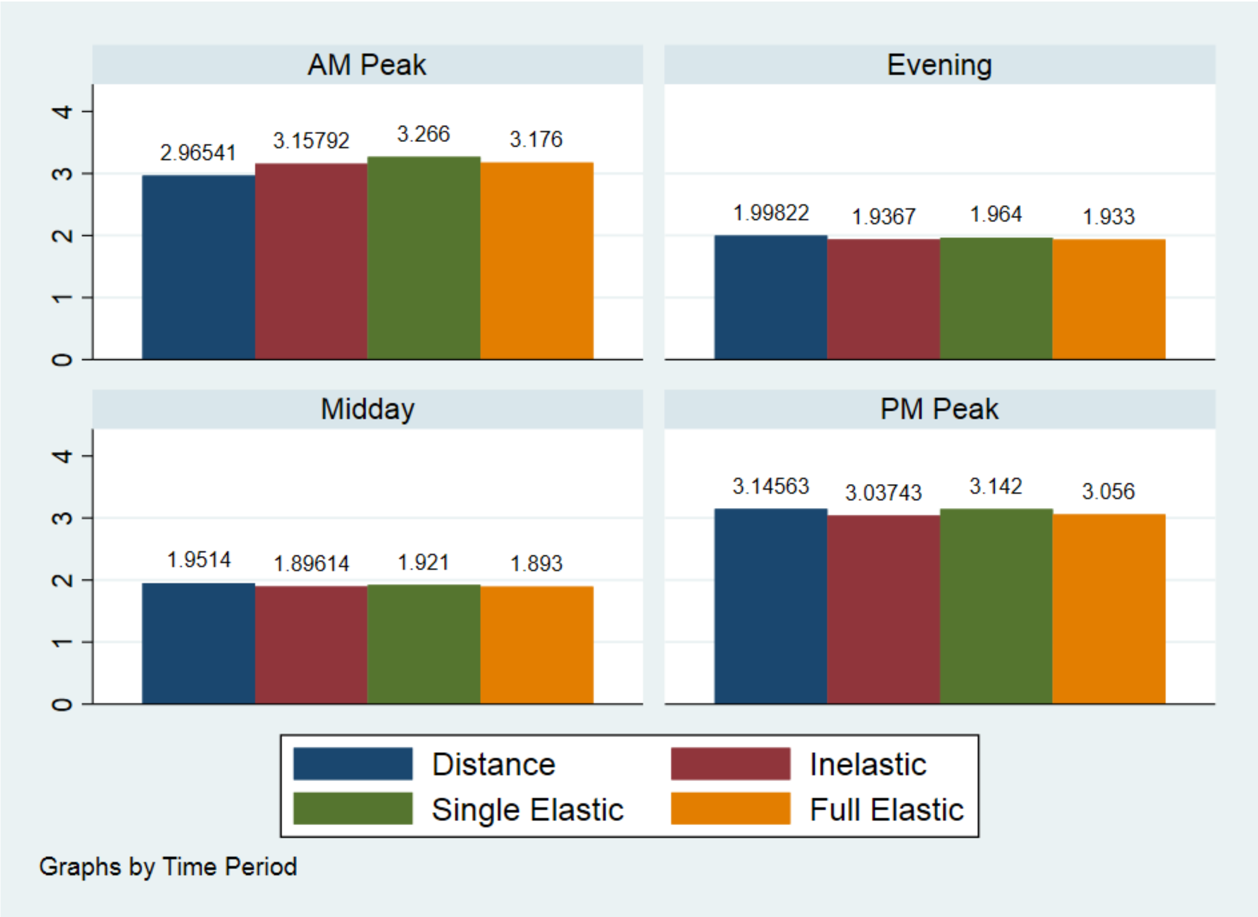


follows the same methodology as the full elastic approach where the fare is one that satisfies the revenue-neutral condition. By gradually incorporating flexibility into the models, I hope to illustrate the contribution of allowing elasticity to vary by distance and income groups.

5.2 Compare Results

In section 4.2, I presented some motivational results which may have suggested that flat fares charge more to low-income riders. Here I present the full results of my analysis after applying demand elasticities to their respective groups and measuring the changes in consumer surplus under a hypothetical flat fare. Whether or not low-income consumers are worse off under a flat fare structure largely depends on if they pay a higher price than the status quo. To help visualize this, I first present an overview of how fares change under both the naive approaches and the full elastic approach. **Figure 6** shows the average fares by time period for each of the four fares: de facto distance based fares are in blue, perfectly inelastic flat fares are in red, single elasticity flat fares are in green, and full elasticity flat fares are in orange. The figure indicates that flat fares are only higher than distance based fares for AM Peak periods. In all periods, single-elasticity fares charge the highest flat fare while full

Figure 6: Fare Comparison



Average fares are reported at the station by time level: distance based fares (blue), flat fares assuming perfect inelasticity (red), flat fares assuming a single level of elasticity (green), and flat fares with multiple elasticities as determined by distance and income level (orange).

elastic flat fares charge more than inelastic flat fares only for Peak periods. However, this figure is misleading in that these averages apply to the entire sample and do not differentiate by the demographics of the riders. In other words, the average "distance" fare paid by one group may be higher or lower than another since not everyone travels the same distance. **Table 8** confirms this by showing lower distance based fares for stations with poverty rates above the median (11.29%) and higher distance based fares for stations with poverty rates below the median.

Table 8: Average Prices by Poverty Rate

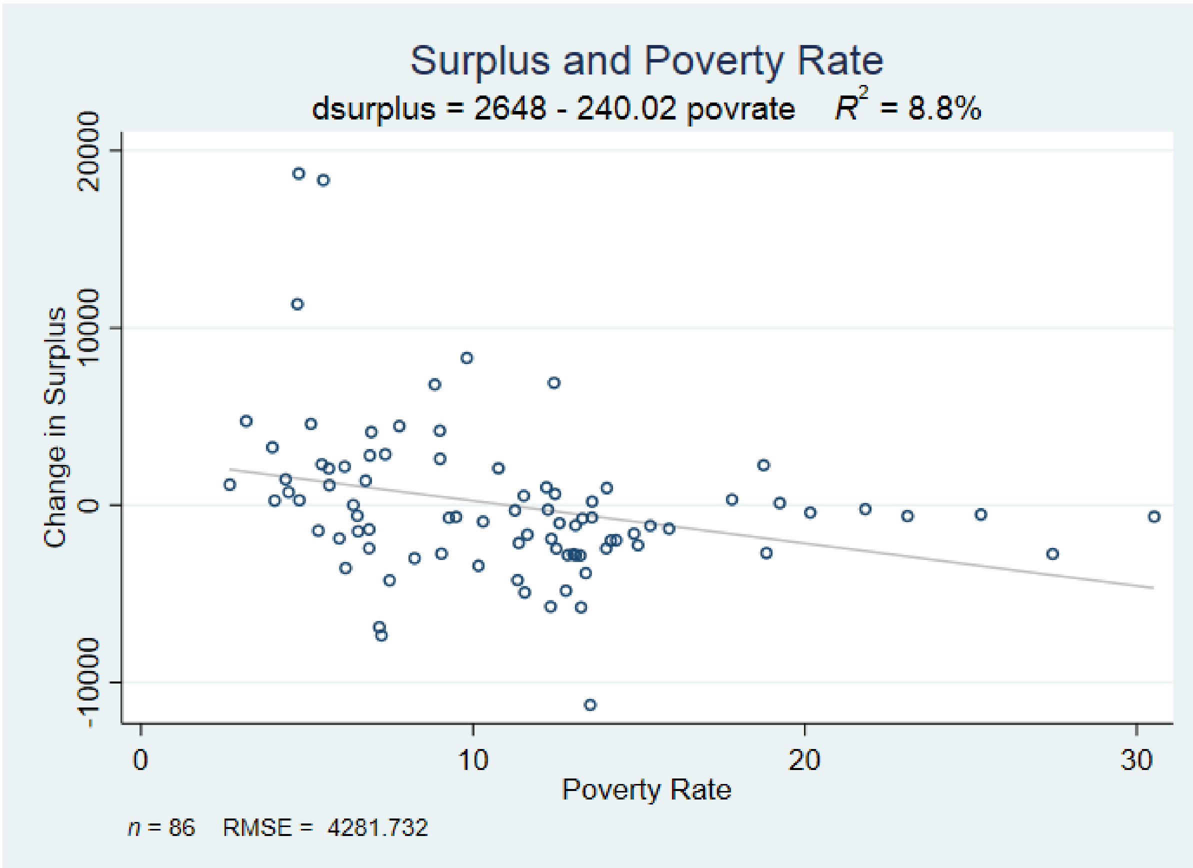
	Above Med.	Below Med.
	mean	mean
Distance Fare	2.330	2.701
No Elast. Flat Fare	2.507	2.507
Single Elast. Flat Fare	2.573	2.573
Full Elast. Flat Fare	2.515	2.515

Average fares compared between stations with poverty rates above and below median are more revealing than averages across the entire sample.

