

# **The Impact of HOV/HOT Lane Creation on Public Transit Ridership: Evidence from the Los Angeles Metro**

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## **Abstract**

Most large cities face transit congestion due to increasing populations. Governments face trade-offs when determining which commuting infrastructure(s) to fund (e.g, public transit, HOV/HOT lanes, road expansion, etc.). A key question is whether commuters substitute across alternative commuting modes when new options are introduced. Substitution can happen because commuters may choose to minimize their travel time and therefore their time costs; in other words, commuters will choose the fastest route. A follow-up question is if commuters make their decision based on minimizing their transportation time. Using a framework that allows for empirical comparison between HOV/HOT lane openings and public transit rails, I find a negative relationship between public transit ridership and an HOV/HOT lane introduction. That is, when an HOV/HOT opens, my statistically significant results suggest that transit ridership for parallel transit lines will decrease approximately -4.69 to -4.76 percent.

## **1 Introduction**

There is much debate in governments as to which commuting infrastructure(s) are best to fund and construct. Some examples of commuting infrastructures and their benefits include: building and expanding roadways to improve connectedness, having more bus routes to alleviate congestion, building rail systems that reduce environmental impacts of travel, and/or constructing high occupancy vehicle (HOV)/high occupancy toll (HOT) lanes that alleviate congestion and provide a faster form of travel.

HOV lanes can only be used by vehicles that have two-plus or three-plus riders, but occupancy requirements vary by road. HOT lanes allow vehicles with lower occupancy than the HOV lane requirement to utilize these lanes as well by way of paying a toll. HOV carools can usually still travel in HOT lanes for free. Public transit is defined as mass transit that is funded by general taxes and ride fares. A busway is an additional lane on a road used specifically for buses. Usually busways and HOV/HOT lanes are created next to each other. No matter the chosen method(s), there will be benefits and costs. A large portion of transit riders have

alternative modes of travel (Kridler 2014), which leads me to ask: will commuters substitute across newly introduced mode choices that may be faster?

One way to gain insight into commuter preferences is to examine which method commuters choose when given multiple mode choices. However, no prior empirical research has been done to investigate if commuters substitute across mode choices from transit to HOV/HOT lane use when new alternatives are introduced. Do commuters still favor taking public transit, or would they rather travel via a newly introduced HOV/HOT lane, which may decrease their travel time? I examine if HOV/HOT lanes are considered substitutes or complements to public transit (i.e., bus and rail) using regression analysis on public transit ridership. In other words, how does HOV/HOT lane creation affect public transit ridership? Answering this question will provide insight to transportation policy makers when determining which commuting infrastructure is preferred by commuters and therefore which is a better investment to its constituents.

If a city is attempting to curb pollution, it is also important for the policy makers to know how many riders will switch from using a more environmentally-friendly railway, bus, and/or busway to a faster HOV/HOT lane carpool, if any. Additionally, it is common knowledge that most public transit is subsidized heavily from general taxes, sometimes upwards of 60 percent (Parry and Small 2009); however, these subsidies can vary from city to city. HOV and HOT lanes have become more frequent in most metropolitan areas, especially in Los Angeles, California largely because of their Congestion Management Program. These projects, along with other public works, (e.g., public transportation) can cost billions of dollars to develop and construct. However, as is known through positive analysis, it is challenging to gain insight of people's optimal preferences due to people over or understating their utility gain.

My hypothesis follows: once an alternative mode is introduced with an HOV or HOT lane opening, parallel public transit ridership on the observed lines will decrease (holding all else equal). I will examine this hypothesis through two different methods using Metro ridership data, Caltrans HOV/HOT lane opening dates, and the United States Energy Information Administration monthly gas prices. The first analytical method accounts for the Red Line extensions that occurred in the late 1990s and 2000, as well as the varying data collection that began in 2006 when Metro combined Purple Line's ridership data with the Red Line's. The second analytical method disregards pre-2006 data on the Red Line to avoid the extensions and data combination. The first method finds that there is about a -4.76 percent decrease in transit ridership when parallel HOV/HOT lane is introduced, while the second method finds there is about a -4.69 percent decrease. Next, I discuss previous literature, the methodology of my empirical approach, the data, and the results. I conclude with discussing the policy implications of this research and further research.

## **2 Literature Review**

There is a large amount of literature in transportation economics. However, there is not a study that directly investigates the relationship between HOV/HOT lanes and public transit. This section contains an overview of general literature that investigates influences of travel behavior. To begin, I discuss Anderson's (2013) research to show the importance of public transit for congestion relief is shown with. Next I investigate the effect of increasing gas prices on traffic and public transit. Further, I examine the efficiency of HOV lanes and public transit. Lastly, I discuss the institutional background regarding the current public transit culture and Los Angeles Metro public transit survey data to lay the foundation and reasoning for my hypothesis.

Even though only 1 percent of the population takes public transit, public transit has a dramatic impact on the relief of traffic congestion in Los Angeles (Anderson 2013). In fact, Anderson (2013) found that there is an increase in traffic delay of 47 percent when public transit ceases. Anderson (2013) was the first to find such significant results. Previously Parry and Small (2009) found that transit only accounted for approximately a 5 percent reduction in traffic delays (qtd. in Anderson 2013). From these findings, Anderson (2013) concludes that large capital investments in transportation infrastructure can lead to positive net benefits. However, no matter the capital investment given, other variables affect traffic congestion as well.

Following intuition, mainline road use is correlated with gasoline prices. In essence, there is a decrease in mainline usage when gas prices rise (Bento, Hughes, and Kaffine 2013). Bento, Hughes and Kaffine (2013) investigate the effects of gas prices on HOV lane usage using Los Angeles traffic data from 2000-2007. They find that HOV lane usage increases when gas prices rise. Further, they find that roads without an HOV lane are more likely to experience no reduction in traffic congestion. Conversely, there is a large reduction in traffic congestion on mainline highways with HOV lanes (Bento, Hughes, and Kaffine 2013). Gas prices also have an effect on public transit ridership.

As gas prices increase, public transit ridership increases as well, according to Currie and Phung (2007), Iseki and Ali (2014), Haire and Machemehl (2007), Mattson (2012), Maley and Weinberger (2009), Yanmez-Tuzel and Ozbay (2010), Stover and Bae (2011). Though all of these authors find varying results, largely due to various methods, models, and locations of study, the results are similar: public transit (particularly, rail transit) has a positive relationship with gas prices.

Currie and Phung (2007) find when gas prices rise 10 percent, the aggregate for all public transit modes increases 1.2 percent (with light rail having the largest increase and bus the smallest). Iseki and Ali (2014) find similar results as the others; however, they also find that fare elasticity has a greater effect than gas price elasticity on public transit ridership. Haire and Machemehl (2007) find an elasticity range from .0665-.2726 with light rail being the lowest and commuter rail being the highest.

