What Explains Recent Trends in Orange County Transportation Authority Bus Ridership?

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16. Abstract
This report investigates the impact of California Assembly Bill 60 (AB 60) on the bus ridership of the Orange County Transportation Authority (OCTA). OCTA bus ridership has been falling each year since 2012, and between 2012 and 2016, it dropped by 19% despite the launches of OCTA Bravo! in 2013 and OC Bus 360 in 2015. Changing socioeconomic conditions, poor connectivity, service quality, and increased competition from TNCs are possible factors behind this negative trend. Another possible reason is the implementation in 2015 of AB-60, which requires the California Department of Motor Vehicles (DMV) to issue a driver's license to applicants who can prove California residency even if they are not legal residents of the United States. In this context, the purpose of this project is to examine to what extent changes in OCTA bus ridership can be partly attributed to the unintended consequences of AB-60 while controlling for differences in transit supply, socioeconomic variables, gas prices, and the built environment. To explain changes in monthly average weekday ridership, we estimated four route-level fixed-effect panel regression models. Our findings suggest that AB 60 negatively impacted bus transit in Orange County. For instance, local routes, which offer the most frequent service, lost on average 186 daily riders on weekdays. To counter this slide in ridership, OCTA may consider adjusting its service, including increasing service frequency on selected routes, and exploring free or discounted pass programs for selected groups to attract new riders.

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What Explains Recent Trends in Orange County Transportation Authority Bus Ridership?

An exploration of the impacts of AB-60 on OCTA's bus ridership

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ABSTRACT

This report investigates the impact of California Assembly Bill 60 (AB 60) on the bus ridership of the Orange County Transportation Authority (OCTA). OCTA bus ridership has been falling each year since 2012, and between 2012 and 2016, it dropped by 19% despite the launches of OCTA Bravo! in 2013 and OC Bus 360 in 2015. Changing socioeconomic conditions, poor connectivity, service quality, and increased competition from TNCs are possible factors behind this negative trend. Another possible reason is the implementation in 2015 of AB-60, which requires the California Department of Motor Vehicles (DMV) to issue a driver's license to applicants who can prove California residency even if they are not legal residents of the United States. In this context, the purpose of this project is to examine to what extent changes in OCTA bus ridership can be partly attributed to the unintended consequences of AB-60 while controlling for differences in transit supply, socioeconomic variables, gas prices, and the built environment. To explain changes in monthly average weekday ridership, we estimated four route-level fixed-effect panel regression models. Our findings suggest that AB 60 negatively impacted bus transit in Orange County. For instance, local routes, which offer the most frequent service, lost on average 186 daily riders on weekdays. To counter this slide in ridership, OCTA may consider adjusting its service, including increasing service frequency on selected routes, and exploring free or discounted pass programs for selected groups to attract new riders.

Keywords: bus ridership; OCTA; AB-60; fixed effects panel regression.

I. INTRODUCTION

Over the last two decades, US transit agencies have experienced a decline in bus ridership: between 2011 to 2017 alone, bus transit lost almost 9.4% of its passenger miles traveled (Dickens & Neff, 2011; Hughes-Cromwick & Dickens, 2018). Some regional agencies such as the Orange County Transportation Authority (OCTA) were particularly affected despite several policy interventions aiming to increase ridership. From 2012 to 2016, OCTA bus ridership dropped by almost 19% despite of the launch of new programs (the Bravo! program in 2013[3] and of OC Bus 360 program in 2015[4], State of OC Transit, 2017). Possibly thanks to these programs, the slide in OCTA ridership slowed down during the pandemic, as bus patronage increased on several revamped lines (Johnson, 2017). By increasing convenience to pay for transit rides, OCTA's mobile ticketing app may have also contributed to these observed improvements.

Changing socioeconomic conditions, poor connectivity, and transit service quality, in addition to increased competition from transportation network companies (TNCs, such as Uber and Lyft) are some of the possible reasons behind the observed decline in bus ridership (State of OC Transit Report, 2017). Another possible explanation is the implementation in 2015 of California Assembly Bill 60 (AB 60), which gave some previously captive transit riders (i.e., riders for which bus was the only available mode, in addition to walking and possible biking) a more flexible alternative to transit. Indeed, AB 60 requires the California DMV to issue a driver's

[3] **Bravo!:** Bravo!, started in 2013 by OCTA, is a rapid bus service program with fewer stops to provide faster and more reliable long-distance service than traditional bus service. It is mainly operated in the Harbor and Westminster corridors (State of OC Transit, 2017).

[4] **OC Bus 360 program:** To increase bus ridership, OCTA introduced OC Bus 360° program in 2015 by improving services through technological innovations, marketing, and service changes. As a part of this program, OCTA reallocated resources from lower demand corridors to highest demand to better serve the riders with high-quality, more frequent, and extended service.

license to applicants who can provide a satisfactory proof of identity and of California residency (California DMV, 2017) even though they may not be legally present in the US.

AB 60 is a component of California's policy that aims at facilitating the daily activities of immigrant communities while enhancing public safety (since people driving without a driver's license are uninsured and likely to flee accident scenes). However, the implementation of AB60 created concerns about its possible impacts on congestion, public transit, and the environmental impacts of transportation. By making it easier for a new group of people to drive instead of taking transit, AB 60 indirectly counteracted some laws and policies that aim to shrink the environmental footprint of transportation. These laws include AB 32 (the California Global Warming Solutions Act of 2006), which requires Californians to reduce their GHG emissions to 1990 levels by 2020, and SB 375 (The Sustainable Communities and Climate Protection Act of 2008), which directed the Air Resources Board to set regional targets for reducing greenhouse gas emissions and help Californian achieve GHG reduction goals for cars and light trucks set by AB 32. While AB 32 and SB 375 clearly aim at reducing VMT and auto dependency in California, AB 60 may indirectly result in more vehicles on the road.

In this context, the purpose of this study is to examine if line-level changes in OCTA bus ridership can be partly attributed to AB 60, while controlling for differences in transit supply, socioeconomic variables, gas prices, the introduction of OCTA's mobile ticketing app, and the built environment (Taylor and Fink, 2013). Although this study focuses on OCTA, our methodology and findings should provide valuable insights for managing transit in areas similar to Orange County. Another contribution of this project is to study changes in OCTA ridership, which seems to have received very little attention from academics so far.

In the next section, we summarize selected papers that have examined changes in transit ridership to inform our methodology and our choice of variables. We then present results of an exploratory analysis that considers the implementation of AB 60, the availability of driver's licenses in Orange County, OCTA bus service, and bus ridership. We then introduce our data and our models, before discussing our results. In the last section, we summarize our key findings, mention some limitations of our work, and offer suggestions for future work.

