Evaluating the Impact of a Newly Added Commuter Rail System on Bus Ridership: A Grouped Ordered Logit Model Approach

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Abstract

The study develops a comprehensive and statistically valid framework to study the impact of new public transportation infrastructure (SunRail commuter train) on existing public transit infrastructure (Lynx bus) in the Orlando metropolitan region. The data for the study is drawn from bus ridership information for six quadrimesters (4-month time periods) - 3 prior to SunRail started operation and 3 after SunRail began operations - allowing us to study time varying effects of SunRail system on bus ridership. The current research formulates and estimates an innovative joint panel grouped ordered response model structure for the ridership analysis. To measure the impact of commuter rail on stop level bus ridership (defined as boarding and alighting), the model system controls for a host of independent variables including stop level attributes, transportation infrastructure variables, transit infrastructure variables, land use and built environment attributes and demographic and socioeconomic variables. The proposed model also accommodates for common unobserved factors affecting boarding and alighting as well as repeated ridership measures for each stop. The elasticity analysis undertaken to predict potential ridership into the near future highlights a worrisome trend of reducing transit ridership.

Key Words: *Bus ridership; Grouped ordered response model; Boarding; Alighting; Headway*

1 INTRODUCTION

The over-reliance on the automobile mode in North American cities in the latter half of the 20^{th} century has resulted in significant reduction in the public transportation mode share (Santos et al. 2011). The consequences of the increased dependence on automobile mode are evident; in 2014, traffic congestion has resulted in a loss of about 6.9 billion hours and 3.1 billion gallons of fuel amounting to a cumulative cost of nearly 160 billion dollars (Santos et al. 2011; Schrank et al. 2015). Furthermore, the increased private vehicle travel contributes to increasing air pollution and greenhouse gas (GHG) emissions - a matter receiving substantial attention given the significant impact on health and safety of future generations (Woodcock et al. 2009). Policy makers are considering several alternatives to counter the negative externalities of this personal vehicle dependence. The development of an efficient multi-modal public transportation system is often the most considered solution. Many urban regions, across different parts of North America, are considering investments in public transportation alternatives such as bus, light rail, commuter rail, and metro (see TP 2016 for public transportation projects under construction or consideration).

An important part of the decision process for motivating policy makers to consider infrastructure spending (for new public transportation infrastructure or expansion of existing public transportation infrastructure) is evidence-based research on the performance of the newly added systems. The evaluation of the impact of public transit infrastructure spending is far from straight forward. The research evaluation should encompass several dimensions of the influence of new public transit investments such as improved transit accessibility, real estate values, increased ridership for existing transit systems, improved active transportation in the region, enhanced safety, potential reduction in automobile ownership and usage. The evaluation will provide a performance review of the new investment while also providing guidelines on how to further improve the system. The exercise might also provide valuable insights for other urban regions considering such investments.

While developing research methodology for analyzing all the aforementioned dimensions is beyond the scope of our paper, our focus is on contributing to transit literature by examining the impact of new transit investments (such as an addition of commuter rail to an urban region) on existing transit infrastructure (such as the traditional bus service already present in the urban region). The process of evaluating the impact of new investments on existing public transit requires a comprehensive analysis of the before and after measure of public transit usage in the region. The main objective of the proposed research effort is to develop a framework to study the impact of new public transportation infrastructure (such as commuter rail) on existing public transit infrastructure (such as bus). Specifically, the current research effort contributes to transit literature by evaluating the influence of a recently inaugurated commuter rail system on traditional bus service demand. We examine the before and after impact of “SunRail” commuter rail system in the Orlando metropolitan region on the “Lynx” bus system.

In this context, existing modeling approaches for analyzing bus ridership and their interaction with independent variables are not directly transferable to examine how ridership is impacted by the addition of commuter rail. There are several challenges in this respect. First, any analysis of the value of new investments should consider adequate data before and after the system operation. Second, the econometric model developed should consider how to accommodate for the impact of commuter rail on the bus system. Specifically, the exact variables and their functional forms to be considered in the ridership models to represent the impact of such additions to the existing system. Third, the econometric models should recognize that the ridership information is considered for the same transit stops over time (i.e. presence of repeated measures) while controlling for various independent variables (such as transit infrastructure and built environment variables).

The proposed research addresses these aforementioned challenges. The data for the study is drawn from bus ridership information for six quadrimesters (4-month time periods) - 3 prior to SunRail introduction and 3 after SunRail operations began - allowing us to study time varying effects of SunRail system on bus ridership. To accommodate for the impact of SunRail, several variables and functional forms are developed. These include identifying transit stops "influenced" by SunRail. We define "influenced" in multiple forms including system level effect, stops close to SunRail stations, and stops on bus routes that intersect with SunRail stations (and the distance of the stop on the route from SunRail station). We also consider time elapsed since SunRail operation started, to capture any time varying influence. Finally, in terms of methodology, the current research formulates and estimates an innovative joint panel grouped ordered response model structure for the ridership analysis. The grouped response framework improves the state-of-the-art in modeling ordered dependent variables by obviating the need for estimating threshold parameters (Yasmin and Eluru 2018). Thus, the grouped response model can offer a true non-linear variant of the linear regression model structure (same number of model parameters as linear regression). In addition, the model framework recognizes the presence of 6 boarding and alighting records across different time periods considered for each stop by considering joint panel model structure that accommodates for the presence of unobserved effects at the stop level. To the best of the author's knowledge, the proposed econometric model structure is the first application of joint panel structure based on the grouped ordered response framework, not only in the transportation literature but also in the econometrics literature.

The remainder of the paper is organized as follows: Section 2 provides a review of relevant literature and position our study in context. Section 3 provides the details of the econometric model frameworks used in the analysis. In section 4, the study area and empirical analysis of the data are described. The model estimation results are presented in Section 5. Section 6 concludes the paper.

2 LITERATURE REVIEW

Examining the performance and/or the impact of public transportation systems is a burgeoning area of research. Of particular relevance to our research is earlier work examining transit ridership. While there have been few studies that explore transit ridership from a national or regional perspective (see for example Taylor et al. 2009; Saidi et al. 2017), a large number of studies examine transit ridership focussing on a specific urban region. The research on ridership can be broadly classified based on the public transit mode under consideration along two streams: (1) rail and metro ridership and (2) bus ridership[1].