Mattson (2008) finds that the elasticity varies by city size, with the aggregate totaling around 1.2 percent for a 10 percent increase in gas prices. The largest elasticities are for medium-small cities, while the smallest elasticities are for small cities (Mattson 2008). Maley and Weinberger (2009) find a difference between regional rails' and city transit elasticities. The regional rail elasticity results are higher than the city transit elasticity results. Yanmez-Tuzel and Ozbay (2010) find that medium-term elasticity results are lower than short-term elasticity results. Stover and Bae (2011) find an elasticity result of .17 of the 11 Washington counties investigated. Among the majority of the literature, light rail, commuter rail, and heavy rail all have larger increases in ridership when gas prices rise than bus. There is a positive relationship between rising gas prices and public transit, while there is a negative relationship between traffic and rising gas prices. This previous research shows gas prices are an important control for my regression. Many other forms of traffic congestion are utilized beyond public transit, most notably HOV lanes. However, there is a lot of controversy surrounding the efficiency of HOV lanes due to the use of road space.

Dahlgren (1995) notes that when a mainline lane was converted to an HOV lane on Santa Monica Freeway in 1976, there was a significant increase in the number of carpools (65

percent) and ridership of buses (250 percent). However, this meant on a four lane highway, 25 percent of the highway's use was geared toward carpoolers and bus riders, yet the ridership in this lane only accounted for 6 percent of vehicles that were carpooling and 3 percent of riders on buses (Dahlgren 1995). The lane was changed back for general use to decrease congestion shortly after (Dahlgren 1995). Though there is a shift from mainline usage to HOV lanes or transit busways, it seems as though most HOV lanes are below capacity. This has called for many cities to seek changing the HOV lanes to HOT lanes to increase capacity and decrease congestion even further. A recent example seen in Los Angeles, California was when Interstate-110 (completed in November 2012) and Interstate-10 (completed in February 2013) altered their lanes to HOT lanes (Metro Expresslanes 2015). The tolling fee changes based on congestion levels in an effort to achieve consistent flows on the highway. Having consistent flows of around 55 mph is a method that research shows decreases CO<sub>2</sub> emissions (Barth and Boriboonsomsin 2010). Nonetheless, public transit also receives criticism largely due to the expense, inefficient travel, and subsequent tax burden.

Rubin, Moore, and Lee (1999) argue that rails will not decongest roads in the long-run with the simple idea that “activity shifts” will lead people to change their location to be closer to the newly accessible rail system. Further, they argue that the wait time for rails and rail transfers makes it a less efficient mode of travel (Rubin, Moore, and Lee 1999). The solution, Rubin, Moore, and Lee argue is creating other alternatives to rails. These alternatives include HOV lanes for only buses or “busways,” and expanding the busing system in general (Rubin, Moore, and Lee 1999). Bus routes are easier to manipulate than rails given they are not stationary (Rubin, Moore, and Lee 1999). Lee, Moore, and Rubin state the El Monte busway in Los

Angeles cost only \$85.3 million (1988), whereas the Blue Line light rail line cost \$877 million (1988). However, what Rubin, Moore, Lee don't take into account are the environmental impacts of busways versus rails. Rails have less environmental impacts than buses because they are electric. Further, as we learned from the Santa Monica freeway, drivers will outcry when the HOV lanes or busways seem to be underutilized and this can cause more congestion. Next, I examine the current national public transit landscape and results from the 2014 Los Angeles Metro survey.

## **2.1 Institutional Background**

The American Public Transportation Association has shown an increase of 9 percent in public transit ridership nationally (including all forms of transit) from 2005 to 2013 even among decreasing gas prices, which might show a larger cultural shift according to Anbinder (2015). This can be misleading, however, because some cities are experiencing massive growth (e.g., Tampa), while others are experiencing massive declines (e.g., Cleveland) (Anbinder 2015). According to Anbinder (2015), Los Angeles was found to have just below a 5 percent decrease in public transit ridership for all transit lines in this time period. This mildly suggests that the ever-expanding HOV/HOT lane infrastructure in Los Angeles might have had an impact on this difference. Though, for the limited transit lines I observe, I do not see any decrease in Los Angeles transit ridership. Los Angeles has continued to expand both the HOV/HOT lane infrastructure as well as their public transit infrastructure in an effort to diminish the effects of population growth (*Facts at a Glance*).

Los Angeles public transit riders typically get to the rail station by walking: 82 percent of bus riders walk, while 62 percent of train riders walk (Kridler 2014). Further, rail riders travel



by car more often to get to the station than do bus riders (25 percent to 10 percent, respectively), which largely supports Rubin, Moore, and Lee's (1999) theory that buses provide the rider more flexibility because of the increased likely of being a closer proximity to a station or stop (Kridler 2014). However, utility for rail riders is most likely increased, as they reported less wait time at the station, on average, which made their trip shorter by 2 minutes (Kridler 2014). Rail riders also have on average higher median incomes by over \$6,000 than bus riders, while all public transit riders' median incomes are much lower on average at \$19,477 than the Los Angeles County level median income of \$56,241 (Kridler 2014). Public transit in LA serves the 23-49 age demographic the most on both rail and bus with 53 percent of this demographic traveling rail and 47 percent traveling bus (Kridler 2014). Lastly, the most interesting statistic related to my research is that rail riders have greater access to a vehicle than bus riders do with 44 percent of rail reporters stating they had a car available to make the same trip they chose with the rail, while only 25 percent of bus riders stated the same (Kridler 2014). These individuals with easy access to vehicles would have another mode choice if a parallel HOV/HOT lane was built along the rail they typically ride. This suggests that public transit and HOV/HOT lanes will be substitutes rather than complements to each other given one would expect individuals to travel via the fastest mode choice, which would most likely travel via the HOV/HOT lane given there is no transfer or wait time to allot for the rider.

### **3 Methods**

I examine transit ridership before and after a parallel HOV/HOT lane opening to examine if HOV/HOT lanes are substitutes or complements to public transit. If a new HOV/HOT lane is built then this creates a new, most likely faster, mode for public transit riders to travel. I

investigate if there is evidence of commuters minimizing travel costs by switching mode choice. This potential shift in use by commuters from public transit to HOV/HOT lane use, if any, is of interest. To examine this topic, I utilize data from the Los Angeles, California Metro public transit system. California is often used for three main reasons. First, it has a large and growing population, and this helps in obtaining plenty of samples to choose from when researching traffic, ridership, or anything alike. Second, Los Angeles, California has been of particular interest in most studies due to its growing and vast infrastructure (e.g. HOV/HOT lanes and transit lines) provided to curb pollution and congestion (*High Occupancy Vehicle Systems* 2015). Third, California has accessible data provided by the state, counties, and localities. This infrastructure provides ample opportunity to conduct comparative studies (e.g., HOV compared to mainline transit, rails versus buses, etc.).

### **3.1 Empirical Approach**

Transit ridership varies over time due to seasonal impacts, gas prices, schooling migration, economic conditions, among other time-varying factors. Commuting behavior notably changes over seasons, as can be seen from the oscillating ridership levels from month-to-month (see Figure 1). These natural seasonal variations can occur from schooling migration, increases in vacationing, and other natural time-varying changes in commuting behavior. Also seen is the natural upward trend in transit ridership (see Figure 1), most likely due to expanding population and/or increasing ridership culture. Lastly, the decline in ridership starting around 2013, most likely due to decreasing gas prices, is notable.

For the first and second time-varying problems I add seasonal effects, line effects, and line effects multiplied by the line's trend. For the third problem, I include average monthly Los Angeles gas prices, adjusted for inflation in 2016 terms.