II. LITERATURE REVIEW

A number of papers have investigated the impacts of increasing gasoline price, emerging new technologies, and socioeconomic variables on transit ridership (Iseki and Ali, 2015; Tang and Thakuriah, 2012; Taylor & Fink, 2003; Taylor et al., 2003, 2009, 2013). However, to the best of our knowledge, no published academic study has investigated the determinants of bus ridership at the line level in the decade before the COVID-19 pandemic to understand pre=pandemic changes in ridership. Furthermore, although transit studies have relied on different approaches, estimated a variety of empirical models, and analyzed different data sources, conclusions from this literature have been criticized for providing inconsistent results (Taylor et al.,2003, 2009, 2013). Finally, investigations on how a policy supporting driving (in our case by making it easier for undocumented immigrants to obtain a driver's license) impacts transit ridership, is still missing from the literature (with two notable exceptions: Barajas, 2021, and Taylor et al., 2020). The following sections provide a critical review of selected papers from the transit literature.

A large number of factors influence transit ridership, including (but not limited to) fares, routes, service frequency, transit stops accessibility, gasoline prices, population and job densities, land use, parking cost and availability, as well as the socioeconomic characteristics of the population who lives in the vicinity of transit lines. However, teasing out the impact of these different factors is not easy (Taylor and Fink, 2013).

One difficulty when analyzing transit ridership is to select the entity to analyze. A number of studies consider cross-sectional datasets that cover a larger number of transit systems. This approach provides more robust and generalizable results (Taylor et al., 2009, 2013) but it is often hampered by data limitations.

An alternative is to rely on panel data, which offers the advantage of jointly considering temporal and cross-sectional variations (Blanchard, 2009; Mattson, 2008).

Blanchard (2009) analyzed a panel dataset (2002 to 2008) to study the impact of increasing fuel prices on public transit ridership in 218 US cities. He found a cross-price elasticity of transit demand with respect to gasoline price ranging from 0.047 to 0.121 for bus transit.

Several other studies have focused on one or a handful of transit agencies, which allowed them to capture time varying factors that impact ridership (Gaudry, 1975; Guo et al., 2007; Witte et al., 2006) and to implement elaborate models that require more detailed data (Guo et al., 2007; Witte et al., 2006).

Another strand of the literature analyzes route level data to capture micro level spatial variations in ridership resulting from new technologies. For example, Tang and Thakuriah, (2012) estimated a linear mixed model to evaluate the effect of the Chicago Transit Authority bus tracker system on route level weekday ridership. In another example, Brakewood et al. (2015) assessed the impact of real-time information provided by web-enabled and mobile devices on public transit ridership in New York City. However, neither study incorporated some important socioeconomic factors (such as income) in their model, nor did they consider the endogeneity of transit supply.

Finally, some studies analyzed station level data to identify local factors that may impact transit ridership (Cardozo et al., 2012; Cervero et al., 2009; Chiou et al., 2015; Gutiérrez et al., 2011; Liu et al., 2014). Chiou et al. (2015) investigated the public transportation patronage in 22 Taiwanese counties using Tobit regressions models (TRM) and geographically weighted regression (GWR). However, they did not consider the competition from other modes and simultaneity in their work.

In California, Cervero et al. (2009) analyzed ridership data from 69 bus stops in Los Angeles County using the Direct Ridership Model (DRM) to identify BRT patronage factors. Although popular, DRM does not consider the attributes of other modes available to travelers (Cervero et al., 2009; Liu et al., 2014), and the way it is typically implemented does not deal with the endogeneity of transit supply.

A difficulty common to line-level studies of transit ridership is the lack of good data on linked trips because unlinked trips do not reflect actual trip making behavior. Most related published studies (Mcleod et al., 1991; is a rare exception) analyzed unlinked trip data from the American Public Transportation Association and the National Transit Database, which suffer from inconsistent reporting (Taylor and Fink, 2013). This approach fails to measure door to door travel and consequently does not accurately reflect trip making behavior (Taylor and Fink, 2013). The omission of some potentially influential variables (because they are difficult to measure, e.g., motor vehicle accessibility and cost, or transit quality) is also problematic because it may lead to omitted variable bias (Taylor and Fink, 2013).

The methods used to explain transit ridership have evolved and improved over time. Earlier papers tend to rely on simpler tools, including regression analysis. One common weakness in the literature is ignoring the endogeneity resulting from the joint determination of transit demand and supply (Taylor and Fink, 2003, 2009).

Some authors (e.g., Gaudry, 1975) argue that a transit agency needs time to understand and respond to changes in demand, so they used the ridership level of the previous year and treat demand and supply functions independently.

Others (e.g., Alperovich et al., 1977) acknowledge that transit agencies could make both short term and long-term supply adjustments, so they use structural equation modeling (SEM) to deal with the simultaneous determination of supply and demand.

An alternative strategy to address simultaneity is multistage least square estimation with instrumental variables (Peng et al., 1997; Taylor et al., 2009). For example, in their study of 265 urbanized areas in the US, Taylor et al., (2009) used a comprehensive list of influential variables and addressed the endogeneity problem via two stage least squares. However, the instrumental variables (total population and percentage of the population voting Democrat in the 2000 presidential election) they used did not fully verify the exclusion restriction assumption of IVs.

Besides endogeneity, the estimation methods discussed above can also suffer from collinearity among independent variables which is more prominent among spatial and socioeconomic variables (Taylor and Fink, 2013).

Another potential weakness of the literature is that interactions between intersecting and parallel routes have rarely been considered. Two notable exceptions are Alperovich et al. (1977) and Peng et al. (1997). Using 2-stage and 3-stage least squares in models that consider transit demand, supply, and inter route effects in simultaneous equation framework, Peng et al. (1997) report strong simultaneity effects between transit demand, supply, and cross route interactions.

Table 1: Summary of the selected papers

Study	Spatial unit of analysis			Factors considered			Method	Variables
	Route	*Area*	*Station*	*Endogeneity*	*Route interaction*	*Linked trips*		
Gaudry (1975)	- -	✓	- -	✓	- -	- -	Recursive model & OLS	*Transport:* Fares, price of non-transportation goods, service characteristics of the competing modes, comfort levels; *socioeconomic:* income and socioeconomic variables
Alperovich et al. (1977)	✓	- -	- -	✓	✓	- -	SEM	*Transport:* transit demand and supply; *socioeconomic:* income, employment
Mcleod et al. (1991)	- -	- -	- -	- -	- -	✓	OLS	*Transport:* fares, bus fleet, dummy variable included for strikes
Peng et al. (1997)	✓	- -	- -	✓	✓	- -	2SLS & 3SLS	*Transport:* boarding, service time, headway, # of seats in the bus, parking spaces, bus frequency/routes/segments; *socioeconomic*: population, income, employment density
Mattson (2008)	- -	✓	- -	- -	- -	- -	Polynomial distributed lag model	*Transport:* gasoline price
Blanchard (2008)	- -	✓	- -	- -	- -	- -	Cross-price elasticity	*Transport:* gasoline price
Taylor et al. (2009)	- -	✓	- -	✓	- -	- -	2SLS	*Transport:* vehicle revenue hours, fare, headways, service frequency, route coverage / density, predicted transit service, freeway lane miles, fuel price, non-transit/non-SOV trips, length of roads in miles, per capita vehicle miles, dummies for primary operators; *socioeconomic/land use:* income, population (total/density), # of college students/poor/immigrants/democratic voters, unemployment, carless households, race, area of urbanization, metropolitan form/economy, regional location
Cervero et al. (2009)	- -	- -	✓	- -	- -	- -	OLS	*Transport:* # of buses/perpendicular feeder bus lines/trains/connecting trains/perpendicular & parallel train lines, service hours, presence of dedicated-lanes/ bus benches/bus schedule/passenger information system/bus-stop/far-side bus stop/BRT-branding/terminal, availability of Park-and-Ride, # of Park-and-Ride spaces; *socioeconomic/land use:* population,

