Predicting Ridership and Travel Time Impacts of Bus Service Changes Using Sketch Planning Methods

by

Tiffany M. Lim

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Authored by:	Tiffany M. Lim Department of Urban Studies and Planning May 15, 2025
Certified by:	Anson F. Stewart Research Scientist Department of Urban Studies and Planning, Thesis Supervisor
Certified by:	John P. Attanucci Research Associate Center for Transportation and Logistics, Thesis Supervisor
Accepted by:	Jinhua Zhao Professor of Cities and Transportation Chair, Transportation Education Committee

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ABSTRACT

Bus service changes range in scale, and understanding their impacts on ridership and travel times can inform decision-making as changes are considered for the bus network. Budgetary limitations are at the heart of service change decisions, resulting in the need for analysts to assess different scenarios and accommodate quick turnarounds. This thesis provides a sketch planning framework for predicting ridership and travel time impacts of bus service changes, with a focus on direct demand models and the use of an open-source multimodal routing algorithm. The framework is designed to be streamlined with the use of data sources and capabilities, such as exporting a General Transit Feed Specification (GTFS) feed of a given bus network scenario, that agencies may have access to through existing transit planning tools.

Direct demand models are developed to estimate bus ridership at the level of approximately one-mile route-segments and time-of-day periods. This level of analysis provides a more disaggregated evaluation of bus ridership than past direct demand models. The models are sensitive to both route and network improvements. New variables designed to capture the relationship between bus routes, including the competitive and complementary nature of routes, are introduced and incorporated in the model development process. These models are developed for the Washington Metropolitan Area Transit Authority (WMATA). A case study analyzing two scenarios in WMATA's Better Bus Network Redesign (BBNR) is presented, with selected route examples to illustrate how the models capture different types of service changes. These routes fall under three categories: routes with no major service changes, routes with improvements in frequency, and routes with re-routing and other improvements.

An open-source multimodal routing algorithm, available through an R package called r5r, is used for travel time analysis. r5r calculates a distribution of door-to-door travel times for a given origin-destination (OD) matrix and returns a selected percentile value from the distribution for each OD pair. The percentile parameter is calibrated through a comparison of estimated travel times and actual travel times recorded in origin-destination-interchange inference (ODX) data. Low percentile values were found to provide travel times close to actual travel times. Additional guidance is provided for interpreting travel times from r5r, and use cases related to calculating travel time impacts between scenarios and evaluating rail competitiveness for a given bus network are explored.

Thesis supervisor: Anson F. Stewart
Title: Research Scientist
Department of Urban Studies and Planning

Thesis supervisor: John P. Attanucci
Title: Research Associate
Center for Transportation and Logistics

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Chapter 1

Introduction

1.1 Background and Motivation

Bus service changes range in scale and can include detours, service restructuring related to span and frequency, and route realignments. Budgetary constraints play a significant role in determining service changes, defining whether service can be added or reduced at any given time. Different packages of service changes are commonly identified and evaluated periodically (e.g., annually) under new budget scenarios or other financial constraints. Existing methods to evaluate different scenarios are commonly heuristic, given the iterative nature of these analyses and a general short turn around to make decisions. The need to evaluate larger service reductions or eliminations has also become increasingly relevant after the COVID-19 pandemic, with ridership still recovering after declines from a national lockdown, work from home policies, and transit agencies in the United States facing current or upcoming operating budget deficits [1]. At the same time, there is a wider trend of bus network redesigns with agencies proposing significant service changes to better align their network with current and future travel patterns, allocate resources more effectively, and/or encourage more transit ridership [2]. These proposed changes are either implemented all at the same time or in phases with changes being reviewed over time. Across all scenarios, the ability to understand the

ridership and travel time impacts of these changes can inform decision-making and internal conversations as changes are made to the network.

Existing public transit planning software, such as Remix and HASTUS, have been adopted by many transit agencies for use in their service planning processes to sketch and plan different service scenarios. Among the software capabilities, these tools allow for agencies to make edits to individual routes and export transit network scenarios in a standardized General Transit Feed Specification (GTFS) format, enabling downstream scenario analyses.

This thesis develops sketch planning methods that leverage existing public transit planning tools and open-source datasets, including population demographics and land use characteristics, to evaluate the customer impacts of bus service changes. Given the iterative nature of these analyses, the proposed methods are designed to minimize work for analysts evaluating scenarios after service changes are identified. These methods are developed for the Washington Metropolitan Area Transit Authority (WMATA), which operates Metrobus and Metrorail service in the Washington D.C. Metropolitan Area, and applied to service changes outlined in their Better Bus Network Redesign (BBNR).

1.2 Objectives and Approach

This thesis aims to develop sketch planning methods to evaluate the customer impacts of bus service changes, specifically ridership and travel time impacts.

For bus ridership analysis, a framework is presented to process GTFS data into approximately one-mile route-segments and time-of-day periods. Direct demand models are developed to estimate ridership, in terms of average boardings. This level of analysis allows for ridership estimates to be sensitive to variations in service and/or demographic characteristics along a route and across time-of-day periods, which is not possible in typical weekday or weekend route-level ridership models. New variables are defined to capture the inter-route relationship between bus routes, including the competitive and complementary impacts among

nearby routes. Existing definitions of variables that capture this inter-route relationship in direct demand models are often categorical, classifying routes as either complementary or competitive based on select criteria. The variables proposed in this thesis are continuous variables calculated at the segment-level, which are intended to be more flexible in capturing the relationship between routes in a given bus network and any variations in characteristics along a route.

For travel time analysis, actual travel times from origin-destination-interchange inference (ODX) data are compared to travel times from r5r, an open-source multimodal routing algorithm. As r5r returns a percentile value from a distribution of travel times for a given origin-destination matrix, the comparison is used to configure the percentile parameter in r5r to obtain travel times close to actual travel times. Additional analysis using r5r is presented, including the evaluation of travel time impacts between scenarios and rail competitiveness for a given bus network.

The proposed methods can be streamlined through automation to allow for iterative analyses. These methods rely on the use of SQL for data querying and R, an open-source computing software, for data processing and analysis. Relevant scripts and models are developed. This work hopes to inform decision-making and expand current practices to enable more structured analysis related to bus service changes within WMATA, which can be transferred to other agencies.

1.3 Thesis Organization

Chapter 2 provides a literature review on analyses of bus service changes, discusses existing methodologies related to ridership and travel time estimation, and describes the contributions of this thesis. Chapter 3 details the methodology used for bus ridership analysis and the model development process. Chapter 4 presents an example of an application of the models developed in Chapter 3 for ridership estimation. Particularly, the models are applied to two

scenarios in WMATA's BBNR, and examples of routes are selected to detail how specific types of service changes are captured in the variables included in the models. Chapter 5 describes a travel time comparison study conducted to configure the percentile parameter in travel time calculation functions in r5r and discusses use cases of travel time analysis. Lastly, Chapter 6 provides concluding remarks, limitations, and recommendations for future work.

Chapter 2

Literature Review

2.1 Ridership Impacts

Ridership estimates can inform decision-making on bus service change proposals, specifically in the context of resource allocation within an agency's operating budget. Ridership models can provide estimates for existing routes with service changes and/or new routes. These estimates can serve as a basis for justifying decisions for selected service changes and can guide conversations when there are competing priorities related to adding or reducing service [3].

Two comprehensive state of practice reviews examined methods for predicting fixed-route ridership across transit agencies in the United States and Canada. A 1982 report reviewed methods across 40 transit agencies, noting the common uses of ridership estimates to evaluate new routes, route realignments, and changes in service hours, headways, or fare [3]. Existing methods included professional judgment, survey techniques, cross-sectional models (e.g., regression models) and time series or panel models (e.g., elasticities). In 2006, a Transit Cooperative Research Program (TCRP) report provided an updated summary of fixed-route transit ridership forecasting and service planning methods based on a survey across 36 transit agencies in the United States and Canada [4]. Similar methods to those in the 1982

report were observed, but with increasing complexity in simpler models due to advancements in GIS, technology, and data availability. The report emphasizes the continued need for easy-to-use methodologies, utilization of readily available data, and cost-efficient analysis methods. Ridership forecasting is highlighted as valuable to agencies as it serves to standardize processes between modelers and service planners, increase credibility for decision-making at senior management and board levels, and provide a basis for prioritization among competing proposals. Both reports stress an ongoing challenge regarding data quality, availability, and forecast accuracy, noting the importance of considering theoretical drawbacks while balancing simplicity for usability.

Voulgaris extends discussion on forecast accuracy by identifying a framework to evaluate the trustworthiness of forecasts in planning, as many factors can influence how estimates are produced [5]. She recommends forecasters and users of estimates to evaluate the transparency of methodological choices (i.e., understanding of input data and model assumptions), internal influence (i.e., bias related to forecasts that are used to support predetermined decisions), and external influence (i.e., bias related to pressure from funding providers and other stakeholders). These factors can inform both the methodological choices and the use of estimates from ridership forecasting models beyond quantitative metrics.

Ridership forecasting models vary in complexity depending on use case and time and resource constraints, from more simplistic models like direct ridership models to more intensive models like a four-step travel regional demand model. Given that the focus of this thesis is on producing first-cut ridership estimates for alternative scenarios, sketch planning approaches, including elasticity methods and direct demand models, are reviewed and discussed in this section. More advanced techniques, including simultaneous equations and trip-based and activity-based models, are also discussed to provide a comprehensive overview of existing methods for estimating ridership impacts.

2.1.1 Elasticity Methods with Panel Data

Elasticities can be used to calculate ridership impacts from a change in a service attribute, given an existing ridership value on a route. A service elasticity is defined by the percentage change in ridership divided by the percent change in the given service attribute for any given service modification. An elasticity value greater than 1 indicates an elastic relationship, where changes in a given service attribute yield larger increases in ridership. Panel data, or data on multiple entities over multiple points in time, can be used to obtain an elasticity [6]. Elasticities are usually determined for a specific variable, such as fare, frequency, or travel time [3]. Therefore, among the observations in the data to estimate an elasticity, the routes would need to experience some type of change to a service attribute in order to capture the relationship between ridership and the corresponding attribute before and after the service change.

The arc elasticity is the most common form among transportation studies, which is based on the demand curve before and after a given service change [3]. This can be defined with two formulations using before and after data:

Log arc elasticity:

$$\eta = \frac{\triangle log\ Q}{\triangle log\ P} = \frac{log\ Q_2 - log\ Q_1}{log\ P_2 - log\ P_1} \tag{2.1}$$

Midpoint (or linear) arc elasticity:

$$\eta = \frac{\triangle Q}{(Q_1 + Q_2)/2} \div \frac{\triangle P}{(P_1 + P_2)/2} = \frac{(Q_2 - Q_1)(P_1 + P_2)}{(P_2 - P_1)(Q_1 + Q_2)} \tag{2.2}$$

where η is the arc elasticity, Q is the demand, P represents the changing attribute, and the subscripts denote two different timepoints [7]. The arc elasticity generally approximates the relationship between ridership and the service attribute closely, but may yield incorrect values for large changes in Q and P.

There are different types of service elasticities previously reported, but frequency elasticities

are most common in literature. Frequency elasticities, for example, measure the sensitivity of ridership to a change in service frequency (e.g., buses per hour passing a location). Typical service frequency elasticities average +0.5 with higher values observed in cases where initial service is infrequent, such as in suburban areas where existing service has 60-minute or 30-minute headways [4], [8]. The elasticity could be greater than +1.0, though this was infrequently reported in literature [8]. Service elasticities may incorporate multiple service attributes involving changes in route alignments or network structures [8]. Service quantity and span of service changes can be captured in a single service elasticity. For example, a study using data from 1992 to 1998 in Santa Clarita, California found a service elasticity of +1.14 from a mix of frequency and span improvements [9].

Elasticities tend to be quick and straightforward to apply on an existing route with ridership data. They can be applied successively if there are multiple factors being changed with the implementation of a set of service changes. However, one drawback of using an elasticity method is that it requires an existing or baseline ridership for each route to obtain a future ridership estimate. In other words, elasticities can only be applied to routes that have ridership data and cannot be applied to estimate ridership for a new route or new route extension, which may be a relevant use case when planning service changes.

2.1.2 Direct Demand Models

Direct demand models are a common sketch planning method to obtain first-cut ridership estimates and compare alternative scenarios. These models estimate ridership as a function of transit service, residential, and employment characteristics along a route [10]. They are commonly developed using regression techniques, such as linear, Poisson, and regularized regression, with cross-sectional ridership data, or data from a point in time [10], [11], [12]. Consequently, the coefficients of the independent variables are determined based on the differences across units of analysis [6]. Compared to the elasticity method, direct demand models can be more flexibly applied to estimate ridership to different service changes on both

existing and new routes, as baseline ridership is not necessary to calculate a future ridership estimate. Some direct demand models may also be developed using panel data [13], [14]. The purpose of the models in these cases is more focused on understanding the effect a factor has on ridership, similar to the elasticity method, rather than estimating ridership for different scenarios.

Cervero et al. described direct demand models as a complementary approach to traditional four-step travel demand models, which are generally used to evaluate regional investments [11]. Unlike traditional four-step travel demand models, direct demand models can be used to analyze the impacts of local initiatives, such as transit-oriented developments, by accounting for variables related to neighborhood density and other land use factors. These models are designed to be sensitive to service as well as socioeconomic characteristics to capture ridership impacts as service changes and can be used to estimate ridership on existing and new routes under different scenarios [3].

One of the main differences across existing direct demand models is the level of analysis for bus ridership estimation. Existing models have estimated ridership at the full route, individual route-segment, and stop level. The choice of level of analysis could depend on multiple factors, such as use case, data availability, and simplicity, but there is a general assumption made in each case. To estimate ridership using direct demand models, characteristics are allocated to each unit. The assumption in each case is that the service and catchment area attributes are homogeneous within the unit of analysis [15]. With more aggregated levels of analysis, like the route level, this assumption may not hold true, particularly in cases where there are variations along routes, such as routes that travel through areas of differing densities and land use types. Additionally, if there are changes at the local level, a route-level model may not be able to capture these effectively. At more disaggregated levels of analysis, such as the stop level, ridership can be estimated at the level at which ridership is observed, and models can capture localized attributes, such as stop amenities or street network characteristics, which can influence ridership [16]. However, since stops can be close together, it could also be difficult

to isolate the characteristics between each stop depending on the network with additional challenges around data availability. There is a general concern around data availability and whether the data used can capture the differences at the chosen level of analysis. The models discussed in this literature review include models focused on estimating ridership or understanding the effects of certain changes on ridership using either cross-sectional or panel ridership data.

Since route-level ridership is a common objective in sketch planning, existing studies have developed models to estimate route-level ridership directly. Stopher developed econometric models to predict route-level bus ridership boardings and alightings for three time periods: weekday peak (i.e., AM and PM peak combined), day, and night periods using cross-sectional ridership data from a 1988 survey [10]. Total population, number of low-income households, and total retail employment were among the tested population and employment characteristics which had a positive effect on ridership. He also created a variable to indicate whether a route passes through a central business district (CBD) tract. Each model had an adjusted R^2 greater than 0.9. Stopher found the models to be sensitive to service changes with expected relationships between service levels and ridership; however, he noted the lack of consideration for inter-route relationships and a potential for future work. Service and/or demographic changes on a single route may not only impact ridership on that route but may often affect ridership levels on parallel or intersecting routes as well.

Nair, Mirzaei, and Ruiz-Juri tested linear and tree-based methods to estimate route-level bus ridership in the Dallas-Fort Worth metropolitan area and found a ridge regression model to perform best with a test R^2 of 0.88 [12]. Though they estimated weekday ridership, they created a frequency variable for peak, midday, and night period to differentiate some of the time-of-day effects. These models used socioeconomic data at the traffic analysis zone (TAZ) level, such as number of households by income group and total retail and service employment. Similar to Stopher, this model also considered whether the route passed through the central business district. The addition of the CBD variable in this model might help distinguish

routes from each other, serving as a proxy of destinations the route serves and accounting for some variation across routes. Though both of these route-level models appear to have high explanatory power, they are unable to account for variations in characteristics along a route and both recommended further study into more disaggregated models (e.g., stop-level) to address this limitation.

Route-segment-level models provide an in-between in terms of level of aggregation compared to a route-level and stop-level model. Segments have been previously defined in different ways in the context of ridership models. Peng et al. developed segments by splitting route-directions based on fare zones and developed a cross-sectional model to estimate ridership [17]. They noted limitations with segments defined by fare zones, as fare zones are sized differently, and believed a stop-level model could address this limitation depending on data availability. The modeling approach taken in this study is discussed in more detail in Section 2.1.3. Berrebi, Joshi, and Watkins developed route-segment-level models, breaking route-directions into segments that were each seven stops [14]. They defined short segments so that the catchment area attributes are representative of potential demand for a given segment. They noted that it would be difficult to capture local variations in ridership at the stop-level given data challenges. This study is described in more detail later in this section when panel methods are discussed. In both of the route-segment-level studies, segment definitions seem to be context-dependent and not one-size-fits-all, as using fare zones or a set number of stops could create inconsistent segments in a different system.

Stop-level models are the most disaggregated level of analysis in existing bus ridership models. Cervero, Murakami, and Miller developed a stop-level linear regression model to estimate bus rapid transit ridership in Los Angeles County [18]. They found service attributes related to frequency to be the most influential on their ridership estimates. Though they tested bus stop and site attributes, such as presence of park-and-ride lots, stop amenities, and a street connectivity index, they found these to not be significant. The final models, however, highlight the importance of service quantity, intermodal connections between bus and rail

(i.e., number of perpendicular daily rail feeder trains), and surrounding population and employment densities on ridership. The R^2 was similarly high to the previously mentioned route-level models, with a value of 0.95.

Other stop-level models have been developed using similar data [15], [16], [19], [20]. Chu developed a stop-level Poisson regression model to estimate weekday total boardings [15]. Her model has a goodness of fit of 0.54 and incorporates socioeconomic variables along with locally available variables, such as Transit Level of Service (TLOS), pedestrian factor term, and upstream and downstream persons and jobs to capture destinations. Chu argues for a preference towards stop-level models in order to capture hyper-local variations, such as the effect on transfer wait times when there are improvements at the intersection of two routes. [15]. Though the interactions between routes and modes appear to be important, it is not clear how large of an effect size such variables would have on ridership at the stop-level and whether this was captured in her model. The travel time-related variables in the final models for predicting weekday total boardings are related to the number of persons and jobs up and downstream without transfer in an hour. Because the unit of estimation matches ground-truth observations, stop-level models provide advantages in their ability to capture characteristics related to the street network, stop amenities, or changes in frequency along a route, assuming data on these characteristics is available [21]. However, for stops that are close together and have overlapping catchment areas, it could be difficult to isolate the characteristics between each stop, which would reduce the model's explanatory power [14]. Dill also developed a stop-level ridership models using linear regression for three different transit agencies and found socio-demographic, transit, and land use variables to provide most of the explanatory power in her models [16]. The adjusted R^2 of these models ranged from 0.53 to 0.69. Though a stop-level model is often framed as a way to capture hyper-local variations, it appears that there is either not always enough local data or not always enough variation in these characteristics. As a result, the correlation of these characteristics to ridership are often low, when compared to other important variables included in the model,

such as service frequency.