5.2.1 Change in Surplus and Poverty

Next, I present the results from the FE model specification for both naive approaches as well as the full elastic approach with ΔCS as the dependent variable. Recall that ΔCS is the difference of consumer surplus under a distance based fare and a flat fare, i.e. $\Delta CS = CS_{flat} - CS_{distance}$. **Figure 7** and **Table 9** show the visual correlation and the regression results for the perfectly inelastic approach. **Figure 8** and **Table 10** show the results under the single-elasticity approach. And **Figure 9** and **Table 11** show the results under the full elastic approach. I present the baseline OLS results in column (1); I then add a vector of controls in column (2); and finally include state fixed effects in column (3). For the naive approaches, the coefficients on poverty rate across all specifications are significant and negative. Notably, the coefficients increase in magnitude with the introduction of race, education, and Metro usage variables. In the perfectly inelastic approach, the Asian share, Other race share, and Metro usage (Metro Rider Share) have statistically significant coefficients. In the "single elasticity" approach, the same coefficients are significant with the addition of educational attainment (as measured by share with a Bachelor's Degree). The implication is that variables with positive and significant coefficients induce a negative bias while variables with negative coefficients induce a positive bias in the baseline OLS specification. With the addition of state fixed effects, the coefficients are still significant at the 1% level but is smaller in the "single elasticity" approach. More importantly, the negative coefficients on poverty rate imply that the higher the poverty level, the higher the likelihood that the net change in consumer surplus is negative.

Figure 7: Naive Approach (Inelastic)



Observations are shown at the station level. Stations with higher levels of poverty are more likely to receive a negative change in consumer surplus under flat fares assuming zero elasticity.

Between these three approaches, the largest difference lies in the change in magnitude of the coefficients before and after the inclusion of elasticity. The coefficients from **Table 10** and *11* are less than half of the inelastic model. This is intuitively sound. Realistically, riders *do* respond to a price change, adhering to a downward sloping demand curve. Therefore, while the magnitude of how much consumer surplus changes is smaller under the elastic approaches, it is more theoretically and statistically accurate. The results for the full elastic approach tell a similar story. Again, the coefficients are negative for poverty rate, Other race share, college education, and Metro usage; and positive for Asian share. Assuming that the coefficient from column (3) provides the least biased estimate, then holding other variables

Table 9: Change in Surplus and Poverty Rate (Inelastic)

	(1)	(2)	(3)
Poverty Rate	-240.0***	-291.2***	-309.0***
	(82.37)	(51.55)	(72.27)
Black Share		37.03	48.09
		(36.93)	(35.74)
Asian Share		406.3**	430.0**
		(181.6)	(185.8)
Other Share		-102.9*	-102.0*
		(53.05)	(54.04)
Bachelor's Degree Share		-181.0	-131.3
		(113.5)	(115.9)
Metro Rider Share		-365.5***	-381.1***
		(85.07)	(93.05)
Constant	2648.0**	11892.9**	10604.3**
	(1209.4)	(5040.6)	(4959.4)
Regression Type	OLS	OLS	FE
Controls	N	Y	Y
State FE	N	N	Y

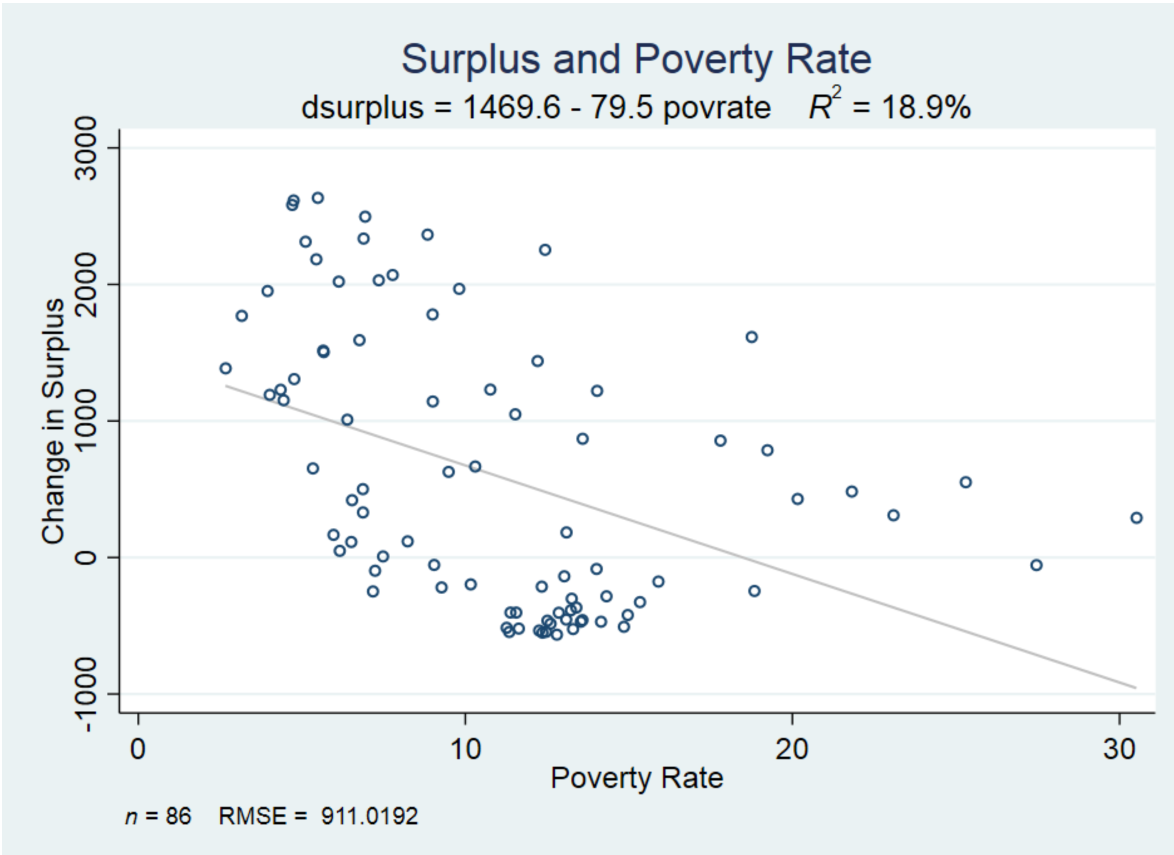
Robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Change in Surplus and Poverty Rate (Single Elasticity)

	(1)	(2)	(3)
Poverty Rate	-79.50***	-123.1***	-90.94***
	(18.37)	(15.54)	(16.34)
Black Share		-1.556	-3.422
		(6.124)	(7.048)
Asian Share		64.46***	53.57***
		(15.89)	(16.67)
Other Share		-22.02**	-21.07**
		(9.559)	(10.50)
Bachelor's Degree Share		-98.20***	-89.24***
		(18.20)	(26.73)
Metro Rider Share		-75.11***	-65.46***
		(14.91)	(13.75)
Constant	1469.6***	5738.7***	5089.4***
	(225.9)	(721.8)	(983.9)
Regression Type	OLS	OLS	FE
Controls	N	Y	Y
State FE	N	N	Y

Robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 8: Naive Approach (Single Elasticity)



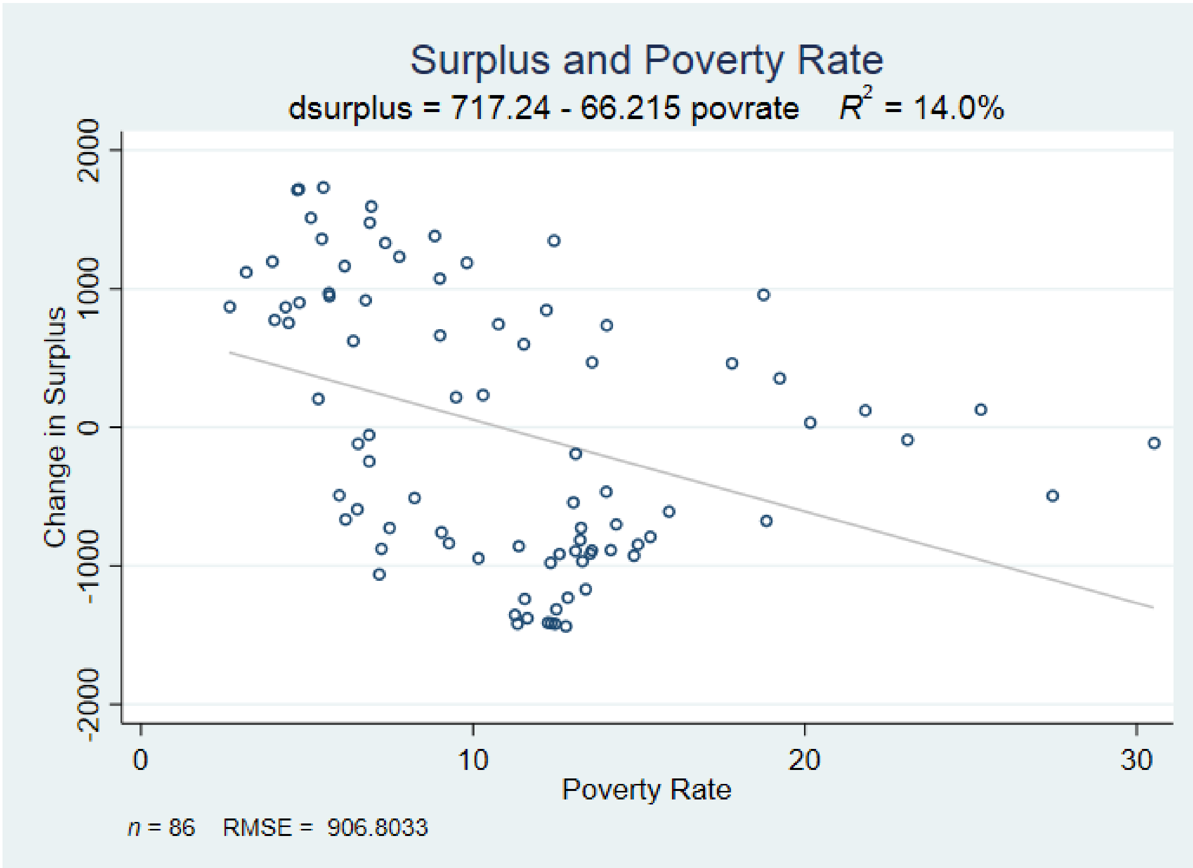
Observations are shown at the station level. Stations with higher levels of poverty are more likely to receive a negative change in consumer surplus under flat fares assuming a single level of elasticity.

constant, every one percent increase in poverty rate is associated with a $89.25 decrease the total Consumer Surplus (per weekday) of a station. In regards to how the three approaches vary statistically, it is also noteworthy that standard errors of the estimates decrease across the three approaches. Therefore, the inclusion of flexible elasticities increases the statistical accuracy of the model.

5.2.2 Consumer Surplus Proxies and Poverty

While these results are convincing, I note that the change in Consumer Surplus is not standardized across observations. Therefore, an evaluation of how poverty rates affect the *percent* change in consumer surplus would be more robust. However, this requires the inverse

Figure 9: Full Approach



Observations are shown at the station level. Stations with higher levels of poverty are more likely to receive a negative change in consumer surplus under flat fares, after llowing for multiple elasticities.

demand function to be defined at the origin (Q = 0). This is not the case given our isoelastic demand function. I therefore use the change in consumer surplus *per rider* as a proxy for a standardized measurement. **Table 12** shows the estimates when consumer surplus per rider is the dependent variable. Again, the coefficients are significant and positive, but we take the coefficient from column (3) as the least biased, which implies that a one percent increase in poverty rate in a station is associated with a $0.0153 decrease in change in surplus per rider, per day. Hence, these results compliment those from the previous section: stations with higher poverty rates are more likely to have a lower amount of consumer surplus *per rider* per weekday under flat fares.

Another variation of this proxy is to evaluate the relationship between the *percent change*

Table 11: Change in Surplus and Poverty Rate (Full Approach)

	(1)	(2)	(3)
Poverty Rate	-66.21***	-119.5***	-89.25***
	(17.79)	(15.15)	(16.16)
Black Share		-3.684	-7.117
		(5.354)	(6.512)
Asian Share		38.01**	24.80
		(18.15)	(18.61)
Other Share		-25.34***	-24.69**
		(8.822)	(9.642)
Bachelor's Degree Share		-99.99***	-100.7***
		(16.52)	(25.90)
Metro Riders Share		-78.66***	-67.85***
		(14.00)	(13.41)
Constant	717.2***	5491.6***	5154.2***
	(216.7)	(710.2)	(1010.5)
Regression Type	OLS	OLS	FE
Controls	N	Y	Y
State FE	N	N	Y

Robust standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Change in Surplus per Rider and Poverty Rate

	(1)	(2)	(3)
Poverty Rate	-0.0104***	-0.0222***	-0.0153***
	(0.00290)	(0.00359)	(0.00459)
Black Share		-0.00128	-0.00129
		(0.00145)	(0.00150)
Asian Share		0.00307	0.00140
		(0.00445)	(0.00483)
Other Share		-0.00525**	-0.00499**
		(0.00224)	(0.00232)
Bachelor's Degree Share		-0.0203***	-0.0162***
		(0.00494)	(0.00578)
Metro Riders Share		-0.0116***	-0.00986***
		(0.00328)	(0.00291)
Constant	0.148***	1.087***	0.882***
	(0.0389)	(0.198)	(0.243)
Regression Type	OLS	OLS	FE
Controls	N	Y	Y
State FE	N	N	Y

Robust standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

in ridership, which we can measure, and the poverty rate. The aim here is provide insight on how flat fares may differentially affect public transit usage across poverty rates without attaching a monetary value to changes in consumer welfare. I therefore repeat the above exercise but with $\%\Delta ridership$ as the dependent variable. **Table 13** produces coefficients with similar signs to those of previous exercises. The coefficient from column (2) suggests that stations with higher poverty rates are more likely to experience a reduction in ridership in a given weekday. However, the coefficient on poverty rate becomes statistically less significant (although still significant at the 10% level) with the introduction of state fixed effects.