								employment/urban density, street connectivity index, distance to the nearest BRT stop
Tang and Thakuriah (2012)	✓	- -	- -	- -	- -	- -	Linear Mixed Effect Model	*Transport:* presence of a tracker, bus/rail fare, 4. Key service route, bus frequency, vehicle revenue hours of rail, # of trains operated in maximum service, gas price; *socioeconomic:* population, unemployment rate; *temperature:* snow fall, precipitation, temperature, *monthly effect dummies*
Cardozo et al. (2012)	- -	- -	✓	- -	- -	- -	DRM & GWR	*Transport:* # of lines/urban & suburban bus lines; *socioeconomic/land use:* population, employment, # of workers/carless households, land use mix, street density
Liu et al. (2014)	- -	- -	✓	- -	- -	- -	DRM & OLS	*Transport:* availability of park-and-ride/feeder bus services, transit frequency, station catchment size, terminal station dummies, station connectivity; *socioeconomic/land use:* age, income, vehicle ownership, ethnic groups, homeownership, population/employment density, land-use mix index, street connectivity, regional accessibility, distance to CBD, walk score (census tract)
Brakewood et al. (2015)	✓	- -	- -	- -	- -	- -	Fixed Effect Model	*Transport:* vehicle revenue miles & fare (bus/rail), real-time information, # of trains operated in peak service, dummy for select bus service/ bike-sharing, gas price; *socioeconomic:* population, unemployment rate; *temperature:* snow fall/precipitation (monthly), temperature, dummy for hurricane sandy
Iseki and Ali (2015)	- -	✓	- -	✓	- -	- -	Fixed Effect model & IV	*Transport:* unlinked trips, fare, vehicle revenue hours, frequency, total # of standing & seating capacity (bus), total annual fund, gasoline price; *socioeconomic:* total # of employees/population/carless households/immigrants/naturalized US citizen, federal highway miles (urban and rural), income, unemployment rate
Chiou et al. (2015)	- -	- -	✓	- -	- -	- -	TRM and GWR	*Transport:* # of intercity & city bus/MRT routes, # of MRT stations, total length of intercity & city bus/MRT routes, average daily frequency of intercity & city bus/MRT routes, average age of intercity bus routes, distance to the nearest

								station/interchange/rail/high-speed rail station/domestic airport; *socioeconomic/land use:* population density, # of households/ low-income households/employed people/collegiate students, % of minors/elders/handicappers/employed people in primary, secondary & tertiary industries, income, car/motorcycle ownership rate, residential/commercial/industrial area (ha), road length
Taylor et al. (2020)	- -	✓	- -	- -	- -	- -	RDM	*Transport:* percentage of drive alone and carpooled Latino immigrant commuters
*Barajas (2021)	- -	- -	- -	✓	- -	- -	DID	*Transport:* Total # of drive alone, carpool, non-motorized and transit trips; *socioeconomic/land use:* age, gender, # of children, cars per driver, race, income, employment status, home ownership, education, medical condition, % of census tract poverty & population density, urban size.

Note:

1. OLS: Ordinary Least Square, SEM: Structural Equation Model, 2SLS: Two stage Least Square, 3SLS: Three Stage Least Square, DRM: Direct Ridership Model, IV: Instrumental Variables, TRM: Tobit Regression Model, GWR: Geographically Weighted Regression, RDM: Regression Discontinuity Models, DID: Difference in difference.
2. *Barajas (2021) analyzed data from the 2009 and 2017 National Household Travel Surveys. This study's unit of analysis is a household.

After this study was concluded, Barajas (2021) & Taylor et al. (2020) investigated the impact of AB 60 on transit use. Both studies concluded that AB 60 has small but statistically significant negative impact on transit ridership. However, Taylor et al. (2020) did not use a robust econometric model and Barajas (2021) did not conduct a route level analysis.

Table 1 provides a summary of the papers discussed above. To the best of our knowledge, there has been no published scholarly analysis of bus ridership in Orange County.

III. EXPLORATORY ANALYSIS

III.1 AB 60 and driving licenses in Orange County

California has long been the US state with the largest number of immigrants. In 2018, 27 percent of Californians (10.6 million) were foreign-born, of which slightly over 20 percent (2.2 million in 2016) were undocumented (American Immigration Council, 2020). Drivers without a driver's license cannot get insurance for their vehicle, which likely results in more hit and run accidents. After studying the impact on traffic safety of AB 60, Lueders et al. (2017) concluded that AB 60 decreased the rate of hit and run accidents, possibly by reducing fears of deportation and vehicle impoundment. As they explain, hit and run behavior tends to delay emergency assistance, increases insurance premiums, and can result in large out of pocket expenses for victims. Hence the passage in California (and several other states) of laws like AB 60.

AB 60 helped one million undocumented immigrants get driver's licenses by 2018 in California alone (California DMV, 2018). California experienced an increase in the number of driver's licenses issued by the DMV over the last decade prior to the COVID 19 pandemic: between 2008 and 2019, this increase was 15.97%. Orange county experienced a similar trend over the same period. Figure 1 shows the total number of annual driving licenses issued by the DMV in Orange County. It shows a gradual annual increase in the total number of driving licenses issued annually by DMV, with a higher percentage (3.64%) for 2015, which is the year when AB 60 was passed in California.

