Passenger Demand Forecasting

FY2019 – FY2028

May 20, 2019

Contents

1. Introduction

Access Services ("Access"), a local governmental agency created in 1994, is the Los Angeles County Consolidated Transportation Services Agency (CTSA) that provides Americans with Disabilities Act (ADA) mandated paratransit service for eligible persons in Los Angeles County. Access is available to any location within ¾ of a mile of any public bus fixed route and within ¾ of a mile around METRO Rail stations during operating hours. The service area covered by Access is divided into six regions and extends into portions of the surrounding counties of San Bernardino, Orange, and Ventura.

HDR, Inc. (HDR) has been providing paratransit demand analysis and forecast to Access for the past fifteen years and was recently commissioned to provide an update.

Objectives of the Study

The paratransit demand analysis relies on historical data and forms the basis for the projections. It involves a detailed and scientific examination, both at the system and regional levels, of trends and movements in trip demand and its constitutive elements such as cancellations, no-shows, missed trips, and trips completed.

More specifically, the key analytical tasks involve:

- Examining the behavior of trip demand over time in relation to both internal changes to Access operations and policies (e.g., new fare structure) and external modeling and socio-economic factors (e.g., fluctuations in fuel prices);
- Identifying potential structural breaks in the data series (caused by changes in market conditions for instance); and
- Estimating the degree of correlation among different variables (such as trip requests and population).

HDR is building upon its database of Access operational statistics, which has been continuously maintained since 2003. The database includes monthly operating and financial data at the regional level since 1995. As part of the analysis update, HDR has reviewed the new data and validated the sampling methods used by Access to produce some of the trip demand and performance measures used in the analysis.

Similar to the annual studies conducted in the past, HDR has assembled historical demographic and socio-economic data (population by age group, employment, retail gasoline prices, consumer price index, etc.) from various state and national sources such as the California Department of Finance, the United States (U.S.) Census Bureau, the Bureau of Labor Statistics (BLS) and the Energy Information Administration (EIA).

In addition to the demand analysis, a peer review and new applicant analysis has been performed. The peer review is a high-level analysis that draws data, in part, from previous HDR projects for large and small agencies such as Washington Metropolitan Area Transit Authority (WMATA) and Riverside Transit Agency (RTA). Additional data come from the Federal Transit Administration's National Transit Database (NTD), Florida Transit Information System (FTIS), New York City Transit's Paratransit Peer Reports, and agency operation and service annual reports. The ultimate objective of the peer review is to identify demand-related issues (increase in customer complaints, high no-show rate and transfer of ridership from other specialized service providers, etc.) that have arisen elsewhere and examine how these issues have been addressed.

The new applicant analysis provides Access with an econometric analysis and a forecast of total new persons applying for their service over the next ten fiscal years. Initially, the purpose of the analysis was to investigate the possible causes of the rapid increase in new applicants starting in 2009. The results of the analysis will help Access better anticipate the impacts of variations in new applicants on its paratransit operations.

Both the trip demand and new applicant analyses in this report build off the model and methodology initially presented in the December 2013 report. Observation data up to October 2018 have been added to the model.

Plan of the Report

The report includes full technical documentation of the models used for this analysis, including historical data, analytical framework, specification experiments and diagnostic tests, forecasting assumptions and any policy scenarios investigated. Following this introduction, a historical overview of key operating measures of Access paratransit trip demand is presented in Section 2. The summary of operations leads to a discussion of performance metrics in Section 3 and the performance-based peer analysis in Section 4. Section 5 describes the demand analysis framework and resulting demand outcomes, while Section 6 reports forecasting assumptions and results. The report concludes with the analysis of new applicants in Section 7.

The report also contains a number of appendices. A list of all acronyms used in the report is provided in Appendix 1. A glossary of all technical terms used in the report is provided in Appendix 2 to further explain the methodology and interpretation of the results. A risk analysis primer is included in Appendix 3. Monthly ridership projections are provided for each region served by Access in Appendix 4. Appendix 5 contains a map of the service area. All data sources and references used throughout the study are listed in Appendix 6.

2. Historical Overview

This section presents a historical overview of paratransit operations data for the six regions served by Access from July 2005 to October 2018. The six regions include Eastern, Northern, Southern, West/Central, Santa Clarita and Antelope Valley. Unless otherwise noted, the discussion pertains to fiscal year (FY) rather than calendar year. The overview is supported by the analysis of the main factors shaping trip demand for Access.

Trip Demand

Passenger trips requested and ridership are used as indicators of the demand for paratransit service. Passenger trip requests include all trips completed, no-shows, cancellations and trips denied. Ridership refers to passenger trips completed.

Trip Requests

Passenger trip requests in Access's entire service area grew from 3.4 million in 2012 to 4.6 million in 2018 – at an average annual rate of 5.3 percent. From 2004 to 2007, trip requests declined, partly because of changes to Access operations. As the U.S. economy recovered after the 2008-09 recession, Access experienced substantial growth in trip requests. During that period, 2010 was the only year with negative growth, which can be explained by an increase in fares and the dropping of a subcontractor in the Southern and West/ Central regions. Since 2010, the number of trips requested has increased by 59.5 percent. In 2017 and 2018, however, trip requests grew by 2.8 percent and 0.4 percent respectively, compared to an average annual rate of 7.7 percent for the previous five fiscal years. This slowdown reflects a decline in new applicants.

Trip demand increased in every region of Access's service area (except for Santa Clarita) from 2013 to 2017. But that upward trend was interrupted in 2018. The largest regions in terms of trip demand remain the Eastern and Southern regions. Since 2013 these two regions have accounted for 61 percent of Access's growth in trip requests. The West/ Central region experienced a drop in trip requests after changes in regional boundaries in September 2006 and September 2007, when portions of the West/ Central region were transferred to the Southern region. Additionally, a change in contractor in November 2009 resulted in a 6.2 percent drop in trip requests for the West/ Central region in 2010. However, in 2017 the West/ Central region exceeded its previous peak number of trip requests experienced in 2003.

These demand and growth estimates are reported in Table 1 on the next page, along with trip requests for "backup", an around-the-clock service provided in case of failure of the carrier (e.g., the vehicle has not arrived by the scheduled pick up time plus the 20-minute on-time window)[1]. Figure 1 shows monthly trip requests for the whole service area from July 2005 to October 2018.

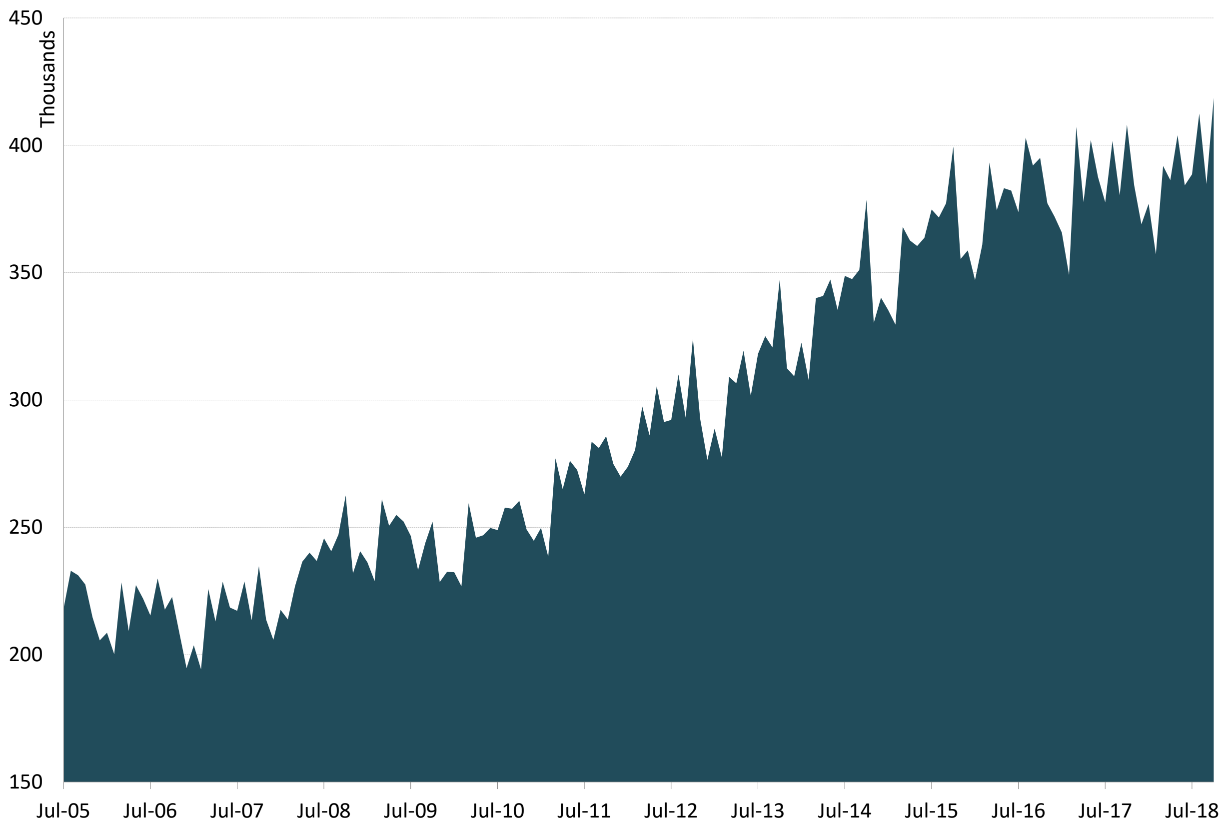
[1] Note that since early 2016 backup trips have been the responsibility of contractors and not Access Services.

Table 1: Trip Requests by Service Region (FY2013 – FY2018)

	FY 2013	FY 2014	FY 2015	FY 2016	FY 2017	FY 2018
TOTAL	3,591,126 5.9%	3,926,569 9.3%	4,215,820 7.4%	4,478,310 6.2%	4,602,401 2.8%	4,621,618 0.4%
Antelope Valley	114,969 33.7%	147,073 27.9%	173,742 18.1%	207,155 19.2%	231,447 11.7%	221,370 -4.4%
Eastern	1,005,145 3.8%	1,080,179 7.5%	1,149,365 6.4%	1,232,867 7.3%	1,287,228 4.4%	1,331,180 3.4%
Northern	687,635 3.8%	742,518 8.0%	778,995 4.9%	800,959 2.8%	808,886 1.0%	784,548 -3.0%
Santa Clarita	58,888 3.9%	55,204 -6.3%	55,792 1.1%	54,984 -1.4%	60,283 9.6%	58,843 -2.4%
Southern	1,164,015 9.0%	1,298,647 11.6%	1,400,202 7.8%	1,489,553 6.4%	1,499,920 0.7%	1,503,154 0.2%
West/ Central	555,694 2.0%	596,688 7.4%	650,432 9.0%	687,089 5.6%	713,938 3.9%	722,432 1.2%
Backup	4,780 -7.9%	6,260 31.0%	7,292 16.5%	5,703 -21.8%	699 -87.7%	91 -87.0%

Source: Access Services

Figure 1: Trip Requests in Service Area, Thousands (July 2005 – October 2018)

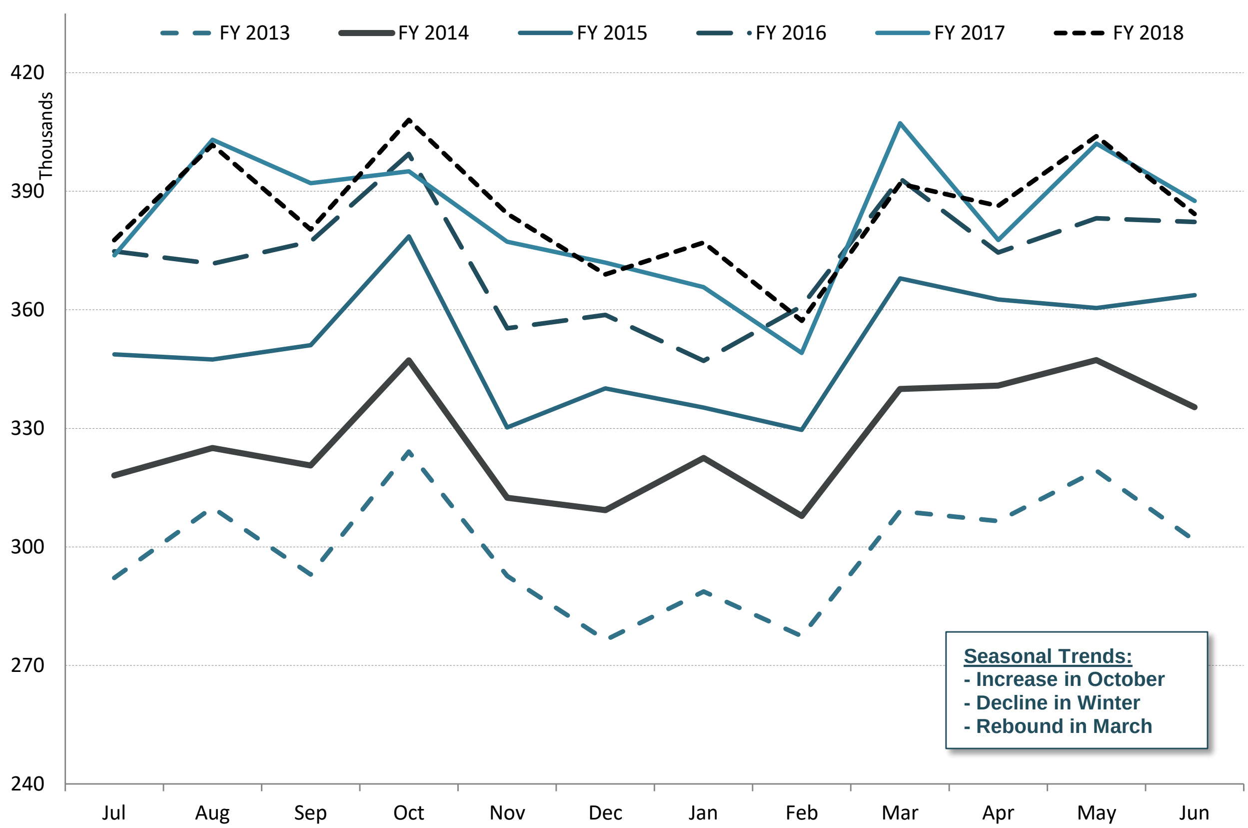


Source: Access Services

Trip demand is rising at a significantly faster pace in geographically smaller service regions than the other regions. From 2008 to 2011, trip requests in Santa Clarita more than doubled, growing from 26,465 to 54,670. During the next six years, trip demand stabilized, growing at an average annual rate of 0.1 percent only. However, trip requests decreased by 2.4 percent in 2018. In Antelope Valley, trip requests grew by 21.9 percent per year on average from 2013 to 2017, and in each of those years Antelope Valley experienced the largest growth rate by any service region. The next largest growth, on average, over the same period was three times less than the growth in Antelope Valley (the Southern region grew by an average of 7.0 percent per year). The growth in Antelope Valley slowed from 19.2 percent in 2016 to 11.7 percent in 2017; however, it still comprised 20 percent of the total trip demand growth in 2017. In 2018, both Santa Clarita and Antelope Valley experienced a slight decline in trip requests.

Figure 2 below depicts the seasonality of paratransit demand, attributed in part to changing weather conditions, over the past six fiscal years. There is a common pattern in variations of trip demand over a twelve-month period. Trip requests tend to peak in spring and October; during summer and winter months the requests are lower in comparison (December, January, and February are the rainiest months in Los Angeles).

Figure 2: Seasonality of Trip Requests, Thousands (FY2013 – FY2018)



Source: Access Services

Passenger Trips Completed

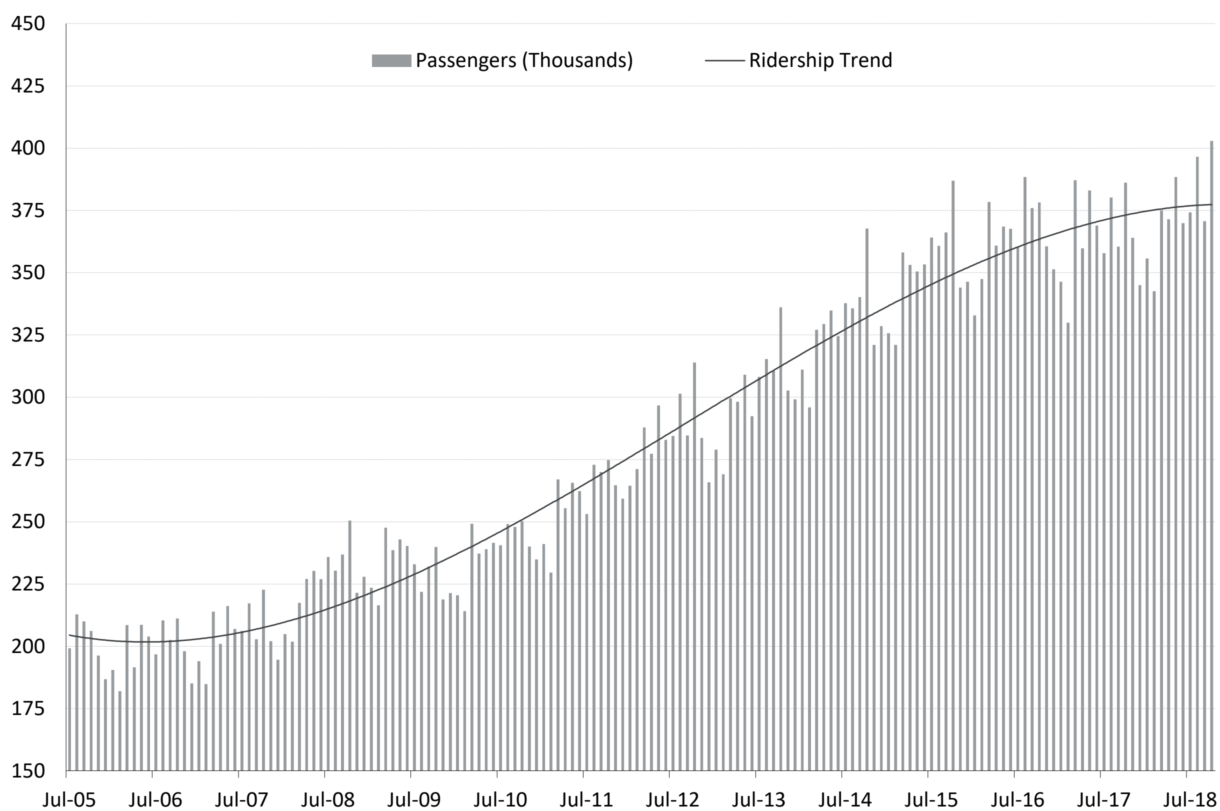
Although trip requests represent the fundamental manifestation of consumer demand, not all requested trips are scheduled. Requests can be cancelled by the customer after considering the expected pickup time. After a trip is scheduled, Access sends a vehicle to the pickup location. But not all of these scheduled trips are completed due to customer no-shows and late cancellations. Access incurs costs on trips that are scheduled and not completed, whereas completed trips generate revenue.

The number of passenger trips completed is the "realized" part of paratransit demand. Passenger trips completed can be divided into six categories: certification trips, ambulatory passengers, wheelchair passengers, personal care attendants (PCA), companions and children five years old and under.

RIDERSHIP

The number of trips completed, or "ridership", is closely related to the number of trip requests, and both have experienced similar trends. As evidenced by the trend line in Figure 3, ridership increased rapidly from 2010 to 2016. During the five years preceding 2017, ridership growth averaged 7.8 percent per year, but slowed to 1.5 percent in 2017 and 0.2 percent only in 2018. This slowdown reflects a decline in new applicants.

Figure 3: Ridership in Service Area (July 2005 – October 2018)



Source: Access Services

As shown in Table 2 below, ridership increased in every service region, except for Santa Clarita, from 2013 to 2016. In 2017, for the first time, ridership decreased in the Southern region, possibly because of operational issues. Of all the regions, Antelope Valley has demonstrated the strongest growth in ridership, which coincides with the growth in trip requests in this region (see Table 1 on page 7). From 2013 to 2017, ridership in Antelope Valley nearly doubled, rising from approximately 111,000 to 221,000. In 2013 alone, ridership increased by 34.7 percent, and the region averaged about 22 percent annual growth from 2013 to 2017. Despite a slowdown in growth in 2017, Antelope Valley still saw an increase in ridership nearly three times larger than any other region, excluding Santa Clarita. Santa Clarita also experienced a large increase in ridership in 2017, growing by 11.5 percent after three consecutive years of declining ridership. However, both regions experienced a decline in ridership in 2018.

While smaller regions (i.e., Antelope Valley and Santa Clarita) have had some of the largest ridership growth rates of all regions since 2007, most of the new ridership in the past five years has come from the steady growth of the largest regions in Los Angeles County (Northern, Eastern, Southern, and West/ Central). The Southern region leads with the most ridership in number since 2013 – its ridership increased by almost 300,000 between 2013 and 2016. The Eastern region is the second largest in the service area and has experienced modest growth since the recession, averaging an annual increase of 5.6 percent over the past six fiscal years. Ridership in the Northern and West/ Central regions increased steadily from 2013 to 2016, averaging annual growth rates of 4.6 percent and 6.0 percent, respectively, before declining or slowing down significantly in 2017 and 2018.

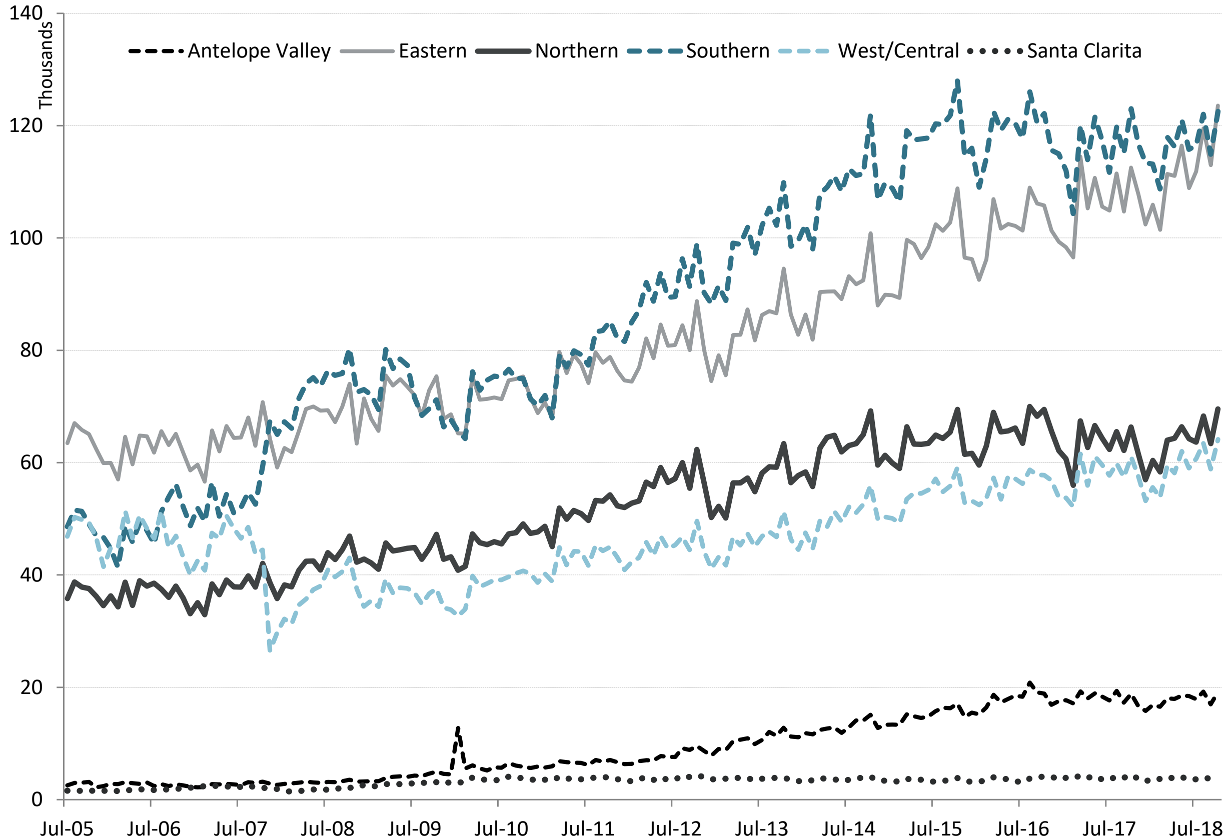
Table 2: Ridership by Service Region (FY2013 – FY2018)

	FY 2013	FY 2014	FY 2015	FY 2016	FY 2017	FY 2018
TOTAL	3,481,204 6.3%	3,794,914 9.0%	4,092,766 7.8%	4,324,186 5.7%	4,389,950 1.5%	4,396,741 0.2%
Antelope Valley	111,263 34.7%	142,292 27.9%	168,313 18.3%	199,634 18.6%	220,951 10.7%	211,816 -4.1%
Eastern	977,840 4.1%	1,052,229 7.6%	1,128,677 7.3%	1,210,011 7.2%	1,253,725 3.6%	1,298,955 3.6%
Northern	668,668 3.1%	722,008 8.0%	756,733 4.8%	776,000 2.5%	776,574 0.1%	752,601 -3.1%
Santa Clarita	46,381 3.9%	43,368 -6.5%	42,489 -2.0%	41,489 -2.4%	46,248 11.5%	45,702 -1.2%
Southern	1,131,881 10.0%	1,254,304 10.8%	1,360,595 8.5%	1,427,293 4.9%	1,406,379 -1.5%	1,392,631 -1.0%
West/ Central	540,810 2.7%	574,640 6.3%	628,999 9.5%	664,319 5.6%	685,425 3.2%	694,909 1.4%
Backup	4,361 -5.7%	6,073 39.3%	6,960 14.6%	5,440 -21.8%	648 -88.1%	127 -80.4%

Source: Access Services

Figure 4 below shows the ridership trend for all service regions since July 2005. Several regions experienced decreases in ridership due to changes in service boundaries and in contractors. Changes in West/ Central and Southern regional boundaries in 2007 and again in 2008 are evidenced by the drastic changes in ridership in those years. After the boundaries changed, West/ Central ridership fell by 3.8 percent in 2007 and again by 18.3 percent in 2008. During the same period, ridership in the Southern region increased by 8.7 percent and then by 25.2 percent.

