Origin-Destination Land Use Ridership Model for Fare Policy Analysis

For the Washington Metropolitan Area Transit Authority

National Center for Smart Growth
Research and Education
University of Maryland, College Park

metro planning

NCSG

September 2015

This page intentionally left blank.

Acknowledgments

This report explores the determinants of ridership on the Washington Metropolitan rail transit system with a focus on the influence of transit fares. The work was performed by The National Center for Smart Growth Research and Education (NCSG) at the University of Maryland with assistance from the Metro Office of Planning of the Washington Metropolitan Area Transit Authority (WMATA). The NCSG, however, is solely responsible for its content.

The NCSG is a non-partisan center for research and leadership training on the subjects of sustainability, growth, land use, transportation, housing, and development in Maryland, in metropolitan regions around the nation, and in Asia and Europe. It was founded in 2000 as a cooperative venture of the College of Agriculture and Natural Resources and three University of Maryland schools: Architecture, Planning and Preservation; Public Policy; and Engineering.

For more information about NCSG, visit: www.smartgrowth.umd.edu

The NCSG gratefully acknowledges the valuable assistance and feedback provided by Michael Eichler and Justin Antos of the Metro Office of Planning as well as editorial and graphic design assistance provided by Alexandra Reese and Tina Morgan of ECONorthwest. The principal authors of this report are:

Dr. Hiroyuki Iseki, PhD

Dr. Chao Liu, PhD

Dr. Gerrit-Jan Knaap, PhD

This page intentionally left blank.

Table of Contents

This page intentionally left blank.

List of Figures

This page intentionally left blank.

List of Tables

This page intentionally left blank.

Executive Summary

To inform transit fare decision making, the Washington Metropolitan Area Transit Authority (WMATA) contracted with the National Center for Smart Growth (NCSG) to help develop an Origin-Destination Land Use Ridership Model (OD-LURM). An OD-LURM uses information on rail ridership between OD station pairs, service levels, characteristics of station area environments, and the cost of travel between OD station pairs to identify factors—including transit fares—that influence rail transit ridership.

Information on the influence of transit fares is critical not only for managing transit ridership and station congestion, but also for maximizing revenues through fare-box recovery, especially in the face of rising costs and growing demand for greater service levels. Fares set too high can discourage transit ridership and reduce fare revenues. Fares set too low encourage ridership, but can also diminish fare revenues (if the per trip fare is too small). Informed fare policy thus requires sound information about how transit ridership responds to changes in fares, or what economists call the transit fare elasticity of demand.

Our analysis finds that the long-run fare elasticity of demand for ridership on the Washington Metrorail system is approximately -0.50, which suggests that a ten percent increase in fares results in a five percent decrease in ridership, and vice versa. Because our estimate is derived from cross section data, it should be viewed as long-run elasticity, defined as changes in ridership that take place over a five-to-seven year period. Long-run elasticities tend to be larger than short-run elasticities because over a longer period, travelers can respond to changes in fares in multiple ways, such as buying a car, changing jobs, or moving to a new neighborhood.

Other important findings include:

- Unlike others, who found off-peak elasticities substantially higher than peak period elasticities, our estimates of fare elasticity vary little between peak and off peak periods.
- Like others, our estimates of fare elasticity vary by distance traveled: elasticities are high for short distance trips (-1.02), mid-range for middle distance trips (-0.36), and low for long distances (-0.12).
- Riders with subsidized fares (senior and disabled riders) or transit benefits have higher elasticities in all three time periods than full-fare riders without benefits.
- Full-fare riders with a transfer on both ends of a Metrorail trip have lower elasticities, while travelers making no transfer or one transfer from rail to bus show elasticities higher in all three time periods.

These results suggest that an increase in fares, especially for long-distance trips, would increase fare revenues. Riders that travel long distances during peak periods have “inelastic” demands. Therefore, the increase in fares will more than offset the decrease in trips.

For several reasons, our estimates should be used with caution. First, ours is among very few attempts to estimate transit fare elasticity using an OD-LURM, and the first to do so for the Washington Metrorail system. Second, the ranges of coefficients of some key variables vary widely, especially for some sub-groups of riders and trips. Finally, the difficulty of integrating the fare system data with the passenger survey data limited our ability to analyze fare elasticities for specific demographic populations.

Although our estimates must be used with caution, our results in general are robust and consistent with expectations. They reveal that ridership is strongly shaped by the spatial distribution of jobs and households and by the cost of alternative modes of travel. Our estimates of fare elasticities are low for long-distance trips and high for short-distance trips, where there are multiple travel options for Metrorail users.

These findings suggest that, as long as households remain located in the suburbs, jobs remain concentrated in the central city, traffic congestion slows travel speeds by car, and parking remains scarce in the central city, the demand for long-distance ridership on the Metrorail system will remain strong and relatively insensitive to fares. It is likely, however, that short-distance trips in the central city, which often involve travel through congested core stations and have viable alternatives (car-sharing, walking, biking) will become even more sensitive to fares over time.

Introduction

Transit service delivery is a complex task that involves interdependent decisions about capital investments, maintenance, service frequency, transit fares, and more. For assistance with transit fare decision making, the Washington Metropolitan Area Transit Authority (WMATA) contracted with the National Center for Smart Growth (NCSG) to help develop an Origin-Destination Land Use Ridership Model (OD-LURM). An OD-LURM uses information on station area environments, ridership between stations, and the cost of travel between stations to identify factors that influence rail transit ridership—including the influence of transit fares.

Information on the influence of transit fares is critical not only for managing transit ridership, but also for maximizing revenues through fare-box recovery. Fares set too high can discourage transit ridership and reduce total fare revenue. Fares set too low encourage ridership, but will also diminish total revenue, due to the low level of fares. Informed fare policy thus requires sound information about how transit ridership responds to changes in fare levels, or what economists call the transit fare elasticity of demand.

The OD-LURM provides an estimate of transit fare elasticity of demand, which decision makers and planners can use to predict changes in ridership and total revenue based on changes in fares. Our findings suggest that the fare elasticity of demand for ridership on the Metrorail system is approximately -0.50 for full-fare riders in the AM peak period, which is to say that a 10 percent increase in fares results in a five percent decrease in ridership, and vice versa. Compared with other estimates in the literature, our estimate is high for a short-run elasticity and low for a long-run elasticity.

We expected that time of day and ridership class might also impact the fare elasticity of demand. But with few exceptions, our estimates are fairly constant over time of day and rider classes. We also found that fare elasticity estimates vary by distance traveled: elasticities are high for short-distance trips (-1.02), mid-range for middle-distance trips (-0.36), and low for long distances (-0.26). We conclude by suggesting that our results provide useful insights for fare policy decision making, but that more detailed research (possibly in combination with other available data) is needed to understand how fares influence ridership at specific times of the day and for specific user classes.

This report explains the methodology used to build and run the model, our statistical approach, and the findings summarized above. It is organized as follows:

- **The Determinants of Transit Demand** discusses the factors that impact ridership.
- **Transit Fare Elasticity** explains the concept of elasticity with a focus on the fare elasticity of demand for transit.
- **Jobs, Households, Transit Ridership, and Transit Fares in the DC Metropolitan Area** presents information about the spatial structure of jobs and households in the Washington metropolitan area, transit ridership, and transit fares.
- **Empirical Strategy** describes key elements of the model, including key variables, units of observation, and statistical methods.
- **Data and Sources** outlines what data we used and where we obtained them.
- **Statistical Results** explains the key findings.
- **Conclusion** describes the implications of the results.

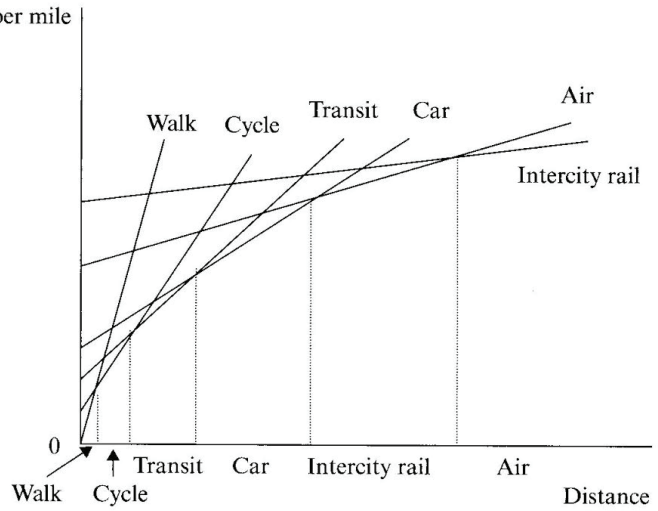
The Determinants of Transit Demand

Demand for transit ridership is generally viewed as a derived demand—it is valued not as a good itself, but as a means to access other goods. Therefore, one can derive its demand from a host of determinants. Factors include:

- The cost (monetary and time) of the transit trip
- The cost (monetary and time) of alternative forms of travel
- The ease of access to goods and services
- The number and types of jobs[1] and households at station locations
- The ease of accessing the station by mode, including foot, bike, bus, or car
- Socioeconomic characteristics of the station area population

These factors do not have a fixed relationship to transit demand; their relationships vary depending on the type of trip. Perhaps the most important trip characteristic is distance traveled. As shown in Figure 1, transit is typically the optimal mode of travel for certain travel distances. These distances exceed distances typically traveled by walking and biking, but are shorter than distances traveled by automobiles. The influence of each of these factors, however, can vary by other trip characteristics that affect transit demand, including time of day and trip purpose.[2]

Figure 1: Dominant Modes of Passenger Transport by Distance



Source: Kenneth Button, 2010, *Transport Economics*, 3rd edition, Edward Elgar, Northampton, MA, USA.

Estimating the determinants of transit ridership and transit fare elasticity requires the development of a transit demand model. There are four ways analysts generally look to model transit ridership:

- **Surveys** are relatively simple to administer and not exceedingly costly. However, they capture perceptions and intentions, not actual travel behavior.
- **Travel demand models** provide a wealth of information about travel behavior for multiple modes. However, they are costly to develop and maintain, and generally developed to model automobile travel demand; transit ridership estimates are a secondary output.
- **Direct ridership models** use station specific information on transit boardings and alighting, built environment characteristics, service levels, and demographics to estimate the determinants of transit ridership at a station level. Since these models are station-specific, they cannot take into consideration trip-specific characteristics like transit fares or travel distances.
- **Origin-Destination Direct Ridership Models** use trip-specific data (distance and fare) on Origin-Destination station (OD-station) pairs, in addition to station-level variables, to estimate the determinants of ridership for different types of trips. Since these models can take into consideration both trip characteristics and station characteristics, they can calculate how ridership responds to fare changes when controlling for a wider range of determinants.