Under these assumptions I estimate:

$$Y_{jt} = \alpha + \beta \text{hov}_{jt} + \beta \ln(\text{gas}_t) + \eta_q + \eta_j + \eta_j * \text{trend} + \varepsilon_{jt}$$

This is a log-level regression. In this model, the dependent variable,  $Y_{jt}$ , is the natural log of average daily ridership for each transit line  $j$  at time  $t$ . The independent variable,  $\text{hov}_{jt}$ , is a binary variable equal to 1 when the HOV/HOT lane is open.  $\ln(\text{gas}_t)$  is the natural log of average monthly Los Angeles gas prices, adjusted for inflation in 2016 terms.  $\eta_q$  is quarter-mean effects to account for seasonality, and  $\eta_j$  are line specific mean effects to account for line variation. Finally, to account for time-varying factors,  $\eta_j * \text{trend}$  accounts is a line specific time trend.

As HOV/HOT lanes usually have several incremental openings<sup>1</sup>, the definition I use for when an HOV/HOT lane is considered open is only when both the northbound and southbound lanes are open<sup>2</sup>.

A large challenge I had to overcome was compensating for rail extensions, most notably for the Red Line. General time-varying factors are accounted for in the fixed effects of season, line, and line\*trend. However, as seen in Figure 1, the Red Line is the outlier showing extreme growth between 1998-2001, which is not seen among any of the other lines. Due to the lack of similarity across lines, this provided a clear hint that this growth was not attributed to abnormal

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<sup>1</sup> An example of this is the I-405 HOV lane: a southbound HOV lane started being built in 2002, but the northbound lane wasn't finished until 2013.

<sup>2</sup> I.e.,  $\text{hov} = 1$  only when both the northbound and southbound lanes are open.

population growth. After investigation, this large growth in the Red Line was attributed to the multiple extensions, which dramatically increased the demand and carrying capacity for the Red Line<sup>3</sup>. The extensions happen in the following order: first, from Union Station to Wilshire in June 1996, then another expansion from Union Station to Hollywood in June 1999, and the final expansion from Union Station to North Hollywood in June 2000.

For this challenge, I use two different methods to account for the Red Line extensions. I will discuss both methods to ultimately show that the results either way are similar and therefore robust. In either method, the same foundational model is used.

The first method accounts for these extensions in the model through including dummy variables for each extension. By doing this I am able to shift the intercept to compensate for the extreme growth in the Red Line's ridership. Further, to account for differential trends, I multiply the extension dummy variables by the Red Line's trend, thereby compensating for the large change in the slope, as well. The second challenge includes changes in data collection for the Red Line. Metro added Purple Line data to the Red Line data beginning in January 2006. With this, I account for the intercept shift and differential trend for the Purple Line data combination, as well<sup>4</sup>. The entire dataset is used for this method (Figure 1).

The second method disregards all of the pre-2006 data for the Red Line to avoid the extensions and Purple Line data combination (see Figure 2). The HOV lane opening doesn't happen until October 2013 for the Red Line. Therefore, I am able to disregard the extensions and Purple Line data combination without much worry. Though, this method does decrease the

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<sup>3</sup> I thank the Director of the District 7 Metro for this information.

<sup>4</sup> The first method's testable model follows:  $\ln(transit_{jt}) = \alpha + \beta_{hov_{jt}} + \beta_{wilshire} + \beta_{hollywood} + \beta_{nhollywood} + \beta_{purple} + \beta_{wilshire*trend} + \beta_{hollywood*trend} + \beta_{nhollywood*trend} + \beta_{purple*trend} + \beta \ln(gas_t) + \eta_q + \eta_j + \eta_j*trend + \epsilon_{jt}$

amount of observations, which may alter results. I use the foundational regression mentioned above for the second method.

Due to unobserved factors that affect ridership and my use of fixed effects, I must split the observed transit lines into an experimental group and a control group (see Figure 3). I don't investigate general bus lines because bus routes can vary dramatically from year-to-year due to road construction, additional routes added, etc. Therefore, the experimental group consists of the following rail lines and busway lines: Red Line (rail line), Orange Line (busway), Silver Line (busway), and the Blue Line (rail line). The following HOV/HOT lane creation dates will be examined for the following roads: Interstate-405, Interstate-110, and Interstate-10. It's important to note that the Blue Line and Silver Line had an HOV at the inception of data collection and then the HOV lane was shut down for conversion to a HOT lane. For this difference, the *hov* dummy equals one pre- and post-HOT lane construction. However, my regression only captures the introduction after the HOT lane is built, which still shows the change of interest. The control group consists of the Green Line and Gold Line. The fixed effects model accounts for varying differences whenever HOV equals 0, which includes pre-HOV and construction periods for all groups and Green Line and Gold Line data throughout all of the years observed.

## **3.2 Data**

Public transit ridership data come from the Los Angeles County Metropolitan Transportation Authority. This data includes average daily ridership (averaged monthly) for weekdays, Saturdays, and Sundays and holidays separated by transit lines. Since travel time costs vary for commuters from weekdays to weekends, I only utilize weekday data. Ridership data also go back as early as July 1990 for some lines to December 2015 for all lines.

Table 1 presents the summary statistics for the observed rail lines and busways. The Silver Line busway has the least amount of observations, due to its recent opening in 2009. While the Blue Line has the largest amount of observations going back to 1990. Using the first method of analysis, the Red Line has the second largest amount of observations at 243. For the second method of analysis, the Red Line only has 119 observations. Regardless of method, the Red Line has the highest mean of all of the observed lines with 100,783 for the first method and 146,144 for the second method. The overall mean for all lines is 53,769 for the first method, but only 51,940 for the second method. For all lines observed with dates back to 2003, ridership data is missing for October 2003 and November 2003 due to miscalculation. As mentioned previously, Figure 1 and Figure 2 show the scattered public transit ridership data for the observed lines.

I use average monthly data for Los Angeles' gas prices from the United State Energy Information Administration. The monthly data is the average of the weekly data contained therein. I use the Bureau of Labor Statistics' website to adjust the monthly gas prices for inflation in 2016 terms.

I use the State of California's Department of Transportation (Caltrans) 2011 HOV Annual Report for District 7 to gain insight of the HOV lane openings. No HOV Annual Reports were available at the time of research for years after 2011. The 2012, 2013, and 2014 reports were never completed, according to a Caltrans spokesman, while the 2015 report was to be completed "soon." With this, anticipated opening dates (rather than confirmed opening dates) were used for the I-405 HOV lane. As seen in Table 2, the HOV/HOT lane openings happen in 2012 and 2013.

## 4 The effect of HOV/HOT lane creation on transit ridership

Figures 4 and Figure 5 plot the pre- and post-HOV/HOT lane ridership data for method 1 and method 2, respectively. I will begin by reviewing results from the first method. Figure 4 marks the pre- and post-HOV/HOT lane ridership data showing a rather insignificant immediate shift in ridership for all of the observed lines. However, there does seem to be a general decline in transit ridership for all of the observed lines after the HOV/HOT lane opening, except for the Silver Line. Figures 6-9 show the pre- and post-HOV/HOT lane introduction for each observed line. Reviewing these results allow the reader to see each observed line's trend more closely.