Similar to stop-level models, Rosen created models to estimate boardings at the grouped-stop level, which did not consider directionality [20]. Bus stops were consolidated into locations to consider inbound and outbound stops as the same joint location. To consolidate bus stops, a buffer of 0.01 miles was created around each bus stop, and bus stops were grouped into locations if their buffers intersected with each other. Log-log regression was used with sociodemographic variables, bus and rail feeder trips, and distance to CBD. The adjusted R^2 was 0.88.

From the review of existing models, it appears that R^2 or similar goodness of fit metrics are used as the main measure of performance instead of before-and-after comparisons to test model accuracy from past service changes. Though the expectations in explanatory power of each model may differ depending on the context of the system and available data, more aggregate models appear to have a higher goodness of fit compared to more disaggregated models. For example, route-level models have an R^2 greater than 0.9, which is very close to 1, compared to stop-level models which may range lower around 0.5 to 0.7. This is expected as available explanatory variables may not fully capture variations in the observed ridership. Despite the trade-off on performance relative to goodness of fit, models with a more disaggregated level of analysis may be more sensitive to changes that occur at the local-level, which could be advantageous depending on the use cases of the model. The choice of level of analysis is dependent on the use cases of the model. It is worth acknowledging that regression methods used to develop direct demand models assume independence of observations, which may affect the model results for any level of analysis. This may be more relevant for stop-level models compared to route-level models as stops in close proximity may be more influential on one another compared to routes in close proximity. Lastly, across all models, validation of estimates using historical service changes appears to be lacking, which aligns with concerns stated in past reports on ridership forecasting [3].

Direct demand models are sensitive to various types of service changes and can be used

to produce ridership estimates. There are, however, some notable differences between models that use cross-sectional data and those that use panel data for estimation, which can inform the interpretation of model results. The study by Berrebi, Joshi, and Watkins is an example of where panel data was used as the focus of the study was to understand the causal effect a change on a frequency has on ridership [14]. They defined short segments so that the catchment area attributes are representative of potential demand for a given segment. They noted that it would be difficult to capture local variations in ridership at the stop-level given data challenges. They also developed two models, one which used cross-sectional data and the other which used panel data, to make a point that the effect of frequency changes on ridership needs to be evaluated within each segment over time instead of an analysis that compares between segments. They found the frequency elasticity or coefficient on the frequency variable in their panel fixed-effects model to be lower than that in their cross-sectional model, attributing this to the fixed-effects approach in controlling for time-invariant endogeneity. For example, for Portland, the frequency elasticity to ridership was 1.36 in the cross-sectional approach, looking at the relationship between segments, while the elasticity was 0.78 in the panel approach, looking at the relationship within a segment. Kerkman et al. uses a similar fixed effects regression approach to estimate ridership and finds similar conclusions in terms of the differences in sensitivities between a cross-sectional and panel approach [22]. The results suggest that cross-sectional models may tend to overestimate the impact of frequency on ridership compared to panel approaches as a result of omitted variables. Depending on the intended use case of a given direct demand model, there appears to be some differences in opinion on the need to address the endogeneity concern in literature. For example, Chu [15] estimates ridership at the stop-level and argues that since frequency is route-specific, supply and demand are not determined simultaneously.

2.1.3 Simultaneous Equation Models

Simultaneous equation models attempt to address the endogeneity problem between supply and demand that was mentioned in the previous section. Studies that use this method assume that service frequency and ridership either have a simultaneous relationship or a two-way relationship [13], [17], [23], [24]. For example, service might be increased in areas where the underlying demand is high, while ridership may be higher where more service is provided. Peng et al. notes that the simultaneity relies on a few assumptions, given that there could be a time lag in the response time between ridership and frequency changes. As long as "planners adjust to short-run demand changes" over time, the relationship between supply and demand can be considered simultaneous. However, this relationship could be re-framed by considering how supply stays constant while demand changes more regularly. Similar to direct demand models, either cross-sectional or panel ridership data can be used to estimate simultaneous equation models.

Among various simultaneous equation methods, the use of instrumental variables (IV) through models, such as two-stage least squares (2SLS), is a common method to address the endogeneity problem between transit supply and demand. This method involves selecting an appropriate IV to estimate the endogenous regressor (e.g., frequency). The second stage would then be a second equation that estimates ridership using the estimated frequency instead of the actual frequency. There are two main criteria for selecting an IV: it has to be correlated to the endogenous regressor and not correlated to the errors, or omitted variables, in the ridership estimation model [25]. Based on Angrist and Krueger, the choice of IVs can be backed by detailed, contextual knowledge on the mechanisms relative to the study [25]. In the case of frequency and ridership, a good IV would need to be correlated to frequency but not correlated to any factors that affect ridership that are not accounted for in the explanatory variables in the second stage equation. This section includes a few examples of studies that used this approach.

Peng et al. developed route-level simultaneous equation models to estimate transit supply, demand, and interaction between routes (i.e., competing and complementary nature of routes) using cross-sectional data [17]. They modeled ridership using a single-equation model, or linear regression, and a simultaneous equation approach, specifically three-stage least squares (3SLS) to compare the results. Some of the key variables used in these models included low-income households, employment density, and various dummy variables to mark the type of route. The equation to estimate competing routes included variables related to the population in the overlapping catchment areas and the frequency on competing routes. The R^2 for the demand equation was 0.74 using 3SLS and 0.75 using ordinary least squares (OLS). Though performance was similar between the two methods, there were differences in the estimated coefficients. For example, in the AM Peak inbound model, seat supply, which was an indicator of service, had a coefficient of 0.303 in the 3SLS model and 0.249 in the OLS model. When the models are applied to a set of service changes, the results revealed that the OLS approach underestimated ridership on the route with service changes and overestimated ridership on competing routes. Additionally, OLS overestimated the net effects of service increases at the system level. The results suggest the importance of capturing the inter-route relationship between intersecting and parallel routes. The expected relationship was observed in the model results, where increases to service on a given route resulted in increases in ridership while ridership on competing routes decrease [17].

Diab et al. developed transit agency-level two-stage least squares (2SLS) models using IVs [13]. Compared to Peng et al., this study used a longitudinal dataset of 103 transit agencies in Canada with observations over a 14 year period. The main purpose of this study was to understand the factors related to transit ridership, similar to the panel study mentioned in the previous section. The two stages involved first estimating revenue hours, or transit supply, with two IVs: total population and total operating budget. The choice of IVs might be appropriate based on precedence in other studies; however, the total operating budget could influence ridership not only through vehicle hours but also through geographical location of

service that is provided, which is not completely captured in existing explanatory variables and may suggest the choice of IVs to be less ideal. The estimated revenue hours are then used as an explanatory variable to estimate linked trips at the agency level. Other explanatory variables were related to different types of households and the share of population with different characteristics, such as seniors, recent immigrants, and postgraduate students. The second stage, however, did not include total population like the first stage did as a control variable. The overall R^2 was 0.969, which may be higher than route-level models as the models are estimating relationships at the agency level.

Patni and Srinivasan developed route-level models using 2SLS models using IVs for transit services in Gainesville, Florida [23]. In this study, the first stage predicted hourly frequency using a dummy variable for weekend service, the length of a route, population, and institutional land use. Since institutional land use was included in the second stage equation, the other three variables are used as IVs. Similar to the previous study, the choice of IVs and related justification are not clearly explained. Arguably, the choice of a dummy variable for weekend service might not be an ideal IV as it could influence monthly ridership. Routes that have weekend service may serve specific origins and destinations that are not entirely controlled for in the explanatory variables in the second stage. Additionally, the same issue with using total population as an IV is also relevant in this study.

Similar to Peng et al., Patni and Srinivasan incorporated variables to capture the inter-route relationships along with commonly used variables related to sociodemographic and land use factors [26]. However, instead of basing the inter-route relationship on overlapping catchment areas, it is determined based on the overlap of transit stops. Routes were grouped into four different categories, ranging from routes with no shared stops to routes with 10 or more shared stops. The model was developed using monthly route-level ridership data. The first stage estimated hourly frequency while the second stage estimated monthly ridership for each route. Based on the model results, routes appear to have a competitive nature only when they share 10 or more stops with other routes based on a sum of vehicle revenue hours

across the other routes. Otherwise, the relationship is complementary between routes and the effect is positive on ridership. The adjusted R^2 for the demand estimation model was 0.611. This model builds on findings from Peng et al. of the significance of capturing the relationship between routes, which allows the estimates of competing routes to be sensitive to increases in overlapping service.

Deepa et al. developed a 2SLS model with IV to estimate fare-stage-cluster-level ridership for the AM peak period in Bengaluru, India [24]. The first stage estimated route-level frequency using total passenger kilometers along the route as an IV. They note that the measure does not influence stop-level boardings and would only influence the length of current riders. The second stage estimates boardings using the estimated frequency, land use, employment, population, and network interaction variables. This model also considers inter-route relationships across routes in the transit network. They defined different categories to classify partly and fully complementary or competing routes depending on the number of overlapping downstream stops and upstream stops. For example, a partly complementary route was defined as a route that shared an upstream stop with another route but no downstream stops. On the other hand, a partly competing route was defined as a route that shared a greater number of downstream stops than the number of non-overlapping downstream stops. To develop inter-route variables for the model, three variables were created: the sum of the frequencies of fully and partly competing routes, the sum of the frequencies of fully complementary routes, and the sum of the frequencies of partly complementary routes were developed. Based on the model results, as expected, the inclusion of a variable that captures the competitive nature of routes results in a negative coefficient. This model also incorporated variables related to Metro presence based on whether a station fell within a 1 kilometer catchment area of a given stop in a fare-stage cluster, though there were only two Metro routes in the study region. They found that fully complementary metro stations had a complimentary effect to ridership where there were overlaps in service for transfers, and competitive stations reduced bus ridership. Other models in literature that involved

Metro-related variables usually are dummy variables to note the presence of a station or terminal.

2.1.4 Trip-based and Activity-Based Models

Trip-based and activity-based models are more time and resource intensive approaches to predicting ridership impacts compared to the methods discussed in the previous sections. Compared to sketch planning methods, these models require detailed travel survey data, similar to household travel surveys, which record trips pursued by an individual over a certain time period, such as a day. Trip-based models, also known as four-step models, are commonly used for regional analyses or large-scale investment decisions and have four components: trip generation, trip distribution, mode choice, and assignment [27]. At a high level, this method involves estimating home-based and non-home based trips, assigning them to origin and destination zones, determining the trip mode, and selecting the route of each trip.

Activity-based models share similarities with trip-based models in terms of their data requirements, but these models consider more of the behavioral aspect of demand. Instead of deriving demand based on zonal trips, demand is derived from activities and the sequencing of multiple activities [27]. Activity-based models are able to account for the interrelation between trips completed by an individual by incorporating factors related to the time of the trip, the trip purpose, and location in determining mode choice [28]. This allows for greater sensitivity to potential land use or policy strategies that are implemented compared to trip-based models.

An example of a limited four-step model is the Simplified Trips-on-Project Software (STOPS) developed by the Federal Transit Administration (FTA). The trip generation and trip distribution steps are replaced by the use of tabulations from the American Community Survey (ACS) Census Transportation Planning Package (CTPP), which provides zone-to-zone flows of workers from their employment location [29]. The most recent version of STOPS uses the 2012-2016 CTPP data. Other data sources that this software leverages includes geographic

files for each state, GTFS feeds and ridership data from transit agencies, traffic analysis zone (TAZ) and TAZ-level current population and employment counts and their forecasts. TAZ is a geographic unit used for planning purposes and are defined by metropolitan planning organizations and state departments of transportation. The size of each zone depends on the context as there may be restrictions on the number of zones in a study area due to computing resources; however, TAZs are generally compatible with Census geographies, such as blocks and block groups [30], [31].

2.2 Travel Time Impacts

Compared to the previous section, which focused on forecasting ridership impacts based on historical ridership totals or characteristics along a route, this section focuses on characterizing the impacts of service changes on a known population of riders using origin-destination (OD) flows from origin-destination-interchange inference (ODX) data. ODX data uses automated fare collection and vehicle location data to infer linked passenger journeys based on when and where they tap their fare card [32]. Each inferred linked passenger journey includes details on a passenger's origin, transfer(s), and destination.

Understanding the travel time impacts of proposed service changes can inform decision-making on bus service change proposals, specifically in the context of accessibility and equity impacts. These estimates provide an additional layer of understanding on how existing customer journeys may be affected in a new service scenario and how impacts may vary across geographical areas. There are multiple routing engines that leverage routing algorithms to calculate travel times for a given OD matrix. These tools allow for quick analysis of many-to-many OD pairs and may provide information on route choice, access, wait, transfer, and in-vehicle travel times, for the shortest or fastest route given certain user-defined constraints.

Higgins et al. provide an overview of different routing engines including ArcGIS Pro, Emme, r5r, and OpenTrip Planner (OTP) [33]. Though there are many inherent differences

across the techniques and capabilities of these tools, there are some main considerations worth noting. Both ArcGIS Pro and Emme are proprietary tools with built-in data sources and models, which could come with several limitations related to tying in additional data sources, consideration of more detailed parameters, constraints on analysis size, and associated costs with licensing. On the other hand, OTP and r5r are free, open-source routing engines available as packages. These tools require readily available input data, including OpenStreetMap (OSM) network file and a GTFS feed to represent the transit network. These tools appear to offer flexibility in use, better understanding of routing processes, more customization in terms of user-defined parameters, such as the consideration of walk parameters to constrain the access and egress to transit, and possible outputs with travel times and detailed options for route choice. Based on a performance analysis for a given 10,000 by 10,000 OD matrix, they also find r5r to have the lowest computation time. Compared to the other tools evaluated, which took anywhere from more than 45 minutes to multiple hours, r5r computed travel times within 8 minutes, indicating that its processes scale well to larger OD matrices. For calculating travel time impacts, r5r appears to have multiple advantages, particularly with regards to computation time as OD matrices may scale to 10,000 by 10,000 or greater when considering bus stops.

Though routing engines offer a quick method to calculate travel times for a given OD matrix and scheduled transit service, the calibration of their parameters could be significant in how the outputs compare to actual travel times. Li et al. conducted a study comparing travel times from a schedule-based GTFS using OTP, automatic vehicle location (AVL) data, and ODX data [34]. They found that the mean and median travel times were longer in the AVL and ODX case compared to travel times from schedules alone. Since AVL and ODX data may capture more operational aspects of travel times related to reliability or congestion that are not considered in a schedule-based approach, this finding highlights the importance of calibrating routing engines for a given use case to reduce the differences between travel times from each approach.

2.3 Conclusion

This chapter reviewed various methods and tools for predicting ridership and travel time impacts for bus service changes. There are many techniques and tools used in existing studies that can be leveraged and built upon for the analysis of bus service changes in this thesis.

Ridership estimation models were categorized into four groups: elasticity methods using panel data, direct demand models, simultaneous equations, and trip-based and activity-based models. There are inherent differences across these models, and the choice of a given modeling technique appears to be influenced by data availability and the use case of the estimates (i.e., to understand the effect a change in a factor has on ridership or to develop first-cut ridership estimates for different scenarios in a quick flexible manner). Depending on the modeling approach, the interpretation of the model results may differ. Simplicity may be an advantage for sketch planning processes while more advanced techniques are better suited for large-scale, regional studies. For predicting impacts of different scenarios of bus service changes, direct demand models appear to provide a desired level of flexibility that allows for ridership predictions of existing and new routes and sensitivity to population, land use, and service factors. Some methods may attempt to account for either simultaneity or endogeneity concerns related to transit supply and demand; however, these methods appear to either not be widely adopted in industry or are not well-justified in terms of their methodology choice. The overall opinion regarding the prevalence and the need to address these issues has also varied in existing studies; however, the choice of methodology affects how the model results can be interpreted, and caution is added to causal claims that one may make from model results. Regardless of the technical approach taken to estimate ridership impacts, an observation across existing studies is the importance of considering the competitive and complementary nature of routes and how that may affect ridership estimates. This consideration has mainly been prevalent in previous simultaneous equations models where the inter-route relationships are based on a condition related to overlapping catchment areas

or overlapping stops through categorical variables. Variables that capture this relationship are further explored and incorporated in ridership models developed in this thesis.

Developing ridership estimation models require either cross-sectional or panel ridership data. Models developed using cross-sectional data determine relationships between independent variables and ridership based on the variability between units. On the other hand, models developed using panel data determine relationships between independent variables and ridership based on the variability within a unit. Models using panel data may be able to control over differences between units that are not captured by available data leading to better estimation of the effects a change in a variable may have on ridership. However, panel approaches would require relatively consistent service in order to have multiple records over time for each unit. This may be difficult to estimate with large changes in service and/or travel patterns (e.g., service elimination during COVID). Given limitations in ridership data with COVID and post-pandemic effects, panel data studies have been focused on data from before 2019. As a result, the models explored in this thesis use cross-sectional data with an assumption that the relationships in the models hold true for the times being predicted for. These models can also be redeveloped as new data becomes available.

Among the existing direct demand models for bus ridership estimation, there has not been a lot of consideration to relationships in different time periods. Additionally, there has not been many studies related to ridership estimation developed using post-COVID ridership data given the considerations around COVID impacts and ridership recovery. Since trends are assumed to be representative in the short-term, the time selected for model development is important. Though different levels of analysis have been considered previously, a fully developed route-segment-level direct demand model for bus ridership estimation has not been tested. This thesis hopes to expand on existing direct demand models for bus analysis by considering multiple time-of-day and day-of-week periods and evaluating ridership at a route-segment-level with different constraints. The methods in this thesis allow for iterative analysis and a streamlined way to redevelop the model as new data becomes available. As

most models are only applied to hypothetical scenarios, a validation study using historical service changes is discussed to gauge the estimates from the direct demand models.

Travel time impacts are also valuable for understanding the impacts of bus service changes. There are licensed and open-source options for routing engines, which are used to calculate travel times for a OD matrix. r5r appears to have the fastest computation times along with customization that may be relevant to evaluating customer journeys. The study by Li et al. recommended further study into calibrating routing engine parameters in order to reduce the differences between travel times estimated from schedule-based approaches and AVL or ODX data, which considers operational aspects that influence travel times [34]. This thesis delves into this calibration aspect through a travel time comparison study using r5r and ODX data and develops guidance for using travel time outputs from r5r. This work lays a foundation for additional downstream analysis that may be explored related to travel time analysis.

