Final Report
February 2020

# Miami-Dade Transit Elasticity of Demand Study

IMG Rebel Advisory, Inc.
Our ref: 23304801
Client ref:

steer

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# 1 Introduction

## Background

1.1 Steer, part of the IMG Rebel Advisory, Inc. team (the Team) was requested to complete a fare policy study of the Metrorail and Metrobus transit systems, operated by Miami-Dade's Department of Transportation and Public Works (DTPW) (the Project). The work has been commissioned by the Citizens' Independent Transport Trust (CITT, the Client). A primary output of the Project is a comprehensive quantitative analysis of the users of Metrorail and Metrobus, in particular their responsiveness to fare changes.

1.2 The analysis includes estimation of a series of ridership demand models for Metrorail and Metrobus. These models detail how ridership on both modes can be expected to change with economic growth, fare changes, and changes in the level of service (LOS) of the transit services.

1.3 The models include estimates of fare *elasticities*, which measure the response of users to fare changes. For the purposes of this study, the elasticity of demand (i.e. ridership) is synonymous with fare elasticity, as the study aims to specifically determine how ridership would change with a change in fare. Elasticities presented in this study are in decimal format and can be interpreted as the percent change in ridership driven by a 1% change in the relevant variable. For instance, an elasticity of -0.36 would indicate that a 1% increase in the variable in question (e.g. fares) would drive a 0.36% decline in ridership. Conversely, an elasticity of 0.96 would indicate that a 1% increase in that variable (e.g. employment) would drive a 0.96% increase in ridership.

1.4 The work completed for the Project yielded a series of detailed elasticity measures for both rail and bus users. These distinct markets were also further refined to identify different behavioral responses by weekday and weekend periods, as weekdays have been shown to have different trip purpose patterns than weekends.

1.5 It is also expected that fare responses could vary by location, with specific bus routes or Metrorail stations exhibiting different response to fare changes. To better understand how behavior might vary by location, the models developed by Steer were further disaggregated into groups of separate routes for buses and groupings of stations for Metrorail.

1.6 The resulting models and their various parameters can be used for a series of policy analyses. At one level, the Metrorail and Metrobus models can be used for forecasting; given assumptions about economic growth, fares, and LOS, the models will generate forecasts for ridership and revenues.

1.7 The models, or specifically the estimated fare elasticities, can be used to assess various fare policies, including the impacts of fare increases on ridership and revenues. The elasticities can be used to assess many other fare-related issues as well, such as whether different fare structures might yield higher ridership while being revenue neutral.

## Key Findings

1.8 The results present Metrorail and Metrobus ridership as fairly inelastic to fare, seen in Table 1, presenting potential for increased farebox recovery, as a 1% increase in fare would lead to less than proportional decrease in ridership across both week parts and modes. This indicates that Miami-Dade County could incrementally increase fares and thereby increase revenue, despite driving a minor decline in ridership.

1.9 The elasticities are further disaggregated in Section 4 of the report discussing estimation results, while this table presents the weighted average elasticity, weighted by each grouping's corresponding ridership. Fares are currently relatively low in relation to other transit systems, $2.25, so the inelastic responses to fare and ridership on the Metrorail and Metrobus conform to expectations.

**Table 1: Weighted Average Fare Elasticity by Mode & Day Type**

| | Bus | | Rail | |
|---|---|---|---|---|
| Variable | Weekday | Weekend | Weekday | Weekend |
| Fare | -0.32 | -0.37 | -0.23 | -0.18 |

1.10 The study finds that fare elasticity varies significantly between Metrorail station groups and between high-growth versus medium- and low-growth Metrobus routes. For Metrorail, fare elasticity during weekdays is highest for stations located in the "central" part of the network (including Government Center, Overtown, and other stations) and lowest for stations located in the "south" part of the network (including Coconut Grove, both Dadeland stations, Vizcaya, and others). This makes intuitive sense due to the presence of a free alternative near centrally-located Metrorail stations, namely the Metromover service. With Metrobus, fare elasticity during weekdays is highest for high-growth routes and lowest for low-growth routes, which also conforms to expectations given the idea of a more "stable" ridership base for low-growth routes that may be less sensitive to fare changes versus ridership on higher-growth routes.

1.11 Metrorail fare elasticities are, in general, lower than Metrobus fare elasticities. This conforms to results in other cities, where differences in income between rail and bus riders and the proportion of discretionary versus commuting trips are both drivers of higher sensitivity to fare changes among bus riders than among rail riders. The effects of a similar fare change on both modes would therefore affect bus ridership more than rail ridership.

1.12 The analysis also attempts to quantify the impact of Transportation Network Companies (TNCs), such as Uber and Lyft, on transit ridership. As TNC ridership data is not typically shared by such companies, the Team instead constructs a hypothetical model to simulate how TNC adoption may look if it follows patterns similar to adoption of other new and innovative products across industries. This is a commonly used analytical method to estimate market size over time of new products and/or services. Using this model, the study finds that the impact of the TNC variable on transit ridership is minimal across modes and times of week.

## Report Structure

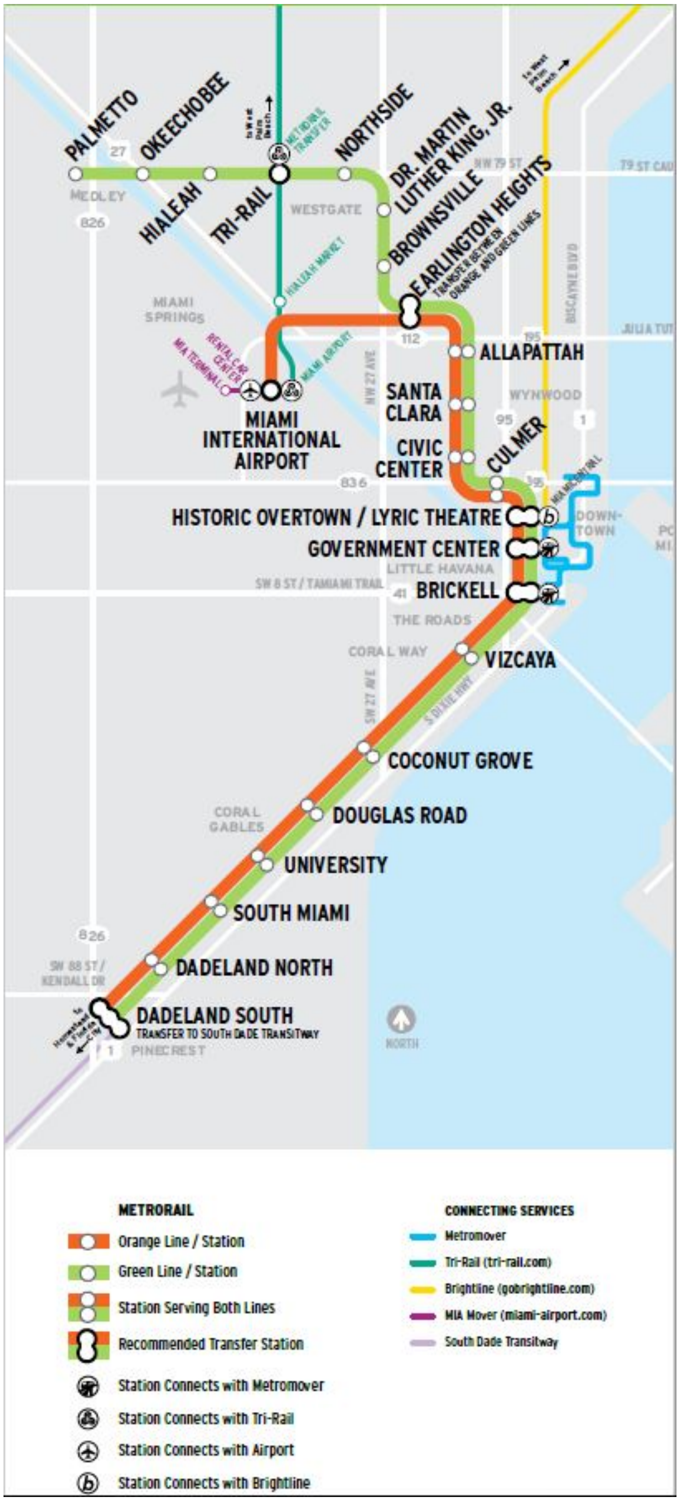
1.13 The structure of the report is as follows: Section 2 provides a description of the existing conditions of the multi-modal transit system operated by DTPW and a summary of socio-economic trends affecting demand for the system. Section 3 describes the methodology and model setup. Section 4 presents estimation results with a framework for interpretation.

# 2 Existing Conditions

2.1 Miami-Dade County DTPW is responsible for the services of Metrobus, the local bus system; Metrorail, the rail rapid transit lines; Metromover, the downtown Miami people mover, and the Special Transportation Service, a shared paratransit service. The Miami-Dade Transit system carried the 14th most bus riders and the 10th most passenger rail riders across transit systems nationwide in 2017.[1] Maps of the Metrorail and Metrobus systems are presented in Figure 1: Metrorail System Map and Figure 2: Metrobus System Map below.

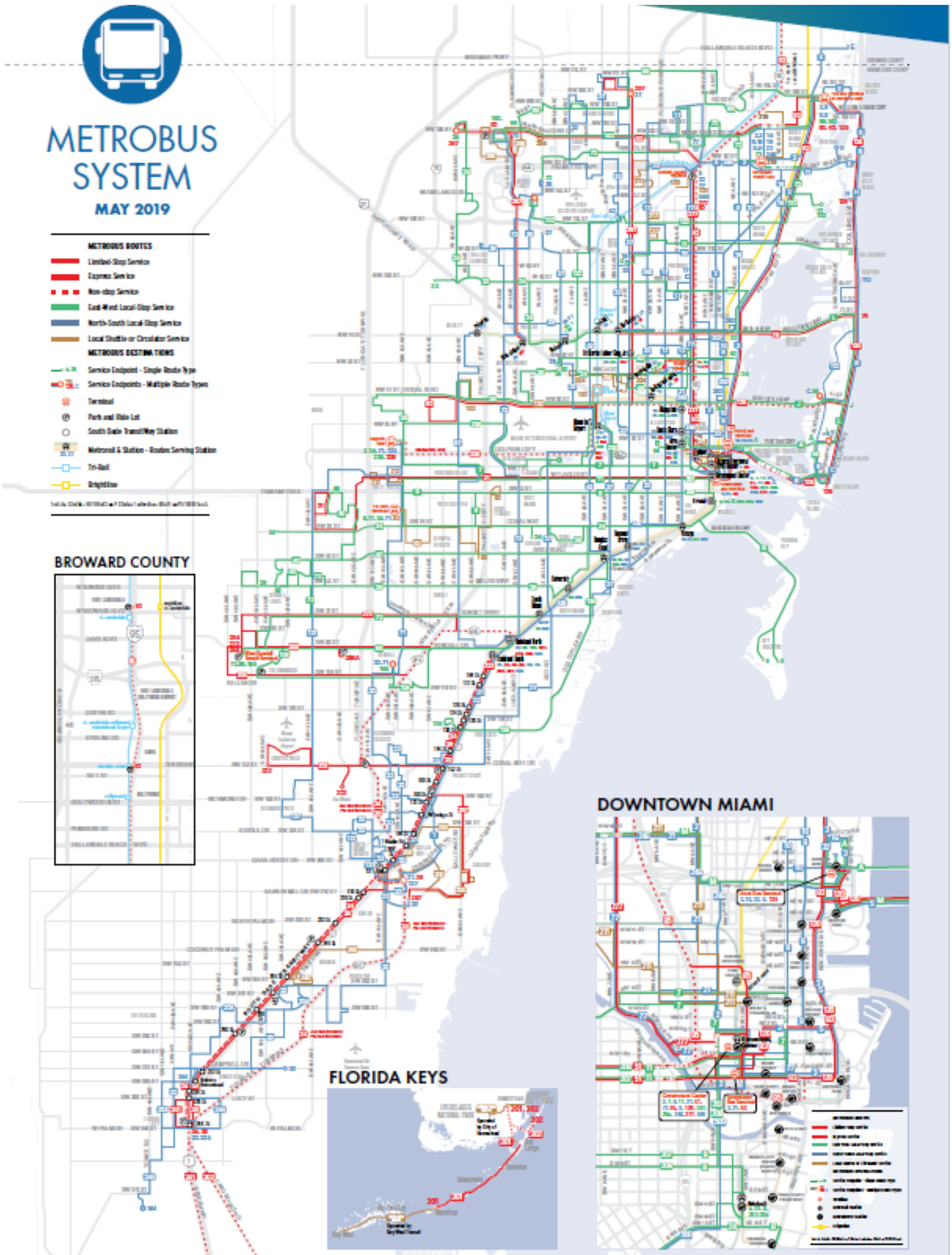
[1] **https://www.transit.dot.gov/ntd/data-product/2017-annual-database-service**. Federal Transit Administration. Retrieved July 5, 2019.

