Passenger Demand Forecasting

FY2017 – FY2026

February 23, 2017

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 thirteen 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, local 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 from 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 a time-series econometric analysis and 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 December 2015 have been added to the model.

Plan of the Report

The report includes full technical documentation of the model 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 and new applicant projections are provided for each region served by Access in appendices 4 and 5. Appendix 6 contains a map of the service area. All data sources and references used throughout the study are listed in Appendix 7.

2. Historical Overview

This section presents a historical overview of paratransit operations data for the six regions served by Access from July 2005 to November 2016. 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 to 4.5 million in 2016, from 3.1 million in 2011 – at an annual rate of 7.7 percent. From 2004 to 2007, trip requests declined. 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 45 percent. In 2016 alone, they increased by 6.5 percent.

Overall, trip demand increased in each of the previous five fiscal years in every region of Access's service area, except for Santa Clarita. In 2016, the largest regions in terms of trip requests were the Eastern and Southern regions. Since 2012 these two regions have accounted for 63 percent of all 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 led to a 6.5 percent drop in trip requests in 2010; this marked the largest decline among all regions in two years. However, in recent years the region has approached the peak number of trip requests it obtained in 2003.

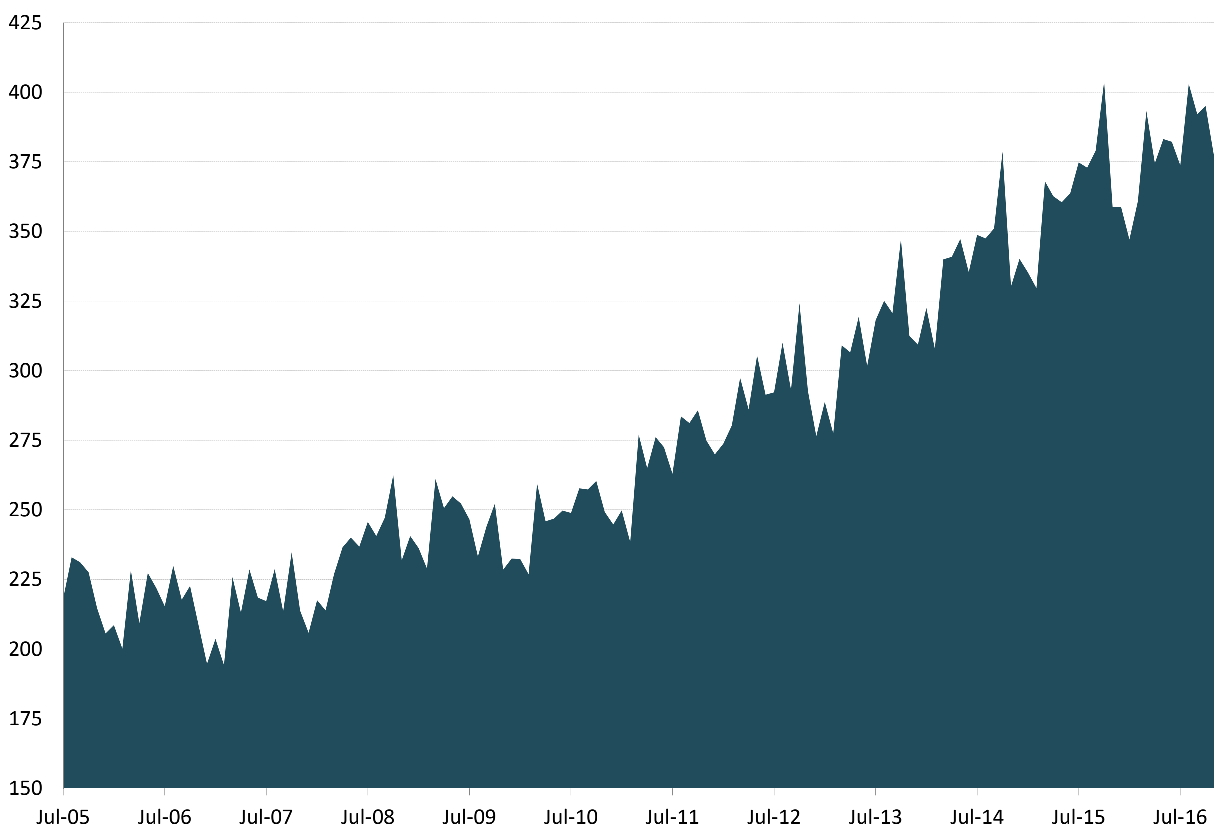
These demand and growth estimates are also reported in Table 1 on the next page, along with trip requests for "backup", an around-the-clock service provided by Access in case of failure of the carrier (e.g., the vehicle has not arrived by the scheduled pick up time plus the 20-minute on-time window). Figure 1 shows monthly trip requests for the whole service area from July 2005 to June 2016.

Table 1: Passenger Trip Requests by Region (FY2011 – FY2016)

	FY 2011	FY 2012	FY 2013	FY 2014	FY 2015	FY 2016
TOTAL	3,096,986 6.9%	3,392,445 9.5%	3,591,126 5.9%	3,926,569 9.3%	4,215,820 7.4%	4,488,996 6.5%
Antelope Valley	75,921 9.4%	86,001 13.3%	114,969 33.7%	147,073 27.9%	173,742 18.1%	207,155 19.2%
Eastern	912,945 4.4%	968,597 6.1%	1,005,145 3.8%	1,080,179 7.5%	1,149,365 6.4%	1,232,867 7.3%
Northern	595,320 9.4%	662,764 11.3%	687,635 3.8%	742,518 8.0%	778,995 4.9%	800,959 2.8%
Santa Clarita	54,670 15.8%	56,704 3.7%	58,888 3.9%	55,204 -6.3%	55,792 1.1%	54,984 -1.4%
Southern	934,062 4.5%	1,068,294 14.4%	1,164,015 9.0%	1,298,647 11.6%	1,400,202 7.8%	1,500,239 7.1%
West/ Central	519,216 12.0%	544,895 4.9%	555,694 2.0%	596,688 7.4%	650,432 9.0%	687,089 5.6%
Backup	4,852 -4.2%	5,190 7.0%	4,780 -7.9%	6,260 31.0%	7,292 16.5%	5,703 -21.8%

Source: Access Services

Figure 1: Monthly Trip Requests, Thousands (July 2005 – June 2016)

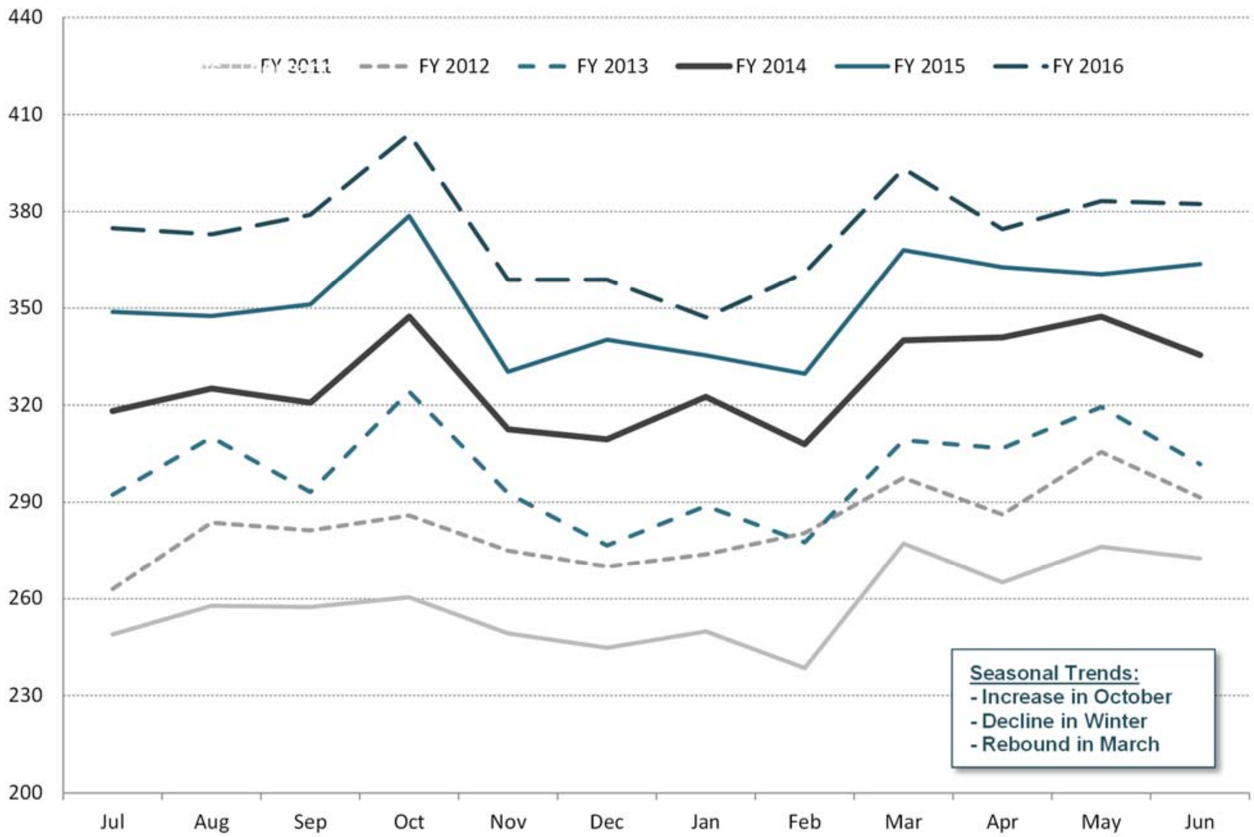


Source: Access Services

Trip demand is rising at a significantly faster pace in geographically smaller service regions than the other regions. Over the last ten fiscal years, trip demand in Santa Clarita and Antelope Valley has increased rapidly. From 2008 to 2010, trip requests in Santa Clarita nearly doubled, growing from 26,465 to 47,231. Since then, trip demand has slowed down considerably, growing at an average annual rate of 2.6 percent. In Antelope Valley, trip requests have grown by 24.6 percent per year on average over the past four fiscal years, and in each of those years Antelope Valley experienced the largest growth by any service region. The next largest growth on average over those four years was three times less than the growth in Antelope Valley – the Southern region grew by an average of 8.9 percent per year. In particular, the growth in Antelope Valley accounted for more than 12 percent of total trip demand growth in 2016, though less than 5 percent of total trip requests came from that region.

Figure 2 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 (FY2011 – FY2016)



Source: Access Services

Passenger Trips Completed

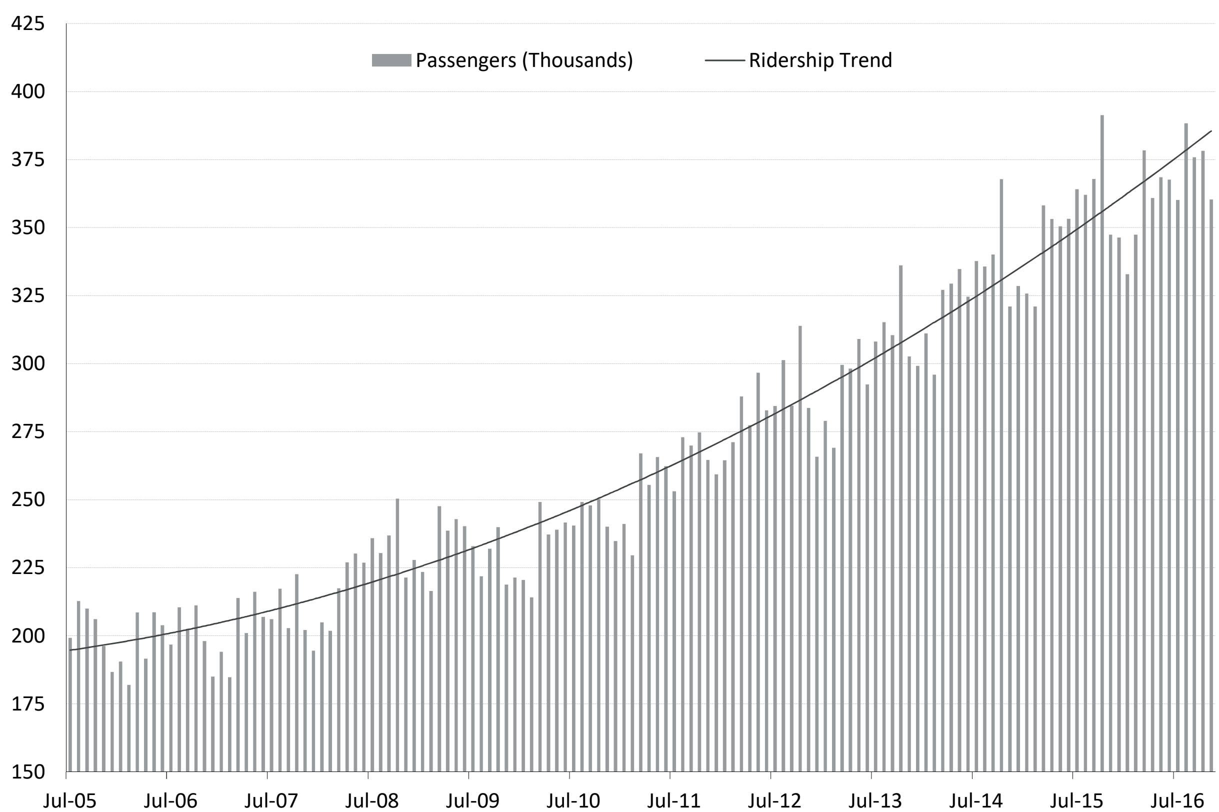
Although trip requests represent the fundamental manifestation of consumer demand, not all requested trips are scheduled. Requests can be denied by Access because of eligibility requirements or cancelled by the customer after considering the expected pickup time. After a trip is scheduled, Access sends 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 over the past decade. As evidenced by the trend line in Figure 3 below, ridership remained fairly stagnant in 2006 and 2007. However, ridership has steadily increased since 2010 and it reached its highest level in 2015. Over the past five years, ridership has grown by 7.8 percent per year on average in the service area.

Figure 3: Ridership in Service Area (July 2005 – June 2016)



Source: Access Services

As shown in Table 2 below, ridership has increased in every service region, except for Santa Clarita, since 2011. 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). Over the past five years, ridership in Antelope Valley has more than doubled, rising from approximately 74, 000 in 2011 to almost 200,000 in 2016. In 2013 alone, ridership increased by 34.7 percent, and the region has averaged about 25 percent annual growth over the past four years.

Smaller regions (i.e., Antelope Valley and Santa Clarita) have had the largest growth rates of all regions, but most of the new ridership in the previous 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 2008 – its ridership has increased by more than 400,000 since 2012. The Eastern region is the second largest in the service area and has experienced modest growth since the recession, averaging an annual increase of 6.2 percent over the past six fiscal years. Ridership in the Northern region has grown steadily and is the only region to have experienced positive growth every year since 2007.

Table 2: Ridership by Service Region (FY2011 – FY2016)

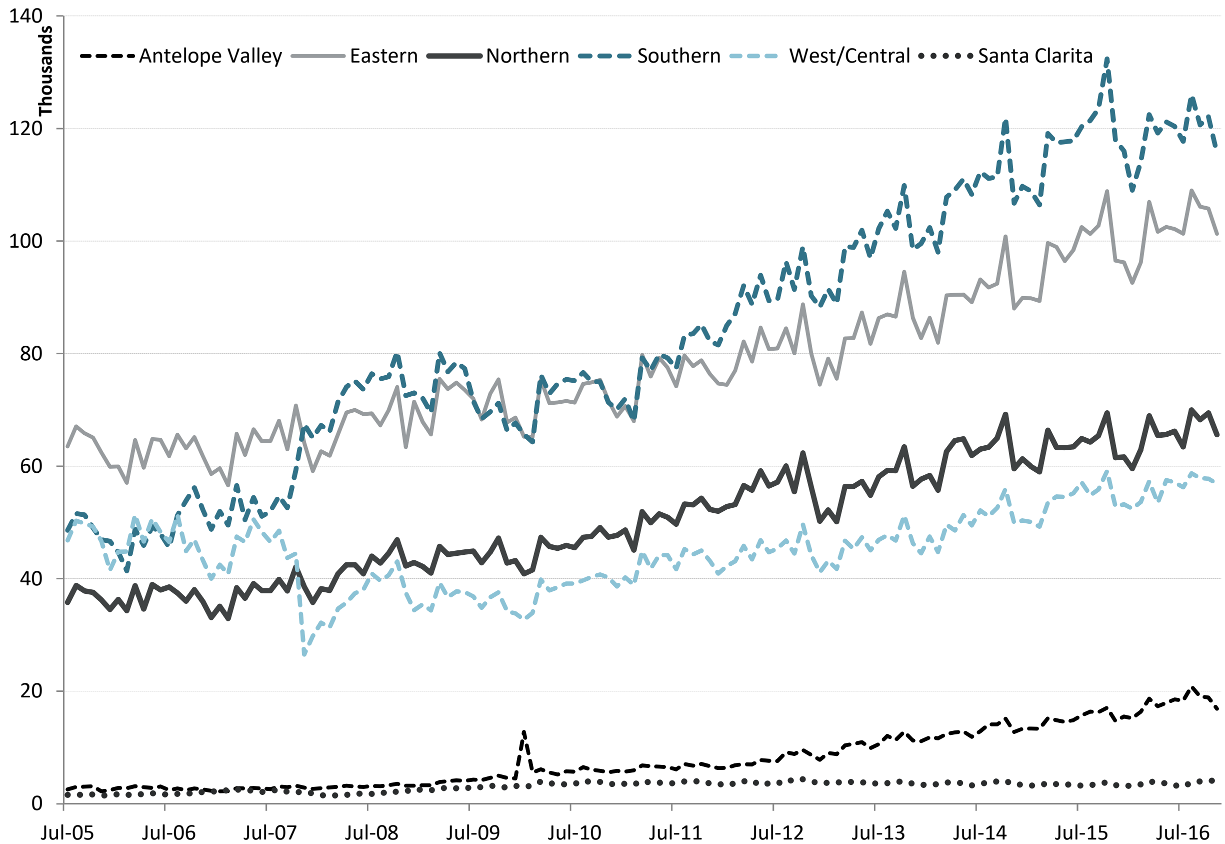
	FY 2011	FY 2012	FY 2013	FY 2014	FY 2015	FY 2016
TOTAL	2,983,849 7.8%	3,275,021 9.8%	3,481,204 6.3%	3,794,914 9.0%	4,092,766 7.8%	4,334,872 5.9%
Antelope Valley	73,818 8.4%	82,583 11.9%	111,263 34.7%	142,292 27.9%	168,313 18.3%	199,634 18.6%
Eastern	887,614 5.1%	938,910 5.8%	977,840 4.1%	1,052,229 7.6%	1,128,677 7.3%	1,210,011 7.2%
Northern	582,464 9.4%	648,509 11.3%	668,668 3.1%	722,008 8.0%	756,733 4.8%	776,000 2.5%
Santa Clarita	44,372 14.0%	44,622 0.6%	46,381 3.9%	43,368 -6.5%	42,489 -2.0%	41,489 -2.4%
Southern	898,519 6.5%	1,029,309 14.6%	1,131,881 10.0%	1,254,304 10.8%	1,360,595 8.5%	1,437,979 5.7%
West/ Central	492,801 13.1%	526,465 6.8%	540,810 2.7%	574,640 6.3%	628,999 9.5%	664,319 5.6%
Backup	4,261 -6.0%	4,623 8.5%	4,361 -5.7%	6,073 39.3%	6,960 14.6%	5,440 -21.8%

Source: Access Services

Figure 4 on the next page shows the ridership trend for all service regions in the past eleven fiscal years. 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 – June 2016)



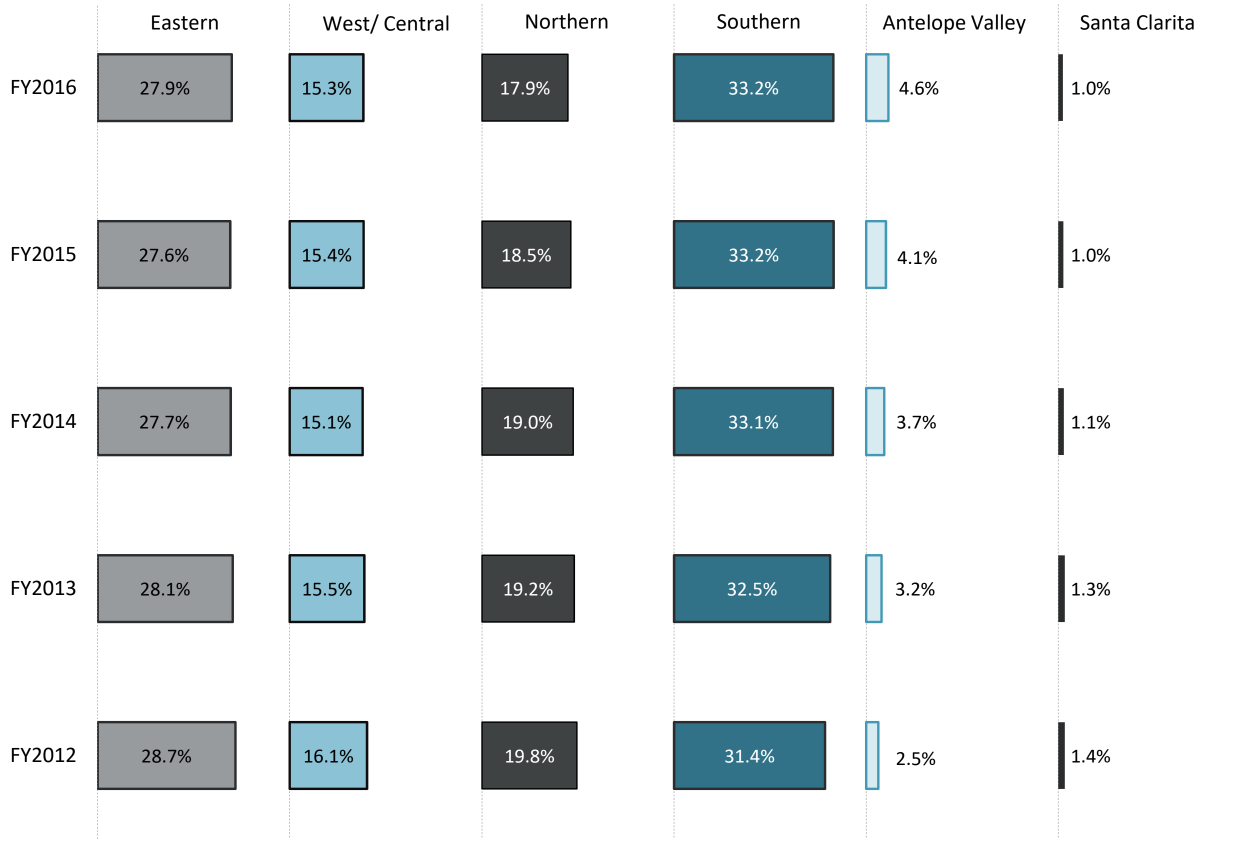
Source: Access Services

DISTRIBUTION OF RIDERSHIP BY SERVICE REGION

In 2016, the Southern region had the largest ridership share (33.2 percent) followed by the Eastern region (27.9 percent). The Northern and West/ Central regions accounted for 17.9 percent and 15.3 percent of total ridership respectively. The Santa Clarita and Antelope Valley regions together accounted for slightly less than 6 percent of total ridership. Figure 5 on the following page displays the distribution of passengers by service region from 2012 to 2016.