In 2014, NCSG and WMATA developed a station-level LURM for the Washington Metro system, based on the direct ridership modeling approach described above. The model used data on the system's 86 Metrorail stations[3] to demonstrate that the built environment surrounding a given station has significant impacts on boardings and alightings at that station. Because the station-level LURM did not include information on fares, it was not suitable for estimating transit fare elasticities. For this reason, we expanded on the data and information obtained from the station-level LURM model to build an OD-LURM.

OD-LURMs are not new to the field of transportation analysis. Analysts have used them to estimate determinants of demand for intercity train and airline travel.[4] Because intercity train and airline tickets are typically sold for specific origins and destinations, data on origin-destination ridership for these modes are readily available. The introduction of smart cards and other advanced ticketing technologies has made it easier for transit agencies to also collect origin-destination trip data for intra-city transit systems. To our knowledge, however, there has been only one OD-LURM model developed for transit.[5]

Transit Fare Elasticities

Demand elasticity measures the change in demand for a good or service in response to the change in another factor, such as its price. The primary focus of this report is on transit fare elasticity. Transit fare elasticity can be defined as the responsiveness of changes in transit ridership to changes in transit fares: the percent change in transit ridership divided by the percent change in transit fare for a specific system over a defined period of time. Mathematically, this can be expressed as:[6]

$$\textbf{Transit Fare Elasticity} = \frac{\textbf{(\% change in transit ridership)}}{\textbf{(\% change in transit fare)}}$$

Transit fare elasticity usually takes a negative sign, representing an inverse relationship between fare and ridership. The higher the fare, the lower the ridership, and vice versa. When the value of transit fare elasticity ranges between 0 and -1 (or between 0 and 1 in its absolute value), the percent change in ridership is less than the percent change in fare. In this case, ridership is said to be *inelastic*. On the other hand, when the value of transit fare elasticity is lower than -1 (or higher than 1 in its absolute value), the percent change in ridership exceeds the percent change in fare. In this case, ridership is said to be *elastic*. When the value of elasticity is exactly at -1, ridership is said to be *unit elastic*. In this case, ridership changes according to the same percentage as the change in fare. The values of transit fare elasticities are influenced by other factors, which we discuss at the end of this section.

Why Transit Fare Elasticity Matters

Information on transit fare elasticity is critical both for the narrow purpose of revenue generation through fare-box recovery, and for the broader purpose of managing the transit system.

Effective transit management goes beyond maximizing revenues. The management agency must ensure that facilities are utilized at an optimal rate, and that underserved populations can access services. Fare policy can impact both of these aspects of transit system management.

With respect to facility utilization, a small fare change can affect ridership throughout the system. For example, lowering fares on underutilized routes and times of day (or increasing fares on congested routes and times of day) can better distribute ridership across routes—the magnitude of impact depends on how sensitive riders are to fares. In this way, understanding transit fare elasticity can help decision makers maximize utilization.

Fare changes can also have a disproportionate impact on low-income residents and those who do not own cars.[7] Understanding how fare changes will impact these populations is an important aspect of ensuring equity within a transit system. Transit elasticities can help decision makers to address this issue.

How Transit Fare Elasticities Are Calculated

Transit fare elasticity is a simple concept that requires a lot of complex analysis. There are two ways to approach transit fare elasticity. The first is to compare changes *within a system*. In this case, analysts collect time series data over periods in which fares have changed, and observe how ridership patterns changed before and after the change in fares. The second option is to compare changes *across systems*. In this case, analysts use cross-section data on multiple systems, and compare how transit ridership varies between systems with different transit fare structures. In general, time series data are better suited for analyzing short-term responses in transit ridership, while cross section data are better suited for analyzing long-term responses in transit ridership.

Although both approaches are relatively simple in concept, it can be complex to correctly assemble and interpret appropriate data.

Unlike the price of a typical good, which is fixed at a constant price per unit, transit fares are more complicated. Even in the same transit system, fares can vary by time of day, length of trip, direction of trip, and by demographic group (student, seniors, and government employees, among other groups, may receive discounts.) Fare changes may not uniformly impact each trip type, thus it is important to appropriately segment trips (ridership) and fare changes.

Additionally, it can be difficult to pinpoint the impact of transit fares on ridership and isolate this impact from other causes. In the short term, ridership can experience seasonal variation (e.g., in the summer, some users may prefer to bicycle to work) or delayed responses to fare changes, both of which might skew fare elasticity results. In the long term, socioeconomic trends can impact ridership. For these reasons, analysts generally recommend the use of year-over-year assessments. All of these factors complicate the estimation of elasticity.

Transit Fare Elasticity Values

Most of the extant research on transit fare elasticity has focused on buses and intercity trains. Some evidence, however, is available on commuter rail, light rail, and heavy rail transit systems. What's more, transit fare elasticities have been shown to vary by:

- **User type** (transit dependent tend to be less elastic than car owners)
- **Trip type** (commuters trips tend to be less elastic than discretionary trips)
- **Geography** (riders in big cities tend to be less elastic than riders in small cities)
- **Direction of price change** (riders tend to be more sensitive to fare increases than fare decreases)
- **Type of price change** (changes in fares per ride tend to be more influential than changes in multi-ride passes)[8]

Finally, because several other factors can affect transit ridership, it is possible to estimate ridership elasticities with respect to other variables, what economists call cross-price elasticity. The cross-price elasticity of transit ridership has been estimated for:

- The price of gasoline (high gas prices increase ridership)
- The price and availability of parking at the destination (ample, cheap parking decreases ridership)
- Service levels (higher levels of service increase ridership)
- Traffic congestion (higher levels of congestion increase ridership)
- Economic activity (higher levels of economic activity increase ridership)

Based on a comprehensive review of transit ridership and its elasticities, Todd Litman offers the following summary of transit elasticities.

Table 1: Transit Elasticity Values

	Market Segment	Short Term	Long Term
Transit ridership WRT transit fares	Overall	-0.50 to -0.20	-0.90 to -0.60
Transit ridership WRT transit fares	Peak	-0.30 to -0.15	-0.60 to -0.40
Transit ridership WRT transit fares	Off-peak	-0.60 to -0.30	-1.00 to -0.80
Transit ridership WRT transit fares	Suburban commuters	-0.60 to -0.30	-1.00 to -0.80
Transit ridership WRT transit service	Overall	0.70 to 0.50	1.10 to 0.70
Transit ridership WRT auto operating costs	Overall	0.15 to 0.05	0.40 to 0.20
Transit ridership WRT transit costs	Overall	0.10 to 0.03	0.30 to 0.15

Note: "WRT" refers to "with respect to."
Source: Litman, 2010.

Jobs, Households, Transit Ridership, and Transit Fares in the DC Metropolitan Area

Our analysis focuses on ridership on the Metrorail system operated by the Washington Metropolitan Area Transit Authority (WMATA). Metrorail opened in March 1976, and has grown to include six rail lines, 91 stations, and 117 miles (188 km) of track. Metrorail and Metrobus serve a combined population of 3.9 million within a 1,500-square mile jurisdiction.[9] In 2014, Metrorail provided 271.2 million trips.[10] It is the second-busiest rapid transit system in the United States in terms of passenger trips, after the New York Subway system.[11]

Most riders enter and exit the system using a stored value card in the form of a permanent, rechargeable card known as SmarTrip. Infrequent riders, such as tourists, use a paper fare card with a magnetic stripe. As with other transit systems, ridership on Metrorail is shaped by the locations of origins and destinations in the region, household preferences and habits, and the cost and convenience of alternative forms of travel. We can further segment ridership by fare-payment arrangement; with or without transfers between bus and rail; and demographics. Each segment may have different levels of sensitivity to fare changes. The following bullets describe each segment (rider class):

- **Fare-payment arrangement:** full-fare riders with no transit benefits (synonymous in this report with "Regular Riders"), full-fare riders with transit benefits, senior and disabled riders with no transit benefits, and senior and disabled riders with transit benefits
- **With or without transfers between bus and rail:** riders with no bus-rail transfers, riders with a transfer from bus to rail, riders with a transfer from rail to bus, riders with two transfers from bus to rail and rail to bus
- **Demographics:** minority riders, low-income riders, and student riders

This section provides an overview of spatial patters of several key variables and the data ranges of two key fare variables considered in this study.

Jobs and Households

The location of jobs and households in the region fundamentally shapes the demand for ridership on the Metrorail system. Much of the region's employment is located in the central business district, while much of the population is distributed throughout the metropolitan area, especially in corridors that radiate out from the city center.[12] For this reason, the dominant travel pattern in the morning peak (5:00 a.m.–9:30 a.m.) is from the periphery to the central city, while the dominant travel pattern in the afternoon peak (3:00 p.m.–7:00 p.m.) is from the central city to the periphery.

Figure 2: Jobs at Each WMATA Metro Station

Several employment centers dominate where commuters travel. Figure 2 illustrates job locations near Metrorail stations. High concentrations of jobs occur near the centrally-located stations of Metro Center, Union Station, Farragut West, Farragut North, and McPherson Square. Ballston is the only station with a relatively high concentration of jobs in the periphery.

Figure 3: Households at Each WMATA Metro Station

As illustrated in Figure 3, household concentrations within a half-mile walking distance of metro stations[13] are also highest in the more centrally located station areas: Columbia Heights, Dupont Circle, Foggy Bottom, U Street, and Court House Stations. However, there are other population and employment concentrations throughout the metro region not located near Metro stations.

As illustrated in Figure 4, parking capacity is greatest in the more distant station areas: Shady Grove, Glenmont, Greenbelt, New Carrollton, Branch Avenue, Largo Town Center Huntington, Francoia-Springfield, and Vianna. This suggests that much of the demand for ridership comes from residents located in the periphery of the metropolitan area.