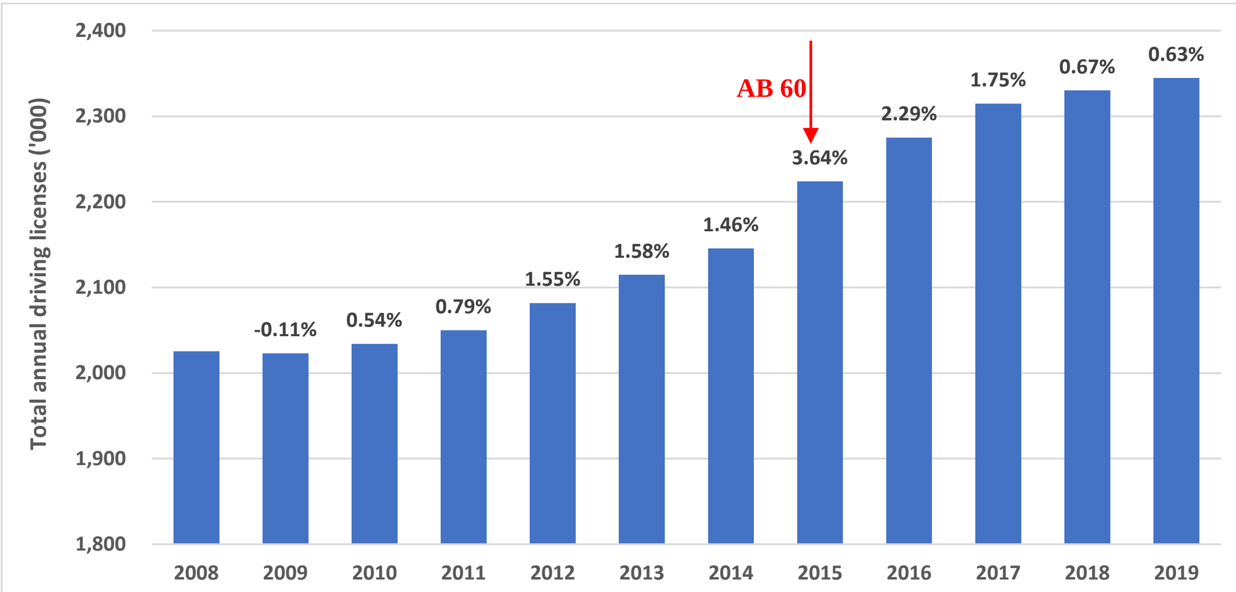


Figure 1. Yearly total driving license issued by DMV in Orange County, CA

Note: % above the bars indicates annual percentage change from the previous year.

(Source: California DMV, 2017)

III.2 OCTA Bus Service

OCTA operates five different bus services: 1) Major corridors; 2) Non-major corridors; 3) Community; 4) Station link; and 5) Express. Table 2 provides a summary of these services. The first two services involve a total of 43 routes (also called local routes), which offer the most frequent service. These routes form a grid on arterial streets and serve denser parts of the county. Figure 2A shows local OCTA routes, which mainly serve Fullerton, Anaheim, Orange, Garden Grove, Santa Ana, Huntington Beach, Costa Mesa, and Irvine.

Table 2. OCTA bus service Characteristics

Routes	Description	Service frequency	Boardings (per revenue hour)	Ridership	Farebox recovery ratio
Major Corridors	22 routes that form a grid on arterial streets	Every 15 minutes (peak period), seven days a week.	33	Annual: 32.2 M boardings Average weekday: 10,000 riders	26%
Non-major Corridors	21 routes that operate on arterials within the grid created by major corridors	Seven days a week; some operate only on weekdays.	20	Annual: 8.4 M boardings Average weekday: 2,000 riders	22%
Community	12 routes that connect pockets of transit demand with major destinations and offer local circulation.	50% of community routes operate seven days a week; the other 50% operate only on weekdays	15	Annual: 1.1 M boardings Average weekday: between 350 and 760 riders	23%
Station Link	12 routes that serve as rail feeder service designed to connect Metrolink stations to nearby destinations.	Operate during weekday peak hours only, morning peak hour: from station to destinations; evening peak hour: from destinations to stations	16	Annual: 0.3 M boardings Average weekday: less than 200 riders	18%
Express	10 routes that connect riders over long distance to destinations within and outside of Orange County	Operate on weekdays and only during peak periods ; use freeways.	9	Annual: 0.2 M boardings	20%

OCTA also operates low frequency buses on community, station link, and express routes (Figure 2B). Community routes link transit pockets and major destinations (for example: Huntington Beach), whereas station links connect Metrolink stations to nearby destinations. Finally, express routes mostly provide long distance service, such as commuting inside and outside

Orange County. There are 12 community routes, 10 express routes, and 12 station link routes, for a total of 77 routes with OCTA's 43 local routes.