**Figure 1: Metrorail System Map**




Source: **www.miamidade.gov/transit**

**Figure 2: System Map**



Source: **www.miamidade.gov/transit**

## Metrorail

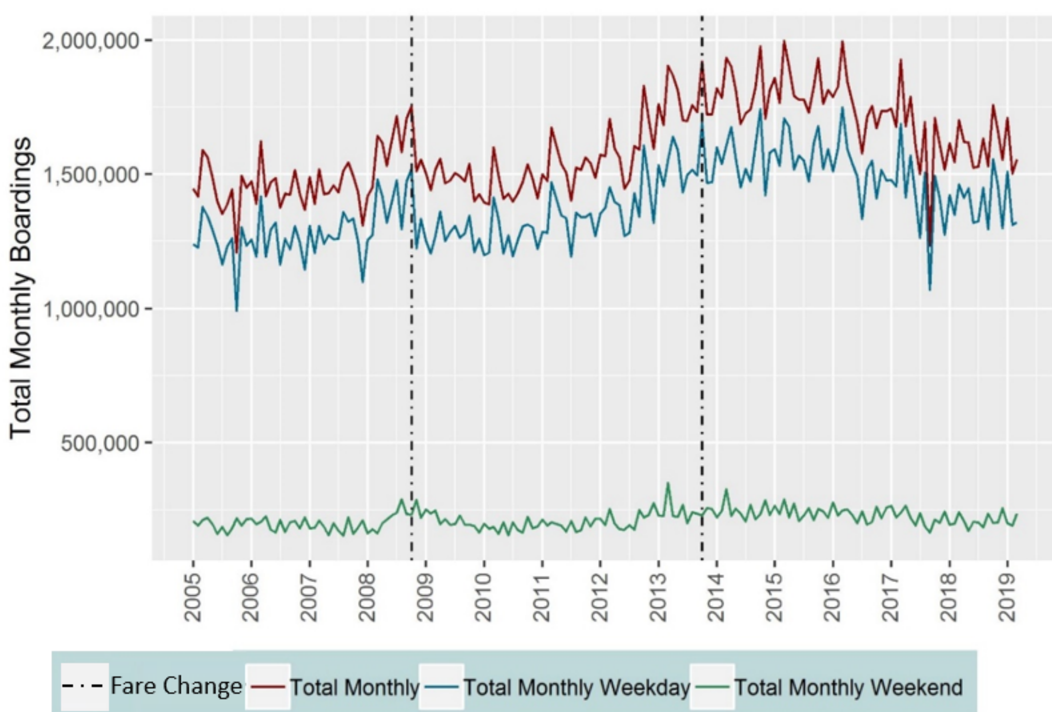
2.2 Metrorail, Miami-Dade's rail rapid transit system consists of the following two lines which include a combined total of 23 stations:

- The Orange Line, consisting of 16 stations, runs from Dadeland South through Downtown Miami to the Miami International Airport station, which opened in 2012.
- The Green Line, consisting of 22 stations, runs from Dadeland South through Downtown Miami, like the Orange Line. However, instead of continuing to the airport, the Green Line continues north from Earlington Heights to Palmetto.

2.3 Figure 3 below presents Metrorail monthly ridership, aggregated across stations, with the vertical dotted lines identifying fare changes that went into effect in 2008 and 2013. Prior to the Recession of 2008, ridership had been steady or slightly growing, and it recovered to pre-recession levels by approximately 2012 with continued growth throughout early 2016. A ridership decline began in 2016, but it has started to level off in the past year.

2.4 The annual mean monthly ridership grew by close to 30% from 2005 to 2015, and it declined by 12% between 2015 and 2018, with weekend ridership declining at a slightly higher rate than in the weekday.

**Figure 3: Metrorail Monthly Ridership - by Total, Weekday, and Weekend**

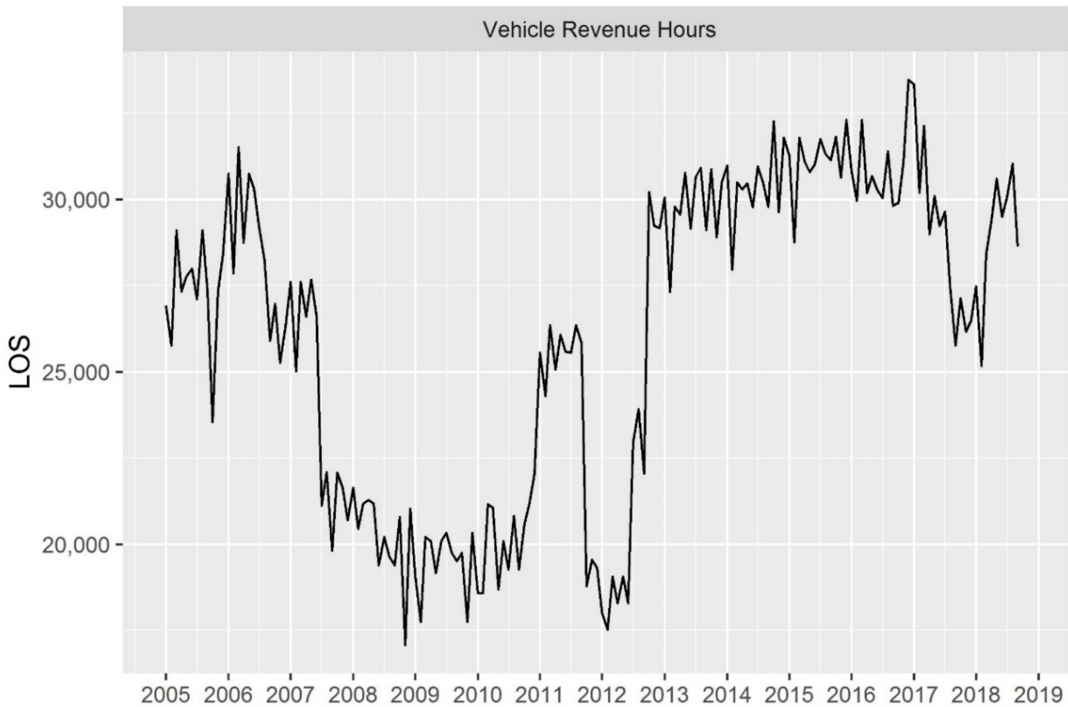



Source: Steer Analysis of Miami-Dade County DTPW data

### Level of Service

2.5 Vehicle Revenue Hours (VRH) was the variable used to represent LOS in the models. Shown in Figure 4, service hours were cut for an extended period from 2007, with the exception of a 2011 spike, until late 2012 when service was extended in response to ridership growth. Service cuts occurring in 2017 are likely related to vehicle repair concerns and were reversed in part with the introduction of new vehicles in November of 2017, part of the planned full vehicle revamp to conclude in 2019.[2]

**Figure 4: Metrorail Vehicle Revenue Hours – by Month**




Source: Steer Analysis of Miami-Dade County DTPW data

### Service Performance Metrics

2.6 Service performance can have a direct impact on ridership, while prolonged issues can have a lasting effect on a system's public image. Service performance metrics were available from October 2013 through September 2018. Metrorail, which has consistently held on-time performance (OTP) rates above 90%, experienced a sharp decline after July 2017, seen in Figure 5 below.

2.7 A spike in service disruptions on Metrorail starting in June 2016 through December 2017, seen in Figure 6, could also be responsible for the drop in Metrorail ridership, in Figure 3, where there is a noticeable drop during that period.

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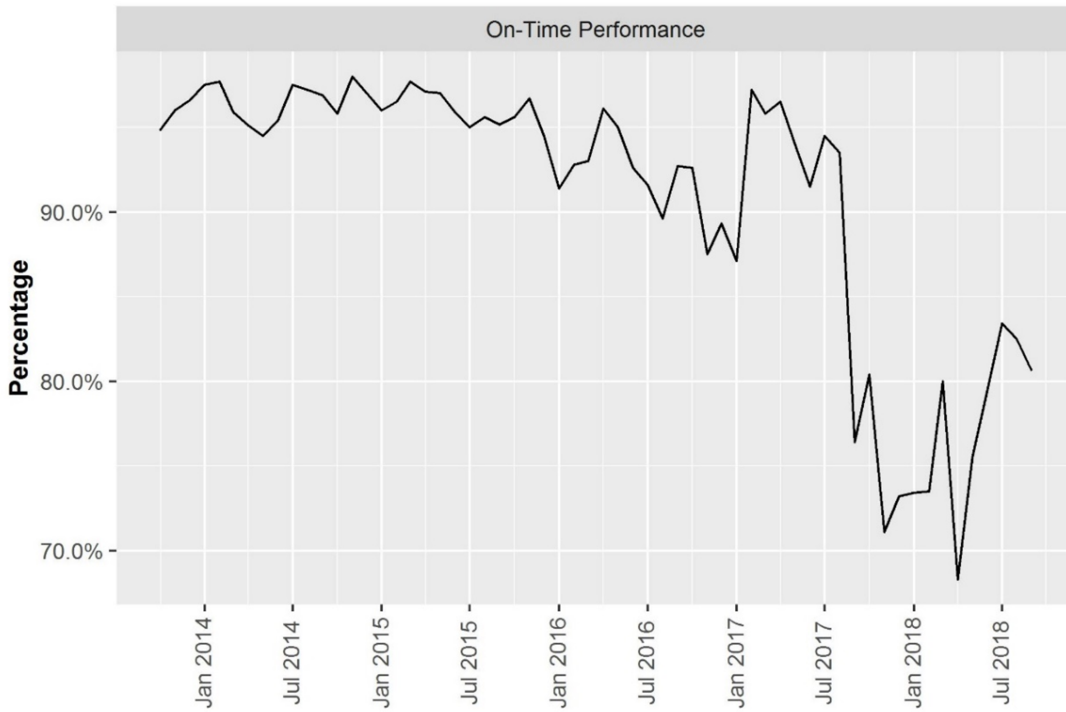
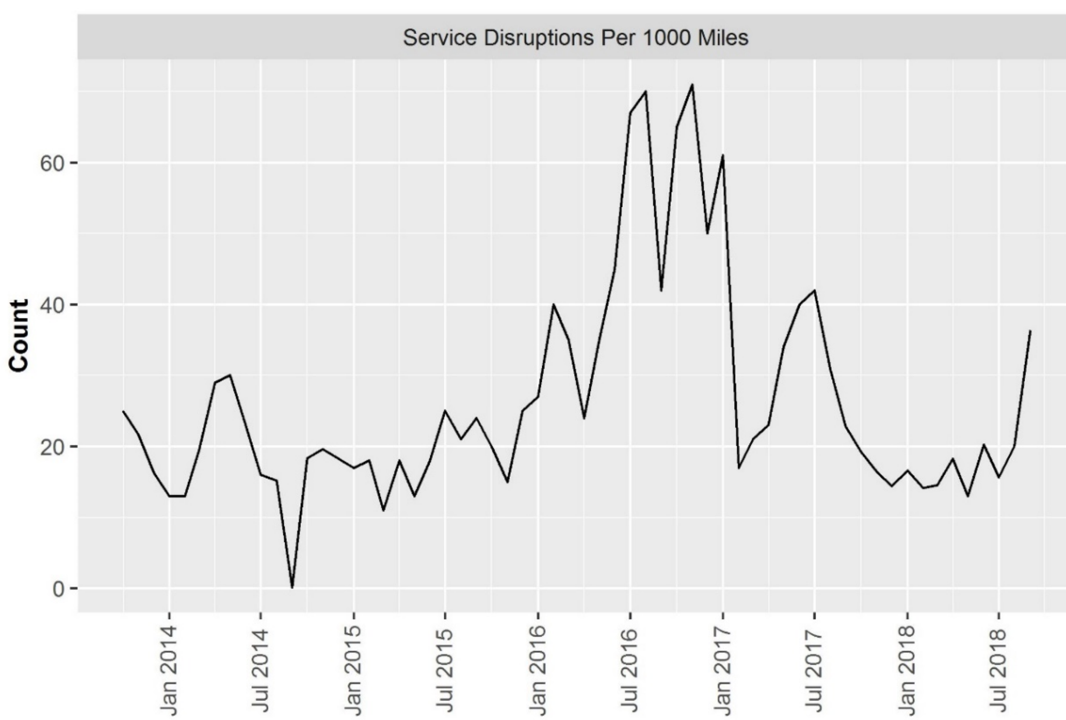
[2] Hanks, Douglas. "Help on the way for furious Metrorail passengers: The first new train in 33 years" *Miami Herald 30 Nov. 2017. Web. 8 July 2019.*