Table 13: % Change in Ridership and Poverty Rate

	(1)	(2)	(3)
Poverty Rate	-0.00171***	-0.00347***	-0.00168*
	(0.000487)	(0.000806)	(0.000856)
Black Share		0.000435	0.000649*
		(0.000413)	(0.000379)
Asian Share		0.00134**	0.00130**
		(0.000587)	(0.000644)
Other Share		0.0000233	0.000122
		(0.000939)	(0.000983)
Bachelor's Degree Share		-0.00125	0.000984
		(0.00112)	(0.00129)
Metro Rider Share		-0.00335***	-0.00314***
		(0.000886)	(0.000777)
Constant	0.0198***	0.117***	0.0286
	(0.00697)	(0.0441)	(0.0478)
Regression Type	OLS	OLS	FE
Controls	N	Y	Y
State FE	N	N	Y

Robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.2.3 Average Change in Welfare

In this section I will summarize the results from previous sections and expand on the implications. It is clear that the net change in consumer surplus is more likely to be negative for low-income riders than high-income riders. But since these coefficients describe how the *change* in the change in consumer surplus per day varies with poverty, it is difficult to extrapolate and generalize the results on a yearly basis. I therefore compare the average change in consumer surplus, percent change in ridership, and the change in *expenditure* between stations whose poverty rates are above and below the median (11.29%) level. To generalize these averages to the annual level, I operate under the strong assumption that ridership in May is representative of other months of the year. **Tables 14-16** present the results. Because demand is assumed to be perfectly inelastic in **Table 14**, change in expenditure is opposite and equal to change in consumer surplus and is omitted. Here, the results show that, on average, stations with high levels of poverty (above the median) experience a $1,637.15 increase in expenditure or an equivalent decrease in consumer surplus per average weekday. With on average 261 weekdays per year, this translates to $427,296.15 in additional expenses for the poor. Unsurprisingly, the same amount is offset by the savings in stations with less levels of poverty (below the median) by construction of the revenue-neutral fare (this is consistent across all approaches). On a per rider basis, riders from poorer stations spend $99.63 more per year than "below median" stations.

Table 14: Average Change in Surplus (Perfectly Inelastic)

	Above Med. mean	Below Med. mean
ΔCS	-1637.149	1637.148
ΔCS per rider	-0.1451331	0.2365868

Averages are for change in consumer surplus and change in consumer surplus per rider in dollars per day, assuming no elasticity. Columns are differentiated by the median poverty rate (11.29%).

When we introduce elasticity in **Table 15**, the change in surplus and expenditures diverge. Change in consumer surplus and consumer surplus per rider is still positive for "above median" but much less than "below median" stations. The results of taking the differences across two columns imply that: stations whose poverty rates are above the median receive $1,131.87 less in surplus per day and roughly $0.16 less surplus per rider, per day, than their less poor counterparts. This translates to $295,418.523 and $40.97 less in surplus and surplus per rider, per year, respectively. In terms of expenditures, while total change in expenditure is close to zero by construction, poorer riders spend an additional \$76.15 per year than less poor riders.

Table 15: Average Change in Surplus and Expenditure (Single Elasticity)

	Above Med. mean	Below Med. mean
ΔCS	26.55824	1158.432
ΔCS per rider	0.0619283	0.218886
ΔExp.	1233.017	-1234.223
ΔExp. per rider	0.1163773	-0.1754175

Averages are for change in consumer surplus, change in consumer surplus per rider, change in expenditure, and change in expenditure per rider, in dollars per day, assuming a single elasticity across observations. Columns are differentiated by the median poverty rate (11.29%).

The story is more compelling when we allow elasticities to vary by income and distance groups in **Table 16**. Now, poorer stations still receive \$266,525.58 less in consumer surplus and \$33.34 less per rider per year. As with previous cases, expenditure by the poor are again higher (\$80.88 per rider) than those that are less poor. The consistency across these three approaches serves as an indication of robustness and supports the claim that a switch to flat fares would be more regressive, especially in terms of achieving equity for the poor. As a result of higher average prices, the poor pay more under a flat fare and receive less in consumer surplus. More equitable fare structures therefore charge more to those who have a higher ability to pay. It is also worth noting that *total* average change in consumer surplus is negative, suggesting that not only is a flat fare more regressive, it is also less economically efficient. I discuss this in further detail in the Conclusions section.

6 Conclusions and Discussions

As expected, different fare structures have different effects on one's level of consumer surplus. This paper uses an exogenous price change in D.C.'s Metro network to determine different riders' price elasticities. Price elasticities therefore allow us to predict how riders

Table 16: Average Change in Surplus and Expenditure (Full)

	Above Med. mean	Below Med. mean
ΔCS	-523.8606	497.3108
ΔCS per rider	-0.0302564	0.0974865
ΔExp.	1335.719	-1337.024
ΔExp. per rider	0.1220732	-0.1878139

Averages are for change in consumer surplus, change in consumer surplus per rider, change in expenditure, and change in expenditure per rider, in dollars per day, *after* allowing for different elasticities. Columns are differentiated by the median poverty rate (11.29%).

will react to hypothetical changes in price. Namely, this paper puts worth the question: how does a change from distance based fares to flat fares affect the amount of consumer surplus received by riders? Moreover, how do the changes vary between Metro stations of different poverty rates? While existing literature have eluded to how flexible fares such as distance based fares promote both horizontal and vertical equity through Gini coefficients or "cost per mile" metrics, I evaluate vertical equity on the basis of consumer surplus as it is also salient to the discussion of economic efficiency.

The results on elasticities show that low-income riders travel shorter distances and are almost twice as elastic as high-income riders. Using the elasticities, we calculated the hypothetical revenue-neutral flat fare which was then used to measure change in consumer surplus. The takeaway from the consumer surplus results is that, holding other demographic variables constant, stations with higher levels of poverty are much more likely to experience a decrease in the amount of consumer surplus received by their riders. Across different levels of elasticity flexibility—from no elasticity to distance/income varying elasticities—we see a transfer of consumer surplus from the poor to the less poor and a transfer of expenditure in the opposite direction. The expenditure results alone imply that poorer riders experience a decrease in their purchasing power, not to mention the poor also rely more on public transportation than those with higher income. Therefore, the implementation of a flat fare in a city with poverty distributions similar to D.C. would fail to promote vertical equity and be considered regressive in nature.

As briefly mentioned towards the end of the previous section, the results also suggest that distance based fares may be more economically efficient. I note that economic efficiency in this context is one in which total surplus is maximized. Under the assumption that public transportation supply is constant, maximizing consumer surplus therefore achieves economic efficiency. Now, elasticity also plays a role in the discussion of efficiency. As suggested by the Ramsay rule, optimal pricing is one that charges people proportional to the inverse of their price elasticity. Hence, those with lower price elasticity should be charged a higher price. The mutual concern for elasticity therefore makes clear the connection between equity and efficiency. Recalling the results from **Table 7**, we saw that higher income individuals are more price inelastic and benefit more from a flat fare. Therefore, not only do fare structures that charge more to the rich redistribute welfare to the poor, it also promotes economic efficiency as high income individuals are also more price inelastic. While this claim has not been empirically proven, the results from this paper certainly provide motivation for further research on public transportation fare structures and their equity and efficiency implications.

The extent to which the results in this paper can be generalized depends largely on how demographics are distributed within other cities. As shown in the Stockholm case study, there is an inverse relationship between distance traveled and poverty rates. This led the researchers to conclude that distance based fares are actually more regressive than flat fares, the opposite of the results from D.C.. However, I note that the demographics in Sweden are relatively homogeneous compared to the rest of the globe. In much of the US, the spatial distribution of income and poverty follows largely that of D.C., with suburbs containing relatively low levels of poverty compared to cities centers. It is also noteworthy that demographics are constantly in flux; the forces of gentrification may disrupt established trends on how wealth is typically distributed in cities across the country. Nevertheless, the results in this paper show that flat fares induce a regressive redistribution of welfare in Washington D.C.. Therefore, if anything, the results presented here are salient for the considerations of transportation agencies around the world aiming to promote social equity for its constituency.

References

[1] Bandegani, Milad, and Meisam Akbarzadeh. 2016. "Evaluation of Horizontal Equity under a Distance-Based Transit Fare Structure." *Journal of Public Transportation*, vol. 19, no. 3, pp. 161–172.

[2] Brown, Anne E. 2018."Fair Fares? How Flat and Variable Fares Affect Transit Equity in Los Angeles." *Case Studies on Transport Policy*, vol. 6, no. 4: pp. 765–773.

[3] Farber, Steven, et al. 2014. "Assessing Social Equity in Distance Based Transit Fares Using a Model of Travel Behavior." *Transportation Research Part A: Policy and Practice*, vol. 67, pp. 291–303.

[4] Glaeser, Edward L., Matthew E. Kahn, and Jordan Rappaport. 2008. "Why Do the Poor Live in Cities? The Role of Public Transportation." *Journal of Urban Economics*, vol. 63, no. 1, pp. 1-24.