The *first stream of studies* on rail and metro ridership examined the influence of station characteristics, transit service attributes, and urban sociodemographic patterns and built environment. A number of studies that examined station choice dimension observed that station attributes including parking space availability and bicycle standing areas, amenities and train frequency, vehicle ownership patterns affect station choice (Chakour and Eluru 2014; Debrezion, Pels, and Rietveld 2007, 2009; Fan et al. 2015; Wardman and Whelan 1999). In a study evaluating

[1] The reader would note that the focus of our research is on stop level ridership – an aggregation of individual travel responses to introduction of a new commuter rail system. For a review of studies on individual travel behavior responses to introduction of new transit systems or changes to existing infrastructure (such as tolls, express lanes, bus rapid transit systems) the reader is referred to Bhat and Sardesai (2006) and Abulibdeh and Zaidan (2018).

rail ridership in Atlanta, Brown and Thompson (Brown and Thompson 2008) observed that employment decentralisation was responsible for drop in ridership. Transit Oriented Development (TOD) that comprises of dense commercial developments is expected to affect ridership positively (Lavery and Kanaroglou 2012; Shoup 2008; Sung and Oh 2011; Dong 2016). Population and job density variables are likely to positively influence ridership (Cervero and Guerra 2011). Studies exploring ridership at metro stations found that retail, service and government land use, accessibility by bus, presence of transfer terminals, walkability in the vicinity of stations are positively correlated with ridership (Chan and Miranda-Moreno 2013; Gutiérrez 2001; Gutiérrez et al. 2011; Lin and Shin 2008).

The *second stream of studies*, closely related to the effort of current study, examine the impact of built environment and urban form at the stop level on bus ridership. The transit ridership variables considered include daily ridership computed as sum of boardings and alightings at a stop level (Ryan and Frank 2009), daily boardings (Banerjee et al. 2005; Chu and Chu 2004; Estupiñán and Rodríguez 2008; Johnson 2003; Pulugurtha and Agurla 2012), time period specific boarding's and alighting's (Chakour and Eluru 2016). The methodologies employed for the analysis range from simple linear or log-linear regression models, geographically weighted negative binomial count models, composite likelihood based ordered regression models. Major independent variables identified to affect transit ridership include land use, urban form and sociodemographic characteristics in the vicinity of the stop, walkability measures, real-time bus schedules, passenger satisfaction, transportation system attributes, transit system operational attributes and unobserved factors that simultaneously affect boardings and alightings (Banerjee et al. 2005; Chakour and Eluru 2016; Chu and Chu 2004; Dill et al. 2013; Estupiñán and Rodríguez 2008; Johnson 2003; Machado et al. 2018; Pulugurtha and Agurla 2012; Tang and Thakuriah 2012).

2.1 Contributions of the Current Study

While several research efforts have explored the influence of a host of independent variables on transit ridership, it is evident from the literature review that no earlier research effort has examined the impact of new transit investment on existing transit demand. Of course, the authors recognize that data availability was a major impediment for the analysis. At the same time, there is also no guidance on how to consider the interactions between commuter rail and bus transit. Further, the earlier research studies on ridership have heavily focussed on linear or log-linear regression approaches (with some exceptions). These approaches impose an implicit structure on the impact of independent variables. Chakour and Eluru (2016) in their recent research relaxed this assumption by estimating a flexible non-linear specification in the form of an ordered regression model. While the approach is definitely less restrictive relative to linear or log-linear models, it adds an additional burden for model estimation with the need to estimate threshold parameters. The number of threshold parameters depends on the number of alternatives (one less than the number of alternatives to be precise). Further, in the standard ordered logit model (or the random parameters ordered logit), the error term is implicitly assumed to follow a standard logistic distribution (or standard normal distribution in ordered probit). More recently, Yasmin and Eluru (2018) proposed a grouped response ordered logit model that obviates the need to estimate thresholds by relating the propensity directly to the observed values. The proposed model also allows for parameterization of variance of the unobserved component. Further, Laman et al. (2018) developed a trivariate copula model based on the grouped ordered response approach in examining various components of incident duration.

The current research effort contributes to the transit demand analysis literature methodologically and empirically by building on the grouped ordered response structure proposed in Yasmin and Eluru (2018). In our proposed approach, the first contribution is to reduce the computational burden by avoiding the estimation of thresholds by recognizing that the thresholds of bus ridership are observed and the propensity can be tied to the observed thresholds while relaxing the standard normal or logistic assumption for the variance. Thus, irrespective of the number of ridership categories generated there is no additional parameter burden. In fact, the approach allows us to estimate exactly the same number of parameters as in the linear or log-linear regression approaches[2]. The model also allows for alternative specific effects in the model structure. A typical assumption in the ordered logit models is the assumption that any independent variable has a monotonic impact on latent propensity. However, it is possible that the same variable can have a non-monotonic effect i.e. alternative specific impacts. Several research efforts have highlighted this in the ordered model structures proposing the generalized ordered logit model (or partial proportional odds model) (see Eluru and Yasmin 2015; Yasmin and Eluru 2013; Wang and Abdel-Aty 2008). In our study, following Yasmin and Eluru (2018), we also accommodate for alternative specific effects. Finally, in the proposed approach we allow for common unobserved effects across multiple dependent variables. In a random parameter ordered variable, the impact of unobserved factors is only considered for one dependent variable. In our study, we allow it to vary across multiple dependent variables (boarding and alighting) and multiple time periods (6 time periods). Thus, we develop a repeated measures model with multiple dependent variables. To be sure, the models developed in Yasmin and Eluru (2018) and Laman et al. (2018) are based on the cross-sectional data i.e. no panel effects (or repeated effects) were considered. The reader would note that the panel joint grouped response structure proposed in our paper is the first application of this methodology in the transportation literature as well as the econometrics literature in general.Empirically, the current research effort makes the following contributions to transit literature. First, by employing data on stop level ridership (weekday boarding and alighting) for three quadrimesters before and after commuter rail installation in a large metropolitan area, the current research effort makes a unique empirical contribution identifying the commuter rail impact while controlling for all other factors affecting ridership. We contribute to transit ridership literature by defining various approaches to incorporate the impact of the new transit system addition (commuter rail) on existing transit system (bus) in the bus ridership model. In addition to accommodating for commuter rail variables, the model system also controls for a host of independent variables including stop level attributes, transportation infrastructure variables, transit infrastructure variables, land use and built environment attributes and demographic and socioeconomic variables.