**Figure 5: Metrorail On-Time Performance– by Month**




Source: Steer Analysis of Miami-Dade County DTPW data

**Figure 6: Metrorail Service Disruptions per 1000 Miles – by Month**




Source: Steer Analysis of Miami-Dade County DTPW data

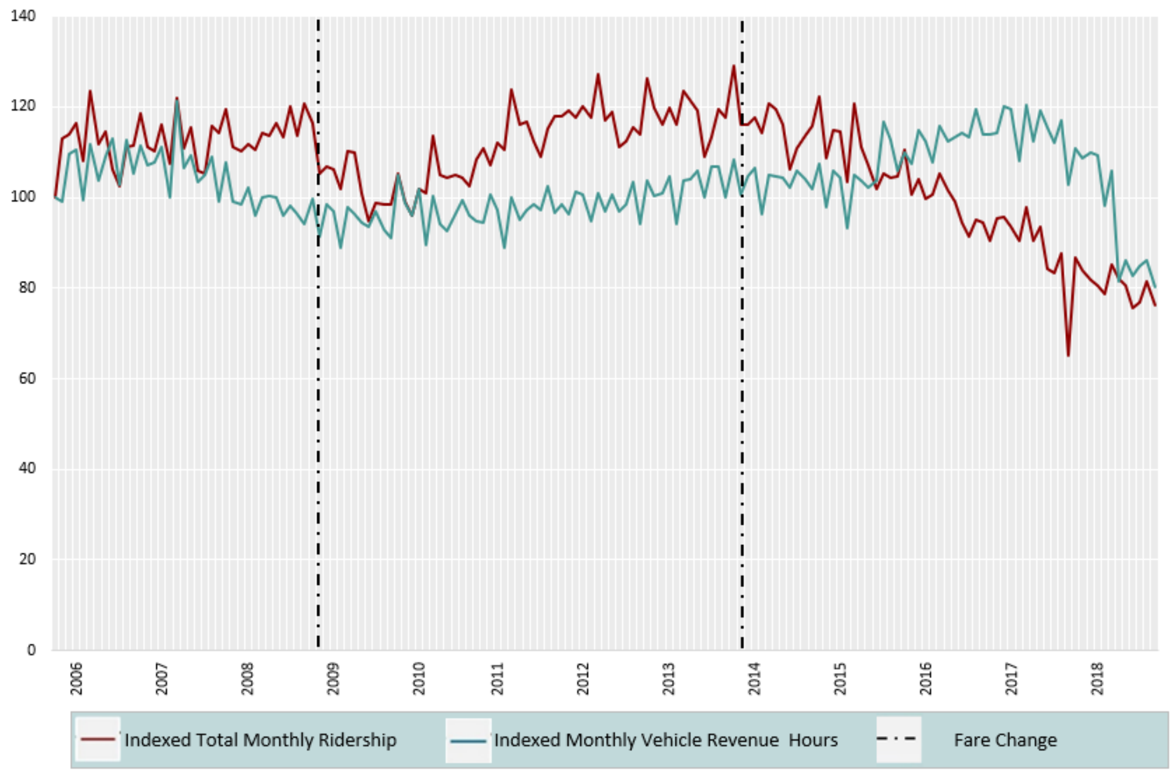
## Metrobus

2.8 In 2019, Metrobus operated 121 surface bus routes, including community shuttles, circulators, and connectors.[3]

2.9 Figure 7 below depicts total monthly bus ridership over time, aggregated over currently active routes, with the vertical dotted lines marking fare changes that went into effect in 2008 and 2013. The annual mean monthly ridership grew by just under 10% from 2005 to 2013 and declined by over 30% between 2013 and 2018, with weekend ridership declining at 35%. Weekend ridership never quite recovered to pre-recession levels, while weekday ridership recovered by 2011 and continued growing through 2013, followed by the decline noted above.

2.10 In comparison to Metrorail, Metrobus experienced lower levels of ridership growth through to 2013 and has experienced a more secular decline in ridership over a longer period of time.

**Figure 7: Indexed Metrobus Total Monthly Boardings and Indexed Vehicle Revenue Hours**




Source: Steer Analysis of Miami-Dade County DTPW data

[3] https://www8.miamidade.gov/transportation-publicworks/routes.asp#9022. Miami-Dade County. Retrieved July 5, 2019.

2.11 **The potential Impact of Transportation Network Companies**

2.12 As discussed above, both Metrorail and Metrobus exhibit declines in ridership over the last several years. This is most pronounced for Metrobus, with the decline since 2013 occurring simultaneously with a period of employment growth. As transit ridership typically increases with economic growth, recent trends suggest a structural change. One possible explanation is the introduction and growth of Transportation Network Companies (TNCs), which have been suggested by research to directly compete with transit[4]. Other research findings reach different conclusions, suggesting instead complementarity between TNCs and transit[5].

2.13 For the Project, the Team could not do an in-depth analysis of the cause of the decline. Rather it is assumed that TNCs, possibly combined with other service-related factors, led to the observed decline[6]. This structural change is therefore controlled for in the estimation process so as not to bias the estimation of other model parameters. We still refer to the structural change as associated with the introduction of TNCs, though the Team does not claim certainty as to the cause of the structural change since 2013.

**Level of Service**

2.14 Vehicle revenue hours declined in early 2018, shown in Figure 8, likely in response to the ridership decline that occurred from 2014-2018. The ridership declines clearly precede the service cuts, meaning that the period of decline was not initially the result of reduced bus service. However, this does confirm the fact that LOS is both responsive to ridership as well as impacting ridership, a point that is discussed later.

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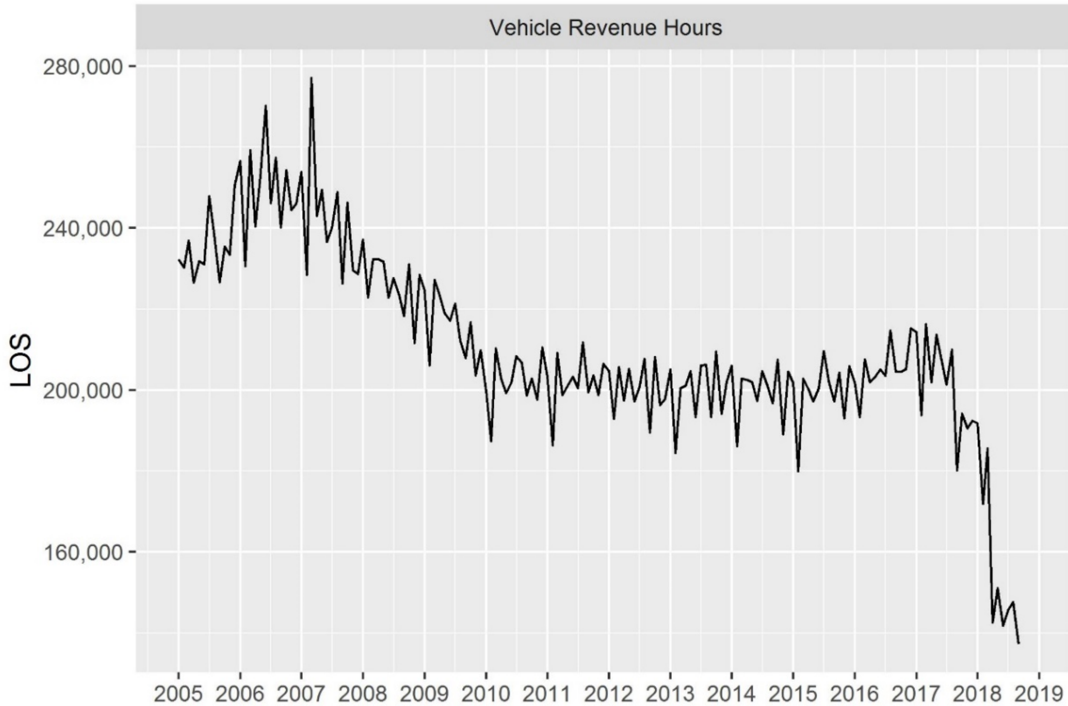
[4] Graehler, M., R. R. A. Mucci and G. D. Erhardt, 2018. "Understanding the Recent Transit Ridership Decline in Major US Cities: Service Cuts or Emerging Modes?". *Paper presented at the 98th Annual Meeting of the Transportation Research Board.* Washington, DC, January 2018.

[5] Hall, J. D., C. Palsson and J. Price, 2018. "Is Uber a Substitute or Complement for Public Transit?". *Journal of Urban Economics.* Vol 108, pp. 36-50.

[6] Note that this could also include the declines in OTP. Unfortunately, given the available data, the IMG Team cannot integrate OTP into the analytical modeling as it does not cover the periods of fare changes. However, the statistical approach the Team used to account for ridership declines is general enough to account for any negative impacts of the OTP declines and subsequent recoveries.

**Figure 8: Metrobus Vehicle Revenue Hours – by Month**




Source: Steer Analysis of Miami-Dade County DTPW data

## Metromover and Special Transportation Service

2.15 The Team was not provided data on the Metromover or Special Transportation Service, as this analysis is focused on Metrorail and Metrobus.

## Fares

2.16 DTPW does not have an extensive history of fare increases. Within the time period covered by the ridership data, 2005-present, there are two fare changes, presented in Table 2 below. These fares are used in modelling to measure the observed ridership response to fare increases.

**Table 2: Historic Fare Changes (2005-present) - Metrobus/Metrorail Base Fare (Nominal)**

| Date | Fare |
|---|---|
| 1/1/2005 | $1.60 |
| 10/1/2008 | $2.00 |
| 10/1/2013 | $2.25 |

Source: DTPW

2.17 In October 2009, DTPW worked with *Cubic Transportation Systems* to update their fare collection system to implement the EasyCard system, which is integrated across Metrobus, Metrorail, and Tri-Rail. This does not mean full fare integration, as there are transfer fees between services, but it does provide discounts from the full-fare required for cash purchases.

2.18 Current methods of fare payment include[7]:

- EasyCard – Monthly
- Easy Pass – Single Ticket Ride
- Easy Pay – App based, purchase of day or week pass

Additionally, differing discount programs are offered for corporations, county employees, senior citizens & Social Security beneficiaries, K-12 students, veterans, low-income residents, and preschool students, amongst others

## Regional Economy

2.19 As discussed earlier, economic and employment growth plays a major role in explaining transit ridership. The Team therefore analyzes employment levels in this section.