Figure 4: Ridership by Service Region (July 2005 – October 2018)



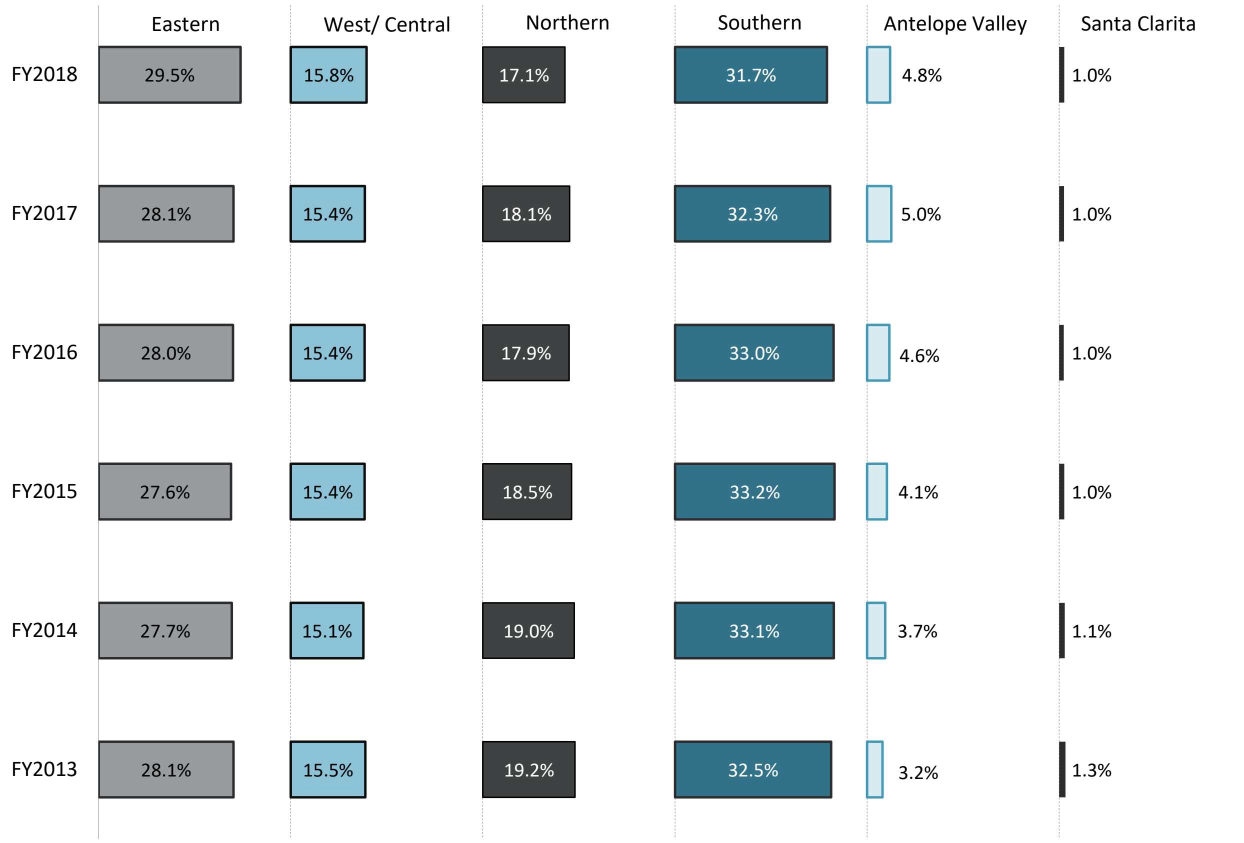
Source: Access Services

DISTRIBUTION OF RIDERSHIP BY SERVICE REGION

In 2018, the Southern region had the largest ridership share (31.7 percent) followed by the Eastern region (29.5 percent). The Northern and West/ Central regions accounted for 17.1 percent and 15.8 percent of total ridership, respectively. The Santa Clarita and Antelope Valley regions together accounted for nearly 6 percent of total ridership. Figure 5 on the following page displays the distribution of passengers by service region from 2013 to 2018.

Despite small fluctuations for the Eastern, West/ Central, and Southern regions in the past six years, their respective shares of ridership have remained fairly steady. The share of the Northern region has steadily decreased, while the share of Antelope Valley has consistently increased over the past since 2013.

Figure 5: Distribution of Passengers by Service Region (FY2013 – FY2018)



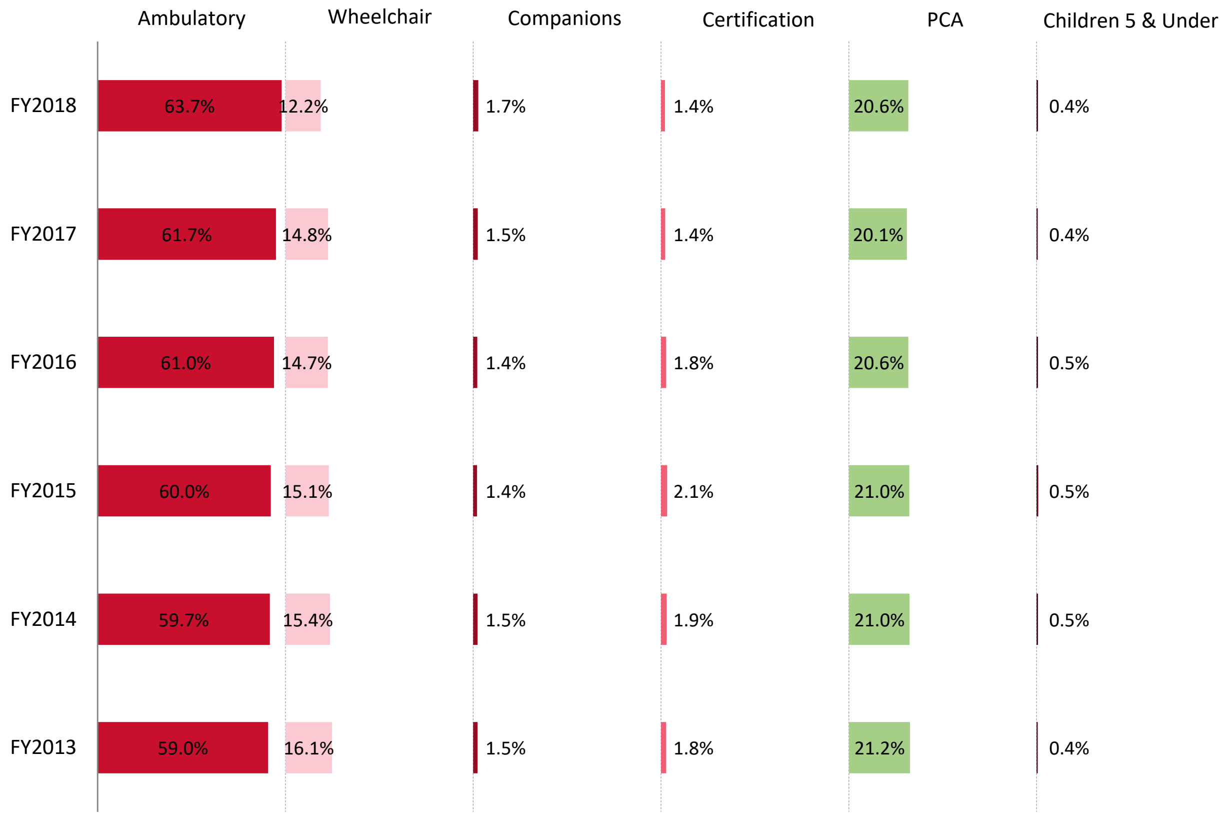
Source: Access Services

RIDERSHIP BY TYPE OF PASSENGER

Trips completed can be divided into six categories: certification trips, ambulatory passengers, wheelchair passengers, personal care attendants (PCA), companions and children five years old and under.

Ambulatory passengers have consistently been the most served by Access. In 2018, ambulatory passengers accounted for 63.7 percent of total ridership. The majority of the remaining trips were taken by persons using wheelchairs (12.2 percent) and PCA (20.6 percent). Over the past six years, trips completed by persons using wheelchairs have decreased while those completed by ambulatory passengers have increased. The rest of passenger trips are distributed among companions, children five years old and under, and certification trips. These passengers had a share of less than 3 percent each of total completed trips in any year. Figure 6 on the next page depicts the distribution of ridership by type of passenger over the last six years.

Figure 6: Distribution of Ridership by Type of Passenger (FY2013 – FY2018)



Source: Access Services

Key Operating Factors

Demand for paratransit service is affected by multiple factors, including fare structure, operating standards, and socioeconomic indicators. Key operating factors that could impact trip demand include inflation adjusted trip fare (real fare), complaint rate, on-time performance, cancellations and no-shows.

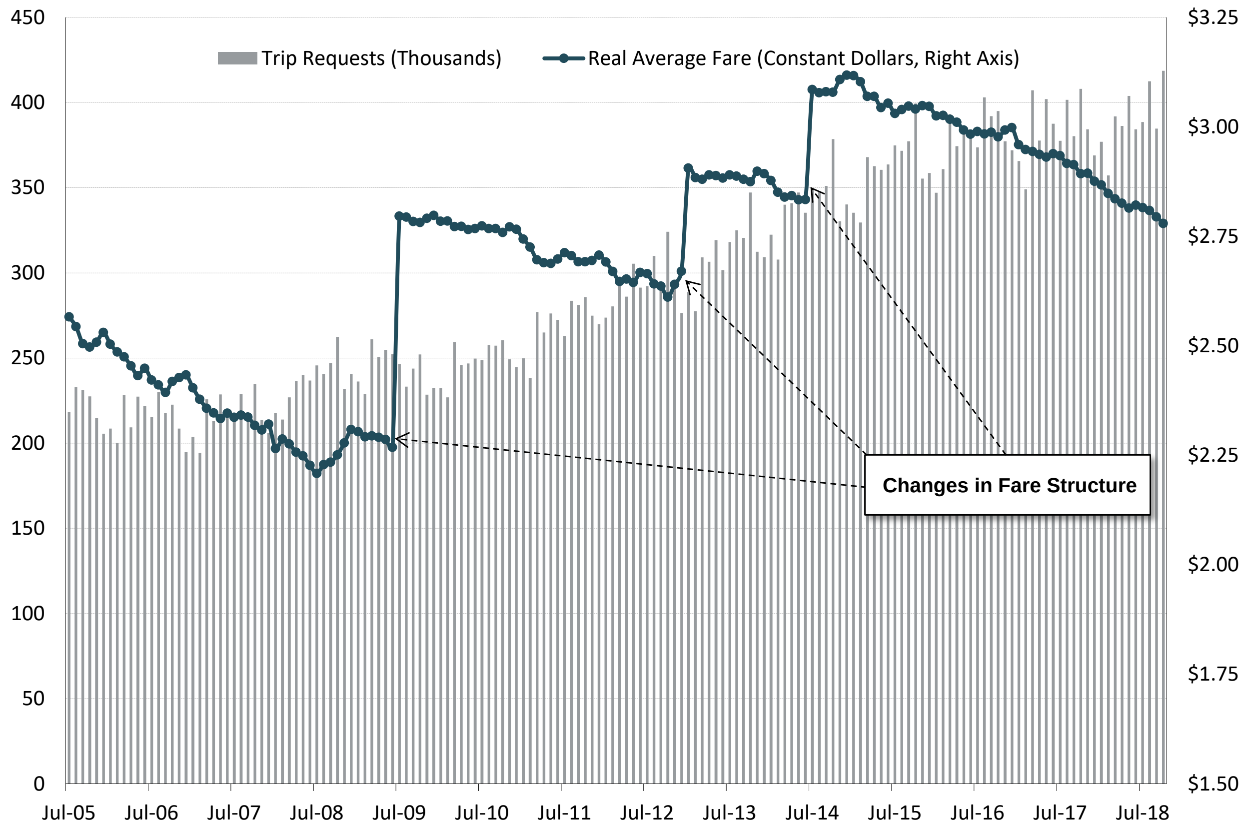
Real Fare

Economic theory and past experience support the existence of an inverse relationship between *real* fare (as opposed to *nominal* fare) and trip requests, sometimes with a slight time lag: all things being equal, a reduction in real fare typically generates an increase in trip requests, whereas an increase in real fare typically generates a reduction in trip requests. The extent of this relationship is measured by the elasticity of demand with respect to real fare, which measures demand responsiveness with respect to price.

The real average fare is computed for each service region in two steps. First, the average nominal fare is computed by dividing total monthly fare revenue (cash, Access Services coupons and Los Angeles County Metropolitan Transit Authority [LACMTA] bus tokens) by the number of passengers who paid for the trip (i.e., ambulatory riders, wheelchair users, and companions). Personal care attendants, and children five years old and under (if traveling as companions) do not pay the fare, as well as passengers on certification trips.

Next, the average nominal fare is deflated by the Consumer Price Index (CPI) for the Los Angeles-Orange County, CA Metropolitan Statistical Area (MSA). This removes all inflationary movements from the nominal fare, allowing the fare to be expressed in constant dollars. Figure 7 below shows the trend in the real average fare along with the number of trip requests in the service area since July 2005.

Figure 7: Trip Requests and Real Average Fare (July 2005 – October 2018)



Sources: Access Services and California Department of Finance

From the figure above, the following noteworthy points stand out:

- The real average fare follows a downward trend;
- The fare change in July 2006[2] induced little, if any, volatility in trip fare;
- The change in fare structure that occurred in July 2009 led to an increase in the real average fare from $2.27 in June 2009 to $2.80 the following month;
- The change in fare structure in January 2013 led to an increase in the real average fare from $2.67 to $2.91; and

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[2] The fare for trips scheduled between 9:00 p.m. and 5:00 a.m. was lowered to $1.50 regardless of distance.

- The change in fare structure in July 2014 led to an increase in the real average fare from $2.83 to $3.09.

Throughout the study period, changes in the fare structure have induced changes in trip demand. For instance, the 2009 fare increase led to a reduction in trip requests from 252,253 in June to 246,582 in July and to 233,203 in August.

Eligibility Evaluations and New Applicants

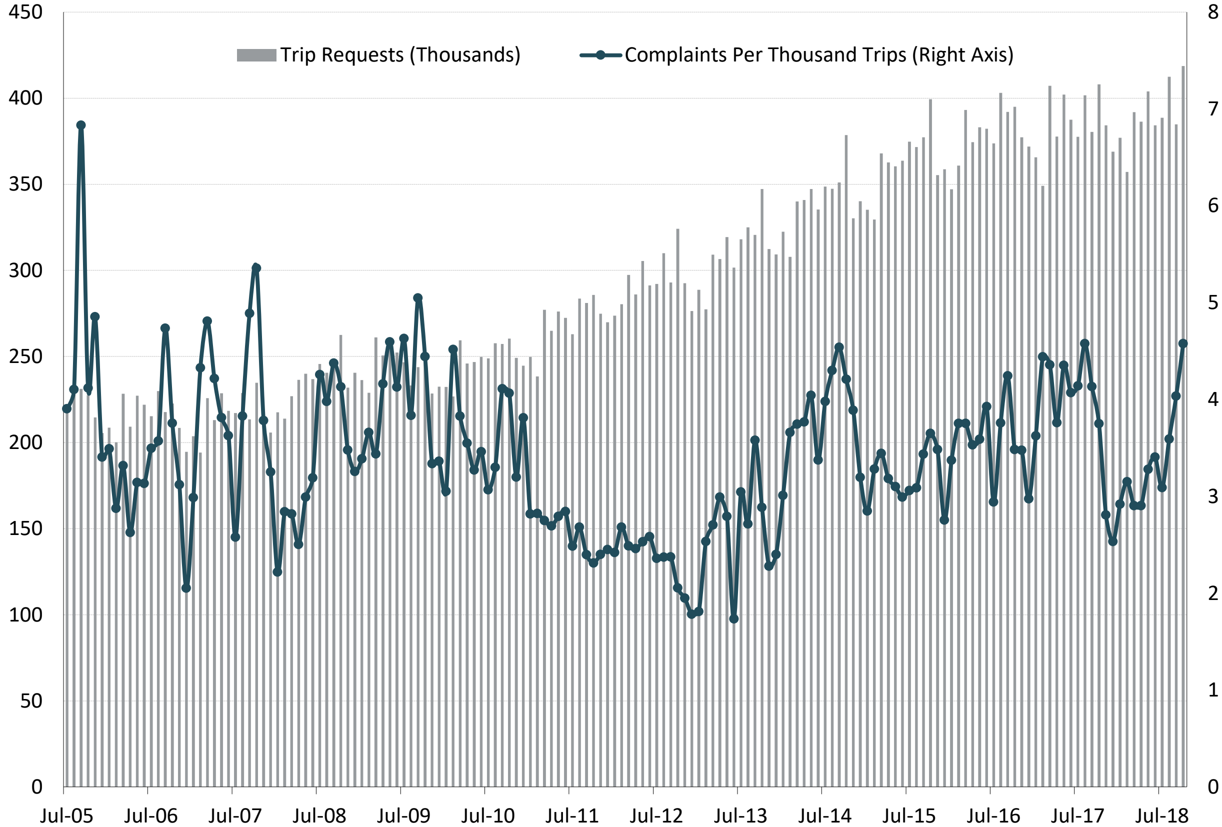
Total eligibility evaluations consist of evaluations of new applicants and recertification applicants. For Access, eligibility is determined through an in-person transit evaluation. It is based on the applicant’s ability to use accessible buses and trains in Los Angeles County. The evaluation is not based solely on the disability, age, or medical conditions of the applicant.

A detailed discussion on eligibility evaluations and new applicants is provided in Section 7, along with the econometric analysis of new applicants only.

Complaint Rate

The complaint rate, defined as the number of passenger complaints per *one thousand* passengers carried, reflects the quality of the service received by customers. Since trip demand is partly defined by the willingness to pay, it is expected that decreases in the complaint rate will result in increases in the number of trip requests (typically with a lag of one or more months) and vice versa. This is depicted in Figure 8, on the next page, where the data in the past thirteen fiscal years show that, overall, improvements in the quality of service coincide with lagged increases in ridership (and vice versa): total trip requests increased from 218,115 in July 2005 to 288,736 by January 2013, while the complaint rate decreased from 3.9 to a minimum of 1.8 complaints per thousand trips completed over the same period, though the complaint rate has increased slightly since then to an average of 3.5. Note that since the complaint rate is a function of the service provided (and thus not an independent variable), the complaint rate is not included in the analysis of trip demand.

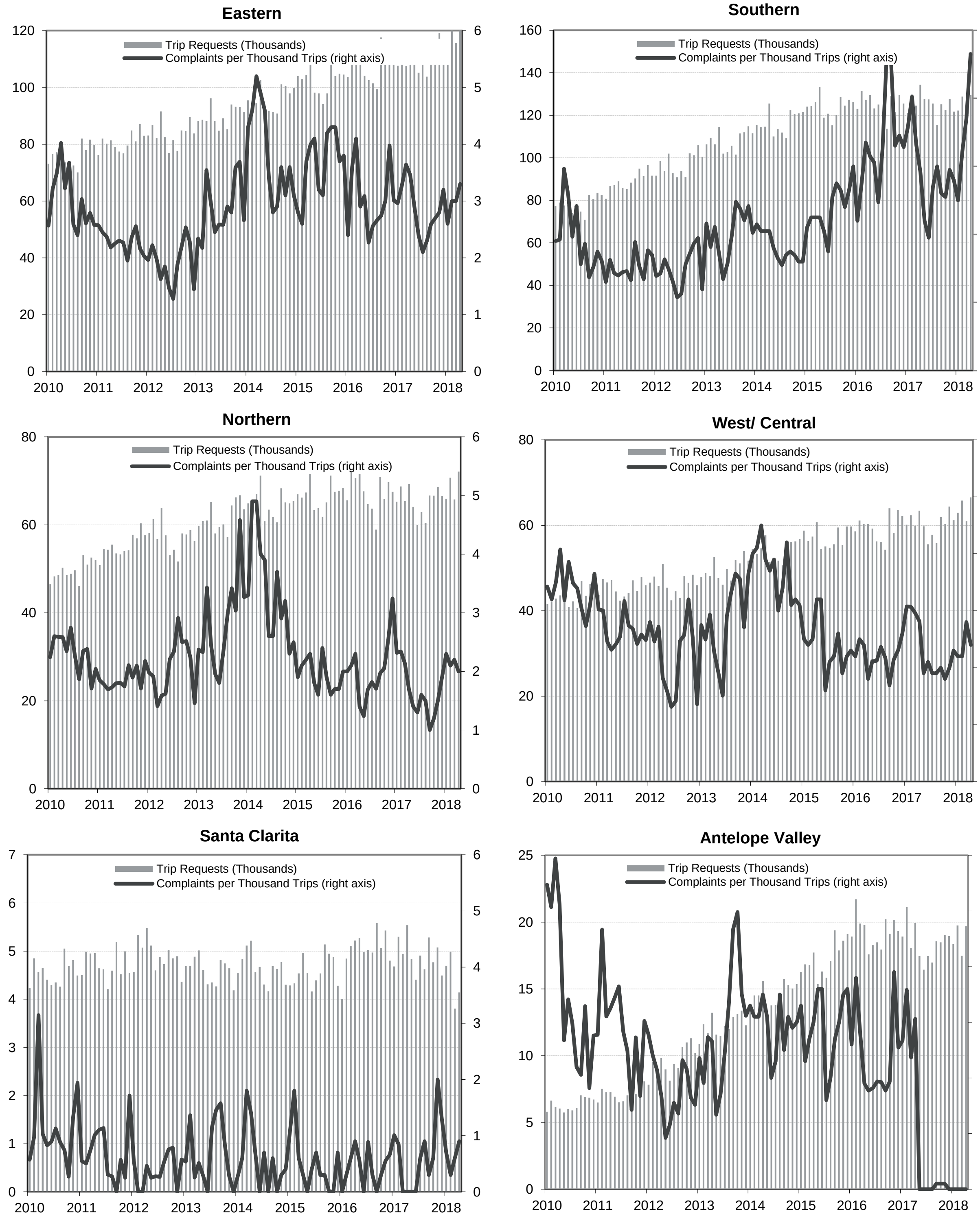
Figure 8: Trip Requests and Complaint Rate (July 2005 – October 2018)



Source: Access Services

Figure 9 on the following page reports the same data by service region, from July 2010 to October 2018.

Figure 9: Trip Requests and Complaint Rate by Service Region (July 2010 – October 2018)

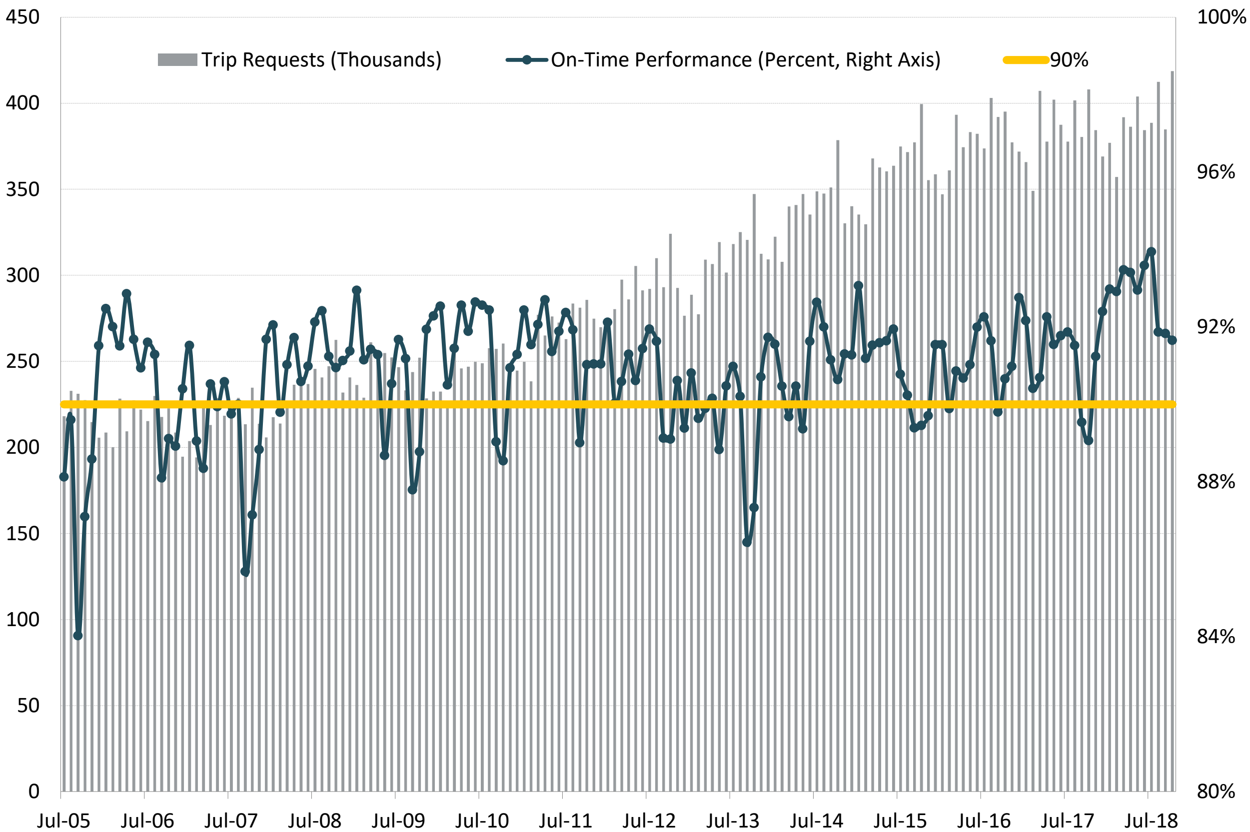


Source: Access Services

On-Time Performance

At the system level, on-time performance averaged 90.9 percent over the period 2006 – 2017, and was slightly higher in 2018, averaging 92.1 percent. These estimates are above the 90 percent benchmark set by Access in the *Year 2000 Strategic and Short-Term Business Plan*. As shown in Figure 10 below, the upward trend in on-time performance through 2014 was interrupted several times with significant drops below the benchmark. These declines coincide with lagged decreases in trip requests, possibly a result of the implementation and/ or suspension of reservation, scheduling, and dispatching software modules[3]. Since then, however, dips below the benchmark have not been large or lasting.