3 ECONOMETRIC METHODLOGY

Let q ($q = 1, 2, \ldots, Q$) be an index to represent bus stops, let t ($t = 1, 2, 3, \ldots, T$) represent the different time periods and j ($j = 1, 2, 3, \ldots, J = 13$) be an index to represent the average weekday boardings or alightings data. We consider thirteen categories for ridership analysis and these

[2] To be sure, a previous research effort has considered the application of a simpler grouped response model. Eluru et al. (2009) have employed the grouped response structure without any alternative specific effects and a different structure of unobserved heterogeneity for residential tenure duration analysis. The unobserved heterogeneity considered in the paper does not include factors affecting multiple ordered dependent variables. Furthermore, the study does not explicitly provide details of the advantages of the framework.

categories are: Bin 1 = ≤5; Bin 2 = 5-10; Bin 3 = 10-20, Bin 4 = 20-30, Bin 5 = 30-40, Bin 6 = 40-50, Bin 7 = 50-60, Bin 8 = 60-70, Bin 9 = 70-80, Bin 10 = 80-90, Bin 11 = 90-100, Bin 12 = 100-120 and Bin 13= >120. The frequency of these 13 categories is provided in Table 1. Then, the equation system for modeling boarding and alighting jointly may be written as follows:

$$B_{qt}^{*} = (\alpha' + \gamma_q')x_{qt} + (\rho_j')z_{qjt} + (\eta'_q)y_{qt} + \varepsilon_{qt}, B_{qt} = j \ \ if\ \psi_{j-1} < B_{qt}^{*} \leq \psi_j \quad (1)$$

$$A_{qt}^{*} = (\beta' + \delta_q')x_{qt} + (\tau_j')z_{qjt} \pm (\eta'_q)y_{qt} + \xi_{qt}, A_{qt} = j \ \ if\ \psi_{j-1} < A_{qt}^{*} \leq \psi_j \quad (2)$$

In equation 1, B_{qt}^{*} is the latent (continuous) propensity for stop level boardings of stop q for the t^{th} time period. This latent propensity B_{qt}^{*} is mapped to the actual grouped ridership category j by the ψ thresholds, in the usual ordered-response modeling framework. In our case, we consider J = 13 and thus the ψ values are as follows: -∞, 5, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100, 120, and +∞. x_{qt} is a matrix of attributes that influence the boardings and alightings (including the constant); α is the corresponding vector of mean coefficients and γ_q is a vector of coefficients representing the impact of unobserved factors moderating the influence of corresponding element of x_{qt}. Further z_{qjt} is a vector of attributes specific to stop q and ridership category alternative j and ρ_j is the vector of corresponding ridership category-specific coefficients. ε_{qt} is an idiosyncratic random error term assumed independently logistic distributed across choice stops and choice occasions with variance λ_B^2.

In equation 2, A_{qt}^{*} is the latent (continuous) propensity for stop level alightings of stop q for the t^{th} time period. This latent propensity A_{qt}^{*} is mapped to the actual grouped ridership category j by the ψ thresholds, similar to boardings. β is the corresponding vector of mean coefficients and $\delta_q$is a vector of coefficients representing the impact of unobserved factors moderating the influence of corresponding element of x_{qt}. Further z_{qjt} is a vector of attributes specific to stop q and ridership category alternative j and τ_j is the vector of corresponding Ridership category-specific coefficients. ξ_{qt} is an idiosyncratic random error term assumed independently logistic distributed across choice stops and choice occasions with variance λ_A^2. The variance vectors for boarding's and alighting's are parameterized as a function of independent variables as follows: $\lambda_B = \exp(\theta' z_{qt})$ and: $\lambda_A = \exp(\vartheta' z_{qt})$. The parameterization allows for the variance to be different across the bus stops accommodating for heteroscedasticity.

η_q represents the vector of coefficients representing the impact of stop level common unobserved factors that jointly influence boardings and alightings. The $'\pm'$ sign indicates the potential impact could be either positive or negative. A positive sign implies that unobserved factors that increase the propensity for boarding for a given reason will also increase the propensity for alighting, while a negative sign suggests that unobserved individual factors that increase the propensity for boarding will decrease the propensity for alighting. In our empirical context, we expect the relationship to be positive. To complete the model structure of the Equations (1) and (2), it is necessary to define the structure for the unobserved vectors γ_q, δ_q and η_q. In this paper, we assume that the three vectors are independent realizations from normal distributions as follows: $\gamma_{qm} \sim N(0, \sigma_m^2)$ $\delta_{qm} \sim N(0, \nu_m^2)$and $\eta_{qm} \sim N(0, \varrho_m^2)$.

With these assumptions, the probability expressions for the ridership category may be derived. Conditional on γ_{qm}, δ_{qm} and η_{qm}, the probability for stop q to have boarding and alighting in category j in the t^{th} time period is given by:

$$P(B_{qt})|\gamma,\eta = \Lambda\left[\frac{\psi_j-\left((\alpha'+\gamma'_q)x_{qt}+(\rho'_j)z_{qjt}+(\eta'_q)y_{qt}\right)}{\lambda_B}\right] - \Lambda\left[\frac{\psi_{j-1}-\left((\alpha'+\gamma'_q)x_{qt}+(\rho'_j)z_{qjt}+(\eta'_q)y_{qt}+\right)}{\lambda_B}\right] \quad (3)$$

$$P(A_{qt})|\delta,\eta = \Lambda\left[\frac{\psi_j-\left((\beta'+\delta'_q)x_{qt}+(\tau'_j)z_{qjt}\pm(\eta'_q)y_{qt}\right)}{\lambda_B}\right] - \Lambda\left[\frac{\psi_{j-1}-\left((\beta'+\delta'_q)x_{qt}+(\tau'_j)z_{qjt}\pm(\eta'_q)y_{qt}\right)}{\lambda_B}\right] \quad (4)$$

where Λ (.) is the cumulative standard logistic distribution.

The complete set of parameters to be estimated in the joint model system of Equations (3) and (4) are $\alpha, \beta, \rho, \tau, \theta$ and ϑ vectors and the following standard error terms: σ_m, ν_m and ϱ_m. Let Ω represent a vector that includes all the standard error parameters to be estimated. Given these assumptions the joint likelihood for stop level boarding and alighting is provided as follows

$$L_q|\Omega = \prod_{t=1}^{T}\prod_{j=1}^{J}\left(P(B_{qt})|\gamma,\eta\right)^{d_{bjt}}\left(P(A_{qt})|\delta,\eta\right)^{d_{ajt}} \quad (5)$$

where d_{bjt} and d_{ajt} are dummy variables taking a value of 1 if stop q has ridership within the j^{th} category for the t^{th} time period and 0 otherwise. Finally, the unconditional likelihood function may be computed for stop q as:

$$L_q = \int_{\Omega} (L_q|\Omega)d\Omega \quad (6)$$

The log-likelihood function is given by

$$\mathrm{Ln(L)} = \sum_{q=1}^{Q}\ln L_q \quad (7)$$

The likelihood function in Equation (7) involves the evaluation of a multi-dimensional integral of size equal to the number of rows in Ω. We apply Quasi-Monte Carlo simulation techniques based on the scrambled Halton sequence to approximate this integral in the likelihood function and maximize the logarithm of the resulting simulated likelihood function (See Bhat 2001; Yasmin and Eluru 2013 for more details). The likelihood functions are programmed in Gauss (Aptech 2016).