Chapter 3

Ridership Analysis

This chapter details the development of direct demand models for bus ridership estimation. The segmentation approach is first discussed to determine an appropriate level of analysis. An overview of data sources is provided along with steps to allocate characteristics to segments. This includes ridership, frequency, demographic and land use characteristics, and network effect variables. Lastly, the steps for model development and final model specifications are presented and evaluated.

3.1 Segmentation Approach

The level of analysis determines the scale relationships between catchment area, transit service, and ridership attributes are estimated. Ideally, the level of analysis is representative of a unit in which attributes can be assumed to be constant within each unit and attributes vary between units [14]. The level of analysis may also be determined based on the use case of the ridership estimates, for example, by state or jurisdiction. To determine the segmentation approach, several levels of analysis were first considered: route level, stop level, segment level, and origin-destination (OD) level. These options vary by level of aggregation and have different considerations, which are discussed in this section.

The route level is the most aggregate option and has commonly been used in direct

demand models for first-cut ridership estimates [10], [12], [18], [19]. Since route-level ridership is a common objective in ridership analyses, estimating ridership directly at the route level could result in simplified processes. However, a main disadvantage for route-level models is its assumption that characteristics of the catchment area and transit service along a route are uniform. As a result, a route-level model is unable to capture local variations that may be present along a route and how these variations affect ridership. This could be significant, especially in cases where routes pass through areas of varying land use characteristics, such as urban and suburban areas, which vary in densities, demographics, and service attributes.

The stop level is a more disaggregated option compared to the route level and has also been observed in existing direct demand models for bus ridership [15], [16]. Stop-level models estimate relationships between stop attributes and ridership. Since ridership is estimated at the level at which ridership (i.e., boardings) is observed, stop-level models provide advantages in their ability to capture characteristics related to the street network, stop amenities, or changes in frequency along a route, assuming data on these characteristics is available. However, for stops that are close together and have overlapping catchment areas, it could be difficult to isolate the characteristics between each stop.

The route-segment level falls between the stop level and the route level in terms of the level of aggregation. Segment-level models allow for variations in catchment area and service characteristics along a route to be captured, assuming the segments are defined so that characteristics are plausibly uniform within the segment but vary between segments. A segment-level approach allows for some of the benefits of a disaggregated model in capturing local variations while providing a consistent unit of analysis. A recent segment-level study defined segments by a set number of bus stops [14]. However, depending on the context of the transit network, the stop spacing might vary across the network and using a set number of bus stops could result in segments with stops from areas with contrasting characteristics.

The OD level is the most complex among the options as it allows for the evaluation of OD flows and transfers. However, the data and computing requirements of this approach is

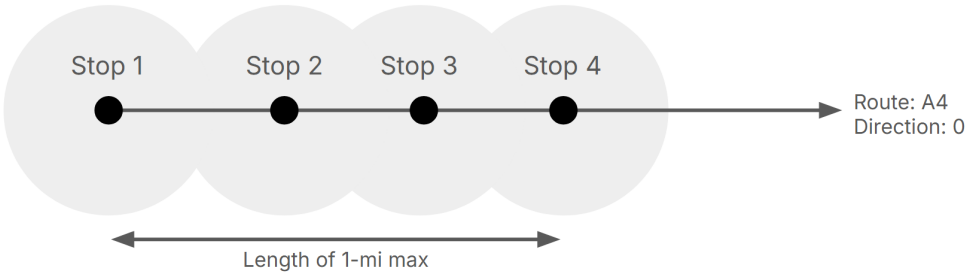


Figure 3.1: Example of a segment (not drawn to scale).

sensitive to the size of the network. For a transit network with 10,000 stops, an OD level analysis would require a 10,000 by 10,000 matrix and evaluation of travel times, which may be more detailed than necessary for the primary use case of producing first-cut ridership estimates and running iterative analyses.

The approach for the level of analysis taken in this thesis is a segment-level model with considerations specific to the use case of estimating ridership for WMATA's Metrobus network. Figure 3.1 illustrates a schematic of a segment for a route-direction. The gray area represents a quarter-mile buffer from the stops in the segment, which is used to allocate catchment area attributes. To ensure segments with plausibly uniform characteristics, two constraints related to segment length and geography were defined for segmentation of a given route-direction. First, the length of a segment cannot be more than 1-mile in length based on stop spacing. The 1-mile length was determined to be a fit value as characteristics within a 1-mile stretch can be expected to be reasonably constant, while allowing for variations to be observed across segments. This first constraint ensures that segments are also made of stops in close vicinity. Second, segments do not cross state boundaries. As WMATA operates Metrobus service in multiple jurisdictions within Washington D.C., Maryland, and Virginia, this served as a loose control for potential differences that might exist at the state level and can be relevant for downstream analyses related to budget and/or jurisdiction-specific analyses. Ridership estimates can be obtained at other zonal levels in post-hoc analyses through spatial allocation methods.

There are differences in ridership patterns on a weekday versus a weekend and across different times of day, or time periods. For example, riders in the AM peak on a weekday could be commuting to work while riders in the midday period include a more diverse mix of travel purposes. To account for these differences, models were developed for each relevant time period and were separated out by weekday, Saturday, and Sunday. For the weekday models, models were developed for the following time periods:

- AM Early (4-6AM)
- AM Peak (6-9AM)
- Midday (9AM-3PM)
- PM Peak (3PM-7PM)
- Early Night (7PM-11PM)
- Late Night (11PM-4AM).

For each weekend day (i.e., Saturday and Sunday), models were developed for the following time periods:

- High service (7AM-8PM)
- Mid service (5-7AM, 8PM-11PM)
- Low service (11PM-5AM).

Breaking out the models by time of day allowed for the exploration of the differences in ridership patterns across time periods and how different variables may have different effects or significance in each period. Consequently, segmentation considered active patterns by each time period, as some patterns may only be active during some time periods.

Segments were first created for each unique pattern for a given route-direction. This was inclusive of any branches or deviations that a route might have. Segments were then selected for each time period based on the active patterns, or patterns that were operating, for each route-direction. Post-processing steps consolidated segments, which ensured that all

unique stops across active patterns for a given route-direction were included and stops were not double counted. For stops that appear in multiple segments for a given route-direction, the segment with the most common pattern, or the most trips, was retained. Branches or deviations from these main segments were then defined as separate segments to retain all stops with service in the given time period.

3.2 Data Sources and Allocation

3.2.1 Ridership and Frequency

Transit data was first collected on WMATA's Metrobus network for the segmentation process described in the previous section. This data was retrieved from transit.land, an open-source repository of historical General Transit Feed Specification (GTFS) data by agency. GTFS feeds hold data on transit stops, routes, and schedules along with geographic location data related to transit service operated by an agency. GTFS data from October 2023 was used for model development. Information about service dates, trips, stop times, and stop information were joined together prior to creating segments for model development. Filtering of any trip information by time period was based on the start time hour of the unique trip. For example, if a trip started at 8:30 AM, all stop times for the trip would fall under the AM Peak period (i.e., 6:00 AM to 9:00 AM), even if some of the stop times in subsequent stops arrive past 9:00 AM.

The dependent variable of the models developed in this study is average boardings by time period and day of week. Automatic passenger count (APC) data was retrieved from WMATA, which has information on stop-level boardings for each trip. Since cross-sectional models rely on the assumption that relationships between independent variables and ridership from a point in time are representative of trends in the short-term, APC data from October 2023 was used for model development. This was a relatively stable month in comparison to other months post-pandemic and had no major holidays or extreme weather events. To

evaluate issues with missing stop trips in the APC data, the distinct trip identifiers were compared between those scheduled in the GTFS data for October 2023 and those recorded in the APC data. This is relevant to ensure the ridership data is representative of the frequency of service used to develop the models. Missed stop trip recordings were a small subset of the data. For example, in October 2023, on weekdays, over 92% of scheduled trips were recorded for each route. Additionally, over 75% of routes have less than 2% of missed trip recordings. Given that a majority of trips were recorded, ridership values were adjusted with a scaling factor determined by the number of trips recorded in the APC data and the number of scheduled trips for each stop trip in the GTFS data, under the assumption that each trip within the time period provides similar boardings. As a note, there were a few route-direction-stops that did not have any ridership data in the month of October compared to their presence in the GTFS data. This made up 8 of 14,131, which is less than 0.06%, of all route-direction-stop records, with half of these being from route W8, a loop route. Segments with these route-direction-stops were removed from the model development process. An average ridership value was calculated for each stop by dividing the monthly total ridership by the number of days of the corresponding day type in the month. The average ridership was then summed across each stop in a segment to get an average ridership value for each segment. This was used as the dependent variable in the models developed in the next section.

Average trips per hour by time period was the main variable capturing service frequency of a given segment. This was calculated by first creating a trip matrix for each time period, which held all the stop times for all trips corresponding to the time period. For example, a trip matrix was made for the AM Peak period based on the Weekday schedule. The trip matrix was then grouped by route, direction, pattern, and stop identifier, and the average trips per hour for each group was calculated by dividing the number of distinct trip ids by the span, or number of hours in the time period. For each route-direction, the average trips per hour for a given stop can be calculated by summing the average trips per hour across all patterns. The average trips per hour can then be obtained for each segment by averaging the

frequency of each stop in the segment. This process captures any variation in frequency along a route-direction in cases where patterns branch off and/or serve a different set of stops.

3.2.2 Demographics and Land Use

Demographic data from the American Community Survey (ACS) 5-Year data series was used, which covers data from 2017 to 2022 at the block-group level. This data was the most recent and disaggregated level available with relevant characteristics for estimating ridership at the time of this work. Potential population characteristics related to age group, school enrollment, educational attainment, employment industry, income, and race were collected for consideration in the model development phase. To allocate block group attributes from ACS data to segments, a quarter-mile buffer was first created for each bus stop in the Metrobus network. The buffers were then combined by segment based on the unique stops in each segment to create a singular geometry representing the catchment area of each segment. ACS data was allocated to each segment using areal-weighted interpolation available in the sf library in R. This method allocates values from the block-group level ACS data to each segment in a proportional manner based on the overlapping area between the segment's catchment area and each block group. One of the assumptions of this method is that the demographic attributes of each block group are uniformly distributed within the block group; however, this might not always be true, particularly in cases where land use varies within a block group. Since more disaggregated, block-level population data is available, a ratio between the interpolated block-level population values and interpolated block-group level population values for each segment served as an adjustment factor for more precise allocation of the population that exists within a segment's catchment area. This factor was multiplied by the values from the first areal-weighted interpolation step.

Using the catchment area developed for each segment, characteristics related to workplace and housing were spatially allocated to each segment. The Longitudinal Employer-Household Dynamics (LEHD) Origin-Destination Employment Statistics (LODES) dataset provides

information on workplace location and corresponding employee count with additional breakdowns, such as by industry and by income group. At the time of this work, 2021 LODES data was available at the block-centroid level. Given the granularity of block-level data, attributes related to number of workers in specific industries, such as professional services, retail, and hospitality, were allocated to a segment if the point location intersected a segment's catchment area. If multiple points fall inside a segment's catchment area, the values of each corresponding attribute are added. The National Housing Preservation Database (NHPD) dataset provides information on active subsidy properties, inclusive of low-income and senior housing, and the total units at each property, which represents the maximum number of assisted units. At the time of this work, the data was last updated in April 2024, and a specific total number of assisted units was not available as units could be under multiple subsidies [35]. Similar to the allocation of LODES data to each segment, the value of total units was added up for all points that fall within a segment's catchment area.

Downstream characteristics can serve as proxies of trip destinations or attractions from a current segment. Downstream workplace and subsidized housing were considered in the model development process. Since the LODES and NHPD datasets are provided as point data, downstream workplace characteristics and downstream subsidized housing units can be calculated for consideration in the model development phase. Using individual stop buffers from a previous step, a spatial intersection was performed with the LODES and NHPD dataset, and the unique identifiers of each workplace location and active subsidy property was stored to each stop. Similarly, the downstream stop identifiers was stored for each segment. Based on the downstream stops for each segment, the identifiers of workplace locations and housing locations were aggregated, and unique identifiers were retained to remove duplicates. Associated values related to workplace characteristics, such as number of workers in professional services, and the total number of units in the subsidized property, were linked and summed up accordingly.

Additional data sources related to land use characteristics and other variables that could

impact ridership on routes were collected; however, they were not included in the final models after preliminary consideration based on model performance or significance, which could be influenced by multiple reasons, such as a lack of variability in the variable across segments or correlation with other included variables. This included points of interest data from OpenStreetMap, such as hotels, places of worship, malls, restaurants and dining services (e.g., bars, cafes, food courts, etc.). Dummy variables for states of each segment were also tested to attempt to capture any differences across jurisdictions. College and university location and enrollment data was collected from the Homeland Infrastructure Foundation-Level Data (HILFD), and elementary and secondary school enrollment data was collected from the National Center for Education Statistics (NCES). Internal data sources provided by WMATA included route service classifications, Supplemental Nutrition Assistance Program (SNAP) retailers, public schools, and hospitals.

3.2.3 Network Effects

Variables were also created to capture transit availability and connectivity. For characteristics within a segment, a binary variable was created to indicate whether a Metrorail station was present within a segment's catchment area. WMATA Metrorail GTFS was obtained for the same period as Metrobus from transit.land. The GTFS feed included transit service information on the six rail lines that WMATA operates in the Washington D.C. Metropolitan Area. This variable served as a proxy on potential transfer opportunities along with a sense of general service availability. Additionally, a smaller catchment area with a tenth of a mile buffer was defined for each segment based on the bus stops in each segment, similar to the development of quarter-mile buffers around stops. This smaller catchment area was used to identify bus routes that were accessible as a potential transfer and/or in close vicinity to the current bus stops. Metrobus routes and TheBus routes, which are operated by Prince George's County in Maryland, were considered as these routes are included in future scenarios in the Better Bus Network Redesign. Two variables were calculated using this smaller catchment

area: within sum frequency and downstream sum frequency. The first variable is the sum of the frequencies of routes within the smaller catchment area. Similarly, the second variable is the sum of the frequencies of routes accessible downstream of a segment to provide a sense of service availability and/or transfer opportunities downstream. Routes were included in the calculation if they had at least one stop within the smaller catchment area.

A shared stop matrix was determined by comparing every route against every other bus route in the system. A similar approach was taken by Patni to look at overlapping stops of bus routes [26]. This resulted in a n by n matrix, with n being the number of routes in the system. The value in each cell represented the number of shared stops the route pair had with each other, based on matching stop identifiers. The shared stop matrix is used to calculated the corridor effect variable, which was designed to capture the shared frequency of overlapping or parallel routes that share downstream stops of the current segment. This is calculated by first retrieving the frequency of each shared route and multiplying it by the ratio of downstream stops shared between the shared and current route. This is then summed across all shared routes to get the total corridor effect, which is high if there are a lot of routes that serve the same stops as the current segment or high frequency routes competing with the current segment. This served as a proxy on complementary or competitive nature of service. The corridor effect is defined by the formula:

$$c_s = \sum_{i=1}^{n} p_i * t_i \tag{3.1}$$

where c_s is the corridor effect for a segment s, p_i is the percent of shared stops downstream with route i, t_i is the number of trips per hour in the time period on route i, and n is the number of routes that have shared stops with the current segment. The contribution of route i to c_s is only considered if route i shares at least one stop with the current segment s, indicative of the ability to take either route to access a percentage of the same downstream stops. A squared corridor effect term was also included in the models. Overlapping routes

can be complementary to one another and provide an increase in ridership on a corridor. However, these benefits likely decrease after a certain threshold (i.e., when there is too much overlapping service) and can be represented in a quadratic form.

3.3 Model Development

Poisson regression models were developed for each time period. Equation 3.2 shows the general form of a Poisson regression model. Equation 3.3 shows the transformed equation to calculate the expected count of Y, or average boardings, given k explanatory variables.

$$log(E(Y|x)) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_k x_k \tag{3.2}$$

$$E(Y|x) = e^{\beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_k x_k} \tag{3.3}$$

Other regression techniques were tested, such as linear regression, regularization methods, and random forest. Poisson regression was selected based on performance and interpretability. For the final models, quasi-poisson models were developed, similar to Berrebi et al., which accounts for overdispersion in the ridership data by relaxing the assumption that the mean has to be equal to the variance [14]. These models produce the same estimates as Poisson regression models, but the standard errors are adjusted to provide a more accurate reading on the statistical significance of the explanatory variables.

Given the large number of variables from the data collection process, variable selection was conducted based on context, the Pearson correlation coefficient with ridership, and use of the variance-inflation factor (VIF) to evaluate multicollinearity. For VIF, a threshold of 5 was used to evaluate the final models. Polynomial terms, such as the squared corridor effect term, may have higher VIF values given the presence of the main term in the model. Descriptive statistics on variables included across the models are summarized in Table 3.1 and Table 3.2 for the weekday and weekend models respectively. Table 3.3 and Table 3.4

show the model results by time period for weekday and weekend days respectively. Some variables, such as stop count, average trips per hour, and total population, are consistently present in each time period, which serve as baseline variables that help to capture the service characteristics of a segment and the underlying population around a segment. As discussed in Section 3.1 on segmentation approach, the values of these variables varies across time periods, depending on the active patterns for each route-direction. Other variables related to population or workplace characteristics may differ between time periods given varying trip purposes.