[5] Kaddoura, Ihab, et al. 2015. "Optimal Public Transport Pricing: Towards an Agent-based Marginal Social Cost Approach." *Journal of Transport Economics and Policy*, vol. 49, no 2, pp. 200-218.

[6] Organisation for Economic Cooperation and Development, 2019. "Poverty Rate" https://data.oecd.org/inequality/poverty-rate.htm

[7] Rubensson, Isak, et al. 2020. "Is Flat Fare Fair? Equity Impact of Fare Scheme Change." *Transport Policy*, vol. 91, pp. 48–58.

[8] United States Census Bureau. 2020. "QuickFacts: Washington D.C., Chicago, New York, United States" https://www.census.gov/quickfacts/fact/table/washingtoncitydistrictofcolumbia,chicagocityillinois,newyorkcitynewyork,US/PST045219

[9] Washington Metropolitan Area Transit Authority. 2013. “Approved Fiscal Year 2013 Annual Budget” https://www.wmata.com/about/records/public_docs/upload/Approved_FY2013_Annual_Budget.pdf

[10] Washington Metropolitan Area Transit Authority. 2019. “System Map” https://www.wmata.com/schedules/maps/index.cfm

A Appendix

Table 17: Summary Statistics (D.C. Block Groups)

	mean	sd	p25	p50	p75
Total Pop. (1000s)	1.44	0.69	0.95	1.31	1.77
Total HH. (1000s)	0.61	0.32	0.38	0.54	0.77
Med. Age	36.57	8.04	31.40	35.30	42.20
Med. HH Inc. (1000s)	83.71	50.08	42.84	76.25	110.23
White Share	0.40	0.33	0.05	0.33	0.73
Black Share	0.50	0.36	0.12	0.50	0.87
Asian Share	0.04	0.04	0.00	0.02	0.06
Other Share	0.04	0.07	0.00	0.01	0.04
Not-Hisp. Share	0.90	0.11	0.87	0.94	0.98
Hisp. Share	0.10	0.11	0.02	0.06	0.13
Non-White Share	0.60	0.33	0.27	0.67	0.95
Poveraty Rate	15.75	13.38	4.75	12.46	24.53
HH Inc. Below $50K Share	0.38	0.23	0.20	0.34	0.56
HH Inc. $50k-$100k Share	0.25	0.11	0.17	0.24	0.32
HH Inc. $100k-$150k Share	0.15	0.09	0.08	0.14	0.21
HH Inc. Above $150k Share	0.22	0.19	0.05	0.17	0.33
HH Pub. Assist. Share	0.04	0.06	0.00	0.01	0.06
HS Diplo. Share	0.16	0.14	0.04	0.13	0.27
BA Share	0.22	0.12	0.13	0.23	0.31
Metro Users Share	0.20	0.13	0.10	0.18	0.28
Observations	450				

Summary statistics are reported for observations in D.C. at the block group level. Samples were restricted to those within 2 miles of a Metro station.

Table 18: Summary Statistics (Maryland Block Groups)

	mean	sd	p25	p50	p75
Total Pop. (1000s)	1.68	0.78	1.12	1.56	2.11
Total HH. (1000s)	0.59	0.27	0.39	0.54	0.74
Med. Age	39.60	8.25	33.80	38.80	44.50
Med. HH Inc. (1000s)	98.85	46.46	64.92	88.89	120.59
White Share	0.42	0.29	0.15	0.40	0.66
Black Share	0.38	0.32	0.09	0.28	0.68
Asian Share	0.09	0.10	0.02	0.06	0.14
Other Share	0.08	0.13	0.00	0.02	0.09
Not-Hisp. Share	0.84	0.18	0.77	0.90	0.96
Hisp. Share	0.16	0.18	0.04	0.10	0.23
Non-White Share	0.58	0.29	0.34	0.60	0.85
Poveraty Rate	6.88	7.30	1.99	4.96	9.66
HH Inc. Below $50K Share	0.26	0.17	0.13	0.23	0.37
HH Inc. $50k-$100k Share	0.30	0.13	0.20	0.30	0.39
HH Inc. $100k-$150k Share	0.19	0.09	0.13	0.19	0.26
HH Inc. Above $150k Share	0.24	0.20	0.08	0.19	0.36
HH Pub. Assist. Share	0.02	0.03	0.00	0.01	0.03
HS Diplo. Share	0.18	0.11	0.09	0.16	0.25
BA Share	0.22	0.10	0.15	0.23	0.29
Metro Users Share	0.10	0.09	0.04	0.08	0.14
Observations	1137				

Summary statistics are reported for observations in Maryland at the block group level. Samples were restricted to those within 2 miles of a Metro station.

Table 19: Summary Statistics (Virginia Block Groups)

	mean	sd	p25	p50	p75
Total Pop. (1000s)	1.60	0.74	1.05	1.47	2.04
Total HH. (1000s)	0.59	0.28	0.39	0.56	0.75
Med. Age	38.58	7.15	33.40	37.90	43.10
Med. HH Inc. (1000s)	123.03	49.81	85.99	117.33	153.75
White Share	0.67	0.19	0.53	0.68	0.81
Black Share	0.10	0.12	0.02	0.05	0.14
Asian Share	0.15	0.12	0.06	0.13	0.21
Other Share	0.05	0.08	0.00	0.01	0.05
Not-Hisp. Share	0.85	0.15	0.80	0.90	0.95
Hisp. Share	0.15	0.15	0.05	0.10	0.20
Non-White Share	0.33	0.19	0.19	0.32	0.47
Poveraty Rate	5.60	6.91	1.03	3.47	7.66
HH Inc. Below $50K Share	0.18	0.15	0.08	0.14	0.24
HH Inc. $50k-$100k Share	0.25	0.13	0.15	0.24	0.34
HH Inc. $100k-$150k Share	0.21	0.10	0.14	0.21	0.27
HH Inc. Above $150k Share	0.35	0.22	0.17	0.34	0.52
HH Pub. Assist. Share	0.01	0.02	0.00	0.00	0.01
HS Diplo. Share	0.11	0.08	0.05	0.09	0.15
BA Share	0.32	0.10	0.26	0.32	0.38
Metro Users Share	0.09	0.10	0.02	0.06	0.11
Observations	961				

Summary statistics are reported for observations in Virginia at the block group level. Samples were restricted to those within 2 miles of a Metro station.

Table 20: Elaticity by Distance Quartiles Alone

	D1	D2	D3	D4
logfare	-0.171**	-0.146***	-0.232***	-0.462***
	(0.0669)	(0.0286)	(0.0463)	(0.0926)

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Quartiles arranged in increasing order.

Table 21: Elaticity by Median Income Quartiles Alone

	I1	I2	I3	I4
logfare	-0.351***	-0.232***	-0.0873*	-0.145***
	(0.0505)	(0.0414)	(0.0462)	(0.0470)