4 EMPIRICAL ANALYSIS

The major focus of the proposed research effort is to evaluate the influence of the recently inaugurated commuter rail system "SunRail" in Orlando on bus ridership while controlling for host of other independent variables. Orlando is one of the most populous cities of Florida. Orlando is a typical American city in the south with the following transportation mode share: automobile (85.7%), public transit (1.0%), walk (9.2%) and bike (1.2%). The main public transit system serving the Orlando metropolitan region is the Lynx transit system. Lynx system serves the population of about 1.8 million in Orange, Seminole, Osceola and Polk County covering 2,500 square miles. The system has 77 daily routes offering about 105,682 rides on weekdays. SunRail, a commuter rail system has been introduced in the city on May 1, 2014. During the study period after May 2014, SunRail system had a 31 miles long line with 12 active stations that connected Volusia county and Orange county (SunRail service has been expanded from April 2016). The system served an average of 3,800 passengers on weekdays in 2015. Figure 1 represents the study area along with Lynx bus route, bus stop, Sunrail line and Sunrail station locations.

For the purpose of our analysis, stop level average weekday boarding and alighting ridership data for 6 quadrimester time periods are considered. These include the following 6-time period: May through August 2013, September through December 2013, January through April 2014, May through August 2014, September through December 2014, January through April 2015. The ridership information was processed for all the 6 time periods and analyzed to ensure data availability and accuracy. The resulting data provided ridership information for 3,745 stops across the 6 time periods. The ridership data was augmented with stop level headway, route length as well as route to stop correspondence for Lynx across the 6-time periods. We consider thirteen categories for ridership analysis and these categories are: Bin 1 = ≤5; Bin 2 = 5-10; Bin 3 = 10-20, Bin 4 = 20-30, Bin 5 = 30-40, Bin 6 = 40-50, Bin 7 = 50-60, Bin 8 = 60-70, Bin 9 = 70-80, Bin 10 = 80-90, Bin 11 = 90-100, Bin 12 = 100-120 and Bin 13= >120. A summary of the system level ridership (boarding and alighting) are provided in Table 2. The average weekday boarding (alighting) across the 6-time periods range from 71,006 (71,029) to 77,940 (76,725).

We have considered several variables related to SunRail. First, we considered a temporal SunRail indicator variable for the six time periods as (0,0,0,0,1,2); each quadrimester data has been defined by the introduction of SunRail. Second, we generated a SunRail effect variable (Yes/No), that identifies bus stops that are affected by SunRail. While there might be a system level effect, it is more realistic to consider the impact of SunRail on stop level ridership based on connectivity as well as proximity from different SunRail stations. For this purpose, we identified specific bus routes that intersect or pass through the SunRail system. Of the 77 bus routes operated by Lynx, we found that 60 routes are within the SunRail influence zone (i.e. pass through SunRail). These routes account for 3,321 out of the 3,745 stops considered in our analysis. Third, we generated station specific distance based measures such as squared distance between SunRail station and the bus stop or stops affected by a particular station (through intersection of bus route and SunRail station).The rest of the independent variable information was generated based on multiple sources including 2010 US census data, 2009-2013 American Community Survey, Florida Geographic Data Library, and Florida Department of Transportation (FDOT) databases. The independent variables considered for the empirical analysis can broadly be categorized as stop level attributes, transportation infrastructure characteristics, built environment attributes, demographic and socioeconomic characteristics, temporal effects and SunRail effects. Stop level attributes include headway, number of bus stops in a buffer around stops. Transportation infrastructure characteristics include bus route, side walk and rail road lengths in a buffer around stops. Built environment attributes include land use mix[3] in a buffer around stops and distance of stop from central business district (CBD). Demographic and socioeconomic characteristics include number of population aged 17 and less, number of population with education at some college level, number of population with education at bachelor level, number of households with low income level and number of owned households by residents. The demographic and socioeconomic characteristics are generated at the census tract level. In terms of Temporal effect, we introduced a variable called "time elapsed" which is the time difference between the most recent quarters from the base quarter (May through August 2013) considered in the current study context. In our case, for the 6 quadrimesters, the variable takes the following values: 0, 1, 2, 3, 4 and 5. Finally the SunRail effect for each station includes variables representing the SunRail station influenced stops and SunRail operation period. Several buffer sizes - 800m, 600m, 400m, and 200m - around the bus stop were employed for variable generation. A summary of the independent variables generated is provided in Table 3. For the sake of brevity, the presentation was restricted to variables found to be significant in the final specified model.

5 MODEL ESTIMATION RESULTS

5.1 Model Specification and Overall Measures of Fit

The empirical analysis involves estimation of different models: 1) independent grouped ordered logit (IGOL) models for boarding and alighting, 2) joint panel mixed grouped ordered logit (JPMGOL) model for boarding and alighting without correlation parameterization, and 3) joint panel mixed grouped ordered logit model for boarding and alighting with correlation parameterization (JPMGOLc). The independent models were estimated to establish a benchmark for comparison. Prior to discussing the estimation results, we compare the performance of these models in this section. As the three models are nested within each other, we employ a likelihood ratio (LR) test to determine the best model between independent and joint models. The LR test statistic is computed as LR = 2 (LL_{UR} - LL_R) where LL_{UR} and LL_R represents the log-likelihood of the unrestricted model and restricted model, respectively. If the LR statistic computed is greater than the corresponding chi-square value at a particular level of significance the unrestricted model is considered to be superior to the restricted model. The number of degrees of freedom used for the chi-square evaluation are determined based on the difference in the number of parameters in the two models.

The log-likelihood values at convergence for the models estimated are as follows: (1) IGOL (with 30 parameters) is -65,230.750, (2) JPMGOL (with 37 parameters) is -44,234.747 and (3) JPMGOLc (with 38 parameters) is -44,232.650. The LR test statistic for comparison between JPMGOLc and JPMGOL is 4.2 (> corresponding chi-square value at the 95% level) and between JPMGOLc and IGOL is 42000 (> corresponding chi-square value at any level of significance).

[3] Land use mix = $\left[\frac{-\sum_k (p_k(ln p_k))}{lnN}\right]$, where k is the category of land-use, p is the proportion of the developed land area devoted to a specific land-use, N is the number of land-use categories within 1mile buffer of the roadway segment.