Transit Trips and Passenger Miles Traveled

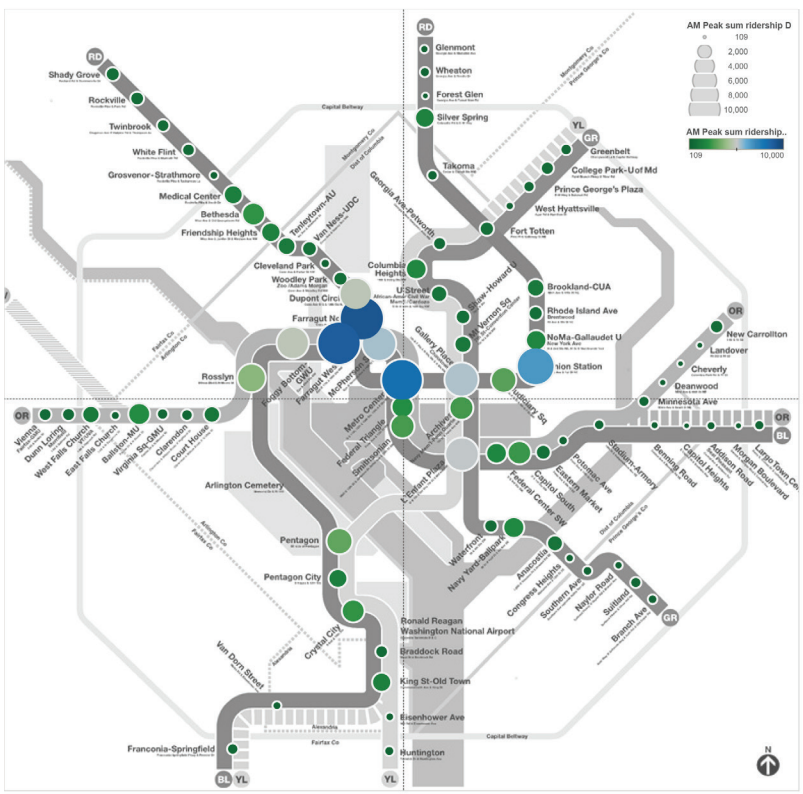
This subsection provides spatial patterns of ridership and passenger miles traveled for full-fare riders with no transit benefits. According to Fare System data, this segment comprises the largest share of total ridership of any single rider class.

Figure 4: Parking Capacity at WMATA Stations

Figure 5: Ridership by Trip Origin at Each WMATA Metro Station, AM Peak, Full-Fare Riders with No Transit Benefits

Ridership and passenger miles traveled reflect the spatial distribution of jobs and households. Although trips by origin stations in the AM peak are relatively evenly distributed, the largest numbers of trips originate in the non-central area stations: Shady Grove, Silver Spring, New Carrollton, Vienna, and West Falls (Figure 5). Because of its connectivity to the intercity rail system, Union Station is the only station near the city center with a large number of origins the AM peak.

Figure 6: Ridership by Trip Destination at Each WMATA Metro Station, AM Peak, Full-Fare Riders with No Transit Benefits



Destinations in the AM peak are centrally located near employment centers (Figure 6). Farragut North, Farragut West, Metro Center, Union Station, and McPherson Square are the stations with the highest number of trip destinations in the AM peak.

Figure 7: Ridership by Trip Origin at Each WMATA Metro Station, PM Peak, Full-Fare Riders with No Transit Benefits

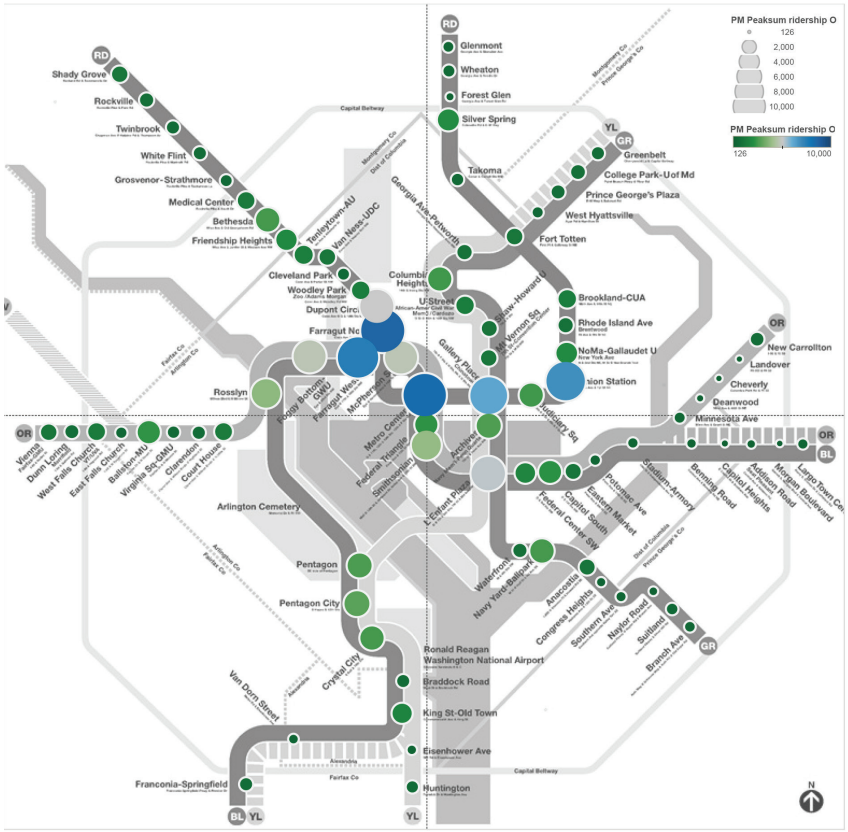


Figure 8: Ridership by Trip Destination at Each WMATA Metro Station, PM Peak, Full-Fare Riders with No Transit Benefits

In the PM peak, the pattern of trips is just the opposite. Trip origins are concentrated in the centrally located stations of Farragut North, Farragut West, Gallery Place, Metro Center, and Union Station (Figure 7).

Trip destinations are dispersed among more stations, though high concentrations occur in the non-central area stations of Union Station, Gallery Place, Dupont Circle, Shady Grove, Pentagon City, and Vienna (Figure 8).

Figure 9: Ridership by Trip Origin at Each WMATA Metro Station, Off-Peak, Full-Fare Riders with No Transit Benefits

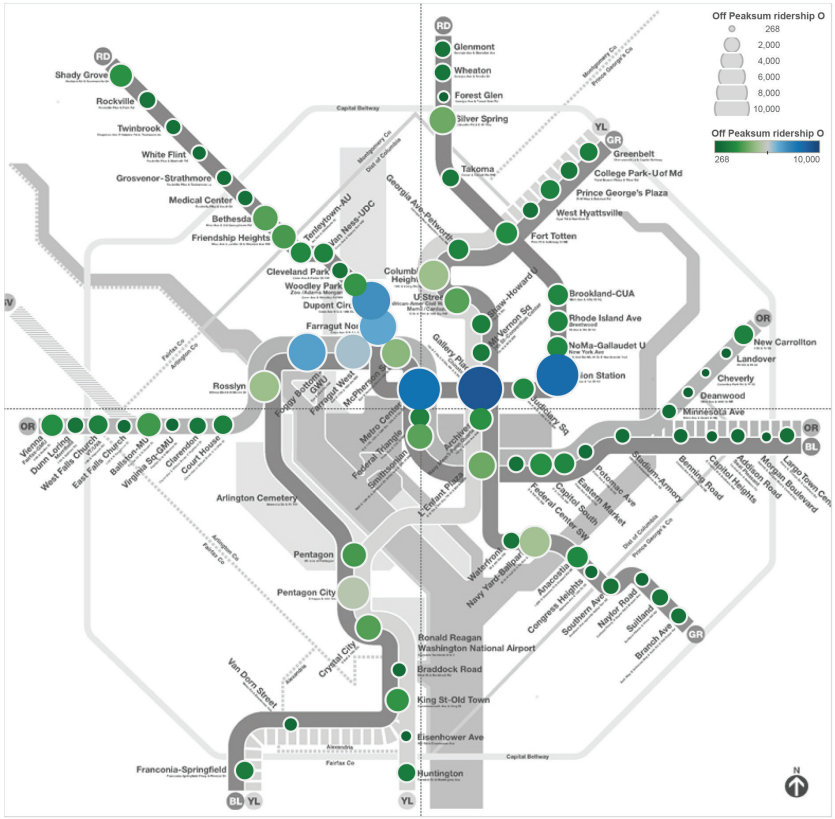
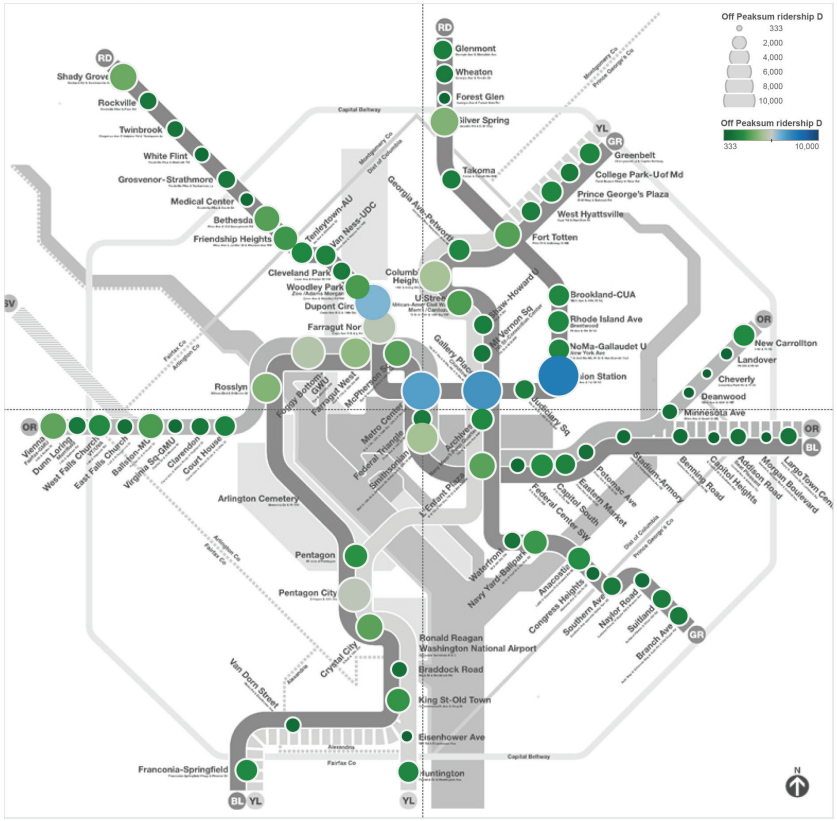


Figure 10: Ridership by Trip Destination at Each WMATA Metro Station, Off-Peak, Full-Fare Riders with No Transit Benefits



In the off-peak period, both trip origins and destinations tend to be centrally located (Figure 9 and 10).