	AM Early		AM Peak		Midday		PM Peak		Early Night		Late Night	
Variable	Mean	s.d.	Mean	s.d.	Mean	s.d.	Mean	s.d.	Mean	s.d.	Mean	s.d.
Stop Count	5.360	2.092	5.322	2.094	5.355	2.086	5.267	2.122	5.350	2.091	5.645	2.101
Log average trips per hour (in time period)	0.093	0.625	0.863	0.556	0.515	0.803	0.795	0.649	0.301	0.757	-0.493	0.743
Log total population	8.193	1.021	8.200	1.067	8.212	1.031	8.159	1.193	8.221	1.118	8.422	1.002
% people of color	71.461	24.288	-	-	-	-	-	-	-	-	-	-
% population with an educational attainment of high school equivalent or lower	-	-	19.947	11.285	-	-	-	-	-	-	-	-
% of workers in industrial sector (home location)	9.940	5.146	-	-	-	-	-	-	-	-	-	-
% of workers in hospitality sector (home location)	4.509	1.816	-	-	-	-	-	-	-	-	-	-
% of workers in retail sector (work location)	-	-	-	-	-	-	13.714	15.599	13.948	15.602	13.230	15.014
Downstream hospitality jobs (00s) (work location)	13.772	19.923	-	-	-	-	-	-	-	-	-	-
Downstream professional services jobs (00s) (work location)	-	-	65.414	148.209	-	-	-	-	-	-	-	-
Downstream retail jobs (00s) (work location)	-	-	-	-	-	-	10.832	11.538	-	-	-	-
Downstream jobs earning under $1,250/month (00s) (work location)	-	-	-	-	16.875	18.951	-	-	17.355	19.586	-	-
Downstream subsidized housing units (00s)	-	-	-	-	-	-	-	-	-	-	10.893	12.238
Metrorail station dummy	-		28.329% of segments		29.247% of segments		28.512% of segments		29.402% of segments		36.470% of segments	
Log within sum frequency	1.737	1.187	2.579	1.406	2.374	1.334	2.583	1.400	2.068	1.308	1.232	0.981
Log downstream sum frequency	2.954	1.059	3.853	1.196	3.598	1.208	3.785	1.287	3.191	1.257	-	-
Corridor effect	-	-	0.974	1.661	0.772	1.347	1.011	1.695	0.610	1.077	-	-
Average boardings in the time period	6.020	9.004	29.632	43.983	44.689	65.962	42.098	67.179	16.127	29.860	5.618	11.486

Table 3.1: Descriptive statistics for variables included in the weekday models.

	Saturday						Sunday					
	High Service		Mid Service		Low Service		High Service		Mid Service		Low Service	
Variable	Mean	s.d.	Mean	s.d.	Mean	s.d.	Mean	s.d.	Mean	s.d.	Mean	s.d.
Stop Count	5.467	2.099	5.428	2.114	5.617	2.142	5.498	2.097	5.477	2.131	5.703	2.165
Log average trips per hour (in time period)	0.604	0.671	0.203	0.669	-0.560	0.741	0.611	0.642	0.143	0.720	-0.464	0.621
Log total population	8.346	0.919	8.362	0.939	8.469	1.000	8.393	0.919	8.414	0.942	8.508	1.005
% of workers in hospitality sector (work location)	-	-	11.471	10.983	-	-	11.669	11.404	11.428	10.855	-	-
% of workers in retail sector (work location)	14.331	15.635	14.108	15.237	13.031	14.867	14.188	15.226	13.663	15.027	12.259	14.289
Downstream retail jobs (00s) (work location)	12.139	12.451	12.504	12.876	-	-	12.414	12.787	12.631	13.244	-	-
Downstream subsidized housing units (00s)	-	-	-	-	11.473	12.231	-	-	-	-	11.708	12.528
Metrorail station dummy	31.825% of segments		32.743% of segments		39.168% of segments		33.202% of segments		34.972% of segments		41.877% of segments	
Log within sum frequency	2.306	1.294	1.990	1.171	1.221	0.974	2.148	1.347	1.827	1.232	1.215	0.953
Log downstream sum frequency	3.487	1.184	3.096	1.105	-	-	3.336	1.204	2.882	1.191	-	-
Corridor effect	0.667	1.155	0.469	0.862	-	-	-	-	0.436	0.833	-	-
Average boardings in the time period	88.950	133.838	16.512	26.659	7.691	16.535	84.837	122.126	14.093	21.812	5.655	11.446

Table 3.2: Descriptive statistics for variables included in the Saturday and Sunday models.

Variable	AM Early	AM Peak	Midday	PM Peak	Early Night	Late Night
Stop Count	0.057***	0.058***	0.068***	0.091***	0.069***	0.027
Log average trips per hour (in time period)	0.940***	1.188***	1.196***	1.312***	1.185***	0.874***
Log total population	0.460***	0.440***	0.225***	0.048*	0.091**	0.190***
% people of color	0.006***	-	-	-	-	-
% population with an educational attainment of high school equivalent or lower	-	0.017***	-	-	-	-
% of workers in industrial sector (home location)	0.038***	-	-	-	-	-
% of workers in hospitality sector (home location)	0.066***	-	-	-	-	-
% of workers in retail sector (work location)	-	-	-	0.005***	0.010***	0.012***
Downstream hospitality jobs (00s) (work location)	0.007***	-	-	-	-	-
Downstream professional services jobs (00s) (work location)	-	0.001***	-	-	-	-
Downstream retail jobs (00s) (work location)	-	-	-	0.015***	-	-
Downstream jobs earning under $1,250/month (00s) (work location)	-	-	0.004***	-	0.003***	-
Downstream subsidized housing units (00s)	-	-	-	-	-	0.027***
Metrorail station dummy	-	0.252***	0.254***	0.614***	0.684***	0.827***
Log within sum frequency	0.035 (.)	0.045*	0.125***	0.231***	0.239***	0.309***
Log downstream sum frequency	0.081**	0.205***	0.193***	0.140***	0.153***	-
Corridor effect	-	0.053*	0.155***	0.064**	0.037	-
Corridor effect (squared term)	-	-0.009**	-0.029***	-0.011**	-0.021 (.)	-
Intercept	-4.335***	-3.474***	-0.840***	-0.359*	-0.760***	-1.318***
Pseudo R^2	0.651	0.667	0.677	0.640	0.600	0.578
n	2118	2591	2431	2669	2357	1286

Note: *(.) $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$*

Table 3.3: Model results of the weekday models by time period.

	Saturday			Sunday		
Variable	High Service	Mid Service	Low Service	High Service	Mid Service	Low Service
Stop Count	0.070***	0.065***	0.049*	0.071***	0.064***	0.0304
Log average trips per hour (in time period)	1.220***	1.174***	1.108***	1.140***	1.070***	1.085***
Log total population	0.314***	0.217***	0.249***	0.312***	0.185***	0.234***
% of workers in hospitality sector (work location)	-	0.006*	-	0.005*	0.006*	-
% of workers in retail sector (work location)	0.007***	0.010***	0.011***	0.007***	0.011***	0.015***
Downstream retail jobs (00s) (work location)	0.014***	0.014***	-	0.013***	0.016***	-
Downstream subsidized housing units (00s)	-	-	0.026***	-	-	0.028***
Metrorail station dummy	0.342***	0.424***	0.785***	0.297***	0.419***	0.732***
Log within sum frequency	0.168***	0.211***	0.277***	0.181***	0.231***	0.284***
Log downstream sum frequency	0.155***	0.122***	-	0.162***	0.094***	-
Corridor effect	0.048	0.061	-	-	0.065	-
Corridor effect (squared term)	-0.016 (.)	-0.080**	-	-	-0.096**	-
Intercept	-1.126***	-1.447***	-1.508***	-1.117***	-1.136***	-1.628***
Pseudo R^2	0.651	0.608	0.577	0.628	0.564	0.541
n	1945	1863	1154	1783	1607	991

Note: *(.) p < 0.1; * p < 0.05; ** p < 0.01; *** p < 0.001*

Table 3.4: Model results of the Saturday and Sunday models by time period.

3.3.1 Model Discussion

Average trips per hour (in time period) was the main frequency term across the models. This variable captures changes in both span of service and frequency for a given time period. For all time periods, this variable has a significant positive impact on bus ridership. When all else remains the same, a 10% increase in the average trips per hour (in time period) resulted in a 8.69% to 12.3% increase in the segment-level ridership estimate[1]. The AM Early and Late Night periods are the only two time periods where ridership is inelastic to frequency with a coefficient of 0.940 and 0.874 respectively. Ridership appears to be most sensitive to

[1]When all else remains the same, the percent change in ridership given a 10% increase in a variable that is log-transformed is calculated by the following formula: $(\frac{x_2}{x_1}^{\beta} - 1) * 100 = (1.10^{\beta} - 1) * 100$. β is the coefficient of the variable in the model, and x_2 and x_1 represent the new and old value of the variable respectively.

changes in frequency in the PM Peak period for weekday service and the High Service period on Saturday for weekend service with a coefficient of 1.312 and 1.220 respectively. These two periods are likely capturing leisure travel and may be related to ridership recovery trends. In addition, discretionary trips may be generally more sensitive to service changes, as these trips could either be completed using other modes or avoided altogether. Past research on transit elasticities also found sensitivity of demand to be higher for off-peak periods compared to periods with commute travel [8], [36].

As defined in Section 3.2.3, within sum frequency and downstream sum frequency are variables capturing general service availability and transfer opportunities within a segment and downstream of a segment. Within sum frequency was included in all of the models and had a significant positive impact on bus ridership. Holding all else constant, a 10% increase in within sum frequency resulted in a 0.33% to 2.99% increase in the segment-level ridership estimate. Downstream sum frequency was included in all of the models except for the late night periods (i.e., Late Night and Low Service periods). This variable also had a significant positive impact on bus ridership. Holding all else constant, a 10% increase in downstream sum frequency resulted in a 0.78% to 1.86% increase in the ridership estimate. In the late night across all days of week, downstream subsidized housing units served as a better proxy of downstream attractions compared to downstream service availability. This makes sense as there are fewer discretionary trips during this time and downstream subsidized housing units may be serving as a proxy of the relevant downstream attractions in this time period already.

The linear and quadratic corridor effect terms capture the inter-route relationship among nearby routes, including the competitive and complementary nature of these routes. The linear term has a positive effect on bus ridership, whereas the squared term has a negative effect on bus ridership. This indicates that the relationship between the corridor effect and ridership follows a downward parabola. When all else remains the same, ridership will first increase as the corridor effect increases, displaying the complementary relationship between routes. This increase in ridership will slow down after the corridor effect surpasses the peak

value. As the corridor effect increases beyond the x-intercept value, it will result in a negative impact to ridership, displaying the competitive relationship between routes. These terms were included in all of the time periods except for the AM Early, Late Night, Low Service, and Sunday High Service periods, which may indicate that overlapping service does not strongly influence ridership in all time periods. Connectivity, service availability, and high service corridors at these times might not encourage more ridership compared to the general ridership in the network during these time periods. Particularly in the late night periods, the sample size is also smaller, which may affect the amount of variation observed in these variables. Though Saturday and Sunday models generally follow the same model specifications, the corridor effect was found to not be statistically significant in the Sunday high service model. This might be a result of different travel patterns compared to the Saturday high service period.

Different population demographics and workplace characteristics were included in the models across time periods to serve as a proxy of trip generators and attractors. These variables may suggest population groups that tend to rely more on transit than other groups and general trends in travel patterns in specific time periods, such as commutes to work in the morning time periods and commutes between home and commercial areas in the evenings. The variables in the final models can be classified as characteristics by home location and characteristics by work location. Home location variables were significant in the AM Early and AM Peak period, which is expected as these may help to capture riders who take transit to commute to work during these time periods. The share of the population who are people of color and have an educational attainment of high school equivalent or lower had a positive effect on ridership. When all else is constant, a 1-unit increase (i.e., increase by 1%) in the share of population that are people of color resulted in a 0.60% increase in the ridership estimate for the AM Early period[2]. Similarly, a 1-unit increase in the share of population

[2]When all else remains the same, the percent change in ridership given a 1-unit increase in a linear variable is calculated by the following formula: $(e^{(x_2-x_1)*\beta}-1)*100 = (e^{\beta}-1)*100$. β is the coefficient of the variable in the model, and x_2 and x_1 represent the new and old value of the variable respectively.

that have an educational attainment of high school equivalent or lower resulted in a 1.72% increase in the ridership estimate for the AM Peak period. These variables serve as an indication for population groups that tend to rely more on transit than other groups. Work location variables were included in the models to capture a sense of destinations. The share of workers in retail sector by work location was significant in the PM Peak, Early Night, and Late Night period. Holding all else constant, a 1-unit increase in this variable resulted in a 0.50% to 1.51% increase in the ridership estimate. This variable may capture a sense of land use in terms of commercial areas, employment centers, and other leisure activities. Similarly, downstream retail jobs by work location was significant in the PM Peak, Mid Service, and High Service periods. When all else is constant, a 100-unit increase in this variable resulted in a 1.31% to 1.51% increase in the ridership estimate. The downstream retail jobs variable serves as a proxy on connections to areas with high commercial activity, which both serves retail workers and encourages discretionary travel in the weekday evenings and daytime periods in the weekend days.

Poisson regression models do not have an equivalent R^2 measure as linear regression models do to evaluate goodness-of-fit. However, the pseudo R^2 measure can be used as a proxy of fit, which ranges from 0 to 1 and reflects the reduction in deviance in the current model compared to that of a null model (i.e., intercept-only model) [37]. Overall, the models appear to fit well to the ridership data at the segment-level. The pseudo R^2 ranges from 0.541 to 0.677, with the lower values observed in the late night and low service periods. These time periods also have smaller sample sizes compared to the time periods with higher pseudo R^2 values.

3.4 Conclusion

This chapter presented the data and methods used to develop direct demand models that estimate route-segment level ridership for a given scenario. These models can be used to

estimate ridership on existing and new routes. Ridership impacts can be calculated by taking the difference between two scenarios. Table 3.5 summarizes the ways in which these models capture different types of service changes and what variables the estimates are sensitive to. These models are sensitive to not only improvements on a given route but also improvements in the network on neighboring routes. The corridor effect variable additionally captures the competitive and complementary nature among neighboring routes.

Since the models are developed using cross-sectional data, the estimated relationships between the independent variables and ridership are determined based on ridership data from a selected point in time. These relationships are assumed to hold true in the future scenarios that these models are used to estimate ridership for. For estimating larger network-wide changes, the models are recommended to be re-estimated as phases of changes are implemented and new data becomes available. The methods described in this chapter for model development can be streamlined and automated, assuming ridership data is standardized and GTFS feeds of corresponding service are available.

To obtain first-cut ridership estimates, the models only require a GTFS feed for a given scenario. This can be generated from existing transit planning tools like Remix, which are used by service planners to create different scenarios. Section 4.1 illustrates a case study using the model to get ridership impacts for routes in the Better Bus Network Redesign.

Type of Service Change	**Relevant Variables**
Span of Service When service begins and ends	- Average trips per hour (in time period)
Service Headway Amount of time scheduled between arrivals	- Average trips per hour (in time period)
Stop Spacing Average number of bus stops per-mile	- Stop count
Route Design Route geometry and alignment	- Total population - Downstream jobs or subsidized housing units - % of workers in x industry or % of jobs in x industry - Metrorail station
Route Design Interactions	- Within sum frequency - Downstream sum frequency - Corridor effect

Table 3.5: Type of service change and relevant variables.

Chapter 4

Evaluating Ridership Impacts

As summarized in Chapter 3, the direct demand models developed in this thesis capture both route and network improvements. As a result, ridership estimates for a given route could change across scenarios if there are service changes in the individual route and/or changes in neighboring routes. Figure 4.1 summarizes the general workflow for producing ridership estimates for a given scenario. Impacts can be calculated by taking the difference between scenarios. The current assumption is that the changes are first made to the network and a GTFS export is produced from Remix, a transit planning software. However, these steps could be completed in other transit software that may be available to an agency. This chapter presents different examples of routes from WMATA's Better Bus Network Redesign (BBNR) as a case study. The examples are selected to illustrate how different variables contribute to the change in ridership estimates observed across two different scenarios and how these variables relate to different types of service changes. A validation study based on a historical set of service changes from WMATA's Frequent Service Network in 2021 is also discussed in this chapter as a way to gauge how the estimates from the models align to actual ridership totals.

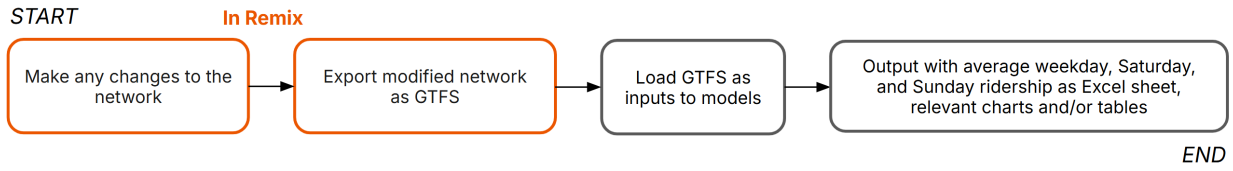


Figure 4.1: General workflow for direct demand model use.

4.1 Better Bus Network Redesign (BBNR)

The BBNR project started in 2022 to redesign the Metrobus network and improve access and connectivity throughout the Washington D.C. Metropolitan Area. As a case study in this thesis, BBNR provides examples of future service changes from improvements in span and frequency to the introduction of new routes and connections. There are two scenarios that can be evaluated as a case study: the Year One network and the Visionary network. The Year One network is scheduled to launch on June 29, 2025 and implements new routes, including renaming of routes, under current resources. This network is the first step towards achieving the Visionary network, which would introduce new 24-hour connections and frequent service throughout the day [38]. The expectation for the Year One network is that system-level total ridership would be similar to the existing total ridership values, with a slight increase if the models are sensitive to the improvements proposed in the service changes in this scenario. On the other hand, the Visionary network is the complete long-term network inclusive of all planned service improvements in the redesign. The expectation for the Visionary network is that system-level total ridership would be higher than the existing total ridership values given the vast improvements across the network.

Table 4.1 shows the total number of routes, estimated ridership, and total vehicle hours for the existing, Year One, and Visionary network by day of week. The total vehicle hours serves as a measure of total service provided, and this measure more than doubles on the weekend days in the Visionary network. A percent change in ridership and in total vehicle hours was calculated for Year One and Visionary using the existing network as a baseline. For

	Existing	Year One	Visionary
Weekday			
Total Routes	210	149	175
Estimated Ridership	379,319	380,211 (+0.2%)	670,111 (+76.7%)
Total Vehicle Hours	10,520	10,711 (+1.8%)	17,079 (+62.3%)
Elasticity	-	0.130	1.230
Saturday			
Total Routes	129	119	160
Estimated Ridership	233,809	256,398 (+9.7%)	528,010 (+125.8%)
Total Vehicle Hours	7,281	8,042 (+10.5%)	14,613 (+100.7%)
Elasticity	-	0.924	1.250
Sunday			
Total Routes	110	103	160
Estimated Ridership	186,908	212,358 (+13.6%)	497,421 (+166.1%)
Total Vehicle Hours	5,920	7,018 (+18.5%)	14,200 (+139.9%)
Elasticity	-	0.734	1.188

Table 4.1: System totals for the Existing, Year One, and Visionary networks.

each scenario, an elasticity was then calculated by dividing the percent change in ridership from the existing network by the percent change in total vehicle hours from the existing network to illustrate the sensitivity of ridership to changes in service.