The LR test computation clearly highlights the superior performance of the JPMGOLc model relative to the other two models.

5.2 Variable Effects

The final specification of the model development was based on removing the statistically insignificant variables in a systematic process based on statistical significance (95% significance level). The specification process was also guided by prior research and parsimony considerations. In estimating the models, several functional forms and variable specifications were explored. The functional form that provided the best result was used for the final model specifications. For variables in various buffer sizes, each variable for a buffer size was systematically introduced (starting from 800m to 200m buffer size) and the buffer variable that offered the best fit was considered in the final specification. In presenting the effects of independent variables, we will restrict ourselves to the discussion of the JPMGOLc model. The model estimates for boarding, alighting and joint effects are presented in Table 4. The variable results across different independent variable categories are presented below.

5.2.1 Stop Level Attributes

As is expected, headway at the stop level has a significant influence on ridership. We observe that with increasing headway, boarding and alighting are likely to reduce. The result highlights how transit frequency directly affects ridership. The results for number of Lynx bus stops in the 800m buffer indicates that the presence of more number of bus stops in an 800m buffer contributes to reduced ridership. The result is in contradiction to earlier work (see Chakour and Eluru 2016). The result is perhaps indicating competition across the stops for the same ridership population.

5.2.2 Transportation Infrastructure Characteristics

Transportation infrastructure offered quite complex effects on total ridership. Bus route length in the buffer has a positive impact on ridership for both boarding and alighting. Interestingly, the influence of buffer size is slightly different for boarding and alighting. The bus route length in the 600 m buffer offered the best fit for boarding whereas the corresponding buffer for alighting was 800 m. The results clearly demonstrate that increasing route length (an indication of higher transit accessibility) is correlated with higher ridership. A similar positive impact is observed for side walk length variables. On the other hand, increasing rail length in the buffer around a stop is related to lower boarding and alighting ridership. The rail length in the 600 m buffer offered the best results for alighting and corresponding buffer size for boarding is 400m. The presence of higher rail road length is a surrogate for the land use in the vicinity.

5.2.3 Built Environment Attributes

Built environment variable estimates indicate significant influence on bus ridership at the stop level. Land use mix variables in different buffer size near bus stop significantly increased the boarding and alighting ridership in Orlando. The impact of land use mix is observed for the 400 m buffer for boarding and the 800 m buffer for alighting. The distance from the CBD variable highlights how in Orlando region, ridership reduces as the distance from CBD increases.

5.2.4 Demographic and Socioeconomic Characteristics

The demographic and socioeconomic variables based on census tract of the bus stop significantly affect the bus ridership in Orlando. The presence of larger share of young population (age 17 and below) contributes to increased level of boarding and alighting. The presence of higher proportion of education level at college and bachelor level reduces ridership. Education at college level effect is significant in the boarding component only. Overall, the effect of education on ridership perhaps is a reflection of higher economic status of the census tracts with higher share of such individuals. The increased presence of low income population is likely to be positively associated with bus ridership, as is expected. On the other hand, increased share of household ownership has a negative influence on public transit ridership, presumably also reflecting the higher economic wealth and more private auto inclination for this group of population.

5.2.5 Temporal and SunRail Effects

The major objective of the paper was to study the influence of SunRail system on bus ridership while also controlling for all other attributes. The variable for SunRail impact is present only for three time-periods. As described earlier, we considered several variables related to SunRail. However, no system level impacts were statistically significant. The interactions of SunRail influenced stops and SunRail operation period are found to be significant for two stations – Church Street and AMTRAK SunRail stations. The Church Street Sunrail station positively affected the alighting ridership but negatively affected boarding ridership. The AMTRAK SunRail station influenced stops are likely to have higher boarding with no perceivable impact on alighting. Finally, the overall temporal variable repenting the time trend of ridership indicates an overall reduction in bus alightings with no impact on boarding. Overall, the results are not as encouraging as is expected of a new commuter rail addition. From our analysis, it appears that the bus ridership is marginally affected by SunRail addition in the region.

5.2.6 Alternative Specific Effects

In the grouped ordered specification of the joint model, we also estimate alternative specific constants for categories considered across different ridership components. It is worthwhile to mention here that it is possible to estimate group-specific effects for each group considered across different components. However, in our joint model specifications, we estimate group-specific effects if it improves data fit. The results of these group specific effects are presented in second row panel of Table 4. With respect to boarding and alighting, group-specific components are estimated for category 1 (ridership ≤ 5) and category 2 (ridership 6-10), respectively. Adding more group-specific components did not improve the data fit further in the current study context and hence are not included in our final joint model specifications. These parameters are similar to constants in discrete choice models and do not really have a substantive interpretation.

5.2.7 Scale Parameter

As indicated earlier, in the JPMGOLc model specification, we introduce scale parameters both in the boarding and alighting components to reflect the variance of the unobserved portion for each group. From Table 4, in the second to last row panel, we can see that the scale parameters are significant for both the dimensions. The result confirms the presence of heteroscedasticity across stops highlighting the appropriateness of the proposed model structure.

5.2.8 Correlation Effects

The estimation results of the correlation effects are presented in last row panel of Table 4. We can see that the dependence effects are significant. Further, from the estimated results we can see that the dependencies are characterized by additional exogenous variables. This provides support to our hypothesis that the dependency structure is not the same across the observations. The various exogenous variables that contribute to the dependency include temporal effect and headway. The parameters represent common correlation between boarding and alighting. As shown in Equation 2 of Section 3, the correlation between the two components could be either positive or negative. In our analysis, we found the positive sign to offer better fit for common correlation. Overall, the results clearly support our hypothesis that common unobserved factors influence the two components. After accommodating for common unobserved heterogeneity, no random parameters (γ and δ) were found to be significant in our model.

6 POLICY ANALYSIS

In order to highlight the effect of various attributes over time on boarding and alighting ridership, an elasticity analysis is also conducted (see Eluru and Bhat 2007 for a discussion on the methodology for computing elasticities). We investigate the change in ridership, due to the change in selected independent variables. Specifically, we compute the change in ridership (both boarding and alighting) for change in headway, sidewalk length, route length, low income population percentage, CBD distance from bus stop, Young population percentage and temporal ID for the thirteen ridership categorise considered. The total boardings and alightings are calculated for all the above categories for the percentage changes of those independent variables considered. The results for the elasticity analysis are presented in Table 5. The reader would note that we present the ridership changes across the ridership categories considered in the model estimation process. These results by category can be translated into simple ridership numbers in a straightforward manner (if needed).