Figure 11: Passenger Miles Traveled by Trip Origin at Each WMATA Metro Station, AM Peak, Full-Fare Riders with No Transit Benefits

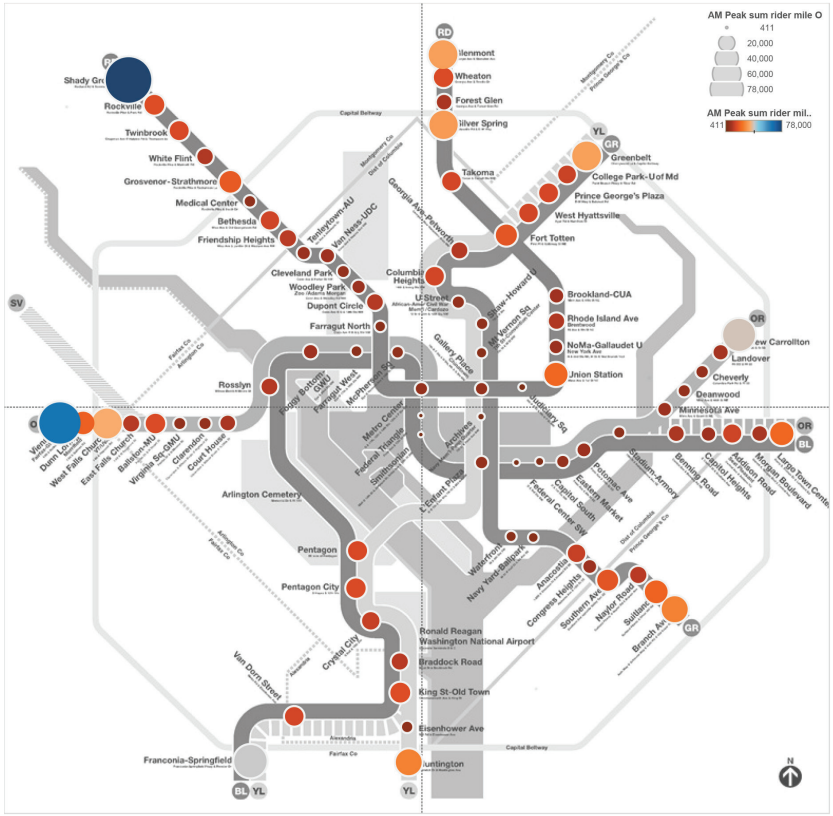


Figure 12: Passenger Miles Traveled by Trip Destination at Each WMATA Metro Station, AM Peak, Full-Fare Riders with No Transit Benefits

The pattern of passenger miles traveled for each O-D pair, calculated by multiplying the number of transit trips by the miles traveled on each trip, reflects the pattern of trips, but is more accentuated (Figures 11-16). Because of the greater distances riders from non-central area stations must travel, riders that originate at these stations generate the largest share of passenger miles traveled in the AM peak: Shady Grove, Vienna, Glenmont, College Park, New Carrolton, Silver Spring, Franconia-Springfield, and West Falls Church (Figure 11).

Figure 13: Passenger Miles Traveled by Trip Origin at Each WMATA Metro Station, PM Peak, Full-Fare Riders with No Transit Benefits

Figure 14: Passenger Miles Traveled by Trip Destination at Each WMATA Metro Station, PM Peak, Full-Fare Riders with No Transit Benefits

The centrally-located stations of Farragut North, Farragut West, McPherson Square, Union Station, and Metro Center generate the largest number of passenger miles traveled by destination during the AM peak (Figure 12). In the PM peak, passenger miles traveled by origin and destination patterns are almost perfectly reversed (Figure 13 and Figure 14).

Figure 15: Passenger Miles Traveled by Trip Origin at Each WMATA Metro Station, Off-Peak, Full-Fare Riders with No Transit Benefits)

Figure 16: Passenger Miles Traveled by Trip Destination at Each WMATA Metro Station, Off-Peak, Full-Fare Riders with No Transit Benefits

In the off-peak, both the origin and destination stations of trips with high passenger miles traveled are Vienna, Shady Grove, Silver Spring, Union Station, Metro Center, and Gallery Place.

Current Fare per Trip and Fare per Mile

Fares in the Metrorail system are based on distance traveled and time of day. Figure 17 shows the fare by composite mile (which equals the average of track miles and straight-line distance in miles between origin and destination stations). Fares generally increase proportionally with trip distance, though base and max fares skew that relationship. There are two fare structures with three main ranges for the peak and off-peak periods. For fiscal year 2015, these fares are:

Peak fares

- Under three miles, $2.15
- Three to 15.59 miles, graduated fare between $2.15 and $5.90
- 15.6 miles and over, $5.90

Off-peak fares

- Under three miles, $1.75
- Three to 10.99 miles, graduated fare between $1.75 and $3.60
- 11 miles and over, $3.60

Figure 17: Peak and Off-Peak Fares by Composite Mile in October, 2014

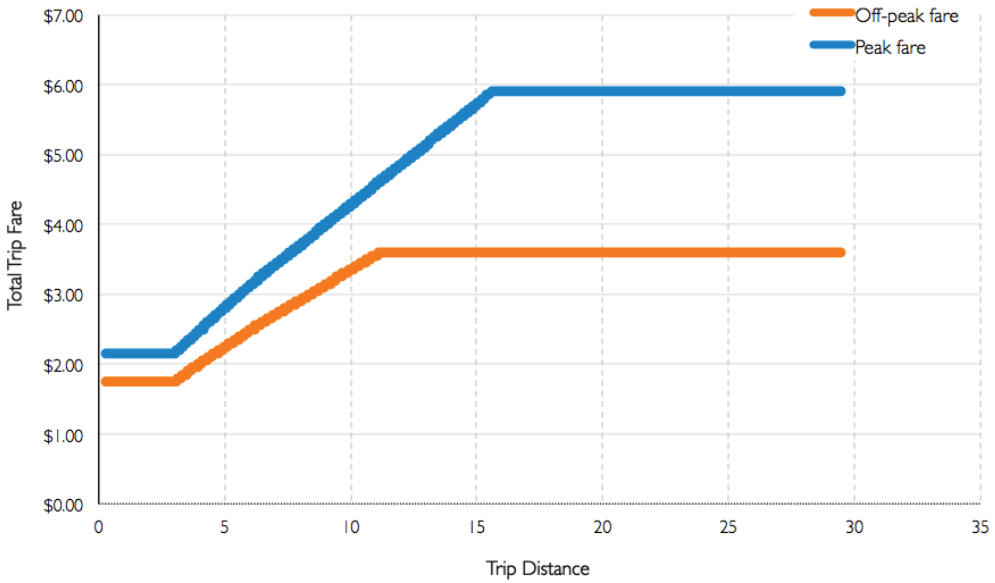


Figure 18 illustrates the structure of fares on a per mile basis.[14] The top graph shows fare per mile over the entire range of distances. The bottom graph shows fare per mile for trips between three and 29.46 miles. Fares per mile vary more extensively over the entire range of trip distances. Fares per mile are high for short-distance trips and low for long-distance trips.

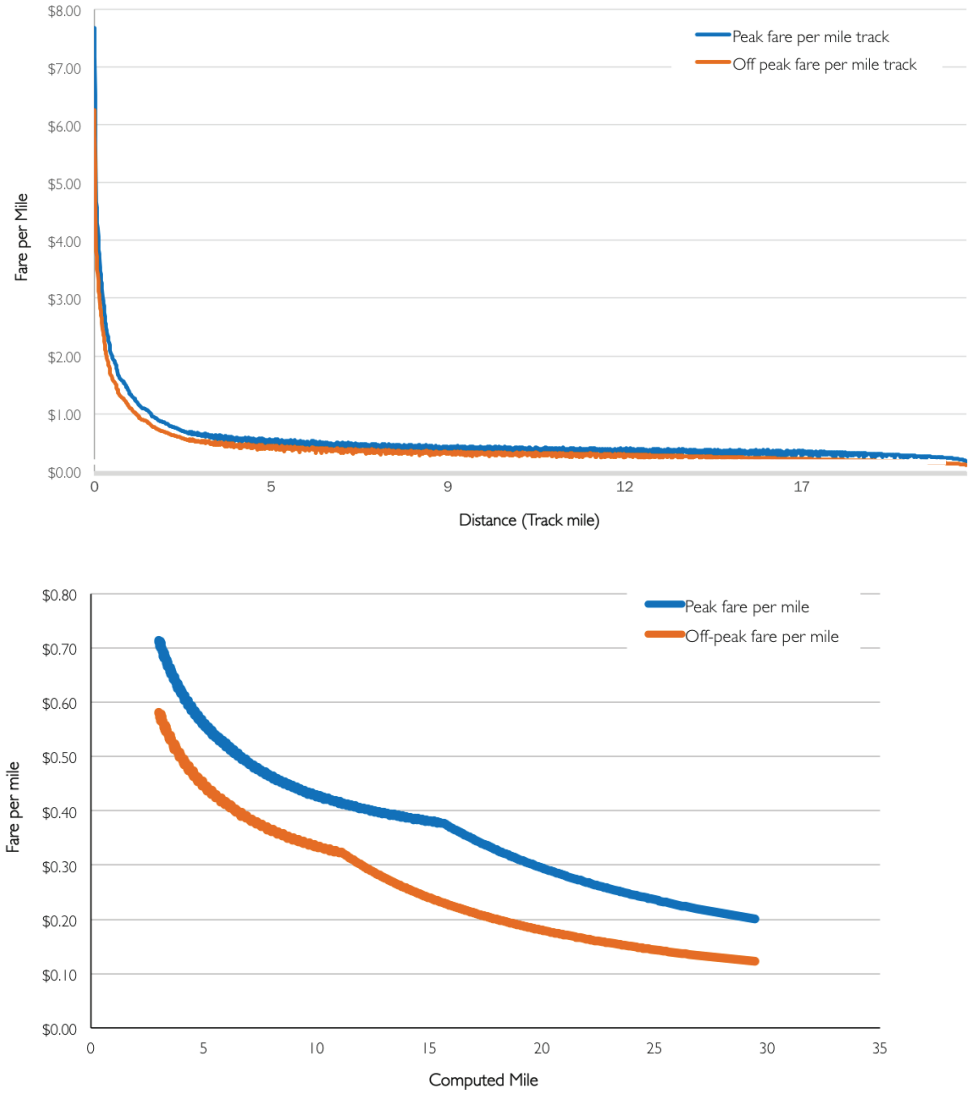
The Overarching Context

The Washington region served by the Washington Metrorail system is characterized by a relatively dispersed distribution of households in suburbs and a relatively concentrated pattern of employment in the central city. As a result, trips in the morning peak tend to originate in the periphery and end in the central city, while trips in the PM peak have the reverse pattern. Trips in the off-peak tend to begin and end at centrally located stations.

Passenger miles traveled tend to follow the pattern of trips. But, because trips that originate in the periphery tend to be longer, they display a more accentuated pattern.

Fares are higher in the peak period than the off-peak period. Shorter trips have lower absolute fares. But, longer trips have lower fares per mile traveled.