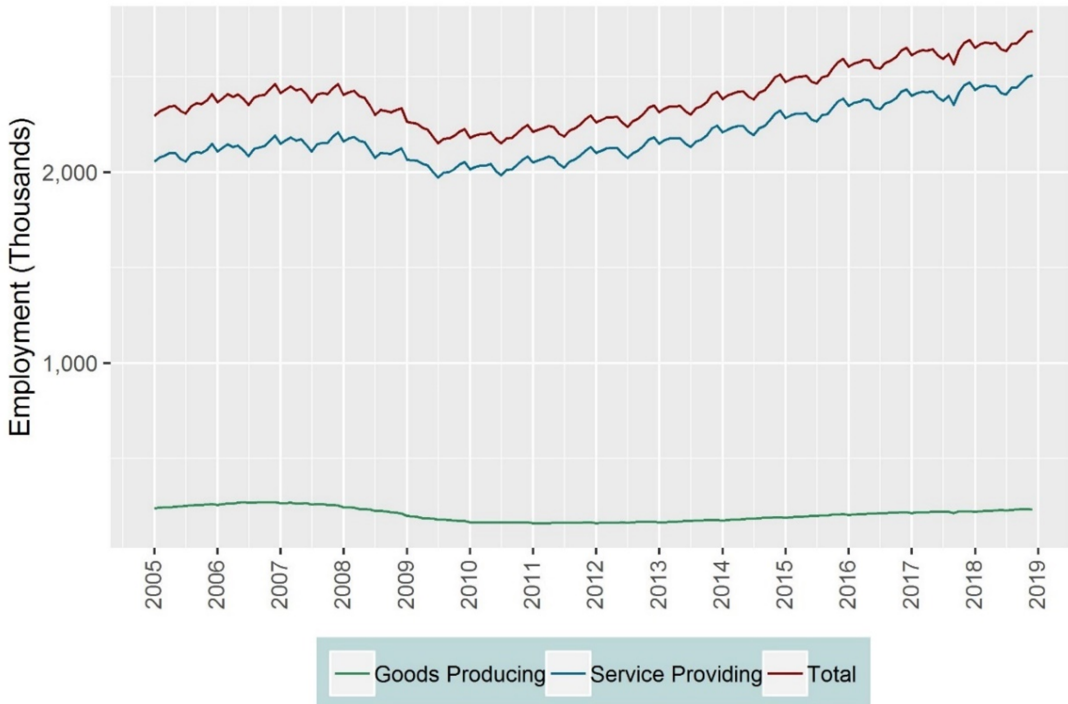
2.20 The Miami – Fort Lauderdale – West Palm Beach Metropolitan Statistical Area (MSA), encompasses Miami-Dade, Broward, and Palm Beach Counties. The MSA has experienced steady employment growth since the recession of 2008, as seen in Figure 9 below. Prior to the recession, employment peaked in 2007.

2.21 The Great Recession resulted in average annual employment decreasing by nearly 10% from 2007 to 2010. Some industries were particularly affected by the recession, with goods-producing employment declining by over 35%.[8] Since reaching the low point in 2010, average annual total employment has grown by just over 20% through 2018, with goods-producing employment growing at a higher rate than service-providing employment over that period but remaining below pre-recession levels.

[7] https://www8.miamidade.gov/global/transportation/transit-pass.page

[8] Goods-Producing Employment covers Natural Resources & Mining, Construction, and Manufacturing employment.

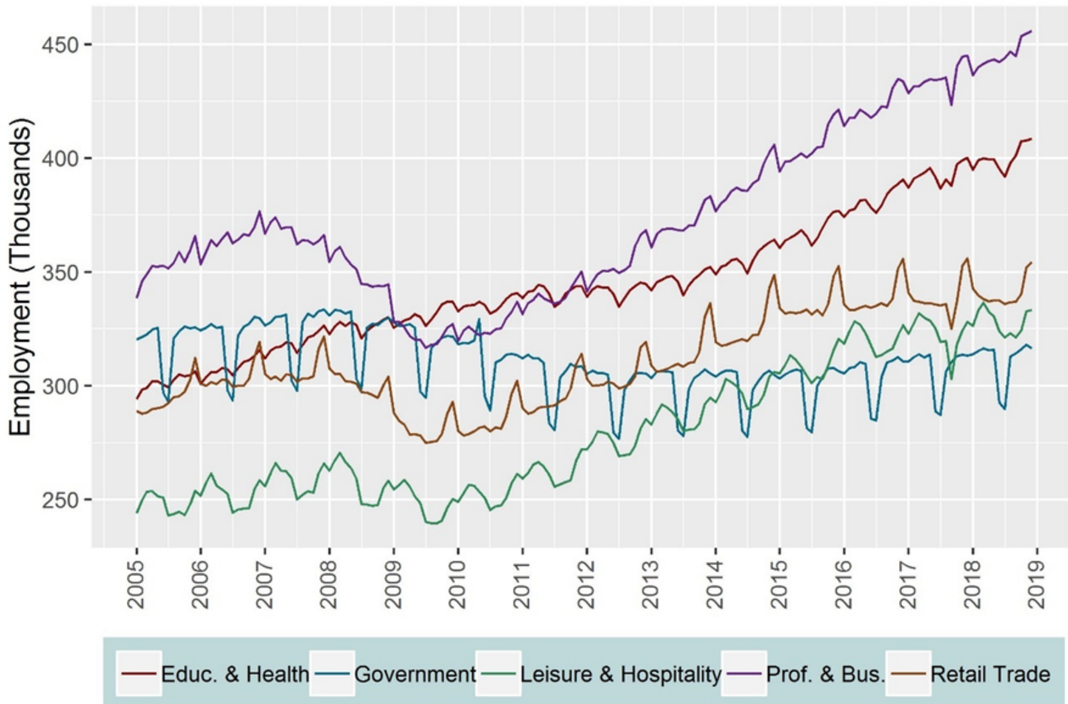
**Figure 9: Miami-Fort Lauderdale-West Palm Beach MSA - Employment Overview**




Source: Steer Analysis of Bureau of Labor Statistics (BLS) Employment Data

2.22 In Figure 10, the top five employment sectors by percent of total are presented, representing just under 70% of total employment in the MSA. Professional and business and retail trade follow similar trends, reflecting the recession of 2008, reaching pre-recession levels between 2012-2014 and exhibiting continued growth since. There is a delayed response to the recession in Government employment versus private employment and a slower recovery. Education and health employment did not experience a significant effect from the recession. Leisure and hospitality employment has experienced accelerated growth after a minimal decline during the recession.

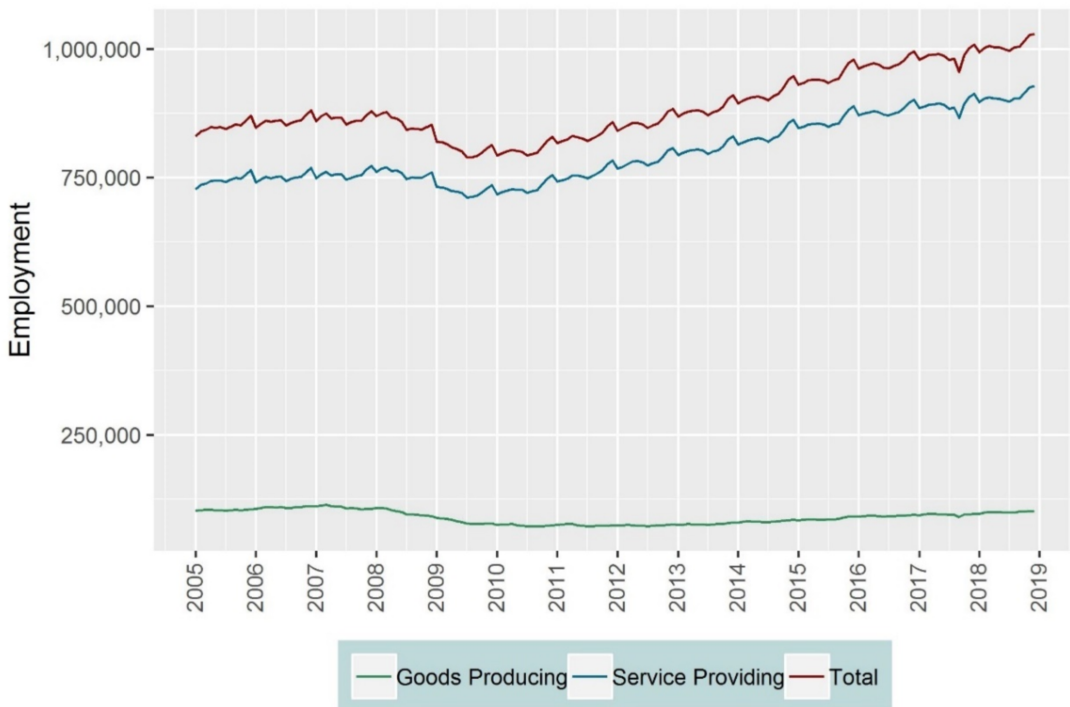
**Figure 10: Miami-Fort Lauderdale-West Palm Beach MSA - Top Five Employment Sectors**




Source: Steer Analysis of BLS Employment Data

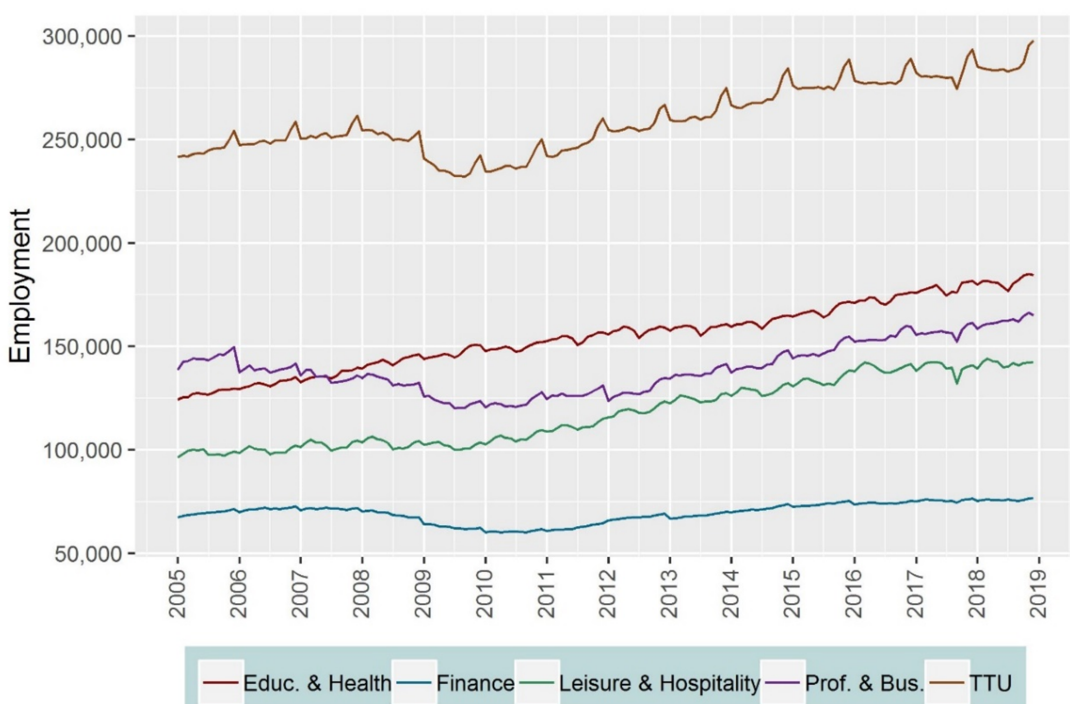
2.23 Miami-Dade County, making up a significant portion of the MSA employment as discussed above, naturally experienced similar employment trends to the MSA, as seen in Figure 11. The major employment sectors are presented in Figure 12, representing over 80% of total employment in the county. Both education and health and leisure and hospitality employment do not decline during the recession, while the other major employment sectors were negatively impacted by the recession. All major sectors experienced growth from 2010 to 2018, headlined by leisure and hospitality and professional and business employment, which have grown by over 30%. Trade, transportation, and utilities (TTU) employment, which is the largest employment aggregate with just under 300,000 employees, follows a similar trend to the professional and business sector.

**Figure 11: Miami-Dade County - Employment Overview**




Source: Steer Analysis of BLS Employment Data

**Figure 12: Miami-Dade County - Top Five Employment Sectors**




Source: Steer Analysis of BLS Employment Data.