Despite growing numbers of riders in the Eastern, West/ Central, and Northern regions in the past five years, their share of ridership decreased with respect to the other regions. Since 2012, the Southern and Antelope Valley regions have increased their respective ridership shares the most compared to the other regions, whereas the Santa Clarita region's share of ridership has remained about the same.

Figure 5: Distribution of Passengers by Service Region (FY2012 – FY2016)



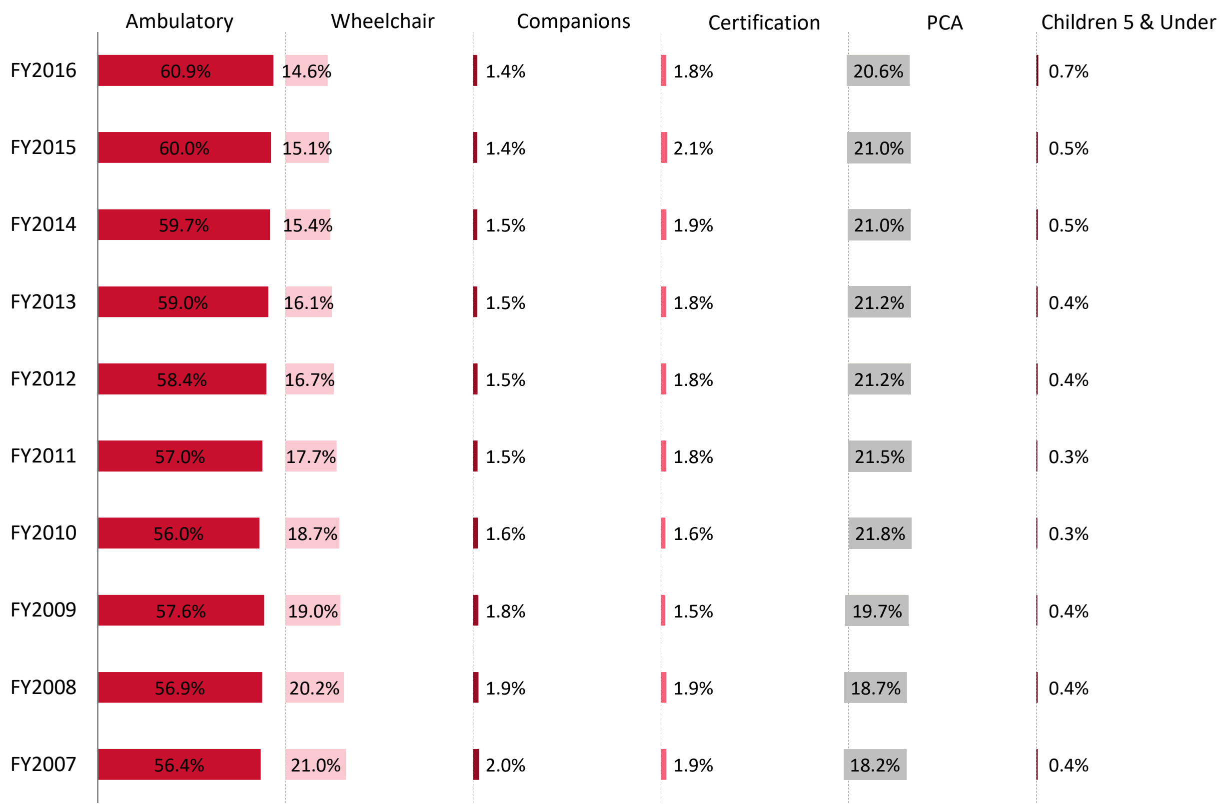
Source: Access Services

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 over the past decade. In 2016, ambulatory passengers accounted for 60.9 percent of total ridership. The majority of the remaining trips were taken by persons using wheelchairs (14.6 percent) and PCA (20.6 percent). Over the years, trips completed by persons using wheelchairs have decreased while those completed by PCA have increased, on average. The rest of passenger trips were 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. Figure 6 on the next page depicts the distribution of ridership by type of passenger over the last ten fiscal years.

Figure 6: Ridership by Type of Passenger (FY2007 – FY2016)



Source: Access Services

Key Operating Factors

Demand for paratransit service is affected by multiple factors, including fare structure, operating standards, and other socioeconomic indicators. Key operating factors that are considered to be impacting trip demand can include inflation adjusted trip fare (real fare), complaint rate, on-time performance, cancellation and no-shows, and population.

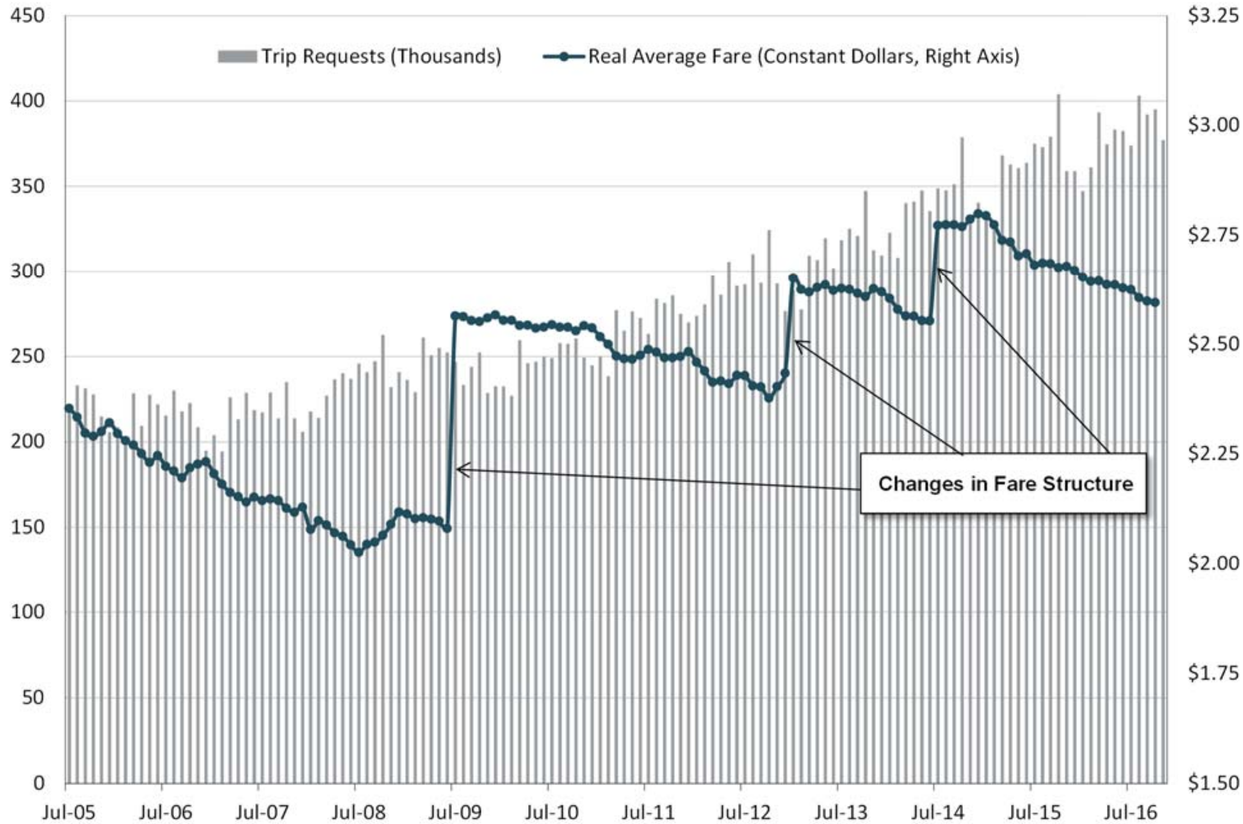
Real Fare

Economic theory and past experience show an inverse relationship between *real* fare (as opposed to *nominal* fare) and trip requests, sometimes with a slight time lag: 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 region in two steps. First, the average nominal fare is computed by dividing total monthly fare revenue (cash, Access Services coupons and Metropolitan Transit Authority (MTA) 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 other passengers on certification trips.

Next, the average nominal fare is deflated by the Consumer Price Index (CPI) for the Los Angeles-Riverside-Orange County, CA metropolitan area. This removes all inflationary movements from the nominal fare price, 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 – June 2016)



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[1] 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 $2.08 in June 2009 to $2.56 the following month;

---

[1] The new (reduced) fare for trips scheduled between 9:00 p.m. and 5:00 a.m. is $1.50 regardless of distance.

- The change in fare structure in January 2013 led to an increase in the real average fare from $2.43 to $2.65; and
- The change in fare structure in July 2014 led to an increase in the real average fare from $2.55 to $2.77.

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

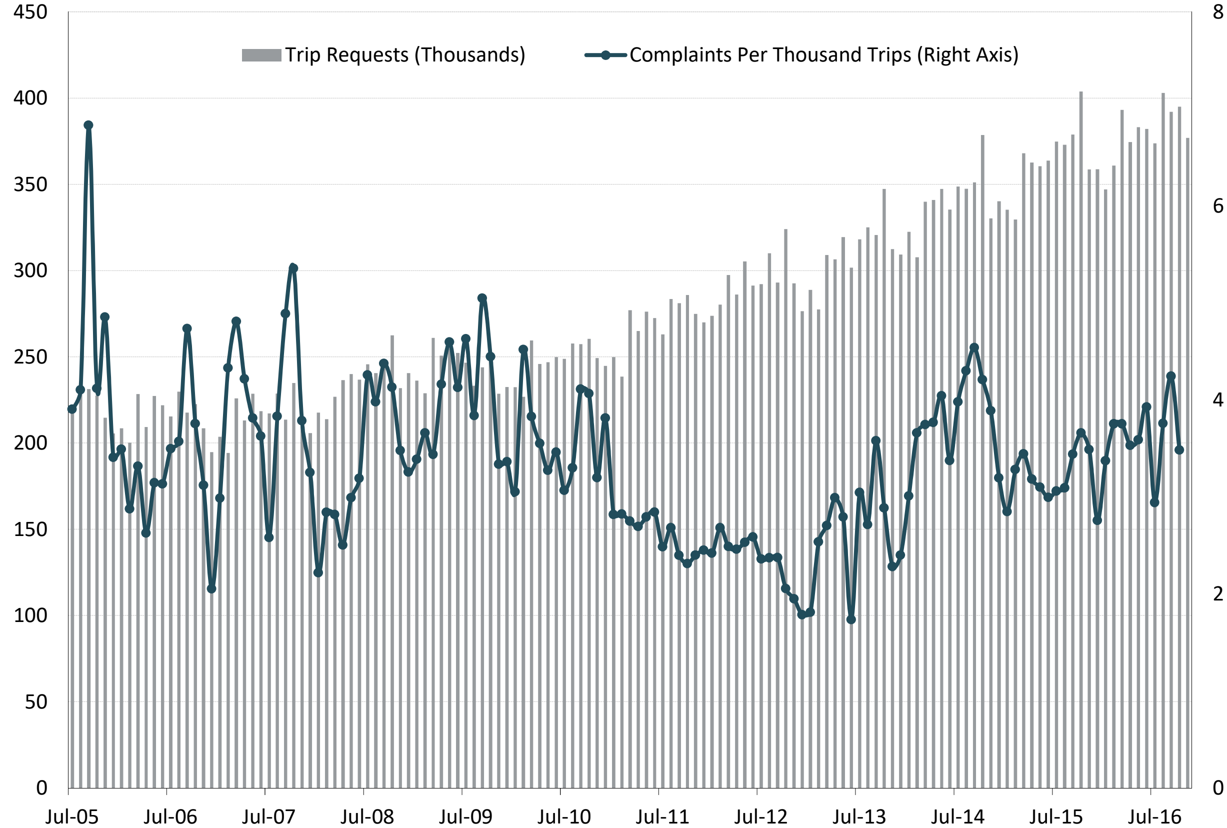
Eligibility evaluations consist of evaluations of individuals as a new applicant or a recertification for paratransit services. For Access, eligibility is determined by an in-person transit evaluation and is based on the individual's ability to use accessible buses and trains in Los Angeles County. The 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 analysis of new applicants to investigate the rapid growth in new applicants starting in 2009.

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 demand is partly defined by the willingness to pay, it is expected that decreases in the complaint rate 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 where the data in the past eleven 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 219,344 at the beginning of 2005 to 382,221 by the end of 2016, and the complaint rate decreased from 6.4 in 2005 to a minimum of 2.3 complaints per thousand trips completed in 2013, though the complaint rate has increased slightly in recent years to a rate of 3.5. However, 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.

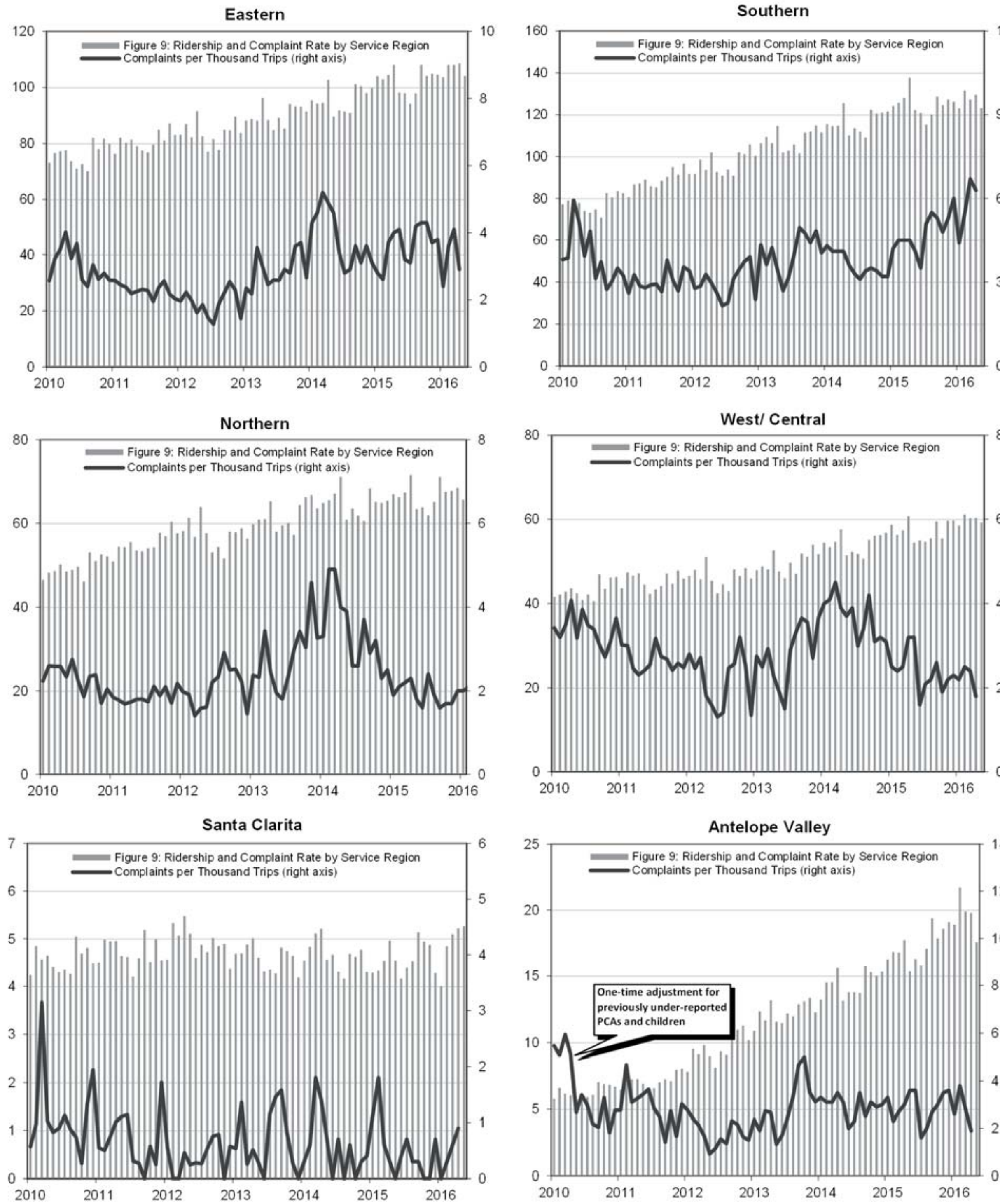
Figure 8: Ridership and Complaint Rate (July 2005 – June 2016)



Source: Access Services

Figure 9 on the following page reports the same data by service region, for fiscal years 2011 to 2016.

Figure 9: Ridership and Complaint Rate by Service Region (July 2010 – June 2016)

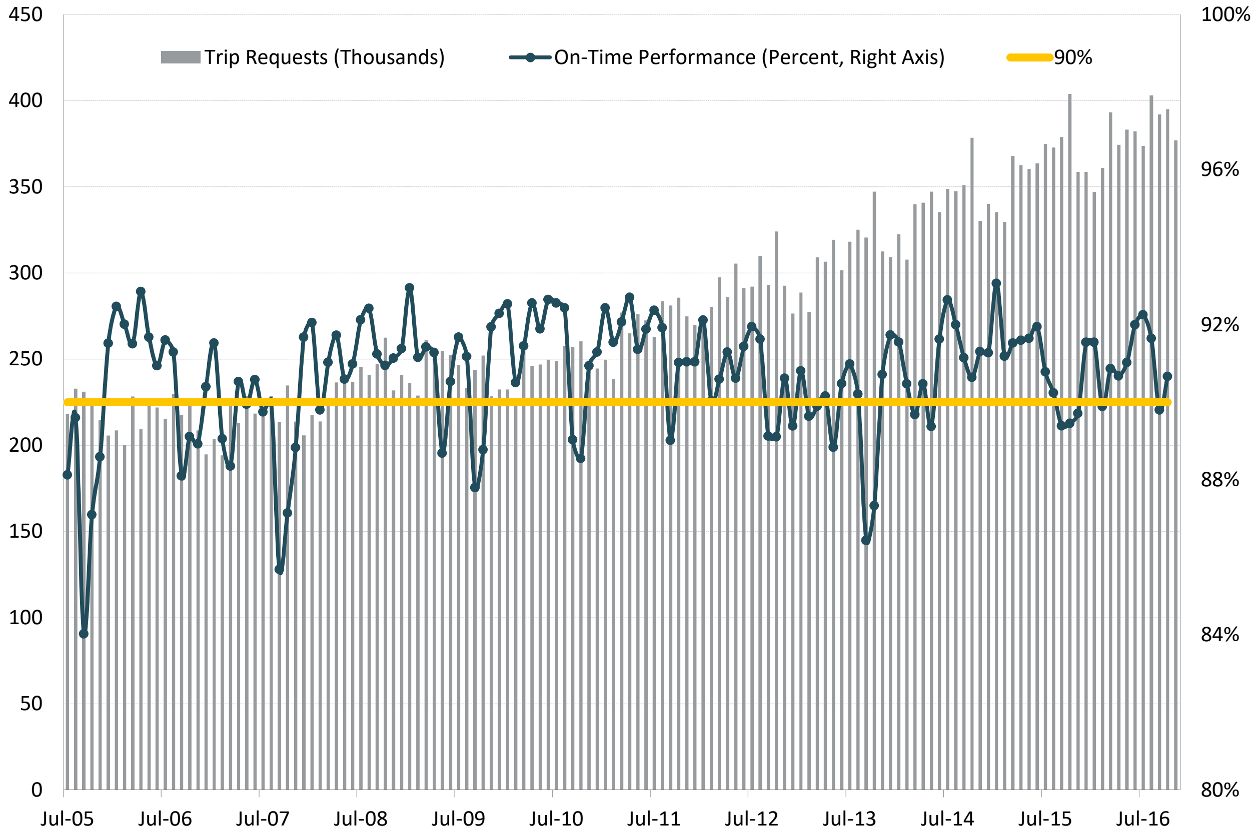


Source: Access Services

On-Time Performance

At the system level, on-time performance averaged 90.7 percent over the period 2006 – 2016. This estimate is 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 in 2013 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[2]. Since then, however, dips below the benchmark have not been large or lasting.