As can be seen through the progression table showing various results of the first method (Table 3), the intercept shifts are dramatically important regarding the magnitude and sign of the coefficient, as is accounting for the differential trends. Otherwise the results are positive and large. Using the basic model (without accounting for fixed effects, intercept shifts and differential trends), the results suggest that an HOV/HOT lane introduction is associated with an increase in transit ridership of 19.2 percent. When including seasonal effects, line effects, and line effects\**trend* (all dubbed as “fixed effects” in the column of the Table 3), along with generating intercept shifts and differential trends the results become negative. To explain further, in Table 3, each extension, along with the Purple Line data combination, are dummies that equal one after the opening of the correlated extension and data combination. This creates the intercept shifts. Further, the extension\**trend* and the Purple\**trend* variables in Table 3 multiplies the correlated dummies by the Red Line's trend (i.e., slope) to compensate for the extreme differential trend seen in Figure 1. As seen in the second column of Table 3, the introduction of an HOV/HOT lane is associated with a -5.75 percent decrease in transit ridership.

When the natural log of gas is used as a control in the regression, the coefficient for HOV/HOT lane increases about 1 percentage point showing that there was omitted variable bias when not including gas prices as a control. The final results indicate that an HOV/HOT lane introduction is associated with a -4.76 percent decline in transit ridership.

The second method shows a negative relationship, as well. With omitting the pre-2006 Red Line data, the results suggest there is an associated decline of -4.69 percent in public transit ridership after the introduction of an HOV/HOT lane. As seen through Table 4, accounting for seasonal effects, line effects, and line effects\**trend* (all dubbed as “fixed effects” in the table) has a large impact on the results. Including fixed effects ultimately changes the coefficient from 26 percent to -5.74 percent. Once again, controlling for gas prices increases the HOV/HOT lane coefficient from -5.74 percent to -4.69 percent.

The results are similar for either method, which shows robustness in the results. Further, both results are significant ( $p < 0.05$ ) and have the same adjusted r-squared. The first method requires accounting for intercept shifts and differential trends due the Red Line extensions, but I’m able to maintain the entire sample. The second method is much less complex, but loses a fair amount of observations.

## **5 Discussion**

Qualifications to this research are justified, as there are limitations. First, with only using Los Angeles as a sample, my results are limited to Los Angeles. Further research would need to be done to prove that other cities’ commuters behave similarly. This is especially notable in cities with very large growth in public transit ridership such as Tampa (Anbinder 2015). Further,



only the railways and busways with parallel HOV/HOT lane openings were investigated. This limited the data available. By only using these rails and busways there are other forms of public transit that still must be investigated such as buses. However, I believe that because the demographics of bus riders tend to be more disadvantaged than rail riders, the results would be even less substantive as bus riders have less access to vehicles to form carpools. Second, and the most substantial limitation to my study, is the fact that actual HOV lane opening dates were not available because the 2012, 2013, 2014 and 2015 HOV Annual Reports were not compiled at the time my research was conducted. Due to this limitation, I was left with only the anticipated openings stated in the 2011 HOV Annual Report, which may have a large impact on the results. Further research would need to be done with updated HOV/HOT lane openings.

It would also be worth investigating the effect of transit line openings on HOV/HOT lane traffic. If my results hold, I would predict that HOV/HOT lane traffic would either stay the same or increase when a parallel transit line is introduced. An even better model to investigate is one that reviews both HOV/HOT lane traffic and transit ridership.

In my model, I do not directly control for fare rates because I've included various fixed effects and fare rates are not volatile. However, Iseki and Ali (2014) found that fare rates affect ridership more than gas prices do. In a future model, including fare rates may have a large impact on results.

For the sake of my research I only count an HOV/HOT lane as introduced or open when both the northbound and southbound lanes are open, assuming that public transit riders would only alternate if there was a faster method for both directions of their travel. However, future

researchers should analyze if commuters do in fact behave in this way. This includes adding to a large literature on mode choice.

Policy implications are difficult to determine from these results, as a reduction in 4.69 percent to 4.76 percent of transit riders is likely not substantial enough to warrant much worry from policy makers. However, this may compound over time for several transit lines, which could have a dramatic impact on how many more cars are on the road. This can lead to a large and unintended environmental impact, which should be considered.

Using the mean of the full sample of ridership, assuming each carpool has three people, my results indicate there would be an additional 1,575-1,600 cars on the road each weekday. Under the same conditions, except now assuming each carpool has two people there would be an additional 2,364-2,399 cars on the road each weekday. Lastly, if each car only has one driver and uses a HOT lane, there would be an additional 4,727-4,798 cars on the road each weekday. This is a large number of cars, especially if the majority of these drivers' travel happens during peak traffic times. This can mean greater congestion for mainline and HOV/HOT lanes, which increases travel time (thereby increasing travel costs) and increases CO<sub>2</sub> emissions. Policy makers may want to advocate for non-parallel HOV/HOT lanes and transit lines to avoid this substitution. Although, this would prove challenging for busways, as the HOV/HOT lanes are usually used for public transit, as well.

As with most policy, depending on the value judgment of the policy makers they may or may not be more inclined to move forward with building an HOV/HOT lane to increase travel efficiency and lower travel costs. Or they may be more inclined to build a rail line to hopefully

diminish the environmental impact of commuting. Nonetheless, this research can be used as a foundation to further examine the relationship between modes of transit.

## **6 Conclusion**

The objective of my thesis was to understand if HOV/HOT lanes are substitutes or complements to public transit. The implications of this study provides policy makers more information of commuter preference and choice when determining which commuting infrastructure(s) would be best to invest in and construct. Further, no prior empirical research has been done on this particular topic through there is a large amount of literature for transportation economics. Because riders may choose to commute via the fastest travel method, thereby diminishing their travel costs, I hypothesized that transit riders would substitute from public transit to HOV/HOT lane use. I use Los Angeles Metro ridership data, Caltrans HOV/HOT lane openings, and EIA's gas prices, adjusted for inflation in 2016 terms from 1990-2015.

Using two various methods, I find that the results from either are similar and therefore robust. The first method compensates for the Red Line's extensions and the Purple Line and Red Line data combination. It does so by using dummy variables to create intercept shifts and then multiplying the dummy variables by the Red Line's trend to account for the differential slope in the Red Line. The second method is less complex, but loses observations because it omits the Red Line's pre-2006 data. Both methods use the natural log of gas prices as a control, given gas prices can have an impact on transit ridership and traffic congestion, as discussed in the literature review. Both methods also use seasonal quarter-mean effects, line effects, and line

effects\**trend*, as well. The first method produces results showing there is an associated -4.76 percent decrease in transit ridership upon the introduction of an HOV/HOT lane. The second method produces results showing there is an associated -4.69 percent decrease in transit ridership upon the introduction of an HOV/HOT lane. Either method creates results that are statistically significant ( $p < 0.05$ ).

Further, the impact of the negative relationship found could be as much as an additional 4,798 cars per weekday on the road. This could have detrimental implications on congestion, which would highlight Anderson's (2013) finding, terrible increases in travel time costs, and a heavy environmental impact that could create unintended externalities. Nonetheless, there are limitations to this research given the assumptions I make, and the limited data available.

Overall I find there is a statistically significant impact of an HOV/HOT lane introduction on public transit ridership. This research lays the foundation for further research to be done so policy makers can be well informed of observed commuter behavior. My research suggests that there can be significant consequences on traffic congestion, travel time costs, and environmental impact if this is not taken into consideration.