Based on Table 4.1, the ridership estimates align with initial expectations given the context of each scenario. Though there is a reduction in the number of total routes, the Year One network observes a similar system-level total ridership as the existing network with a slight increase. For example, the weekday ridership for Year One is 380,211 and the existing ridership is 379,319, resulting in a 0.2% increase. Similarly, the Visionary network observes a much higher system-level total ridership compared to the existing network given the drastic increase in service hours and improvements in service. For example, the Saturday ridership for Visionary is 528,010 and the existing ridership is 233,809, resulting in a 125.8% increase. There also appear to be differences in sensitivity across day of week. When looking at the Visionary case, Saturday ridership seems to be most sensitive to changes in vehicle hours with the highest system-level elasticity of 1.250 compared to weekday and Sunday periods

with elasticity values of 1.230 and 1.188 respectively. This observation may indicate either differences in travel patterns by day of week or the effects types of changes may have, as increasing vehicle hours could be a result of either increasing span of service and frequency or adding service in new areas. The largest service changes generally occurred on the weekend days compared to the weekday case, in terms of the percent of total vehicle hours, especially in the Year One network. This could impact the system-level elasticity that is calculated in this table as the models account for network effects too. It is worth noting that these estimates are based on models developed from existing service under the current network with the assumption that these relationships hold true in the scenarios being estimated on. In reality, there would be multiple phases implemented in between the Year One and Visionary networks, which provides opportunities to redevelop the direct demand models as new data becomes available under the redesigned network and potentially be more representative for the Visionary network.

In the following sections, route examples are presented to illustrate the key variables that influence estimated ridership impacts between two scenarios and demonstrate a workflow to interpret the estimates from the direct demand models. The routes fall under three categories: routes with no major service changes, routes with improvements in frequency, and routes with re-routing and other improvements. The ridership impact for the selected routes is determined based on the difference in ridership estimate between the Year One network and the Visionary network. The comparison was not conducted against the existing network as routes in the existing network had multiple representative routes in the BBNR scenarios. For each route, a breakdown of the ridership estimates is provided for a sample weekday time period to illustrate the relationships between the types of service changes and the variables that affect the ridership estimates. Though these are first-cut ridership estimates, interpreting the estimates provides a sense check on whether the ridership impact falls within reason based on the context of the route, the proposed service changes, and professional judgment. These details are discussed for each route.

4.1.1 Routes with No Major Service Changes

Routes with no major service changes may experience ridership impacts across scenarios if there are changes in neighboring routes. The variables related to network effects in the direct demand models used to estimate ridership contribute the most to the change in ridership in this case. These variables are related to the frequency of neighboring routes and complementary or competitive bus service. This includes the within sum frequency, downstream sum frequency, and corridor effect terms. As general service availability increases along a route, network effects are expected to have a positive effect on ridership as there are new transfer opportunities and/or more service to reach existing or new destinations. The within sum frequency and downstream sum frequency focus on capturing service availability within and downstream of a given segment, while the corridor effect terms capture the complementary and competitive nature of routes by considering overlapping downstream stops. If there is a high frequency route that shares the same downstream stops and can be boarded at at least one of the stops in the given segment, the squared term of the corridor effect would counteract some of the positive effects of having more service for the given segment.

An example of a route with no major service changes is route D34, which is illustrated in Figure 4.2. D34 runs from West Hyattsville to Metro Center, providing connections to downtown from Maryland. The route provides connections to four Metrorail stations including West Hyattsville, Brookland-CUA, Gallery Place, and Metro Center. Across these stations, transferring to any of the six Metrorail routes is possible. Points of interest on this route include two high schools, a university, a recreation center, a shopping center, supermarkets, and a library. Based on public feedback reported from engagement conducted as part of the BBNR, this route appears to serve as a feeder route, providing major connections to downtown, Metrorail service, and schools for areas with sparse transit options while also supporting shorter trips that are not possible by existing rail service [39].

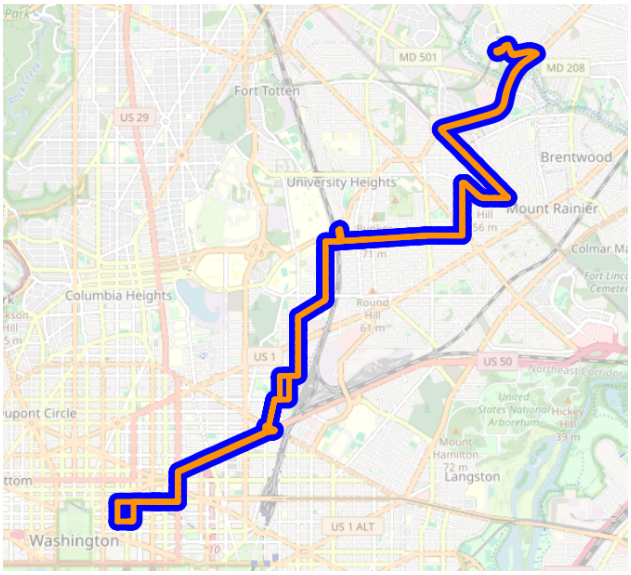
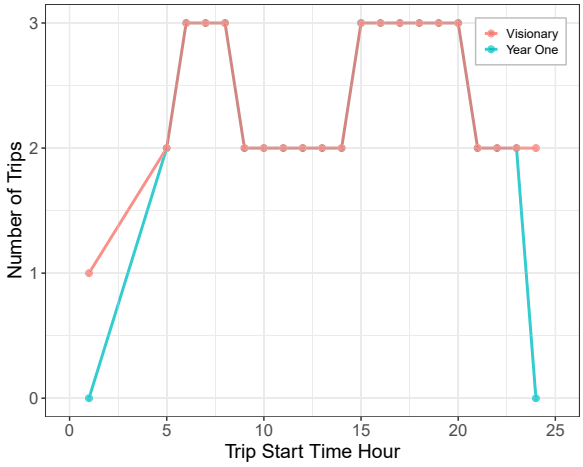


Figure 4.2: Route D34 in the Year One (orange) and Visionary (blue) networks.

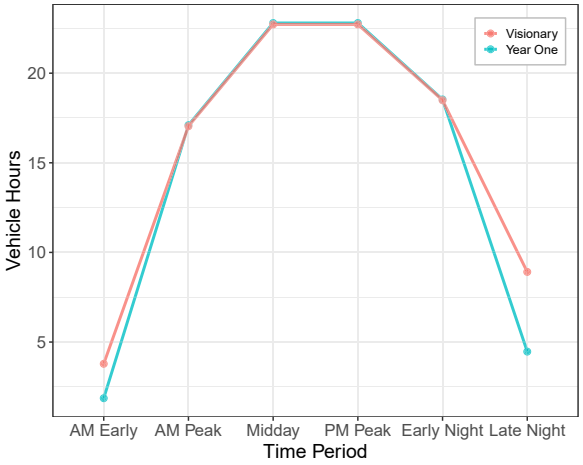
Figure 4.3a and Figure 4.3b illustrate the number of trips per hour for one direction by trip start time hour and the number of vehicle hours by time period for each scenario respectively. Figure 4.3c shows the estimated ridership by time period for each scenario. Based on these figures, the frequency and vehicle hours were consistent across most weekday time periods, except for the AM Early and Late Night time periods. Though this route had no changes in either route geometry or service during most time periods, ridership increases were still observed from Year One to Visionary across all time periods.

To take a closer look at the ridership impact, the PM Peak time period can be further evaluated as an example. During this time period, the route-level ridership estimate increases by 144 from 1,008 to 1,152, which is a 14% increase in ridership. Given that the PM Peak time period is a four-hour period from 3PM to 7PM and the frequency during this period is 3 trips per hour, this increase translates to an average of 36 more boardings per hour, 12 more boardings per trip on the route (both directions) or 6 boardings per trip on each route-direction.

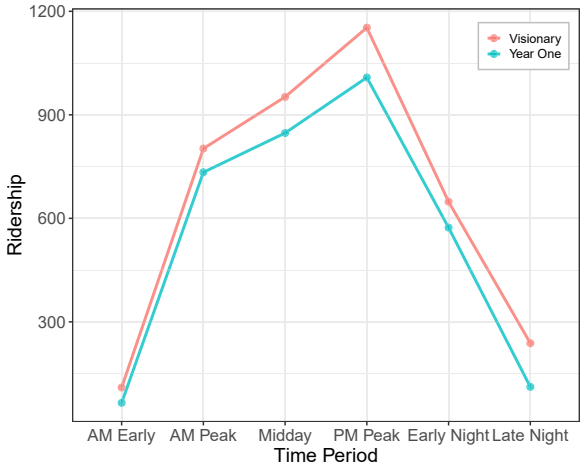
Waterfall charts can be used to show the percent contribution of each variable to the change in log(ridership) for a given route and time period. The contribution is calculated



(a) Number of trips per hour for one direction by trip start time hour.



(b) Number of vehicle hours by time of day.



(c) Estimated ridership by time of day.

Figure 4.3: Weekday trips per hour, vehicle hours by time period, and estimated ridership by time period for route D34.

using the coefficient of and change in the explanatory variables. The log-linear form of the Poisson regression model to estimate ridership for a segment is given in Equation 4.1, where i is the segment index, $\beta^\top$ is a vector of the coefficients of the explanatory variables, and x_i is a vector of the values of the explanatory variables for segment i. The total log(ridership) for each route can then be calculated using Equation 4.2 and Equation 4.3 for the Year One and Visionary network respectively, which sums the values across segments for each route. In these equations, Y is average boardings, y_1 denotes Year One, vis denotes Visionary, i and j

are segment indices, and R and R' are route indices for the two scenarios. Note that these equations illustrate a simplified version of the models with only two explanatory variables, x and z, and their coefficients, β and γ, for demonstration purposes. Equation 4.4 is obtained from taking the difference between the log(ridership) totals in each scenario, with each term representing the contribution of the corresponding variable. The contribution of x to the change in log(ridership) between Year One and Visionary can be obtained using Equation 4.5, which divides the β term in Equation 4.4 by the difference in log(ridership). The contribution of x captures the combined effect of the variable's coefficient and the change in the variable between two scenarios.

$$log\ Y_i = \beta_0 + \boldsymbol{\beta}^\top \mathbf{x_i} \tag{4.1}$$

$$\sum_{i \in R} log\ Y_i^{y_1} = \beta \sum_{i \in R} x_i^{y_1} + \gamma \sum_{i \in R} z_i^{y_1} \tag{4.2}$$

$$\sum_{j \in R'} log\ Y_j^{vis} = \beta \sum_{j \in R'} x_j^{vis} + \gamma \sum_{j \in R'} z_j^{vis} \tag{4.3}$$

$$\sum_{j \in R'} log\ Y_j^{vis} - \sum_{i \in R} log\ Y_i^{y_1} = \beta \left(\sum_{j \in R'} x_j^{vis} - \sum_{i \in R} x_i^{y_1} \right) + \gamma \left(\sum_{j \in R'} z_j^{vis} - \sum_{i \in R} z_i^{y_1} \right) \tag{4.4}$$

$$\text{Share of the change in log(ridership) from } x = \frac{\beta \left(\sum_{j \in R'} x_j^{vis} - \sum_{i \in R} x_i^{y_1} \right)}{\sum_{j \in R'} log\ Y_j^{vis} - \sum_{i \in R} log\ Y_i^{y_1}} \tag{4.5}$$

Figure 4.4 displays a waterfall chart that illustrates the percent contribution of each variable to the change in log of ridership observed between the two scenarios. Note that the percent contribution is calculated relative to the change in log of ridership given the use

of Poisson regression, but the direction and relative size of these bars can be interpreted to show the relevant variables in each case. Based on the chart, most of the change in log of ridership was influenced by the within sum frequency and downstream sum frequency terms with a contribution of 55.8% and 35.8% to the change in log(ridership) respectively. These terms capture an increase in general service availability and transfer opportunities and could encourage more bus ridership. Given the context of this route, the increase could be explained by more high school and/or university students traveling home from school or to other afterschool and evening activities or residents traveling to or from work to other destinations. There was a slight change in stops served, resulting in the 12.1% contribution, but the catchment area attributes remained constant. The corridor effect terms also capture the nature of improvements on other routes. The net negative contribution from these terms indicates the presence of improvements on routes that share stops with D34. One of these routes is route D32, which shares a downtown section with route D34 and also serves Metro Center. The frequency of this route increased from 3 trips per hour to 4 trips per hour.

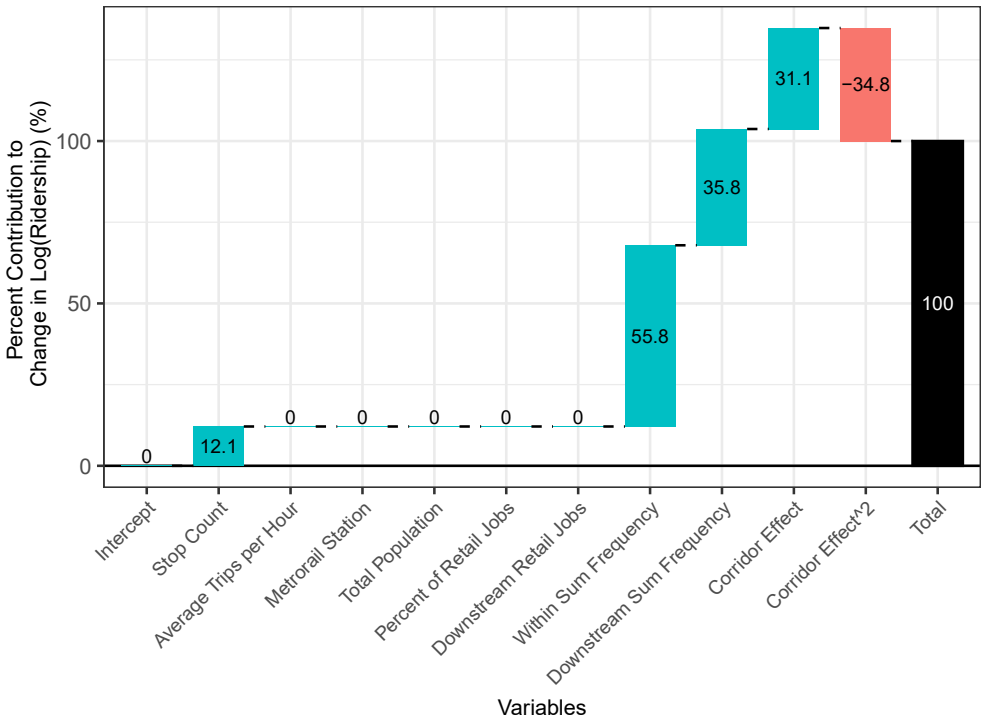


Figure 4.4: Percent contribution to the change in log(ridership) for route D34 (PM Peak).

4.1.2 Routes with Improvements in Frequency

Routes with improvements in frequency may experience ridership impacts across scenarios from these improvements alone. The average trips per hour term used in the models captures changes in both frequency and span of service. If there are improvements across the network, there could also be other contributing factors related to network effects that can influence the ridership impact on a given route.

An example of a route that experiences improvements in frequency is route D46, which is illustrated in Figure 4.5. D46 runs from Takoma to Petworth, providing Metrorail connections at its terminal stops with connections to the Red and Green Lines. Similar to the previous route, the points of interests on this route include libraries, recreation centers, supermarkets, and a high school. Additionally, the route provides connections to downtown with opportunities to transfer to other bus or rail routes while supporting shorter trips not possible by existing rail service.

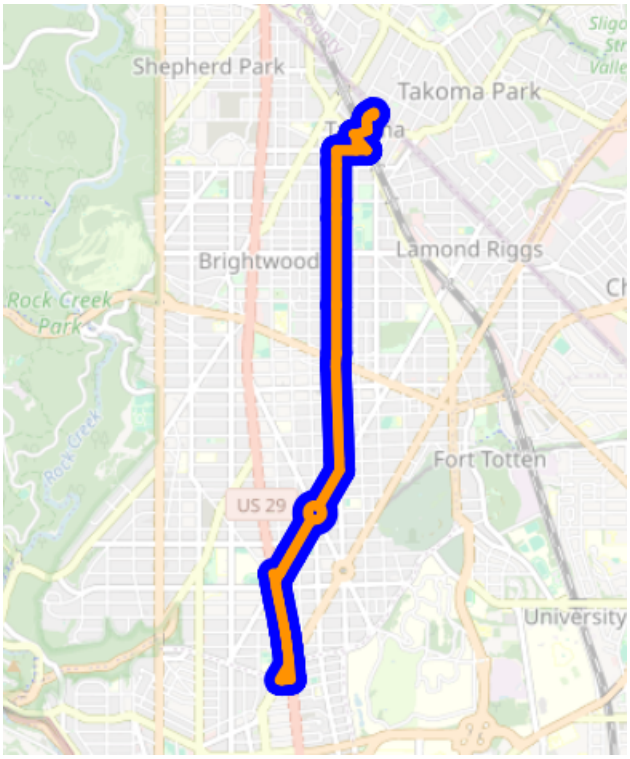
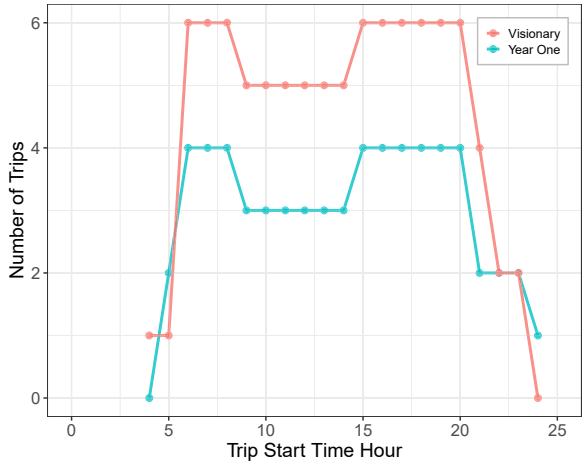
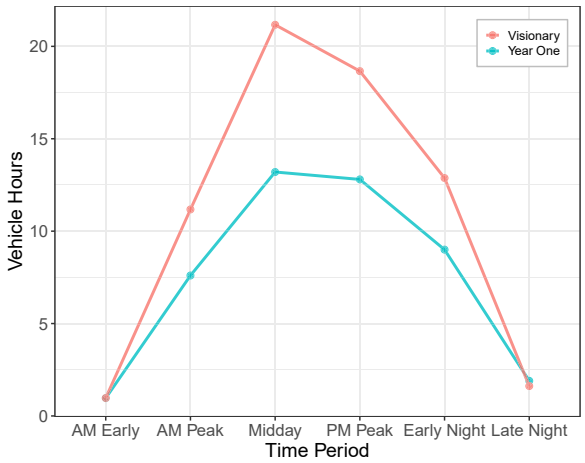


Figure 4.5: Route D46 in the Year One (orange) and Visionary (blue) networks.