Figure 10: Trip Requests and On-Time Performance (July 2005 – June 2016)



Source: Access Services

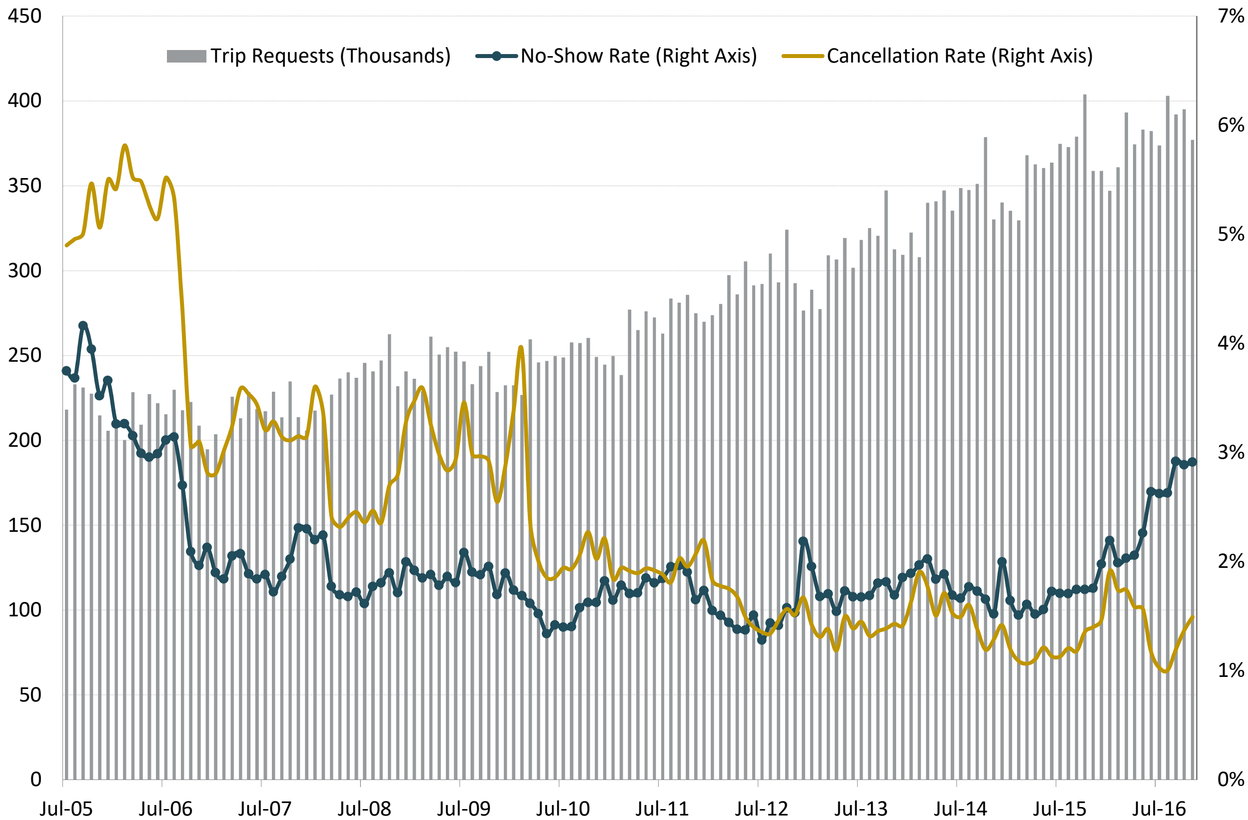
Cancellations and No-shows

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 eleven fiscal years, these measures have shared similar trends, with

[2] Note that in September 2013 the graph indicates a drop in on-time performance. 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[3], and in 2016 again. In 2016, the no-show rate averaged only 2.0 percent, compared to 4.6 percent in 2005. Overall, fluctuations in no-show and cancellation rates do not coincide with changes in trip requests, as illustrated in Figure 11.

Figure 11: Trip Requests and No-Show and Cancellation Rates (July 2005 – June 2016)



Source: Access Services

Population

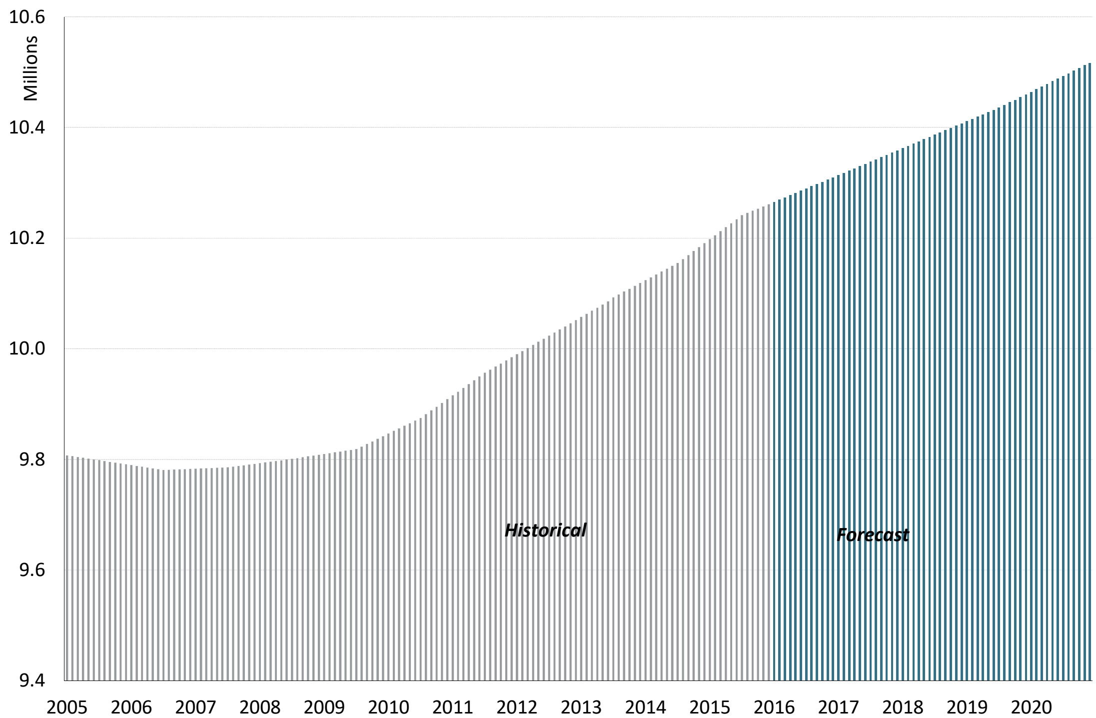
The demand for paratransit services may also be affected by the number of people living in the service area. Population data for Los Angeles County are collected from the Demographic Research Unit at the California Department of Finance (DoF) and the Southern California Association of Governments (SCAG). An annual growth rate of 0.55 percent is projected between 2016 and 2021.

---

[3] 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.

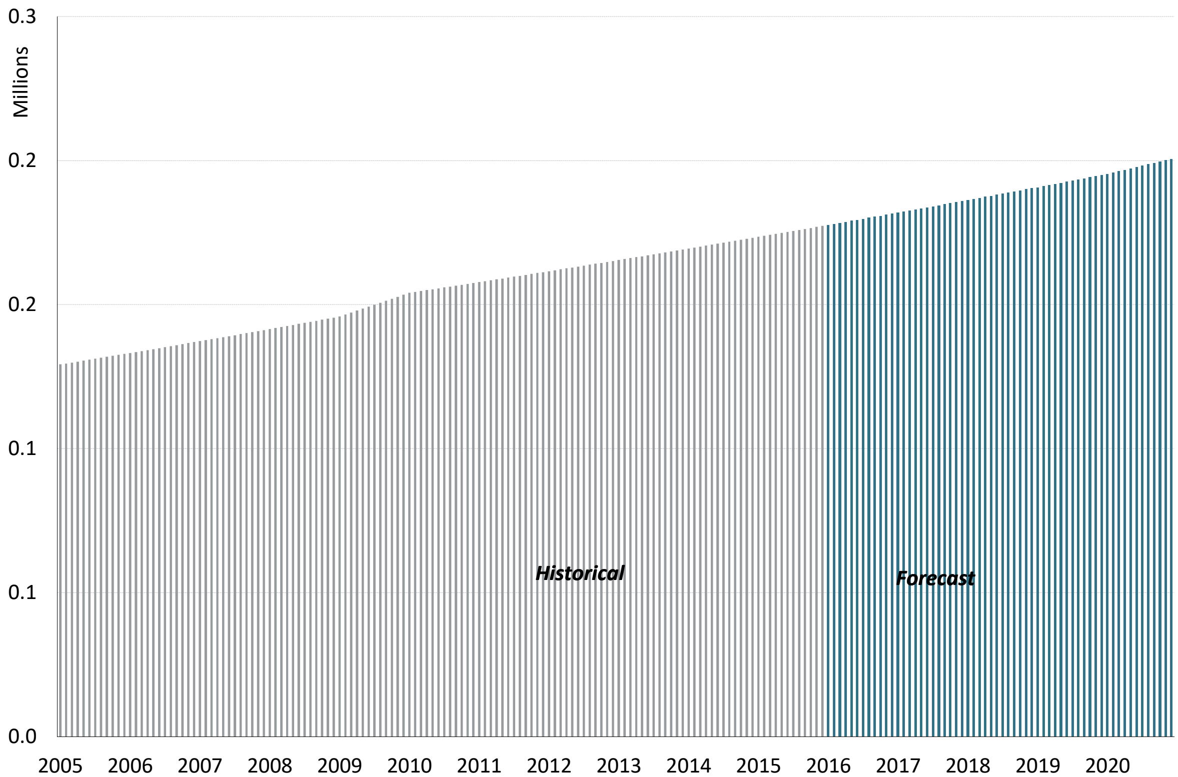
Alternately, the senior population (85 years old and above) is growing at a much faster pace. From 2004 to 2010, this group grew by more than 3 percent per year and is expected to continue to grow at an annual rate of 2.4 percent through 2021, in part due to the growing Asian American and Latino American 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 2021)



Sources: California Department of Finance, Demographic Research Unit and Southern California Association of Governments

Figure 13: Senior Population in Los Angeles County (July 2005 – June 2021)



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. To maintain transparency and accountability, 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 findings 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 (PTF) of 30 percent of the Regional Transportation Authority (RTA) sales tax and Chicago real estate transfer tax (RETT) 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)[4] 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[5]. 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;

---

4 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.

5 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.

- Southeastern Pennsylvania Transportation Authority (SEPTA) in Philadelphia, PA; and
- Washington Metropolitan Area Transit Authority (WAMATA) 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); and
- City of Los Angeles Department of Transportation (LADOT).

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[6]:** *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[7] 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[8]:** *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)[9]:** *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[10]:** *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;
- **Service Quality (*Perceived*) – describes the transit agency's service as perceived by customers:** *On-time performance* demonstrates the level of satisfaction that

---

6 Kittelson & Associates, Inc. et al., op. cit.

7 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.

8 Kittelson & Associates, Inc. et al., op. cit.

9 Ibid.

10 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[11] 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)[12];
- National Transit Database (NTD);
- New York City Transit Paratransit Peer Reports; and
- Agency Operation and Service Annual Reports[13] [14].

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

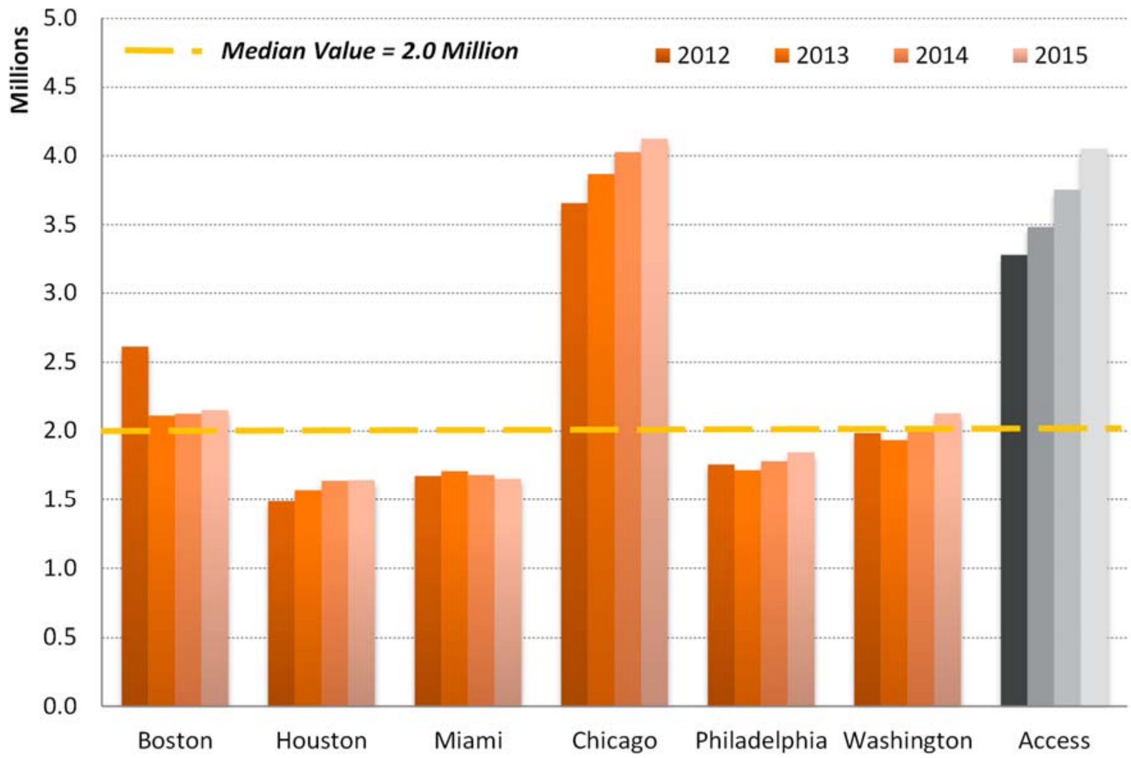
Passenger demand in terms of passenger trips or trip requests is an indicator of service utilization. Because the number of passenger trips is commonly reported and provided by each agency, it is used to quantify demand in the peer review. Other demand measures, such as trip requests, are less readily 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.

---

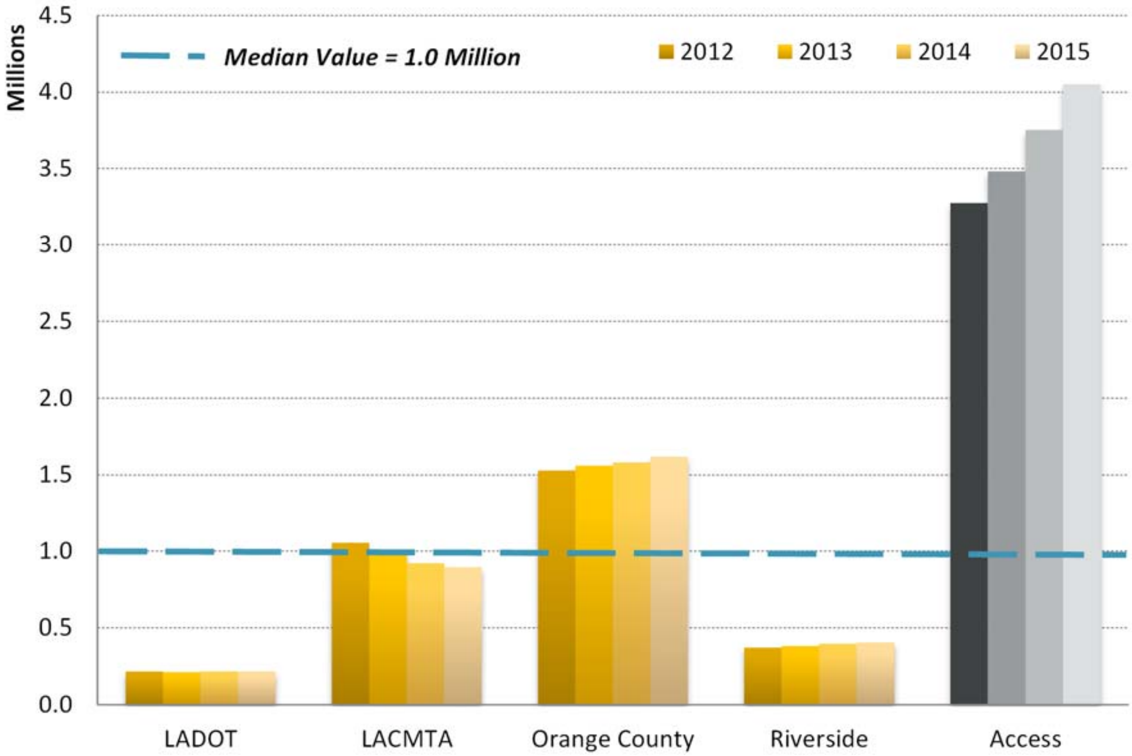
11 This was the most recent data available through FTIS.
12 Available at http://www.ftis.org.
13 OCTA − Transit Division Performance Measurements Report; WMATA − MetroAccess Monthly Operations Report; Pace − Suburban Service Budget & Regional ADA Paratransit Budget; MDT − Miami-Dade Transit Paratransit Operations Monthly Reports; MTA Houston – Metro Business Plan & Budget.
14 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.

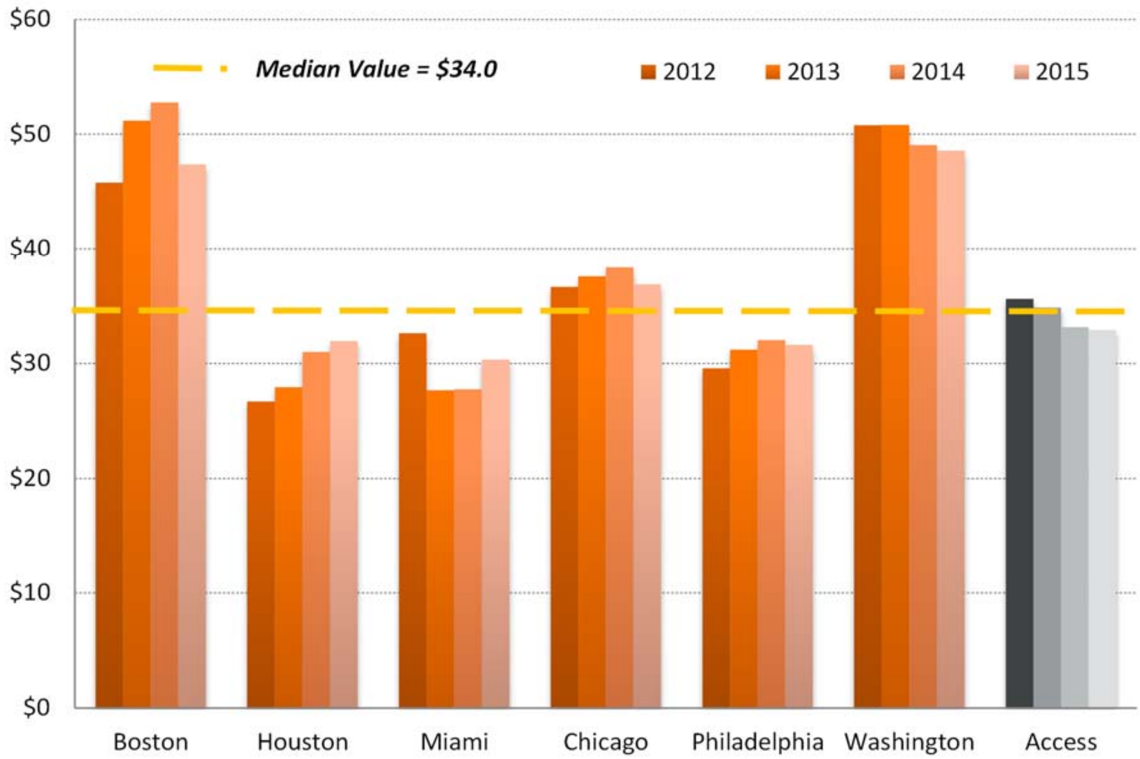
Cost Efficiency

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 $34.0. 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 dollars per trip.

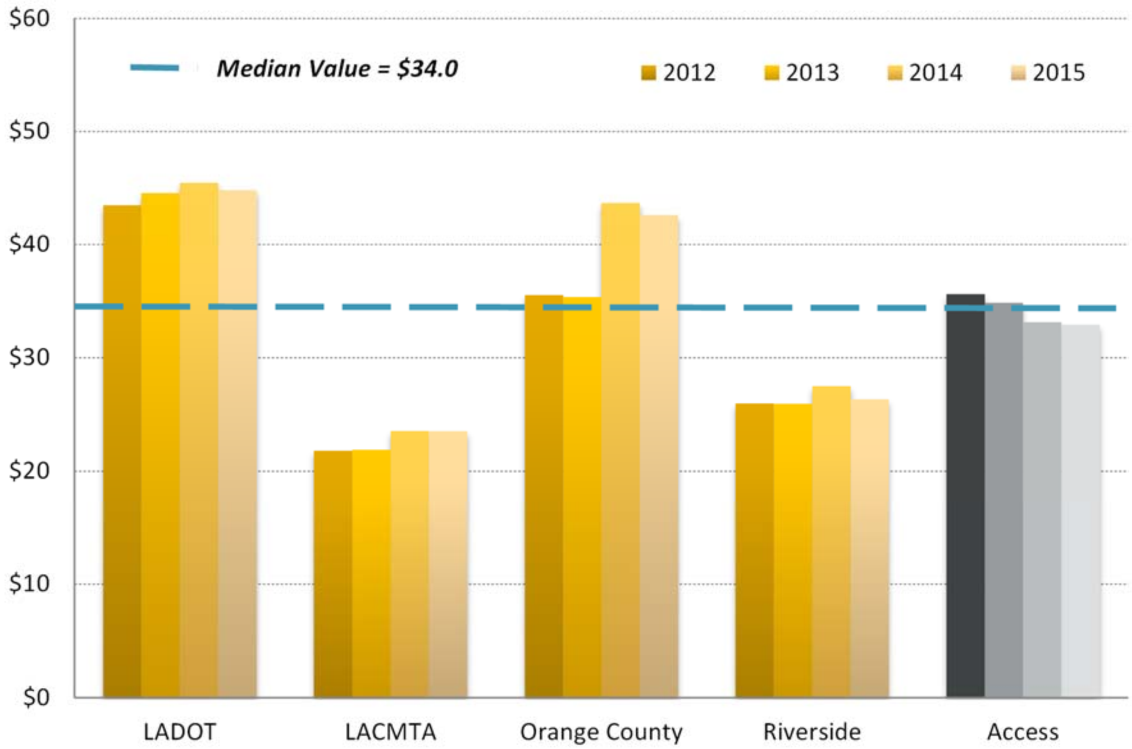
This disparity could be due to discrepancies across agencies in employee compensation and their responses to the 2008-2009 economic recession. The real cost per trip for Access has slowly decreased from 2010, declining 2.6 percent per year on average.