Figure 10: Trip Requests and On-Time Performance (July 2005 – October 2018)



Source: Access Services

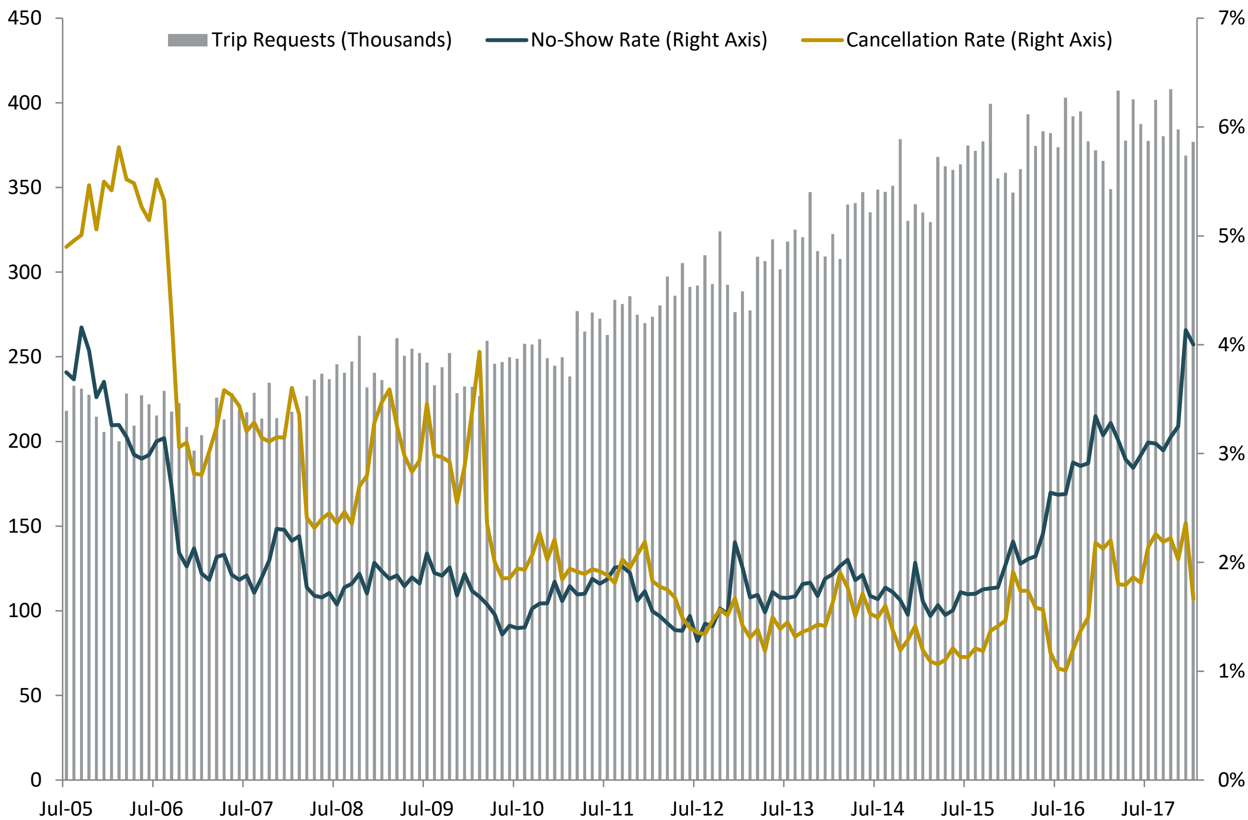
Cancellations and No-shows

The no-show rate is defined as the number of no-shows divided by the number of trip requests. Likewise, the cancellation rate is the number of cancellations divided by the number of trip requests. For the past twelve fiscal years, these measures have shared similar trends, with

[3] Note also that the graph indicates a drop in on-time performance in September 2013. This drop was driven by a decrease in the on-time performance data for Santa Clarita, which turned out to be simply a lapse in the data collection.

some disparity from 2007 to 2009, potentially due to a policy change[4], and in 2016 again. In 2017, the no-show rate averaged 3.0 percent, compared to 2.0 percent in 2016. The cancellation rate in 2017 averaged 1.7 percent, which was slightly higher than the 2016 average of 1.5 percent. Overall, fluctuations in no-show and cancellation rates do not coincide with changes in trip requests, as illustrated in Figure 11 below.[5]

Figure 11: Trip Requests and No-Show and Cancellation Rates (July 2005 – October 2017)



Source: Access Services

Population

The demand for paratransit services may also be affected by demographic or socioeconomic factors such as the number of people living in the service area. Population data for Los Angeles County are collected from the Demographic Research Unit at the California Department of Finance (DoF) and the Southern California Association of Governments (SCAG). Though the

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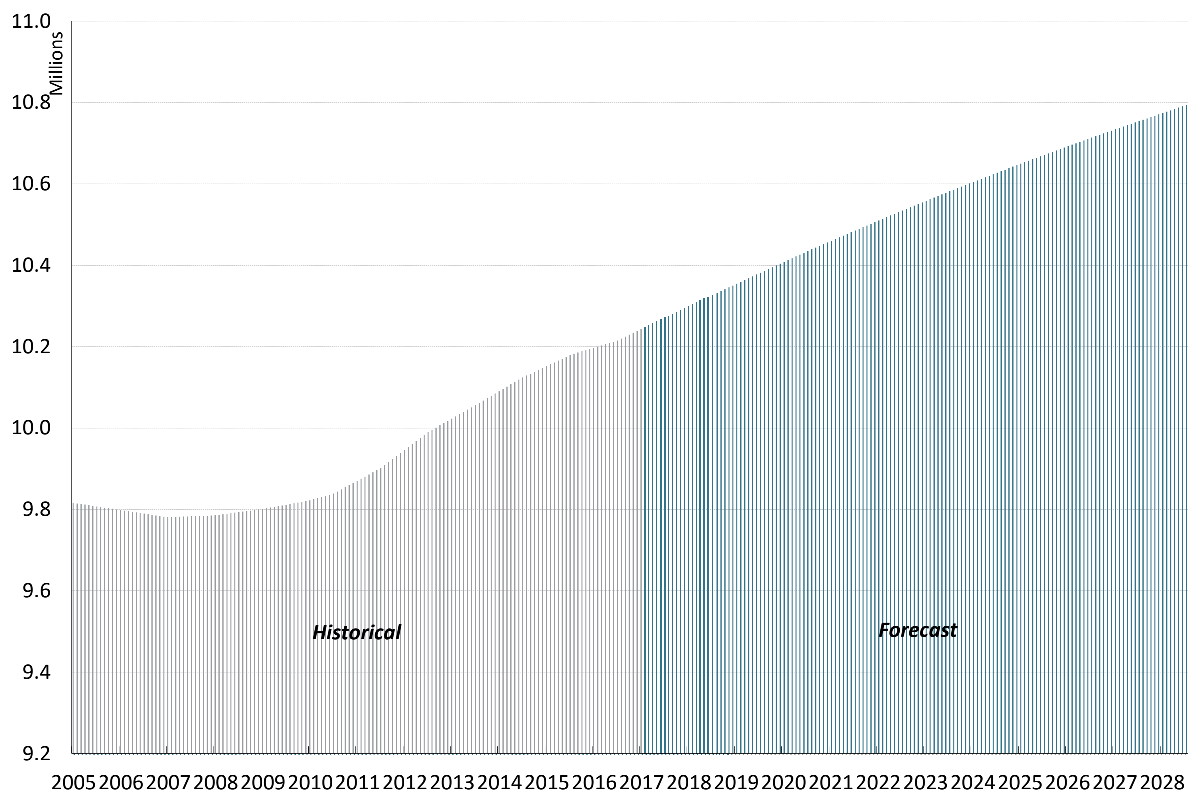
[4] A late standing order cancellation policy has been effective since February 1st, 2007. Under this new policy, riders are allowed an unlimited number of cancellations, as long as they are made by 10:00 p.m. the night before service. Trips that are cancelled after this time are classified as late standing order cancellations. A rider is allowed a maximum of six late standing order cancellations (or 10 percent of his/her trips, whichever is greater) in a 60-day period. Riders who cancel more often than this are subject to revocation of their standing order trip.
[5] No-shows and cancellations shown in Figure 11 reflect billing data, not operations data. They do not account for all booked trips and thus are underestimated. As a part of the next update, HDR will revise the no-show and cancellation historical data.

annual population growth rate is projected to remain above 0.50 percent through 2021, it is expected to decline steadily over the next ten years.

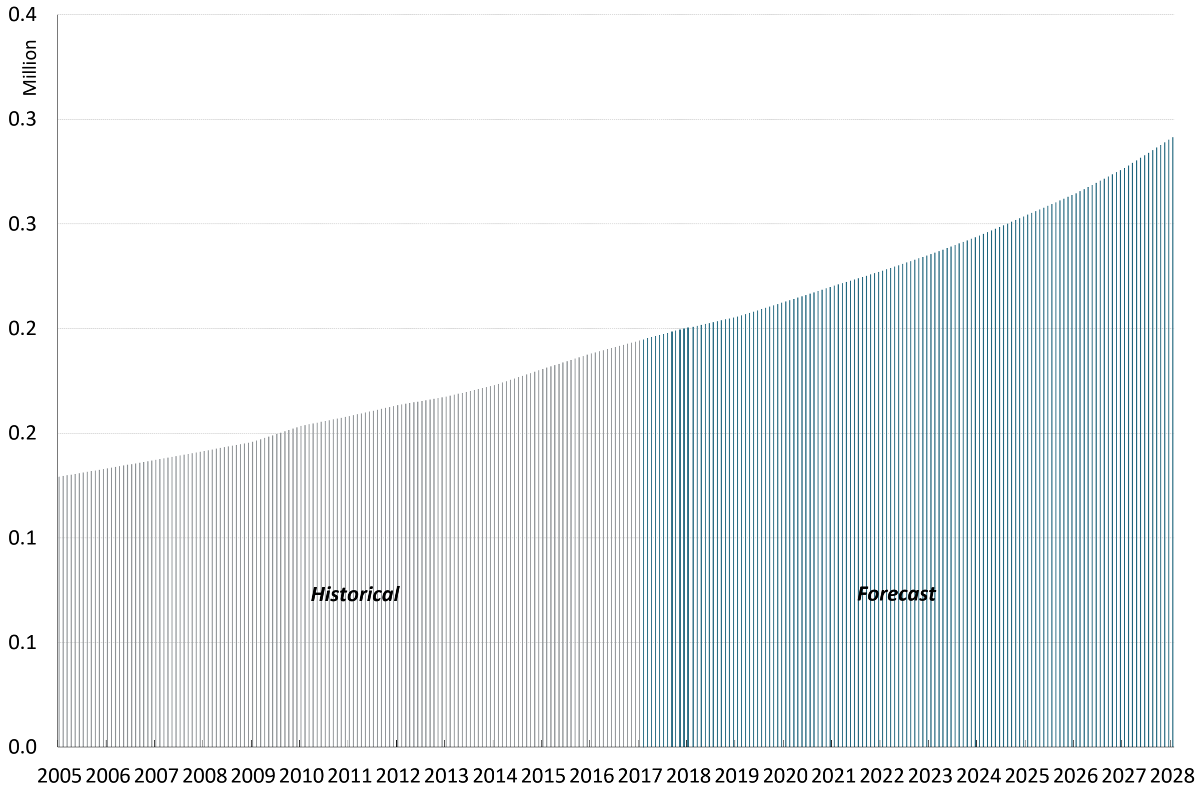
Alternately, the senior population (85 years old and above) is growing at a much faster pace. From 2010 to 2017, this group grew by 3.4 percent per year and is expected to continue to grow at an annual rate of 3.8 percent through 2028, in part due to the growing Asian American and Latino American senior populations. Figure 12 and Figure 13 below illustrate the trends in total population and senior population in Los Angeles County.

Figure 12: Total Population in Los Angeles County (July 2005 – June 2028)



Source: California Department of Finance, Demographic Research Unit

Figure 13: Senior Population in Los Angeles County (July 2005 – June 2028)



Source: California Department of Finance, Demographic Research Unit

3. Performance Metrics

Adding to the review of Access's operations and performance statistics is a comparative assessment of key performance metrics from a sample of paratransit agencies. The comparison sheds some light on how performance is being tracked and monitored by different agencies and the assessment may help Access to develop initiatives for establishing new performance goals in the future. Furthermore, ongoing oversight of performance can help Access plan for the lingering impact of the economic recession in terms of tax revenue (primary funding source for public transit), as well as uncertainty in gasoline prices. The discussion also serves as an introduction to the peer analysis of Access's operations and quality of service, which is presented in Section 4.

Agencies establish and track performance metrics for reporting, planning, and funding purposes. In this section, a set of key performance metrics additional to those already introduced in earlier sections are presented for a sample of paratransit service systems. While details of the selection process of the comparison agencies are explained in the peer analysis (Section 4), agencies are selected primarily because the metrics are recorded in agency reports that are readily available online. Metrics that are measured differently from those introduced in earlier sections are provided with definitions or explanations on how they differ from those provided by Access.

Overall, Access has been reporting similar metrics in terms of service delivery and coverage. Access may consider providing in its annual report additional metrics on service solvency, completeness, and maintenance such as subsidy per passenger, vehicle no-shows ("missed trips"), and miles between road calls, etc. In terms of safety, Access may consider reporting total accidents that aggregate the numbers provided in the different management summaries of the Board Box Report.

Other observations are as follows:

- Customer complaint rates are usually measured by the number of complaints per 1,000 trips. For Pace Suburban Bus Division (Pace), the metric is measured by complaints per 100,000 passenger miles;
- Washington Metropolitan Area Transit Authority (WMATA), Orange County Transportation Authority (OCTA), and Access measure excessively late vehicles slightly differently. WMATA reports any trips over 30 minutes past window; Access reports "late 4" trips – category of late trips wherein the vehicle arrives more than 45 minutes after the end of the 20-minute on-time window; while OCTA measures service delivery failures (SDF), a unique measurement specific to the program. This indicator is an occurrence when a vehicle does not arrive at the pick-up location until 90 minutes after the conclusion of the 30-minute on-time window;
- All sample agencies publish accidents rates except for WMATA. Preventable vehicle accidents are counts of incidents concerning physical contact between a paratransit vehicle and other vehicles, objects, or pedestrians where the operator is determined to

be at fault. The standardized measurement is accident counts multiplied by 100,000 and then divided by the total vehicle miles;

- Pace and OCTA publish miles between road calls, a maintenance performance indicator that measures the vehicle miles between mechanical failures of a vehicle used for public transit during revenue service. Road calls may cause a delay in service and necessitate removing the vehicle from service until repairs are made; and
- Subsidy per passenger is reported by Pace. Subsidy includes Public Transportation Fund of 30 percent of the Regional Transportation Authority sales tax and Chicago real estate transfer tax collected.

Table 3: Sample of Performance Metrics Published in Annual/ Monthly Reports

Metric		Access	OCTA	WMATA	Pace	MDT
Service Coverage	Total Passengers	✓	✓	✓	✓	✓
	Total Trips Requested	✓				✓
	Total Trips Scheduled					
	Total Trips Delivered	✓		✓		✓
	Contract Revenue Miles	✓				
	Contract Revenue Hours	✓		✓	✓	✓
	Average Trip Distance	✓		✓	✓	✓
	Vehicles in Service				✓	
	Passengers per Hour	✓			✓	
Service Delivery	On-Time Performance	✓	✓			✓
	Hour Late Trips	✓		✓		
	Service Complaints	✓				
	No-Show (Customer)	✓	Discontinued	✓	Discontinued	✓
	No-Show (Vehicle)			✓		
	Late Cancelation	✓	Discontinued	✓	Discontinued	✓
Service Solvency	Cost per Revenue Vehicle Hour	✓	✓		✓	
	Subsidy per Passenger				✓	
	Farebox Recovery Ratio*	✓	✓	✓	✓	✓
Service Safety	Preventable Vehicle Accidents	✓	✓		✓	✓
Other	Miles between Road Calls		✓		✓	
	Average Initial Hold Times or Call Response**	✓		✓		

Sources: OCTA –Transit Division Performance Measurements Report; WMATA – MetroAccess Monthly Operations Report; Pace – Suburban Service Budget &Regional ADA Paratransit Budget; MDT – Miami-Dade County Transit (Miami, FL) Paratransit Operations Monthly Report.

*Notes: *Farebox recovery ratio is a measure of the proportion of operating costs covered by passenger fares; calculated by dividing the farebox revenue by total operating expenses.*

***Metrics refers to customer service delay in seconds.*

4. Peer Analysis

A peer review is a valuable management tool designed to help improve an agency's service and operation performance. Ultimately, the goal of the peer review is to better understand an agency's strengths and weaknesses so as to formulate strategies to improve its performance. For Access, the objective of the customized peer review is to compare similar paratransit agencies (in terms of operational statistics, size, and geography) to identify demand-related issues (such as increased customer complaints, high no-show rate, and low on-time performance) that have risen elsewhere and to examine how these issues have been addressed. The findings may also be useful to Access management in formulating policy scenarios.

Methodology

The peer review approach relies on a methodology developed for the Transportation Research Board (TRB)[6] that consists of the following steps:

1. Define the performance areas to be assessed;
2. Establish a peer group based on guidance provided by Access and using the FTIS database;
3. Gather and process performance data for all selected peers; and
4. Compare performance data and identify areas of improvement.

The selection of the peer group is primarily based on operational statistics, size and geography, as well as HDR's prior experience with different transit agencies in obtaining relevant data. To verify that the appropriate agencies are selected, likeness scores computed within the FTIS database are utilized[7]. The resulting six agencies, each providing paratransit services, form the national peer group:

- Massachusetts Bay Transportation Authority (MBTA) in Boston, MA;
- Metropolitan Transit Authority (MTA) of Harris County in Houston, TX;
- Miami-Dade Transit (MDT) in Miami, FL;
- Pace Suburban Bus Division in Chicago, IL;
- Southeastern Pennsylvania Transportation Authority (SEPTA) in Philadelphia, PA; and

[6] Kittelson & Associates, Inc. et al. *A Methodology for Performance Measurement and Peer Comparison in the Public Transportation Industry*. TCRP Report 141, Transportation Research Board, National Research Council, Washington, D.C., 2010.

[7] The scores determine the level of similarity between a potential peer agency and the target agency with respect to a number of screening/grouping criteria accounting for both an agency's operating characteristics (annual vehicle miles operated, annual operating budget, etc.) and the socio-economic profile of the service area (population, percentage of low-income people, etc.). A total likeness score is then calculated. A total likeness score of 0 indicates a perfect match between two agencies. Higher scores denote greater levels of dissimilarity between two agencies. In general, a total likeness score lower than 0.50 indicates a good match, a score between 0.50 and 0.74 represents a satisfactory match, and a score between 0.75 and 0.99 suggests that potential peers may be available, but caution should be exercised to investigate potential differences that may make them unsuitable. Finally, peers with scores greater than or equal to 1.00 should not be considered in a performance peer review.

- Washington Metropolitan Area Transit Authority (WMATA) in Washington, D.C.

To assess how Access performs within the Los Angeles region, a group of regional peer agencies are selected based on relative proximity to the region. The four selected agencies are:

- Orange County Transportation Authority (OCTA);
- Riverside Transit Agency (RTA);
- LACMTA - Small Operators (LACMTA) (non-ADA service; and
- City of Los Angeles Department of Transportation (LADOT) (non-ADA service).

A standard peer review requires a level of effort that exceeds the current scope of the study. Instead, a selection of performance areas of interest to Access is assessed. More specifically, the following five areas have been considered:

- **Service utilization – measures how passengers use the service that is provided[8]:** *Passenger trip* is the demand for the service and it is the main indicator of service utilization. Passenger trip is also used to compute two other important indicators: 1) *Late cancellation rate,* which is the percentage of trips cancelled less than two hours within the negotiated time window and 2) *No show rate,* which is the percentage of trips where customers did not show up within the allotted 20-minute pick-up time window or canceled a Standing Order[9] trip later than 10 p.m. of the day prior to schedule pick-up;
- **Cost efficiency – assesses an agency's ability to provide service outputs within the constraints of service inputs[10]:** *Operating cost per passenger trip* is the cost to provide service for each passenger demanding the service. Cost components included in operating cost are wages and fringe benefits, utilities, causalities and liabilities, services, fuel and lube, tire, etc.;
- **Productivity – considers how many passengers are served per unit of service (hours, miles, vehicles, or employee full-time equivalents)[11]:** *Passenger per revenue hour* compares the demand for the provided service to a time-specific unit of service;
- **Cost effectiveness – compares the cost of providing service to the outcomes resulting from the provided service[12]:** *Farebox recovery ratio* measures how much of a transit agency's operating costs are covered by fare revenue and the agency's ability to recover (in full or in part) the cost of providing transit service. Revenue generated is used as the outcome resulting from the provided service; and
- **Service Quality (*Perceived*) – describes the transit agency's service as perceived by customers:** *On-time performance* demonstrates the level of satisfaction that

[8] Kittelson & Associates, Inc. et al., op. cit.
[9] A Standing Order trip is a series of pre-scheduled trips based on repeated trips of same time and destinations, for an extended period of time on the same day(s) of the week.
[10] Kittelson & Associates, Inc. et al., op. cit.
[11] Ibid.
[12] Ibid.

passengers of the service experience. A trip is considered on time if the vehicle arrives within a 20/30-minute pick-up window.

The review of the areas of interest introduced covers data from fiscal years 2012 to 2015[13] to account for short-term trends and identify potential outliers in the data during the four-year period. The data are collected from the following sources:

- Florida Transit Information System (FTIS)[14];
- National Transit Database (NTD);
- New York City Transit Paratransit Peer Reports; and
- Agency Operation and Service Annual Reports[15] [16].

Note also that all monetary metrics are adjusted for inflation and expressed in constant 2015 dollars using the U.S. Consumer Price Index (CPI). Removing inflation allows a trend analysis to clearly show whether an agency's real costs are increasing or decreasing.

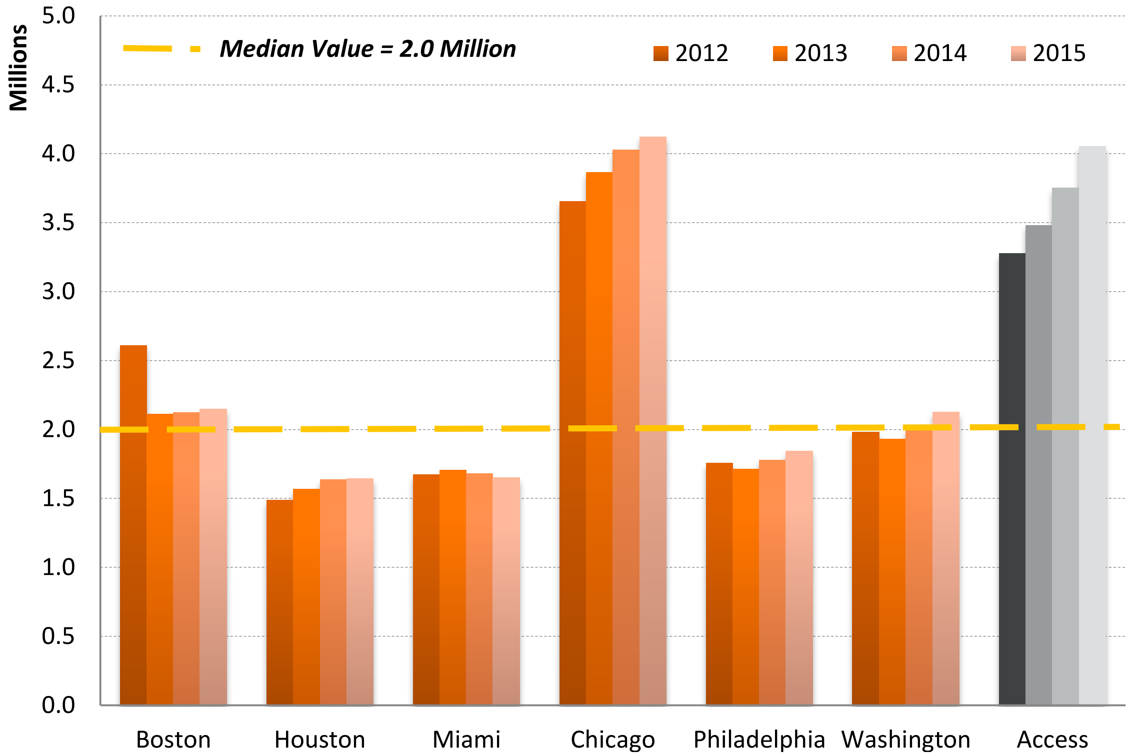
Service Utilization

Passenger demand in terms of passenger trips or trip requests is an indicator of service utilization. Because the number of passenger trips is commonly reported and provided by each agency, it is used to quantify demand in the peer review. Other demand measures, such as trip requests, are less readily available. Access is one of the largest paratransit agencies in terms of passenger demand, providing the second highest number of trips among all paratransit systems nationwide in 2016. The only system larger than Access in the peer group, in terms of ridership, is Pace in Chicago. Ridership for the selected peer systems are displayed in Figure 14 on the next page.