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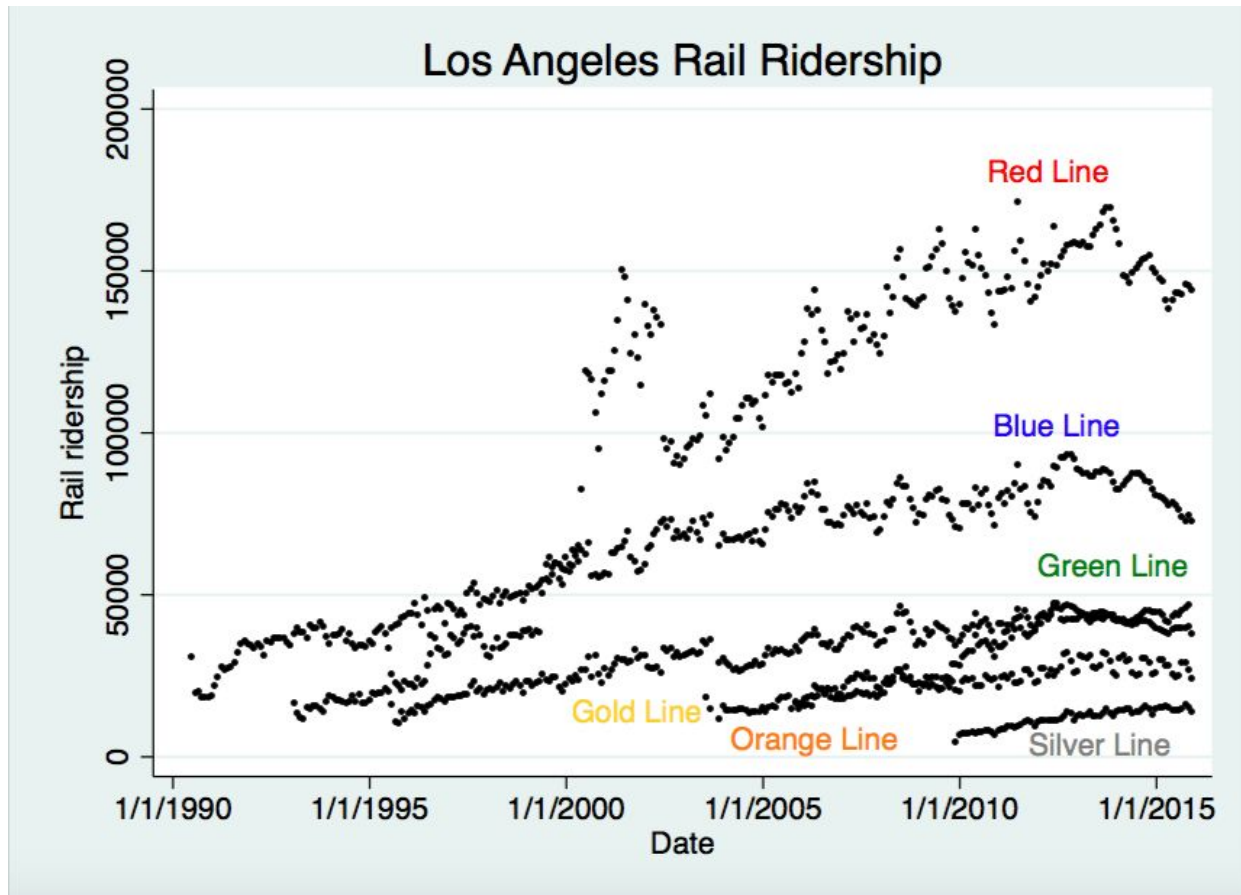
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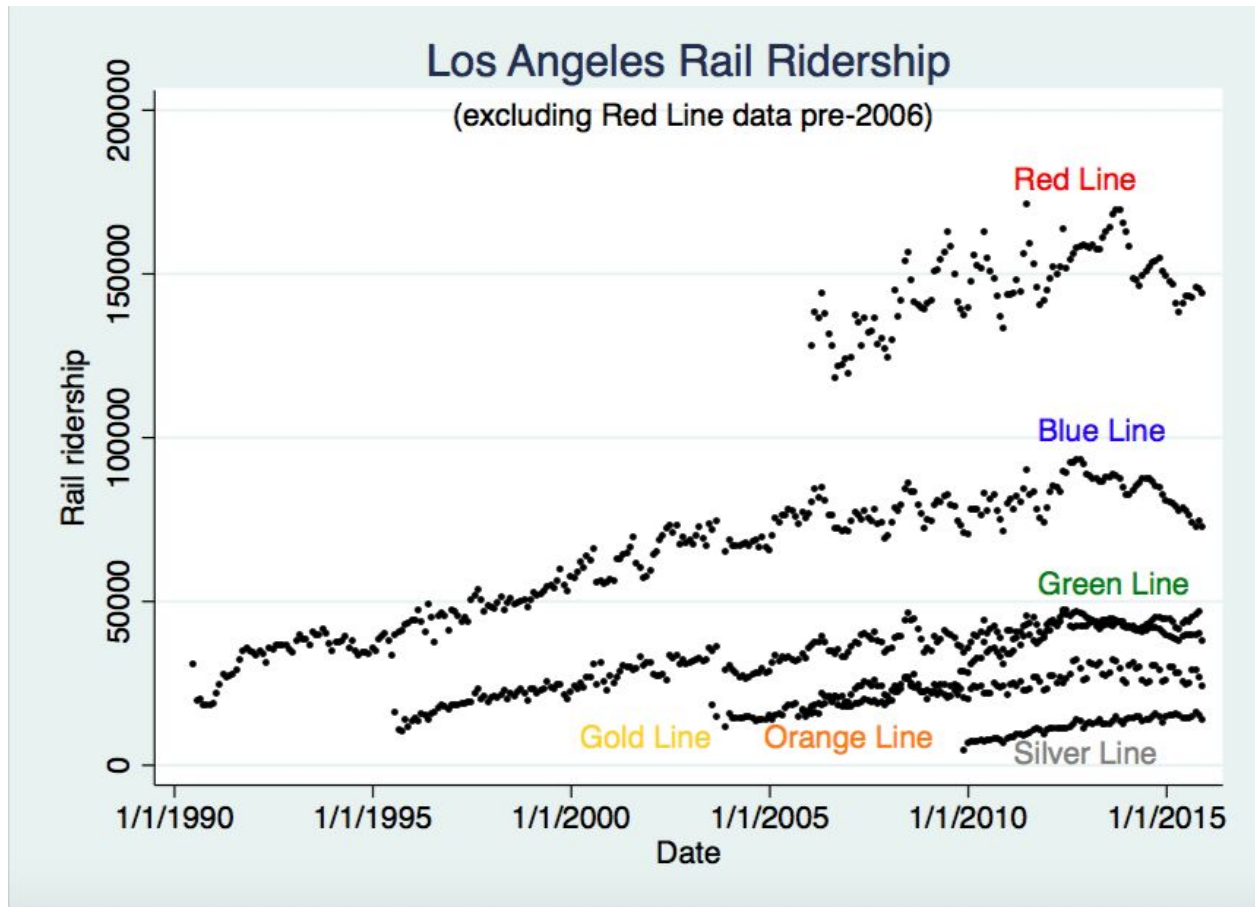
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## 7 Figures