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)

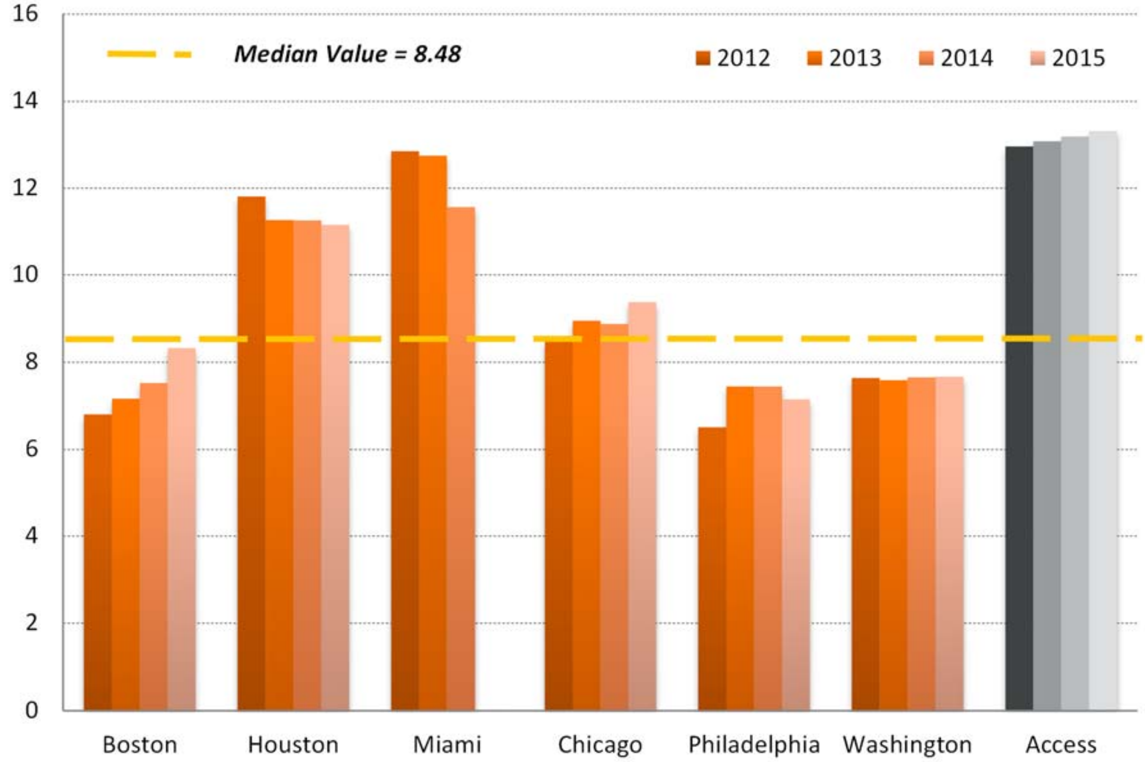
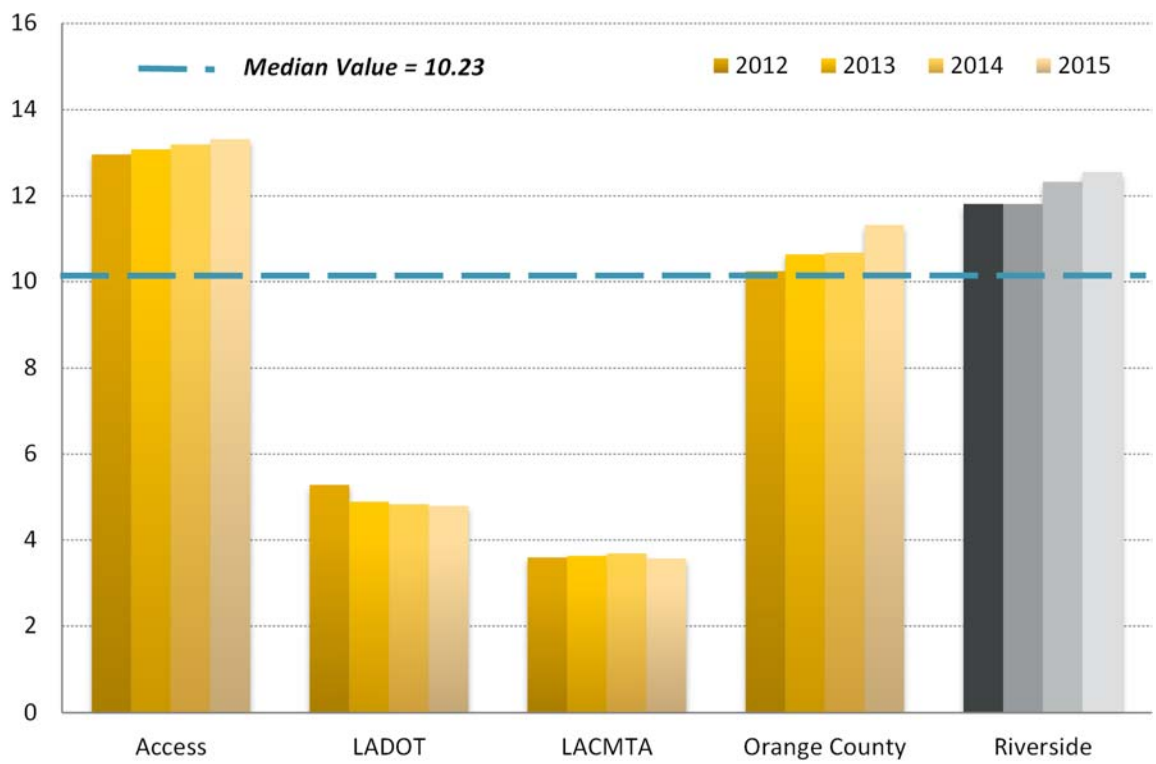


Figure 19: Regional Peer Review, Trip Length in Miles (FY2012 – FY2015)

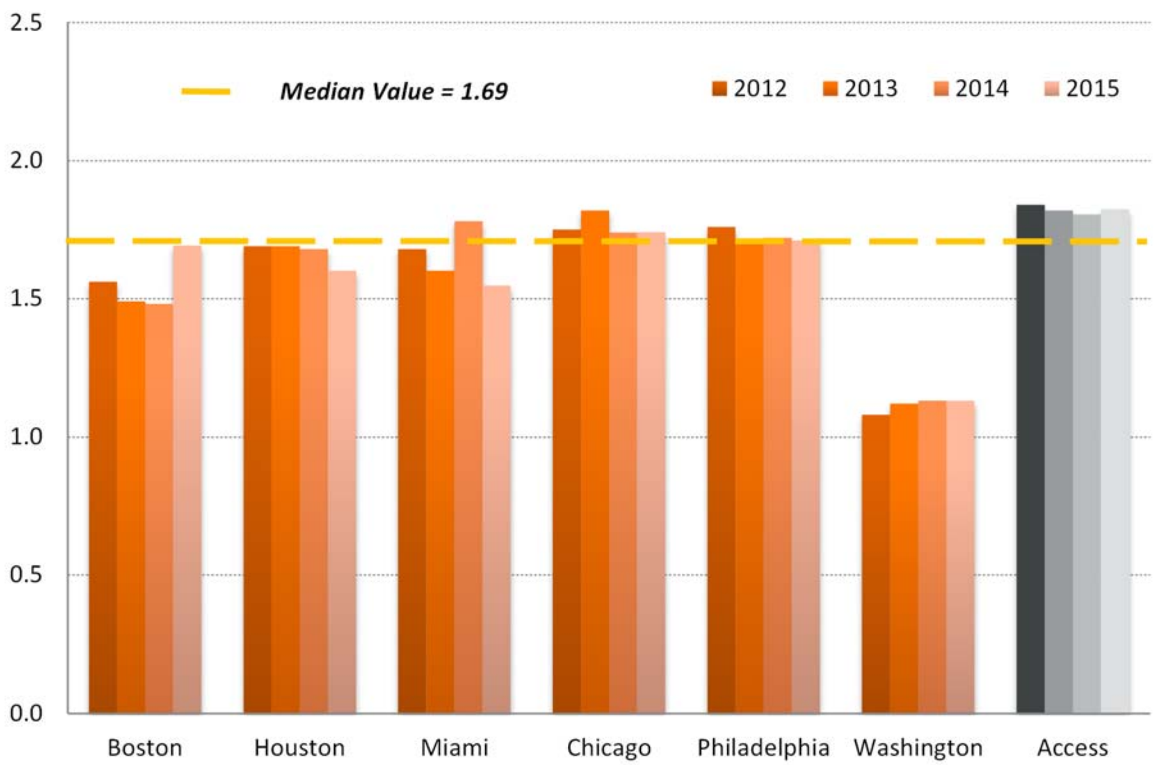


Productivity

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)

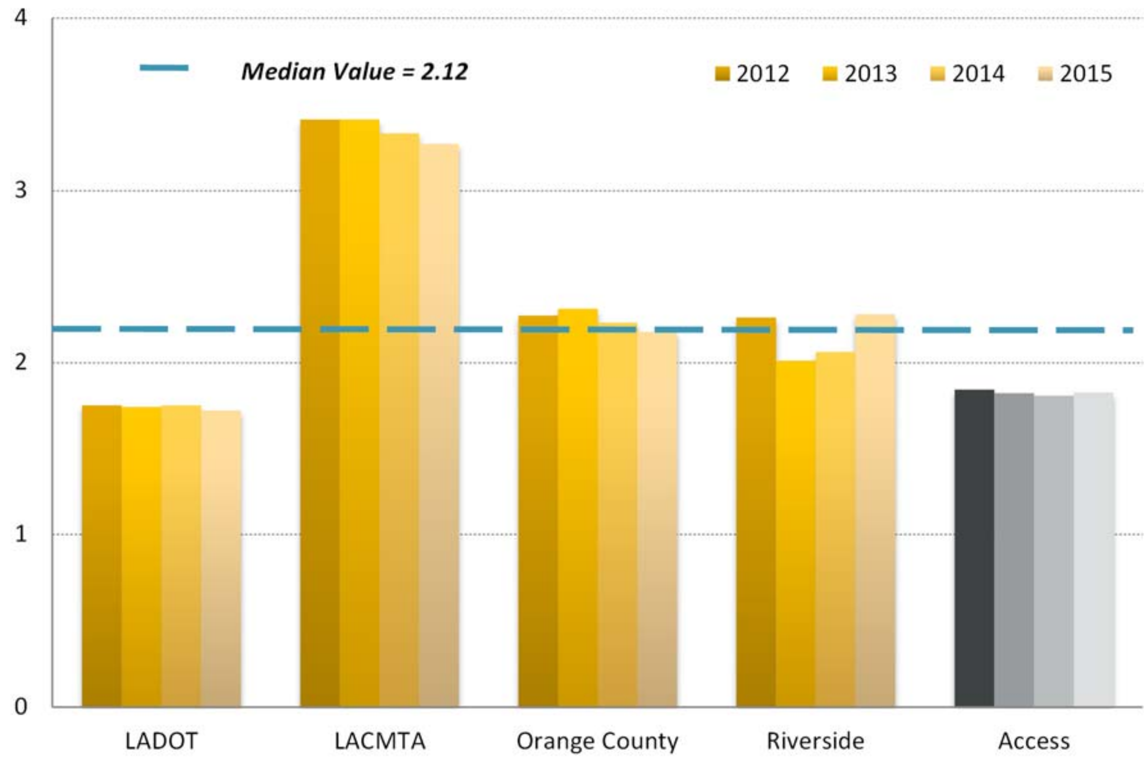


Access averages 1.8 passengers per revenue hour which is higher than the national peer systems – the median value being 1.7 passengers. The least productive system is WMATA, averaging 1.1 passengers per revenue hour.

Among peer agencies in the Greater Los Angeles region, the median value is 2.1, 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)

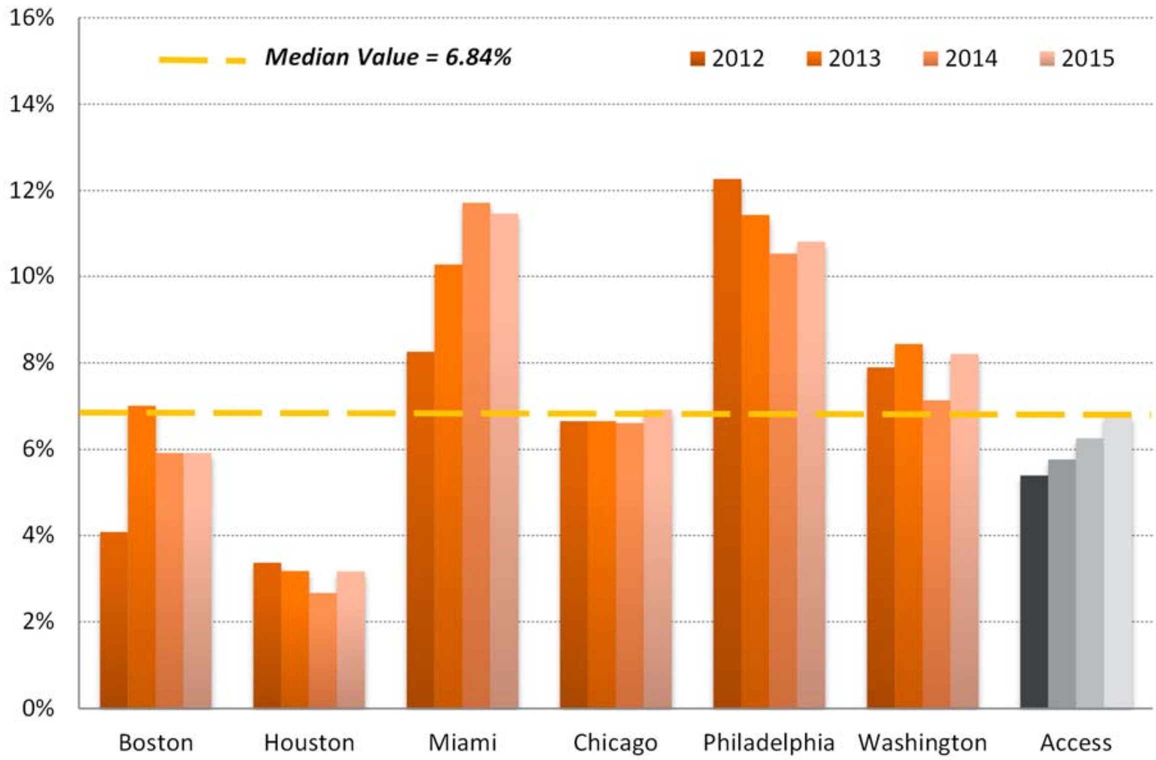


Cost Effectiveness

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.

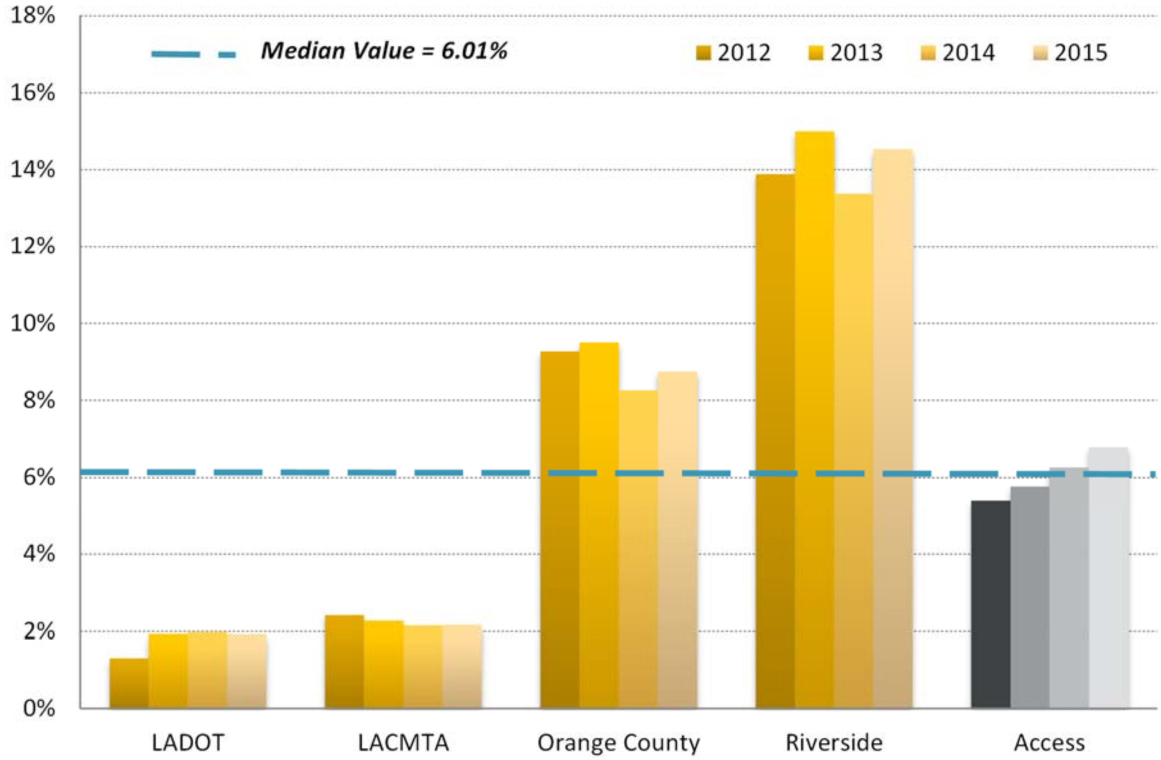
Access has an average farebox recovery ratio of 6.0 percent, just under the median value of 6.8 percent for national peer systems. The farebox recovery ratio for Access steadily increased from 5.4 percent to 6.8 percent during the observation period, unlike its national peers. Farebox recovery ratios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

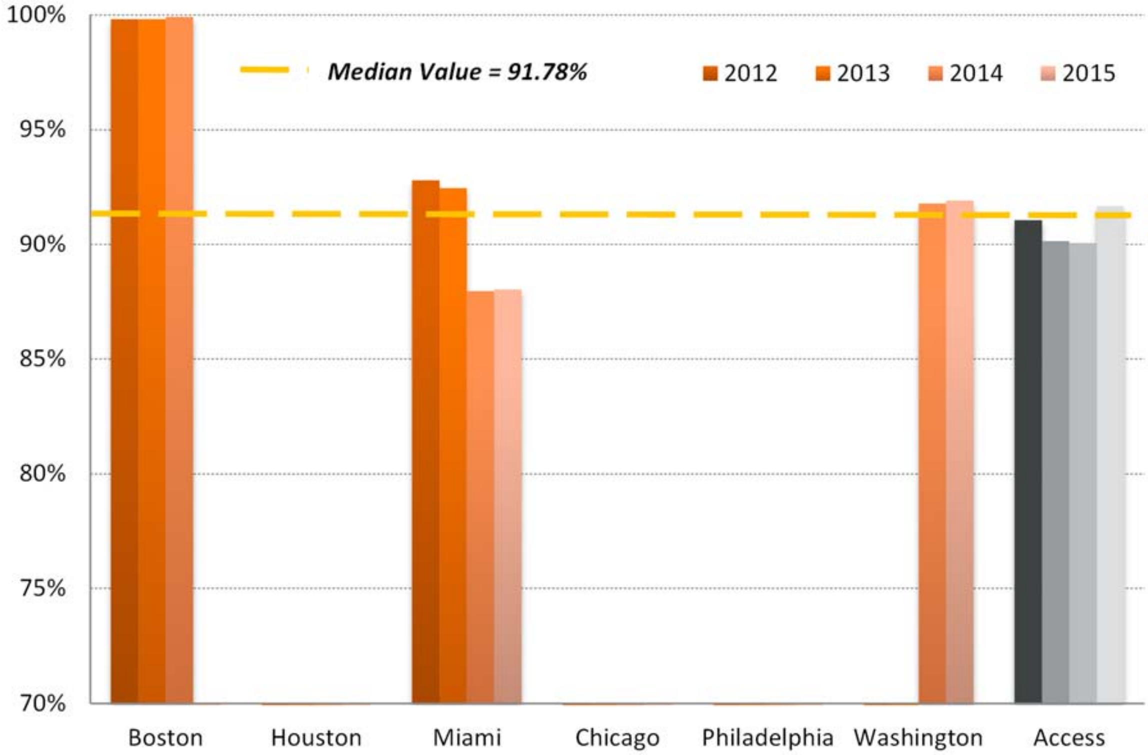
Figure 23: Regional Peer Review, Farebox Recovery (FY2012 – FY2015)



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[15])



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. The analysis of regional trends suggests that Access may consider investigating how other agencies were able to achieve higher passengers per revenue hour with relatively low operating costs per passenger trip.