Access averages about 3.6 million passenger trips a year which is well above the median value of 2.0 million for national peer systems. Since 2012, the average annual ridership growth for Access has been 7.8 percent, which is the highest annual growth among national peers.

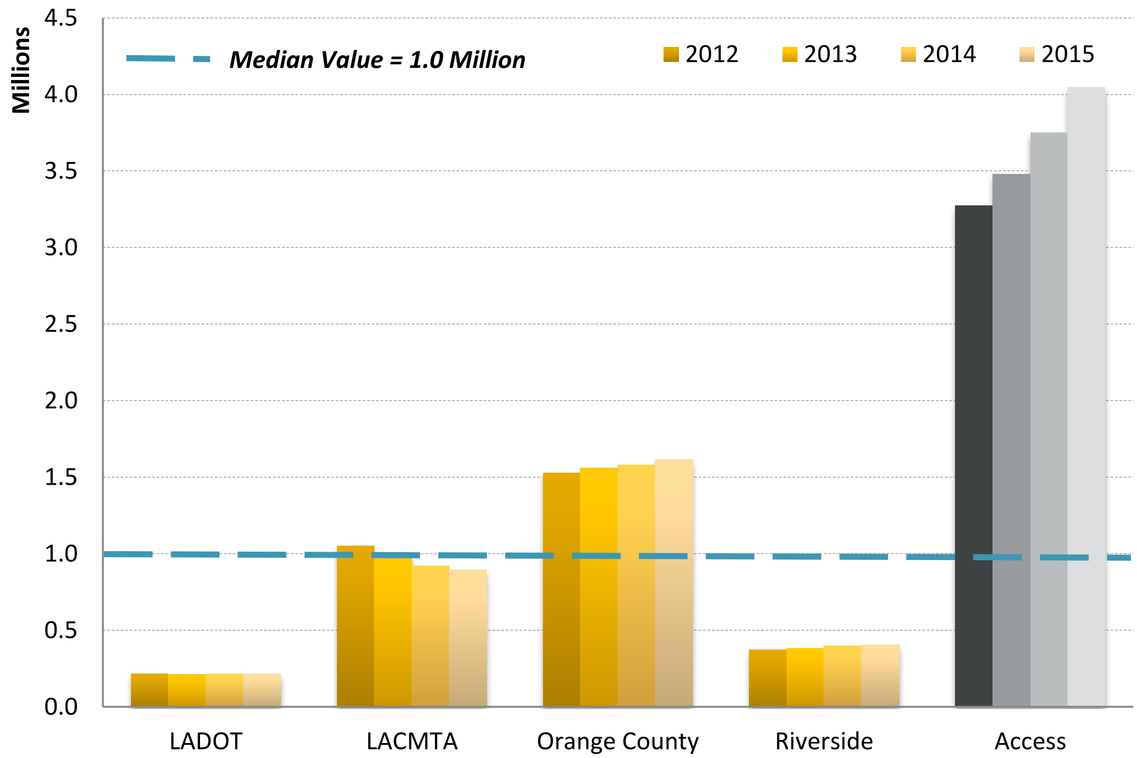
[13] This was the most recent data available through FTIS.
[14] Available at http://www.ftis.org.
[15] OCTA − Transit Division Performance Measurements Report; WMATA − MetroAccess Monthly Operations Report; Pace − Suburban Service Budget & Regional ADA Paratransit Budget; MDT − Miami-Dade Transit Paratransit Operations Monthly Reports; MTA Houston – Metro Business Plan & Budget.
[16] Data on service quality are somewhat incomplete. In particular, complaint rate and late cancellation data are not readily available.

Figure 14: National Peer Review, Passenger Trips (FY2012 – FY2015)



Access is the largest and the fastest growing paratransit agency in the Greater Los Angeles region. Ridership for some other agencies in the region is stagnant or declining while Access continues to increase its number of passenger trips every year. On average, Access serves nearly twice as many passengers as OCTA, which is the next largest paratransit agency in Los Angeles. The median value for ridership among regional peers is 1.0 million, which is substantially lower than the Access average of 3.6 million passengers per year. The number of passenger trips for other agencies in the region are displayed in Figure 15.

Figure 15: Regional Peer Review, Passenger Trips (FY2012 – FY2015)



The economic crisis may have affected ridership numbers in the Greater Los Angeles region in 2010. The recession led to a decline in tax revenues which translated into funding shortages for paratransit agencies in the area. Many agencies responded by cutting service, revising policies and increasing fares, and every agency experienced ridership decreases through this period. However, it is evident in the data that Access has recovered since then.

No-show and late cancellation rates are also considered drivers of service utilization as they indicate the percentage of trips that were scheduled, but not completed. These are important to include because agencies incur costs but do not generate revenue on these trips. However, Access is one of few service systems that track uncompleted trips – many agencies do not have the requisite information for a peer system comparison on this metric so it is not presented here.

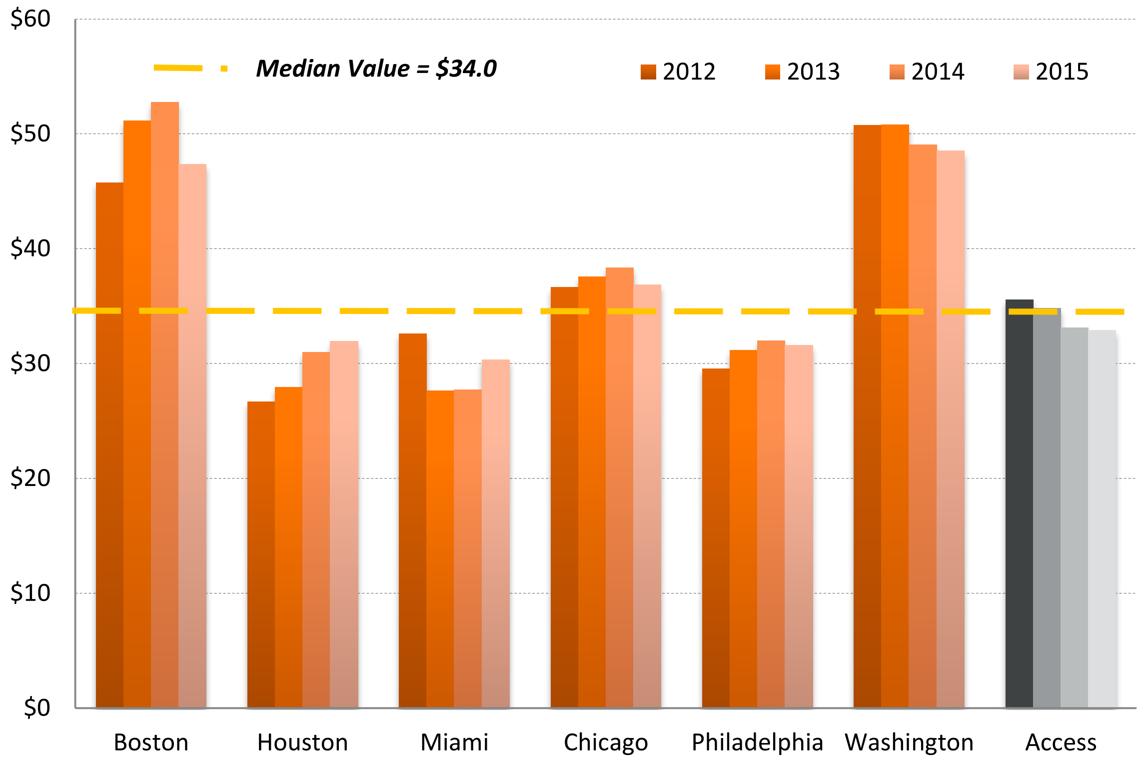
Cost Efficiency

System cost efficiency is quantified as the operating cost per passenger trip. Operating costs include the total expenses to operate and maintain the transit system, which includes labor, fuel, maintenance, taxes and other costs associated with transit operations. According to the NTD 2012 profiles for top 50 reporter agencies, employee benefits and wages typically account for at least half of all operations and maintenance expenses. The operating cost per trip, expressed in 2015 dollars, is displayed for all national and regional peer systems in Figure 16 and Figure 17, respectively.

The average operating cost for Access from the data is about equal to the median value for national peer systems of $34. There is a disparity in operating costs for some of the other national paratransit systems—agencies in Washington and Boston have average operating costs over 40 dollars per trip while agencies in Philadelphia, Houston and Miami have average costs under 30 dollars per trip. Chicago's agency decreased their operating costs significantly after 2010 and now they have average around $37 per trip.

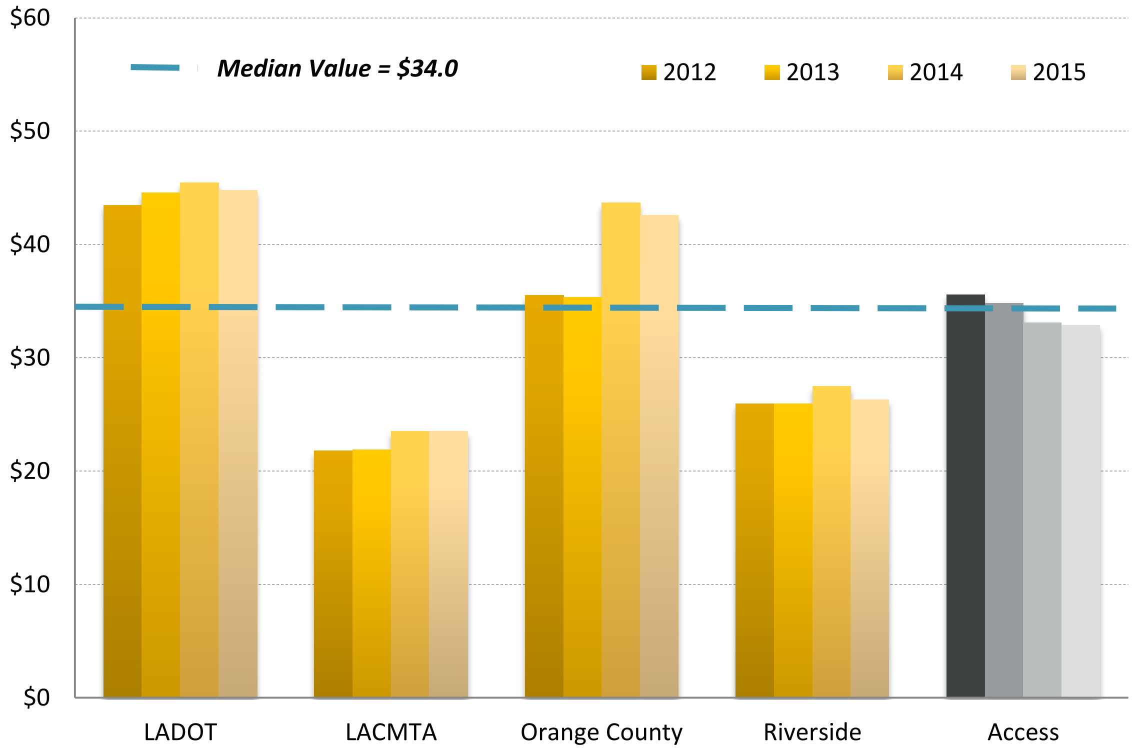
This disparity could be due to discrepancies across agencies in employee compensation and their responses to the 2008-2009 economic recession. The real cost per trip for Access has slowly decreased from 2010, declining 2.6 percent per year on average.

Figure 16: National Peer Review, Real Operating Cost per Passenger Trip (FY2012 – FY2015)



The operating cost per trip for Access also compares favorably to regional peer systems, as the median value per trip for other Los Angeles systems is the same as the national median (as shown in Figure 17). In terms of operating cost per trip, Access does not seem to benefit from economies of scale by having more riders than its regional peer agencies. This could be because Access also covers a larger service area that spans multiple regions, increasing the length of each trip.

Figure 17: Regional Peer Review, Operating Cost per Passenger Trip (FY2012 – FY2015)



Regional average trip length may be important to consider when assessing the cost efficiency of an agency. An agency covering a large service area such as Access may be at a disadvantage in terms of cost efficiency because vehicles have to cover longer distance to deliver services, thus making trips more expensive to provide. Each year from 2012 to 2015, Access had the longest trip length among regional and national peer systems, averaging 13.3 miles traveled per trip. The average trip length for Access is more than double the average trip length for LADOT (4.9 miles) and almost three times the average length for LACMTA (3.6 miles). RTA, OCTA, and the MTA of Harris County have almost comparable average trip lengths to Access, with 12.1, 10.7, and 11.4 miles per trip, respectively. Figure 18 and Figure 19 below illustrate the difference in trip lengths among the national and regional peers.

Figure 18: National Peer Review, Trip Length in Miles (FY2012 – FY2015)

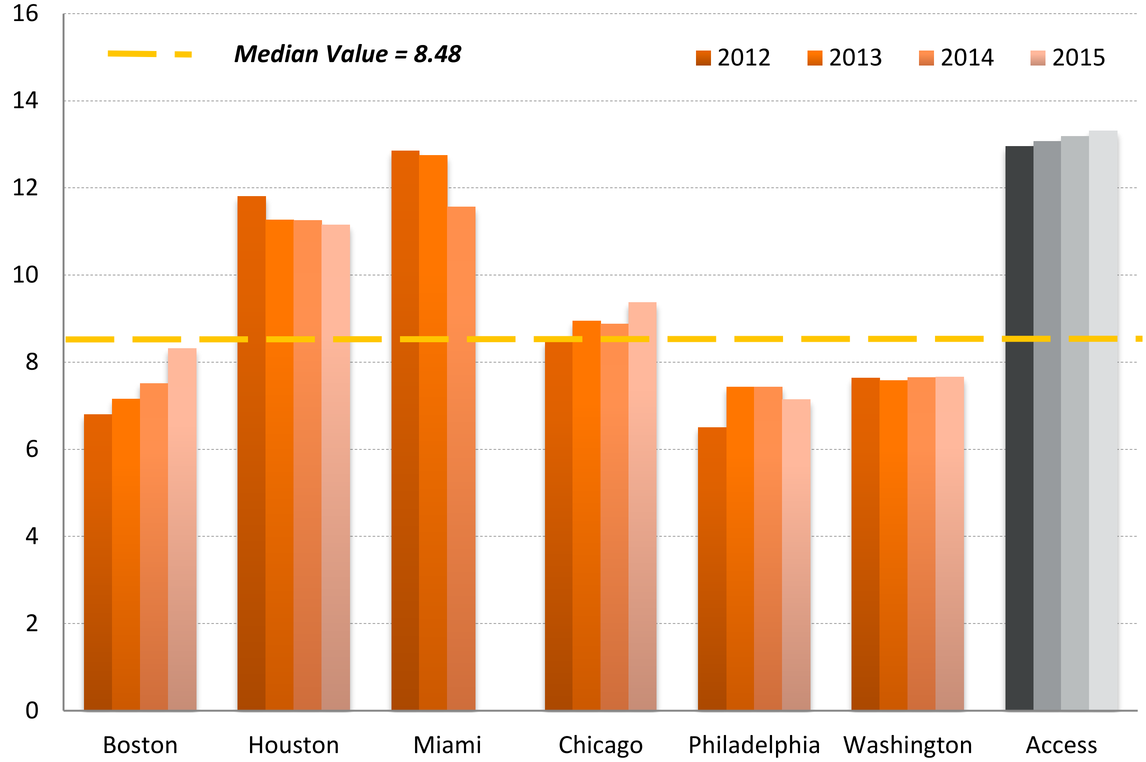
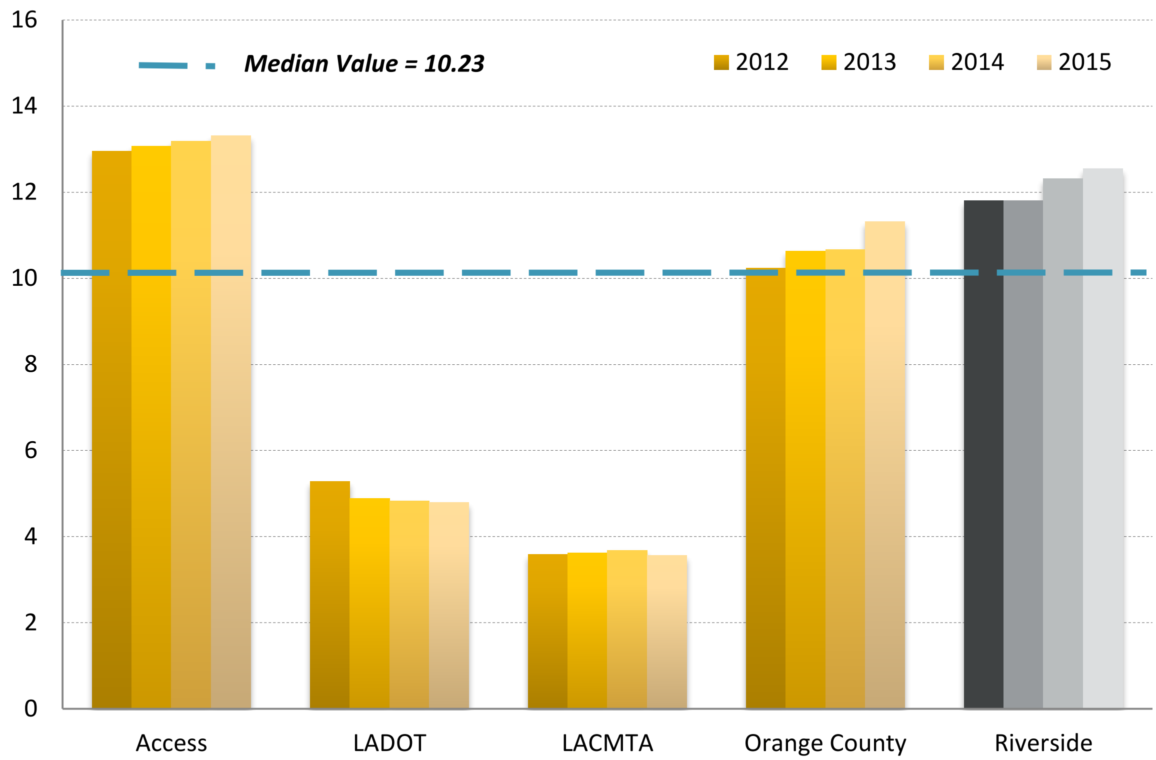


Figure 19: Regional Peer Review, Trip Length in Miles (FY2012 – FY2015)

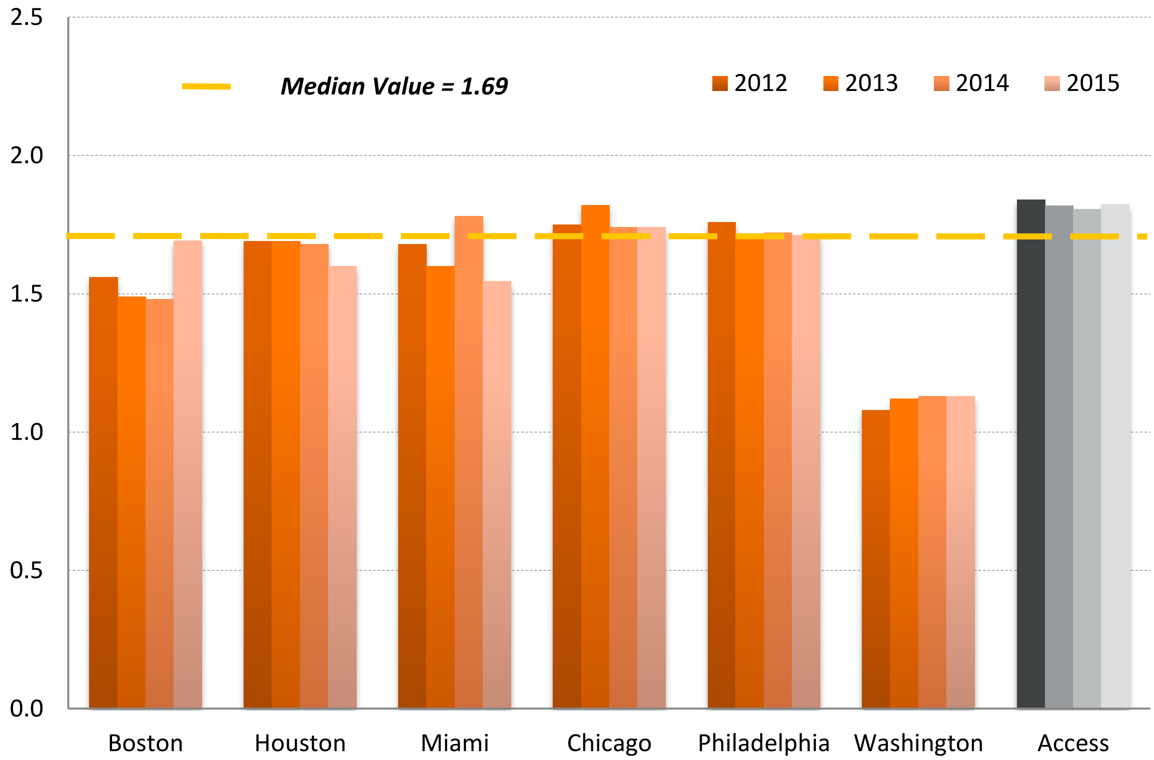


Productivity

The number of passengers per revenue hour indicates how many passengers an agency serves for each hour that vehicles are earning revenue. Agencies that serve more passengers per hour are deemed more productive. The number of passengers per revenue hour is a good indicator of productivity in a system, but it has some drawbacks as a metric because the size of the service area and trip length can greatly affect the number of passengers per revenue hour.

Access has the largest service area of the national peer systems, covering more than 4,000 square miles, so it might be expected that Access would be less productive in terms of passengers per revenue hour in comparison with some of its peer agencies, because it takes more time on average to serve the same number of passengers. The number of passengers per revenue hour for Access and all national peer systems is shown in Figure 20.

Figure 20: National Peer Review, Passengers per Revenue Hour (FY2012 – FY2015)

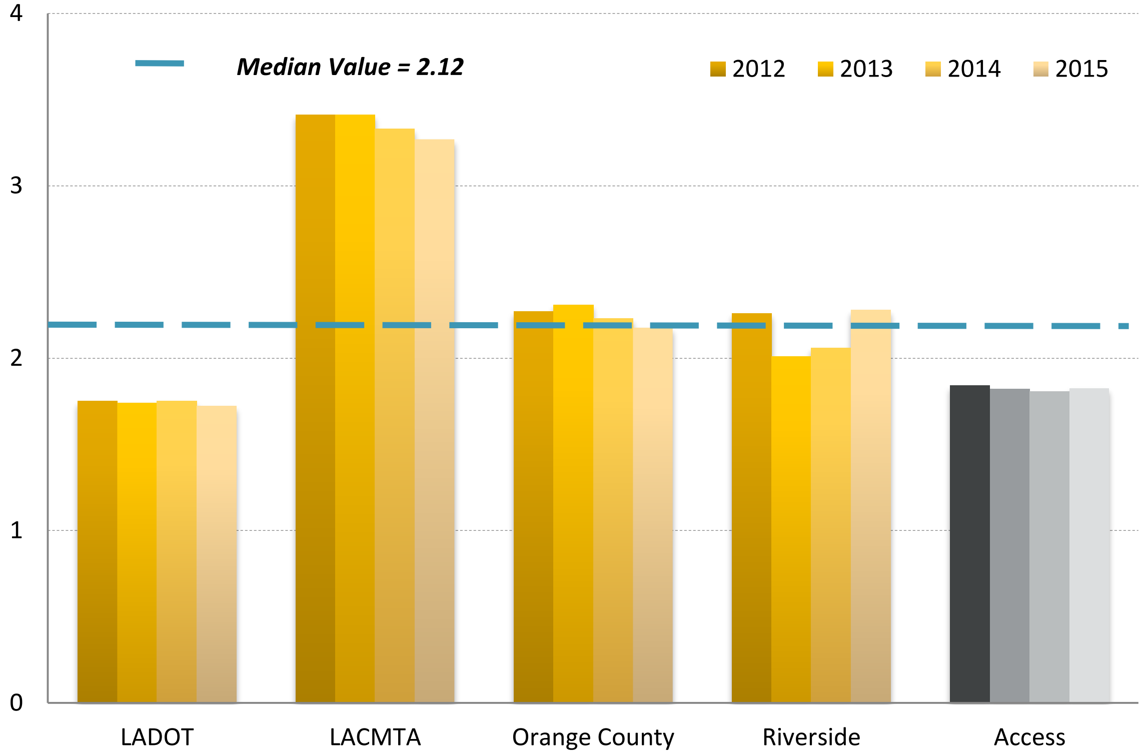


Access averages 1.8 passengers per revenue hour which is higher than the national peer systems – the median value being 1.7 passengers. The least productive system is WMATA, averaging 1.1 passengers per revenue hour.

Among peer agencies in the Greater Los Angeles region, the median value is 2.12, as shown in Figure 21. In contrast, Access consistently lands around 1.8 and is on par with LADOT.

As suggested earlier, the discrepancy in passengers per revenue hour among national and regional peer systems is potentially due to the relative size of service areas. By covering a smaller area, it is easier to serve more passengers per revenue hour because less time is spent traveling to pick up and deliver the passenger to their destination.