Figure 18: Peak and Off-Peak Fare per Mile Track Mile



Empirical Strategy

To estimate the determinants of Metrorail ridership and fare elasticity, we developed an OD-LURM for the WMATA rail system. This section describes the four most important dimensions of the model and their statistical implications. These dimensions are:

- The use of OD-station pairs as units of analysis
- The use of passenger miles traveled as the measure of transit demand and fare per mile as the measure of transit fare
- The estimation of point elasticity
- The disaggregation of fare elasticity by time, distance, and ridership class

OD-station Pairs

To examine the determinants of transit ridership and fare elasticity, we use OD-station pairs as units of analysis. Currently, the WMATA Metrorail system has 91 stations. This analysis only includes 84 stations. It excludes: (1) five Silver Line stations that were not yet open in May 2014, the month from which the ridership data were obtained; and (2) the Arlington Cemetery and Ronald Reagan Washington National Airport, which have unique ridership and fare characteristics.[15]

The total number of OD-station observations varies is based on the subset of riders considered. The maximum number of OD-station pairs in the analysis is 6,972.[16] This analysis excludes OD-station pairs with no ridership for the subset of riders in question.

The use of OD-station pairs as units of analysis has two important statistical implications. First, because multiple OD-pairs share the same origin (or destination) station, the variance structure of the error terms is hierarchical in nature. In most cases, observations from the same cluster that share the same origin (or destination) station are expected to have smaller variance, compared to those taken from different clusters. When analyzing data in this nested structure, a standard ordinary least squares method will produce biased estimated coefficients and standard errors (especially for station-level variables), compromising the validity of results.[17] We addressed this problem by applying mixed-level regression analysis method in the form of cross-classification.[18]

Second, each OD-pair can simultaneously be grouped into two clusters (one by origin station and the other by destination station), which requires a specification of cross-classification within the multi-level regression framework. These clusters are neither hierarchical nor nested within one another.[19] Each contains two levels of independent variables. First-level independent variables are those obtained for OD-station pairs. Second-level variables are those obtained for each origin or destination station, including land use variables as well as random effects that can be attributed to either origin or destination stations, but not explained by their attributes.

Passenger Miles Traveled and Fare per Mile

While our model includes many variables that influence transit ridership, our focus is on fare elasticity. Transit fare elasticity is the quantitative impact of the change in transit demand (the dependent variable) that results from a change in transit fares (the independent variable). Arriving at a quantitative value requires an accurate measure for both transit demand and transit fares.

Transit demand can be measured in trips, distance traveled, or passenger miles.[20] Most studies of fare elasticity, many of which focus on bus travel, use ridership counts as measures of transit demand—in large part because data on distance traveled were not available. Through its electronic fare card, WMATA can assess passenger miles by trip. Therefore, this analysis measures transit demand in terms of passenger miles traveled for each OD-station pair.[21]

Theoretically, we assert that passenger miles traveled is a better measure of transit demand than transit trips. Trips vary in length, and long trips provide more utility to the rider than short trips, holding other things constant. Therefore, riders with long trips may be less responsive to fare increases. Further, the cost of providing transit services increases with distance. Thus from a management perspective, it is more useful to compare the costs of providing transit services with the revenues from providing transit service on a per mile basis.

The empirical case for using passenger miles traveled as the measure of demand and fares per mile as the measure of fares is even more compelling: this specification produces much better results. The reasons for the better results reflect the underlying structure of fares and ridership in the Washington Metrorail system. As described above, a large number of trips on the Metrorail system are commute trips between the suburbs and the central city. These are trips for which the total fare per trip is high. Using number of trips and fare per trip yielded a low correlation between trips and fares and a positive fare elasticity. But, this is incorrect: it is illogical that an increase in fares would cause an increase in ridership. The problem is that trips from the suburbs to the central city are long, so although the fare per trip is high, the fare per mile is low. Thus, the correlation between fare per mile and passenger miles traveled is high, and such a specification results in estimates of fare elasticity that are negative and within reasonable ranges.

Because our data come from the WMATA fare system, we are able to identify exactly how far each passenger traveled. In the analysis, we use passenger miles traveled for each OD-station pair as the dependent variable and fare per track mile as the key independent variable.

The Use of Point Elasticity

Elasticities can be defined and estimated in multiple ways. The two most common ways are arc elasticity and point elasticity. Arc elasticity of demand is a point-to-point measure: it is the ratio of the percentage change of one variable between two given points to the percentage change of the other variable between those same two points.[22] In contrast, point elasticity is elasticity of demand at a specific point on the demand curve, as opposed to between two points.

Our model uses point elasticity. From a pragmatic point of view, it is a better fit for the data used. The primary reason is that we converted all continuous variables in this study to log form. Estimated coefficients from a model with a logarithmic form of both dependent and independent variables are directly interpreted as point elasticities.

The skewed distribution of the independent variable, passenger miles traveled (PMT), is the reason behind the log form for all continuous variables. A highly skewed PMT violates the assumptions of ordinary least squares estimation. After taking the log of PMT, the distribution more closely approximates a normal distribution and makes ordinary least squares a more appropriate statistical strategy.

In addition to transit fares and passenger miles, all the other continuous independent variables in this study were converted to log form, for several reasons. First, log transformation results in a more normal distribution. In addition, log transformation enables all the estimated coefficients to be interpreted as elasticities.

Fare Elasticity Disaggregation

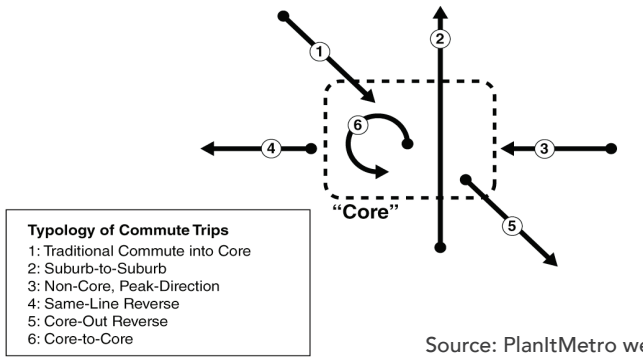
Although it is reasonable to assume point elasticities to be constant for along all points on a *single demand curve*, elasticities will vary systematically *across demand curves* by time, distance traveled, and ridership class. Therefore, for decision makers to use elasticities for setting fares, they must have accurate elasticities for each subset.

To assist in transit fare decision making, we explored the impacts of each of the following factors on transit fare elasticity. We only report a subset of our analysis in this report. The complete results of the

additional analyses are contained in the Appendix. The factors we explore in this report, their sub-populations, and the accompanying data notes are below.

- **Period of Travel:** AM peak period, PM peak period, and Midday/ Evening periods combined. Midday and Evening time periods were merged to increase the number of observations of selected OD-station pairs.
- **Rider Classes:** full-fare regular riders without transit benefits, riders with transit benefits, senior and disabled riders without transit benefits, senior and disabled riders with transit benefits. A subset of data for each of these rider classes was directly obtained from the Fare System data.
- **Transfers:** no transfers, one transfer accessing rail from bus, one transfer egressing from rail to bus, two transfers on both ends. A subset of data for each of these rider classes was directly obtained from the Fare System data.
- **Demographic groups:** minority riders, low-income riders, university student riders. We used information from the Passenger Survey in conjunction with the Fare System dataset to estimate the ridership of each demographic segment.[23] Because the analysis estimated daily ridership in terms of OD-station pairs in this crude way (regardless of the number of survey takers for each OD-station pair), special caution is required in the interpretation and use of estimated coefficients from this regression analysis.
- **Metro 2025 Station trips:** stations considered for station capacity improvements/capital investments in Metro Strategic Plan 2013-2025.
- **Maximum load point:** trips that cross a maximum load (or a highest in-vehicle ridership) point on each of the Metrorail lines in the AM and PM peak periods.

Figure 19: Typology of Commute Trips



Source: PlanItMetro website on May 6th, 2013.

- **Travel distance:** WMATA's initial distance categories were (a) 0-3 miles, (b) 3-6 miles, (c) 6-15 miles, and (d) a range of distance related to the maximum cap fare (approximately 15 or more miles). This analysis also considered more discrete distance categories with at increments of one mile.
- **Trip typology:** This typology consists of six types of trips that take into account locations and directions of trips as well as whether or not to cross a max load point (Figure 19).[24] This analysis combined categories when it found no difference in fare elasticity.

Data and Data Sources

To estimate the OD-LURM, we obtained data in three general categories: (1) data that characterize origin-destination station pairs, (2) data that characterize station environments, (3) and data that characterize transit riders. This chapter summarizes key information about these data and their sources. Refer to the Appendix for more detail.

Data that Characterize Origin-Destination Station Pairs Obtained from the Fare System Data

The primary data used for this analysis come from the WMATA Fare System data file. This dataset contains trip information for each OD-station pair, including: origin and destination stations, ridership, fare paid, distance, rail travel time, media type, monetary instrument, whether an OD-station pair goes through a "max load point," whether an OD-station pair is associated with Metro 2025 station, time of day, rider class, and whether the rider accessed the system via a bus-to-rail or rail-to-bus transfer.

For each OD-station pair, we also added information on: travel time by auto by time of day, travel time by bus by time of day, travel time by bike, and the number of customers using park and ride lots. We obtained these data from a variety of sources including the NCSG data inventory, the Capital Bikeshare website, the Metropolitan Washington Council of Governments, and WMATA.

Major rider classes within this data set include: those with transit benefits (e.g., a transit subsidy from the federal government) and senior and disabled riders who pay half the peak fares regardless of time of travel.

Data that Characterize Station Environments Obtained from the Station-level Data

The second set of data includes information about the environments that surround stations, defined as the walk shed of each station. NCSG compiled most of these data for an earlier study.[25] Station-level data include information on the built environment, frequency of transit service, and sociodemographic characteristics of nearby residents.

WMATA and NCSG made several updates to the existing data set. WMATA updated data on employment and parking in May 2015. For each station, we collected data on whether it had bike-share facilities and the extent of connectivity to bus service.

Data that Characterize Transit Riders Obtained from the Passenger Survey Data

The third set of data includes information on transit riders: the number of minority, low income, and university student riders. We collected this information from the 2012 WMATA Passenger Survey. This survey included information from survey respondents on the origin and destination stations of their trips as well as their race, income, and travel purpose.

Table 2 presents descriptive statistics for four key variables: daily ridership, daily PMT, fare, and fare per mile for full-fare riders with no transit benefits in three time periods.