## Transit Data Description

Data which was provided by DTPW and collected by the Team was used to establish a database for econometric modelling work. The database includes:

- Monthly ridership, split by weekday and weekend, for both Metrobus and Metrorail;
    - Time-span: 2005 – February 2019
    - Source: DTPW
- Monthly vehicle revenue hours and miles, for both Metrobus and Metrorail;
    - Time-span: 2005 – September 2018
    - Source: DTPW
- Monthly service performance metrics, including on-time performance, for Metrorail;
    - Time-span: October 2013 – September 2018
    - Source: DTPW
- Historic Fares;
    - Time-span: 2005-present
    - Source: DTPW
- Monthly historic employment by industry for the surrounding MSA.
    - Time-span: 2005-2018

    Source: Bureau of Labor Statistics

# 3 Methodology and Model Setup

## General approach

3.1 Steer developed multivariate econometric demand models that are in keeping with practice in transit planning and economics. The models treat demand for transit as *derived demand,* meaning that the level of economic activity best represents the factors that generate commutation, leisure, tourism, and other trips on transit. In order for the models to generate an unbiased fare elasticity for analysis and projections, the models need to include all the factors that influence demand. Besides the economic activity that generates transit trips, the models need to include fares as well as a measure of LOS during the estimation phase.

3.2 The models followed the structure below, with station (or route) *i*, and time *t*:

$$(1)\quad Y_{it} = X_{it}\beta_i + TNC + Fixed\,Effects + \epsilon_{it}$$ [9]

As is typical in passenger transportation, Steer postulates that users of the multimodal lines are motivated by various factors that determine their desired use of the service. Demand for each station or route is generated by a series of variables (represented by $\beta_i$), including regional employment growth (which drives commutation); growth in leisure employment (which captures the drivers of discretionary trips by residents and non-residents); LOS[10] (service changes affecting user mode choice by changing transit trip frequency and total travel time); *TNC* is a variable that identifies the period where TNCs have operated (a period which, as discussed, is associated with recent ridership declines and may reflect a net effect after accounting for competition and complementarity to an alternative mode of transportation), and fares, whose estimated coefficient reveals the price sensitivity of users (affecting users' mode choice by changing trip cost)[11].

3.3 Another aspect of the model detailed in (1) is controls for *fixed effects*. Fixed effects controls are a benefit of the panel structure, allowing the models to control for time-invariant fixed effects, i.e. inherent differences between routes/stations. An example for this is that Government Center,

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[9] The explanatory variables are represented by the matrix X. β is a vector of coefficients that details the influence of the various explanatory variables on the volume of riders in a given period. The fixed effects term controls for time invariant fixed effects. The variable ε is a random error term.

[10] LOS impacts the non-pecuniary cost of travel for transit users, principally wait time and in-vehicle time.

[11] Time series panel data is multi-dimensional, with both cross-sectional and time-series dimensions. In this case, the cross-sectional dimension is the station for Metrorail and route for Metrobus, and the time-series dimension is the date, with monthly observations by station or route from 2005 through the beginning of 2019.

which is connected to the Metromover and located in Downtown Miami, is inherently different from Palmetto, located in a residential setting with fewer transfer modes. Additionally, the panel structure increases the number of observations the models are estimated from, improving model reliability.

**Controlling for simultaneity bias**

3.4 The LOS variable is included in the models and is essential to understanding ridership trends accurately. However, as mentioned previously, LOS both affects ridership while also being influenced by prevailing ridership trends. The causation between ridership and LOS goes both ways, which can result in what is known as *simultaneity bias,* a situation common in econometrics that requires a particular estimation strategy.[12]

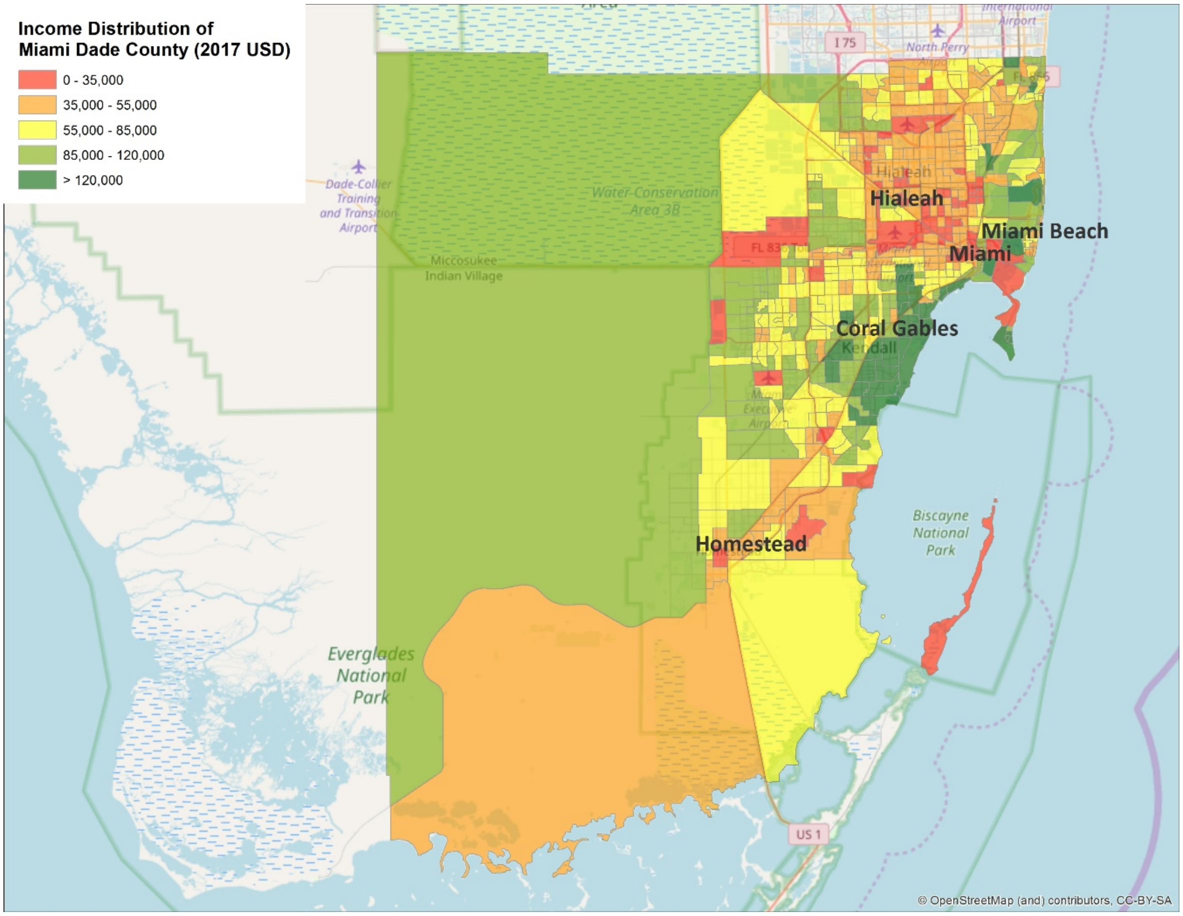
## Model Segmentation

3.5 The ridership for Metrorail and for Metrobus had to be broken down by geographic market to account for potentially different growth trends based on station/route location and the areas and people they service. Metrorail ridership is available by station and Metrobus ridership by route.

Figure 13, depicting median income by census tract, will be referenced throughout the model segmentation discussion as it aids in understanding where specific stations and routes are located. While local income levels do not enter explicitly into the estimation of ridership and fare elasticities, it is instructive in helping to understand differences in local elasticity estimates.

[12]A typical problem encountered in estimating models such as (1) is the two-way causality between ridership and LOS: LOS changes in response to changes in ridership, but ridership is itself influenced by LOS. If simultaneity bias is not accounted for, the endogeneity in the demand models of the service levels can lead to biased estimates of model coefficients. In order to control for simultaneity bias, Steer used a two-stages least squares estimator, which is the most widely-used technique to control for simultaneity in demand modeling. Two-stage least squares generates an “instrument” for LOS that is correlated with the endogenous variable but not to the error terms. This instrument is essentially a stand in variable for LOS. Replacing the LOS variable with the instrumental variable generates unbiased and robust model results. In this case, Steer used a lag of the LOS variable as the instrumental variable to address the endogeneity issue.

**Figure 13: Miami-Dade County - Income Distribution by Census Tract**



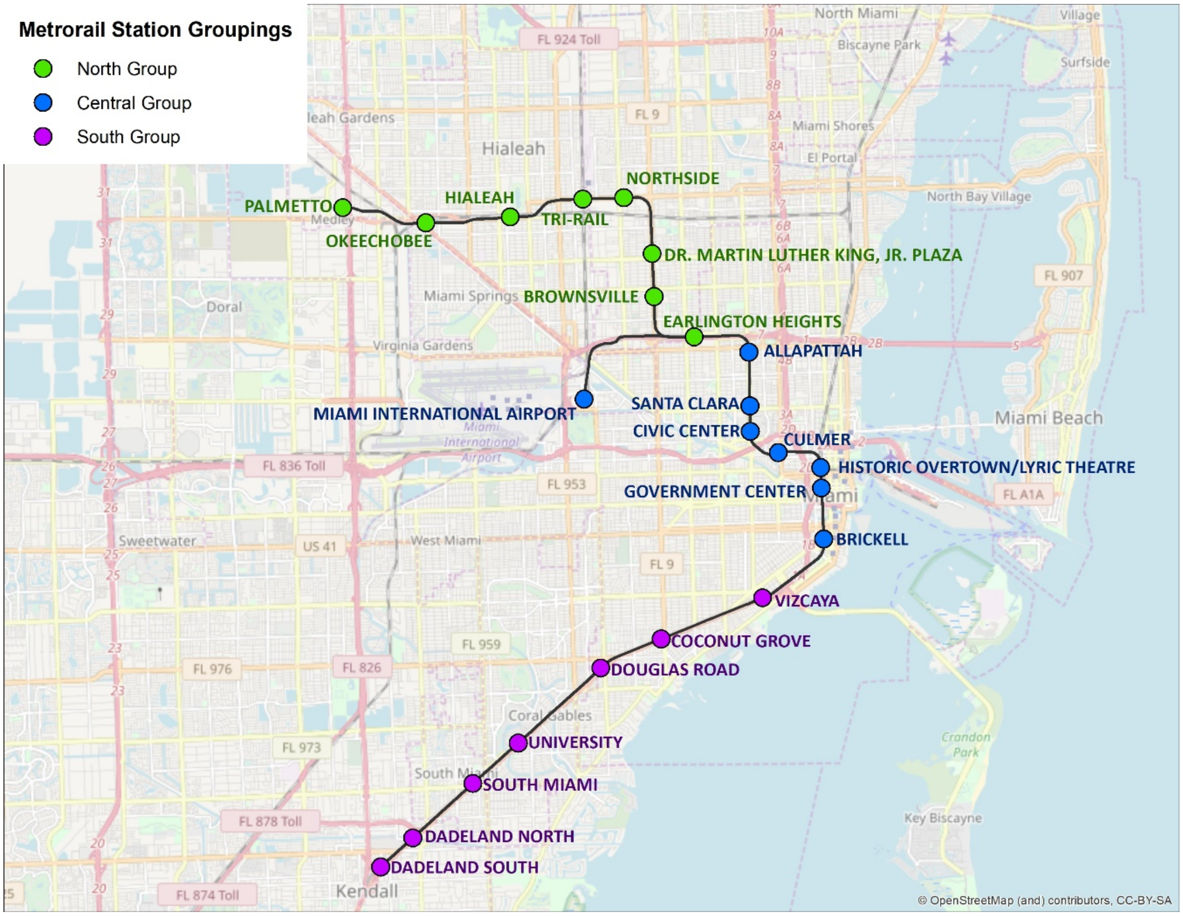

Source: American Community Survey (2013-2017 5-Year Estimates)

## Metrorail

3.6 Based on the clustering of Metrorail stations, the rail ridership data was segmented into 'North', 'Central', and 'South' groups, which also corresponded to stations with similar growth patterns being grouped together, shown in Figure 14.

**Figure 14: Metrorail Station Groupings**

7




3.7 The North group corresponds to a mixed-use locality with both employment centers and residential properties[13].

3.8 The North group consists of eight Metrorail stations:

Palmetto located in the town of Medley,
Okeechobee, Hialeah and Tri-Rail in the city of Hialeah,
Northside and Dr. Martin Luther King Jr Plaza in Gladview, and
Brownsville and Earlington Heights located in Brownsville.