Several observations can be made from the results presented in Table 5. First, headways, sidewalk length, CBD distance from bus stop and route length are the most important variables in terms of high ridership categories. These results indicate that ridership is more sensitive to transit attributes and endorse the need to invest in improving transit infrastructure and service in order to encourage transit usage. Second, the effect of higher percentage of low income population further indicates that reduced accessibility to private automobile increases more transit usage. Finally, and most importantly, with time the results indicate a reduction in the overall ridership numbers, a worrisome trend for the transit system. Based on our findings to increase the ridership, services related to public transit (improvement of headway and route length increasing) should be considered.

7 CONCLUSION

In this study, we examined the impact of new transit investments (such as an addition of commuter rail to an urban region) on an existing public transit system (such as the traditional bus service already present in the urban region). Specifically, the study developed a comprehensive and statistically valid framework in studying the impact of new public transportation infrastructure (such as commuter rail, “SunRail”) on existing public transit infrastructure (such as bus, “Lynx”) in the Orlando metropolitan region. The data for the study is drawn from bus ridership information for six quadrimesters - 3 prior to installation of SunRail and 3 after installation of SunRail - allowing us to study time varying effects of SunRail system on ridership. To measure the impact of commuter rail on stop level bus ridership the model system controlled for a host of independent variables including stop level attributes, transportation infrastructure variables, transit infrastructure variables, land use and built environment attributes, demographic and socioeconomic variables. The ridership categorised considered at each stop were: Bin 1 = ≤5; Bin 2 = 5-10; Bin 3 = 10-20, Bin 4 = 20-30, Bin 5 = 30-40, Bin 6 = 40-50, Bin 7 = 50-60, Bin 8 = 60-70, Bin 9 = 70-80, Bin 10 = 80-90, Bin 11 = 90-100, Bin 12 = 100-120 and Bin 13= >120.

The study formulated and estimated an innovative grouped ordered response model structure for the ridership analysis. The proposed model accommodates for common unobserved factors affecting boarding and alighting as well as repeated measures for each stop. The empirical analysis involved estimation of three different models: 1) independent grouped ordered logit (IGOL) models for boarding and alighting, 2) joint panel mixed grouped ordered logit (JPMGOL) model for boarding and alighting without correlation parameterization, and 3) joint panel mixed grouped ordered logit model for boarding and alighting with correlation parameterization (JPMGOLc). The comparison exercise based on information criterion clearly highlights the superiority of the joint model with the correlation parameterization in terms of data fit compared to independent model. Two variables representing the impact of interactions representing station specific SunRail influenced stops and SunRail operation period were found to have marginal impact on bus ridership. In our research, in order to highlight the effect of various attributes over time on boarding and alighting ridership, an elasticity analysis was also presented. We investigated the change in ridership due to the change in selected independent variables. The elasticity analysis highlights a worrisome trend of reducing transit ridership with time. Significant investments in transit infrastructure can arrest this trend.

The findings offer significant utility to transit planners and agencies not only in Orlando but also for similar cities across the country. The models developed for Lynx bus ridership can be utilized for predicting ridership for project expansions and/or modification. For instance, Lynx agency can employ the transit ridership models to evaluate ridership changes with addition or modification of transit routes in Orlando region. Major recommendations from our research for transit agencies include: (1) increasing bus frequency for high ridership stops, (2) addition of bus shelters, (3) redesign routes to match with land use patterns, and (4) enhance the spatial and temporal connectivity between SunRail and Lynx systems. The model results would be suitable for similar cities where there is an opportunity for increasing ridership.

To be sure, the research is not without the limitations. The proposed research methodology develops a demand forecasting system for bus systems with explicit guidance on various specifications to incorporate the influence of commuter rail system. However, the proposed system does not explicitly consider the two-way interaction between bus and rail systems. The availability of high-resolution data on macroeconomic characteristics such as employment rate, gas prices over the various time periods of analysis might be beneficial for improving the model specification. It would also be interesting to examine the influence of spatial effect across different bus stops in future research efforts. Finally, there exists a possibility that stop level headway is actually influenced by expected ridership. Hence, in future research efforts it might be appropriate to consider headway as an endogenous variable in modeling ridership.

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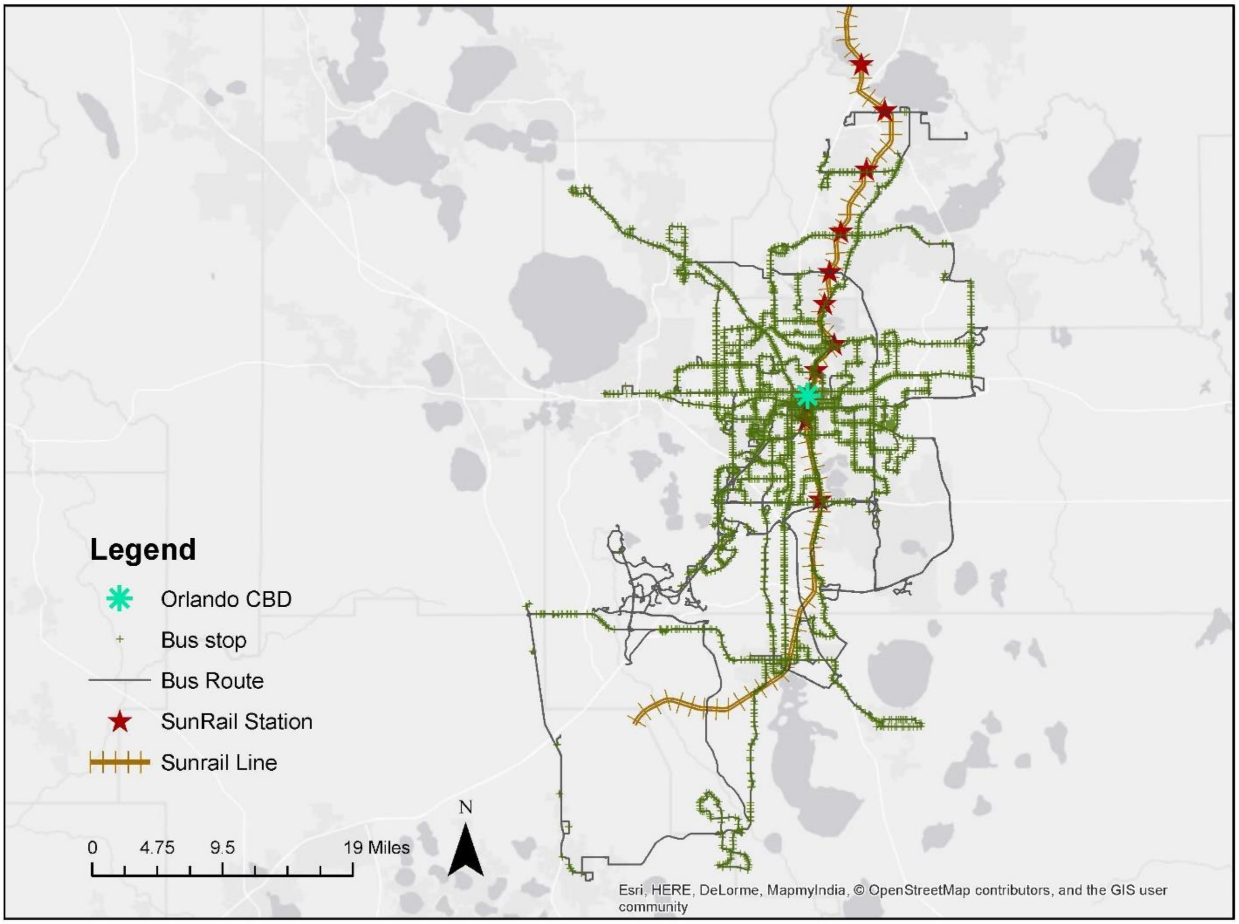