**Figure 1:** Full sample dataset of transit ridership, scattered by month.

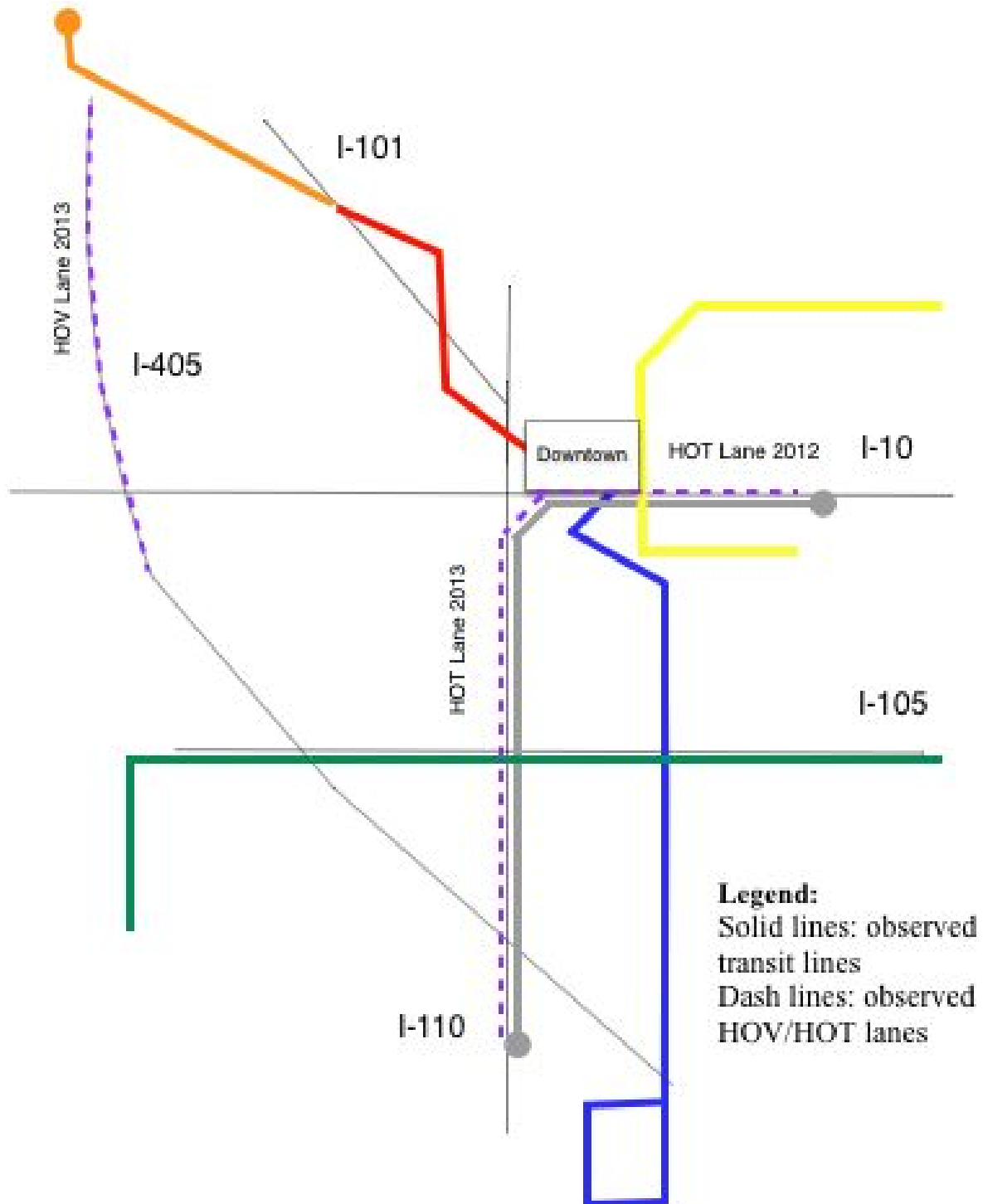


**Figure 2:** Partial dataset excluding pre-2006 Red Line data, scattered by month.

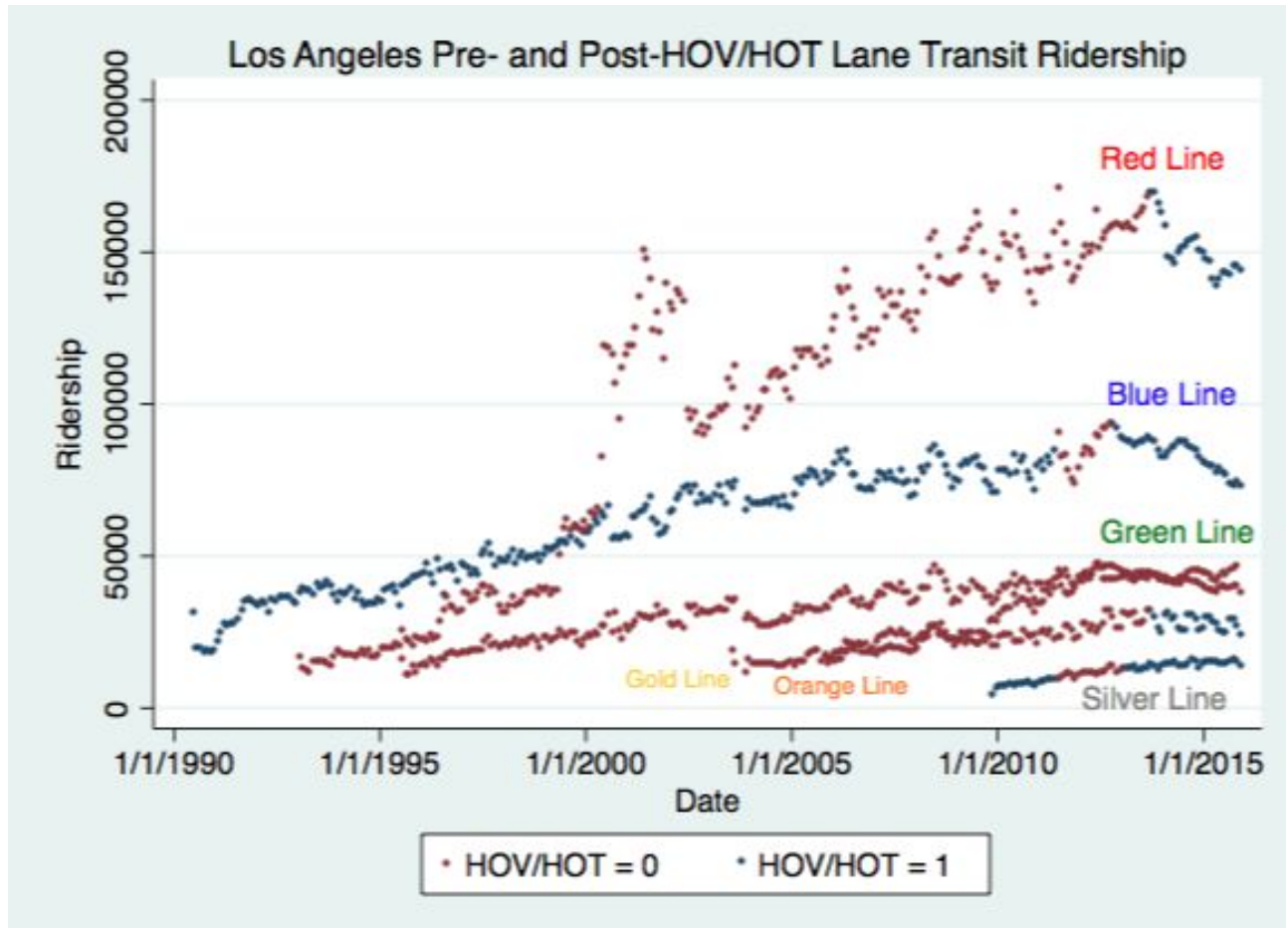




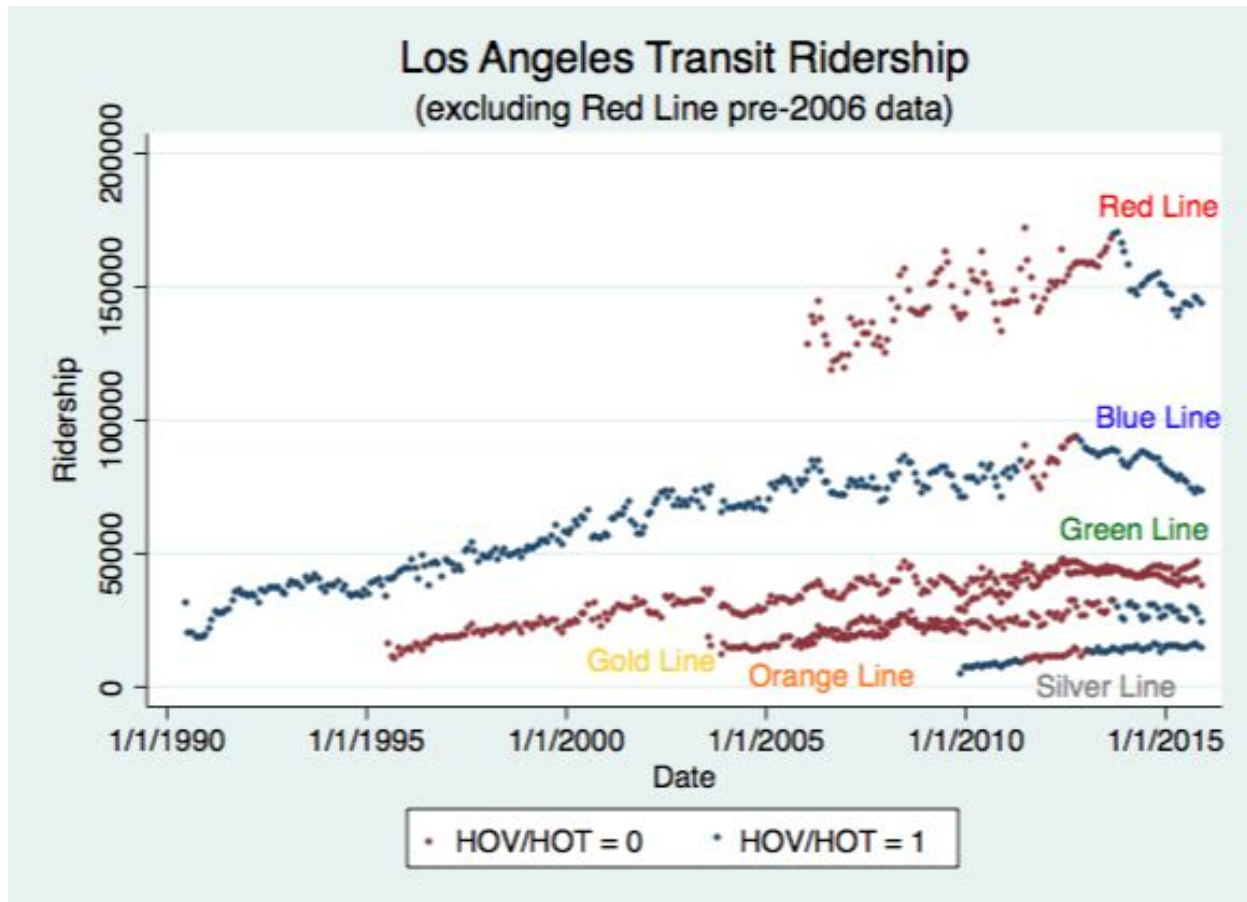
**Figure 3:** Los Angeles Map of observed lines and parallel HOV/HOT lanes. The treatment