3.9 Together, these localities constitute a region of mixed use with many residential communities along with pockets of industrial and retail employment which represent lower-income ranges than other regions connected by the Metrorail network.

3.10 The Central group consists of:

Allapattah, Santa Clara, and Civic Center stations in the neighborhood of Allapattah,
Culmer and the Historic Overtown/Lyric Theatre stations in the Overtown neighborhood,
Government Center station in the Central Business District,
Brickell station in the Brickell neighborhood, and

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[13] **https://www.hialeahfl.gov/467/About-Hialeah**. City of Hialeah. Retrieved July 8th, 2019

Miami International Airport.

3.11 The large cities and the tourist areas contribute to a region with average incomes higher than the North group but lower than the South group.

3.12 The South group consists of:

Vizcaya station in Little Havana,
Coconut Grove and Douglas Road stations in Coral Way,
University station in Coral Gables,
South Miami station in South Miami, and
Dadeland North and Dadeland South stations in Dadeland.

3.13 Coral Gables and South Miami are towns experiencing increased development in the region and have the highest incomes of the areas serviced by Metrorail.

*Weekend Model Structure*

3.14 To provide additional stability, meaning more statistically significant elasticities, the Metrorail weekend models were aggregated so that all stations are included in one model instead of separate models for each station region. This allowed for a larger number of observations and proved successful in producing stable and intuitive results for weekend rail ridership.

**Metrobus**

3.15 The Metrobus serves a region much larger than that served by Metrorail. The Metrobus network stretches from the southern part of Broward County, with several routes and stops in Miami-Dade County, and has two routes that run to Monroe County. As mentioned on page 10, Metrobus experienced a significant decline between 2014 and 2019 resulting in negative CAGRs for most routes during this time period. For Metrobus, groupings were based on route ridership CAGRs between 2015 and 2018; these groups are shown in Table 3. The groups represent the Low, Medium, and High CAGRs relative to the rest of the group. Routes with positive growth were not explicitly separated because they were not numerous enough to separate into a unique grouping. CAGRs by route are shown in Appendix A.

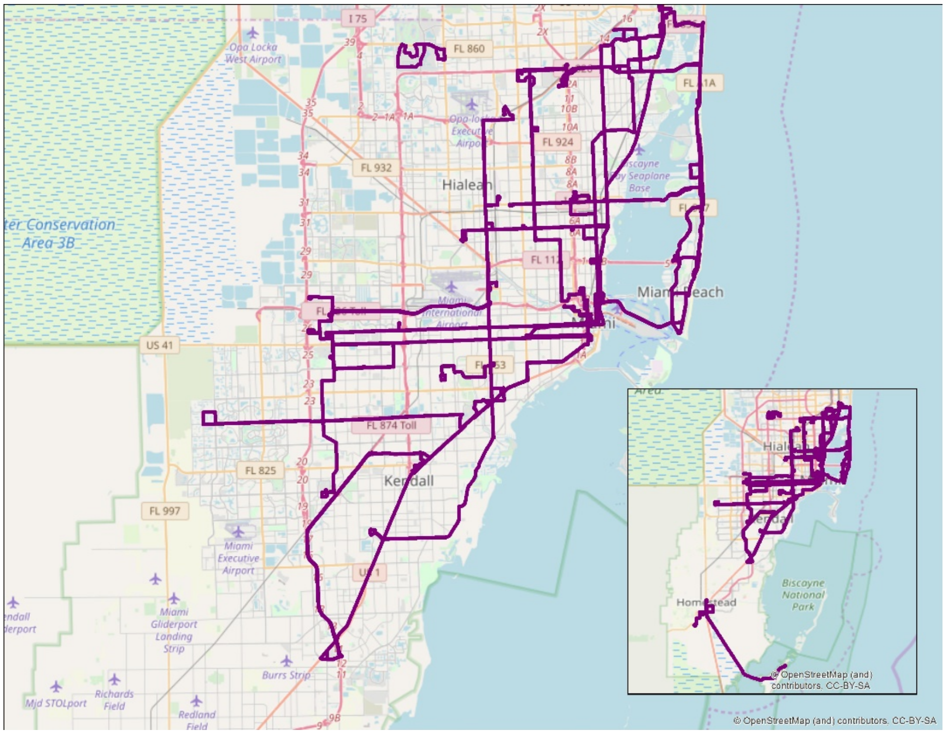
**Table 3: Bus Groupings - Ridership CAGR Ranges (2015-2018)**

| Route Grouping | Ridership CAGR between 2015 and 2018 |
|---|---|
| Low | (52.82%) - (11.31%) |
| Medium | (11.13%) - (7.01%) |
| High | (7.00%) - 11.90% |

*Low Routes*

3.16 As shown in Figure 15, the Low group consists of 26 routes in the weekday and 22 routes in the weekend that cluster around the east end of Miami-Dade County, routes serving the areas between the CBD and the inland City of Sweetwater, and routes that travel along the east coast south towards Cutler Bay. Two outlier routes were the North Pointe Circulator in Hialeah and the Card Sound Express that goes to Key Largo, Monroe County. Overall, the routes service areas with a variety of employment industries, and there are a large concentration of routes in the CBD.

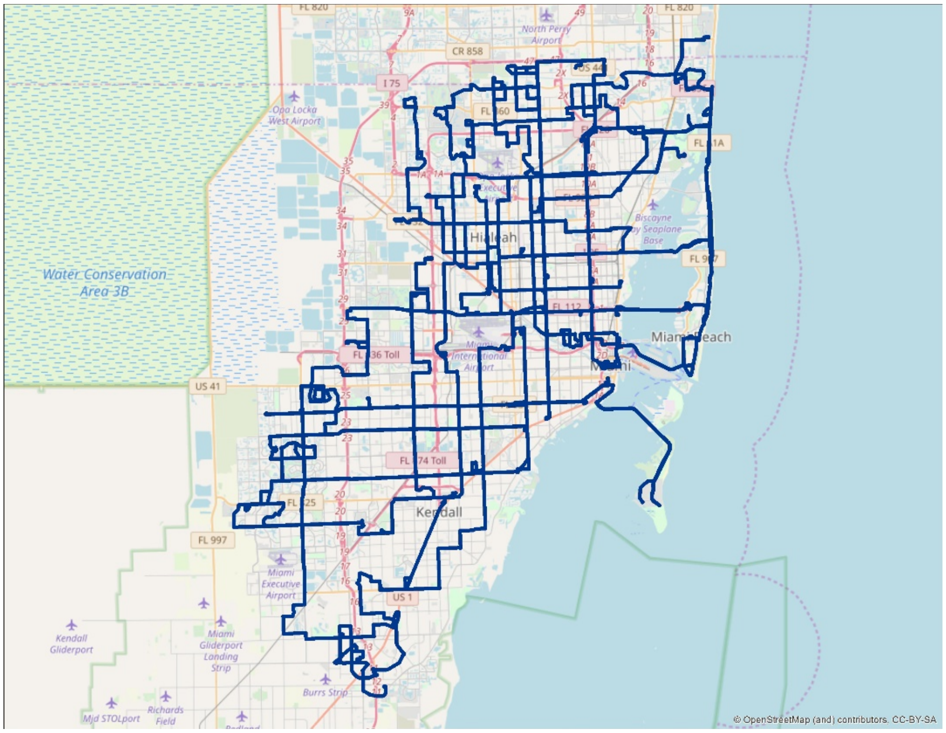
**Figure 15: Metrobus Low Group**




*Medium Routes*

3.17 The Medium group are made up of 30 routes in the weekday and 27 routes in the weekend. As shown in Figure 16, the routes are concentrated from the northern part of the network to Cutler Bay. These routes cover central Miami-Dade County, including the City of Miami, and might be capturing channels that connect stable employment areas as well as areas with upcoming developments.

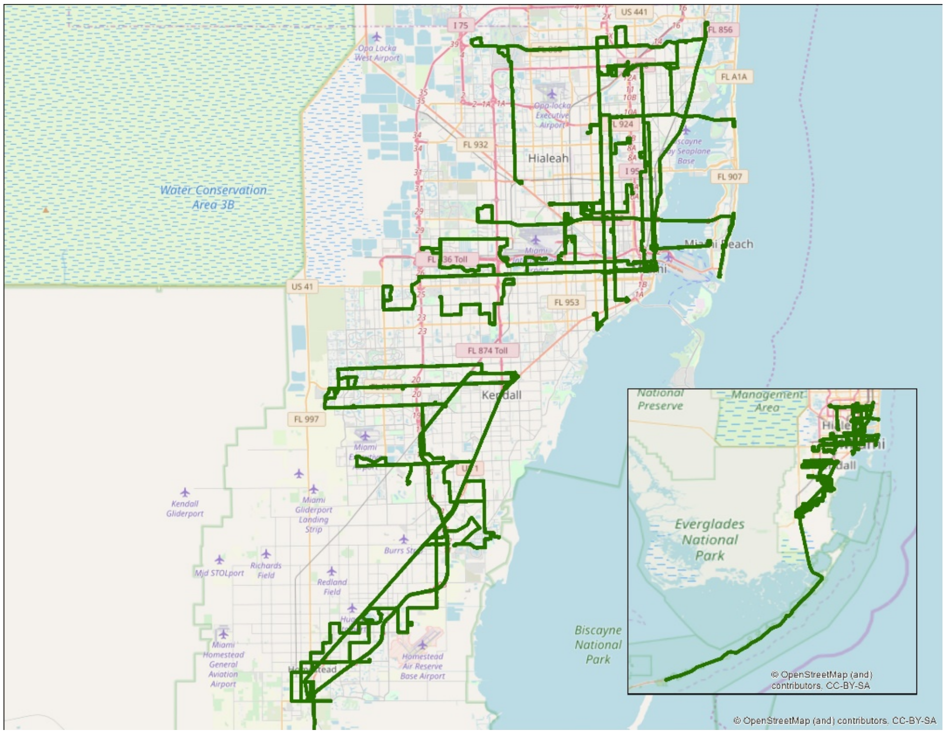
**Figure 16: Metrobus Medium Group**




*High Routes*

3.18 The High group has 25 weekday routes and 17 weekend routes. Unlike the other two groups, the High group has a more distinctive separation of clustering as shown in Figure 17. The routes run from the northern part of the Metrobus network to the CBD, from Dadeland to Homestead, and they include the Dade-Monroe Express going to Marathon, Monroe County. The group does not include routes that service areas such as Coral Way, Coral Gables, and South Miami, nor areas that correspond to the South group of the Metrorail network.

**Figure 17: Metrobus High Group**




## Data constraints

3.19 The ridership, fare, and LOS variables of the data set had certain attributes that needed to be accounted for thus constrained potential modeling approaches. The attributes and their impact on the model are described below.

**Fare**

3.20 The fare variable is our primary independent variable of interest used to determine the elasticity of demand. For elasticities to be computed, it is essential for the data to have as many fare changes as possible. This is because the model can better capture responses to fare changes the more changes there are to observe. The dataset for these variables begins in January 2005 and ends in March 2019. During this period, there were two fare changes, from $1.60 to $2.00 in October 2008 and from $2 to $2.25 in October 2013. While this is less variation than would be ideal, the model does produce stable and statistically significant results even with two fare changes.

**Level of Service Data**

3.21 VRH was the variable used to represent LOS in the models. However, this data was available only until September 2018. This limited the modeling time period to January 2005 to September 2018. The other LOS variables considered were Vehicle Revenue Miles (VRM) and OTP. Using VRM produced slightly less robust models and OTP data was only available from October 2013 to September 2018. For this reason, VRH was deemed the best variable to represent the LOS.

**Miami International Airport Station**

3.22 The Metrorail started operations at the Miami Intermodal Center on July 28th, 2012 and the Metrorail stop now appears as Miami International Airport on Metrorail schedules. As such, there is no ridership data prior to July 2012 for this station. Due to the unique nature of a rail station with an airport connection, the Miami International Airport Metrorail station was initially modeled on its own. However as the resulting model fit was unsatisfactory, and because ridership trends were consistent with other Central stations, it was grouped into the Central category as described in paragraph 3.10.

**Bus Ridership Data**

3.23 The bus ridership data Steer received had 145 routes. For modeling, the data was limited to only the 89 bus routes that were identified to be active as of July 9th, 2019 so that the data is comparable over time. Additionally, certain routes such as routes 12 and 21 and routes 207 and 208, are combined during certain times of the year and thus these routes were combined in a way to avoid double-counting.