Table 2: Descriptive Statistics for Key Variables for in the AM Peak, PM Peak, and Off-Peak Periods

	Population Subset	OD station Pairs	Avg. Daily Ridership Count	St Dev. of Daily Ridership	Avg. Daily Transit Miles Traveled	St Dev. of Transit Miles Traveled	Avg. Fare ($)	St Dev. of Fare	Avg. Fare per Mile ($ / Mile)	St Dev. of Fare per Mile
AM Peak: Peak Fare	All Full-Fare Riders	6,904	18.4	44.5	147	421	3.95	1.27	0.51	0.51
	No transfer	6,857	14.1	38.5	111	359	3.95	1.27	0.51	0.51
	Transfer from bus to rail (ingress-transfer)	5,826	3.2	9.8	26	78	3.89	1.28	0.53	0.53
	Transfer from rail to bus (egress-transfer)	5,252	1.1	2.1	11	18	3.99	1.27	0.50	0.47
	Transfer on both ends	4,433	1.1	2.4	10	18	3.94	1.27	0.51	0.52
	Riders w/ Transit Benefits	6,045	12.9	34.7	104	343	3.85	1.26	0.54	0.53
	Senior & Disabled Riders	5,484	1.3	2.3	12	24	1.90	0.63	0.27	0.26
	Senior & Disabled Riders w/ Transit Benefits	1,900	1.0	1.6	9	20	1.82	0.63	0.32	0.36
	Minority Riders	2,652	19.2	33.8	173	383	3.71	1.24	0.56	0.54
	Low-Income Riders	905	6.3	5.8	51	58	3.53	1.20	0.56	0.47
	Student Riders	277	5.1	4.2	38	41	3.38	2.15	0.59	0.23
PM Peak: Peak Fare	All Full-Fare Riders	6,949	20.2	20.2	150	366	3.96	1.27	0.51	0.50
	No transfer	6,937	16.4	38.8	119	313	3.95	1.27	0.51	0.50
	Transfer from bus to rail (ingress-transfer)	5,969	1.0	1.9	9	15	3.91	1.27	0.52	0.52
	Transfer from rail to bus (egress-transfer)	5,912	2.8	8.3	23	68	3.90	1.27	0.52	0.52
	Transfer on both ends	4,507	0.8	1.7	6	11	3.91	1.27	0.51	0.50
	Riders w/ Transit Benefits	6,401	10.7	28.5	83	273	3.87	1.26	0.60	0.54
	Senior & Disabled Riders	6,078	1.3	2.1	10	20	1.91	0.62	0.27	0.26
	Senior & Disabled Riders w/ Transit Benefits	2,313	0.7	1.3	7	16	1.76	0.61	0.33	0.35
	Minority Riders	2,679	27.5	38.9	216	382	3.71	1.24	0.56	0.54
	Low-Income Riders	617	18.7	27.8	118	198	3.32	1.15	0.61	0.52
	Student Riders	450	11.3	9.9	74	62	3.50	1.20	0.58	0.45
Off Peak: Off Peak Fare	All Full-Fare Riders	6,720	26.0	45.7	182	308	2.90	0.70	0.40	0.42
	No transfer	6,611	8.1	18.5	58	145	2.89	0.70	0.40	0.42
	Transfer from bus to rail (ingress-transfer)	4,756	0.5	1.0	5	8	2.84	0.71	0.41	0.44
	Transfer from rail to bus (egress-transfer)	4,773	1.3	3.0	10	20	2.86	0.70	0.40	0.42
	Transfer on both ends	2,896	0.5	0.9	4	6	2.85	0.70	0.40	0.38
	Riders w/ Transit Benefits	6,409	6.0	13.1	40	94	2.87	0.70	0.41	0.43
	Senior & Disabled Riders	6,324	2.0	3.1	14	20	1.94	0.63	0.26	0.26
	Senior & Disabled Riders w/ Transit Benefits	2,592	0.3	0.5	2	5	1.75	0.61	0.34	0.36
	Minority Riders	1,698	31.4	33.2	182	207	2.56	0.70	0.53	0.55
	Low-Income Riders	959	20.7	18.7	119	112	2.51	0.68	0.50	0.44
	Student Riders	394	17.8	16.1	105	98	2.51	0.70	0.49	0.44

Note: * off-peak fare and off-peak fare per distance are used for the subsets.

Table 3 shows descriptive statistics of independent variables that were found statistically significant in the most parsimonious models using subsets of full-fare riders with no transit benefits in three time periods.

Table 3: Descriptive Statistics for Independent Variables Included in Final Specifications in Regression Analysis

	Variable	Level	Count	Mean	Std. Dev	Min
AM Peak Period	Passenger miles traveled (miles)	OD	6,904	147	421	0
	Peak or off-peak fare per track mile	OD	6,904	$0.51	$0.50	$0.17
	Auto travel time per mile (minutes/mile)	OD	6,904	3.4	1.4	0.6
	Bus travel time per mile (minutes/mile)	OD	6,904	10	4	1
	Parking users	OD	6,904	0	0	0
	1,000 households in 0.5 miles	O	84	5	5	0
	Parking capacity	O	84	711	1,281	0
	Bus line count	O	84	39	21	6
	Miles from the core (miles)	O	84	6	4	0
	Jobs in 0.5 miles	D	84	10,778	13,577	67
	Trains per Hour in the peak	D	84	35	15	20
	Bus line count	D	84	39	21	6
PM Peak Period	Passenger miles traveled (miles)	OD	6,949	150	366	0
	Peak or off-peak fare per track mile	OD	6,949	$0.51	$0.50	$0.17
	Auto travel time per mile (minutes/mile)	OD	6,949	3.4	0.6	0.1
	Bus travel time per mile (minutes/mile)	OD	6,949	10	4	1
	Parking users	OD	6,949	2	10	0
	Jobs in 0.5 miles	O	84	10,721	13,555	67
	Bus Line Count	O	84	39	21	6
	1,000 households in 0.5 miles	D	84	5	5	0
	Bus line count	D	84	39	21	6
Off-Peak Period	Passenger miles traveled (miles)	OD	6,720	182	308	1
	Peak or off-peak fare per track mile	OD	6,720	$0.40	$0.42	$0.10
	Auto travel time per mile (minutes/mile)	OD	6,720	2.1	1.1	0.1
	Parking users	OD	6,720	1	5	0
	1,000 households in 0.5 miles	O	84	5	5	0
	Bus line count	O	84	39	21	6
	1,000 households in 0.5 miles	D	84	5	5	0
	Night and weekend jobs	D	84	842	1,123	5
	Median household income ($)	D	84	$70,307	$28,430	$25,318
	Bus line count	D	84	35	15	20

Statistical Results

We analyzed more than 30 subsets of data, taking into account time of day, distance traveled, rider class, Metro 2025 station trips, maximum load points, and trip typology, as well as more than 150 different variables.[26] We first report full regression results for full-fare riders with no transit benefits.[27] These riders represent the highest share or riders on the WMATA Metrorail system.[28] Then we report the estimates of fare elasticity for all rider classes, taking into account a variety of factors listed above.

The Determinants of Metro Ridership

Table 4 shows full results of regression analysis for full-fare riders with no transit benefits in the AM peak, PM peak, and off-peak periods. The independent variables are listed in the first column, followed by an indication of whether the independent variable is an attribute of the (1) OD-station pair, (2) Origin Station, or (3) Destination Station. Estimated coefficients, standard errors, and P-values are then presented for variables found to be statistically significant in each model at the 0.05 significant level.[29]

Overall, the signs and magnitudes of estimated coefficients are consistent with expectations. The pseudo R-squared obtained from the square of correlation between the dependent variable and the predicted dependent variable are 0.479, 0.523, and 0.428 for AM peak, PM peak, and off-peak periods, respectively. These values indicate that the model explains approximately half the variance of the dependent variable.

The coefficients on travel times of competing modes—private automobiles and buses—are positive and generally significant, as expected. *Auto travel time per mile* was statistically significant in all time periods, while *bus travel time per mile* was significant only in the peak travel periods. The positive sign of these estimated coefficients indicate that, as the time it takes to travel one mile in an automobile or bus increases, the greater the number of passenger miles traveled on Metrorail PMT.

Estimated coefficients for *parking users* are all positive and significant. This implies that Metrorail riders who use a SmarTrip card to pay for parking at a Metrorail station after taking a Metrorail trip have higher PMT, as expected.

We examined the effects of M25 stations (those with high congestion) on passenger miles traveled using dummy variables. When one of the OD-stations is an M25 station, PMT increases by 80 percent, 55 percent, and 64 percent in the AM peak, PM peak, and off-peak periods, respectively.[30] When both OD-stations are an M25 station, PMT increases by 159 percent, 103 percent, and 1.05 percent in the AM peak, PM peak, and off-peak periods, respectively.[31] These percentages reflect the simple fact that PMT between OD-stations is higher when one or two of these stations are high ridership stations.

The station-level variables are all significant with expected signs. As expected, housing on the **origin** side and jobs on the **destination** side produce higher PMTs in the AM peak period, while jobs on the **origin** side and housing on the **destination** side produce higher PMTs in PM peak period. This finding simply reflects the dominant direction of commuting trips in each time period.

All estimated coefficients for the effects of housing and jobs on PMT fall between 0 and 1 in absolute value. The job variables show higher elasticity values than the household variables: 0.508 for jobs on the **destination** side is higher than 0.077 for households in the AM peak period; 0.358 for jobs on the **origin** side is higher than 0.197 for households in the PM peak period. For the off-peak period, housing exhibited smaller effects on both the **origin** side (0.036) and on the **destination** side (0.125). While the overall job coefficient is not significant, nighttime and weekend jobs (defined by NAICS code) at **destination** stations are significant with a coefficient of 0.120.[32]

In the AM peak period, *parking capacity* and the number of feeder bus lines on the origin side and the number of trains per hour and the number of bus lines on the **destination** side are statistically significant,

Table 4: Regression Analysis Results for Full-fare Riders with No Transit Benefits in the AM Peak, PM Peak, and Off-peak Period