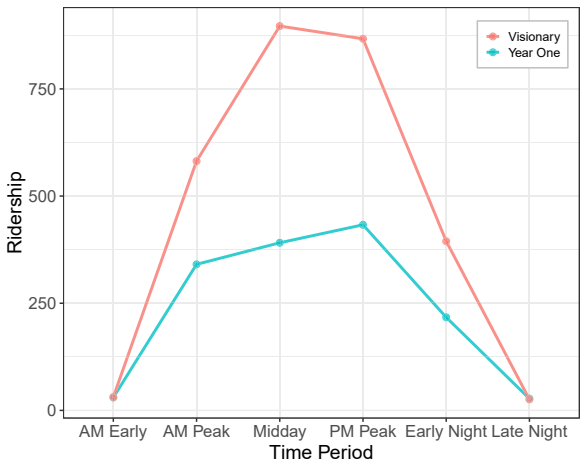
Figure 4.6a and Figure 4.6b display the number of trips per hour for one direction by trip start time hour and the number of vehicle hours by time period respectively for each scenario. Figure 4.6c shows the estimated ridership by time period for each scenario. Based on these figures, the frequency and vehicle hours increased across the AM Peak, Midday, PM Peak, and Early Night periods. These increases in frequency coupled with network effects from improvements in neighboring routes resulted in ridership increases across the same time periods from Year One to Visionary.



(a) Number of trips per hour for one direction by trip start time hour.



(b) Number of vehicle hours by time of day.



(c) Estimated ridership by time of day.

Figure 4.6: Weekday trips per hour, vehicle hours by time period, and estimated ridership by time period for route D46.

The Midday time period can be further evaluated as an example to better understand the estimated ridership impact. For this time period, the route-level ridership estimate increases by 505 from 391 to 896, which is a 129% increase in ridership. Since the Midday time period is a six-hour period from 9AM to 3PM and there are 5 trips per hour per direction, this increase translates to an average of 84 more boardings per hour, 16 more boardings per trip on the route (both directions), or 8 more boardings per trip on each route-direction. Figure 4.7 shows the waterfall chart for the Midday time period for route D46 illustrating the percent contribution of each variable to the change in log of ridership between the two scenarios. Based on the chart, 73.6% of the change in log of ridership came from an increase in average trips per hour, with smaller effects from the network effect variables. The midday frequency increased from 3 trips per hour to 5 trips per hour, which is equivalent to a change from a 20-minute headway to a 12-minute headway. This improvement in frequency could encourage more ridership as potential wait times are substantially reduced. The network effect variables capture a general increase in service availability along the route and transfer opportunities, which resulted in an overall positive contribution to the change in log of ridership. This could be interpreted as increased access to more destinations and reduced wait times related to transfers from improvements in frequency on both current and neighboring routes.

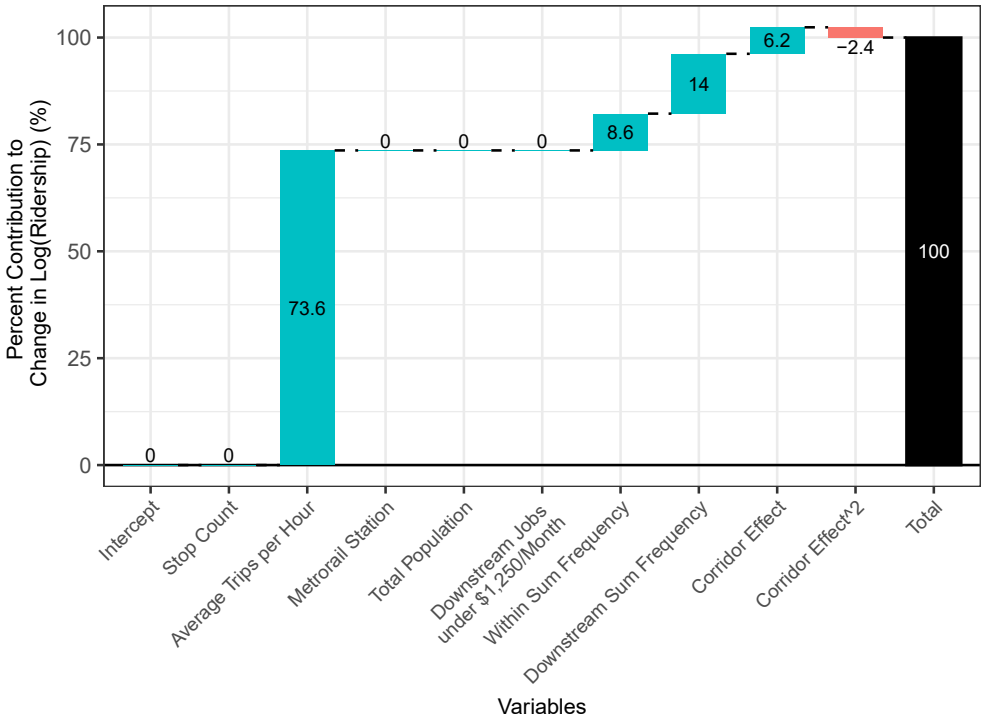


Figure 4.7: Percent contribution to the change in log(ridership) for route D46 (Midday).

4.1.3 Routes with Re-routing and Other Improvements

Routes with re-routing and other improvements may experience ridership impacts across scenarios from all variables included in the model. This includes catchment area attributes related to population or employment characteristics, the average trips per hour or frequency term, which captures frequency and span changes, and network effect variables.

An example of a route with re-routing and additional improvements is route A1X, which is illustrated in Figure 4.8. A1X runs from Pentagon City to Potomac Yard in the Year One network and extends south to terminate at Huntington in the Visionary network. A1X in the Year One scenario mirrors a bus rapid transit route, Metroway, in WMATA's existing network. This route runs parallel to the Yellow and Blue Lines and provides connections to both routes at Pentagon City, Crystal City, Braddock Road (in the Year One scenario), and Huntington (in the Visionary scenario) along with access to multiple commercial areas and centers in Arlington and Alexandria.

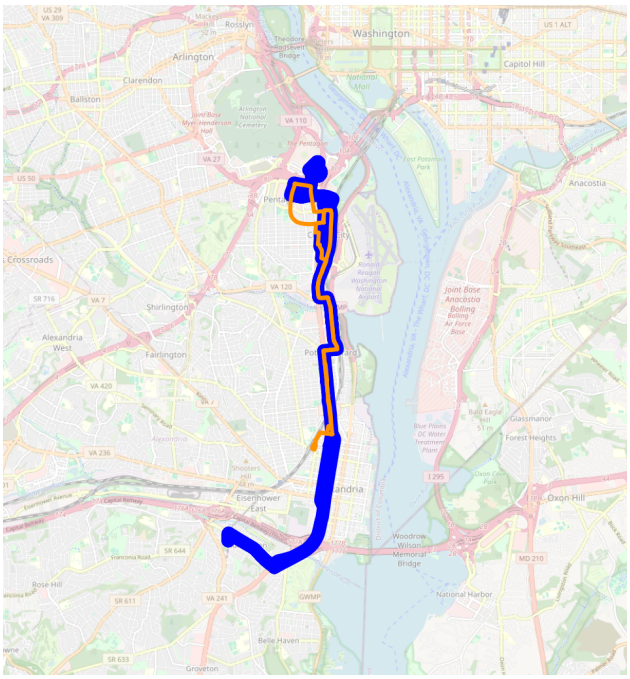
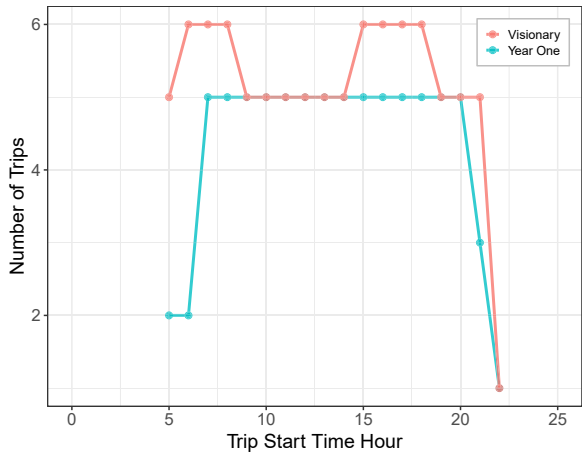


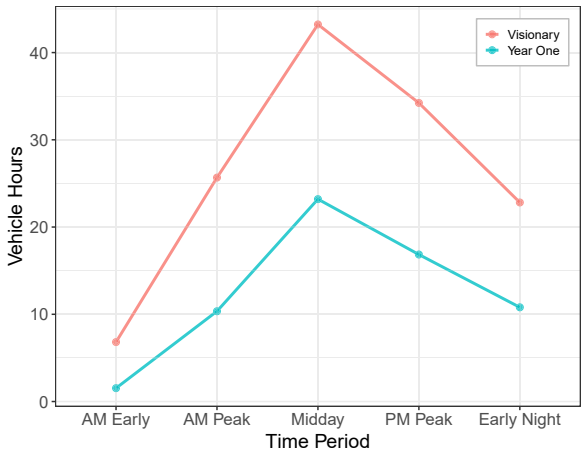
Figure 4.8: Route A1X in the Year One (orange) and Visionary (blue) networks.

Figure 4.9a and Figure 4.9b display the number of trips per hour for one direction by trip start time hour and the number of vehicle hours by time period respectively for each scenario. Figure 4.9c shows the estimated ridership by time period for each scenario. Based on these figures, the frequency and vehicle hours increased across the AM Early, AM Peak, Midday, PM Peak, and Early Night periods in the Weekday. These increases in frequency coupled with network effects from improvements in neighboring routes resulted in ridership increases across the same time periods from Year One to Visionary.

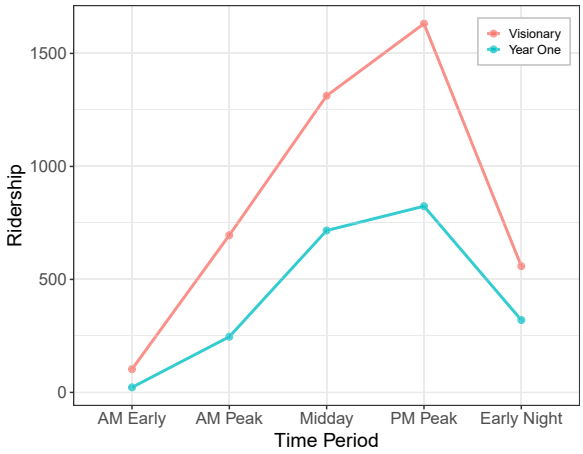
The PM Peak time period can be further evaluated to better understand the estimated ridership impact. For this time period, the route-level ridership estimate increases by 489 from 824 to 1,313, which is a 59% increase in ridership. Since the PM Peak time period is a four-hour period and there are 6 trips per hour per direction, this increase translates to an average of 122 more boardings per hour, 20 more boardings per trip on the route (both directions), or 10 more boardings per trip on each route-direction. The vehicle hours approximately doubles from 16.9 to 34.2 given the increase in trips per hour and the route extension. Figure 4.10 shows the waterfall chart for the PM Peak time period for route A1X



(a) Number of trips per hour for one direction by trip start time hour.



(b) Number of vehicle hours by time of day.



(c) Estimated ridership by time of day.

Figure 4.9: Weekday trips per hour, vehicle hours by time period, and estimated ridership by time period for route A1X.

illustrating the percent contribution of each variable to the change in log of ridership between the two scenarios.

Based on the chart, 59% of the change in log of ridership was caused by the increase in average trips per hour, with smaller effects from other service, catchment area, and network effect variables. The PM Peak frequency increased from 5 trips per hour to 6 trips per hour, which is equivalent to a change from a 12-minute headway to a 10-minute headway. Though the route provides high-frequency service in both instances, the improvement can encourage

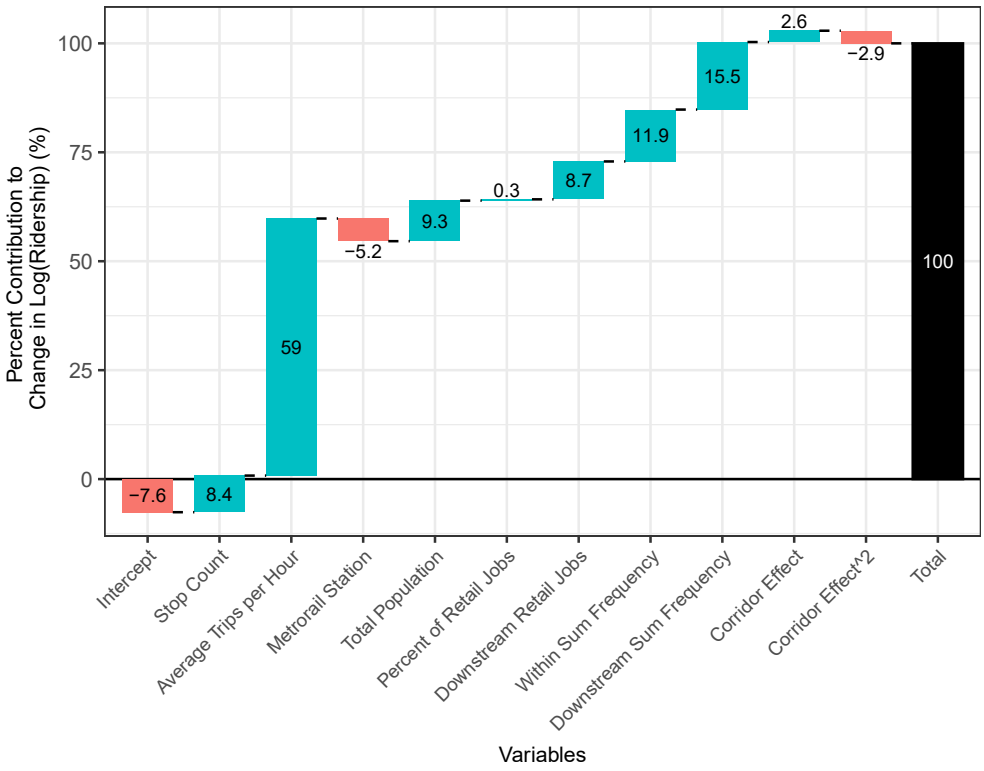


Figure 4.10: Percent contribution to the change in log(ridership) by variable for route A1X (PM Peak).

more ridership as wait times are reduced, crowding may be reduced, and service is frequent enough that one may be less likely to have to plan their trip in advance. The re-routing of the route from the Year One network to the Visionary network changes the stops and catchment area of the route. The stop count increases, which increases the boarding opportunities along with an increase in the population and jobs captured by the route. Note that the intercept has a negative contribution because the intercept is negative in the model definition. In the Visionary scenario, the route extends to Huntington, which is the terminal station of the Yellow Line and offers connections to multiple bus routes that serve areas beyond rail service areas and service areas on A1X. This contributes to the positive contribution observed to the change in log of ridership from the network effect terms.

4.2 Validation

To validate the model estimates, a before-and-after study was conducted using a set of historical service changes. The Frequent Service Network (FSN) implemented in September 2021 was used for the validation study. This was the most recent set of service changes that was relatively close to the model development time period (i.e., October 2023). The focus of the validation study is on the percent change in ridership rather than the raw ridership estimates given the difference in time frame between the model development data and the validation study data. This package of service changes included frequency improvements and all-day service on 36 routes along with improvements or restoration of service on 69 other bus routes [40]. Given the types of service changes implemented across routes, the ridership estimates are expected to be sensitive to both individual and network-level improvements that are captured in the variables in the models.

Figure 4.11 shows the average boardings by month and day of week for each month from January 2021 to December 2022. Average Metrobus ridership generally follows an upward trend during this time frame, which is due to ridership recovery after COVID impacts. In this time period, there were also notable events that may have effects on bus ridership and influence the interpretation of the results in this validation study. In October 2021, a derailment resulted in the suspension of the 7000-series rail cars, which drastically reduced Metrorail service as 60% of the fleet was removed [40]. These rail cars were not fully phased into the system until after the study period. In January 2022, severe weather coupled with a surge in COVID cases resulted in a notable decrease in ridership. In February 2022, weekday bus service is restored and ridership generally appears to trend in a similar manner as the beginning of 2021.

The main challenges in this study are isolating the effect of the FSN from the ridership recovery trend and choosing appropriate before and after periods to evaluate. There is a difficulty in isolating the effect of ridership recovery apart from the effect of the implementation

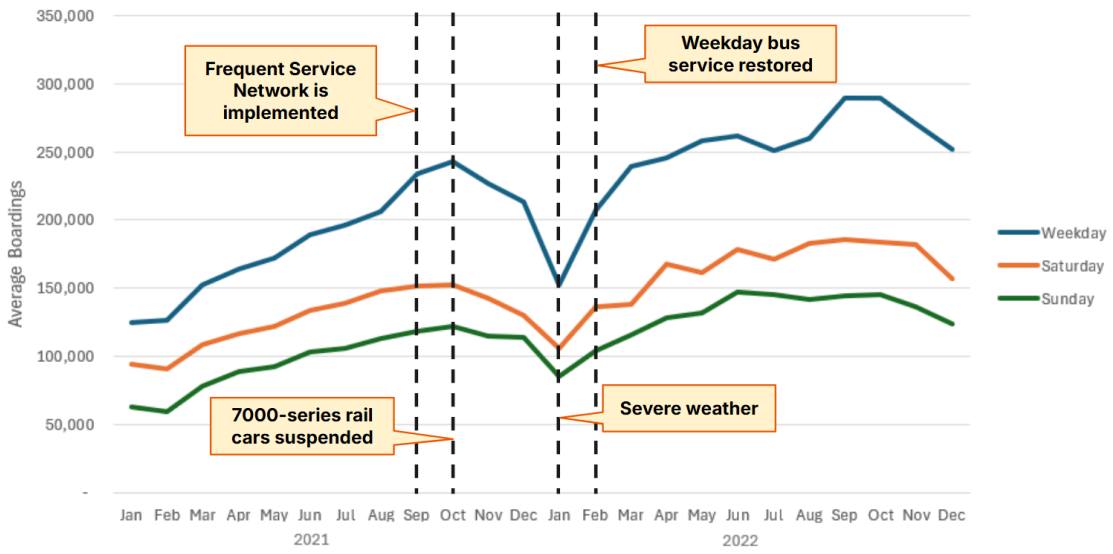


Figure 4.11: Average Metrobus boardings by month and day of week from January 2021 to December 2022.

of service changes during this time frame. Furthermore, choosing a before-after period for this study comes with caveats, as it is not clear how long it may take to observe the full effect of the service changes associated with the FSN. Though this study is imperfect because of the aforementioned considerations, the results can provide insight into where the estimates fall within certain bounds.