groups include: the Blue Line rail with I-110 HOT lane, Silver Line busway with I-110 HOT lane, Red Line rail with I-405 HOV lane, and Orange Line busway with I-405 HOV lane. The control group includes: the Green Line and Gold Line.



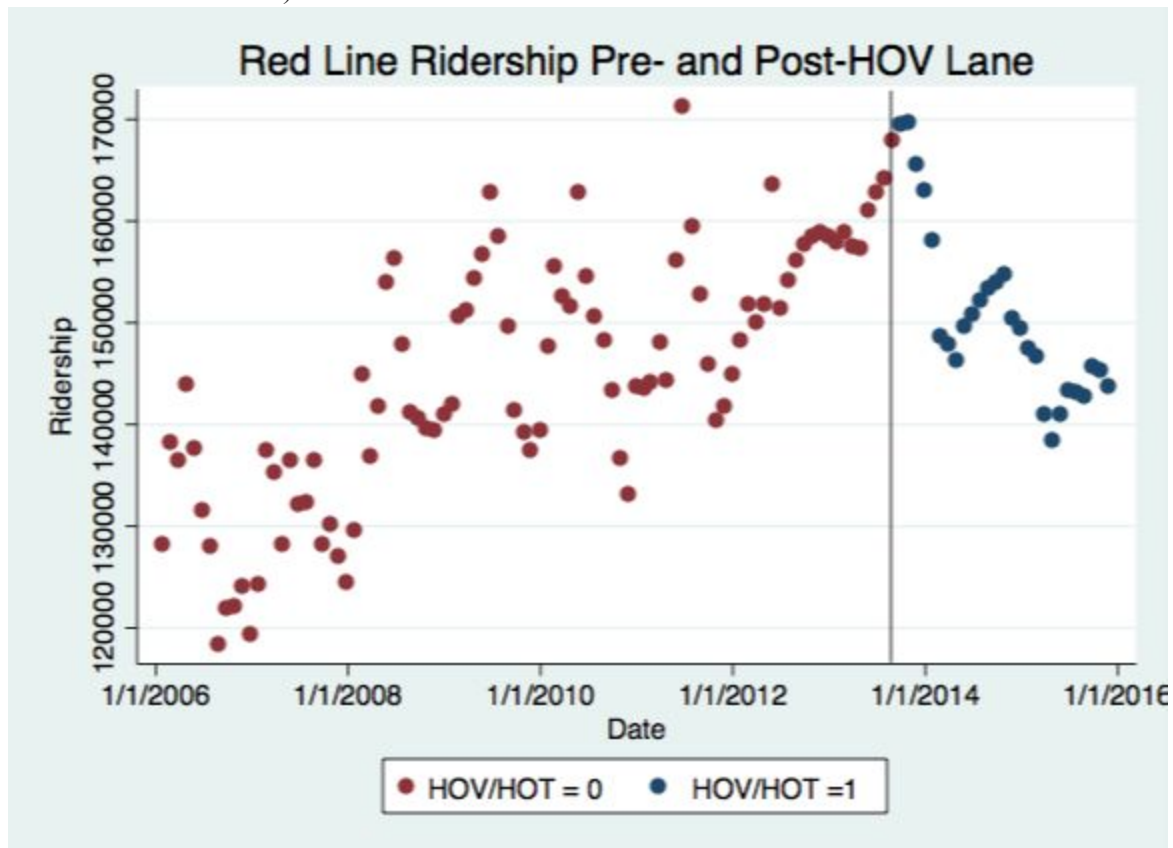
**Figure 4:** Full sample pre- and post-HOV/HOT lane transit ridership, scattered by month.