Figure 1 Public Transit System (LYNX and SUNRAIL) of Orlando

Table 1 Frequency of the 13 ridership categories for boarding and alighting[4]

Ridership Category (Bin)	Frequency		Percent		Cumulative Percent	
	Boarding	Alighting	Boarding	Alighting	Boarding	Alighting
1	10694	10251	51.0	48.9	51.0	48.9
2	3642	3706	17.4	17.7	68.4	66.6
3	2955	3123	14.1	14.9	82.5	81.4
4	1168	1340	5.6	6.4	88.0	87.8
5	641	700	3.1	3.3	91.1	91.2
6	433	483	2.1	2.3	93.1	93.5
7	305	293	1.5	1.4	94.6	94.9
8	226	195	1.1	.9	95.7	95.8
9	174	172	.8	.8	96.5	96.6
10	115	113	.5	.5	97.1	97.2
11	78	77	.4	.4	97.4	97.5
12	144	120	.7	.6	98.1	98.1
13	395	397	1.9	1.9	100	100.0

[4] The reader should note that while we have alternatives with very small percentage, as we do not estimate alternative effects for these categories there is no impact on model estimation stability.

Table 2 Summary Statistics of Lynx Bus Ridership (August 2013 to April 2015)

Time-period	**Quarter Name**	**Boarding**		**Alighting**	
		Mean	**Standard Deviation**	**Mean**	**Standard Deviation**
1	August-13	22.30	160.51	21.95	152.86
2	December-13	20.88	151.85	20.61	143.49
3	April-14	20.54	157.83	20.32	151.89
4	August-14	21.51	162.01	21.38	154.30
5	December-14	20.32	151.18	20.39	146.65
6	April-15	20.65	156.02	20.52	149.57

Table 3 Descriptive Statistics of Independent Variables

Variable Name	Variable Description	Minimum	Maximum	Mean
Stop Level Attributes				
Headway	Headway in minutes	1.11	60.00	37.63
No of Bus stop in a *800 m buffer*	(Number of bus stops in 800m buffer)/10	0.10	9.30	1.79
Transportation Infrastructure Characteristics				
Bus route Length in a	Bus route length in kilometers			
600 m buffer	(Bus route length in 600 m buffer)/10	0.11	6.06	0.51
400 m buffer	(Bus route length in 400 m buffer)/10	0.05	4.17	0.27
Side walk length in a *800 m buffer*	Side walk length in kilometers	0.00	13.27	3.16
Secondary highway length in a	Secondary highway length in kilometers			
800 m buffer	Secondary highway length in 800 m buffer / Total road length in 800 m buffer	0.00	1.00	0.34
Rail road length in a *800 m buffer*	Rail road length in kilometers	0.00	6.04	0.31
Local road length in a	Local road length in kilometers			
800 m buffer	Local road length in 800 m buffer / Total road length in 800 m buffer	0.00	1.00	0.65
Built Environment Attributes				
Residential area in a	Residential area in square kilometers			
800 m buffer	Residential area in 800 m buffer / Total area in 800m buffer	0.00	1.00	0.32
600 m buffer	Residential area in 600 m buffer / Total area in 600m buffer	0.00	1.00	0.31
Central Business area distance (km)	(Central Business area distance)/10	0.00	5.06	1.18
Demographic and Socioeconomic Characteristics				
Age 65 and up	(People age 65 and up)/Census Area	-6.36	3.23	-1.07
Education level - 9 to 12 grade	Education level 9 to 12 grade / Census Area	-8.04	2.41	-1.50
Low Income Category (<30k)	Low income People (<30k)/Census Area	-8.55	2.85	-0.77
Vehicle Ownership - No vehicle	Vehicle Ownership - No Vehicle / Census Area	-8.55	1.58	-2.11
Household ownership	Household Ownership / Census Area	-6.87	3.36	-0.53
Temporal and SunRail Effects				
Church Streets SunRail station influenced stops*SunRail operation period	Interaction term of SunRail influenced bus stops for Church Streets station and SunRail operation period	0.00	1.00	0.18
AMTRAK SunRail station influenced stops*SunRail operation period	Interaction term of SunRail influenced bus stops for AMTRAK station and SunRail operation period	0.00	1.00	0.06

Table 4 Panel Joint Group Ordered Logit Model Results

Variable Name	Boarding		Alighting	
	Estimates	**t-stat**	**Estimates**	**t-stat**
Constant	-8.062	-4.634	-6.779	-4.828
Stop Level Attributes				
Headway	-1.015	-48.520	-0.710	-40.330
No of Bus stop in a *800 m buffer*	-9.051	-21.032	-7.810	-19.086
Transportation Infrastructure Characteristics				
Bus route Length in a				
800 m buffer	---	---	9.91	26.995
600 m buffer	16.479	26.689	---	---
Side walk length in a *800 m buffer*	4.645	23.496	3.518	19.328
Rail road length in a				
600 m buffer	---	---	-7.044	-11.654
400 m buffer	-17.429	-14.379	---	---
Built environment Attributes				
Land Use mix area in a				
800 m buffer	---	---	22.357	11.985
400 m buffer	14.110	7.969	---	---
Central Business area distance (km)	-13.849	-27.009	-9.696	-21.332
Demographic and socioeconomic Characteristics				
Age up to 17	10.816	17.363	8.256	14.462
Education at some college level	-4.771	-12.647	---	---
Education bachelor	-7.822	-18.026	-6.722	-17.780
Low income (<30K)	7.720	12.399	4.717	8.141
HH Ownership	-5.733	-10.349	-6.160	-12.325
Temporal and SunRail Effects				
Church streets SunRail station influenced stops*SunRail operation period and before after of SunRail	-4.098	-4.543	0.963	2.301
AMTRAK SunRail station influenced stops*SunRail operation period	3.605	3.391	---	---
Temporal ID (0,1,2,3,4,5)	---	---	-0.466	-6.005
Alternative Specific Effects				
Constant – Alternative 1 (≤5 ridership)	50.755	106.590	28.919	74.165
Constant – Alternative 2 (6-10 ridership)	24.148	67.405	13.248	42.599
Scale Parameter				
Constant	3.211	565.330	1.672	218.060
Correlation Effects				
Variable Name	**Estimates**		**t-stat**	
Constant	55.137		133.697	
Temporal ID (0,1,2,3,4,5)	1.945		28.823	
Headway	0.400		40.647	