A before and after period was selected at least a few months before and after the FSN was implemented. For consistency and to control for seasonality, an average of weekday, Saturday, and Sunday ridership was taken over a three-month period from March to May in 2021 and 2022. The main measure for comparison was the percent change in ridership between the before and after periods. To account for baseline recovery, the percent change in ridership in the before-and-after period was calculated for a subset of routes in the system that had no individual service changes. This assumes that the increase in ridership on these routes is solely attributed to ridership recovery. However, this might not be the case as these routes could be influenced by neighboring routes that had improvements, or in other words, network effects. Additionally, these routes could be representative of a certain typology or area, which could influence the results. To obtain the impact from FSN, the baseline recovery

was subtracted from the actual percent change in ridership in the before-and-after period.

Table 4.2 shows the before-and-after comparison between actual ridership totals and estimated totals. Since the models were developed using data from October 2023 and the FSN was implemented in September 2021, the focus of the validation study is solely on the estimated before-and-after percent change in ridership. The actual percent change in ridership in the before-and-after period can be understood as the upper bound, since it is inclusive of the effects of all the events that occurred during this time period along with the general ridership recovery trend. The estimates are not expected to be above these values. The impact from FSN, which is the percent change in ridership after deducting the baseline recovery, can be understood as the lower bound. If network effects are accounted for in the calculation of the baseline recovery, the baseline recovery rate would have been lower, resulting in a higher lower bound. Nevertheless, the results appear to show the estimated percent change in ridership or ridership impact from the FSN to fall within the lower and upper bounds. The estimates may gravitate more towards overestimation where the estimates are very close to the upper bound, particularly in the case of Sunday with an estimate of 48.1% and upper bound of 49.6%. The results may also suggest that there are potentially large network changes resulting in large network effects, since the FSN involves service changes that span across many routes. This may affect Sunday more than the other days and could be related to the model specifications, which were developed using ridership data from October 2023. There may be diminishing returns that are not accounted for in the models, particularly when there are large changes proposed across the network. This could inform future model improvements that capture some aspects of the relationship, such as the relationship between rail and bus which is discussed in Section 5.2.

	Percent Change			
Day of Week	**Actual**	**Baseline Recovery**	**Impact from FSN**	**Estimates**
Weekday	57.0%	47.1%	9.9%	19.3%
Saturday	41.8%	15.2%	26.6%	31.8%
Sunday	49.6%	16.0%	33.6%	48.1%

Table 4.2: Percent change in before and after ridership by day of week for FSN.

4.3 Conclusion

The models developed in Chapter 3 were applied to various service changes in this chapter. Though these models can be used to produce first-cut ridership estimates for routes in a given scenario, the estimates are developed based on trends from a point in time. It is recommended that the estimates for future scenarios are reviewed to ensure they fall within a reasonable range given the context of the routes in the network.

This chapter first presented examples of routes with different types of service changes and their estimated ridership impact. The context of each route was discussed along with an evaluation into a selected time period and how the variables in the corresponding model contributed to the change in the log of ridership experienced by the route. This workflow could be followed to evaluate estimates in future model applications. A validation study using a historical set of service changes was also summarized in this chapter. This study revealed that the model estimates fall within a determined lower and upper bound based on actual ridership values from the FSN. However, some of the estimates may have a tendency towards overestimation, particularly in the case of Sunday service. Potential reasons for these observations could be related to the limitations of the study, the characteristics of existing Sunday service in the model development data, and other factors that may not be captured in the model. In particular, the network effect variables could be overcompensating on some of the ridership impacts observed as improvements on neighboring routes generally produces a positive effect on ridership on a given route. One of these factors includes the interaction between bus and rail services, which is not currently considered in depth in the current models and is discussed in more detail in Section 5.2.

Chapter 5

Travel Time Analysis

Multimodal routing algorithms allow for travel time analysis for different transit scenarios. Routing engines, such as the R package r5r, leverage these algorithms to calculate travel times for large origin-destination (OD) matrices. These tools can be used to understand the travel time impacts of service changes. This chapter first outlines a travel time comparison study conducted to configure the percentile parameter in r5r using actual travel times from existing journeys recorded in origin-destination-interchange inference (ODX) data. The percentile parameter directly affects the travel time estimates, as r5r first creates a distribution of travel times for a given OD matrix. The data sources and input parameters are described, along with additional guidance for using r5r to calculate travel times. Applications of r5r in the context of bus service changes are discussed, and a preliminary analysis on the relationship between bus and rail service is explored through calculating rail competitiveness metrics.

5.1 Travel Time Comparison

This section details the travel time comparison study conducted using actual travel times from ODX data and travel times from r5r. The purpose of this study was to explore r5r functions, determine an appropriate percentile parameter for r5r, and document additional guidelines for using its travel time outputs. r5r is also used for exploratory analyses related to

travel time impacts, such as evaluating rail competitiveness, which is outlined in Section 5.2.

5.1.1 Data Collection and Tools

The multimodal door-to-door routing engine used in this study was r5r, which is provided through an R package with functions to calculate travel times and related accessibility metrics [41]. r5r calculates travel times for many-to-many OD pairs and creates a distribution of travel times by calculating travel times for journeys departing every minute within the specified time window. A representative travel time can be selected as a percentile value or point from the distribution for each OD pair. This percentile value is the main parameter calibrated through this study.

The required inputs to create a network for routing with transit in r5r includes an OpenStreetMap (OSM) network file and General Transit Feed Specification (GTFS) file. A clipped OSM network file was retrieved using Osmium [42]. A GTFS feed that has transit service information from October 2019 was pulled from transit.land, an open data platform for historical GTFS feeds. There are multiple user-defined inputs for r5r functions, such as mode, max walk time, max trip duration, departure time, time window, and percentile [43]. The assumptions used in this study were a 3 mile per hour walk speed, a max walk time of 15 minutes, and a max trip duration of 120 minutes. The maximum walk time restricts the access, egress, and transfer times, while the max trip duration places a limit on the upper bound of travel times to include potential longer trips.

Two travel time functions in the r5r package were considered for travel time calculations: "travel_time_matrix" (referred to as "ttm") and "expanded_travel_time_matrix" (referred to as "ettm"). The first function calculates different percentiles of total travel times for many-to-many OD pairs without returning any other details. The second function provides a more disaggregated output, returning the total travel time and breakdown of travel time components for each routed journey departing every minute within a specified time window for each OD pair. The use of ettm allows for the removal of individual journeys, which may

be outliers, before taking a certain percentile of the total travel times. For example, some OD pairs may consist of shorter trips, and r5r may return travel times for a walk-only route instead of the desired bus travel time. Though a detailed approach could be ideal, there are notable differences between the two functions in terms of performance and computing requirements. In comparing the total travel time outputs using both functions, the differences appeared to be minor across ODs, and the use of ttm was determined to be sufficient for the purposes of this study.

ODX data on existing journeys of the first quarter of 2019 were collected from Trace, which is WMATA's implementation of ODX. ODX data has inferred linked passenger journeys with their origin and destination, which are determined using automated fare collection (i.e., when and where customers tap their fare card) and vehicle location data [32]. Only trips that started during the AM Peak period (i.e., 6AM to 9AM) were included in the study. Trace provides individual linked passenger journeys, composed of one or more fare stages. One limitation of the dataset is that it only captures a subset of OD pairs since Metrobus riders are not required to tap out when alighting and may use non-card payment methods. However, for the purpose of comparing actual travel times to travel times from a routing engine, the data is still adequate and provides a large enough sample. The data was then filtered to only retain unique OD pairs that had at least 30 occurrences to ensure a representative sample of travel times. For each OD pair, the median travel time was taken across its records and this was used as the baseline travel time for comparison to travel times from r5r. Each record had a start stop, end stop, and median travel time calculated.

The journey data was filtered to only OD pairs that started and ended at a bus stop. The choice to exclude any bus-rail OD pairs was due to the close proximity of some bus stops and rail stations, which could result in incorrect routing and comparison as r5r does not distinguish bus stops and rail stops separately in the context of origin and destination points. For example, if rail and bus modes are allowed in a given run of r5r and the origin was a bus stop that was at a rail station, the route for an OD pair that technically starts

at a bus stop could be given a rail only path and the corresponding travel time would not be representative of the time of the path taken in the Trace data. For the purposes of determining an appropriate percentile parameter for r5r, only bus stop to bus stop OD pairs were assessed to ensure a fair comparison of travel times. This resulted in a total of 7,696 OD pairs.

Table 5.1 details the travel time components included in r5r and Trace, including bus and rail for completeness. There are three inherent differences to note between the definitions of travel times in r5r and those in the Trace data, which can impact the comparison:

1. r5r determines routes that provide the fastest travel time, but riders might not always take the fastest route.

2. r5r determines travel times based off of schedules, which does not take into account any operational aspects (e.g., traffic congestion or delays) that are captured in the Trace travel times.

3. r5r includes access, wait, and egress times while Trace (bus) does not since it records travel times based on tapping in when boarding a bus and an inferred alighting from a bus.

Since transit stops are used as the origins and destinations for r5r, the access and egress times are expected to be low or close to 0. Therefore, the main differentiating factor between r5r and Trace for bus trips is the wait time component. A higher percentile could inflate total travel times from r5r through additional wait times, which could compensate for congestion and unreliability effects reflected in Trace. However, a higher percentile travel times could also be unrealistic if the whole headway is added to the total travel time as a wait time component. To determine an appropriate percentile parameter, different percentiles of total travel time, ranging from 5th to 50th percentile, were considered in this study.

	Travel Time Source		
Travel Time Components	**r5r**	**Trace (Bus)**	**Trace (Rail)**
Access time	✓	-	✓(gated)
Wait time	✓	-	✓
In-vehicle time	✓	✓	✓
Transfer time	✓	✓	✓
Egress time	✓	-	✓(gated)

Table 5.1: Travel time components by travel time source.

5.1.2 Results

Table 5.2 displays summary statistics of the travel times in minutes for these OD pairs from Trace and r5r. The median travel times were calculated for each OD pair in the filtered Trace dataset. For the same OD pairs, r5r was used to calculate a distribution of travel times within the AM Peak time window. Different percentiles of these travel times, including 5th, 10th, 15th, 25th, and 50th, were then taken for comparison. Based on this table, it is clear that the overall distribution of r5r travel times shifts to the right as the r5r percentile value increases. For example, the mean of the 5th percentile travel times is 18.3 minutes while the mean of the 50th percentile travel times is higher at 25.2 minutes. This is expected as the travel times are taken from a point in the distribution closer to the right tail. Additionally, travel times from higher percentiles of the travel time distribution likely include longer wait times and/or longer travel times potentially with different routing depending on the departure time and frequency of the service. The table also indicates that high percentiles, including median travel times, are not as close to actual travel times according to Trace. The mean of Trace travel times is 19.2 minutes, which is the closest to the mean of the 10th percentile travel times, 19.5 minutes.

Figure 5.1 illustrates a box plot of the residuals in minutes from comparing Trace median travel times to different percentile values of travel time from r5r. Positive values represent OD pairs where r5r travel times are shorter than actual travel times, while negative values represent OD pairs where r5r travel times are longer than actual travel times. Based on the

		r5r				
	Trace	**5th Percentile**	**10th Percentile**	**15th Percentile**	**25th Percentile**	**50th Percentile**
n	7,696					
Mean	19.2	18.3	19.5	20.5	22.0	25.2
SD	11.1	9.8	10.1	10.4	10.9	11.8
25th Percentile	10.0	11.0	12.0	12.0	14.0	16.0
50th Percentile	17.0	17.0	18.0	19.0	20.0	23.0
75th Percentile	26.0	24.0	25.0	27.0	28.0	32.0

Table 5.2: Summary statistics for bus stop to bus stop travel times.

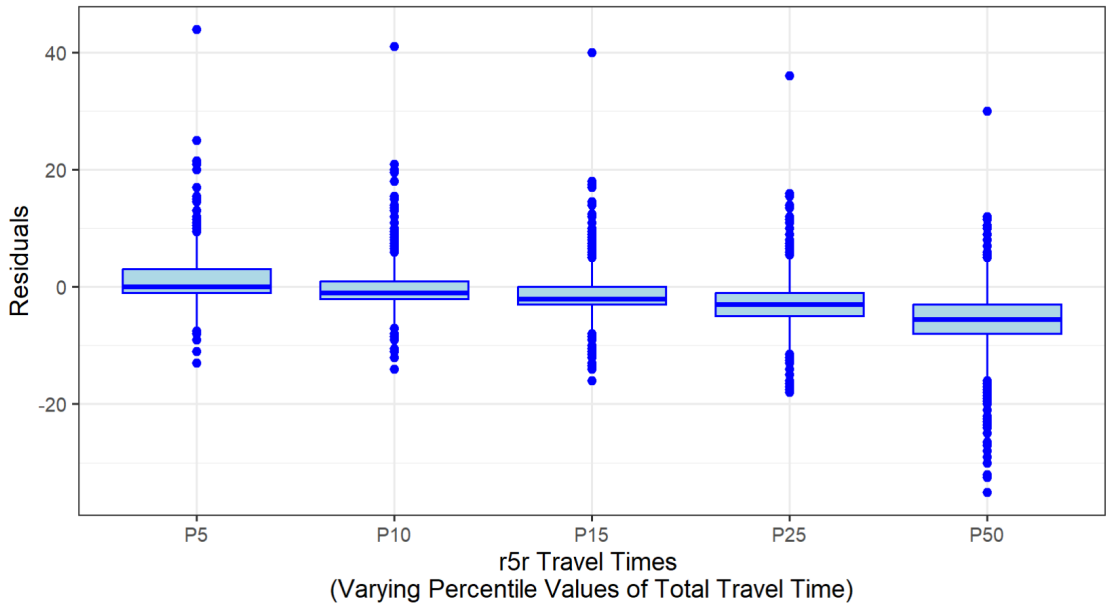


Figure 5.1: Residuals comparison across different percentile values of total travel times.

distributions of the residuals for each percentile of travel time from r5r, the 10th percentile appears to provide the closest match to Trace median travel times. For the 10th percentile, the median is close to 0 and the interquartile range is the smallest, indicating generally low variation in the residuals. When looking at the 50th percentile, or median travel times from r5r, it is clear that the travel times are overinflated and considering larger than observed wait times or travel times for the given OD pairs depending on the routing.

Figure 5.2 illustrates the 10th percentile travel times from r5r against the Trace median travel times. The solid black lines represents the y = x line, where r5r travel times are equal to Trace median travel times. The dashed solid black lines indicate a ±10% difference from the y = x line, where either r5r travel times are 10% greater than Trace median travel times

or vice versa. Ideally, the points are expected to be symmetric about and fall close to the y = x line, indicating that the r5r travel times match Trace relatively well. The OD pairs with a larger sample size in Trace also match most closely with the travel times from r5r compared to OD pairs with smaller sample sizes, which appear to have more variation. This is not surprising as OD pairs with larger sample sizes would have a median travel time closer to that of a routing engine, as influence from outliers, including trips that were impacted by operational factors, would be minimized.

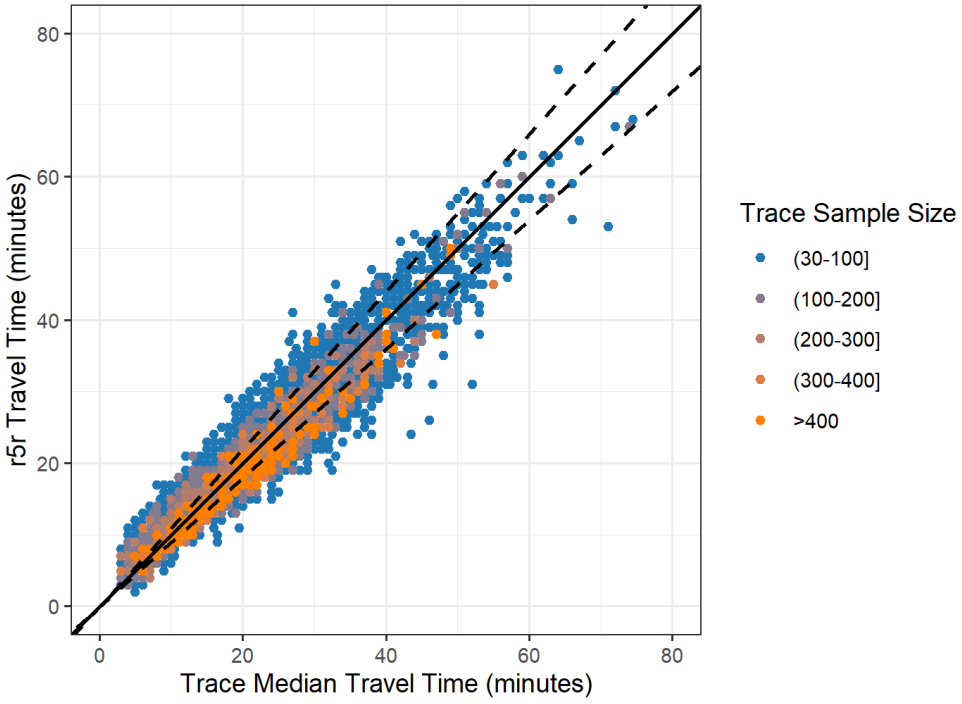


Figure 5.2: r5r travel times (10th percentile) vs. Trace median travel times.

5.1.3 Conclusion

This section compared travel times from ODX data to travel times from r5r. The comparison study illustrates that r5r generally works well and is able to provide reasonable travel time estimates with an appropriate percentile parameter value. For bus stop to bus stop OD pairs, the 10th percentile travel times from r5r appeared to provide close travel times to actual travel times from Trace. With the percentile parameter calibrated, travel time impacts can

be calculated for a given OD matrix and transit scenario, allowing for the analysis of travel time impacts by comparing travel times for a given OD between scenarios. Travel times can also be evaluated from a given origin of interest using isochrones and other visualizations.

From evaluating outliers more closely, there are general takeaways that have been identified for interpreting the travel time estimates:

1. Wait times might not be realistic as they are dependent on the departure time and headway of the first route in a journey. The maximum wait time for a given OD pair is the headway of the first route. Unrealistic wait times can also appear when there are gaps in span of service within the time window. Therefore, the time window should be specified appropriately.

2. Some OD pairs may be routed to a walk-only route if the origin and destination are close to each other. Since the walk mode has to be enabled to allow for transfers in the current version of the function, r5r could route by walking instead of transit, if it is the fastest path at the departure time. This could be restricted by the "max_walk_time" parameters; however, this parameter also defines the max access, egress, and transfer times, which could affect the routing of linked trips. In cases when removing walk-only routes is important, an alternative is to use the ettm function and remove walk-only routes from the distribution before taking a percentile value for each OD pair.