Dependent Variable: Ln(Passenger Miles Travelled)		**AM Peak Period**			**PM Peak Period**			**Off-peak Period**		
Independent Variables	**Level**	**Coef.**	**Std. Err.**	**P>|z|**	**Coef.**	**Std. Err.**	**P>|z|**	**Coef.**	**Std. Err.**	**P>|z|**
Ln(peak or off-peak fare per track mile)	OD	-0.503	0.035	0.000	-0.541	0.027	0.000	-0.419	0.024	0.000
Ln(auto travel time per mile)	OD	0.323	0.047	0.000	0.278	0.039	0.000	0.353	0.030	0.000
Ln(bus travel time per mile)	OD	0.218	0.044	0.000	0.211	0.035	0.000	-	-	-
Ln(bus travel time)	OD	0.088	0.011	0.000	-	-	-	-	-	-
Ln(parking users)	OD	0.456	0.023	0.000	0.310	0.008	0.000	0.353	0.008	0.000
One M25 Station (0-1)	OD	0.590	0.140	0.000	0.441	0.107	0.000	0.499	0.099	0.000
Two M25 Stations (0-1)	OD	0.952	0.284	0.001	0.712	0.217	0.001	0.720	0.202	0.000
Ln(1,000 households in 0.5 miles)	O	0.077	0.020	0.000	-	-	-	0.036	0.013	0.007
Ln(jobs in 0.5 miles)	O	-	-	-	0.358	0.077	0.000	-	-	-
Ln(parking capacity)	O	0.080	0.025	0.002	-	-	-	-	-	-
Ln(bus line count at station)	O	0.269	0.132	0.042	0.361	0.107	0.001	0.327	0.089	0.000
Ln(miles from the core of an origin station)	O	0.296	0.091	0.001	-	-	-	-	-	-
Ln(1,000 households in 0.5 miles)	D	-	-	-	0.197	0.041	0.000	0.125	0.040	0.002
Ln(jobs in 0.5 miles)	D	0.508	0.107	0.000	-	-	-	-	-	-
Ln(night and weekend jobs)	D	-	-	-	-	-	-	0.120	0.039	0.002
Ln(trains per hour in the peak period)	D	0.402	0.190	0.034	-	-	-	-	-	-
Ln(bus line count at station)	D	0.285	0.132	0.031	0.408	0.102	0.000	0.312	0.108	0.004
Ln(median household income)	D	-	-	-	-	-	-	-0.292	0.116	0.012
Constant		-1.491	0.855	0.081	-1.801	0.532	0.001	3.458	1.361	0.011
Number of Samples		6,904			6,949			6,720		
R-squared*		0.479			0.523			0.428		

Note: The dashes indicate that variables were statistically insignificant.
Note: * R-squared here is obtained by the square of correlation between the dependent variable and the predicted dependent variable.

with positive effects on PMT. The coefficient on the variable miles from the core of an **origin** station is statistically significant in the AM peak model. In the PM peak period, coefficients on the number of feeder bus lines on the **origin** side as well as on the **destination** side are statistically significant with a positive sign.

Finally, in the off-peak period, the number of *feeder* bus lines on both the origin and destination sides and median household income on the destination side are statistically significant. The coefficient on the latter variable has a negative sign, indicating that the lower the household income in neighborhoods of a destination station, the higher the PMT. This means that low-income household travelers contribute to the higher ridership in the off-peak period.

Fare Elasticity

Estimated coefficients for the variable, fare per mile, are -0.503, -.541, and -0.419 for AM peak, PM peak, and off-peak periods, respectively. This indicates that a 10 percent increase in fare per mile leads to a reduction in ridership by 5.0 percent, 5.4 percent, and 4.2 percent in each period, respectively. Estimated elasticity values in the PM peak period are slightly higher (in the absolute value) than in AM peak period, as expected. This is because the AM peak period has a higher share of commuters who have less flexibility in the time and model of travel.

In contrast, we were surprised to find that PMT is less elastic in the off-peak period than in the AM and PM peak periods.

Fare Elasticity by Distance

We examined the effects of distance on fare elasticity for full-fare riders with no transit benefits in the three different time periods. As shown in Table 5, fare elasticity is consistently higher for short-distance trips than for long-distance trips. Short trips are likely have more viable substitutes: walking, biking, Uber, taxi, or a bus when in the city center. In contrast, it is more difficult to find alternative modes of travel that are efficient and affordable for long-distance trips. It is likely that the high cost of parking in the city center plus traffic congestion on freeways and major arterials combine to make it difficult for people to switch from Metrorail to a private car.

Table 5: Summary of Fare Elasticity by Distance for Full-fare Riders with No Transit Benefits

Trip Distance	AM Peak	PM Peak	Off-Peak
Less than 3 miles	-1.019	-1.053	-0.892
3 to 6 miles	-0.356	-0.420	-0.539
6 miles or over	-0.120	-0.178	-0.264

Fare Elasticity by Rider Class

Table 6 presents a summary of estimated fare elasticity by rider class for each of the three time periods. Within each time period, it disaggregates results by the use of M25 stations, the passage of maximum load points, and the trip typology. To estimate fare elasticity using more than 30 subsets, we used each of the three specifications discussed in the previous section as the base for each time period for regression for the rest of rider classes. In other words, we used the same specification across rider classes in each period.

This section begins with brief methodological notes. It then summarizes of "main elasticity" findings by rider class, first by incidence of transfer and then by other rider class segment. It then discusses the impact of M25 stations, maximum load points, and trip elasticities.

Methodological Notes

The subsets of senior and disabled riders with transit benefits, low-income riders, and university student riders do not populate a sufficient number of OD-station pairs to support multi-level regression

analysis. We estimated ridership of minority riders, low-income riders, and student riders using the information from the 2012 Passenger Survey. This integration of the Fare System data with the Passenger Survey data was very difficult due to data limitations on the latter dataset, resulting in a very limited ability to analyze fare elasticities and obtain results that can be interpreted reasonably. A special caution is required to interpret estimated fare elasticity values for these rider classes.

In regard to the effects of WMATA trip typology on fare elasticity, we used three trip type categories—(a) Types 2 and 5, (b) Types 1, 3, and 6, and (c) Type 6—for the analysis of riders with transit benefits in the PM peak period, as we found no difference in the effect of trip type on fare elasticity between types 2 and 5 and between types 1, 3, and 6. The analysis of all other rider classes used two trip categories—Type 2 (suburb-to-suburb trips) and all the rest combined—because only type 2 trips showed a difference in estimated fare elasticities.

Main Elasticities

We divided full-fare riders into four categories based on the number of transfers between bus and rail, and found that trip transfers impact fare elasticities. Travelers that make one transfer from bus to rail during the AM peak have the highest elasticities. PM peak and off-peak riders with no transfers or one transfer from rail to bus have the second-highest elasticities. Riders with transfers on both ends tend to have the lowest elasticities, as these riders likely have fewer alternatives (indicated by the length and complexity of their trips).

Across all time periods, riders receiving transit benefits, and all senior, disabled, minority, low-income, and university student riders generally exhibit higher elasticities than riders with no transit benefits. This finding contradicts our expected outcome that travelers with transit subsidies, reduced automobile access, or lower incomes would be transit-dependent and, therefore, less sensitive to fare changes. Our finding that these groups are sensitive to fare changes may be explained by the fact that many travelers within these segments have fixed budgets and may make fewer trips as fares increase so to not increase their total transportation expenditure. These are assumptions that require cautious use and further analysis.

M25 Station

The effects of M25 stations on elasticity are twofold: (1) trips not involving M25 stations are more inelastic, and (2) trips with two M25 stations are very elastic.[33]

Maximum Load Points

Most trips that cross a maximum load point are peak period commuting trips between the suburbs and central city. Because these trips tend to be long distance, they typically have lower elasticities. Although this pattern is generally true, it is less clear when comparing the effects of maximum load points on different rider classes.

Trip Typology

The effect of WMATA trip typology was clearly delineated only for Type 2 trips, which are suburb-to-suburb and generally long-distance trips. Type 2 trips are more inelastic than other types of trips in both AM and PM peak trips. We cannot confirm that this pattern absolutely exists for the last four rider classes, due to limitations within those data subsets.

Table 6: Summary of Fare Elasticity by Rider Class by Time of Day

		Full-fare Riders with No Transit Benefits					Other Rider Classes					
		All full-fare Riders	With no transfer	With a transfer from bus to rail (ingress-transfer)	With a transfer from rail to bus (egress-transfer)	With a transfer on both ends	**Riders with Transit Benefits**	**Senior & Disabled Riders**	**Senior & Disabled Riders with Transit Benefits**	**Minority Riders**	**Low-income riders**	**Student Riders**
Note for Data Sources		Using the information from the Fare System Data								Using the information also from the Passenger Survey		
AM Peak												
Main		-0.503	-0.738	-0.780	-0.647	-0.465	-0.861	-0.812	-1.425	-0.912	-1.096	-1.240
M25	No M25 Station	-0.316	-0.556	-0.490	-0.444	-0.263	-0.652	-0.795	-	-0.940	-1.140	-1.310
	One M25 Station	-0.684	-0.903	-0.993	-0.855	-0.609	-1.078	-1.115	-	-0.930	-0.920	-1.105
	Two M25 Stations	-1.023	-1.238	-1.532	-1.391	-1.132	-1.378	-1.586	-	-0.917	-0.920	-1.127
Max Load Point (AM)	Crossing No MLP	-1.101	-1.281	-1.366	-1.260	-1.101	-1.495	-1.429	-	-0.998	-0.990	-1.079
	Crossing MLP	-0.260	-0.936	-0.946	-0.823	-0.346	-1.116	-1.402	-	-1.154	-1.070	-0.919
WMATA Trip Typology	Type 2 Trip	-0.115	-0.328	-0.370	-0.292	-0.064	-0.369	-0.906	-	-0.780	-1.100	-0.802
	All Other Trips	-0.963	-0.795	-0.789	-0.811	-0.874	-0.920	-1.300	-	-0.195	0.070	-0.611
PM Peak												
Main		-0.538	-0.596	-0.499	-0.747	-0.276	-0.611	-0.760	-1.339	-0.684	-0.937	-0.681
M25 (1)	No M25 Station	-0.342	-0.402	-0.274	-0.465	-0.053	-0.444	-0.617	-	-0.500	-0.798	-0.626
	One M25 Station	-0.689	-0.748	-0.696	-0.929	-0.436	-0.730	-0.862	-	-0.699	-0.867	-0.781
	Two M25 Stations	-1.134	-1.192	-1.043	-1.523	-0.994	-0.757	-1.136	-	-1.104	-1.220	-0.150
Max Load Point (AM)	Crossing No MLP	-1.103	-1.129	-1.076	-1.432	-0.998	-1.179	-1.210	-	-0.961	-1.055	-0.829
	Crossing MLP	-0.923	-0.969	-0.893	-1.132	-0.550	-1.793	-1.162	-	-0.539	-1.004	-0.642
WMATA Trip Typology	Type 2 Trip	-0.164	-0.246	-0.113	-0.217	0.165	-0.302	-0.672	-	-0.427	-0.846	-0.590
	All Other Trips	-0.923	-0.878	-1.248	-0.805	-1.030	-1.039	-1.008	-	-0.919	-1.016	-0.778
		-	-	-	-	-	-1.546	-	-	-	-	-
Off-peak												
Main		-0.419	-0.488	-0.336	-0.488	-0.308	-0.422	-0.625	-1.087	-0.705	-0.718	-0.648

Notes: (1) The subsets of "senior & disabled riders with transit benefits," "Low-income riders" and "University Student Riders" do not have a sufficient number of OD-station pairs to support multi-level regression analysis. (2) Caution is required when interpreting the results for "minority riders," "low-income riders," and "student riders" because of the use of the information from the passenger survey. Regression analysis used a "dependent variable" in these three rider classes. (3) Different trip categories were used for "Riders with Transit Benefits" in the PM peak period (highlighted in light blue): (a) Types 2 and 5, (b) Types 1, 3, and 6, and (c) Type 6.