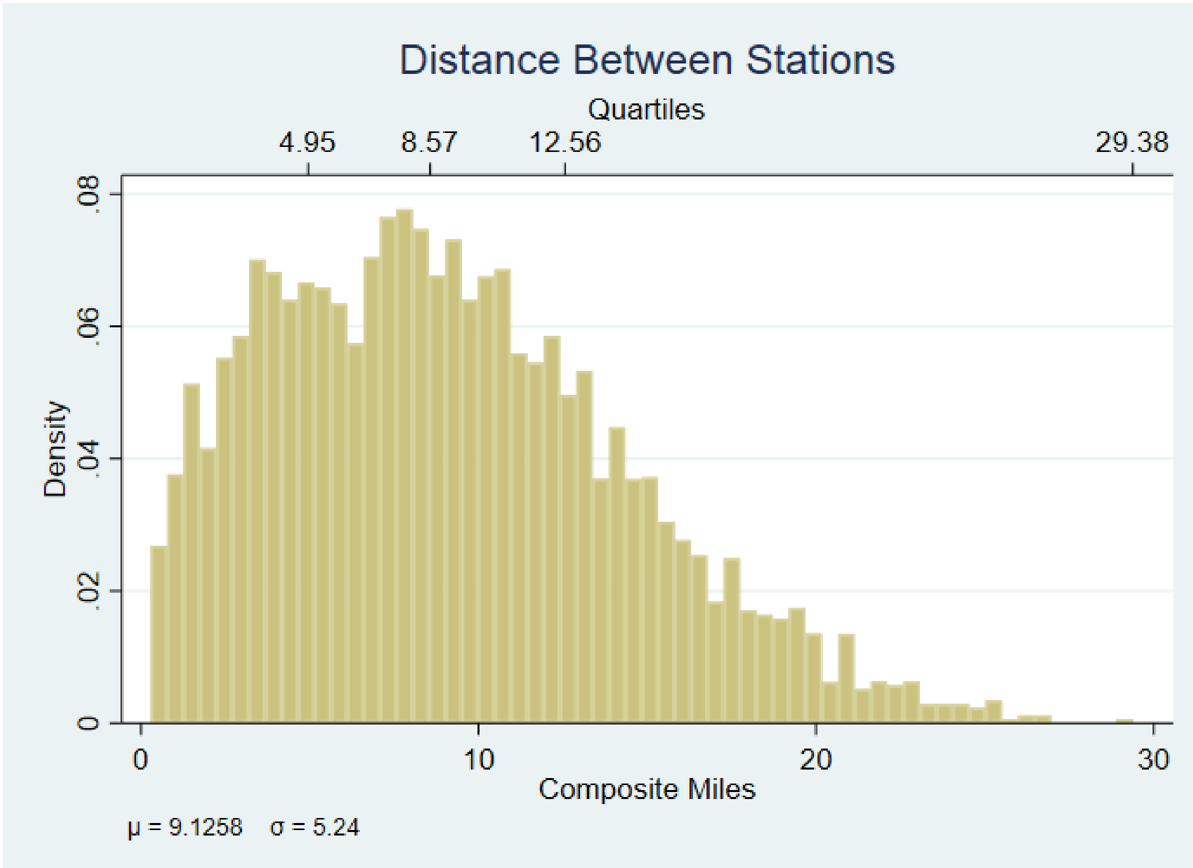
Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Quartiles arranged in increasing order.

Figure 10: D.C. Metro Map

Figure 11: Distance Between Stations Distribution



Distribution of distances between Origin and Destination station (measured in Composite Miles) are at the OD pair by time period level (OD-t).

Table 22: Elasticity by Median Earnings by Distance Quartiles

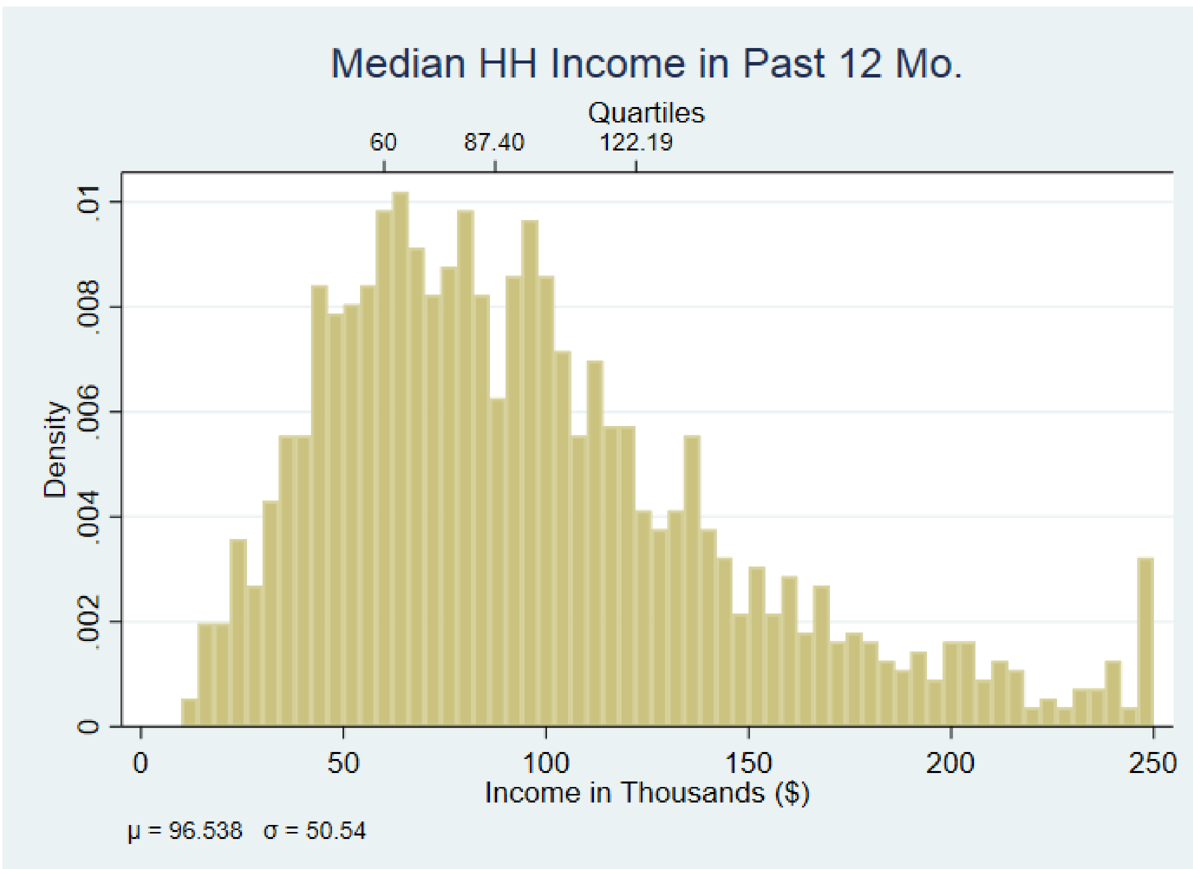
	I1	I2	I3	I4
D1	-0.334**	-0.142	-0.151	-0.0892
	(0.157)	(0.112)	(0.122)	(0.155)
D2	-0.198***	-0.171***	-0.0790	-0.116*
	(0.0568)	(0.0509)	(0.0654)	(0.0547)
D3	-0.384***	-0.275**	0.00498	-0.190*
	(0.0940)	(0.0849)	(0.0835)	(0.0914)
D4	-0.993***	-0.530**	-0.255	-0.153
	(0.233)	(0.181)	(0.146)	(0.166)