## Variable Selection

**Employment**

3.24 Employment variables for models were selected for each of the six groupings based on the employment industries that were associated with the geographic Metrorail station locations and Metrobus routes. Below is a description of the employment variables by day of week and Grouping.

*Metrorail*

**Weekday**

3.25 All the Weekday models use employment for the Miami MSA which consists of three major employment centers: Palm Beach in Palm Beach County, Pompano Beach and Fort Lauderdale in Broward County and Miami in Miami-Dade County. These three centers may be benefitting from agglomeration network effects (positive effects of urban employment centers being located close together) which would involve transport between the different centers thus playing a role in transit ridership.

**Weekday North**

The educational, health, and leisure industries tend to be most representative of the state of the economy in larger cities. The Metrorail North group has three rail stations in Hialeah, the sixth largest city in Florida, and as such using Miami MSA education, health, and hospitality & leisure employment produced the most robust results in terms of model fit and employment elasticity.

**Weekday Central**

The Central group's employment is similar to the employment variable of choice for the North group. However, the Miami-Dade County education and health services employment variable fared the best. The exclusion of hospitality and leisure employment may be attributed to the professional and support services such as education and health outweighing the tourism industry in the area.

**Weekday South**

The South group's employment variable is the same as that of the North group. The Miami MSA education, health, and hospitality & leisure variables reflect a region made up of larger cities such as Coral Gables and South Miami.

**Weekend**

3.26 The Weekend model has the most robust results with the Miami-Dade County education and health services employment variable. Unlike the Weekday models, the Weekend models are not primarily driven by employment, being affected also by weekend leisure activities and employment in such industries. Though the hospitality and leisure employment variable produced significant and reasonable model outputs, education and health services employment is more representative of the economy as a whole and thus captures other weekend ridership patterns as well.

*Metrobus*

**Weekday**

3.27 The Metrobus network covers a larger region than the Metrorail network but has a clustering of routes in the CBD district. This dichotomy is reflected in half of the six models using the Miami MSA employment and half using Miami-Dade County employment.

**Weekday Low**

For this group, the models used Miami-Dade County professional and business services employment. Since the Low group routes tend to focus on the Central part of the Metrobus network area, this selection reflects people commuting to work from their homes along a bus network to the employment hub. The Miami employment center has been a historical business district and as such these routes may be stable routes without much growth over the past few years.

**Weekday Medium**

The Medium group consists of routes clustered in the Central zone but traversing the northern part of the network to Cutler Bay, a city about 20 miles south of Miami. The sprawl of this group could be attributed to economic development occurring in other parts of the region, urging commuters to travel further. As such, the Medium group Weekday models use the Miami MSA private service-providing industries employment, representative of a geographically expansive Miami employment center.

### Weekday High

For the High group models, Allapattah, in the Northern region, is one of Miami's largest industrial areas[14] and the southern part of the High group is an agricultural region[15]. Both these industries are categorized as goods-producing industries, and the use of the Miami MSA goods-producing employment variable reflects this pattern by producing robust results.

## Weekend

### Weekend Low

The Low group Weekend models use the Miami MSA private service-providing industries employment, which is the largest industry in the region. This employment reflects the state of the economy, implying increased leisure trips as the economy improves.

### Weekend Medium

Like the Low group Weekend models, the Medium group models use the Miami MSA private service-providing industries employment to represent the state of the economy as a whole and to capture weekend leisure trips to the area.

### Weekend High

The High group Weekend models use the Miami-Dade County professional and business services employment, which has grown by over 30% from 2010 to 2018.

## TNC Variable

3.28 UberX, the largest TNC service in the US, entered Miami in June 2014[16] and was legalized in May 2016[17]. To capture the growth in this alternative transport mode, a TNC variable was included in all models except the Metrorail Weekend ridership model. This variable had a logistic function to replicate the "S-shaped" trajectory of TNC supply and adoption by users: this S-shape is a typical representation of the adoption of any new technology and is frequently used in empirical analyses of new product adoption by consumers. The S-shape represents an initial accelerating growth in the adoption phase that reaches a peak growth rate followed by gradually slowing growth as the market eventually approaches and then reaches saturation.

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[14] *Allapattah, MPO Community Background Report, Miami-Dade County*, Florida International University, January 1st, 2011.

[15] **http://www.dade-agriculture.org/p/who-we-are.html** , Dade County Farm Bureau. Retrieved on July 9th, 2019.

[16] Elfrink, Tim. "UberX Will Launch in Miami Today, Defying Miami-Dade's Taxi Laws" *Miami New Times* 04 June 2014. Web. 9 July 2019.

[17] Hanks, Douglas. "Uber and Lyft are now legal in Miami-Dade, and taxi owners vow to fight back" *Miami Herald* 03 May 2016. Web. 9 July 2019.

**LOS Variables**

The LOS variable, VRH, was used to measure the quality of service and the impact it has on ridership over time. VRH represents the number of hours each vehicle (buses or trains) was in use by month and is measured in hours.

# 4 Estimation Results

4.1 The objective of the modelling effort was to calculate the fare elasticity of demand for both the Metrorail and the Metrobus transit systems for weekdays and weekends. In these models, the LOS variable, VRH, is the endogenous variable, and this is instrumented on its own lag which is the VRH lagged by one month.

4.2 In total, ten models were produced to capture the variations in impact by transit system, day of week, and groupings within transit systems. The Metrorail system has four models in total, three models for the weekday period, for the north, central, and south groups, and one model for all stations for the weekend period. The Metrobus system has six models in total, three models in each of the weekday and weekend periods for the low, medium, and high groups.

4.3 Overall, all models produced significant elasticities within the expected range for the fare and employment variables. The VRH variable has unexpectedly large elasticities for the Metrobus Low group (both weekday and weekend) but is consistent across the other models. Lastly, the TNC variable has very low elasticities, implying a 1% increase in TNC activity is associated with a 0.002% - 0.007% decrease in ridership across all models. While the relationship is one of association (rather than a conclusive causation), it is noted the relationship is highly significant in all models.

## Metrorail Models

**Weekday North**

4.4 Shown below in Table 4, the weekday north model produced a fare elasticity of -0.17, which is interpreted as a 1% increase in the fare corresponding to a 0.17% decrease in ridership. This estimate is significant at the 99% confidence level. The secondary variables of interest are employment and VRH, which had elasticities of 0.98 and 0.21 respectively and are both significant at the 99.9% confidence level. Employment elasticity is the lowest of the weekday models but falls within the expected range. For a better model fit, a dummy variable was included to capture slightly different growth patterns for the Hialeah, Northside, and Tri-Rail stations.

**Table 4: Metrorail Weekday North Model Summary Results**

| Variable | Elasticity | |
|---|---|---|
| Fare | -0.169 | ** |
| Employment | 0.976 | *** |
| VRH | 0.205 | *** |
| TNCs | -0.002 | *** |

Signif. codes: ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05

### Weekday Central

4.5 Shown below in Table 5, the weekday central model has a noticeably higher magnitude fare elasticity than the other Metrorail weekday models. The fare elasticity for this model implies that a 1% increase in the fare corresponds with a 0.37% decrease in ridership. Employment has a higher elasticity of 1.29 than the low weekday model but slightly lower than the south model's employment elasticity. Additionally, Steer included dummy variables for the Overtown station prior to 2008 and for Brickell after 2013 due to different growth patterns. Overtown shows a significant increase in ridership between 2006 and 2009, which is opposite to the trend observed in the other stations during this timeline. Between 2013 and 2014, the Brickell station had a growth rate approximately 9% higher than the rest of the central group, and this trend of higher growth continues through 2016.

**Table 5: Metrorail Weekday Central Model Summary Results**

| Variable | Elasticity | |
|---|---|---|
| Fare | -0.365 | *** |
| Employment | 1.289 | *** |
| VRH | 0.192 | *** |
| TNCs | -0.002 | *** |

Signif. codes: '***' 0.001 '**' 0.01 '*' 0.05

### Weekday South

4.6 Shown below in Table 6, the weekday south model has the lowest magnitude fare elasticity of all the models, and the elasticity can be interpreted as a 1% increase in fares corresponds to a 0.10% decrease in ridership. The employment variable has an elasticity of 1.48, which is the highest of the three weekday models. Unlike the other two weekday Metrorail models, an additional dummy did not improve the model fit, and as such none were included.

**Table 6: Metrorail Weekday South Model Summary Results**

| Variable | Elasticity | |
|---|---|---|
| Fare | -0.096 | * |
| Employment | 1.479 | *** |
| VRH | 0.119 | *** |
| TNCs | -0.004 | *** |

Signif. codes: '***' 0.001 '**' 0.01 '*' 0.05

### Weekend

4.7 Shown below in Table 7, the fare elasticity on the weekend Metrorail model was the second highest in magnitude, just after the weekday central model, of all the Metrorail models. The fare elasticity implies that a 1% increase in fares corresponds to a 0.18% decline in ridership. The elasticity of the employment variable was the lowest of the Metrorail models at 0.723. However, the VRH elasticity was the highest of the Metrorail models and is on the upper limit of the VRH elasticities range for all models. The weekend ridership saw significant declines between 2008 and

2010, and for this reason a single dummy variable was added to account for changes in those three years.

**Table 7: Metrorail Weekend Model Summary Results**

| Variable | Elasticity | |
|---|---|---|
| Fare | -0.18 | ** |
| Employment | 0.723 | *** |
| VRH | 0.334 | *** |

Signif. codes: '***' 0.001 '**' 0.01 '*' 0.05

## Metrobus

### Weekday Low

4.8 Shown below in Table 8, the weekday low model has the lowest magnitude for fare elasticity of all the Metrobus models. The fare elasticity can be interpreted as a 1% increase in fares corresponds to a 0.20% decrease in ridership. The employment variable has one of the lower elasticities of 0.775, but weekday low has an abnormally high VRH elasticity of 1.05. No additional dummies were added for this model.

**Table 8: Metrobus Weekday Low Model Summary Results**

| Variable | Elasticity | |
|---|---|---|
| Fare | -0.204 | * |
| Employment | 0.775 | *** |
| VRH | 1.052 | *** |
| TNCs | -0.007 | *** |

Signif. codes: '***' 0.001 '**' 0.01 '*' 0.05

### Weekday Medium

4.9 Shown below in Table 9, the fare elasticity on the weekday Metrobus medium group ridership is -0.36, implying a 1% increase in fares corresponds to a 0.36% decline in ridership. The employment variable has an elasticity of 0.99 which is on the higher end of the range of elasticities for the Metrobus models. Due to variations in growth during different time periods and to produce a fare elasticity that best fits the most recent data, the models were run with data from 2010 onwards.

**Table 9: Metrobus Weekday Medium Model Summary Results**

| Variable | Elasticity | |
|---|---|---|
| Fare | -0.355 | *** |
| Employment | 0.994 | *** |
| VRH | 0.177 | *** |
| TNCs | -0.005 | *** |

Signif. codes: '***' 0.001 '**' 0.01 '*' 0.05

### Weekday High

4.10 Shown below in Table 10, the weekday high group model's fare elasticity can be interpreted as a 1% increase in fares corresponds to a 0.36% decline in ridership. The employment variable has the lowest elasticity of all the models run of 0.64. Like the Low group, the model was found to have a better fit and elasticities that were more representative of the recent data when using data from 2007 onwards. Additionally, Steer included a dummy variable for September 2017 to handle the impact of Hurricane Irma. This was included only in the High routes.

**Table 10: Metrobus Weekday High Model Summary Results**

| Variable | Elasticity | |
|---|---|---|
| Fare | -0.364 | ** |
| Employment | 0.635 | *** |
| VRH | 0.239 | *** |
| TNCs | -0.003 | |

Signif. codes: '***' 0.001 '**' 0.01 '*' 0.05

### Weekend Low

4.11 Shown below in Table 11, the weekend low model had the highest magnitude fare elasticity of demand, implying that a 1% increase in fares corresponds to a 0.45% decline in ridership. The employment variable had a mid-range elasticity of 1.1 but an abnormally high VRH elasticity of 1.31. For fit purposes and for representation of the most recent data, the model was run on data after 2007.