3. If all transit modes are allowed, r5r could provide a Metrorail route for an origin at a bus stop. The input data for origins and destinations into r5r functions are points with coordinates and no additional constraints. The mode distinction becomes important and OD pairs should ideally be separated out if a study of the impacts of bus and rail travel times is desired. Since Metrorail service has a relatively high frequency and rail travel times are generally less variable from schedules than bus travel times, 10th percentile or lower percentile values are likely appropriate for rail travel time analysis.

4. Origins and destinations are snapped to the network created by r5r. There may be

cases where extraneous access or egress times are added to the travel time as a result of street access definitions. For Metrorail, platform access and egress times might be excluded in r5r. Additionally, OSM data is crowd-sourced and could have incorrect or missing data. In cases where routing is more complex than expected, filtering the OSM data to select certain types of roads to build the r5r network may alleviate unexpected complex routing.

5.2 Rail Competitiveness

This section delves into an application of r5r for exploratory work of the relationship between rail and bus service in the context of estimating bus ridership. The direct demand models developed in Chapter 3 account for the presence of Metrorail stations, which provides a positive effect on bus ridership in the models. However, if additional bus service is provided parallel to existing rail service, such as in the case of the route example presented in Section 4.1.3, improvements on a given bus route may not yield as large of an increase in ridership and there may be a sense of diminishing returns on service improvements. This is currently not captured in detail in the current model specification and can be further explored for inclusion into a future iteration of ridership models.

5.2.1 Data Collection

With the segments from the direct demand models and a GTFS feed representing the transit network for each corresponding scenario, rail competitiveness could be evaluated along a route-direction using segments as origins and destinations to determine how many of these OD pairs have a rail alternative. For example, if a route-direction has 4 segments, there would be a total number of 6 OD pairs (i.e., 1-2, 1-3, 1-4, 2-3, 2-4, and 3-4). Out of these possible OD pairs, the following metrics could be quickly calculated with the use of r5r:

1. The number of and percent of ODs that have a rail option

2. The number of and percent of ODs where rail is faster than bus

This exploratory work only evaluated the Midday time period for inbound route-directions. To calculate these metrics, bus and rail travel times were calculated separately for the same OD pairs given the combinations of segments on each route-direction. The centroid of each segment was used as the origin and destination points. The same input parameters as defined in Section 5.1.1 were used in r5r. This includes the choice of using 10th percentile values of travel times. This percentile value was assumed to be appropriate for calculating rail travel times given the relative high frequency of and general performance of rail service. If rail offers similar levels of access as a given route-direction, there may be diminishing returns on bus route improvements across our model variables.

Though these metrics can serve as proxies on rail competitiveness in terms of travel time, it is worth noting the difficulty in capturing all the factors that influence rail competitiveness in a sketch planning model that estimates ridership at the segment-level. In reality, this relationship is more complex with not only travel time playing a role but also external factors like fare (i.e., rail being distance-based vs. bus being flat fare), weather (i.e., presence of shelters, access and egress conditions), and perception of safety related to a given route for a journey. The disutility of transfers may also affect mode choice. This is tied to transfer-related walking, waiting, environmental conditions, complexity of modal connections, and cost [44], [45]. These external factors can be better evaluated in a more disaggregated travel demand model at the OD-level.

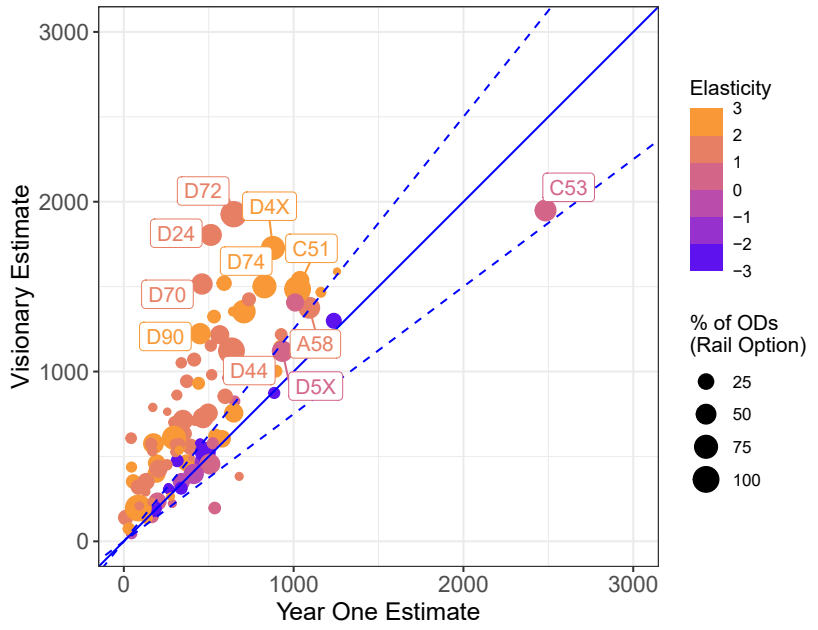
5.2.2 Findings and Discussion

Figure 5.3a and Figure 5.3b display the change in ridership estimate from Year One to Visionary with the symbology based on the route-level elasticity, calculated by dividing the percent change in ridership by the percent change in vehicle hours to capture the sensitivity of ridership to service provided, and either the percent of ODs with a rail option or the percent of ODs where rail is faster. Each point represents a single route-direction, and routes

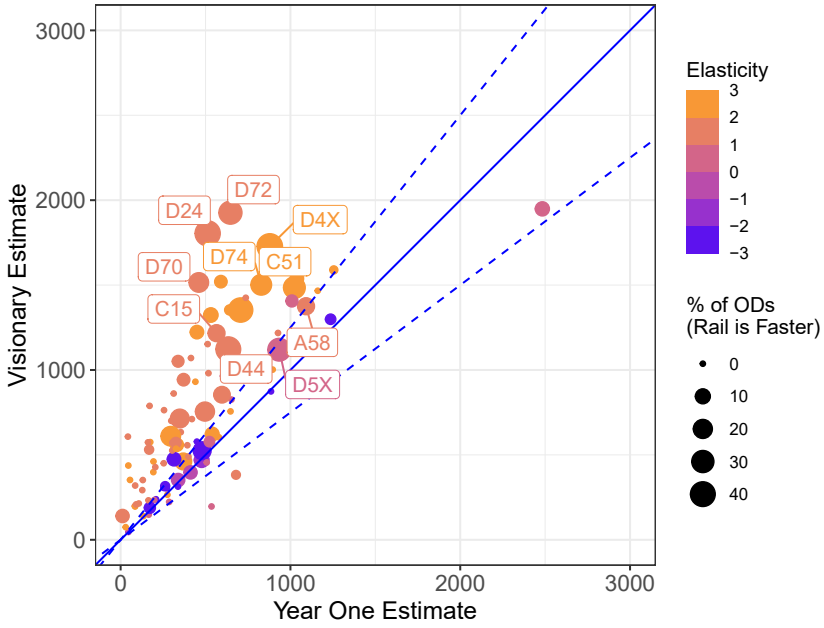
with higher values of the defined rail competitiveness metrics are labeled. The solid blue line indicates the y = x line, where the Year One estimate is equivalent to the Visionary estimate for a given route-direction, while the dashed blue lines indicate a ±25% change in ridership between the two scenarios. It is clear that a lot of route-directions have high elasticity values and similarly high increases in ridership between the two scenarios given route and/or network improvements that the models capture. Though the elasticity values might indicate a higher than expected sensitivity to service changes, the change in vehicle hours used to calculate the elasticity in these figures could be indicative of increases in frequency, span of service, and/or re-routing to new service areas. Therefore, the elasticity on its own may not necessarily provide a sense of whether routes are under or overestimating on its own.

In the first figure, it seems like many route-directions have some percent of ODs with a rail option and there is not a lot of distinct variation between this metric with regards to routes with lower or higher estimates. In the second figure, the percent of ODs where rail is faster than bus appears to have more variation than the first metric and captures the travel time aspect of both modes. It appears that many of the higher ridership routes with higher elasticities also have higher percent of ODs where rail is faster, which provides a sense of their service areas and the presence of parallel rail service. There could be a sense of diminishing returns that needs to be captured particularly on routes that serve areas with high transit service intensity as the frequency and network effect variables may support a more positive effect on ridership from these improvements in service intensity. Most of these routes have a prefix of "D", "C", or "A", which indicate DC downtown and crosstown routes and routes in Arlington and Alexandria area, which align with the service areas with higher Metrorail service availability and likely more bus service and transfer opportunities overall.

In general, capturing rail competitiveness in a future iteration of ridership models could be valuable for further study. This could affect all the variables and effect sizes in the model to some extent. It is expected that these metrics may have a larger impact on routes that serve downtown areas with high transit service availability, and there could be diminishing



(a) Percent of ODs where rail is an option.



(b) Percent of ODs where rail is faster.

Figure 5.3: Visionary vs. Year One estimates by route-level elasticity and rail competitiveness metrics.

returns in ridership from large improvements captured in network effect variables. If this was implemented in a future iteration of the direct demand models developed in this thesis,

the metrics would need to be calculated at the segment-level, likely by considering the destinations downstream of a given segment, similar to the calculation of other downstream metrics described in Chapter 3. Other metrics related to travel time could be defined. The current metrics are simplistic for straightforward calculation and assume that each OD pair based on the segments of a given route-direction are weighed equally. However, these are likely not equal if one were to account for underlying demand and consideration of these weights would require more detailed analysis at the OD-level.

Chapter 6

Conclusion

6.1 Summary

This thesis presented a sketch planning framework to predict ridership and travel time impacts of bus service changes through direct demand models and the use of a multimodal routing algorithm (also referred to as a routing engine). The methods discussed are intended to provide a streamlined workflow to enable iterative analyses of different scenarios. Importantly, the models can be redeveloped as new data becomes available. Existing transit planning tools, such as Remix and HASTUS, allow analysts to edit networks and export a given scenario as a GTFS feed, which can be used as a main input into the workflows outlined in this thesis. As these tools are increasingly adopted by transit agencies, these methods can be transferable and built upon.

In Chapter 3, direct demand models were estimated at the route-segment level by time-of-day periods for the Washington Metropolitan Area Transit Authority (WMATA). The segment-level approach captures multiple variations in characteristics along a route that are generally unavailable using typical weekday or weekend route-level models. Additionally, developing models for each time period by day of week (i.e., Weekday, Saturday, and Sunday) offers a more nuanced understanding of relevant variables and how they relate to bus ridership.

Across the models, the pseudo R^2 values indicate a good fit for estimating bus ridership. These models are sensitive to route and network improvements and can be used to obtain first-cut ridership estimates for new and existing routes. They incorporate catchment area attributes related to population, employment, and land use characteristics, transit service attributes, and network effect variables. The network effect variables include within sum frequency, downstream sum frequency, and the corridor effect terms. Within sum frequency and downstream sum frequency capture transit availability and connectivity and are calculated as the sum of the frequencies of routes within and downstream of a segment, respectively. A corridor effect variable was defined to serve as a proxy of the competitive and complementary nature of bus routes. Instead of classifying routes as either competitive or complementary, the corridor effect variable evaluates neighboring routes at the segment-level based on three factors. These include the possibility of taking another route in the current segment, the extent of overlapping service based on shared downstream stops, and the frequency of the neighboring route. These network effect variables were included in most models, except for the low service, early morning, or late night periods. More service availability, connectivity, and/or overlapping service may not encourage more ridership than the existing ridership in those time periods.

In Chapter 4, the direct demand models were applied to two scenarios in WMATA's Better Bus Network Redesign (BBNR), and route examples were selected to illustrate how different types of service changes are reflected in the model variables. For a route that has no major service changes, the ridership impact is mainly influenced by network effect variables, which include within sum frequency, downstream sum frequency, and the corridor effect terms. The first of these two variables capture general service availability and transfer opportunities within and downstream of a segment based on the frequencies of unique routes, while the corridor effect reflects the competitive and complementary nature between routes. For a route that has improvements in frequency, the ridership impact is primarily influenced by the average trips per hour (in time period) term, which accounts for both span of service and

frequency changes. Lastly, for a route that has re-routing and other improvements, all of the variables in the models could factor into the ridership impact as there could be frequency improvements, changes to route geometry, and network level improvements. Any changes to route geometry would alter the segments along the route, their catchment area, and related attributes (e.g., total population, share of workers in a certain industry, etc.). At the same time, the frequency and network effect terms reflect the route and network improvements. In general, the variables included in the models ensure that the estimates are sensitive to a wide range of potential service changes, including changes to span of service, service headway, stop spacing, and route design.

A validation study using historical service changes from the Frequent Service Network (FSN), which was implemented in September 2021, was also discussed. Though the validation study was limited by a few factors, such as the difficulty in isolating the COVID-related ridership recovery trend, the percent change in estimated ridership before and after the implementation was compared to the percent change in actual ridership. The baseline ridership recovery trend was assumed to be the percent change of routes that had no individual service changes. The actual ridership values provided an upper bound (i.e., the percent change in ridership without accounting for the underlying recovery trend) and a lower bound (i.e., the percent change in ridership after subtracting the assumed baseline ridership recovery trend). The comparison revealed that the estimates fell within the lower and upper bounds, which provides an encouraging indication on the estimated ridership impacts being within a reasonable range. However, the estimates appear to be closer to the upper bound for some days more than others, specifically for Sunday service, which is likely related to the limitations of the models and study further detailed in Section 4.2.

In Chapter 5, a multimodal door-to-door routing engine, r5r, was explored for use in calculating travel times. r5r calculates a distribution of travel times for a given origin-destination (OD) matrix and returns a selected percentile value from the distribution. A comparison study between actual travel times from origin-destination-interchange inference

(ODX) data and travel times from r5r was conducted to calibrate the percentile parameter. Higher percentile values resulted in longer travel times, which primarily came from longer wait time components or different routes with longer travel times. For bus stop to bus stop OD pairs, 10th percentile travel times were recommended for analyses using total travel times. Additional guidance on using the travel time functions and estimates from r5r were summarized in this chapter.

Exploratory work on evaluating rail competitiveness and its relationship to bus ridership was also introduced in Chapter 5. Rail competitiveness is not accounted for in the current direct demand models and could be incorporated in future iterations to capture potential diminishing returns of large improvements in the bus network. Segments created in the direct demand model process were used as origins and destinations, and metrics were defined to evaluate rail competitiveness at the route-direction level. For a given route-direction, the number of segment to segment OD pairs that have a rail option and where rail is faster than bus were identified. The results show that higher ridership routes that were most sensitive to service changes, in terms of vehicle hours provided, also had a higher percent of ODs where rail is faster. This aligns with initial expectations as these routes serve downtown areas with high transit service availability and hints at the potential of diminishing returns on large improvements that are currently captured in the network effect variables. It is well established that there are many other factors beyond travel times that affect mode choice and rail vs. bus competitiveness; however, the findings from this preliminary work indicate potential of future research into rail competitiveness. Potential avenues for future work are detailed in Section 6.3.

6.2 Limitations

There are some limitations to note in the current methodology on predicting ridership and travel time analysis.

Direct demand models were developed using cross-sectional data. When using these models for prediction, there is an assumption that these relationships hold true in future scenarios that are evaluated. However, this may only be an appropriate assumption for a short-term period in the future and a scenario that is similar to the existing network (i.e., within range of existing data), such as regular service changes that occur once or twice a year. In the case of the Visionary network in WMATA's BBNR example described in Section 4.1, though estimates were produced, it is recommended that an incremental process be taken, with the models being re-estimated after the first phases of the network redesign are implemented, and when new data becomes available whenever both ridership and service levels are relatively stable.

For calibrating r5r, the percentile parameter was chosen based on a comparison study between actual travel times and estimated travel times from r5r in one time period only (i.e., AM Peak). This value could vary for different time periods, and other user-defined parameters could also influence the results. The sensitivity of these parameters were not thoroughly explored in this research.

6.3 Future Work

This thesis presented a sketch planning framework for estimating ridership and travel time impacts of bus service changes. The developed models can be used to produce first-cut ridership estimates for a given bus network scenario. Leveraging a routing engine, like r5r, enables analysis of travel time impacts and downstream evaluation of alternative scenarios. There are multiple avenues of research to build on the methods discussed in this thesis.

First, rail competitiveness was preliminarily evaluated at the route-direction level in Section 5.2 and could be further explored at the segment-level. Variables related to rail competitiveness could be defined and incorporated into the current direct demand models, similar to other downstream variables. This would account for the interaction between bus

and rail services, particularly when they are parallel to one another and compete for the same riders.

Second, there are opportunities to leverage ODX data or location-based services (LBS) data for additional analysis related to the impacts of bus service changes. LBS data, for example, provides information on non-transit OD pairs and travel patterns at a zonal level. Origin and destination points could be determined using existing techniques, like dasymetric interpolation. This would enable the use of r5r for routing to evaluate travel times of various transit and non-transit OD pairs to understand how transit compares to other modes. Two potential use cases could be to evaluate travel time impacts on existing journeys when bus services are eliminated or changed significantly and quantify competitiveness between modes for different scenarios from a travel time standpoint. There are likely many possibilities for travel time-related analyses. Future work could also explore modeling ridership at the OD-level, allowing for more detailed consideration of factors, such as travel times, fares, and transfers.

Third, future research could look at conducting retrospective analyses of bus service changes with the existing methodology, assuming ridership data becomes available after service changes are implemented. It would be informative to conduct a more in-depth critique of these methods when used to estimate for alternative scenarios by comparing estimates to actual ridership estimates across multiple sets of service changes. Though a validation study was conducted in this thesis, the study was imperfect given the difficulties related to selecting a before and after period and the general COVID-related ridership recovery trend during the time period of evaluation. Additionally, direct demand models can be used to estimate ridership for a given scenario, but the time it may take for ridership to reach those levels after service changes are implemented in actuality is not well-known or considered in the current work. After the implementation of service changes, it could be valuable to compare the estimated ridership to actual ridership from various time points to evaluate how ridership changed in the short-term (i.e., 1 to 3 months) and long-term (i.e., 6 months or more).

Lastly, panel approaches could be explored to provide a point of comparison to the effect sizes of variables and ridership estimates from the current direct demand models. At the time of this research, comprehensive panel data was not available given COVID impacts and ridership recovery. Ideally, there would be multiple years of recent data with relatively consistent service and regular ridership levels (i.e., not fluctuating within each year). Panel approaches can control for differences across time and segments, which are difficult to fully capture with available data at the cross-sectional level. These methods could address endogeneity concerns as described in Chapter 2 and impact the model estimation. It would be informative to compare both the effect sizes of model variables and the estimates from these alternative panel methods to those from a cross-sectional approach.

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