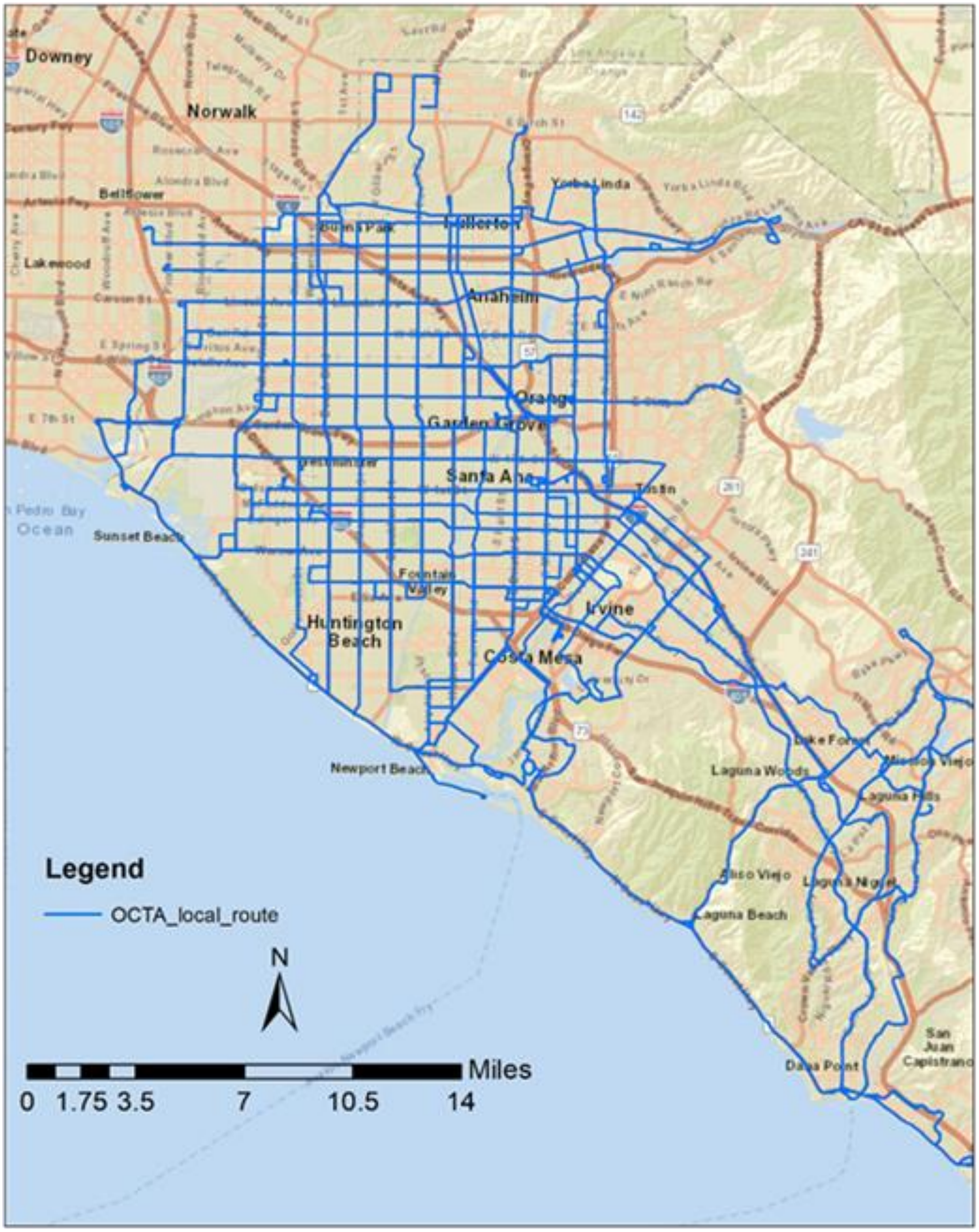


Figure 2A. Local bus routes

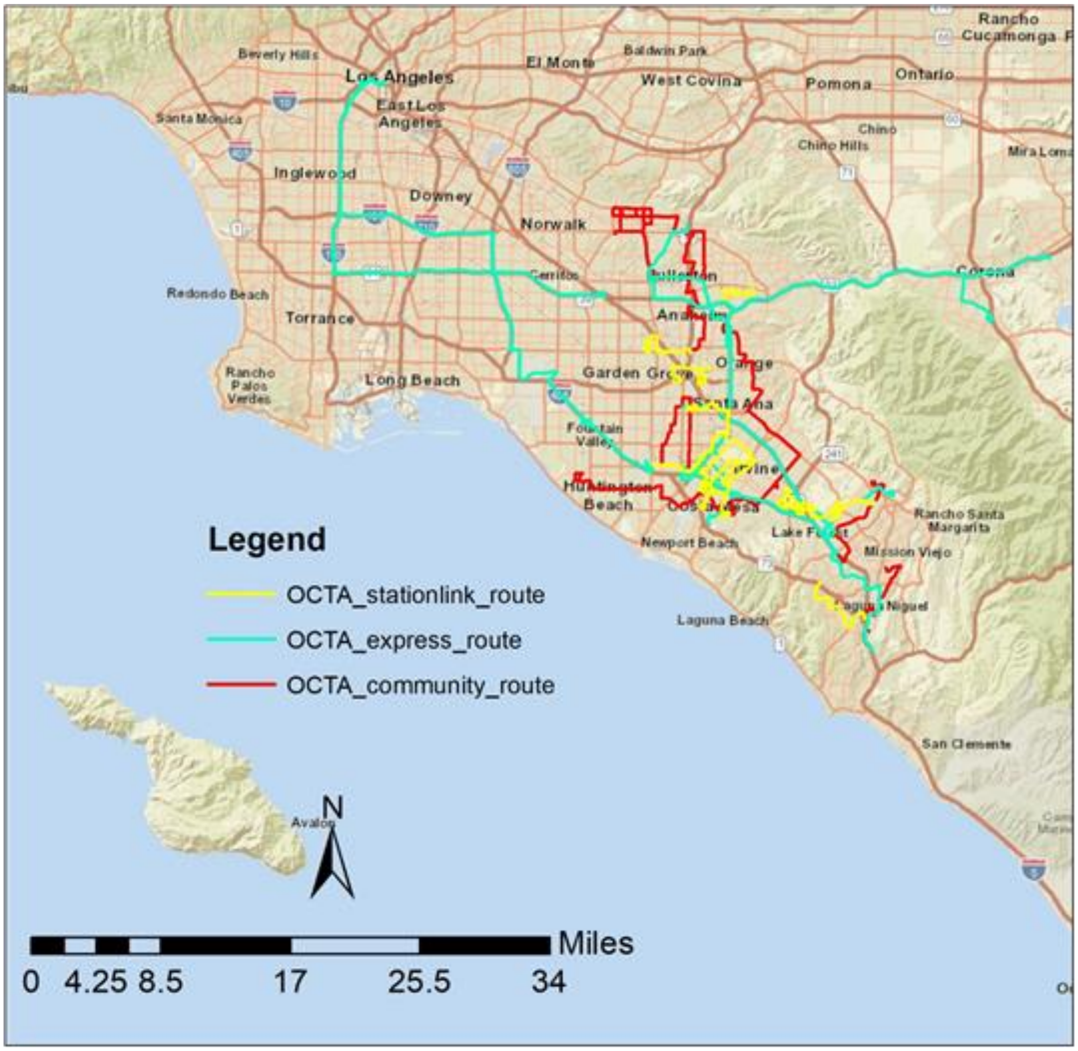
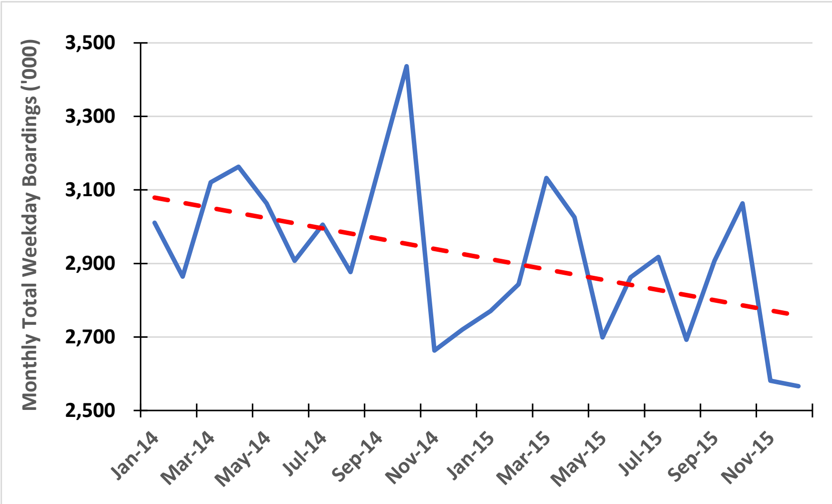


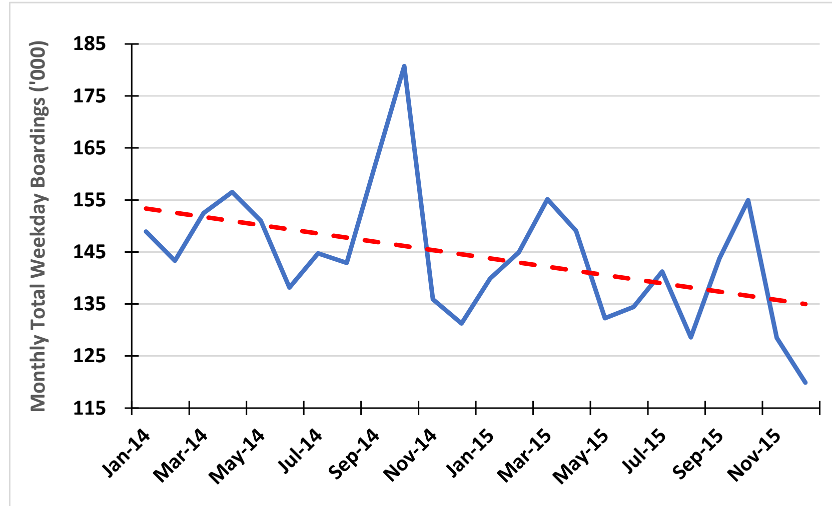
Figure 2B. OCTA Community, Station Link, and Express Bus Routes

III.3 Bus ridership between 2014 and 2015:

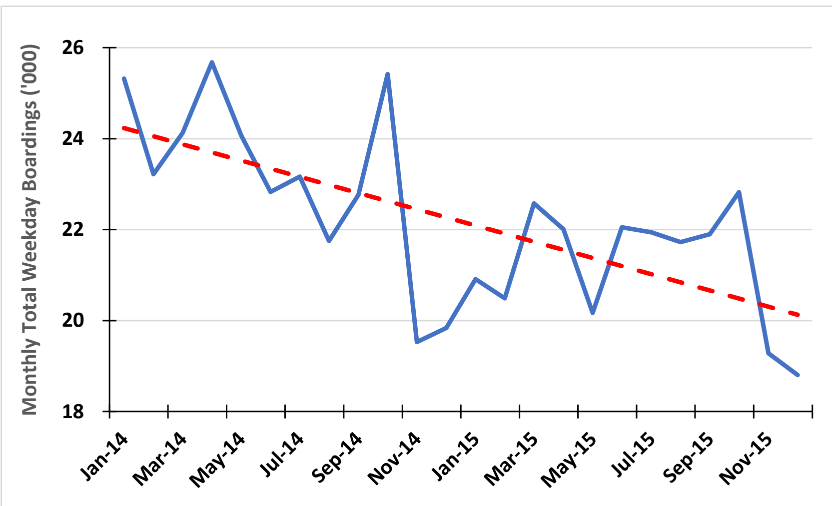
The dependent variable for our models is monthly average weekday OCTA bus boardings on selected routes for 2014 and 2015; data were provided by OCTA. Figure 3 shows the monthly route level total weekday boardings for OCTA for four different routes over these two years. A negative trend can be observed over this period.



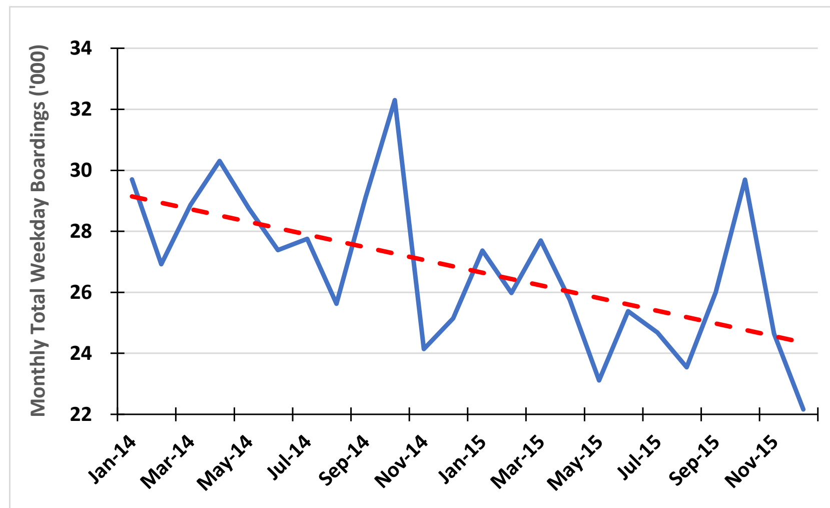
Panel A. Local Routes



Panel B. Community Routes



Panel C. Express Routes



Panel D. Station-Link Routes

Figure 3. Monthly route-level total weekday boardings for OCTA (2014-2015)

Several points can be inferred from Figure 3:

- There was a sharp decrease in total monthly ridership on local routes during November 2014, May 2015, and November 2015. Between January 2014 and December 2014, ridership fell by 9.6%; the rate decrease was 7.4% for 2015.
- A negative trend can be observed for community routes too, but the decrease is sharp in November 2014 (similar to local routes), May 2015, August 2015, and at the end of 2015. Between January and December 2015, community routes lost 14.3% of their riders.
- Like local and community routes, express routes lost ridership (-10.1%) in 2015.
- Station link routes lost ridership in both years: -15.3% in 2014 and -19.0% in 2015.
- It is also apparent from Figure 3 that the bus boarding peaks at the beginning of each seasons and declines at the end of each season. Such patterns can be associated with the academic year and student vacations. However, comparing these four seasonal peaks between 2014 and 2015, we note that the boarding peaks in 2015 are much lower than in 2014, which can be attributed to AB 60.

IV. DATA AND MODELS

IV.1 Dependent variables

Average weekday route level boarding data were compiled for each month from January 2014 to December 2015 (24 months). We selected these two years because AB 60 was passed at the beginning of January 2015 and one of our goals was to assess its impact on OCTA bus ridership.

IV.2 Explanatory variables

Apart from a binary variable that tracks the passage of AB 60, explanatory variables for this model can be organized into two groups: 1) internal variables, which are under the control of OCTA; and 2) external variables, which are not.

Our internal variables include average bus vehicle revenue hours, and average bus frequency. For our external variables, we considered three rail variables (rail vehicle revenue hours, rail fare, and trains operating at peak service) and some monthly economic variables for different OC cities. The latter include gasoline price, multi family home rent by ZIP code, and unemployment rate. We also created interaction terms between AB 60 and the months of 2015 to capture the progressive impacts of AB 60. Table 3 provides summary statistics for our model variables and indicates their sources.

In addition, we gathered the following variables, which are likely to impact transit ridership: county level monthly average population, occupation, percentage of Hispanics, college enrollment, percentage of foreign born, and household income, all from American Community Surveys. However, these variables do not vary much between 2014 and 2015 (changes range from 0.75% for Non-Hispanic people to 2.66% for "sales and service"). For smaller geographies, these variables are not available monthly. We therefore excluded these variables from our analyses.

Several papers have shown that gasoline prices can substantially impact transit ridership (e.g., see Taylor, 2003; Iseki and Ali, 2015). Monthly retail gasoline prices for Orange County were collected from Gas Buddy. Figure 4 shows that monthly gasoline prices fluctuated substantially between January 2014 and December 2015, with a maximum of $4.31 per gallon in April of 2014 and a minimum of $2.40 in January of 2015.

Table 3: Summary Statistics.

Description		Mean	Std. Dev.	Min.	Max.
Dependent variable					
Route level monthly average weekday boarding[1]	Local	3428.7	3013.1	122.2	14052.1
	Community	460.7	249.7	55.6	1012.7
	Express	104.2	63.5	15	236.0
	Station-Links	104.8	60.7	12.9	231.5
Explanatory variables					
Route level monthly average bus vehicle revenue hours[1]	Local	2306.6	1492.5	266.6	7039.5
	Community	720.7	261.1	245.3	1488.9
	Express	214.7	109.9	41.8	478.8
	Station Links	152.7	56.8	60.5	322
Route level monthly average bus frequency[1]	Local	1.9	0.8	0.7	3.9
	Community	1.1	0.2	0	1.9
	Express	3.0	1.4	0.6	5.8
	Station Links	2.5	0.6	1.3	3.4
Route level monthly average multi-family rent ($)[2]	Local	1820.4	157.9	1365.1	2286
	Community	1880.5	151.9	1491.2	2210.5
	Express	1794.5	148.3	1345.1	2064
	Station Links	1826.9	199.7	868.1	2181.6
Route level monthly average unemployed people [3]	Local	5433.5	2075.5	1087.3	9551.8
	Community	4489.7	2498.6	827	9208
	Express	6218.5	1321	3394.1	10027.2
	Station Links	6474.7	3357.8	900	12900
Monthly average rail vehicle revenue hours[4♣]		1856.5	68.1	1725.3	1989.9
Monthly average rail fare ($)[4♣]		5.8	0.1	5.7	6
Monthly rail scheduled vehicles operating at peak service hours[4♣]		258.2	35.5	223	294
Monthly average gasoline price (cents/gallon)[5♣]		350.2	49.5	254	431

Data sources: [1]: OCTA; [2]: Zillow; [3]: OC Chamber of Commerce; [4]: SCCRA, Metrolink; and [5]: gasbuddy.com. ♣: county-level variables.