[15] 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

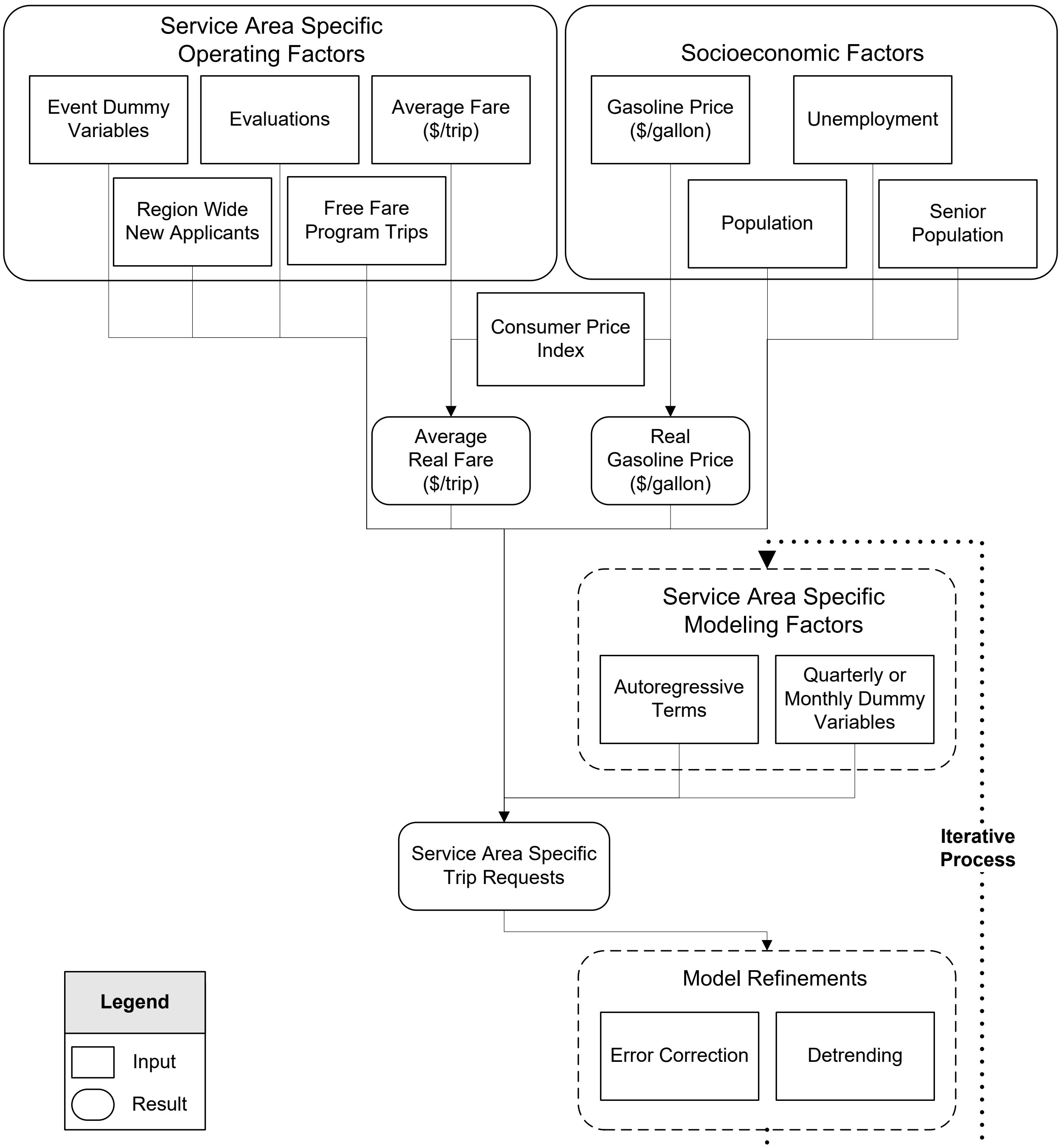
This section presents the methodology used to estimate trip demand for Access paratransit as well as the results of the analysis. The methodology involves statistical methods for studying historical trends and econometric techniques for determining factors that drive paratransit demand. The combined 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 agencies. 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 potentially 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 demand, and in terms of the model's accuracy in predicting demand.

There are six regression models, one for each region. Service region-specific 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, total eligibility evaluations, 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 4 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.

Table 4: 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:

$D(Log(\text{Trip Requests}_t)) = \beta_1\, D(Log(\text{Real Average Fare}_t)) + \beta_2\, D(Log(\text{Real Gasoline Price}_{t-1})) +$

$\beta_3\, D(Log(\text{Eligibility Evaluations}_t)) + \beta_4\, D(Log(\text{Unemployment}_{t-1})) + \beta_5\, \text{Dummy Variables} + \ldots$

$\text{other variables} \ldots + \beta_6\, AR(.) + \ldots + \text{Error}_t$

Equation (1)

Where:

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

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

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

$D(Log(\text{Eligibility Evaluations}_t))$ is the first difference in the natural log of the number of eligibility evaluations at time t.

$D(Log(\text{Unemployment}_{t-1})$ 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,…, 6 are the coefficients to be estimated.

Service Region-Specific Estimation Results

For the Eastern region, trip requests are assumed to be a function of the real average fare (lagged one month) in the Eastern region, unemployment (lagged two 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 December 2008 and January 2009 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 5.

Table 5: Regression Results – Eastern

Dependent Variable is Difference(Log(Trip Requests – Eastern))
Sample: 2004M07 2016M11
Included observations: 149

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Constant	0.02	0.00	5.49	0.00
Difference(Log(Real Average Fare_E (-1)))	-0.29	0.13	-2.34	0.02
Difference (Log(Unemployment (-2)))	0.12	0.06	1.94	0.05
Difference (Log(Real Gas Price (-1)))	0.06	0.04	1.58	0.12
December 2008 Dummy	0.12	0.05	2.31	0.02
January 2009 Dummy	-0.06	0.03	-2.23	0.03
Spring Dummy Variable	-0.02	0.01	-1.64	0.10
Summer Dummy Variable	-0.01	0.01	-2.39	0.02
Fall Dummy Variable	-0.05	0.01	-6.26	0.00
First-order Autoregressive Term	-0.64	0.07	-9.22	0.00
Second-order Autoregressive Term	-0.26	0.07	-3.78	0.00
Twelfth-order Autoregressive Term	0.47	0.05	10.13	0.00

R-squared	0.73	Mean dependent variance	0.00
Adjusted R-squared	0.71	S.D. dependent variance	0.06
S.E. of regression	0.03	Akaike info criterion	-3.88
Sum squared residual	0.15	Schwarz criterion	-3.62
Log likelihood	302.18	Hannan-Quinn criterion	-3.78
F-statistic	30.95	Durbin-Watson stat	2.05
Probability (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 this region (lagged one month), unemployment (lagged two 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 6.

Table 6: Regression Results – Antelope Valley

Dependent Variable is Difference(Log(Trip Requests – Antelope Valley))
Sample: 2004M07 2016M11
Included observations: 149

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Constant	0.05	0.01	3.51	0.00
Difference(Log(Real Average Fare_AV (-1)))	-0.09	0.04	-2.41	0.02
Difference(Log(Unemployment_AV (-2)))	0.30	0.15	1.92	0.06
August 2004 Dummy Variable	-0.29	0.13	-2.28	0.02
October 2004 Dummy Variable	0.56	0.05	12.16	0.00
November 2005 Dummy Variable	-0.22	0.09	-2.55	0.01
January 2010 Dummy Variable	1.00	0.41	2.46	0.02
February 2010 Dummy Variable	-0.85	0.36	-2.35	0.02
Spring Dummy Variable	-0.04	0.02	-1.83	0.07
Summer Dummy Variable	-0.02	0.02	-1.31	0.19
Fall Dummy Variable	-0.07	0.02	-3.50	0.00
First-order Autoregressive Term	-0.41	0.06	-6.58	0.00
Twelfth-order Autoregressive Term	0.28	0.10	2.97	0.00

R-squared	0.81	Mean dependent variance	0.01
Adjusted R-squared	0.79	S.D. dependent variance	0.15
S.E. of regression	0.07	Akaike info criterion	-2.38
Sum squared residual	0.67	Schwarz criterion	-2.09
Log likelihood	190.97	Hannan-Quinn criterion	-2.26
F-statistic	43.13	Durbin-Watson stat	1.79
Probability (F-statistic)	0.00		

As depicted in the table, the regression estimates a negative coefficient for the real average fare variable (-0.09). 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 two months), real gasoline prices (lagged one month), one event dummy variable, seasonality dummy variables, and autoregressive terms that correct for possible correlation between the residuals. Coefficient estimates are reported in Table 7.

Table 7: Regression Results – Northern

Dependent Variable is Difference(Log(Trip Requests – Northern))
Sample: 2004M08 2016M11
Included observations: 148

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Constant	0.02	0.00	4.02	0.00
Difference(Log(Real Average Fare_N))	-0.27	0.11	-2.49	0.01
Difference(Log(Unemployment (-2)))	0.21	0.07	3.13	0.00
Difference (Log(Real Gas Price (-1)))	0.07	0.03	2.50	0.01
February 2011 Dummy Variable	-0.06	0.03	-2.08	0.04
Spring Dummy Variable	-0.01	0.01	-1.38	0.17
Summer Dummy Variable	-0.01	0.01	-1.79	0.08
Fall Dummy Variable	-0.04	0.01	-4.30	0.00
First-order Autoregressive Term	-0.54	0.08	-7.12	0.00
Second-order Autoregressive Term	-0.22	0.08	-2.85	0.01
Fifth-order Autoregressive Term	0.16	0.05	3.03	0.00
Twelfth-order Autoregressive Term	0.43	0.06	7.68	0.00

R-squared	0.70	Mean dependent variance	0.00
Adjusted R-squared	0.68	S.D. dependent variance	0.06
S.E. of regression	0.03	Akaike info criterion	-3.89
Sum squared residual	0.15	Schwarz criterion	-3.66
Log likelihood	298.51	Hannan-Quinn criterion	-3.79
F-statistic	32.43	Durbin-Watson stat	2.02
Probability (F-statistic)	0.00		

As depicted in the table, the regression estimates a negative coefficient for the real average fare variable (-0.27). 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), the real price of gasoline (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 remaining 2001, 2004 and 2005 dummy variables represent one-time deviations in the level of trip requests from average historical levels. Coefficient estimates are reported in Table 8.

Table 8: Regression Results – Southern

Dependent Variable is Difference(Log(Trip Requests – Southern))
Sample: 2000M07 2016M11
Included observations: 197

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Constant	0.02	0.01	3.00	0.00
Difference(Log(Real Average Fare_S))	-0.28	0.09	-2.97	0.00
Difference (Log(Unemployment (-2)))	0.18	0.08	2.24	0.03
Difference (Log(Real Gas Price (-1)))	0.09	0.04	2.39	0.02
April 2004 Dummy Variable	0.15	0.05	3.02	0.00
November 2007 Dummy Variable	0.19	0.09	2.06	0.04
February 2005 Dummy Variable	-0.11	0.02	-6.88	0.00
March 2001 Dummy Variable	0.12	0.06	2.06	0.04
Spring Dummy Variable	-0.02	0.01	-1.29	0.20
Summer Dummy Variable	-0.01	0.01	-1.35	0.18
Fall Dummy Variable	-0.03	0.01	-2.69	0.01
First-order Autoregressive Term	-0.35	0.06	-6.43	0.00
Twelfth-order Autoregressive Term	0.51	0.05	9.65	0.00

R-squared	0.64	Mean dependent variance	0.01
Adjusted R-squared	0.62	S.D. dependent variance	0.06
S.E. of regression	0.04	Akaike info criterion	-3.57
Sum squared residual	0.27	Schwarz criterion	-3.32
Log likelihood	366.68	Hannan-Quinn criterion	-3.47
F-statistic	23.56	Durbin-Watson stat	2.06
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 gasoline prices.

The study finds that trip requests in Santa Clarita are likely driven by real average fare in the Santa Clarita region (lagged three months), unemployment (lagged two months), eligibility evaluations in the region (lagged three months), seasonality dummy variables, and autoregressive terms that correct for possible correlation between the residuals. Coefficient estimates are reported in Table 9.

Table 9: Regression Results – Santa Clarita

Dependent Variable is Difference(Log(Trip Requests – Santa Clarita))
Sample: 2010M07 2016M11
Included observations: 77

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Constant	0.04	0.01	4.26	0.00
Difference(Log(Real Average Fare_SC (-3)))	-0.07	0.04	-1.69	0.10
Difference (Log(Unemployment (-2)))	0.45	0.14	3.14	0.00
Difference(Log(Eligibility Evaluations_SC (-3)))	0.04	0.01	3.24	0.00
Spring Dummy Variable	-0.05	0.02	-3.22	0.00
Summer Dummy Variable	-0.01	0.01	-0.86	0.39
Fall Dummy Variable	-0.05	0.02	-3.42	0.00
First-order Autoregressive Term	-0.50	0.11	-4.40	0.00
Fourth-order Autoregressive Term	-0.39	0.10	-4.01	0.00

R-squared	0.63	Mean dependent variance	0.00
Adjusted R-squared	0.58	S.D. dependent variance	0.08
S.E. of regression	0.05	Akaike info criterion	-3.05
Sum squared residual	0.16	Schwarz criterion	-2.74
Log likelihood	127.31	Hannan-Quinn criterion	-2.93
F-statistic	12.73	Durbin-Watson stat	2.03
Probability (F-statistic)	0.00		

The coefficient on the Eligibility Evaluations variable indicates that as more people apply for the service, total trip demand in the region increases.

For West/ Central region, trip requests are driven by real average fare in the region, eligibility evaluations in the region, unemployment (lagged two months), real price of gasoline, 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 remaining 2005 dummy variable represents a one-time deviation in the level of trip requests from average historical levels. Coefficient estimates are reported in Table 10, and they represent the same relationships between trip requests and the model variables discussed above.

Table 10: Regression Results – West/ Central

Dependent Variable is Difference(Log(Trip Requests – West/ Central))
Sample: 2004M08 2016M11
Included observations: 148

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Constant	0.02	0.01	4.25	0.00
Difference(Log(Real Average Fare_WC))	-0.27	0.16	-1.72	0.09
Difference (Log(Eligibility Evaluations_WC))	0.13	0.03	4.41	0.00
Difference (Log(Unemployment (-2)))	0.13	0.07	1.75	0.08
Difference (Log(Real Gas Price))	0.13	0.05	2.42	0.02
November 2007 Dummy Variable	-0.37	0.03	-11.80	0.00
March 2005 Dummy Variable	0.09	0.04	2.46	0.02
Spring Dummy Variable	-0.01	0.01	-1.70	0.09
Summer Dummy Variable	-0.02	0.01	-1.98	0.05
Fall Dummy Variable	-0.04	0.01	-5.08	0.00
First-order Autoregressive Term	-0.48	0.06	-7.38	0.00
Fifth-order Autoregressive Term	0.26	0.09	2.89	0.00

R-squared	0.71	Mean dependent variance	0.00
Adjusted R-squared	0.69	S.D. dependent variance	0.07
S.E. of regression	0.04	Akaike info criterion	-3.44
Sum squared residual	0.23	Schwarz criterion	-3.18
Log likelihood	267.80	Hannan-Quinn criterion	-3.34
F-statistic	27.88	Durbin-Watson stat	2.09
Probability (F-statistic)	0.00		

6. Demand Forecasts

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

Forecasted Explanatory Variables

As explained in the forecasting assumptions section, each regional 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 historic observations.

Real Average Fare

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

Table 11: Current Fare Structure

<table>
<tr><th>Region</th><th>Distance (miles)</th><th>Fare ($)</th></tr>
<tr><td>Eastern Region</td><td rowspan="4">0 to 19.9

20 or greater</td><td rowspan="2">$2.75</td></tr>
<tr><td>West/ Central Region</td></tr>
<tr><td>Southern Region</td><td rowspan="2">$3.50</td></tr>
<tr><td>Northern Region</td></tr>
<tr><td rowspan="3">Antelope Valley</td><td>Within Antelope Valley</td><td>$2.00</td></tr>
<tr><td>To/From Basin</td><td>$7.00</td></tr>
<tr><td>To/From Santa Clarita</td><td>$7.00</td></tr>
<tr><td rowspan="3">Santa Clarita</td><td>Within Santa Clarita</td><td>$2.00</td></tr>
<tr><td>To/From Basin</td><td>$6.00</td></tr>
<tr><td>To/From Antelope Valley</td><td>$7.00</td></tr>
</table>

Source: Access Services

Fares are assumed to hold constant at current levels throughout the forecast period. Table 12 below reports the average nominal fares by region used to forecast trip demand.

Table 12: Board Approved Nominal Base Fares (FY2017 – FY2026)

Fiscal Year	Eastern, West/ Central, Southern, & Northern	Antelope Valley	Santa Clarita
2017-2026	$2.83	$2.08	$2.04

Source: Access Services

The Los Angeles-Riverside-Orange County 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[16]. 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 13: Los Angeles-Riverside-Orange County Consumer Price Index for All Urban Consumers (FY2017 – FY2026)

Fiscal Year	Median	Lower 10% Limit	Upper 10% Limit
2017	252.4	245.8	259.1
2018	258.2	249.7	266.5
2019	263.9	255.6	272.8
2020	269.2	260.7	277.8
2021	273.9	265.2	282.5
2022	278.6	270.1	287.5
2023	283.5	275.2	292.0
2024	288.5	280.1	297.1
2025	293.6	285.0	302.3
2026	298.7	290.3	307.2

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

Eligibility Evaluations by Service Region

Table 14 and Table 15 below report the forecasting assumptions for the number of evaluations of eligibility applications over the next 10 fiscal years. Eligibility evaluations are only presented below for Santa Clarita and West/ Central as these are the only two regions with appropriate model specifications of trip demand to include the eligibility application variable[17]. The lower and upper 10 percent estimates are derived from a historical analysis of statistical uncertainty (as measured by the standard deviation) in the variables.

---

[16] California Department of Finance, Economic Research Unit, *Economics* http://www.dof.ca.gov/Forecasting/Economics/

[17] Note that because several regions include the AR(12) term in the trip demand models, and because the eligibility data start in 2004, including the eligibility data in these demand models will mean fewer data points. The eligibility variable was not included for regions where the variable was not significant.

Table 14: Santa Clarita Eligibility Evaluations (FY2017 – FY2026)

Fiscal Year	Median	Lower 10% Limit	Upper 10% Limit
2017	25	24	27
2018	27	25	29
2019	28	26	30
2020	29	27	32
2021	31	29	33
2022	33	31	35
2023	34	32	37
2024	36	34	38
2025	38	36	40
2026	40	38	42

Source: HDR assumptions based on historical trends

Table 15: West/ Central Eligibility Evaluations (FY2017 – FY2026)

Fiscal Year	Median	Lower 10% Limit	Upper 10% Limit
2017	562	528	596
2018	577	532	621
2019	626	582	670
2020	678	634	721
2021	735	691	779
2022	796	751	842
2023	864	818	907
2024	937	892	980
2025	1,015	969	1,059
2026	1,100	1,055	1,145

Source: HDR assumptions based on historical trends

Gasoline Price

Table 16 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)[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.

---

[18] U.S. Department of Energy, Energy Information Administration, *Annual Energy Outlook 2016* http://www.eia.gov/forecasts/aeo/er/tables_ref.cfm.

Table 16: Real Gasoline Price per Gallon in California (FY2017 – FY2026)

Fiscal Year	Median	Lower 10% Limit	Upper 10% Limit
2017	$2.84	$2.67	$3.01
2018	$3.05	$2.83	$3.27
2019	$3.29	$3.06	$3.50
2020	$3.58	$3.36	$3.81
2021	$3.79	$3.56	$4.01
2022	$3.93	$3.70	$4.15
2023	$4.01	$3.79	$4.23
2024	$4.08	$3.86	$4.31
2025	$4.13	$3.91	$4.35
2026	$4.19	$3.96	$4.41

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

Unemployment

Table 17 below shows annual projections for unemployment in Los Angeles County. Median estimates are derived from recent unemployment projections published by the Bureau of Labor Statistics (BLS)[19]. 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.

Table 17: Unemployment in Los Angeles County (FY2017 – FY2026)

Fiscal Year	Median	Lower 10% Limit	Upper 10% Limit
2017	269,955	244,318	295,619
2018	269,099	234,479	302,087
2019	264,275	231,013	298,036
2020	260,805	228,286	293,752
2021	261,055	226,352	294,654
2022	260,790	226,364	294,195
2023	260,739	227,120	293,246
2024	260,257	226,636	294,108
2025	260,274	227,596	293,924
2026	260,316	227,438	293,203

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

[19] U.S. Department of Labor, Bureau of Labor Statistics, *Employment Projections* http://www.bls.gov/emp/home.htm.

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 2017 through 2026.

Operations Forecasts

Ridership forecasts are derived from passenger trip requests based on the average completion rate observed at the service area level in 2016. 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 are summarized in Table 18 below.

At the mean, the number of trip requests is expected to grow by 1.4 million (a 36 percent increase) and reach 6.1 million by 2021. Passenger trips completed are forecast to rise by 4.0 percent in 2017. The ridership annual growth rate is expected to increase slightly throughout the forecast period, from 4.0 percent in 2017 to 7.3 percent in 2021.

Table 18: Operations Forecasts, Mean Expected Outcome (FY2017 – FY2021)

Fiscal Year	2017	2018	2019	2020	2021
Passenger Trip Requests (thousands)	4,643	4,944	5,292	5,674	6,090
% Change	4.0%	6.5%	7.0%	7.2%	7.3%
Cancellations (thousands)	59	62	67	72	77
No-Shows	77	82	88	94	101
Passengers (thousands)	4,508	4,799	5,137	5,508	5,913
% Change	4.0%	6.5%	7.0%	7.2%	7.3%

Note: FY2017 projections include actual estimates through November 2016.