Figure 21: Regional Peer Review, Passengers per Revenue Hour (FY2012 – FY2015)

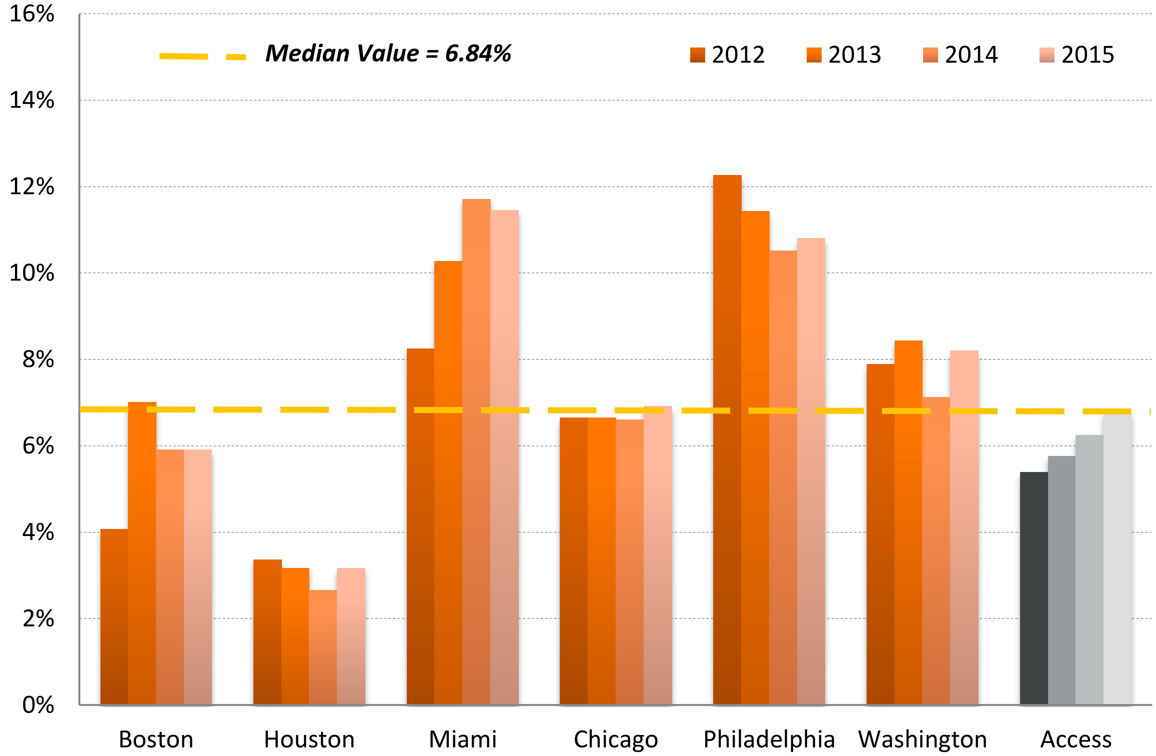


Cost Effectiveness

Farebox recovery ratio is the percentage of passenger fare revenues out of total operating expenses. As discussed earlier, factors such as wages, benefits, fuel, insurance, maintenance and trip length all contribute to the operating cost for each paratransit agency. The farebox recovery ratio is an indicator of the share of total operating costs that is covered by passenger fares. It is used to quantify cost effectiveness because it measures the return of each dollar as revenue over cost. A higher percentage means that passenger fares make up a greater portion of the agency's operating costs.

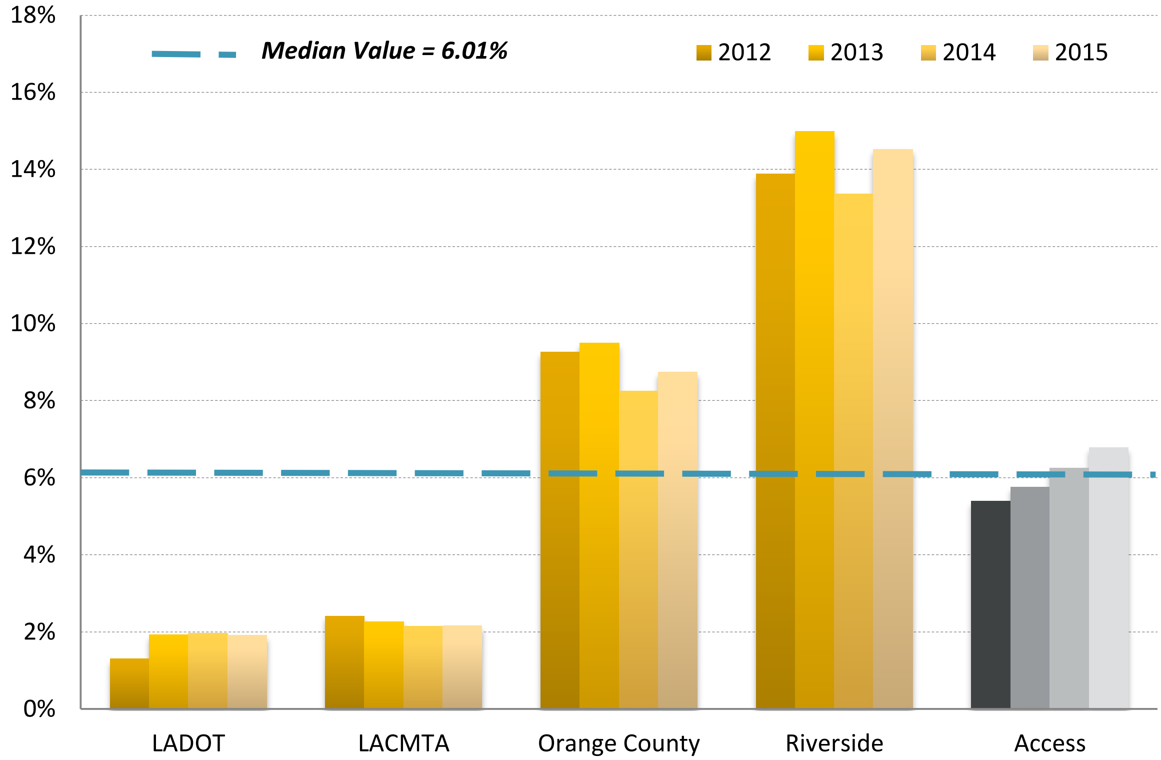
Access has an average farebox recovery ratio of 6.0 percent, just under the median value of 6.8 percent for national peer systems. The farebox recovery ratio for Access steadily increased from 5.4 percent to 6.8 percent during the observation period, unlike its national peers. Farebox recovery ratios for national peer systems are displayed in Figure 22.

Figure 22: National Peer Review, Farebox Recovery (FY2012 – FY2015)



The farebox recovery ratios for regional peer systems are displayed in Figure 23. The median value among regional peers is 6.0 percent, equal to the average farebox recovery ratio for Access. Access has a higher average farebox recovery ratio than LADOT and LACMTA, but it has a lower ratio than agencies in Orange County and Riverside County.

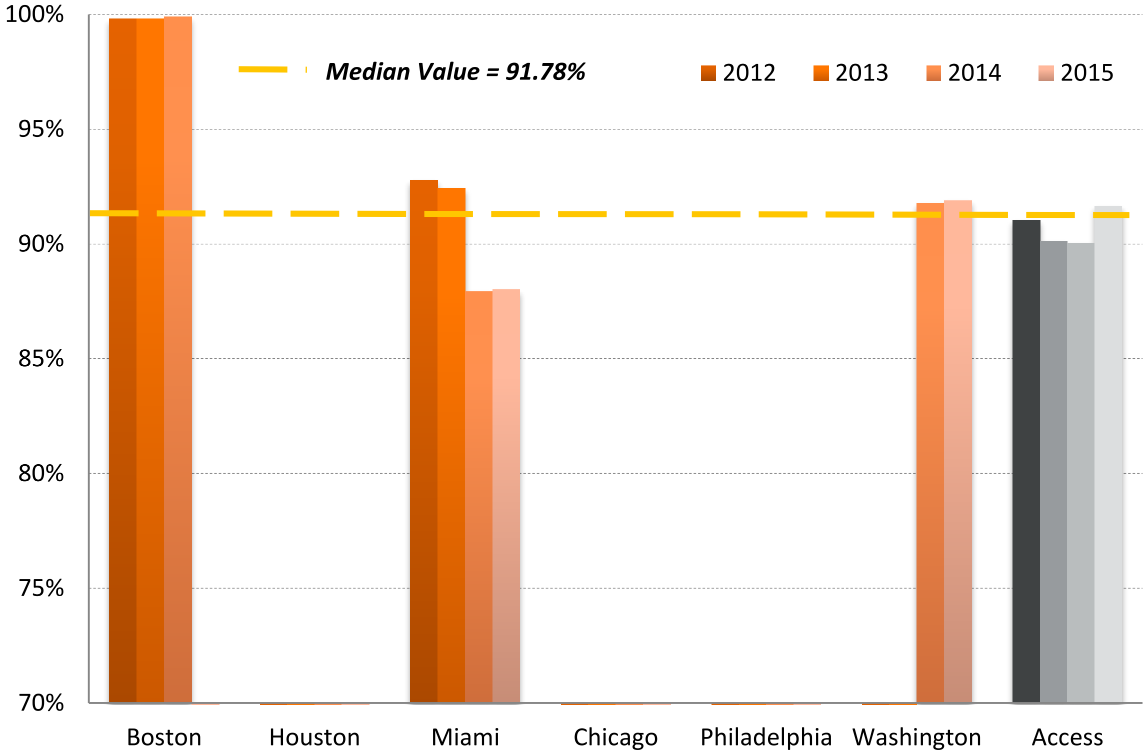
Figure 23: Regional Peer Review, Farebox Recovery (FY2012 – FY2015)



Service Quality

Many agencies do not have data on service quality that are readily available, making a peer system comparison difficult. On time performance is a measure of service quality that is often tracked and reported by paratransit agencies. Agencies differ slightly on the definition of the time window that constitutes a trip being completed on time, with pick-up windows ranging from 20 to 30 minutes from the scheduled pick-up time. Figure 24 shows the percentage of trips that were completed on time among national and regional peer systems.

Figure 24: National Peer Review, On Time Performance (FY2012 – FY2015[17])



The percentage of trips completed on time for Access Services is below the median value of 92 percent for national and regional agencies. Access's average on time performance was lower than OCTA's (94.6 percent), the only regional peer with on time performance data. There is some fluctuation over time in Access's performance in terms of service provided and perceived, but not to the degree of OCTA and MDT. Boston's paratransit agency was able to maintain a high on time performance from 2012 to 2014, close to 100 percent.

[17] Data were not available for all years and for all agencies, so national and regional peers are displayed together on a single graph for comparison.

5. Analysis of Paratransit Demand

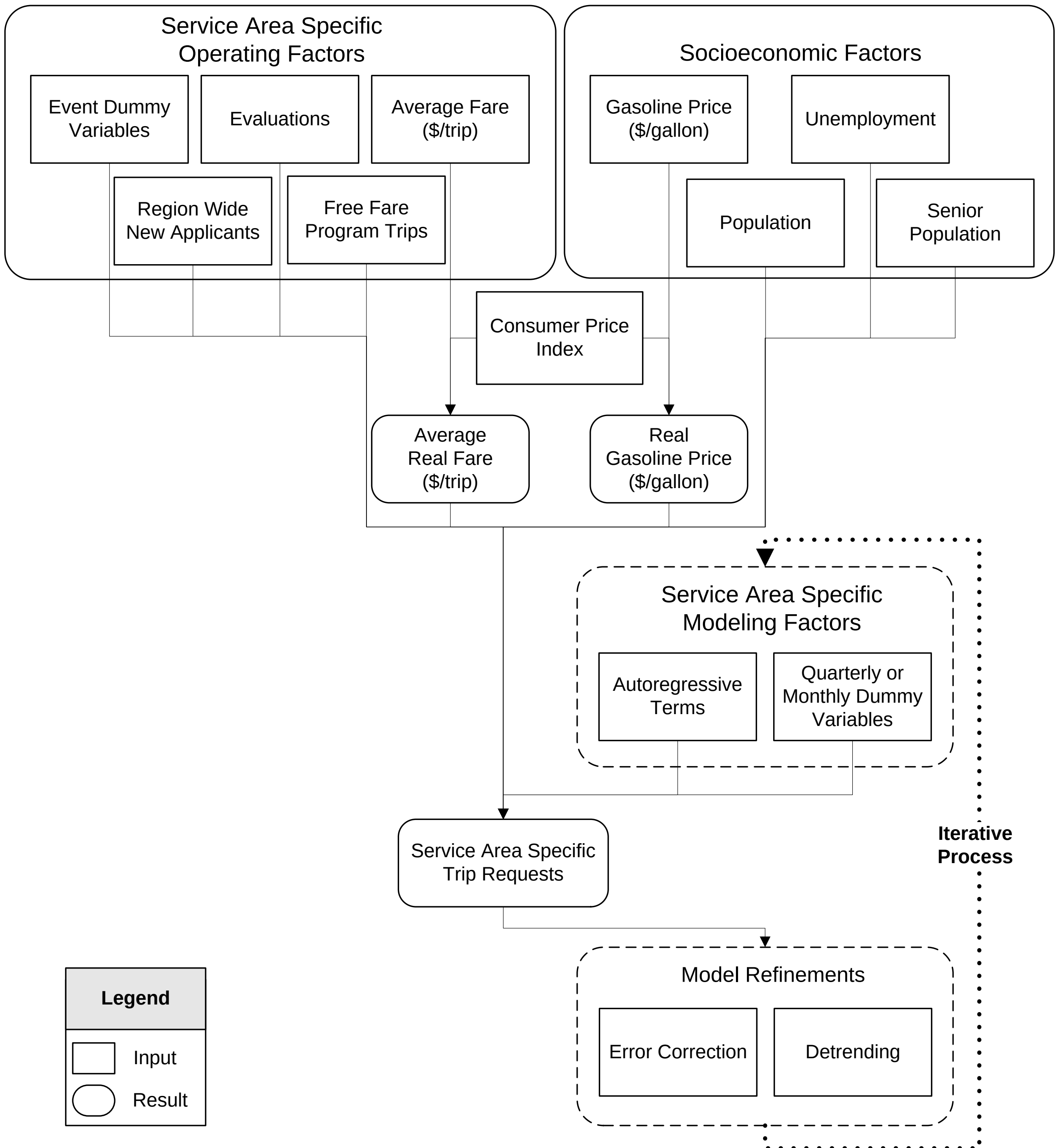
This section presents the methodology used to estimate trip demand for Access paratransit as well as the results of the analysis. The methodology involves statistical methods for studying historical trends and econometric techniques for determining factors that drive paratransit demand. The combined analysis leads to a series of econometric equations that quantify the factors that determine paratransit demand. These factors are examined for each service region using monthly operating data and other socio-economic data (unemployment, real gas price, etc.) from federal, state, and local sources. Additional variables are used in the model to capture the impacts of seasonality and specific events that may influence the level of paratransit demand. The results of this analysis identify which factors – and quantify the extent to which changes in these factors – affect trip demand.

Methodological Framework

Prior to estimating the service region-specific regression models, a conceptual model or framework is developed to illustrate how operating and socioeconomic factors can impact trip demand. The schematic – also referred to as a structure and logic model – shows the inputs that are tested by the model, and how the inputs relate to each other (an example is provided in Figure 25 on the next page). Data availability is crucial in determining the final model structure. The number of observations impacts the robustness of the model, both in terms of the model's ability to identify key factors that affect trip demand and in terms of the model's accuracy in predicting trip demand.

There are six regression models, one for each service region. These models are independent of each other – although regions share some operational events, which are addressed by using date-specific dummy variables. Each model is also independent in terms of service quality (such as customer satisfaction), alternative transportation modes available, and general travel demand patterns.

Figure 25: Structure and Logic Diagram of the Paratransit Demand Model



Overview

The demand analysis and forecasting process in this study consists of seven main steps:

1. Identify all explanatory variables of paratransit demand;
2. Estimate service region-specific equations (six) with the appropriate regression technique (e.g., ordinary least squares, or two-stage least squares) and functional form (e.g., linear, semi-log, or log-log);

3. Select best performing models, based on the regression statistics (i.e., adjusted R-squared, t-statistics and F-statistic);
4. Assess the model accuracy using residuals;
5. Develop a forecast based on steady-state analysis;
6. Conduct a risk analysis of ridership forecast; and
7. Simulate trip demand under alternate fare scenarios.

The analysis reveals that trip demand is driven by four key factors: the real average fare, the real gasoline price, unemployment, and seasonality. Other factors such as income and population may also influence trip demand; however the strength of these effects is not statistically discernible over the study period. Table 5 on the next page summarizes all the variables tested in the regression analysis and reports data availability and sources. In the summary table, the variables are grouped into three categories: operating factors (those over which paratransit managers exercise some control), socioeconomic factors, and modeling factors.

Model Performance

Table 4 below compares HDR's ridership forecast (most likely outcome) with actual ridership for the last five annual updates. The forecast is for the entire service area over a 12-month period. In 2014, 2015 and 2016 the projections were within +/- 2 percent of actual ridership. In 2017, ridership growth slowed down significantly as a result of an unforeseen, dramatic decline in the number of applicants. Note finally that ridership growth has fluctuated a lot over the past 10 years: the largest increase was +10.1 percent (FY 2009) and the largest decline was -1.6 percent (FY 2010).

Table 4: Ridership, Actual Data vs. Forecast (2014 – 2018)

Period	Actual Ridership	Projected Ridership	Mean Percentage Error (MPE)	Mean Absolute Percentage Error (MAPE)
Jan 2014 – Dec 2014	3,953,898	3,906,254	1.2%	2.5%
Nov 2014 – Oct 2015	4,189,422	4,274,938	-2.0%	2.5%
Jan 2016 – Dec 2016	4,370,389	4,421,551	-1.2%	2.0%
Dec 2016 – Nov 2017	4,375,341	4,611,029	-5.1%	5.1%
Jan 2018 – Dec 2018	4,458,410	4,365,582	2.1%	2.3%

Table 5: Variables Tested in Regression Analysis

Factors	Data Availability	Sources	Impact on Trip Demand
Modeling Factors			
September 11th	N/A (dummy variable)	N/A	Not significant
Weather/Seasonality	Available (temperatures and precipitations for Los Angeles) and modeled using quarterly dummy variables	California Department of Water Resources	Seasonal factors significant
Month Indicator	Dummy Variables	N/A	Significant but not as strong as seasonal dummy variables
Socioeconomic Variables			
Population	Available on a yearly basis at the county level	U.S. Census Bureau and California Department of Finance	Not significant
Labor Force	Available on a monthly basis at the county level	Bureau of Labor Statistics	Not significant
Employment	Available on a monthly basis at the county level	Bureau of Labor Statistics	Not significant
Unemployment	Available on a monthly basis at the county level	Bureau of Labor Statistics	Significant for Eastern, Northern & Southern
Unemployment Rate	Available on a monthly basis at the county level	Bureau of Labor Statistics	Not significant
Inflation	Available on a monthly basis at the MSA level	California Department of Finance	N/A
Personal Income	Available on a quarterly basis at the county level	Bureau of Economic Analysis	Not significant
Retail Gasoline Price	Available on a monthly basis at the state level	Energy Information Administration	Significant for Eastern, Southern & West/ Central
Operating Factors			
Fare			
Real Fare	Data on fare structure and fare revenue are available	Access Services (fare); California Department of Finance (CPI-U)	Significant
Eligibility			
Total Evaluations of New Applicants	Available at the service area level	Access Services	Significant for Santa Clarita & West/ Central
Recertified Customers	N/A	Access Services	N/A
New Eligibility Standards (Fall 2005)	N/A (dummy variable)	Access Services	Significant for Antelope Valley
Regional New Applicants	Annual estimates available for FY 2005 to current	Access Services	Significant for Northern
Service & Operation			
Free Fare Program Ridership	Available at the service area level	Access Services	Significant for Eastern, Northern & West/ Central
Changes in service boundary	N/A (dummy variable)	Access Services	Significant for Southern & West/ Central
Implementation of Free Fare Program (September 2000)	N/A (dummy variable)	Access Services	Not significant
Elimination of Same-Day Service (July 2003 - July 2005)	N/A (dummy variable)	Access Services	Not significant
Enforcement of no-show policy (Fall 2005)	N/A (dummy variable)	Access Services	Not significant
Implementation of ADEPT software	N/A (dummy variable)	Access Services	Not significant
Introduction of TAP ID Card	N/A (dummy variable)	Access Services	Not significant
Introduction of debit payment	N/A (dummy variable)	Access Services	Not significant

Estimation Results

Each of the six service region models is estimated separately in EViews (a statistical software package) with monthly data using the ordinary least squares (OLS) method. First difference log-log functional forms (or constant elasticity models) are preferred over others (i.e., linear or semi-log models) because of their fit and robustness. Within a double-log model (or constant elasticity model) specification, the coefficients can be directly interpreted as elasticity coefficients, in other words they indicate the percentage change in the dependent variable brought about by a one-percent change in the associated explanatory variable, other things being equal. For the current study, an elasticity coefficient indicates how (positive or negative relationship) and to what extent trip requests are affected by changes in the associated variable, holding everything else constant. Each model is linearly additive so that the general form of each model can be written as:

D(Log(Trip Requests$_t$)) = β_1 D(Log(Real Average Fare$_t$)) + β_2 D(Log(Real Gasoline Price$_{t-1}$)) +

β_3 D(Log(Unemployment$_{t-1}$)) + β_4 Dummy Variables + …other variables … + β_5 AR(.) + … +

Error$_t$

Equation (1)

Where:

D(Log(Trip Requests$_t$) is the first difference in the natural log of the number of trip requests at time t.

D(Log(Real Average Fare$_t$) is the first difference in the natural log of the real average fare at time t.

D(Log(Real Gasoline Price$_{t-1}$) is the first difference in the natural log of real gasoline price in California lagged one month.

D(Log(Unemployment$_{t-1}$) is the first difference in the natural log of unemployment in Los Angeles County lagged one month.

Dummy variables account for data outliers or specific events – they take on the value of 1 for specific periods and 0 otherwise. Each variable can represent a month of a particular year, or several months within a year (e.g., spring, summer, fall, and winter).

AR(.) is an autoregressive term with specific lags to account for possible correlation between monthly ridership data.

Error$_t$ is the regression error at time t.

And β_i, i = 0,…, 5 are the coefficients to be estimated.

Note that eligibility is no longer included in the regression models because of data limitations (the eligibility data have displayed large, unexplained fluctuations over the past four years) and potential multicollinearity (both trip requests and new applicants are likely determined by the same factors).

Service Region-Specific Estimation Results

For the Eastern region, trip requests are assumed to be a function of the real average fare in the Eastern region, unemployment (lagged three months), real gasoline prices (lagged one month), event dummy variables, seasonality dummy variables, and autoregressive terms that correct for possible correlation between the residuals. The dummy variables in August 2008 and December 2008 are included to account for deviations in trip request levels from the region's average historical trends. Coefficient estimates for each significant variable are reported in Table 6 below.

Table 6: Regression Results – Eastern

Dependent Variable is Difference(Log(Trip Requests – Eastern))
Sample: 2004M07 2018M12
Included observations: 174

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Constant	0.02	0.00	8.54	0.00
Difference(Log(Real Average Fare_E))	-0.26	0.09	-3.05	0.00
Difference (Log(Unemployment (-3)))	0.19	0.04	4.65	0.00
Difference (Log(Real Gas Price (-1)))	0.08	0.03	2.45	0.02
August 2008 Dummy	-0.04	0.01	-2.72	0.01
December 2008 Dummy	0.07	0.02	3.29	0.00
Spring Dummy Variable	-0.02	0.01	-3.30	0.00
Summer Dummy Variable	-0.01	0.00	-2.60	0.01
Fall Dummy Variable	-0.05	0.01	-10.31	0.00
First-order Autoregressive Term	-0.80	0.06	-12.54	0.00
Second-order Autoregressive Term	-0.38	0.06	-6.17	0.00
Twelfth-order Autoregressive Term	0.38	0.04	9.37	0.00

R-squared	0.74	Mean dependent var	0.00
Adjusted R-squared	0.72	S.D. dependent var	0.06
S.E. of regression	0.03	Akaike info criterion	-3.92
Sum squared resid	0.17	Schwarz criterion	-3.69
Log likelihood	354.38	Hannan-Quinn criter.	-3.83
F-statistic	38.32	Durbin-Watson stat	2.03
Prob(F-statistic)	0.00		

As illustrated by the coefficients in the table, trip requests in the Eastern region decrease with a rise in real fares. Trip requests are predicted to increase with a rise in unemployment or real gasoline prices. For most forms of transit, a rise in unemployment would likely be associated with a decrease in demand for travel, considering that for the general population, the primary use of transportation is for commuting to and from work. However, paratransit users do not use Access primarily for commuting to and from work. Also, rising unemployment can lead riders to shift from other more expensive modes of transit to using Access. The positive coefficient on unemployment in the model reflects these facts.

For Antelope Valley, trip requests are driven by real average fare in the region (lagged one month), unemployment (lagged three months), event dummy variables, seasonality dummy variables, and autoregressive terms that correct for possible correlation between the residuals. In particular, the November 2005 dummy variable denotes service changeover (Southland Transit over Antelope Valley Transit Authority) and new eligibility procedures (restricted eligibility). The dummy variable in January 2010 accounts for a change in the type of software being used across all service areas for tracking passengers. The dummy variables in 2004 account for one-time deviations in trip request levels from the region's average historical trends. Coefficient estimates are reported in Table 7 below.