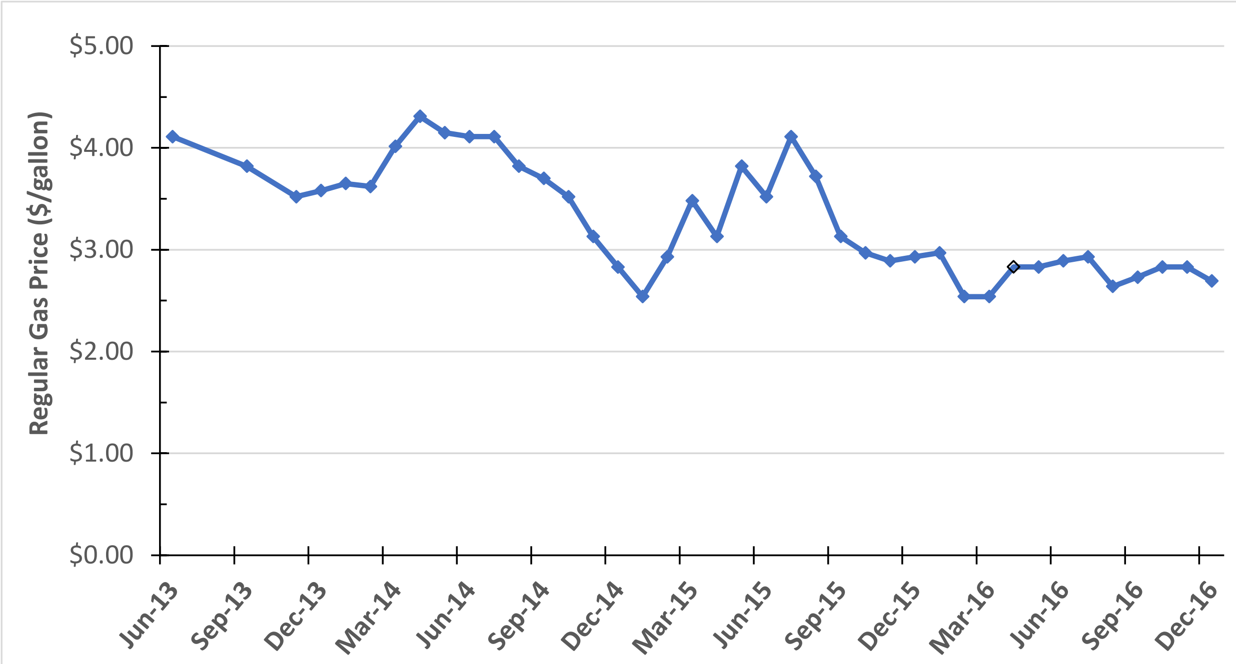


Figure 4: Monthly average gasoline price in Orange County (2013-2019).
Source: gasbuddy.com

We also collected monthly average multi-family rent data by ZIP code from Zillow (https://www.zillow.com/). Using weighted averages of bus stops inside a ZIP code boundary, we calculated multi-family house rent data at the line level. In order to associate the ZIP code data to each route, we first calculated the number of stops of each zip code boundary and then spatially joined these data with four different types of OCTA routes. Finally, we used Stata to associate line-level attributes of GIS data and obtain monthly line-level average multi-family house rents.

A number of papers have shown the importance of employment levels on transit ridership (e.g., see Taylor, 2003; Tang and Thakuriah, 2012; Taylor and Fink, 2013; Brakewood et al., 2015): transit ridership tends to increase when employment is higher, but it decrease with increasing household income. We obtained employment data from the OC Chamber of Commerce and followed the same process as for multi-family housing rents to calculate the monthly weighted average of unemployment rate at the OCTA line level; in this case, the data were available at the city level.

Rail variables (Orange County has three lines and 11 stations) were included because rail service impacts bus ridership (as a complement or a substitute). Systemwide rail service attributes were collected from the Southern California Regional Rail Authority (SCRRA) and Amtrak. We included rail vehicle revenue hours, rail fare and trains operating during peak service hours to capture the impact of rail on OCTA bus ridership. Our analysis includes the Orange County and Inland Empire Orange County (IEOC) lines. To model rail fares, we collected monthly average passenger fares for Orange County and IEOC lines.

IV.3 Model Specification

Using ordinary least square regression to explain monthly average weekday route-level bus boardings as a function of the explanatory variables described above would yield inconsistent estimates in this case because the i.i.d. assumption (i.i.d.: independently and identically distributed errors with zero mean) does not hold. Indeed, the error terms consist of two unobserved route level effects: an individual error and an idiosyncratic error. Solutions to address this problem include using either a fixed effect panel or a random effect panel regression model. Although less efficient, a fixed effect model is more suitable here because random effect models assume no correlation between the unobserved heterogeneity and the other control variables. Therefore, to explain monthly changes in OCTA bus ridership, we estimated four route-level fixed-effect panel regression models for the four service routes of OCTA. For route $z \epsilon \{1, …., N\}$ and month $t \epsilon \{1, …., T\}$, our fixed effect model can be written:

$$B_{zt} = \alpha_0 + \alpha_1 \cdot VRHB_{zt} + \alpha_2 \cdot BF_{zt} + \alpha_3 \cdot VRHT_t + \alpha_4 \cdot RF_t + \alpha_5 \cdot MFHR_{zt} + \alpha_6 \cdot G_t + \alpha_7 \cdot U_{zt} + \sum_{j=14}^{24} \alpha_j \cdot M_j \cdot AB60 + \beta_z + \gamma_t + \varepsilon_{zt} \quad (1)$$

In Equation (1):

- B_{zt} denotes monthly average weekday boardings for bus route *z* during month *t*;
- $VRHB_{zt}$ and BF_{zt} denote the monthly average vehicle revenue hours and frequency for bus route *z* during month *t*;
- $VRHT_t$ and RF_t are the monthly average vehicle revenue hours and fare for OC and IEOC rail lines;
- $MFHR_{zt}$ and U_{zt} represent route level monthly average multi-family home rent and number of unemployed people;
- G_t represent the monthly average gasoline price;
- $M_j \cdot AB60$ are interaction terms for the months of 2015 after the passage of AB 60;
- β_z and γ_t are fixed effect intercepts for each route; and
- ε_{zt} is an error term.

Mean differencing removed route-level unobserved effect. It is less efficient, but it yields unbiased and consistent estimates if our model is correctly specified (Wooldridge, 2010).