Projections by service region are presented in Table 19 on the next page and monthly estimates are reported in Appendix 4.

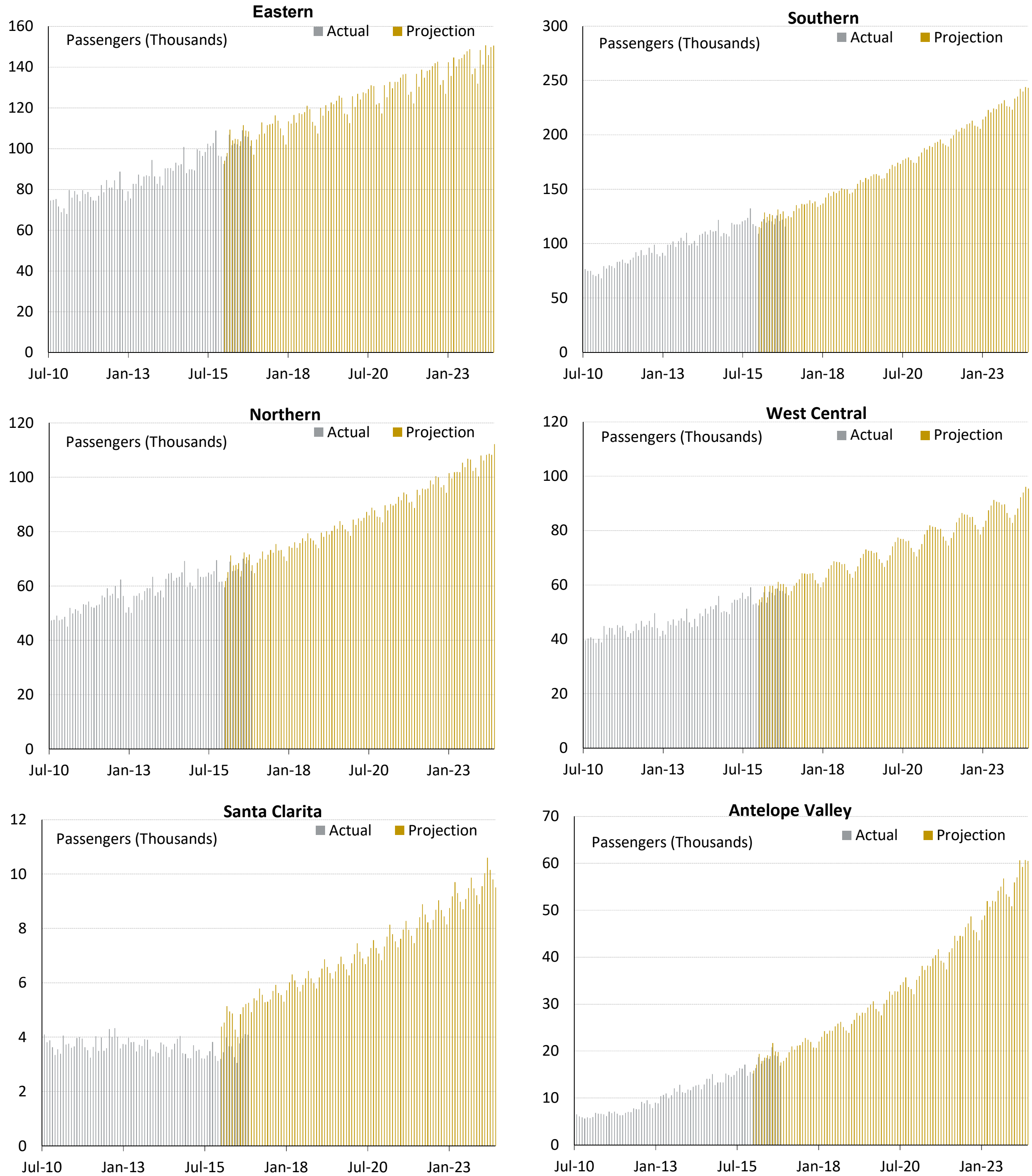
Table 19: Ridership Forecasts by Service Region, Mean Expected Outcome (FY2017 – FY2026)

Fiscal Year	Total	Eastern	Antelope Valley	Northern	Southern	Santa Clarita	West/ Central	Backup
2016	4,334,872	1,210,011	199,634	776,000	1,437,979	41,489	664,319	5,440
2017	4,507,845	1,252,662	226,731	808,937	1,474,850	47,237	692,078	5,348
	4.0%	3.5%	13.6%	4.2%	2.6%	13.9%	4.2%	-1.7%
2018	4,799,412	1,307,867	257,323	851,110	1,595,071	51,922	729,396	6,722
	6.5%	4.4%	13.5%	5.2%	8.2%	9.9%	5.4%	25.7%
2019	5,137,155	1,366,283	297,996	901,233	1,733,860	56,409	774,178	7,195
	7.0%	4.5%	15.8%	5.9%	8.7%	8.6%	6.1%	7.0%
2020	5,508,335	1,427,094	345,703	954,684	1,889,539	61,158	822,441	7,716
	7.2%	4.5%	16.0%	5.9%	9.0%	8.4%	6.2%	7.2%
2021	5,912,627	1,489,434	402,878	1,014,676	2,059,565	66,688	871,106	8,282
	7.3%	4.4%	16.5%	6.3%	9.0%	9.0%	5.9%	7.3%
2022	6,348,773	1,553,254	470,074	1,079,975	2,242,994	72,838	920,747	8,892
	7.4%	4.3%	16.7%	6.4%	8.9%	9.2%	5.7%	7.4%
2023	6,816,556	1,618,322	548,493	1,149,707	2,439,601	79,630	971,256	9,547
	7.4%	4.2%	16.7%	6.5%	8.8%	9.3%	5.5%	7.4%
2024	7,323,125	1,685,570	639,999	1,224,086	2,652,383	86,936	1,023,896	10,256
	7.4%	4.2%	16.7%	6.5%	8.7%	9.2%	5.4%	7.4%
2025	7,872,064	1,755,094	746,763	1,303,362	2,882,243	94,984	1,078,595	11,024
	7.5%	4.1%	16.7%	6.5%	8.7%	9.3%	5.3%	7.5%
2026	8,471,770	1,827,681	871,350	1,387,761	3,132,777	103,658	1,136,680	11,863
	7.6%	4.1%	16.7%	6.5%	8.7%	9.1%	5.4%	7.6%

Note: FY2017 projections include actual estimates through November 2016.

The following figures provide a graphical comparison of service region-specific ridership observations (July 2010 – November 2016) with mean expected forecasts (December 2016 – June 2024). They provide illustrations of how historical trends may have influenced the forecasts.

Figure 26: Ridership by Service Region (July 2010 – June 2024)



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[20]; 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[21]. Table 20 below shows projected population levels and associated steady state trip requests over the period 2017 – 2026.

Table 20: Steady State Scenario (FY2017 – FY2026)

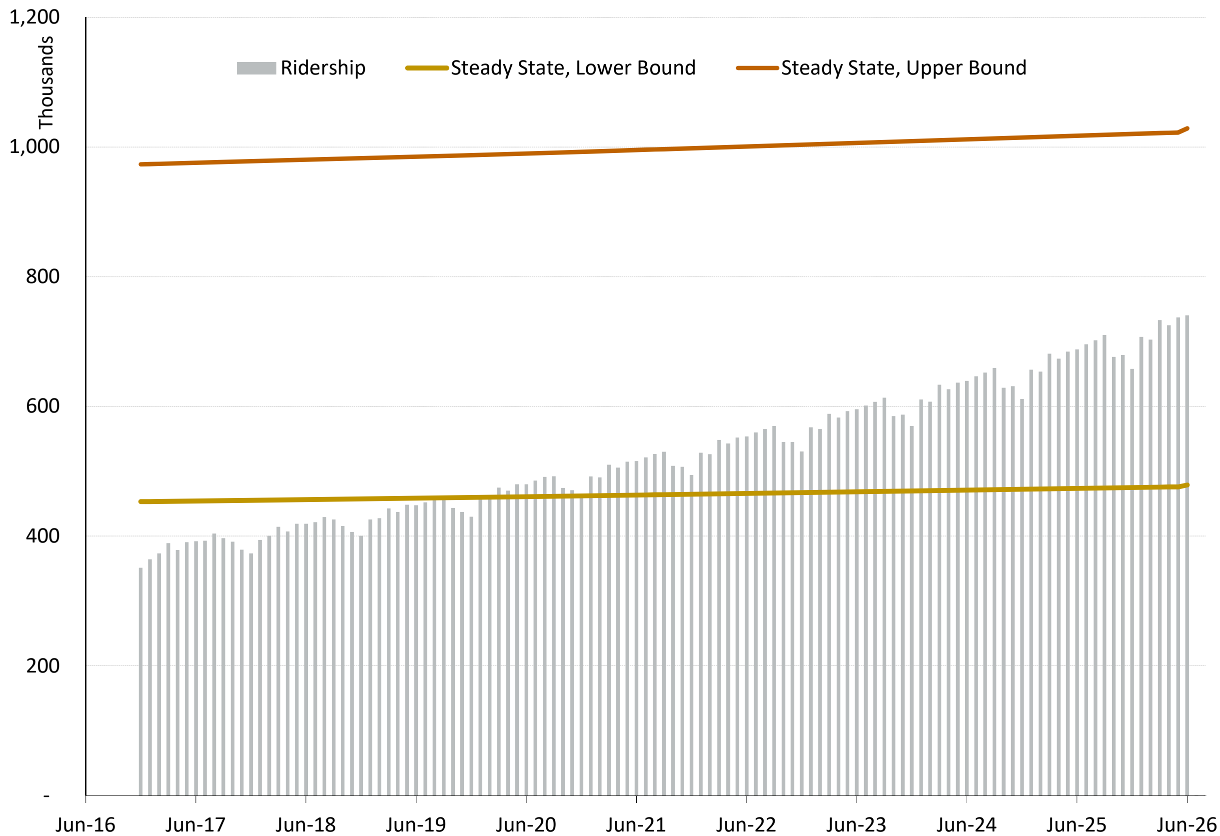
		Lower Bound	Upper Bound
1. Population in the Service Area	FY 2017	10,289,656	10,289,656
	FY 2018	10,338,205	10,338,205
	FY 2019	10,386,983	10,386,983
	FY 2020	10,435,991	10,435,991
	FY 2021	10,493,101	10,493,101
	FY 2022	10,550,524	10,550,524
	FY 2023	10,608,261	10,608,261
	FY 2024	10,666,314	10,666,314
	FY 2025	10,724,684	10,724,684
	FY 2026	10,783,374	10,783,374
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		103	103
6. Steady State Yearly Trip Requests (1*2*3*4*5)	FY 2017	5,440,228	11,683,885
	FY 2018	5,465,897	11,739,012
	FY 2019	5,491,686	11,794,399
	FY 2020	5,517,597	11,850,048
	FY 2021	5,547,792	11,914,896
	FY 2022	5,578,151	11,980,100
	FY 2023	5,608,677	12,045,660
	FY 2024	5,639,370	12,111,579
	FY 2025	5,670,231	12,177,858
	FY 2026	5,701,261	12,244,501

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

20 A regular user is defined as an active customer who uses Access Services at least six times per month.
21 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.

As shown in Figure 27, trip demand is expected to remain below the upper bound of the market potential through 2026.

Figure 27: Ridership Projections and Steady State Scenario (December 2016 – June 2026)



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 an 80 percent confidence interval estimated around the central predictions.

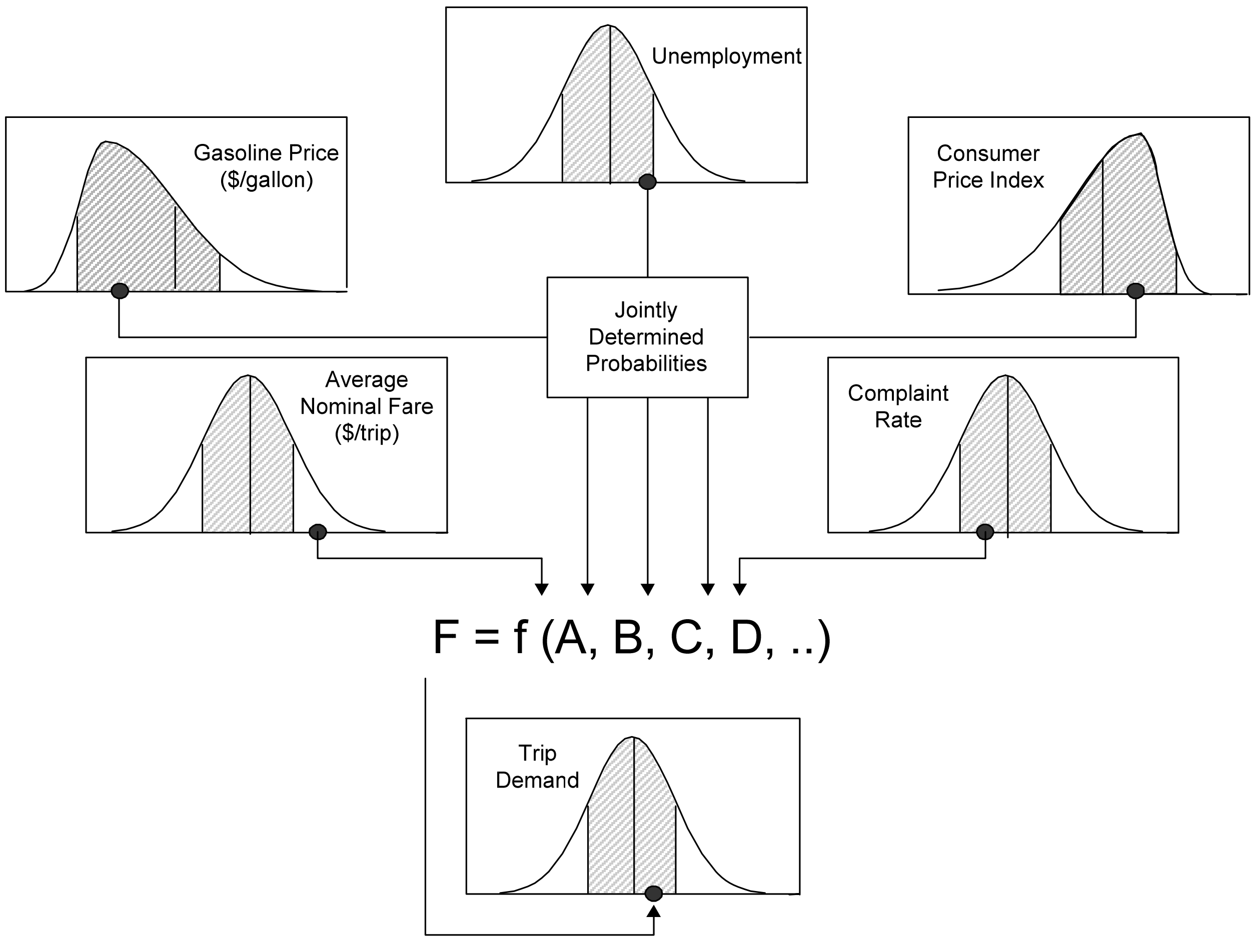
Risk Analysis Process

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

Figure 28: 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 29 on the following page reports the aggregated results under three probabilistic alternatives: the mean expected outcome is presented along with the lower and upper 10 percent estimates.

Figure 29: Ridership Forecasts (December 2016 – June 2026)

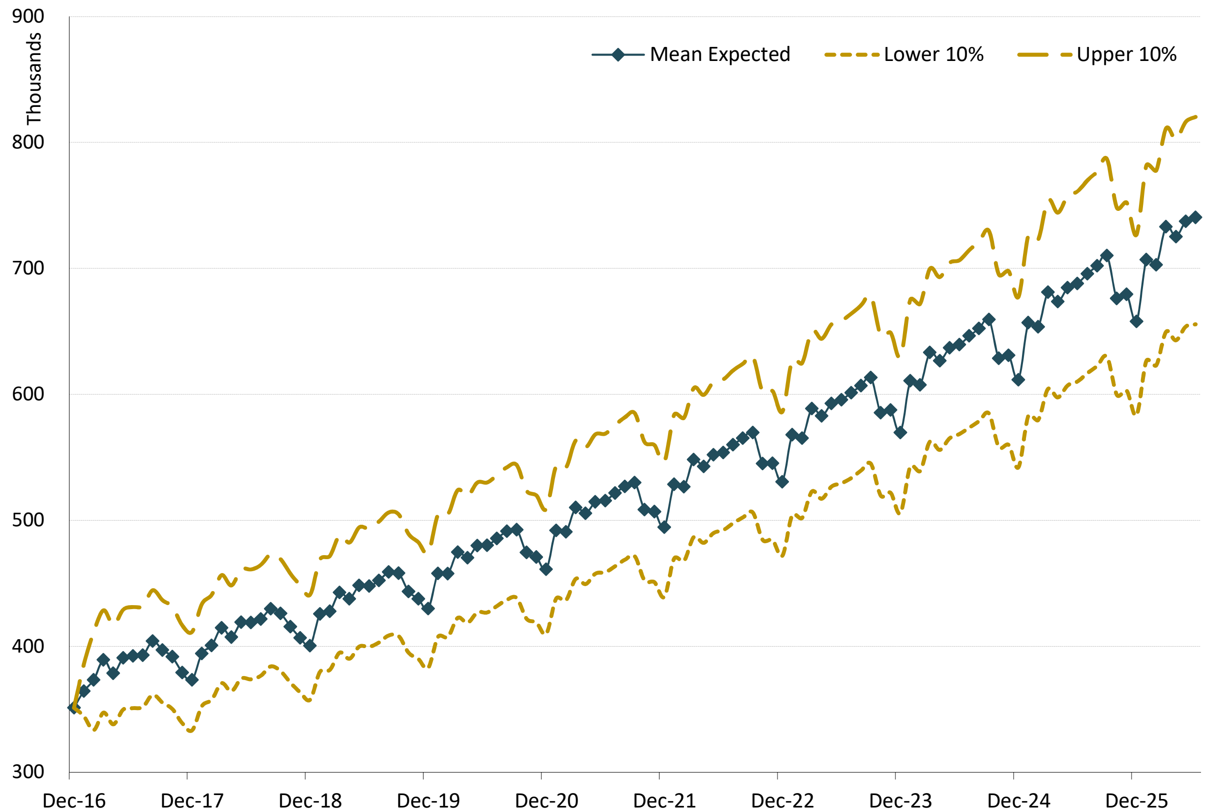
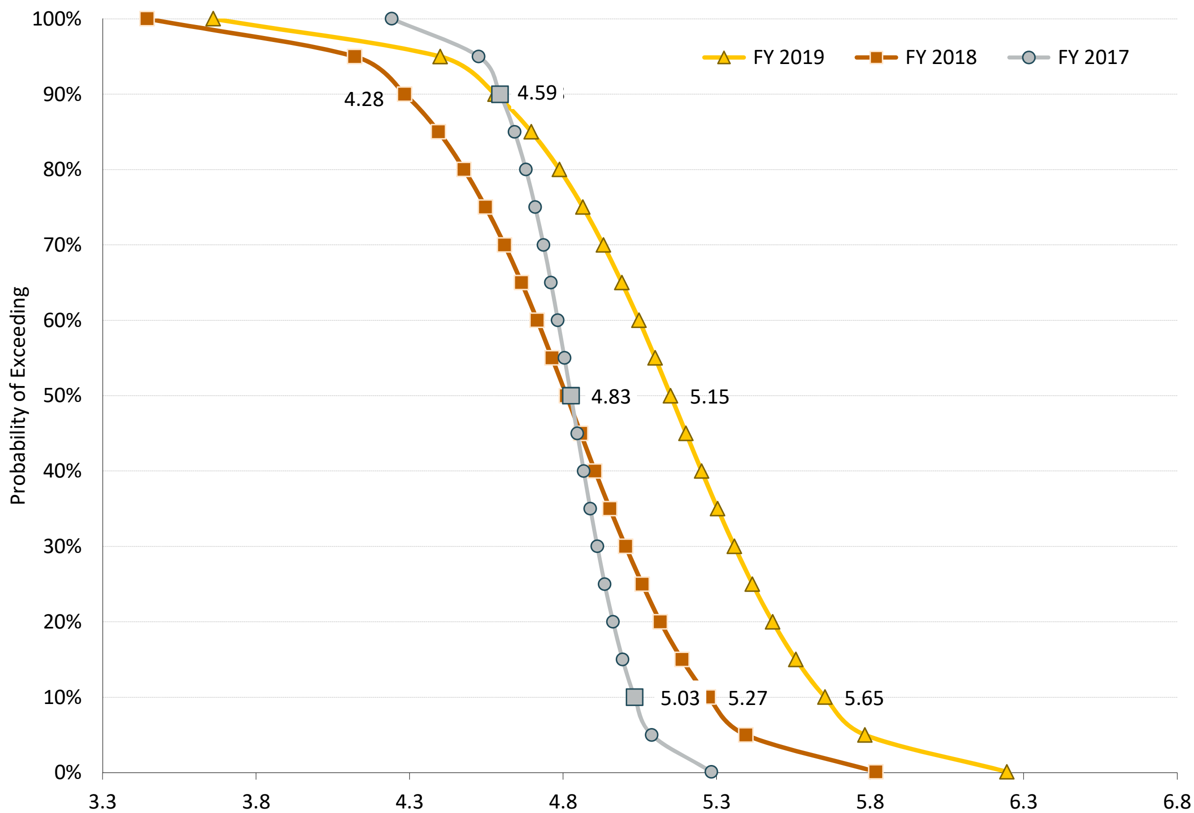


Table 21 reports monthly ridership estimates (mean, lower and upper 10 percent estimates) in 2019 and Figure 30 on the next page shows a series of probabilistic results for 2017 to 2019.