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

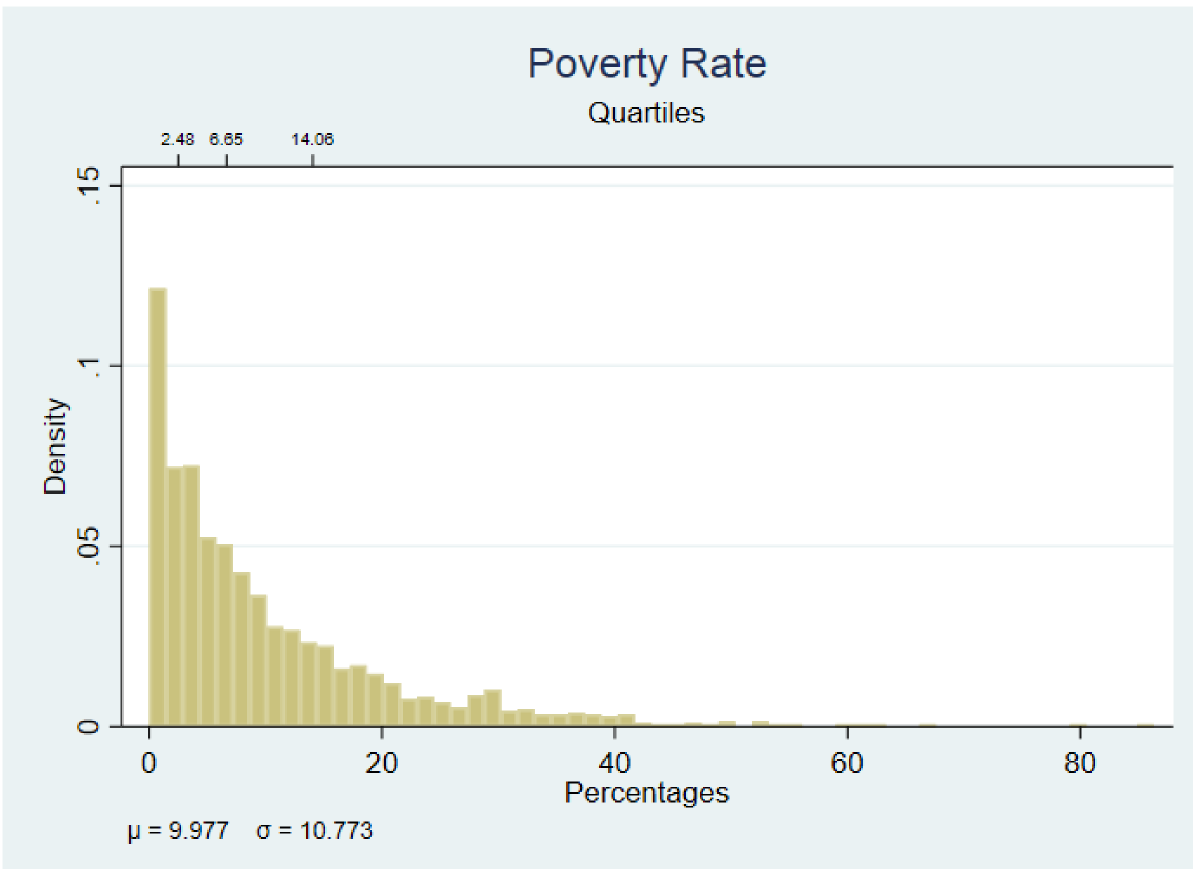
Price elasticities varying by distance and income are reported. Columns indicate Median Income quartiles while rows indicate Distance quartiles. For example, the first entry in the matrix reports the elasticity of riders whose income and distance traveled fall in the bottom quartiles, respectively.

Figure 12: Median HH Income Distribution



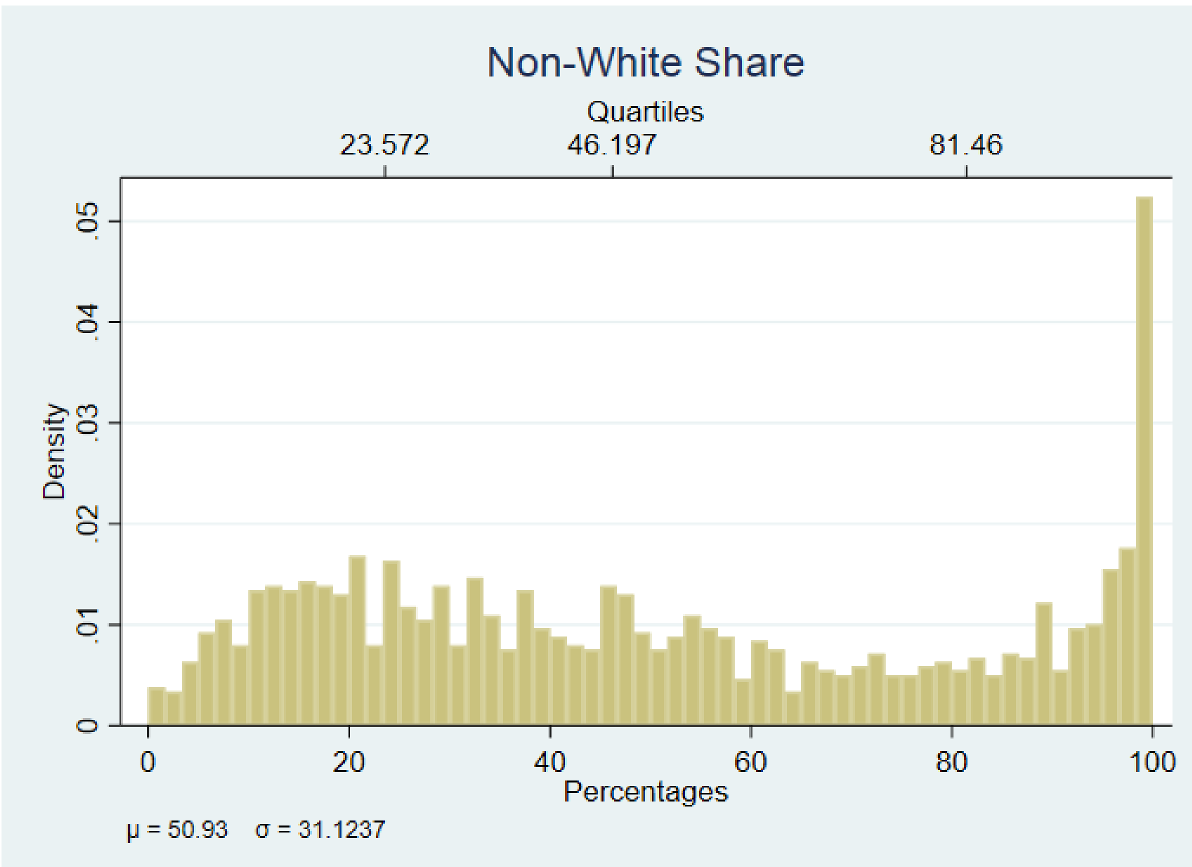
Distributions of median household income (thousands of $) are at the *block group* level. Block groups sample restricted to those within 2 miles of a Metro Station.

Figure 13: Poverty Distribution



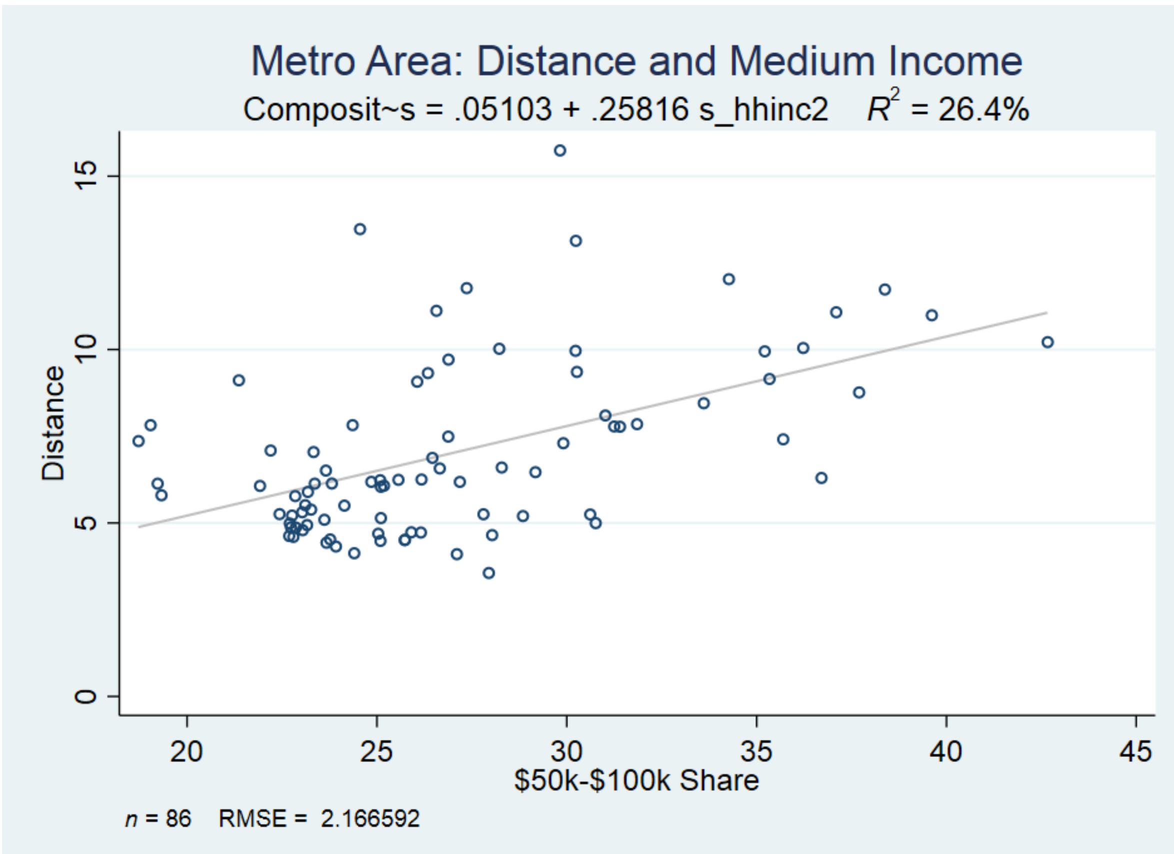
Distributions of poverty rates (in percentages) are at the *block group* level. Block groups sample restricted to those within 2 miles of a Metro Station.