Table 7: Regression Results – Antelope Valley

Dependent Variable is Difference(Log(Trip Requests – Antelope Valley))
Sample: 2004M07 2018M12
Included observations: 174

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Constant	0.05	0.01	4.41	0.00
Difference(Log(Real Average Fare_AV (-1)))	-0.17	0.04	-3.98	0.00
Difference(Log(Unemployment_AV (-3)))	0.30	0.09	3.13	0.00
August 2004 Dummy Variable	-0.27	0.10	-2.58	0.01
October 2004 Dummy Variable	0.53	0.05	11.60	0.00
November 2005 Dummy Variable	-0.19	0.06	-3.31	0.00
January 2010 Dummy Variable	1.00	0.12	8.01	0.00
February 2010 Dummy Variable	-0.86	0.42	-2.05	0.04
Spring Dummy Variable	-0.04	0.01	-3.15	0.00
Summer Dummy Variable	-0.02	0.01	-1.41	0.16
Fall Dummy Variable	-0.09	0.02	-5.17	0.00
First-order Autoregressive Term	-0.38	0.05	-7.01	0.00
Fifth-order Autoregressive Term	0.25	0.06	3.95	0.00
Twelfth-order Autoregressive Term	0.30	0.07	4.48	0.00

R-squared	0.82	Mean dependent variance	0.01
Adjusted R-squared	0.80	S.D. dependent variance	0.14
S.E. of regression	0.06	Akaike info criterion	-2.57
Sum squared residual	0.65	Schwarz criterion	-2.30
Log likelihood	238.76	Hannan-Quinn criterion	-2.46
F-statistic	51.95	Durbin-Watson stat	1.93
Probability (F-statistic)	0.00		

As depicted in the table, the regression estimates a negative coefficient for the real average fare variable (-0.17). This implies that, other things held constant, trip requests will decrease when real fares increase in the region.

Results for the Northern region show that trip requests are a function of the real average fare in the Northern region, unemployment (lagged three months), real gasoline prices (lagged one month), event dummy variables, seasonality dummy variables, and autoregressive terms that correct for possible correlation between the residuals. Coefficient estimates are reported in Table 8 below.

Table 8: Regression Results – Northern

Dependent Variable is Difference(Log(Trip Requests – Northern))
Sample: 2004M07 2018M12
Included observations: 174

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Constant	0.03	0.00	6.80	0.00
Difference(Log(Real Average Fare_N))	-0.28	0.12	-2.41	0.02
Difference(Log(Unemployment (-3)))	0.20	0.04	4.52	0.00
Difference (Log(Real Gas Price (-1)))	0.07	0.03	2.12	0.04
February 2011 Dummy Variable	-0.07	0.03	-2.55	0.01
February 2017 Dummy Variable	-0.05	0.01	-3.56	0.00
Spring Dummy Variable	-0.02	0.01	-2.71	0.01
Summer Dummy Variable	-0.01	0.00	-2.28	0.02
Fall Dummy Variable	-0.05	0.01	-8.71	0.00
First-order Autoregressive Term	-0.66	0.08	-8.31	0.00
Second-order Autoregressive Term	-0.29	0.08	-3.68	0.00
Fifth-order Autoregressive Term	0.15	0.05	3.00	0.00
Twelfth-order Autoregressive Term	0.37	0.05	6.82	0.00

R-squared	0.72	Mean dependent variance	0.00
Adjusted R-squared	0.69	S.D. dependent variance	0.06
S.E. of regression	0.03	Akaike info criterion	-3.87
Sum squared residual	0.18	Schwarz criterion	-3.61
Log likelihood	350.31	Hannan-Quinn criterion	-3.76
F-statistic	31.10	Durbin-Watson stat	2.07
Probability (F-statistic)	0.00		

As depicted in the table, the regression estimates a negative coefficient for the real average fare variable (-0.28). This again implies that, other things held constant, trip requests will decrease when real fares increase in the region.

For the Southern region, the regression results indicate that trip requests are driven by real average fare in the Southern region, unemployment (lagged two months), real gasoline price (lagged one month), several one-time event dummy variables, seasonality dummy variables, and autoregressive terms that correct for possible correlation between the residuals. In particular, the November 2007 dummy variable represents the impact of a change in regional boundaries (part of West/ Central was transferred to Southern). The February 2005 dummy variable represents a one-time deviation in the level of trip requests from average historical levels. Coefficient estimates are reported in Table 9 below.

Table 9: Regression Results – Southern

Dependent Variable is Difference(Log(Trip Requests – Southern))
Sample: 2001M07 2018M12
Included observations: 210

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Constant	0.02	0.01	2.56	0.01
Difference(Log(Real Average Fare_S))	-0.23	0.09	-2.70	0.01
Difference (Log(Unemployment (-2)))	0.18	0.07	2.46	0.01
Difference (Log(Real Gas Price (-1)))	0.08	0.03	2.34	0.02
April 2004 Dummy Variable	0.16	0.04	3.90	0.00
February 2005 Dummy Variable	-0.12	0.02	-7.57	0.00
November 2007 Dummy Variable	0.18	0.04	4.55	0.00
February 2017 Dummy Variable	-0.05	0.02	-2.38	0.02
Spring Dummy Variable	-0.01	0.01	-1.09	0.28
Summer Dummy Variable	-0.01	0.01	-1.65	0.10
Fall Dummy Variable	-0.03	0.01	-3.03	0.00
First-order Autoregressive Term	-0.30	0.05	-5.67	0.00
Fifth-order Autoregressive Term	0.20	0.05	4.26	0.00
Twelfth-order Autoregressive Term	0.51	0.05	11.11	0.00

R-squared	0.68	Mean dependent variance	0.01
Adjusted R-squared	0.66	S.D. dependent variance	0.06
S.E. of regression	0.04	Akaike info criterion	-3.71
Sum squared residual	0.25	Schwarz criterion	-3.47
Log likelihood	404.47	Hannan-Quinn criterion	-3.61
F-statistic	29.47	Durbin-Watson stat	2.13
Probability (F-statistic)	0.00		

Similar to the Eastern and Northern regions, total trip requests in the Southern region are expected to increase with decreasing real average fares and increasing unemployment levels and real gas prices.

The study finds that trip requests in Santa Clarita are likely driven by real average fare in the Santa Clarita region (lagged two months), unemployment (lagged two months), seasonality dummy variables, and autoregressive terms that correct for possible correlation between the residuals. Coefficient estimates are reported in Table 10 below.

Table 10: Regression Results – Santa Clarita

Dependent Variable is Difference(Log(Trip Requests – Santa Clarita))
Sample: 2009M07 2018M12
Included observations: 114

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Constant	0.03	0.01	3.88	0.00
Difference(Log(Real Average Fare_SC (-2)))	-0.49	0.30	-1.63	0.11
Difference (Log(Unemployment (-2)))	0.27	0.12	2.29	0.02
Spring Dummy Variable	-0.06	0.02	-3.61	0.00
Summer Dummy Variable	-0.01	0.01	-0.52	0.61
Fall Dummy Variable	-0.06	0.02	-3.68	0.00
First-order Autoregressive Term	-0.43	0.07	-6.43	0.00
Fourth-order Autoregressive Term	-0.33	0.07	-4.62	0.00
Twelfth-order Autoregressive Term	0.32	0.08	3.94	0.00

R-squared	0.65	Mean dependent variance	0.00
Adjusted R-squared	0.62	S.D. dependent variance	0.08
S.E. of regression	0.05	Akaike info criterion	-3.06
Sum squared residual	0.26	Schwarz criterion	-2.82
Log likelihood	184.16	Hannan-Quinn criterion	-2.96
F-statistic	21.31	Durbin-Watson stat	2.14
Probability (F-statistic)	0.00		

For the West/ Central region, trip requests are driven by real average fare in the region, unemployment (lagged three months), real price of gasoline (lagged one month), event dummy variables, seasonality dummy variables, and autoregressive terms that correct for possible correlation between the residuals. In particular, the November 2007 dummy variable represents the lagged impact of a change in regional boundaries between the West/ Central and Southern regions mentioned above. The March 2005 dummy variable represents a one-time deviation in the level of trip requests from average historical levels. Coefficient estimates are reported in Table 11, and they represent the same relationships between trip requests and the model variables discussed above.

Table 11: Regression Results – West/ Central

Dependent Variable is Difference(Log(Trip Requests – West/ Central))
Sample: 2004M07 2018M12
Included observations: 174

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Constant	0.03	0.01	6.73	0.00
Difference(Log(Real Average Fare_WC))	-0.30	0.13	-2.25	0.03
Difference (Log(Unemployment (-3)))	0.13	0.05	2.70	0.01
Difference (Log(Real Gas Price(-1)))	0.13	0.04	3.14	0.00
March 2005 Dummy Variable	0.06	0.02	2.45	0.02
September 2006 Dummy Variable	-0.10	0.03	-3.44	0.00
November 2007 Dummy Variable	-0.40	0.05	-7.33	0.00
December 2007 Dummy Variable	0.15	0.06	2.61	0.01
Spring Dummy Variable	-0.03	0.01	-3.32	0.00
Summer Dummy Variable	-0.02	0.01	-2.70	0.01
Fall Dummy Variable	-0.07	0.01	-8.44	0.00
First-order Autoregressive Term	-0.40	0.06	-6.69	0.00
Fifth-order Autoregressive Term	0.16	0.06	2.90	0.00
Twelfth-order Autoregressive Term	0.45	0.06	7.96	0.00

R-squared	0.79	Mean dependent variance	0.00
Adjusted R-squared	0.77	S.D. dependent variance	0.07
S.E. of regression	0.04	Akaike info criterion	-3.74
Sum squared residual	0.20	Schwarz criterion	-3.47
Log likelihood	340.56	Hannan-Quinn criterion	-3.63
F-statistic	41.85	Durbin-Watson stat	2.25
Probability (F-statistic)	0.00		

6. Demand Forecasts

The following sections present the assumptions used to forecast trip demand, trip request projections, and a risk analysis of all projections. The risk analysis is used to account for the inherent uncertainty of the future. Therefore, all forecasted explanatory variables and trip demand numbers are presented within a risk analysis framework.

Forecasted Explanatory Variables

As explained in Section 5, each service region trip demand model depends on a number of forecasted explanatory variables. To account for uncertainty in these forecasts, all explanatory variables identified in the trip demand regressions are presented in this section within a risk analysis framework. This means that each variable is assigned a central or median estimate and a range (i.e., a probability distribution) representing an 80 percent confidence interval, based on historical observations.

Real Average Fare

The following table summarizes the current detailed fare structure by region.

Table 12: Current Fare Structure

Region	Distance (miles)	Fare ($)
Eastern Region	0 to 19.9	$2.75
West/ Central Region		
Southern Region	20 or greater	$3.50
Northern Region		
Antelope Valley	Within Antelope Valley	$2.00
	To/From Basin	$7.00
	To/From Santa Clarita	$7.00
Santa Clarita	Within Santa Clarita	$2.00
	To/From Basin	$6.00
	To/From Antelope Valley	$7.00

Source: Access Services

Fares are assumed to hold constant at current levels throughout the forecast period (2019 – 2028). Table 13 below reports the average nominal fares by region used to forecast trip demand.

Table 13: Average Nominal Fares (FY2019 – FY2028)

Fiscal Year	Eastern, West/ Central, Northern & Southern	Antelope Valley	Santa Clarita
2019-2028	$2.81	$2.02	$2.02

Source: Access Services

The Los Angeles-Orange County, CA Consumer Price Index for All Urban Consumers (CPI-U) is used to remove all inflationary movements from the average fare variable, allowing the fare to be expressed in constant dollars. The following table presents the CPI-U projections used to express the average fare in real terms. Median estimates are based on recent projections by the California DoF[18]. The lower and upper ten percent estimates are derived from a historical analysis of statistical uncertainty (as measured by the standard deviation) in the variable.

Table 14: Los Angeles-Orange County, CA Consumer Price Index for All Urban Consumers (FY2019 – FY2028)

Fiscal Year	Median	Lower 10% Limit	Upper 10% Limit
2019	271.2	264.8	277.7
2020	281.0	272.7	290.5
2021	290.9	282.6	299.9
2022	301.2	292.3	310.3
2023	309.3	300.0	319.1
2024	317.5	307.3	326.1
2025	324.0	314.2	332.7
2026	330.9	322.4	340.8
2027	338.6	329.2	347.2
2028	346.1	336.8	354.6

Sources: California Department of Finance and HDR assumptions based on historical trends.

Gasoline Price

Table 15 below shows annual projections for the real retail gasoline price (including sales tax) in California. Median estimates are derived from recent gasoline price projections published by the Energy Information Administration (EIA)[19]. The lower and upper ten percent estimates are derived from a historical analysis of statistical uncertainty (as measured by the standard deviation) in the variable.

Table 15: Real Gasoline Price per Gallon in California (FY2019 – FY2028)

Fiscal Year	Median	Lower 10% Limit	Upper 10% Limit
2019	$3.51	$3.32	$3.68
2020	$3.48	$3.25	$3.75
2021	$3.68	$3.45	$3.90
2022	$3.81	$3.58	$4.04

[18] California Department of Finance, Economic Research Unit, *Economics* http://www.dof.ca.gov/Forecasting/Economics/
[19] U.S. Department of Energy, Energy Information Administration, *Annual Energy Outlook 2019* https://www.eia.gov/outlooks/aeo/pdf/aeo2019.pdf

Fiscal Year	Median	Lower 10% Limit	Upper 10% Limit
2023	$3.91	$3.68	$4.16
2024	$4.08	$3.83	$4.29
2025	$4.23	$3.98	$4.46
2026	$4.36	$4.13	$4.62
2027	$4.51	$4.29	$4.73
2028	$4.69	$4.46	$4.92

Sources: Energy Information Administration and HDR assumptions based on historical trends.

Unemployment

Table 16 below shows annual projections for unemployment in Los Angeles County. Median estimates are derived from recent unemployment projections released by Caltrans[20]. The lower and upper 10 percent estimates are derived from a historical analysis of statistical uncertainty (as measured by the standard deviation) in the variable using BLS data.

Table 16: Unemployment in Los Angeles County (FY2019 – FY2028)

Fiscal Year	Median	Lower 10% Limit	Upper 10% Limit
2019	229,763	205,247	253,636
2020	225,934	193,220	259,104
2021	234,285	203,659	266,180
2022	244,673	211,742	276,723
2023	252,866	220,334	285,816
2024	264,139	226,592	297,545
2025	273,290	240,145	306,751
2026	279,544	243,784	307,814
2027	279,715	245,655	311,738
2028	280,419	249,481	313,335

Sources: U.S. Census Bureau and HDR assumptions based on historical trends.

Paratransit Demand Forecast Results

Using the regression models presented in Section 5 and the forecasting assumptions reported above, service region-specific demand projections are developed for fiscal years 2019 through 2028.

[20] The California Economic Forecast. *California County-Level Economic Forecast 2018-2050*. Prepared for Caltrans. September 2018.

Operations Forecasts

Ridership forecasts are derived from passenger trip requests based on the average completion rate observed at the service region level in the recent past. Cancellations and no-shows are derived in the same way. Note that a 0 percent denial rate is assumed throughout the forecast period. Operations forecasts through 2023 are summarized in Table 17 below.

At the mean, the number of trip requests is expected to grow by nearly 1.0 million (a 20 percent increase from 2018) and reach 5.6 million by 2023. Passenger trips completed are projected to grow by just 0.9 percent in 2019. The ridership annual growth rate is expected to increase gradually thereafter, to reach 6.5 percent in 2023.

Table 17: Operations, Central Forecasts (FY2019 – FY2023)

Fiscal Year	2019	2020	2021	2022	2023
Passenger Trip Requests (thousands)	4,610	4,672	4,919	5,224	5,562
% Change	-0.3%	1.4%	5.3%	6.2%	6.5%
Cancellations (thousands)	84	85	89	95	101
No-Shows	140	142	150	159	169
Passengers (thousands)	4,436	4,485	4,723	5,016	5,342
% Change	0.9%	1.1%	5.3%	6.2%	6.5%

Note: 2019 projections include actual estimates through December 2018.

Ridership projections by service region are presented in Table 18 below and monthly estimates are reported in Appendix 4.

Table 18: Ridership by Service Region, Central Forecasts (FY2019 – FY2028)

Fiscal Year	Total	Eastern	West/ Central	Northern	Southern	Antelope Valley	Santa Clarita	Backup
2018	4,396,741	1,298,955	694,909	752,601	1,392,631	211,816	45,702	127
2019	4,435,580	1,364,738	722,169	766,002	1,330,032	208,321	44,144	174
	0.9%	5.1%	3.9%	1.8%	-4.5%	-1.7%	-3.4%	37.4%
2020	4,485,320	1,408,339	752,580	788,027	1,275,509	215,033	45,653	179
	1.1%	3.2%	4.2%	2.9%	-4.1%	3.2%	3.4%	2.8%
2021	4,722,755	1,485,531	806,014	841,850	1,301,192	239,302	48,676	189
	5.3%	5.5%	7.1%	6.8%	2.0%	11.3%	6.6%	5.3%
2022	5,016,032	1,567,504	866,145	902,719	1,356,589	270,682	52,192	201
	6.2%	5.5%	7.5%	7.2%	4.3%	13.1%	7.2%	6.2%
2023	5,341,676	1,652,473	930,410	967,764	1,427,010	307,926	55,880	214
	6.5%	5.4%	7.4%	7.2%	5.2%	13.8%	7.1%	6.5%

Fiscal Year		Total	Eastern	West/ Central	Northern	Southern	Antelope Valley	Santa Clarita	Backup
2024		5,688,351	1,738,279	998,888	1,035,148	1,506,951	349,301	59,556	228
		6.5%	5.2%	7.4%	7.0%	5.6%	13.4%	6.6%	6.5%
2025		6,077,967	1,833,288	1,074,917	1,110,209	1,597,912	397,715	63,682	243
		6.8%	5.5%	7.6%	7.3%	6.0%	13.9%	6.9%	6.8%
2026		6,470,496	1,925,092	1,152,957	1,185,184	1,689,392	449,918	67,694	259
		6.5%	5.0%	7.3%	6.8%	5.7%	13.1%	6.3%	6.5%
2027		6,871,133	2,015,208	1,233,809	1,261,036	1,782,520	506,594	71,692	275
		6.2%	4.7%	7.0%	6.4%	5.5%	12.6%	5.9%	6.2%
2028		7,303,969	2,110,758	1,321,572	1,342,453	1,882,517	570,445	75,932	292
		6.3%	4.7%	7.1%	6.5%	5.6%	12.6%	5.9%	6.3%

Note: 2019 projections include actual estimates through December 2018.

Steady State Analysis

The paratransit demand analysis also accounts for possible market saturation in the future. Saturation would be followed by steady-state (or constant) demand growth – demand growth that reflects population changes. The saturation level of demand is estimated by multiplying population of the service area by:

- Proportion of persons with mobility disabilities among the population (maximum potential registration);
- Maximum percentage of persons with mobility disabilities who actually register with Access (maximum penetration of potential registration);
- Maximum percentage of registrants who become regular users[21]; and
- Average number of trip requests per regular user and per year.

Data from the California DoF and the U.S. Census Bureau are used to estimate the market saturation level in the future[22].

[21] A regular user is defined as an active customer who uses Access Services at least six times per month.
[22] Population historical data and projections are from the California Department of Finance, Demographic Research Unit. The maximum potential registration rate is based on U.S. DOT, *ADA Paratransit Handbook*, 1991.

Table 19 on the following page shows projected population levels and associated steady state trip requests over the period 2019 – 2028.

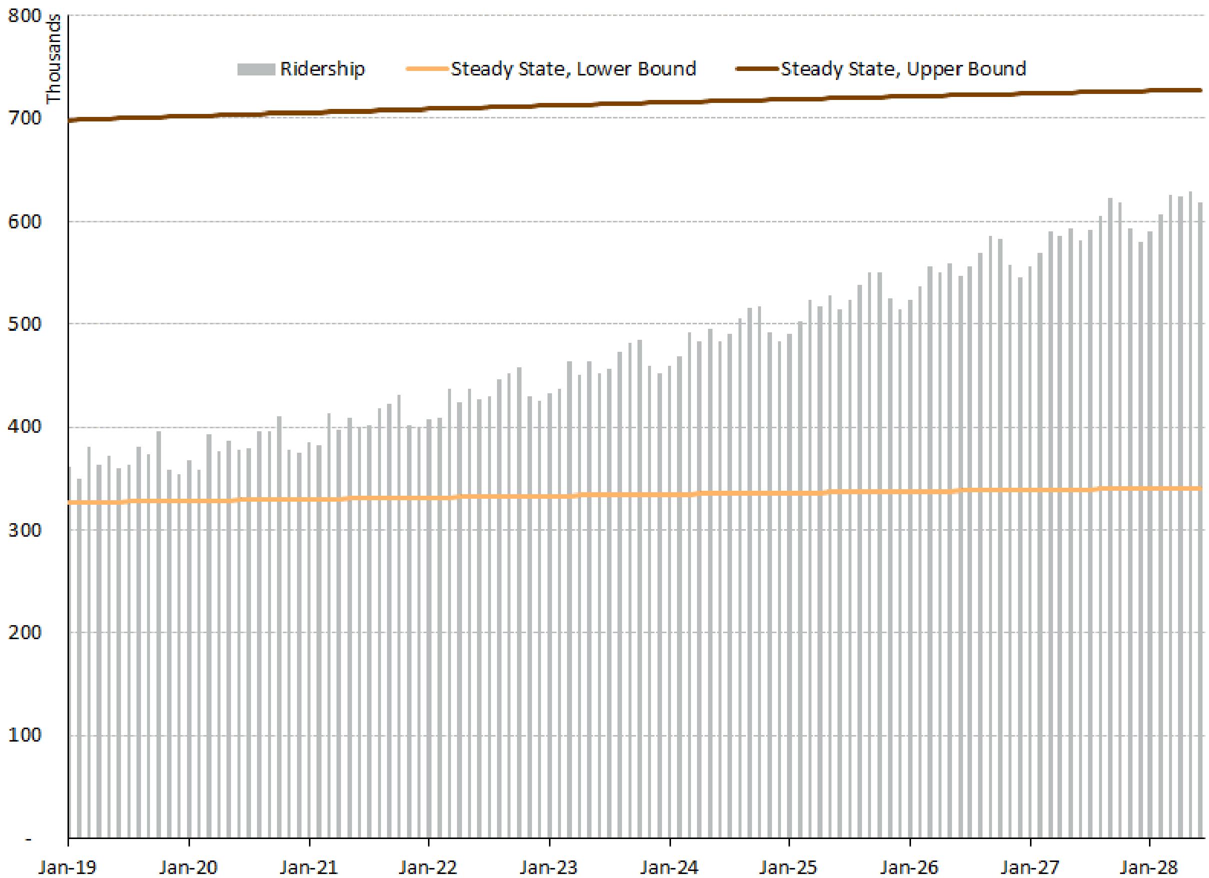
Table 19: Steady State Scenarios (FY2019 – FY2028)

		Lower Bound	Upper Bound
1. Population in the Service Area	FY 2019	10,354,790	10,354,790
	FY 2020	10,408,402	10,408,402
	FY 2021	10,460,234	10,460,234
	FY 2022	10,510,157	10,510,157
	FY 2023	10,558,402	10,558,402
	FY 2024	10,604,886	10,604,886
	FY 2025	10,649,800	10,649,800
	FY 2026	10,692,934	10,692,934
	FY 2027	10,734,295	10,734,295
	FY 2028	10,774,346	10,774,346
2. Maximum Potential Registration		2.5%	4.0%
3. Maximum Penetration of Potential Registration		60%	80%
4. Percent of Registrants Who Are Regular Users		34.2%	34.2%
5. Trip Requests Per Year & Per Regular User		73	73
6. Steady State Yearly Trip Requests (1*2*3*4*5)	FY 2019	3,918,414	8,380,678
	FY 2020	3,938,702	8,424,068
	FY 2021	3,958,316	8,466,019
	FY 2022	3,977,208	8,506,425
	FY 2023	3,995,464	8,545,472
	FY 2024	4,013,055	8,583,094
	FY 2025	4,030,051	8,619,445
	FY 2026	4,046,373	8,654,355
	FY 2027	4,062,025	8,687,832
	FY 2028	4,077,181	8,720,247

Sources: Access Services, California Department of Finance, U.S. Census Bureau and HDR.

As shown in Figure 26 on the following page, trip demand is expected to remain below the upper bound of the market potential through 2028.

Figure 26: Ridership Projections and Steady State Scenario (January 2019 – June 2028)



Risk Analysis

To account for uncertainty, ridership forecasts are generated in a risk analysis framework. The lower and upper forecasts are derived by considering the upper and lower bounds of a 70 percent confidence interval estimated around the central predictions.