Multicollinearity is not an issue here as the maximum VIFs for four models are below 10 (Maximum VIF for four routes: local routes: 4.88, community routes: 9.49, express routes: 6.81, station-link: 6.68).

We also conducted endogeneity tests to check whether bus vehicle revenue hours is exogenous. For both the Durbin (1954) and Wu–Hausman statistic, and Wooldridge's (1995) robust score test, we found that the test statistics is insignificant, so we are confident that our model does not suffer from an endogeneity problem.

V. RESULTS AND DISCUSSIONS

Results were estimated using Stata 15. They are presented in Table 4. Our panel data is unbalanced with N=40 routes, T=2 years, NT=960 observations for local routes, 353 observations for Community routes, 240 observations for Express routes, and 288 observations for Station Links.

Table 4 shows that all the signs of the control variables are as expected (except for bus vehicle revenue hours for local routes). Even though some of the variables are not significant (for example, bus frequency), we kept those to emphasize that we took them into account in our analysis. Importantly, our results show that the coefficient of the AB 60 binary variable is negative and statistically significant for all four bus services, which confirms our starting hypothesis that AB 60 made it easier for a large segment of the captive OCTA ridership to drive private cars, resulting in a loss of ridership. Let us now discuss In the following sections, we discussed the results of individual parameters of our model.

V.1 Internal Factors

Bus vehicle revenue hours is significant only for local routes. The results implies that on an average, the daily boarding on each local route decreased by 0.29 boarding from an increase in revenue hours of service. The measure of increasing bus revenue hours might not be enough for these local routes and for this reason the coefficient for this variable has a negative value.

Conversely, bus frequency is significant for community routes which means that due to increasing bus frequency the daily ridership on these routes increased by 20.26 boardings for each unit increase in monthly average route frequency.

Table 4: Fixed Effect Results by Route Type

Variables	**Local Routes (1)**	**Community Routes (2)**	**Express Routes (3)**	**Station Link Routes (4)**
Monthly average route level bus VRH	-0.29*	0.01	0.06	0.02
Monthly average route level bus frequency	53.43	20.26*	5.05	-23.91
Monthly average rail VRH	-0.26	-0.13*	-0.02	-0.00
Monthly average rail fare ($)	-590.47‡	-190.52†	- -	- -
Monthly average route level multi family home rent ($)	0.30	-0.01	0.04	0.01
Monthly average gas price (cents/gallon)	1.81‡	0.16	0.09‡	0.04
Monthly average route level unemployed people	0.05†	0.00	0.00	0.00
Monthly average people in service and sales occupations ('000)	- -	-1.42	-1.46‡	-0.56
February2015*AB60	61.38‡	-3.42	-2.69	1.77
March2015*AB60	46.91*	-13.28	-6.90*	-3.83
April2015*AB60	18.68	-23.51	-8.42	-9.68
May2015*AB60	-304.02‡	-73.88†	-17.33†	-14.34
June2015*AB60	-314.90‡	-98.29†	-17.08†	-16.45*
July2015*AB60	-487.38‡	-106.18‡	-30.76‡	-27.48‡
August2015*AB60	-419.57‡	-96.66‡	-19.91‡	-21.97†
September2015*AB60	-51.33	-50.28	-18.04†	-10.34
October2015*AB60	76.51†	-14.45	-19.53†	-2.73
November2015*AB60	-250.14‡	-72.14†	-31.73‡	-13.43
December2015*AB60	-390.54‡	-112.13†	-40.84‡	-30.39†
Constant	6500.36‡	2681.88†	972.25‡	491.71
Observations	**960**	**353**	**240**	**288**
R^2	0.380	0.342	0.398	0.214

*p < 0.1, † p < 0.05, ‡ p < 0.01.
Our dependent variable is route level average weekday boarding. VRH stands for Vehicle Revenue Hours.

V.2 Impact of external factors

Our results suggest that between 2014 to 2015, the impact of external factors on OCTA bus ridership is comparatively more important than the impact of internal interventions. Among other external factors, we see that train fares have a significant negative impact on bus ridership, especially on local routes. For local routes, when the average train fare increases by one dollar, average monthly weekday bus ridership decreased by 590 boardings. Similarly, a one-dollar fare increase is associated with a 190 drop in average monthly weekday bus ridership on community routes. The likely explanation is the complementary nature of bus and train services in Orange County.

In 2014-15, the impact on boardings from changes in gasoline price was comparatively greater on local routes. On average, for every cent increase in gas price, the average monthly weekday bus ridership increased by 1.8 boardings on local routes, controlling for other factors (Brakewood et al., 2015.)

Unemployment has a positive coefficient value, but its impact is small. Similarly, certain types of occupation have a negligible impact on bus ridership. However, we see strong seasonal effects via the monthly interaction terms with the AB 60 binary variable, which is expected.

V.3 Impacts of AB 60

Ridership decreased in all routes due to AB 60 and the impact was greater on local routes. Between May and August, ridership decreased substantially, particularly on local and community routes. For example, in July 2015 compared to July 2014, local routes lost on average around 487 boardings daily whereas community routes lost 106 riders daily. But for the community routes, the impact was greater in December; community routes lost 112 riders daily.

A negative impact can be observed for the other two types of service routes too. Express routes lost on an average 31 boardings daily and station-link routes lost 27 riders daily in July of 2015 compared to the year 2014.

We also note that local routes have positive coefficient values for February and March 2015, which shows an increase in boardings for these months. One possibility is that AB 60 did not have an immediate impact on the local routes after it passed on January 2015.

VI. CONCLUSIONS

In this study, we evaluated the impact of AB 60 on bus ridership of Orange County. We estimated fixed effect panel regression models for different types of OCTA routes to explain route level monthly average weekday bus ridership over a two years period, while controlling for transit vehicle revenue hours, service frequency, and some economic variables. Our findings indicate that AB 60 had a large negative impact on all of OCTA's bus routes, although they were not uniform in time. In particular, local routes on an average lost 186 daily riders on weekdays.

This study fills a gap in the literature by providing empirical evidence of the unintended consequences on transit of a law designed to give more economic opportunities to illegal immigrants and to increase road safety. To the best of our knowledge, this study is also the first to examine bus transit in Orange County, which is the third-most-populous county in California, and the sixth-most-populous in the US. Second only to San Francisco County, it is also the second densest county in California (statisticalatlas.com).

The long-term decline in transit ridership in OC is problematic in the context of California's efforts to rein in vehicle miles traveled to reduce congestion, improve air quality, and achieve the state's greenhouse gas reduction targets. In addition to improving service (frequency on selected routes) and expanding successful initiatives such as the Bravo! and the OC Bus 360 programs, OCTA may consider offering free transit pass programs financed using the insurance model (Saphores et al., 2020).

There are several limitations of this study. First, we focused only on bus transit, but we did not evaluate how this law might affect OCTA rail traffic. Second, we could not evaluate the impact of Uber and Lyft on bus ridership as these data were not available. In addition, we were not able to get very detailed gasoline price data. Addressing these limitations is left for future work.

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