**Table 11: Metrobus Weekend Low Growth Model Summary Results**

| Variable | Elasticity | |
|---|---|---|
| Fare | -0.449 | *** |
| Employment | 1.1 | *** |
| VRH | 1.313 | *** |
| TNCs | -0.007 | *** |

Signif. codes: '***' 0.001 '**' 0.01 '*' 0.05

### Weekend Medium

4.12 Shown below in Table 12, the fare elasticity for the weekend medium group implies a 1% increase in fares corresponds to a 0.35% decrease in ridership. The employment elasticity is the highest of all models at 1.85 while the VRH elasticity is on the lower side at 0.125. As some of the routes showed a different growth pattern from 2014 onwards, a dummy variable was added to account for this. Like other Metrobus models, the model was run on data from 2008 onwards to better represent more recent ridership growth patterns.

**Table 12: Metrobus Weekend Medium Model Summary Results**

| Variable | Elasticity | |
|---|---|---|
| Fare | -0.345 | * |
| Employment | 1.852 | *** |
| VRH | 0.125 | * |

| | | |
|---|---|---|
| TNCs | -0.006 | *** |

Signif. codes: ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05

**Weekend High**

4.13 Shown below in Table 13, the weekend high model has a fare elasticity of 0.31 implying a 1% increase in fare corresponds to a 0.31% decrease in ridership. Both the employment variable and the VRH variable have mid-range elasticities of 1.46 and 0.25 respectively. Like the other Metrobus models, the models were run on data from 2010 onwards to capture the most recent ridership growth patterns.

**Table 13: Metrobus Weekend High Growth Model Summary Results**

| Variable | Elasticity | |
|---|---|---|
| Fare | -0.305 | * |
| Employment | 1.454 | *** |
| VRH | 0.252 | *** |
| TNCs | -0.005 | *** |

Signif. codes: ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05

## Commentary on results

4.14 Overall, fare elasticities on all the models were significant and between -0.10 and -0.45, indicating a 1% increase in fares would lead to a 0.10% to a 0.45% decline in ridership depending upon the transit mode, rail station region, and/or bus route growth pattern. These are within the range of fare elasticities observed for transit in other geographies. The other two variables of interest are the employment variables and the VRH variable. Both these elasticities were significant across all models, though the VRH variable had some elasticities outside of the expected range.

4.15 The estimation yields highly significant models that conform to both demand theory and results for similar analyses for other transit systems.

**Comparison Across Modes**

4.16 The average weekday Metrobus fare elasticity is -0.32 which is somewhat higher in magnitude than that of the weekday Metrorail at -0.23. Higher bus elasticities are observed on other systems as well, reflecting such factors as the shorter nature of bus trips and the fact that walking or biking may be a more realistic alternative than in the situation with rail. Metrorail routes may be used specifically for commuting to the central Miami area and are thus less sensitive to fare changes.

4.17 It is notable that the average weekend fare elasticity for the Metrobus, which is estimated to equal -0.37, is almost double the magnitude of that of the Metrorail weekend model. This difference could be attributed to the higher proportion of short distance, discretionary trips using Metrobus on weekends.

**Metrorail**

*Comparison Across Metrorail Weekday and Weekend*

4.18 Upon comparing the Metrorail weekday ridership results to the weekend ridership results, the magnitude of the weekend model's fare elasticity is much higher than that of the weekday north and slightly higher than that of the weekday south models, but much lower than the fare elasticity magnitude of the weekday central model. The elasticity on the VRH variable is almost double that of the average Metrorail weekday elasticity. The weekend model's higher sensitivity to fare changes compared to two of the three weekday groups is expected as leisure trips are discretionary trips and individuals have greater flexibility to change their plans.

*Comparison Across Metrorail Groupings*

4.19 Within groups for the Metrorail models, the central group has the highest fare elasticity, almost double the average of the other Metrorail models. This may be attributed to the central region having multiple stations, Government Center and Brickell, in downtown Miami which are competing with a free alternative, the Metromover, for intra-downtown trips.

4.20 While the north group's fare elasticity magnitude is in the middle of the range, that of the south group's fare elasticity is quite low. One potential reason for this is that a majority of trips are made by commuters who cannot easily switch to other modes or may not have access to many transit alternatives. This is supported by the fact that the area is a large white-collar employment center.

4.21 With regard to employment, the elasticities increase from north to central to the south localities. This would imply that the Metrorail is being used most for commuting purposes in the south group area and least in the north group area. This corresponds to the economies of the three areas, where the north area has both residences and industrial locations, the central group has high tourism and includes the central business district, and the south area is a large employment center.

**Metrobus**

*Comparison Across Metrobus Weekday and Weekend*

4.22 The weighted average weekday fare elasticity for Metrobus was -0.32 for the weekday and -0.37 for the weekend models. This small range suggests that trip purposes are less distinct than is the case with Metrorail.

4.23 However, the average weekday employment elasticity is much lower than that of the weekend models. One explanation could be that growth in trips during the weekend includes the effects of tourism, which may be imperfectly represented in the employment variables used.

4.24 The VRH elasticity, which represents the LOS, was significant for all models but high for the low group and will be discussed later. The weighted average VRH elasticity (excluding outliers) is 0.20 for the weekday models and 0.17 for the weekend models.

*Comparison Across Metrobus Groupings*

4.25 Within groups, the weekday models' fare elasticities increase when going from low to high groups. This can be interpreted as the Low group routes being more established routes servicing specific communities that may be the only transport to certain attractions making them less sensitive to fare changes.

4.26 The medium group routes may be to the attractions that have other, more competitive transportation alternatives and may connect more stable commuter routes as well as specific tourist attractions. As described in paragraph 3.17, these routes are concentrated in the northern and central parts of the bus network, which covers commuters traveling to the CBD as well as tourist attractions. As such, there is a medium level of sensitivity to fare changes for this group.

4.27 For the high group, this may include new regions of development or routes without frequent transit between their origins and destinations as well as availability of other competitive transportation options, and this may explain the higher sensitivity to fare.

4.28 With respect to employment elasticities, the medium group has the highest employment elasticity and could be interpreted as these routes being connected to new employment centers or serving as connectors to other transit options. Similarly, the weekday high group has a low employment elasticity, and this may coincide with fewer attraction zones.

4.29 For the weekend models, an opposite trend is observed where, as a route's ridership growth rate increases, its fare elasticity decreases. This could be attributed to the fact that low growth routes may be stable routes with more commuter and repetitive trip purposes that are taken during the week, but trips may be more discretionary during the weekend and vice-versa for the medium and high groups.

4.30 The elasticities for VRH, the LOS variable, are within the expected range for the medium and high groups but abnormally high for the low growth group. This may be because the LOS variable is for all bus routes, and if this is not representative of the LOS trends on the low growth routes, unexpected results could follow.

## Conclusions

4.31 Steer was able to successfully apply transportation demand modelling theory and econometric tools to the Miami-Dade transit system. Ridership on Metrorail and Metrobus are affected in expected ways by economic growth, LOS, and fares.

4.32 The results present Metrorail and Metrobus ridership as fairly inelastic to fare, meaning there is potential for increased farebox recovery. Fares are currently relatively low for public transit trips, $2.25, so the inelastic response to fare and ridership on the Metrorail and Metrobus conforms to expectations.

4.33 The models outlined have the potential to be used for ridership forecasting and the estimated fare elasticities can be used in planning level tools to assess various fare policies, including the impacts of fare increases on ridership and revenues. The results of the current work can be used to assess many other fare-related issues as well, such as whether different fare structures might yield higher ridership while being revenue neutral.

# A Bus Route Growth Rates

**Table 14: Bus Routes - Low Group - CAGR's (2005-2015 & 2015-2018)**

| Route | 2005-2015 | 2015-2018 |
|---|---|---|
| 11 | (1.9%) | (12.9%) |
| 115/117 | N/A | (49.5%) |
| 136 | (0.2%) | (21.6%) |
| 16 | (4.4%) | (11.9%) |
| 202 | (13.9%) | (13.3%) |
| 207/208 | 1.4% | (16.3%) |
| 211 | N/A | (20.9%) |
| 212 | (20.4%) | (15.1%) |
| 246 | (15.3%) | 3.1% |
| 286 | N/A | (12.6%) |
| 3 | (2.2%) | (11.3%) |
| 302 | N/A | (5.1%) |
| 31 | (2.4%) | (14.3%) |
| 338 | N/A | (0.7%) |
| 344 | (10.9%) | (5.6%) |
| 42 | (1.8%) | (17.0%) |
| 500 | (12.0%) | (15.7%) |
| 56 | (0.9%) | (16.7%) |
| 62 | (4.7%) | (16.2%) |
| 71 | (5.2%) | (11.4%) |
| 79 | N/A | (27.8%) |
| 8 | (1.3%) | (17.3%) |
| 9 | (1.0%) | (12.8%) |
| C | 0.1% | (52.8%) |
| H | (8.9%) | (36.6%) |
| S | (0.4%) | (11.8%) |

Source: Steer Analysis of Metrobus Ridership Data

**Table 15: Bus Routes - Medium Group - CAGR's (2005-2015 & 2015-2018)**

| Route | 2005-2015 | 2015-2018 |
|---|---|---|
| 1 | (9.5%) | (8.5%) |
| 104 | (1.1%) | (8.7%) |
| 120 | N/A | (9.4%) |
| 135 | N/A | (7.3%) |
| 137 | 2.2% | (7.6%) |
| 19 | N/A | (7.1%) |
| 24 | (5.9%) | (7.9%) |
| 27 | (1.5%) | (8.9%) |
| 277 | 6.5% | (11.1%) |
| 29 | (2.3%) | (7.0%) |
| 297 | N/A | (9.9%) |
| 32 | (3.6%) | (8.8%) |
| 33 | (1.5%) | (7.2%) |
| 36 | (0.5%) | (9.4%) |
| 37 | 2.9% | (7.6%) |
| 40 | (2.5%) | (8.4%) |
| 52 | (1.9%) | (7.2%) |
| 54 | (1.0%) | (8.1%) |
| 57 | 4.1% | (9.1%) |
| 72 | 0.5% | (8.1%) |
| 73 | 1.9% | (7.4%) |
| 75 | (5.5%) | (10.3%) |
| 77 | (0.4%) | (8.8%) |
| 87 | (0.7%) | (7.4%) |
| 99 | 9.6% | (8.4%) |
| B | (0.2%) | (9.3%) |
| E | 1.7% | (10.5%) |
| J | (3.9%) | (8.7%) |
| L | 0.0% | (10.2%) |
| M | (5.1%) | (10.0%) |

Source: Steer Analysis of Metrobus Ridership Data

**Table 16: Bus Routes - High Group - CAGR's (2005-2015 & 2015-2018)**

| Route | 2005-2015 | 2015-2018 |
|---|---|---|
| 10 | 0.3% | (5.8%) |
| 150 | N/A | (4.6%) |
| 17 | (0.6%) | (6.5%) |

| | | |
|---|---|---|
| 183 | 12.1% | (6.7%) |
| 2 | (2.9%) | (4.9%) |
| 200 | 3.8% | 7.8% |
| 204 | N/A | (2.6%) |
| 22 | 1.1% | (6.5%) |
| 238 | (4.3%) | (5.9%) |
| 252 | (1.9%) | (6.8%) |
| 254 | N/A | (3.4%) |
| 267 | (9.0%) | (0.1%) |
| 272 | N/A | (6.9%) |
| 287 | 1.8% | (5.1%) |
| 288 | N/A | (0.9%) |
| 301 | N/A | (3.1%) |
| 34 | 3.4% | 5.6% |
| 35 | (1.4%) | (3.2%) |
| 38 | 3.4% | (4.2%) |
| 46 | (19.4%) | 1.0% |
| 51 | (0.9%) | (5.5%) |
| 7 | (1.5%) | (4.9%) |
| 82 | (0.9%) | 1.0% |
| 88 | (0.6%) | (7.0%) |
| 93 | N/A | (3.9%) |
| A | (13.2%) | 11.9% |
| G | (4.5%) | (6.9%) |

Source: Steer Analysis of Metrobus Ridership Data steergroup.com