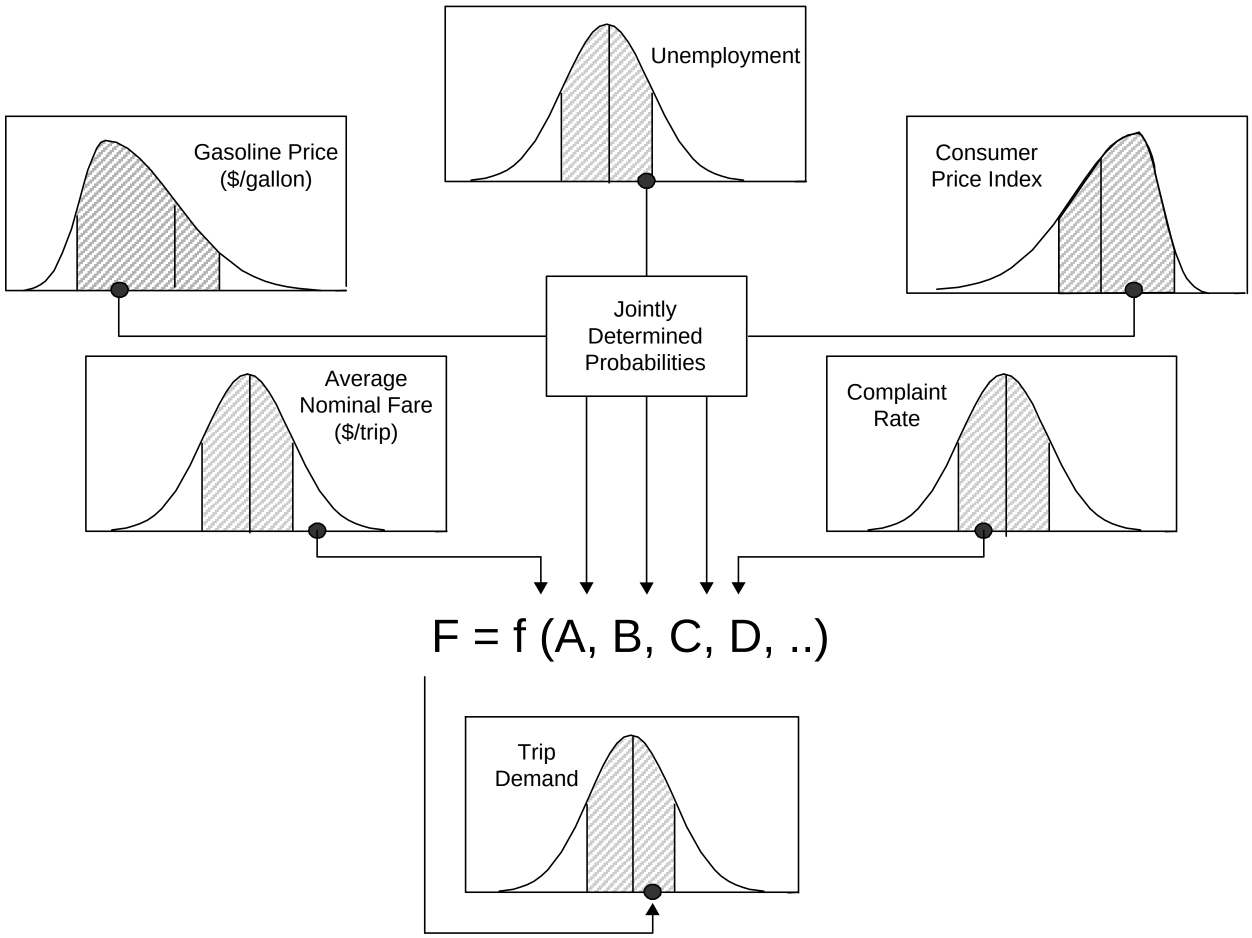
Risk Analysis Process

A typical risk analysis process consists of five steps:

1. Define the structure and logic of the forecasting problem (i.e., identification of key variables affecting paratransit demand);
2. Investigate historical trends of explanatory variables;
3. Assign estimates and ranges (probability distributions) to each variable and forecasting coefficient;
4. Engage experts in an assessment of the model and all underlying assumptions; and
5. Produce risk-based forecast.

Figure 27 below illustrates the risk analysis process where all the variables are entered as ranges to lead to a probability distribution for the trip demand forecast.

Figure 27: Risk Analysis of Paratransit Demand Forecast



Risk Analysis of Ridership

Monthly ridership projections for each service region are developed within a risk analysis framework to produce probabilistic outcomes. The service area total is then obtained by aggregating service region estimates. Figure 28 on the following page reports the aggregated results under three probabilistic alternatives: the central forecast is presented along with the lower and upper 15 percent estimates.

Figure 28: Ridership Forecasts (January 2019 – June 2028)

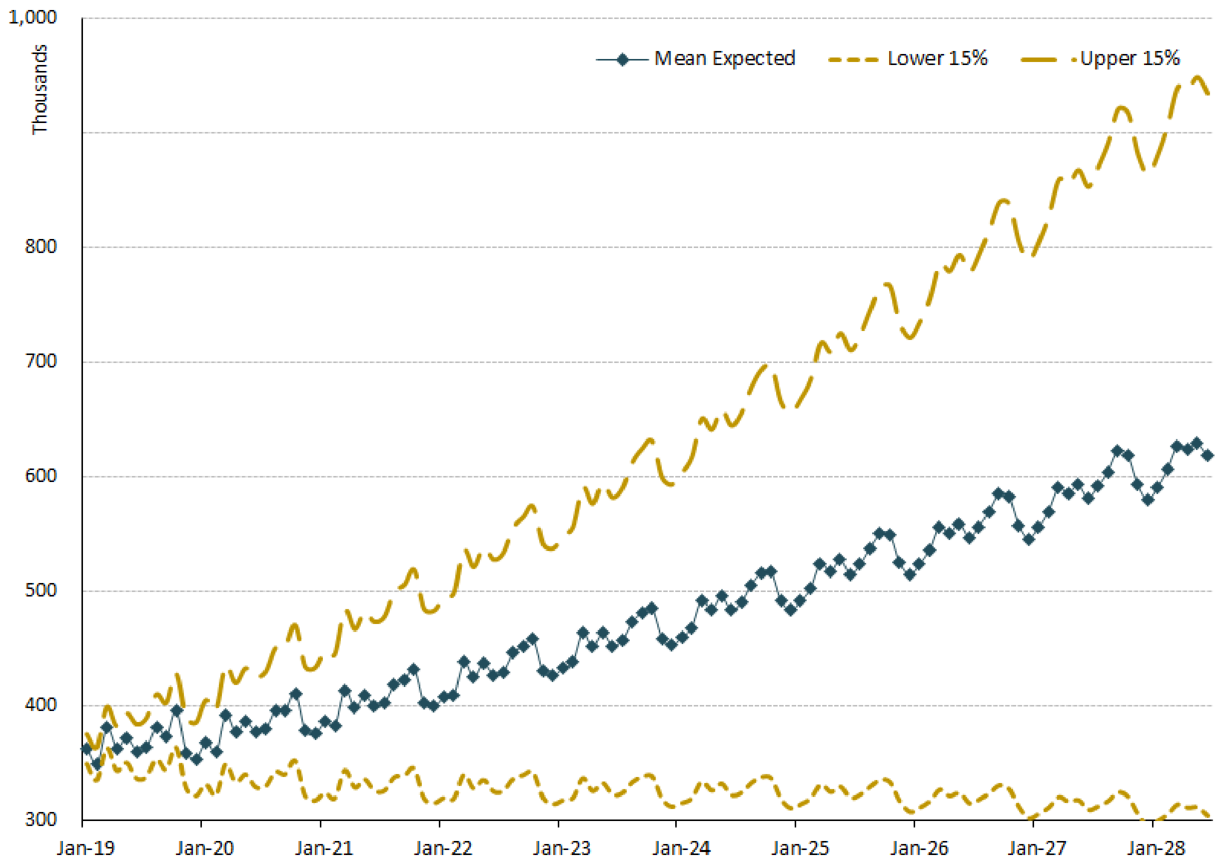


Table 20 below reports monthly ridership estimates (central, low and high projections) in 2021.

Table 20: Risk-Adjusted Monthly Ridership Forecasts (FY2021)

Month	Central	Low (85% Probability of Exceeding)	High (15% Probability of Exceeding)
Jul-20	379,484	329,546	429,422
Aug-20	396,152	342,090	450,214
Sep-20	395,751	340,094	451,409
Oct-20	410,906	351,437	470,374
Nov-20	377,723	321,227	434,220
Dec-20	375,120	317,258	432,981
Jan-21	385,774	324,085	447,464
Feb-21	382,107	319,304	444,910
Mar-21	413,438	343,408	483,468
Apr-21	397,755	328,549	466,961
May-21	408,902	335,739	482,064
Jun-21	399,642	325,900	473,385
FY 2021	4,722,755	3,978,636	5,466,874

Alternate Fare Scenario

An additional set of projections are provided under an alternate fare scenario. Starting July 1, 2019 the current fare structure would be replaced by a flat fare of $1.00 for all trips (i.e., irrespective of the distance) within the service area.

Under this alternate scenario, trip demand in 2019 is identical to the base case reported in Table 17, as the proposed fare change does not take effect until the following fiscal year. Reducing the fare to $1.00 will boost ridership to 5.8 million passengers in 2020 (a 31.9 percent increase over 2019). Throughout the remainder of the forecast period, annual growth rates in ridership are expected to be similar to those reported under the base case scenario.[23]

Table 21: Operations, Central Forecasts under Alternate Fare Scenario (FY2019 – FY2023)

Fiscal Year	2019	2020	2021	2022	2023
Passenger Trip Requests (thousands)	4,610	6,092	6,420	6,817	7,257
% Change	-0.3%	32.1%	5.4%	6.2%	6.5%
Cancellations (thousands)	84	111	116	124	132
No-Shows	140	185	195	207	221
Passengers (thousands)	4,436	5,849	6,164	6,546	6,969
% Change	0.9%	31.9%	5.4%	6.2%	6.5%

Note: 2019 projections include actual estimates through December 2018.

Ridership projections by service region are reported in Table 22 on the next page. The West/ Central region would benefit the most from the fare reduction in 2020 with an increase of 41.8 percent (+301,851 passengers).

[23] Note that under a free fare scenario, ridership would increase until market saturation was achieved (i.e., paratransit demand in Los Angeles County was 100 percent satisfied). The steady state analysis (Section

Table 19 on page 54) shows that market saturation in 2020 would correspond to 7.81 million passenger trips (upper bound estimate), a 76 percent increase over 2019. Ridership would then increase at the same pace as population (steady state growth).

Table 22: Ridership by Service Region, Central Forecasts under Alternate Fare Scenario (FY2019 – FY2028)

Fiscal Year	Total	Eastern	West/ Central	Northern	Southern	Antelope Valley	Santa Clarita	Backup
2018	4,396,741	1,298,955	694,909	752,601	1,392,631	211,816	45,702	127
2019	4,435,580	1,364,738	722,169	766,002	1,330,032	208,321	44,144	174
	0.9%	5.1%	3.9%	1.8%	-4.5%	-1.7%	-3.4%	37.4%
2020	5,848,760	1,852,198	1,024,020	1,052,291	1,617,204	241,308	61,506	234
	31.9%	35.7%	41.8%	37.4%	21.6%	15.8%	39.3%	34.1%
2021	6,164,485	1,953,718	1,096,727	1,124,164	1,649,767	271,008	68,855	247
	5.4%	5.5%	7.1%	6.8%	2.0%	12.3%	11.9%	5.4%
2022	6,546,157	2,061,526	1,178,546	1,205,445	1,720,004	306,546	73,828	262
	6.2%	5.5%	7.5%	7.2%	4.3%	13.1%	7.2%	6.2%
2023	6,968,904	2,173,274	1,265,989	1,292,303	1,809,290	348,725	79,044	279
	6.5%	5.4%	7.4%	7.2%	5.2%	13.8%	7.1%	6.5%
2024	7,418,344	2,286,123	1,359,167	1,382,284	1,910,647	395,581	84,245	297
	6.4%	5.2%	7.4%	7.0%	5.6%	13.4%	6.6%	6.4%
2025	7,922,993	2,411,076	1,462,618	1,482,516	2,025,975	450,410	90,081	317
	6.8%	5.5%	7.6%	7.3%	6.0%	13.9%	6.9%	6.8%
2026	8,430,837	2,531,813	1,568,805	1,582,634	2,141,961	509,530	95,757	337
	6.4%	5.0%	7.3%	6.8%	5.7%	13.1%	6.3%	6.4%
2027	8,948,593	2,650,330	1,678,818	1,683,923	2,260,038	573,714	101,412	358
	6.1%	4.7%	7.0%	6.4%	5.5%	12.6%	5.9%	6.1%
2028	9,507,511	2,775,994	1,798,236	1,792,644	2,386,823	646,025	107,409	380
	6.2%	4.7%	7.1%	6.5%	5.6%	12.6%	5.9%	6.2%

Note: 2019 projections include actual estimates through December 2018.

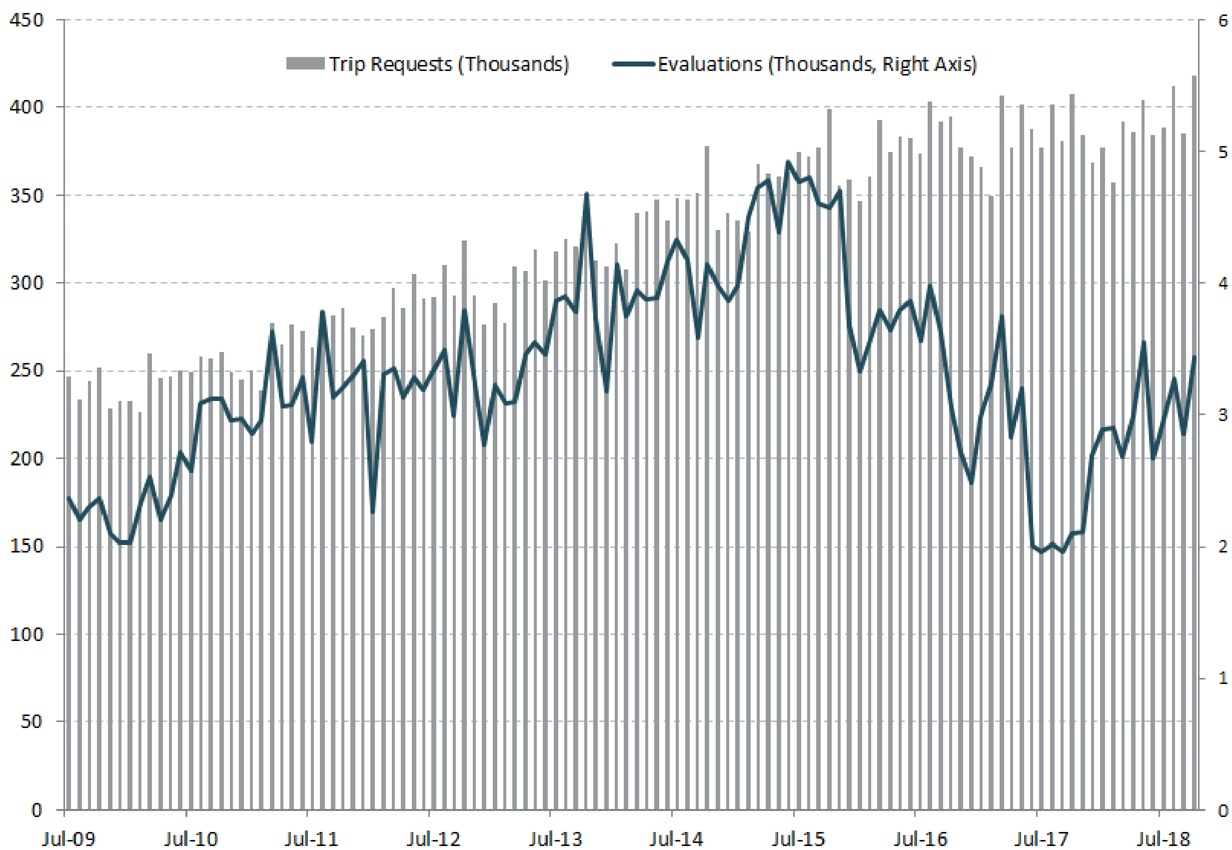
7. Analysis of New Applicants

Access experienced rapid growth in new applicants for its ADA complementary paratransit service after 2009. One possible explanation is that riders diverted to Access from other specialized transportation services that cut service or shut down because of the economic recession. Since 2016, however, the trend in new applicants has been downward and erratic. Other factors impacting the number of new applicants may include changes in the Free Fare program and the eligibility process. The results of the following analysis will help Access better anticipate the impacts of variations in new applicants on paratransit demand and operations.

Methodological Framework

The approach aims at integrating the analysis of new applicants into the demand analysis framework presented in Section 5. Service region-specific new applicant data are derived from eligibility evaluation data provided by Access. Figure 29 below reports the trends in trip requests and eligibility evaluations for all regions. It shows evaluations increasing at rates as high as (and occasionally higher than) those of trip requests from 2010 to 2015. The drop observed in December 2015 and the consecutive re-alignment result from changes to Access's evaluation process (e.g., greater emphasis on customer's previous fixed-route transit usage).

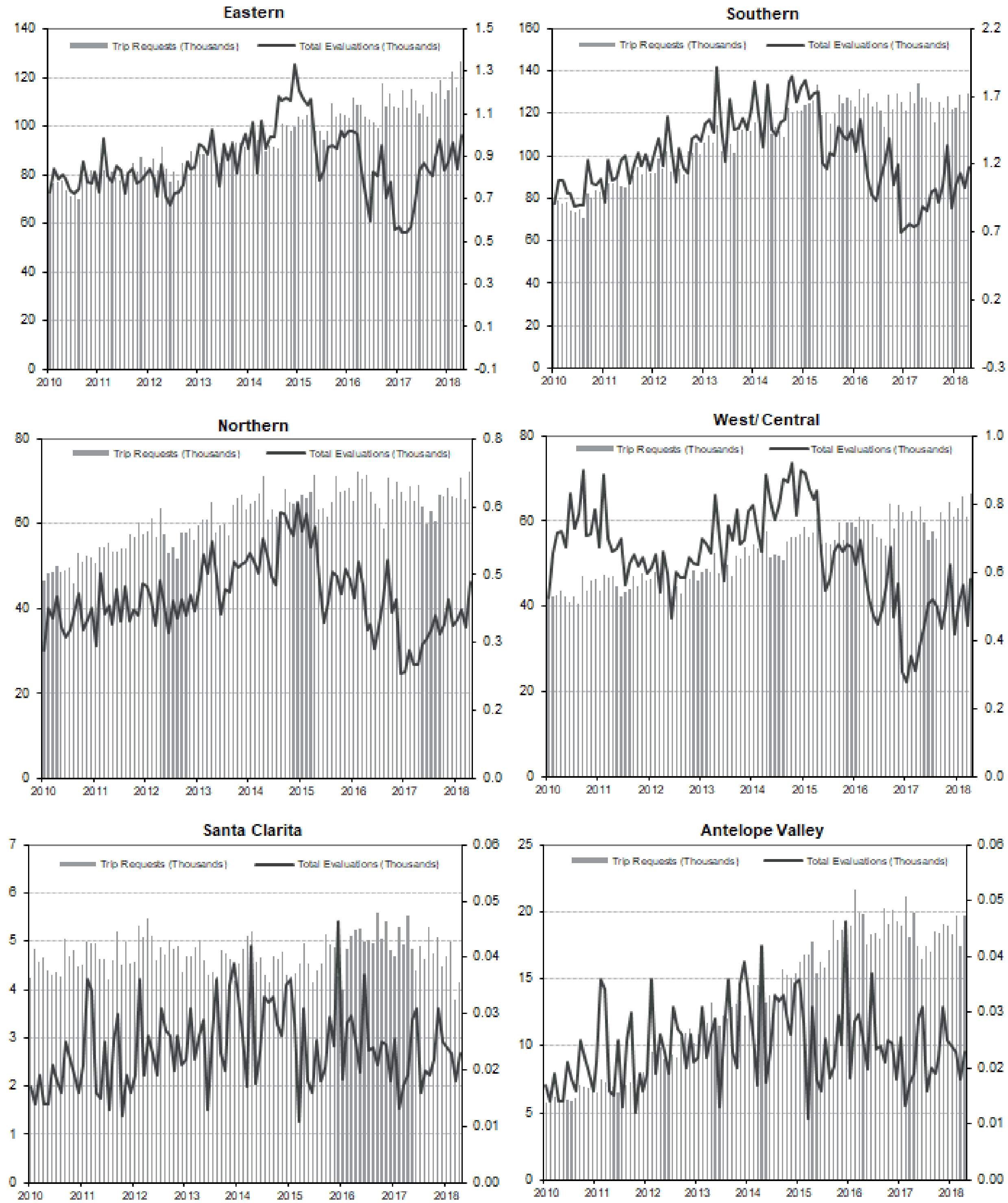
Figure 29: Trip Requests and Eligibility Evaluations (July 2009 – October 2018)



Source: Access Services

Data on service region eligibility evaluations are presented in Figure 30 on the following page. The charts show that while eligibility evaluations and trip requests are highly correlated, they may not be so for certain regions such as Antelope Valley and Santa Clarita. Moreover, the volatility in eligibility evaluations, and ultimately in the new applicant data, may reflect the need for dummy variables to capture service region-specific events.

Figure 30: Trip Requests and Eligibility Evaluations by Service Region (July 2009 – October 2018)



Source: Access Services

Overview of Methods

Total evaluation applicants (i.e., new applicants and recertification applicants) and new applicants are sometimes found to be statistically significant factors in explaining trip demand in service regions. Thus for these regions, the explanatory variables already used in the demand analysis (e.g., real average fare) cannot be applied in this new applicant analysis again – the recursive use of variables lead to the regression models being underspecified[24]. The inability to utilize some of the explanatory variables reduces the flexibility in the modeling specifications.

If the new applicant (or total evaluation) data were statistically relevant for the majority of the service region trip demand models, one option would be to incorporate this data into the demand forecasting framework in two steps, using a Two-Stage Least Squares (2SLS) approach. The first stage models new applicants as a dependent variable that is explained by instrumental variables such as population and eligibility standards. The second stage uses the predicted values of new applicants from the first stage to explain passenger demand. However, this regression technique is not utilized here as new applicant data are found non-stationary in levels and can thus significantly compound modeling errors into the service region demand models.

Instead of 2SLS, a time series analysis approach could be used. In this case, statistical properties of the new applicant data are investigated and historical trends are used to generate the forecast. The resulting models are of pure time-series specifications in which lagged terms of the dependent variable are used as independent variables to explain trend dependency and habit formation. Event date-specific dummy variables are added to provide explanations of sudden deviations in historical trends.

Estimation Results

Though disaggregated data for new applicants are available by service region, new applicant projections are estimated for the service area as a whole. New applicants per region are then calculated from the service area totals, based on the historic distribution of new applicants by region.

Estimating new applicants for the service area provided more robust projections. Modeling new applicants by region provides fewer data points, particularly for the smaller regions. In addition, estimating new applicants for the service area avoids multicollinearity issues that could arise with service region-specific new applicant models. New applicants are found to be a statistically significant factor in explaining trip demand in two regions: Santa Clarita and West/ Central. Thus if new applicants were modeled separately for each region, models for Santa Clarita and West/ Central could not contain any of the same explanatory variables as those estimating trip demand, as this would lead to multicollinearity. This limitation would mean leaving out certain

[24] A regression model is said to be underspecified when there are insufficient degrees of freedom to estimate the coefficients of interest. This problem occurs when there are fewer equations than the number of unknowns.

explanatory variables that could otherwise provide a more accurate estimate of new applicants. Modeling new applicants at the service area level avoids this issue.

Table 23 below presents the regression model used to estimate new applicants for the service area. The model indicates that new applicants for Access depend on socioeconomic factors including the real price of gasoline and the unemployment rate. The model also includes two dummy variables to account for various deviations in new applicant levels from the service area's average historical trends. Note that, unlike the regression models presented in Section 5, the following regression model was estimated with quarterly historical data to avoid the large (and unexplained, for the most part) month-to-month variations in new applicants observed after 2015 (see Figure 29 on page 60).

Table 23: New Applicant Regression Results – Service Area

Dependent Variable is Difference(Log(New Applicants))
Sample: 2007Q1 2018Q3
Included observations: 47

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Constant	0.01	0.02	0.75	0.46
Difference(Log(Real Gas Price(-4)))	0.43	0.12	3.49	0.00
Difference(Log(Unemployment Rate (-4)))	0.38	0.18	2.14	0.04
2017Q1 Dummy Variable	0.22	0.10	2.09	0.04
2017Q3 Dummy Variable	0.29	0.10	2.75	0.01

R-squared	0.56	Mean dependent variance	0.01
Adjusted R-squared	0.50	S.D. dependent variance	0.15
S.E. of regression	0.10	Akaike info criterion	-1.59
Sum squared residual	0.43	Schwarz criterion	-1.35
Log likelihood	43.38	Hannan-Quinn criterion	-1.50
F-statistic	10.32	Durbin-Watson stat	1.97
Probability (F-statistic)	0.00		

As indicated by the coefficients in the table above, new applicants are increasing with the real price of gasoline (lagged four months) and the unemployment rate (lagged four months). As explained for the trip request models in Section 5, the relationship between unemployment and ridership is different for paratransit services than it is for other forms of public transit (e.g., fixed-route bus service). More precisely, the primary use of Access is not for work commuting purposes. In addition, during difficult economic times, riders who might otherwise use taxis or other more costly forms of transportation may switch to using Access. Therefore, increasing unemployment is associated with increasing new applicants for Access.

New Applicant Forecasts

HDR only provides estimates for new applicants. Based on the econometric model presented above, the number of new applicants is projected on a quarterly basis through 2028. The projections are reported by fiscal year in Table 24 on the following page. The forecasts suggest that after declining dramatically in 2017 and 2018, new applicants are likely to decrease slightly again in 2019 before rising at a pace similar to that of ridership (see Table 18 on page 52).