Table 21: Risk-Adjusted Monthly Ridership Forecasts (FY2019)

Month	Mean Expected Outcome	90% Probability of Exceeding	10% Probability of Exceeding
Jul-18	422,241	377,289	464,844
Aug-18	430,254	384,558	473,605
Sep-18	426,580	380,367	469,644
Oct-18	416,239	371,819	458,643
Nov-18	407,170	363,187	448,591
Dec-18	401,037	358,030	442,157
Jan-19	426,205	380,510	469,252
Feb-19	428,389	382,306	472,151
Mar-19	443,336	395,450	488,149
Apr-19	438,266	391,062	483,276
May-19	449,003	399,965	494,996
Jun-19	448,435	399,866	494,430
FY 2019	5,137,155	4,584,409	5,659,739

Figure 30: Probability Distribution of Ridership, in Millions (FY2017 – FY2019)



Note: FY2017 projections include actual estimates through November 2016.

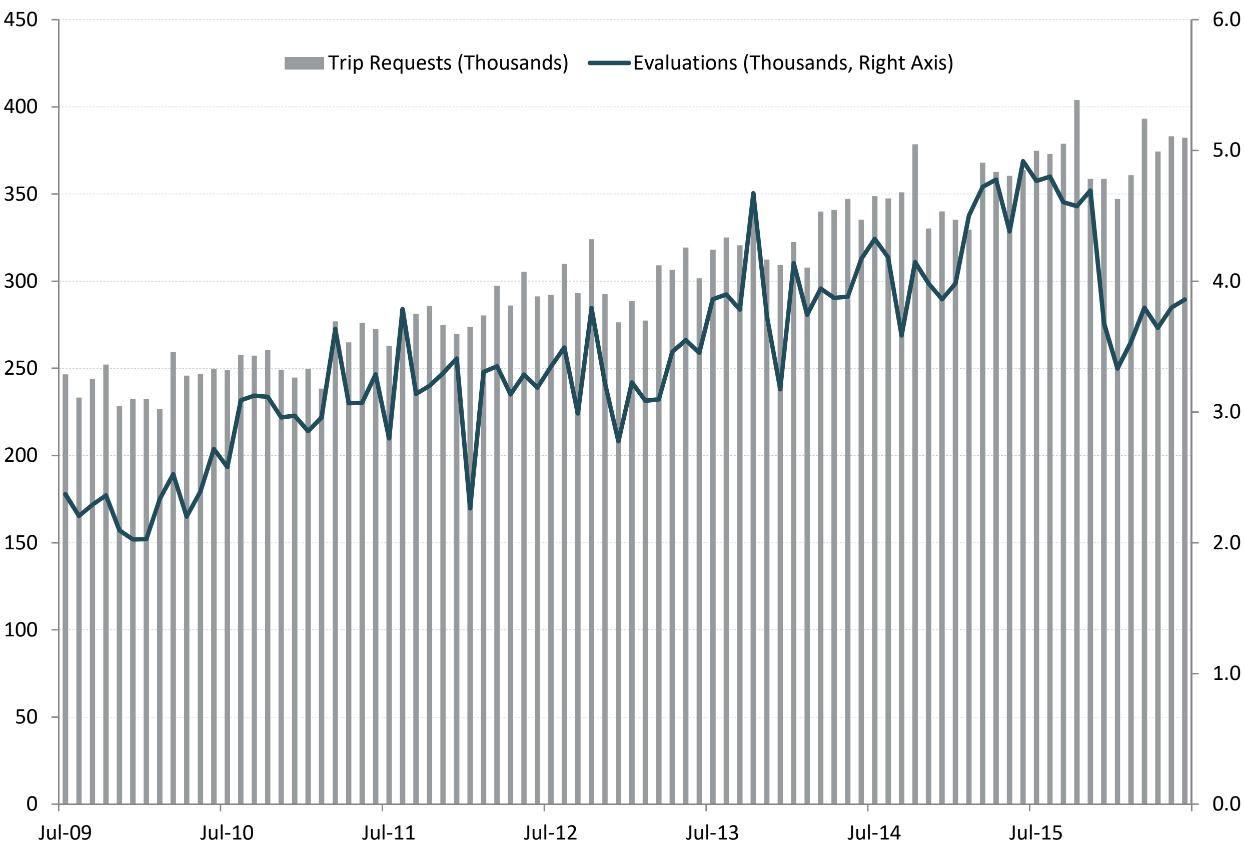
7. Analysis of New Applicants

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. 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 31 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).

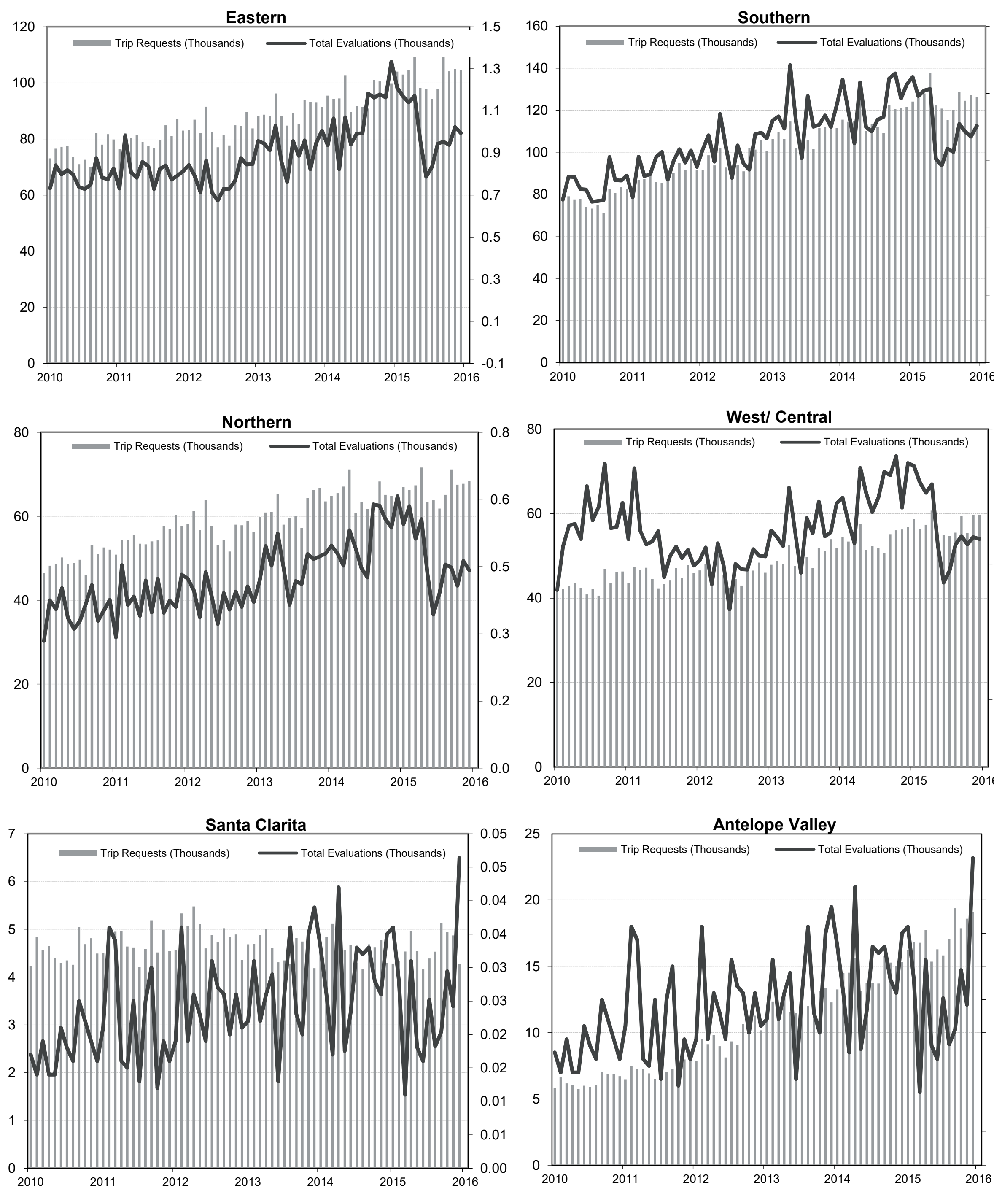
Figure 31: Trip Requests and Eligibility Evaluations (July 2009 – June 2016)



Source: Access Services

Data on service region eligibility evaluations are presented in Figure 32 below. The charts show that while eligibility evaluations and trip requests are highly correlated, they may not be so for certain regions such as West/ Central 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 32: Trip Requests and Eligibility Evaluations by Service Region (July 2009 – June 2016)



Overview of Methods
New applicants or total evaluation applicants – which include new applicants and recertification applicants – were found to be statistically significant factors in explaining trip demand in two of the six regions. Thus for these regions, the variables already used in the demand analysis cannot be applied in this new applicant analysis again – the recursive use of modeling variables lead to the regression models being underspecified[22]. 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 therefore significantly compound modeling errors into the service region demand models.

Instead of 2SLS, time series analysis is 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
While disaggregated data for new applicants was available by region, new applicant projections are estimated for the service area as a whole. New applicants per region are 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 (or total evaluations) were 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 explanatory variables that could otherwise provide a more accurate estimate of new applicants. Modeling new applicants at the service area level avoids this issue.

---

[22] 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.

Table 22 below presents the model used to estimate new applicants for the service area. The model estimates that new applicants for Access depend on socioeconomic factors including the real price of gasoline and the unemployment rate (lagged one month). The model also includes several dummy variables to account for various deviations in new applicant levels from the service area's average historic trends. In particular, the September 2007 dummy variable accounts for the dip in new applicants that occurred when a portion of the original West/ Central region became part of the now Southern region. Finally, the model includes seasonality dummy variables (to capture cyclical trends in the new applicant data) and autoregressive terms (to correct for possible correlation between the residuals).

Table 22: Regression Results – Service Area

Dependent Variable is Difference(Log(New Applicants))
Sample: 2005M03 2016M09
Included observations: 139

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Constant	-0.02	0.01	-2.03	0.04
Difference (Log(Real Gas Price))	0.40	0.12	3.36	0.00
Difference (Log(Unemployment Rate (-1)))	0.398	0.21	1.86	0.06
March Dummy Variable	0.08	0.04	1.85	0.07
August Dummy Variable	0.07	0.04	1.76	0.08
October Dummy Variable	0.17	0.03	5.42	0.00
April 2006 Dummy Variable	-0.34	0.11	-2.94	0.00
September 2007 Dummy Variable	-0.30	0.11	-2.64	0.01
January 2014 Dummy Variable	0.33	0.11	2.94	0.00
March 2016 Dummy Variable	0.34	0.12	2.91	0.00
December 2015 Dummy Variable	-0.24	0.11	-2.10	0.04
Fourth-order Autoregressive Term	-0.20	0.08	-2.60	0.01

R-squared	0.42	Mean dependent variance	0.00
Adjusted R-squared	0.37	S.D. dependent variance	0.14
S.E. of regression	0.11	Akaike info criterion	-1.47
Sum squared residual	1.55	Schwarz criterion	-1.19
Log likelihood	115.08	Hannan-Quinn criterion	-1.36
F-statistic	7.73	Durbin-Watson stat	2.21
Probability (F-statistic)	0.00		

As indicated by the coefficients in the table above, new applicants are increasing with the real price of gasoline and the unemployment rate. As explained for the trip request estimates in Section 5, the relationship between unemployment and ridership is different for paratransit services than it is for other forms of transportation. That is, 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. Thus intuitively, increasing unemployment is associated with increasing applications for Access.

New Applicant Forecast

Based on the econometric model presented above, new applicants are projected through 2026. The forecast is presented by fiscal year in Table 23 below. The annual forecasts suggest that aside from Eastern and Antelope Valley, new applicant trends are likely to align with those of ridership in each region reported in Table 19. Monthly estimates are reported in Appendix 6.

Table 23: New Applicant Forecasts by Service Region, Mean Expected Outcome (FY2017 – FY2026)

Fiscal Year	Total	Eastern	Antelope Valley	Northern	Southern	Santa Clarita	West/ Central
2016	39,337	10,287	2,283	4,632	14,712	231	7,192
2017*	32,090	8,261	2,059	3,748	11,923	246	5,854
	-18.4%	-19.7%	-9.8%	-19.1%	-19.0%	6.3%	-18.6%
2018	33,629	8,346	2,223	3,948	12,545	255	6,312
	4.8%	1.0%	7.9%	5.3%	5.2%	4.0%	7.8%
2019	36,690	9,106	2,425	4,308	13,687	279	6,886
	9.1%	9.1%	9.1%	9.1%	9.1%	9.1%	9.1%
2020	40,221	9,982	2,658	4,723	15,004	305	7,549
	9.6%	9.6%	9.6%	9.6%	9.6%	9.6%	9.6%
2021	43,774	10,863	2,892	5,140	16,330	332	8,216
	8.8%	8.8%	8.8%	8.8%	8.8%	8.8%	8.8%
2022	47,310	11,741	3,126	5,555	17,649	359	8,880
	8.1%	8.1%	8.1%	8.1%	8.1%	8.1%	8.1%
2023	50,829	12,614	3,358	5,968	18,962	386	9,541
	7.4%	7.4%	7.4%	7.4%	7.4%	7.4%	7.4%
2024	54,517	13,530	3,602	6,401	20,338	414	10,233
	7.3%	7.3%	7.3%	7.3%	7.3%	7.3%	7.3%
2025	58,342	14,479	3,854	6,850	21,765	443	10,951
	7.0%	7.0%	7.0%	7.0%	7.0%	7.0%	7.0%
2026	62,511	15,513	4,130	7,340	23,320	474	11,734
	7.1%	7.1%	7.2%	7.1%	7.1%	7.2%	7.1%

**Annual percent changes for FY 2017 should be used with caution as FY 2016 totals include data points that were re-estimated.*

New applicant forecasts are also developed within a risk analysis framework. Table 24 presents the median, 10th and 90th percentile results for 2017 to 2019.

Table 24: Risk-Adjusted New Applicant Forecasts (FY2017 – FY2019)

	FY2017	FY2018	FY2019
Mean Expected Outcome	32,090	33,629	36,690
10th Percentile (90 % Probability of Exceeding)	28,316	26,170	28,558
90th Percentile (10 % Probability of Exceeding)	35,696	40,714	44,313

Appendix 1: List of Acronyms

2SLS	Two-stage Least Square
AR	Autoregression
BLS	Bureau of Labor Statistics
CTSA	Consolidated Transportation Services Agency
DoF	(California) Department of Finance
EIA	Energy Information Administration
FTIS	Florida Transit Information System
FY	Fiscal Year
LACMTA	Los Angeles County Metropolitan Transit Agency
LADOT	City of Los Angeles Department of Transportation
MDT	Miami-Dade Transit
Metro	Metropolitan Transit Authority of Harris County (Houston)
NTD	National Transit Database
OCTA	Orange County Transportation Authority
OLS	Ordinary Least Squares
RTA	Riverside Transit Agency
WMATA	Washington Metropolitan Area Transit Authority
MBTA	Massachusetts Bay Transportation 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.

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 (FY2017 – FY2026)

Month	Total	Eastern	Antelope Valley	Northern	Southern	Santa Clarita	West/ Central	Backup
Jul-16	360,129	101,298	18,316	63,429	117,738	3,053	56,253	42
Aug-16	388,378	108,984	20,827	69,994	126,036	3,768	58,722	47
Sep-16	375,926	106,122	19,077	68,239	120,637	3,957	57,850	44
Oct-16	378,241	105,773	18,884	69,456	122,133	4,110	57,777	108
Nov-16	360,382	101,308	16,891	65,595	115,640	4,087	56,861	0
Dec-16	351,889	94,057	17,157	62,643	119,826	3,717	53,769	721
Jan-17	364,919	101,857	17,828	66,561	118,686	4,105	55,376	506
Feb-17	373,813	103,670	18,688	67,247	122,957	3,980	56,748	524
Mar-17	389,758	109,238	19,836	69,793	128,145	4,344	57,857	546
Apr-17	379,078	104,024	19,180	66,981	125,166	4,169	59,029	531
May-17	391,352	108,002	19,982	68,683	129,210	3,970	60,957	548
Jun-17	392,798	108,329	20,066	70,318	128,677	3,978	60,880	550
FY 2017 Total	4,506,664	1,252,662	226,731	808,937	1,474,850	47,237	692,078	4,167

Note: Data cells shaded in blue represent actual observations.

Month	Total	Eastern	Antelope Valley	Northern	Southern	Santa Clarita	West/ Central	Backup
Jul-17	393,415	108,704	20,725	69,386	129,306	4,043	60,700	551
Aug-17	404,643	112,591	21,526	72,442	132,339	4,272	60,906	567
Sep-17	397,475	110,199	21,168	70,219	129,815	4,447	61,070	557
Oct-17	392,251	106,473	20,719	70,306	131,276	4,221	58,706	549
Nov-17	379,638	103,240	19,630	68,075	126,536	4,169	57,456	532
Dec-17	373,828	98,863	19,550	66,434	128,260	3,977	56,220	524
Jan-18	394,846	109,842	20,862	71,654	129,692	4,298	57,946	553
Feb-18	401,150	108,749	21,781	71,133	134,790	4,521	59,613	562
Mar-18	415,244	112,946	22,928	73,081	138,403	4,741	62,563	582
Apr-18	407,881	109,289	22,405	71,094	136,086	4,577	63,859	571
May-18	419,610	113,738	23,050	72,785	139,784	4,389	65,277	588
Jun-18	419,432	113,235	22,979	74,501	138,784	4,265	65,080	587
FY 2018 Total	4,799,412	1,307,867	257,323	851,110	1,595,071	51,922	729,396	6,722

Month	Total	Eastern	Antelope Valley	Northern	Southern	Santa Clarita	West/ Central	Backup
Jul-18	422,241	114,196	23,895	73,501	140,629	4,450	64,978	591
Aug-18	430,254	117,264	24,464	76,193	142,849	4,628	64,254	603
Sep-18	426,580	115,565	24,818	74,496	141,862	4,830	64,411	597
Oct-18	416,239	109,553	23,746	73,680	141,863	4,626	62,187	583
Nov-18	407,170	107,812	23,053	72,298	138,072	4,501	60,863	570
Dec-18	401,037	104,015	22,563	70,870	139,200	4,345	59,482	562
Jan-19	426,205	116,158	24,409	76,447	142,212	4,652	61,730	597
Feb-19	428,389	112,524	25,197	74,965	146,729	4,892	63,481	600
Mar-19	443,336	117,544	26,579	77,020	149,935	5,153	66,484	621
Apr-19	438,266	114,834	26,031	75,723	148,248	4,938	67,877	614
May-19	449,003	118,776	26,664	77,093	151,648	4,770	69,424	629
Jun-19	448,435	118,041	26,575	78,947	150,614	4,623	69,007	628
FY 2019 Total	5,137,155	1,366,283	297,996	901,233	1,733,860	56,409	774,178	7,195

Month	Total	Eastern	Antelope Valley	Northern	Southern	Santa Clarita	West/ Central	Backup
Jul-19	452,891	119,679	27,693	77,806	153,323	4,818	68,937	634
Aug-19	459,628	122,084	28,215	80,450	154,945	5,026	68,264	644
Sep-19	458,699	121,063	28,938	79,203	155,185	5,226	68,441	643
Oct-19	444,146	113,534	27,390	77,588	153,907	5,019	66,085	622
Nov-19	438,208	113,131	26,895	76,852	151,046	4,876	64,792	614
Dec-19	430,419	108,982	26,075	75,246	151,484	4,706	63,323	603
Jan-20	458,439	121,759	28,430	81,015	155,914	5,039	65,639	642
Feb-20	458,211	116,727	29,161	79,187	159,748	5,295	67,451	642
Mar-20	475,323	122,987	30,870	81,417	163,170	5,595	70,617	666
Apr-20	470,952	120,293	30,227	80,608	161,785	5,359	72,021	660
May-20	480,633	123,646	30,943	81,577	164,968	5,176	73,651	673
Jun-20	480,788	123,209	30,868	83,734	164,062	5,021	73,220	673
FY 2020 Total	5,508,335	1,427,094	345,703	954,684	1,889,539	61,158	822,441	7,716

Month	Total	Eastern	Antelope Valley	Northern	Southern	Santa Clarita	West/ Central	Backup
Jul-20	486,256	125,212	32,197	82,512	167,316	5,233	73,105	681
Aug-20	492,054	127,076	32,770	85,239	168,448	5,474	72,358	689
Sep-20	493,297	126,677	33,750	84,335	169,611	5,693	72,540	691
Oct-20	475,064	117,901	31,811	82,052	167,153	5,465	70,017	666
Nov-20	471,543	118,527	31,410	81,902	165,110	5,302	68,633	661
Dec-20	461,649	113,696	30,324	80,012	164,792	5,126	67,053	647
Jan-21	492,687	127,122	33,222	86,100	170,543	5,493	69,516	690
Feb-21	491,389	121,414	33,975	84,231	173,859	5,793	71,429	688
Mar-21	510,798	128,764	36,048	86,522	177,859	6,119	74,771	715
Apr-21	506,162	125,591	35,257	86,018	176,486	5,847	76,254	709
May-21	515,345	128,708	36,100	86,615	179,582	5,660	77,958	722
Jun-21	516,382	128,746	36,014	89,139	178,806	5,482	77,472	723
FY 2021 Total	5,912,627	1,489,434	402,878	1,014,676	2,059,565	66,688	871,106	8,282