Figure 14: Non-White Share Distribution



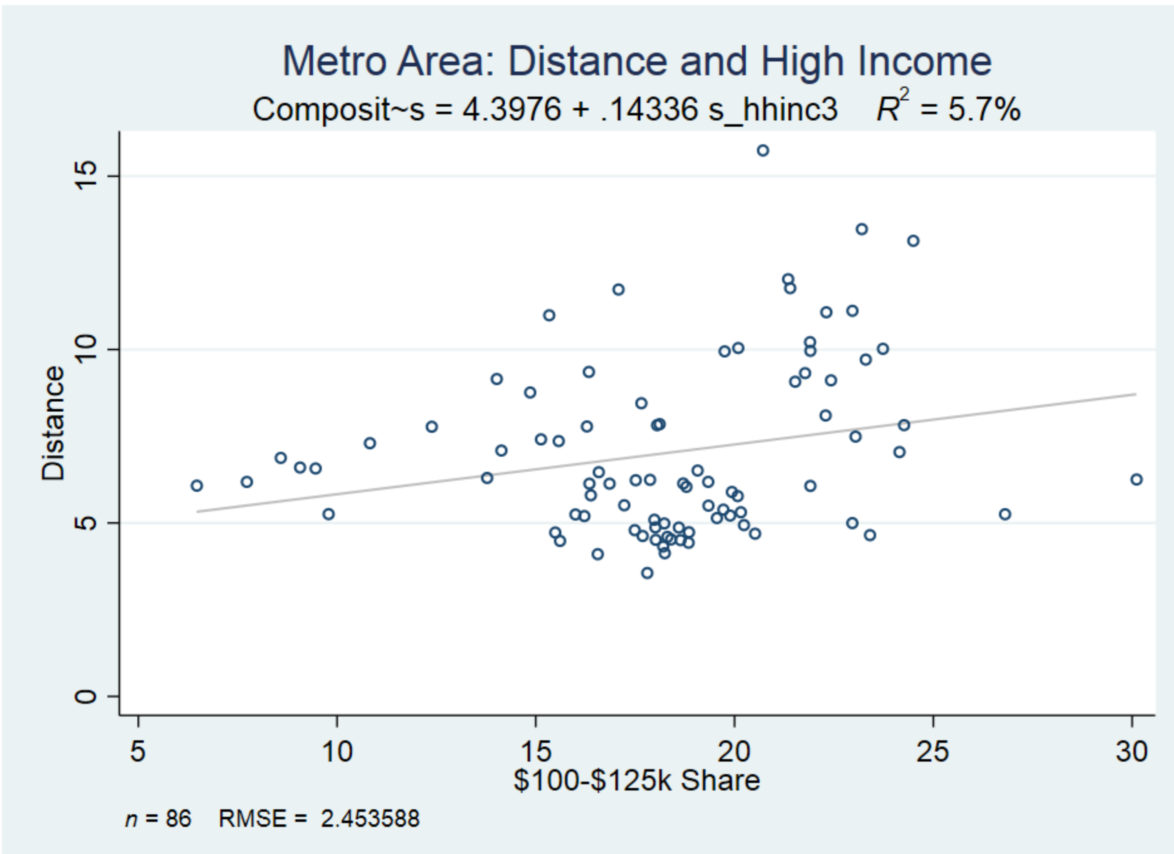
Distribution of non-White share (in percentages) are at the *block group* level. Block groups sample restricted to those within 2 miles of a Metro Station.

Figure 15: Distance and Income Correlation (1)



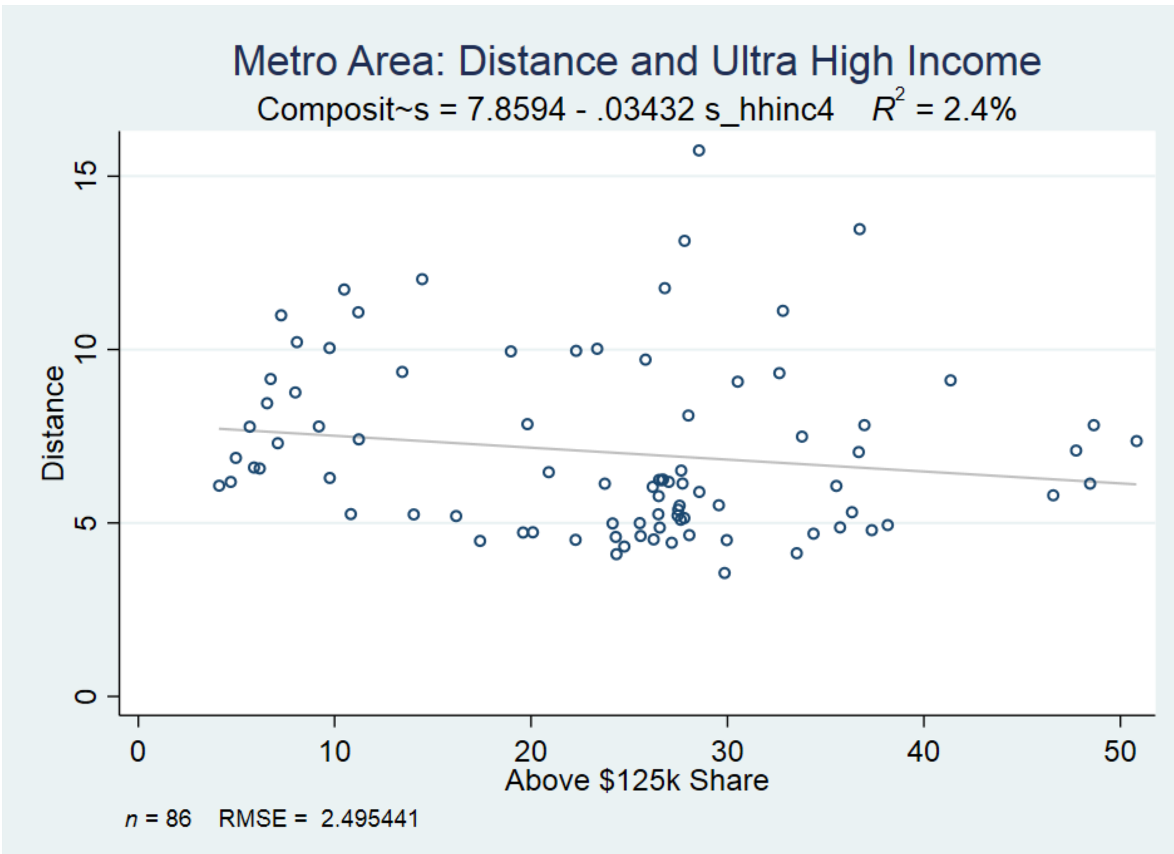
Correlations between the average distance riders travel and the share of individuals whose annual income fall within the $50,000 to $100,000 range show medium-income level riders, on average, travel longer distances. Observations at the station level.

Figure 16: Distance and Income Correlation (2)



Correlations between the average distance riders travel and the share of individuals whose annual income fall within the $100,000 to $125,000 range show high-income level riders, on average, travel longer distances. Observations at the station level.

Figure 17: Distance and Income Correlation (3)



Correlations between the average distance riders travel and the share of individuals whose annual income is above $125,000 show ultra-high-income riders travel, on average, shorter distances. Observations at the station level.