Table 24: New Applicants by Service Region, Central Forecasts (FY2019 – FY2028)

Fiscal Year	Total	Eastern	West/ Central	Northern	Southern	Antelope Valley	Santa Clarita
2018	18,987	5,640	2,992	2,462	6,689	1,000	204
2019	20,657	6,159	3,340	2,664	7,141	1,157	195
	8.8%	9.2%	11.6%	8.2%	6.8%	15.7%	-4.3%
2020	21,833	6,510	3,530	2,816	7,548	1,223	206
	5.7%	5.7%	5.7%	5.7%	5.7%	5.7%	5.7%
2021	22,401	6,679	3,622	2,889	7,744	1,255	212
	2.6%	2.6%	2.6%	2.6%	2.6%	2.6%	2.6%
2022	24,046	7,170	3,888	3,101	8,313	1,347	227
	7.3%	7.3%	7.3%	7.3%	7.3%	7.3%	7.3%
2023	25,953	7,738	4,196	3,347	8,972	1,454	245
	7.9%	7.9%	7.9%	7.9%	7.9%	7.9%	7.9%
2024	27,943	8,332	4,518	3,604	9,660	1,566	264
	7.7%	7.7%	7.7%	7.7%	7.7%	7.7%	7.7%
2025	30,103	8,976	4,867	3,882	10,407	1,687	285
	7.7%	7.7%	7.7%	7.7%	7.7%	7.7%	7.7%
2026	32,398	9,660	5,238	4,178	11,200	1,815	306
	7.6%	7.6%	7.6%	7.6%	7.6%	7.6%	7.6%
2027	34,615	10,321	5,596	4,464	11,967	1,940	327
	6.8%	6.8%	6.8%	6.8%	6.8%	6.8%	6.8%
2028	36,842	10,985	5,957	4,751	12,737	2,064	348
	6.4%	6.4%	6.4%	6.4%	6.4%	6.4%	6.4%

Note: 2019 estimates include actual observations through October 2018.

New applicant forecasts are also developed within a risk analysis framework. Table 25 below presents the central forecasts, along with low and high forecasts (representing a 70 percent confidence interval) for the period 2019 – 2021.

Table 25: Risk-Adjusted New Applicant Forecasts (FY2019 – FY2021)

	FY2019	FY2020	FY2021
Central	20,657	21,833	22,401
Low (85% Probability of Exceeding)	18,337	16,263	14,558
High (15% Probability of Exceeding)	22,976	27,402	30,244

Note: 2019 estimates include actual observations through October 2018.

Appendix 1: List of Acronyms

2SLS	Two-stage Least Square
ADA	Americans with Disabilities Act
AR	Autoregression
BLS	Bureau of Labor Statistics
CPI	Consumer Price Index
CPI-U	Consumer Price Index for All Urban Consumers
CTSA	Consolidated Transportation Services Agency
DoF	(California) Department of Finance
EIA	Energy Information Administration
FTIS	Florida Transit Information System
FY	Fiscal Year
LADOT	City of Los Angeles Department of Transportation
MBTA	Massachusetts Bay Transportation Authority
MDT	Miami-Dade Transit
MSA	Metropolitan Statistical Area
(LAC)MTA	(Los Angeles County) Metropolitan Transit Authority
NTD	National Transit Database
OCTA	Orange County Transportation Authority
OLS	Ordinary Least Squares
PCA	Personal Care Attendant
RTA	Riverside Transit Agency
SCAG	Southern California Association of Governments
SDF	Service Delivery Failure
SEPTA	Southeastern Pennsylvania Transportation Authority

TRB	Transportation Research Board
WMATA	Washington Metropolitan Area Transit Authority

Appendix 2: Glossary of Technical Terms

Autoregression

The use of a lagged dependent variable as an independent variable in a regression model.

Backcasting

Estimation of observed values from a regression model. The estimated values can then be compared with the actual values to assess how accurate the model is.

Dependent Variable

A variable whose values are explained by changes in one or more variables (independent variables). The dependent variable is regressed on independent variables.

Dummy Variable

A binary variable which takes on the value of 1 if the observation belongs to a category and 0 (zero) if it does not.

Elasticity

A measure of the responsiveness of a variable to changes in another variable. In the context of regression analysis, it indicates the percentage change in the dependent variable brought about by a one-percent change in the associated explanatory variable, other things being equal. An elasticity of 1 (in absolute value) indicates that the dependent variable is perfectly elastic, while an elasticity of 0 indicates that the dependent variable is perfectly inelastic.

Explanatory Variable

A variable used to explain another variable (dependent variable). Also called independent variable.

First Difference

A time-series variable (X_t) is “first differenced” by taking the difference of adjacent time periods, where the earlier time period is subtracted from the later time period ($X_t – X_{t-1}$). Differencing is a popular and effective method of removing trend from a time-series to provide a clearer view of the true underlying behavior of the series.

F-statistic

A statistic reported in the regression output that measures the joint significance of independent variables. A high value means that the independent variables are jointly significant.

Independent Variable

A variable used to explain another variable (dependent variable). Also called explanatory variable.

New Applicant

A person who is not an Access customer and submits an application. Differs from a recertification applicant (i.e., an Access customer who is applying for recertification of eligibility).

Nominal Fare

Value of fare actually paid by customers. Unlike real fare, it is not adjusted for inflation (i.e., it includes the effect of inflation).

Ordinary Least Squares (OLS)

The simplest and most common method of fitting a straight line to a sample of data: by minimizing the sum of the squares of the deviations of the data from the line. Used extensively in regression analysis.

Panel Data Analysis

Panel data analysis is a hybrid of cross-sectional analysis and time series analysis. Panel data refer to multi-dimensional data observed over time for the same entities (e.g., regions served by Access). It allows to control for variables that cannot be observed or measured across entities (e.g., monthly unemployment data is not available at the sub-county level); or variables that change over time but not across entities (e.g., eligibility requirements). In other words, panel data analysis accounts for individual heterogeneity.

Regression

A statistical procedure used to estimate the dependence of one variable, the dependent variable (e.g., ridership), on one or more other variables, the independent variables (e.g., fare).

Residual (or error)

Represents what is left unexplained by the regression model. It is the difference between the observed value of a variable and the fitted value as calculated by the regression model.

R-Squared (R^2)

The square of the correlation coefficient, which estimates the percent of the total variation in the dependent variable attributed to the variation in the independent variables. It is used to evaluate the adequacy of a regression model. Also called coefficient of determination.

Serial Correlation

Serial correlation (of the residuals), or autocorrelation, occurs when residual error terms from observations of the same variable at different times are correlated. Residuals can be positively or negatively correlated. The absence of serial correlation is one of the key assumptions of the classical linear regression model.

Stationary

A time-series is stationary if the mean and the variance of the series are constant over time.

Time Series

A time series is a sequence of observations which are ordered in time.

Time Series Analysis

Time series analysis refers to statistical methods to analyze time series data. Unlike regression analysis, which requires the use of independent variables, time series analysis focuses on comparing values of time series at different points in time in order to identify patterns. A time series model is typically used for forecasting purposes.

t-statistic

A statistic reported in the regression output that measures the significance of an independent variable by evaluating the differences in means between the independent variable and the dependent variable.

Two-Stage Least Square (***2SLS or TSLS)***

A regression technique for simultaneous equation models that involves a two-stage process. The technique is often employed in the presence of an endogenous explanatory variable on the right-hand side of a regression equation. In the first stage, a variable Y_1 is regressed on several instruments; in the second stage, a variable Y_2 is regressed on the fitted values of Y_1 from the first stage.

Appendix 3: Risk Analysis Primer

The result of a risk analysis is both a forecast and a quantification of the probability that the forecast will be achieved. Not unlike modern weather forecasting, in which the likelihood of rain is projected with a statement of probability ("there is a 20 percent chance of rain tomorrow"), Risk Analysis is intended to provide a sense of perspective on the likelihood of future events. Risk Analysis is an easily understandable, but technically robust method that allows planners and decision-makers to select the level of risk within which they are willing to plan and make commitments.

The further into the future projections are made, the more uncertainty there is and the greater the risk is of producing forecasts that deviate from actual outcomes. Projections need to be made with a range of input values to allow for this uncertainty and for the probability that alternative economic, demographic, and technological conditions may prevail. The difficulty lies in choosing which combinations of input values to use in computing forecasts, and how to use those forecasts to produce a final estimate.

Forecasts traditionally take one of two forms: first, a single "expected outcome," or second, one in which the expected outcome is supplemented by alternative scenarios, often termed "high" and "low" cases. Both approaches fail to provide adequate perspective with regard to probable versus improbable outcomes.

The limitation of a forecast with a single expected outcome is clear: while it may provide the single best guess, it offers no information about the range of probable outcomes. The problem becomes acute when uncertainty surrounding the underlying assumptions of the forecast is especially high. The high case-low case approach can actually exacerbate this problem because it gives no indication of how likely it is that the high and low cases will actually materialize. Indeed, the high case usually assumes that most underlying assumptions deviate in the same direction from their expected value; and likewise for the low case. In reality, the likelihood that all underlying factors shift in the same direction simultaneously is just as remote as everything turning out as expected.

A common approach to providing added perspective on reality is through "sensitivity analysis," whereby key forecast assumptions are varied one at a time in order to assess their relative impact on the expected outcome. A problem here is that the assumptions are often varied by arbitrary amounts. A more serious flaw in this approach is that in the real world, assumptions do not veer from actual outcomes one at a time; it is the impact of simultaneous differences between assumptions and actual outcomes that would provide true perspective on a forecast.

Risk Analysis provides a way around the problems outlined above. It helps avoid the lack of perspective in "high" and "low" cases by measuring the probability or "odds" that an outcome will actually materialize. This is accomplished by attaching ranges (probability distributions) to the forecasts of each input variable. The approach allows all inputs to be varied simultaneously within their distributions, thus avoiding the problems inherent in conventional sensitivity analysis.

The approach also recognizes interrelationships between variables and their associated probability distributions.

Appendix 4: Ridership Forecast by Region (FY2019 – FY2028)

Month	Total	Eastern	West/ Central	Northern	Southern	Antelope Valley	Santa Clarita	Backup
Jul-18	374,195	111,819	60,728	63,630	116,504	17,868	3,643	3
Aug-18	396,535	119,533	63,473	68,286	122,000	19,208	3,984	51
Sep-18	370,675	112,949	58,827	63,383	114,893	16,946	3,672	5
Oct-18	402,893	123,557	64,126	69,569	122,548	19,178	3,915	0
Nov-18	361,715	111,690	58,734	61,870	109,346	16,573	3,484	18
Dec-18	342,602	104,759	55,572	58,448	104,704	15,869	3,240	10
Jan-19	362,096	112,220	57,932	63,060	108,294	16,750	3,825	14
Feb-19	349,427	108,829	56,996	60,207	103,611	16,183	3,588	14
Mar-19	380,844	118,123	63,420	66,838	110,077	18,379	3,992	15
Apr-19	362,792	113,687	59,943	63,018	105,534	16,914	3,682	15
May-19	371,663	115,881	62,532	64,167	107,940	17,490	3,639	15
Jun-19	360,144	111,692	59,887	63,526	104,582	16,964	3,480	14
FY 2019 Total	4,435,580	1,364,738	722,169	766,002	1,330,032	208,321	44,144	174

Note: Data cells shaded in blue represent actual observations.

Month	Total	Eastern	West/ Central	Northern	Southern	Antelope Valley	Santa Clarita	Backup
Jul-19	363,462	114,675	61,347	62,446	104,732	16,723	3,524	15
Aug-19	381,416	117,959	63,748	66,538	111,218	18,051	3,886	15
Sep-19	373,281	117,147	62,132	64,980	107,332	17,826	3,848	15
Oct-19	395,800	124,724	65,877	69,325	112,776	19,102	3,981	16
Nov-19	358,768	112,678	59,578	63,310	102,363	17,148	3,676	14
Dec-19	353,341	110,229	58,548	61,648	102,749	16,559	3,595	14
Jan-20	368,063	116,197	60,541	65,421	104,689	17,352	3,848	15
Feb-20	359,193	112,873	60,494	62,811	102,037	17,228	3,735	14
Mar-20	391,983	122,074	66,604	69,432	110,374	19,290	4,194	16
Apr-20	376,577	119,596	63,485	66,418	104,783	18,399	3,881	15
May-20	386,333	121,288	66,489	68,090	107,623	19,044	3,784	15
Jun-20	377,101	118,899	63,735	67,609	104,832	18,310	3,701	15
FY 2020 Total	4,485,320	1,408,339	752,580	788,027	1,275,509	215,033	45,653	179

Month	Total	Eastern	West/ Central	Northern	Southern	Antelope Valley	Santa Clarita	Backup
Jul-20	379,484	120,781	65,410	66,139	105,085	18,358	3,696	15
Aug-20	396,152	122,769	67,527	70,446	111,629	19,632	4,133	16
Sep-20	395,751	125,543	67,317	69,974	108,644	20,103	4,154	16
Oct-20	410,906	129,746	69,901	73,139	113,000	20,911	4,192	16
Nov-20	377,723	118,765	63,524	68,085	104,234	19,132	3,969	15
Dec-20	375,120	117,938	63,194	66,302	105,366	18,455	3,850	15
Jan-21	385,774	121,419	64,534	69,574	106,889	19,270	4,074	15
Feb-21	382,107	119,681	65,611	67,659	105,610	19,495	4,036	15
Mar-21	413,438	128,871	71,129	74,035	113,536	21,418	4,433	17
Apr-21	397,755	125,915	68,098	71,085	107,773	20,713	4,155	16
May-21	408,902	127,907	71,441	73,075	111,105	21,328	4,030	16
Jun-21	399,642	126,197	68,330	72,336	108,320	20,488	3,955	16
FY 2021 Total	4,722,755	1,485,531	806,014	841,850	1,301,192	239,302	48,676	189

Month	Total	Eastern	West/ Central	Northern	Southern	Antelope Valley	Santa Clarita	Backup
Jul-21	401,934	126,983	70,434	70,888	108,892	20,767	3,955	16
Aug-21	418,396	129,135	72,158	75,352	115,365	21,951	4,418	17
Sep-21	422,166	133,827	72,872	75,341	112,756	22,884	4,469	17
Oct-21	431,814	135,076	74,533	77,799	116,562	23,372	4,456	17
Nov-21	401,920	125,866	68,231	73,282	108,606	21,645	4,274	16
Dec-21	399,066	125,033	68,085	71,072	109,909	20,838	4,112	16
Jan-22	407,073	126,674	68,962	74,210	111,173	21,695	4,342	16
Feb-22	408,470	127,147	71,040	72,907	110,796	22,212	4,353	16
Mar-22	437,803	135,506	75,886	78,901	118,719	24,043	4,730	18
Apr-22	424,419	132,916	73,508	76,628	113,155	23,699	4,496	17
May-22	436,607	135,618	76,933	78,665	116,805	24,235	4,332	17
Jun-22	426,362	133,723	73,503	77,674	113,849	23,342	4,254	17
FY 2022 Total	5,016,032	1,567,504	866,145	902,719	1,356,589	270,682	52,192	201

Month	Total	Eastern	West/ Central	Northern	Southern	Antelope Valley	Santa Clarita	Backup
Jul-22	429,534	133,997	76,128	76,490	114,824	23,803	4,276	17
Aug-22	445,856	136,812	77,386	80,926	121,059	24,922	4,733	18
Sep-22	452,011	142,079	78,890	81,216	118,742	26,246	4,819	18
Oct-22	457,829	141,382	79,741	83,229	122,230	26,460	4,769	18
Nov-22	430,302	133,872	73,543	78,923	114,626	24,719	4,602	17
Dec-22	425,765	132,010	73,330	76,308	115,936	23,749	4,415	17
Jan-23	432,438	132,819	73,875	79,438	116,963	24,674	4,651	17
Feb-23	437,870	135,219	76,772	78,539	117,181	25,445	4,695	18
Mar-23	463,671	142,097	80,956	84,167	124,179	27,243	5,009	19
Apr-23	451,022	139,419	78,949	81,955	118,967	26,913	4,802	18
May-23	463,283	142,633	82,186	83,830	122,678	27,341	4,596	19
Jun-23	452,096	140,132	78,653	82,744	119,624	26,410	4,514	18
FY 2023 Total	5,341,676	1,652,473	930,410	967,764	1,427,010	307,926	55,880	214

Month	Total	Eastern	West/ Central	Northern	Southern	Antelope Valley	Santa Clarita	Backup
Jul-23	456,960	140,626	81,782	81,910	121,048	27,019	4,557	18
Aug-23	472,909	143,958	82,588	86,171	127,057	28,111	5,004	19
Sep-23	481,058	149,202	84,898	86,870	125,102	29,831	5,136	19
Oct-23	484,414	147,657	85,001	88,556	128,335	29,794	5,053	19
Nov-23	458,821	141,466	79,054	84,398	120,975	28,021	4,888	18
Dec-23	452,542	138,337	78,704	81,559	122,356	26,874	4,693	18
Jan-24	459,418	139,359	79,147	84,776	123,279	27,905	4,935	18
Feb-24	468,116	143,083	82,791	84,243	124,037	28,925	5,018	19
Mar-24	492,033	148,534	86,470	89,658	131,260	30,743	5,348	20
Apr-24	483,535	147,548	85,374	88,240	126,405	30,789	5,159	19
May-24	495,273	150,834	88,306	89,935	130,133	31,118	4,926	20
Jun-24	483,271	147,677	84,775	88,831	126,963	30,169	4,838	19
FY 2024 Total	5,688,351	1,738,279	998,888	1,035,148	1,506,951	349,301	59,556	228

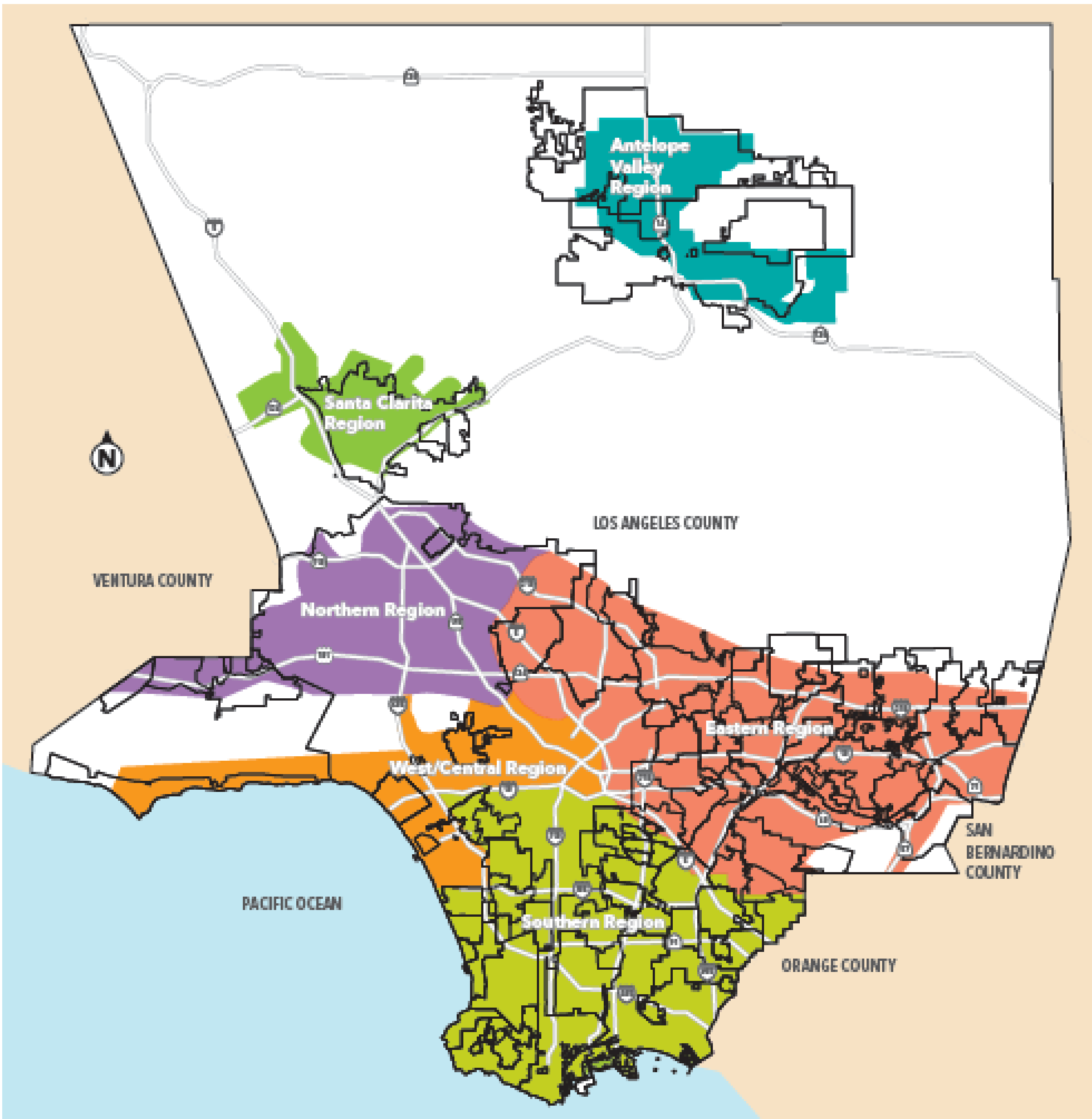
Month	Total	Eastern	West/ Central	Northern	Southern	Antelope Valley	Santa Clarita	Backup
Jul-24	490,021	148,842	88,298	88,278	128,768	30,912	4,904	20
Aug-24	505,205	152,260	88,705	92,360	134,493	32,024	5,342	20
Sep-24	515,251	157,368	91,801	93,494	132,933	34,120	5,513	21
Oct-24	516,645	155,562	91,112	94,828	135,886	33,836	5,401	21
Nov-24	491,608	149,826	85,341	90,642	128,557	31,988	5,234	20
Dec-24	483,293	145,469	84,663	87,569	129,917	30,621	5,035	19
Jan-25	491,051	147,215	85,130	90,872	130,753	31,786	5,275	20
Feb-25	502,130	151,547	89,433	90,676	132,001	33,062	5,390	20
Mar-25	523,908	156,003	92,719	95,986	138,534	34,962	5,684	21
Apr-25	516,788	155,701	92,034	94,535	134,020	34,976	5,503	21
May-25	527,196	158,500	94,543	96,035	137,647	35,201	5,250	21
Jun-25	514,869	154,995	91,139	94,935	134,402	34,227	5,151	21
FY 2025 Total	6,077,967	1,833,288	1,074,917	1,110,209	1,597,912	397,715	63,682	243

Month	Total	Eastern	West/ Central	Northern	Southern	Antelope Valley	Santa Clarita	Backup
Jul-25	523,330	156,932	94,916	94,602	136,534	35,086	5,239	21
Aug-25	537,544	160,016	95,021	98,512	142,048	36,252	5,675	22
Sep-25	549,949	165,316	98,893	100,160	140,931	38,746	5,881	22
Oct-25	549,575	163,491	97,410	101,128	143,552	38,229	5,744	22
Nov-25	524,529	157,671	91,857	96,904	136,218	36,285	5,572	21
Dec-25	514,409	152,473	90,734	93,613	137,530	34,670	5,369	21
Jan-26	523,225	155,014	91,339	96,965	138,285	35,994	5,607	21
Feb-26	536,007	159,413	96,194	97,109	139,998	37,519	5,753	21
Mar-26	556,328	163,424	99,178	102,338	145,819	39,536	6,010	22
Apr-26	550,171	163,606	98,852	100,777	141,625	39,459	5,831	22
May-26	558,788	165,591	100,874	102,093	145,067	39,577	5,564	22
Jun-26	546,640	162,146	97,690	100,982	141,786	38,565	5,449	22
FY 2026 Total	6,470,496	1,925,092	1,152,957	1,185,184	1,689,392	449,918	67,694	259

Month	Total	Eastern	West/ Central	Northern	Southern	Antelope Valley	Santa Clarita	Backup
Jul-26	556,356	164,646	101,584	100,825	144,193	39,528	5,558	22
Aug-26	569,684	167,205	101,506	104,591	149,586	40,774	5,999	23
Sep-26	584,928	173,104	106,123	106,800	148,944	43,699	6,235	23
Oct-26	582,727	171,183	103,873	107,412	151,190	42,965	6,080	23
Nov-26	557,425	165,028	98,565	103,155	143,851	40,905	5,898	22
Dec-26	545,723	159,380	96,900	99,636	145,080	39,013	5,694	22
Jan-27	555,513	162,509	97,747	103,019	145,770	40,517	5,928	22
Feb-27	569,691	166,764	103,064	103,513	147,939	42,286	6,102	23
Mar-27	589,782	170,817	105,861	108,679	153,589	44,453	6,359	24
Apr-27	585,686	171,751	106,131	107,396	149,715	44,493	6,176	23
May-27	592,570	172,938	107,667	108,566	152,969	44,511	5,896	24
Jun-27	581,048	169,884	104,788	107,443	149,695	43,451	5,765	23
FY 2027 Total	6,871,133	2,015,208	1,233,809	1,261,036	1,782,520	506,594	71,692	275

Month	Total	Eastern	West/ Central	Northern	Southern	Antelope Valley	Santa Clarita	Backup
Jul-27	591,604	172,635	108,718	107,455	152,358	44,520	5,895	24
Aug-27	604,429	174,766	108,594	111,129	157,692	45,880	6,346	24
Sep-27	622,721	181,498	113,904	113,897	157,532	49,258	6,608	25
Oct-27	618,539	179,259	110,936	114,171	159,401	48,309	6,438	25
Nov-27	592,953	172,772	105,873	109,874	152,069	46,099	6,242	24
Dec-27	579,806	166,918	103,607	106,116	153,205	43,900	6,036	23
Jan-28	590,544	170,390	104,815	109,557	153,874	45,615	6,271	24
Feb-28	606,002	174,527	110,490	110,386	156,465	47,641	6,468	24
Mar-28	626,297	178,873	113,186	115,503	161,976	50,001	6,732	25
Apr-28	623,781	180,190	113,984	114,490	158,385	50,164	6,543	25
May-28	629,068	180,757	115,012	115,520	161,415	50,088	6,250	25
Jun-28	618,226	178,173	112,454	114,357	158,146	48,969	6,102	25
FY 2028 Total	7,303,969	2,110,758	1,321,572	1,342,453	1,882,517	570,445	75,932	292

Appendix 5: Service Area Map



Source: Access Services

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