Month	Total	Eastern	Antelope Valley	Northern	Southern	Santa Clarita	West/ Central	Backup
Jul-21	522,361	130,750	37,568	87,822	182,419	5,711	77,360	732
Aug-21	527,626	132,243	38,217	90,629	183,285	5,966	76,547	739
Sep-21	530,702	132,489	39,408	89,957	185,170	6,203	76,731	743
Oct-21	509,129	122,583	37,077	87,075	181,654	5,978	74,048	713
Nov-21	507,450	124,044	36,692	87,374	180,280	5,794	72,555	711
Dec-21	495,154	118,384	35,345	85,107	179,136	5,605	70,884	694
Jan-22	529,358	132,569	38,803	91,570	186,176	6,031	73,468	741
Feb-22	527,272	126,417	39,608	89,743	188,972	6,313	75,480	739
Mar-22	548,794	134,551	42,085	91,973	193,757	6,667	78,992	769
Apr-22	543,567	130,811	41,124	91,758	192,158	6,406	80,548	761
May-22	552,775	134,002	42,127	92,024	195,334	6,181	82,334	774
Jun-22	554,584	134,412	42,020	94,941	194,654	5,982	81,799	777
FY 2022 Total	6,348,773	1,553,254	470,074	1,079,975	2,242,994	72,838	920,747	8,892

Month	Total	Eastern	Antelope Valley	Northern	Southern	Santa Clarita	West/ Central	Backup
Jul-22	560,808	136,224	43,839	93,509	198,538	6,251	81,662	785
Aug-22	565,991	137,640	44,588	96,380	199,281	6,509	80,800	793
Sep-22	570,585	138,355	45,997	95,941	201,725	6,800	80,968	799
Oct-22	545,747	127,388	43,244	92,463	197,261	6,508	78,118	764
Nov-22	545,727	129,585	42,834	93,211	196,450	6,346	76,537	764
Dec-22	531,035	123,128	41,220	90,537	194,505	6,139	74,763	744
Jan-23	568,639	138,180	45,299	97,455	202,834	6,587	77,488	796
Feb-23	565,916	131,627	46,195	95,634	205,164	6,904	79,601	793
Mar-23	589,528	140,325	49,125	97,779	210,878	7,293	83,302	826
Apr-23	583,600	136,118	47,975	97,861	208,906	6,981	84,941	817
May-23	593,265	139,555	49,156	97,801	212,346	6,755	86,821	831
Jun-23	595,714	140,198	49,023	101,135	211,712	6,558	86,253	834
FY 2023 Total	6,816,556	1,618,322	548,493	1,149,707	2,439,601	79,630	971,256	9,547

Month	Total	Eastern	Antelope Valley	Northern	Southern	Santa Clarita	West/ Central	Backup
Jul-23	602,155	141,765	51,152	99,577	215,883	6,817	86,117	843
Aug-23	607,666	143,325	52,020	102,529	216,598	7,145	85,198	851
Sep-23	613,456	144,300	53,677	102,284	219,513	7,448	85,375	859
Oct-23	585,655	132,434	50,450	98,238	214,242	7,107	82,365	820
Nov-23	586,993	135,266	49,993	99,387	213,895	6,931	80,699	822
Dec-23	569,942	128,038	48,084	96,328	211,199	6,672	78,823	798
Jan-24	611,177	144,028	52,869	103,723	220,841	7,175	81,685	856
Feb-24	607,918	137,060	53,890	101,932	222,770	7,507	83,909	851
Mar-24	633,674	146,252	57,332	103,958	229,455	7,985	87,805	887
Apr-24	627,012	141,657	55,970	104,362	227,012	7,617	89,516	878
May-24	637,356	145,370	57,366	104,013	230,825	7,392	91,497	893
Jun-24	640,120	146,074	57,197	107,755	230,152	7,139	90,907	896
FY 2024 Total	7,323,125	1,685,570	639,999	1,224,086	2,652,383	86,936	1,023,896	10,256

Month	Total	Eastern	Antelope Valley	Northern	Southern	Santa Clarita	West/ Central	Backup
Jul-24	646,994	147,516	59,685	106,043	234,631	7,473	90,739	906
Aug-24	652,896	149,291	60,698	109,060	235,368	7,801	89,764	914
Sep-24	659,695	150,379	62,631	109,044	238,679	8,085	89,953	924
Oct-24	629,073	137,689	58,863	104,447	232,641	7,782	86,771	881
Nov-24	631,499	141,083	58,336	105,990	232,644	7,555	85,006	884
Dec-24	612,081	133,107	56,098	102,486	229,256	7,268	83,010	857
Jan-25	657,201	150,075	61,697	110,418	240,214	7,843	86,033	920
Feb-25	653,500	142,664	62,875	108,626	241,790	8,252	88,378	915
Mar-25	681,491	152,314	66,902	110,547	249,528	8,750	92,495	954
Apr-25	674,116	147,430	65,299	111,278	246,532	8,334	94,299	944
May-25	685,255	151,419	66,941	110,638	250,865	8,043	96,389	960
Jun-25	688,265	152,127	66,737	114,785	250,094	7,800	95,759	964
FY 2025 Total	7,872,064	1,755,094	746,763	1,303,362	2,882,243	94,984	1,078,595	11,024

Month	Total	Eastern	Antelope Valley	Northern	Southern	Santa Clarita	West/ Central	Backup
Jul-25	695,758	153,501	69,645	112,959	254,961	8,120	95,598	974
Aug-25	702,172	155,511	70,822	116,029	255,759	8,501	94,566	983
Sep-25	710,059	156,629	73,087	116,248	259,460	8,877	94,763	994
Oct-25	676,577	143,242	68,680	111,072	252,702	8,512	91,422	948
Nov-25	679,899	147,112	68,068	112,963	253,011	8,232	89,561	952
Dec-25	658,324	138,427	65,457	109,075	248,975	7,981	87,487	922
Jan-26	707,488	156,428	71,992	117,543	261,296	8,572	90,668	991
Feb-26	703,356	148,513	73,360	115,749	262,601	9,004	93,144	985
Mar-26	733,713	158,619	78,065	117,574	271,452	9,483	97,493	1,027
Apr-26	725,657	153,518	76,192	118,595	267,858	9,076	99,402	1,016
May-26	737,819	157,737	78,109	117,689	272,815	8,819	101,616	1,033
Jun-26	740,949	158,444	77,872	122,266	271,886	8,481	100,961	1,038
FY 2026 Total	8,471,770	1,827,681	871,350	1,387,761	3,132,777	103,658	1,136,680	11,863

Appendix 5: New Applicant Forecast by Region (FY2017 – FY2026)

Month	Total	Eastern	Antelope Valley	Northern	Southern	Santa Clarita	West/ Central
Jul-16	2,925	821	154	335	1,085	14	516
Aug-16	3,250	856	178	388	1,223	24	581
Sep-16	2,896	817	160	351	1,067	23	478
Oct-16	2,345	642	143	252	872	20	417
Nov-16	2,658	647	167	317	995	15	516
Dec-16	2,537	636	162	293	955	15	476
Jan-17	2,509	611	166	288	962	21	460
Feb-17	2,515	634	201	310	878	25	469
Mar-17	2,664	661	225	305	939	29	505
Apr-17	2,641	635	182	303	1,008	18	495
May-17	2,597	651	171	299	983	19	474
Jun-17	2,553	650	151	308	956	23	466
FY 2017 Total	32,090	8,261	2,059	3,748	11,923	246	5,854

Note: Data cells shaded in blue represent new applicant observations.

Month	Total	Eastern	Antelope Valley	Northern	Southern	Santa Clarita	West/ Central
Jul-17	2,485	621	134	286	938	18	487
Aug-17	2,615	660	142	323	968	20	502
Sep-17	2,579	650	168	303	962	16	480
Oct-17	3,022	731	201	350	1,161	20	560
Nov-17	2,991	728	188	357	1,120	17	581
Dec-17	2,914	730	186	336	1,097	17	547
Jan-18	2,871	699	190	330	1,101	25	527
Feb-18	2,734	689	218	337	954	27	509
Mar-18	2,908	721	246	333	1,025	32	551
Apr-18	2,873	691	198	329	1,097	19	538
May-18	2,830	710	186	326	1,072	20	517
Jun-18	2,808	715	166	339	1,051	25	512
FY 2018 Total	33,629	8,346	2,223	3,948	12,545	255	6,312

Month	Total	Eastern	Antelope Valley	Northern	Southern	Santa Clarita	West/ Central
Jul-18	2,724	681	146	314	1,028	20	534
Aug-18	2,865	723	156	354	1,060	22	550
Sep-18	2,821	711	184	331	1,053	17	524
Oct-18	3,294	796	220	381	1,265	21	611
Nov-18	3,255	793	205	389	1,219	18	632
Dec-18	3,168	794	202	366	1,192	19	595
Jan-19	3,122	760	207	358	1,197	27	573
Feb-19	2,976	750	237	366	1,038	30	554
Mar-19	3,171	786	268	363	1,118	35	601
Apr-19	3,135	754	216	359	1,197	21	587
May-19	3,092	775	203	356	1,171	22	564
Jun-19	3,068	781	181	371	1,148	28	560
FY 2019 Total	36,690	9,106	2,425	4,308	13,687	279	6,886

Month	Total	Eastern	Antelope Valley	Northern	Southern	Santa Clarita	West/ Central
Jul-19	2,980	745	160	344	1,125	22	585
Aug-19	3,136	791	170	387	1,161	24	603
Sep-19	3,091	779	201	363	1,153	19	575
Oct-19	3,614	874	241	418	1,388	23	670
Nov-19	3,575	870	225	427	1,339	20	694
Dec-19	3,481	873	222	402	1,310	20	653
Jan-20	3,429	835	227	394	1,315	29	629
Feb-20	3,267	823	261	402	1,140	33	609
Mar-20	3,476	862	294	398	1,226	38	659
Apr-20	3,433	826	237	393	1,311	23	643
May-20	3,383	848	222	390	1,281	24	618
Jun-20	3,355	854	198	405	1,256	30	612
FY 2020 Total	40,221	9,982	2,658	4,723	15,004	305	7,549

Month	Total	Eastern	Antelope Valley	Northern	Southern	Santa Clarita	West/ Central
Jul-20	3,256	814	175	375	1,229	24	638
Aug-20	3,424	864	186	423	1,267	26	658
Sep-20	3,374	851	220	397	1,259	21	627
Oct-20	3,941	953	263	456	1,513	26	731
Nov-20	3,894	948	245	465	1,458	22	756
Dec-20	3,787	949	242	437	1,426	22	711
Jan-21	3,728	908	247	428	1,429	32	684
Feb-21	3,552	895	283	437	1,239	35	662
Mar-21	3,778	937	319	432	1,332	41	716
Apr-21	3,729	897	257	427	1,424	25	699
May-21	3,672	921	241	423	1,390	26	670
Jun-21	3,639	927	215	440	1,362	33	664
FY 2021 Total	43,774	10,863	2,892	5,140	16,330	332	8,216

Month	Total	Eastern	Antelope Valley	Northern	Southern	Santa Clarita	West/ Central
Jul-21	3,529	882	190	407	1,332	26	692
Aug-21	3,710	936	202	458	1,373	29	713
Sep-21	3,654	921	238	429	1,363	22	679
Oct-21	4,265	1,031	284	493	1,638	28	791
Nov-21	4,213	1,026	265	503	1,577	23	818
Dec-21	4,095	1,027	261	473	1,541	24	769
Jan-22	4,028	981	267	462	1,545	34	739
Feb-22	3,836	966	306	472	1,338	38	715
Mar-22	4,076	1,011	345	467	1,437	44	773
Apr-22	4,023	968	277	461	1,536	27	754
May-22	3,960	993	260	456	1,499	28	723
Jun-22	3,921	999	231	474	1,467	35	715
FY 2022 Total	47,310	11,741	3,126	5,555	17,649	359	8,880

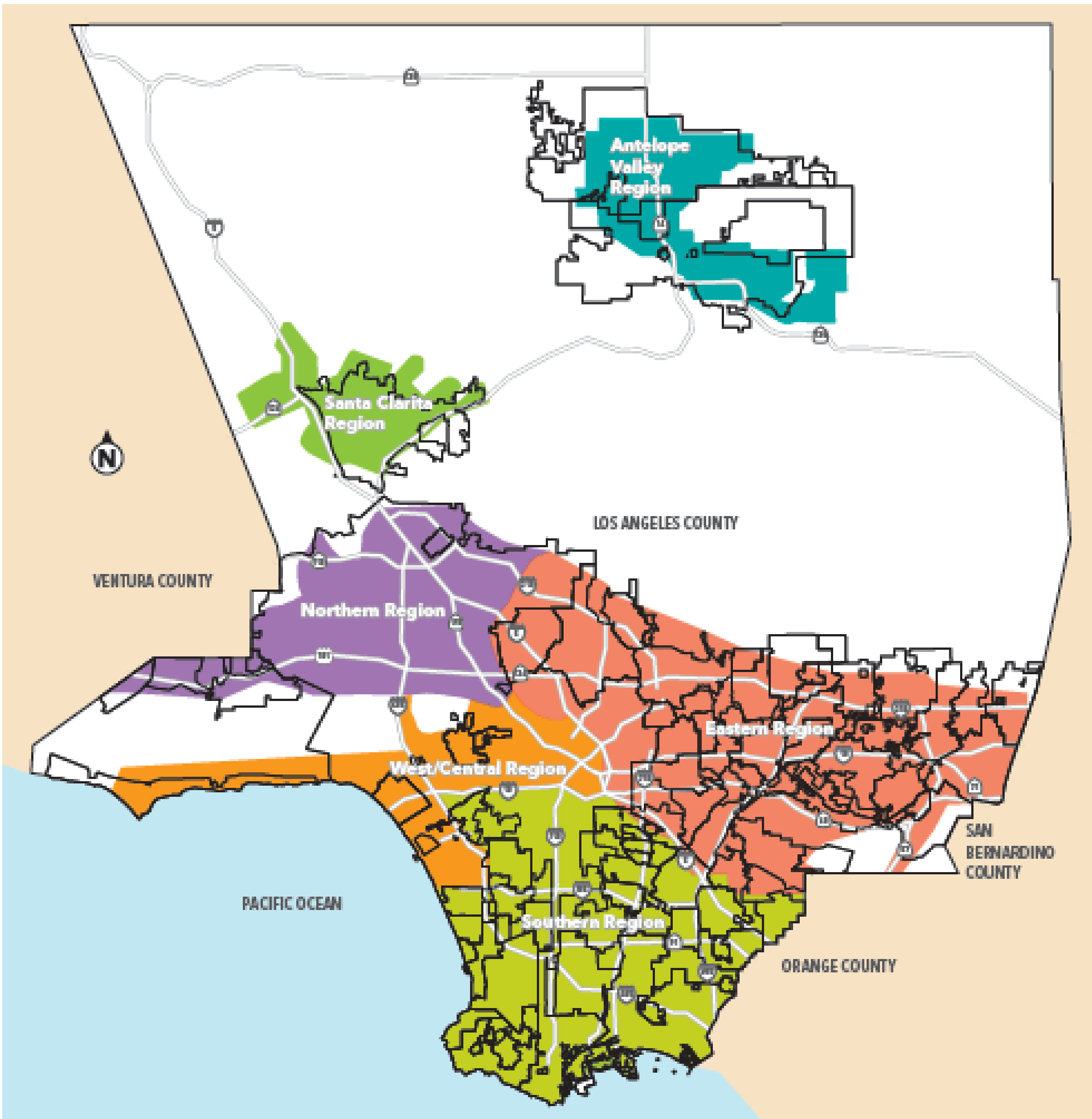
Month	Total	Eastern	Antelope Valley	Northern	Southern	Santa Clarita	West/ Central
Jul-22	3,801	950	204	438	1,435	28	745
Aug-22	3,993	1,008	217	493	1,478	31	767
Sep-22	3,930	991	256	462	1,466	24	731
Oct-22	4,585	1,108	306	531	1,761	30	850
Nov-22	4,525	1,102	285	540	1,694	25	879
Dec-22	4,396	1,102	281	508	1,655	26	825
Jan-23	4,327	1,054	286	497	1,659	37	794
Feb-23	4,117	1,037	328	507	1,437	41	767
Mar-23	4,377	1,086	370	501	1,544	48	830
Apr-23	4,318	1,039	298	495	1,649	29	809
May-23	4,249	1,065	279	489	1,609	31	776
Jun-23	4,209	1,072	248	508	1,575	38	768
FY 2023 Total	50,829	12,614	3,358	5,968	18,962	386	9,541

Month	Total	Eastern	Antelope Valley	Northern	Southern	Santa Clarita	West/ Central
Jul-23	4,079	1,020	219	470	1,540	30	800
Aug-23	4,287	1,082	233	529	1,586	33	824
Sep-23	4,217	1,063	275	496	1,574	26	784
Oct-23	4,919	1,189	328	569	1,889	32	912
Nov-23	4,855	1,182	305	580	1,818	27	943
Dec-23	4,718	1,183	301	545	1,776	28	885
Jan-24	4,641	1,130	307	533	1,780	40	852
Feb-24	4,415	1,112	352	543	1,540	44	823
Mar-24	4,694	1,164	397	537	1,655	51	890
Apr-24	4,630	1,114	319	530	1,768	31	867
May-24	4,553	1,142	299	524	1,724	33	831
Jun-24	4,509	1,148	266	545	1,687	41	822
FY 2024 Total	54,517	13,530	3,602	6,401	20,338	414	10,233

Month	Total	Eastern	Antelope Valley	Northern	Southern	Santa Clarita	West/ Central
Jul-24	4,369	1,092	235	504	1,650	32	857
Aug-24	4,589	1,158	249	566	1,698	35	882
Sep-24	4,515	1,138	294	531	1,685	28	839
Oct-24	5,265	1,273	351	609	2,022	34	976
Nov-24	5,196	1,265	327	620	1,946	29	1,009
Dec-24	5,046	1,265	322	583	1,899	30	947
Jan-25	4,965	1,209	328	570	1,904	42	911
Feb-25	4,723	1,190	377	581	1,648	47	880
Mar-25	5,021	1,245	424	575	1,770	55	951
Apr-25	4,953	1,192	341	567	1,892	33	928
May-25	4,873	1,222	320	561	1,845	35	890
Jun-25	4,827	1,229	285	583	1,807	43	880
FY 2025 Total	58,342	14,479	3,854	6,850	21,765	443	10,951

Month	Total	Eastern	Antelope Valley	Northern	Southern	Santa Clarita	West/ Central
Jul-25	4,678	1,170	251	539	1,766	34	917
Aug-25	4,912	1,240	267	606	1,818	38	944
Sep-25	4,833	1,219	315	568	1,803	30	899
Oct-25	5,639	1,363	376	652	2,165	37	1,046
Nov-25	5,563	1,354	350	664	2,083	31	1,081
Dec-25	5,405	1,355	345	624	2,034	32	1,014
Jan-26	5,319	1,295	352	610	2,040	45	976
Feb-26	5,064	1,276	404	623	1,767	50	943
Mar-26	5,382	1,335	455	616	1,898	59	1,020
Apr-26	5,312	1,278	366	609	2,029	35	995
May-26	5,227	1,310	344	602	1,979	38	954
Jun-26	5,178	1,319	305	625	1,938	47	944
FY 2026 Total	62,511	15,513	4,130	7,340	23,320	474	11,734

Appendix 6: Service Area Map



Source: Access Services

Appendix 7: References and Data Sources

Access Services Inc. FY2015/2016 Annual Report.

Access Services Inc. Access Services Rider's Guide. June 2015.

California Department of Finance, Demographic Research Unit, *Demographics*

http://www.dof.ca.gov/Forecasting/Demographics/

California Department of Finance, Economic Research Unit, *Economics*

http://www.dof.ca.gov/Forecasting/Economics/

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.

Miami-Dade County Transit. Paratransit Operations Monthly Report. September 2012.

Miami-Dade County Transit. Paratransit Operations Monthly Report. September 2013.

Miami-Dade County Transit. Paratransit Operations Monthly Report. September 2014.

Miami-Dade County Transit. Paratransit Operations Monthly Report. September 2015.

New York City Transit, Department of Buses, Paratransit Division. Paratransit Peer Report FY2011-2012.

New York City Transit, Department of Buses, Paratransit Division. Paratransit Peer Report FY2012-2013.

New York City Transit, Department of Buses, Paratransit Division. Paratransit Peer Report FY2013-2014.

New York City Transit, Department of Buses, Paratransit Division. Paratransit Peer Report FY2014-2015.

Orange County Transportation Authority. Transit Division Performance Measurements Report Fiscal Year 2012-13 Fourth Quarter.

Orange County Transportation Authority. Transit Division Performance Measurements Report Fiscal Year 2014-15 First Quarter.

U.S. Department of Energy, Energy Information Administration. *Annual Energy Outlook 2016*. July 2016.

U.S. Department of Energy, Energy Information Administration. *Petroleum Product Prices for California* http://tonto.eia.doe.gov/dnav/pet/pet_pri_gnd_dcus_sca_w.htm

U.S. Department of Labor, Bureau of Labor Statistics, *Consumer Price Index*

http://www.bls.gov/cpi/home.htm

U.S. Department of Labor, Bureau of Labor Statistics, *Employment Projections*

http://www.bls.gov/emp/home.htm

U.S. Department of Labor, Bureau of Labor Statistics, *Local Area Unemployment Statistics*

http://www.bls.gov/lau/home.htm

U.S. Department of Transportation, Urban Mass Transportation Administration. ADA Paratransit Handbook. Prepared for the UMTA Task Force on the Americans with Disabilities Act. UMTA-MA-06-0206-91-1. September 1991.

Washington Metropolitan Area Transit Authority. MetroAccess Monthly Operations Report Fiscal Year 2012.

Washington Metropolitan Area Transit Authority. MetroAccess Monthly Operations Report Fiscal Year 2013.

Washington Metropolitan Area Transit Authority. MetroAccess Monthly Operations Report Fiscal Year 2014.

Washington Metropolitan Area Transit Authority. MetroAccess Monthly Operations Report Fiscal Year 2015.