Table 5 Elasticity Analysis

Boarding													
Categories	**Bins**												
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
Headway													
10% Decrease	-4.21%	1.42%	3.10%	4.06%	4.44%	4.80%	5.14%	5.46%	5.75%	6.03%	6.29%	6.62%	7.30%
25% Decrease	-9.59%	3.19%	8.19%	11.40%	12.74%	14.05%	15.33%	16.57%	17.76%	18.92%	20.02%	21.49%	24.82%
Sidewalk at 800 m buffer													
10% Increase	-1.52%	0.07%	0.98%	1.62%	1.90%	2.18%	2.46%	2.74%	3.03%	3.33%	3.62%	4.01%	5.15%
25% Increase	-3.77%	3.98%	4.72%	5.46%	6.21%	6.99%	7.80%	8.64%	9.49%	10.68%	14.30%	-3.77%	3.98%
Route Length at 600m buffer													
10% increase	-0.84%	0.00%	0.51%	0.89%	1.06%	1.23%	1.40%	1.59%	1.79%	2.00%	2.21%	2.49%	3.66%
25% increase	-2.08%	-0.03%	1.24%	2.21%	2.65%	3.08%	3.53%	4.01%	4.52%	5.07%	5.64%	6.46%	9.89%
Low Income population													
10% increase	-0.61%	0.21%	0.49%	0.69%	0.78%	0.88%	0.98%	1.07%	1.15%	1.23%	1.28%	1.33%	1.35%
25% increase	-1.52%	0.47%	1.20%	1.73%	1.98%	2.25%	2.51%	2.76%	3.00%	3.20%	3.37%	3.52%	3.60%
CBD from bus stop													
10% Decrease	-1.69%	0.60%	1.37%	1.82%	2.01%	2.18%	2.36%	2.54%	2.71%	2.88%	3.04%	3.21%	3.56%
25% Decrease	-4.09%	1.41%	3.48%	4.78%	5.31%	5.83%	6.34%	6.86%	7.38%	7.90%	8.38%	8.97%	10.11%
Young population (Age 0 to 17 years old)													
10% increase	0.32%	-0.11%	-0.26%	-0.36%	-0.41%	-0.48%	-0.54%	-0.62%	-0.69%	-0.75%	-0.78%	-0.78%	-0.63%
25% increase	0.81%	-0.38%	-0.68%	-0.88%	-0.98%	-1.10%	-1.22%	-1.36%	-1.49%	-1.59%	-1.64%	-1.57%	-1.12%
Alighting													
Categories	**Bins**												
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
Headway													
10% Decrease	-3.59%	0.88%	2.64%	3.04%	3.35%	3.98%	3.84%	5.03%	6.20%	6.00%	5.53%	6.63%	7.26%

25% Decrease	-8.25%	1.83%	6.50%	8.87%	9.36%	10.81%	11.69%	13.66%	19.35%	18.97%	18.27%	20.35%	25.20%
Sidewalk at 800 m buffer													
10% Increase	-1.47%	0.08%	0.80%	0.98%	1.85%	1.90%	2.08%	2.37%	3.46%	3.88%	3.79%	4.18%	5.26%
25% Increase	-3.64%	-0.05%	2.09%	2.11%	4.69%	4.83%	5.28%	5.72%	8.82%	10.30%	10.77%	10.81%	15.06%
Route Length at 800m buffer													
10% increase	-1.11%	-0.04%	0.50%	0.81%	1.28%	1.48%	1.75%	1.68%	2.81%	3.93%	3.36%	3.20%	4.69%
25% increase	-2.70%	-0.29%	1.25%	2.06%	3.56%	3.18%	4.21%	4.94%	7.07%	8.87%	10.10%	9.54%	13.12%
Low Income population													
10% increase	-0.47%	0.21%	0.31%	0.40%	0.34%	0.43%	0.88%	0.81%	1.26%	1.42%	1.05%	0.90%	0.93%
25% increase	-1.17%	0.45%	0.77%	0.98%	1.02%	0.91%	2.15%	2.09%	3.20%	3.85%	2.54%	2.26%	2.48%
CBD from bus stop													
10% Decrease	-1.46%	0.35%	1.17%	1.35%	1.54%	2.01%	1.86%	2.23%	2.46%	2.56%	2.88%	3.83%	3.00%
25% Decrease	-3.53%	0.76%	2.89%	3.67%	3.87%	5.15%	5.20%	6.01%	6.91%	6.42%	7.72%	10.93%	8.56%
Young population (Age 0 to 17 years old)													
10% increase	0.30%	-0.11%	-0.20%	-0.35%	0.03%	-0.25%	-0.91%	-0.38%	-0.92%	-1.20%	-1.17%	-0.69%	-0.24%
25% increase	0.78%	-0.48%	-0.60%	-0.65%	0.33%	-1.00%	-2.26%	-0.91%	-1.43%	-2.26%	-2.80%	-1.94%	0.13%
Temporal ID													
2016 (6,7,8,9,10,11)	3.53%	-0.94%	-2.58%	-3.57%	-3.91%	-4.48%	-4.76%	-6.92%	-8.99%	-7.80%	-8.21%	-9.77%	-10.11%
2017 (9,10,11,12,13,14)	3.42%	-0.95%	-2.65%	-3.68%	-4.07%	-4.67%	-4.95%	-7.40%	-9.78%	-8.36%	-8.83%	-10.75%	-11.21%

Note: Bin 1 = ≤5; Bin 2 = 5-10; Bin 3 = 10-20, Bin 4 = 20-30, Bin 5 = 30-40, Bin 6 = 40-50, Bin 7 = 50-60, Bin 8 = 60-70, Bin 9 = 70-80, Bin 10 = 80-90, Bin 11 = 90-100, Bin 12 = 100-120 and Bin 13= >120 ridership in each stop