Conclusion

This report presents the result of NCSG's efforts to construct an OD-LURM that builds on our previous work on a DRM. Our objective was to augment our understanding of the determinants of transit ridership on the Washington Metrorail system with a particular focus on transit fare elasticity.

We are far from the first to explore these issues. A large volume of literature has been written on the determinants of the demand for multiple modes of public transportation and their respective fare elasticities of demand. The results have varied, though the weight of evidence suggests that the fare elasticity of demand for public transportation—including intra-city rail—is inelastic, with a range of about -0.9 and -0.3. The weight of evidence also suggests, however, that fare elasticities vary by mode, time of travel, trip purpose, passenger class, length of trip, direction of fare change, and more. In short—it's complicated.

Origin-Destination LURMs use OD-station pairs as units of observation and rely on variations in characteristics of OD trip, stations at each end of a trip, and passengers to provide estimates of the determinants of transit ridership, including the influence of fares. Such an empirical strategy has not been commonly used for intra-urban rail transit systems, largely because data on origins and destinations for individual transit trips was difficult (while not impossible) to obtain before the adoption of smartcards.

For both theoretical and empirical reasons, we use passenger miles traveled as a measure of transit demand (in place of trips), and fare per mile as a measure of fares (in place of fare per trip). We specify all variables in logarithmic terms to enable the interpretation of the coefficients as point elasticities. Because we rely on cross section variation in fares and travel demand, our estimates should be viewed as elasticities over the long-run, which are different from short-run elasticities, that are often obtained from a before-and-after study and longitudinal-data analysis.

Our analysis finds that the fare elasticity of demand for ridership on the Metrorail system is approximately -0.50, which suggests that a 10 percent increase in fares results in a five percent decrease in ridership, and vice versa. Compared with other estimates, our estimate is high for a short-run elasticity and low for a long-run elasticity. We found:

- Our estimates are fairly constant over the time of day, although others have found off-peak elasticities to be substantially lower than peak-period elasticities.
- Our estimates vary by distance traveled. As expected, elasticities are high for short-distance (three miles or less) trips (-1.02); mid-range for middle distance (3-6 miles) trips (-0.36); and low for long distances (-0.26).
- Generally, riders with subsidized fares (senior and disabled riders) or transit benefits have higher elasticities in all three time periods than full-fare riders without benefits.
- Full-fare riders with a transfer on both ends of a Metrorail trip have lower elasticities, while travelers making no transfer or one transfer from rail to bus show elasticities higher in all three time periods.
- Trips not involving M25 stations are inelastic and trips with two M25 stations are elastic.
- Trips crossing a maximum load point generally have high elasticities.
- Type 2 trips have low substantially lower elasticities than all other trip types combined in both peak periods.

These results provide preliminary support for proposals to raise fares, especially for long distance trips, if the objective is to increase fare

revenues. Riders that travel long distances during peak periods have "inelastic" demand, which means that a fare increase will cause a less than proportional decrease in passenger miles traveled. Therefore, the increase in total revenues to WMATA will offset the decrease in number of riders.

But considerable caution is warranted for several reasons. First, ours is among very few attempts to estimate transit fare elasticities using an OD-LURM, and the first to do so for the Washington Metrorail system. Second, the properties of data for the key variables led to a relatively wide range for the estimates—in particular for some sub-groups of riders and trips. Finally, the gap between the Fare System data and the Passenger Survey data was too substantial to reconcile for a rigorous analysis of demographic subsets.

We recommend two additional avenues of research. First, we would explore in more depth the variation in estimates of elasticity by rider class and time of day to get a better understanding of why estimates of fare elasticities are lower for off-peak periods, and higher for riders with benefits and low incomes. Second, we would set up a quasi-experiment to test the effects of a change in fare structure on ridership and fare revenues over time. Without such a quasi-experiment, any estimate of transit fare elasticity using cross section data alone to predict the effect of a change in fare structure is based on the strong assumption that short–term temporal differences in fares reflect long-term cross section differences in fares.

Although the explanatory power of our estimates is not comparatively high and must be interpreted with caution, our results in general are robust and consistent with expectations. They reveal that ridership is strongly shaped by the spatial distribution of jobs and households and by the cost of alternative modes of travel.

These findings suggest that as long as households remain located in the suburbs; jobs remain concentrated in the central city; traffic congestion keeps the time cost of travel by automobile and bus relatively high; and parking in the central city remains costly and scarce, the demand for transit ridership on the Metrorail system is likely to remain strong, regardless of the level of fares. This may change, however, as more alternatives such as Capital Bikeshare and Uber become more familiar, available, and convenient in high-density areas.

This page intentionally left blank.

Endnotes

[1]We used North American Industry Classification System (NAICS) codes to classify types of jobs by time of day (i.e. midday and evening jobs and nighttime and weekend jobs).

[2]Kenneth Button, 2010.

[3]The Metrorail system has since expanded to 91 stations.

[4]See: Wardman, M., 1997, "Inter-urban Rail Demand, Elasticities, and Competition in Great Britain: Evidence from Direct Demand Models," *Transportation Research Part E: Logistics and Transportation Review*, 33(1), 15-28; Fridstrom, L. and H. Thune-Larsen, 1989, "An Econometric Air Travel Demand Model for the Entire Conventional Domestic Network: The case of Norway," *Transportation Research B*, 23B(3), 213-223.

[5]Duncan, M., 2010, "To park or to develop: trade-off in rail transit passenger demand," J*ournal of Planning Education and Research*, 30(2), 162-181

[6]Todd Litman, 2010, *Transportation Elasticities: How Prices and other Factors Affect Travel Behavior*, Victoria Transportation Policy Institute.

[7]Those who do not have easy access to private automobiles for economic and physical reasons are called transit dependents or captive riders. In response to fare changes, these transit dependents may have to continue traveling by transit, change their travel destinations, or give up trips.

[8]Todd Litman. 2010.

[9]Based on a personal phone conversation with a Washington Metropolitan Area Transit Authority staff in September, 2015. National Transit Database in 2013 shows service area statistics of 950 square-miles and a population of 3.7 million, as well as 1,322 square-miles of Washington, DC-Virginia, and Maryland urbanized area.

[10]American Public Transportation Association (APTA), 2014, *Transit Ridership Report Fourth Quarter and End-of-Year 2014*, available at http://www.apta.com/resources/statistics/Pages/ridershipreport.aspx. Last checked on August 29th, 2015.

[11]APTA, 2008, *Heavy Rail Transit Ridership Report*, available at https://web.archive.org/web/20090206112918/http://www.apta.com/research/stats/ridership/riderep/documents/08q3hr.pdf.

[12]Demographia United States Central Business Districts (Downtowns) With Data for Selected Additional Employment Areas, available at: http://www.demographia.com/db-cbd2000.pdf

[13]The term "half-mile" refers to the non-overlapping walk sheds for stations. These walk sheds are fairly small and tend to underemphasize the concentration of jobs in the central business district in Figure 2.

[14]We used both track mile and composite mile to calculate fare per mile, as well as passenger miles traveled. The use of track mile resulted in more clear results in regression analysis.

[15]The exclusion of these two stations from the analysis is the result of a discussion with WMATA.

[16]6,972 equals the product of 84 and 84, minus 84, which counts the number of OD-pairs with the same origin and destination stations (e.g., from Dupont Circle to Dupont Circle).

[17]Michael Duncan, 2010, "To Park or To Develop: Trade-off in Rail Transit Passenger Demand," *Journal of Planning Education and Research*, 30(2), 162-181

[18]We used cross-classification as we have two second-level group variables, such as origin stations and destination stations, that contain the first-level variable of OD-station pairs.

[19]O'Connell and McCoash, 2008, "Chapter 1 Introduction Pedagogy and Context for Multilevel Models," *Multilevel Modeling of Educational Data*.

[20]Todd Litman, 2010.

[21]Balcombe et al., 2004.

[22]Balcombe et al., 2004; Michael D. Meyer and Eric Miller, *2001 Urban Transportation Planning, 2nd edition*.

[23]In addition, another approach in which a percentage from the Passenger Survey was used as an independent variable interacted with the fare per mile variable. But it did not produce any better results.

[24]This trip typology was described on the PlanItMetro website on May 6th, 2013. The "core" area in downtown in Figure 19 is determined by the maximum load point on each rail line, as explained on the website.

[25]WMATA station-level Land Use Ridership Model, conducted in 2014.

[26]In detail, we tested a number of specifications using multiple combinations of the main variables for this study—ridership, fare, passenger miles traveled using track mile and composite mile, fare per mile using track mile and composite mile—to select the best combination of a dependent variable and an independent variable of fare. In addition, we tested the numerous numbers of combinations of 34 OD-station level variables, 65 origin station level variables, 65 destination station level variables, and some interaction terms of these variables. We also tested the locations of stations relative to the downtown core in a more discrete way, while they were not found statistically significant.

[27]The results of all variables included in regression for all the other rider classes are presented in appendix B. Through a very careful process, a set of variables that are statistically significant were identified using the subset of full-fare riders in each time period. This selection of independent variables was applied to the subsequent analysis of the rest of subsets of the other rider classes. In other words, a selection of independent variables tested is same for all subsets in each time period.

[28] 55 percent, 61 percent, and 76 percent of ridership belong to this rider class in each of AM peak, PM peak, and off-peak periods, respectively.

[29]In the table, the dashes indicate that variables were statistically insignificant, and were not included in the final most parsimonious models.

[30]These three numbers are computed by the exponential of each of the three estimated coefficients—0.590, 0.441, and 0.499.

[31]These three numbers are computed by the exponential of each of the three estimated coefficients—0.952, 0.712, and 0.720.

[32]While another variable—midday and weekend jobs on the destination side was also found statistically significant, it was not included due to a large number of missing values, which substantially reduces the number of observations in regression analysis.

[33]It would require an analysis of ridership between OD-stations in combination with travel distance and spatial distribution of these M25 stations in order to fully understand the effects on fare elasticity.