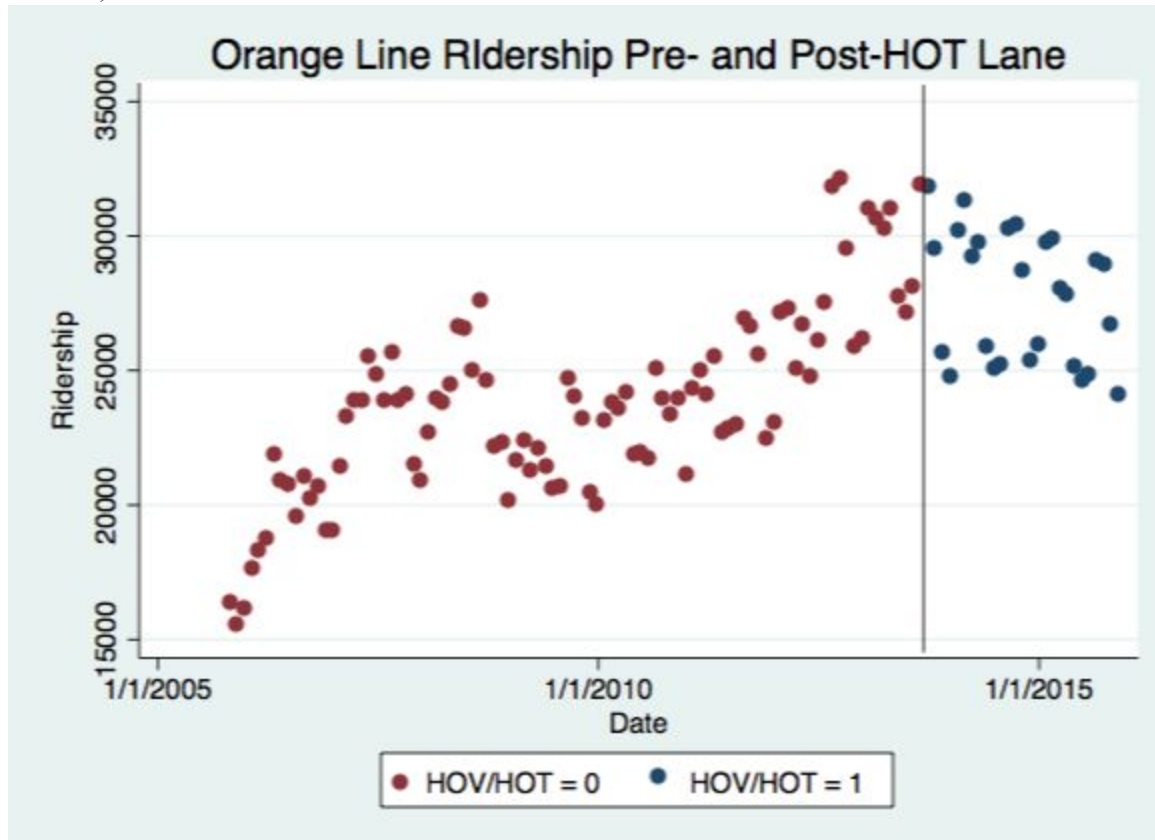
**Figure 5:** Partial dataset, excluding pre-2006 Red Line data, pre- and post-HOV/HOT lane, scattered by month.



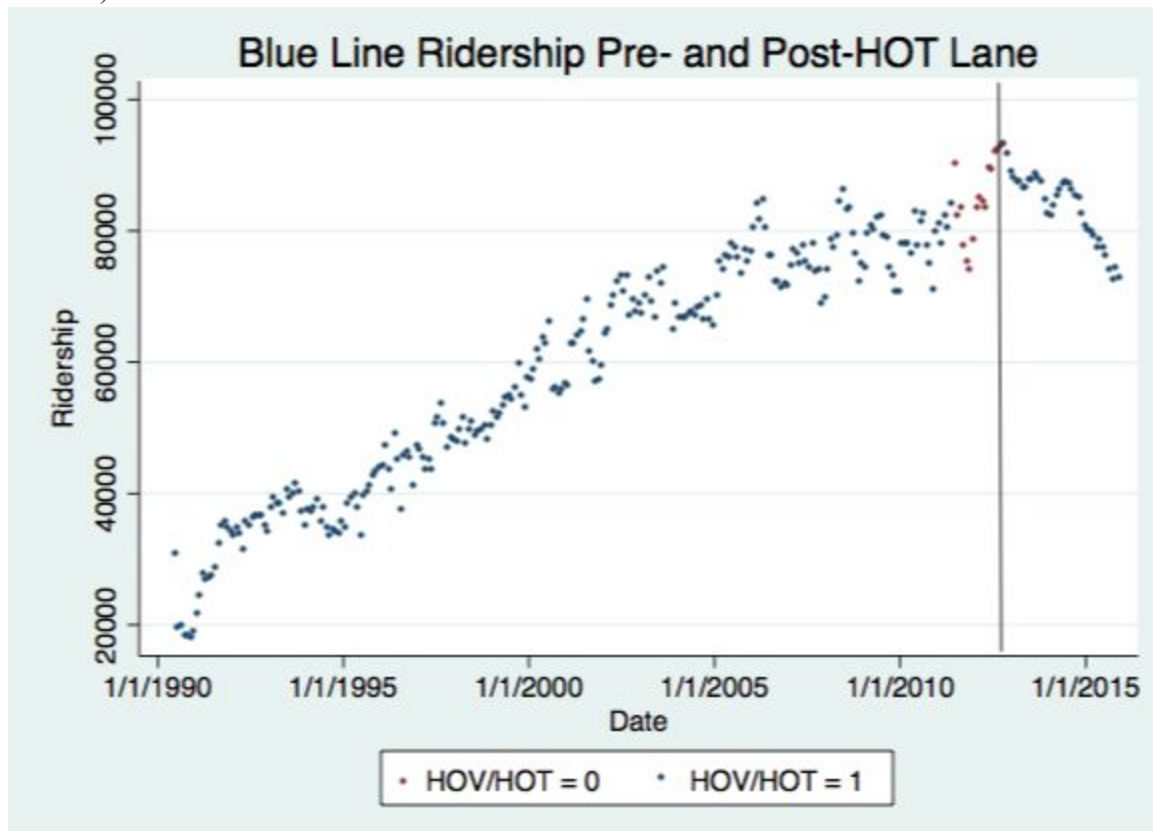
**Figure 6:** Red Line rail ridership pre- and post-HOV lane, excluding pre-2006 data ( $hov = 1$  October 2013 onward).



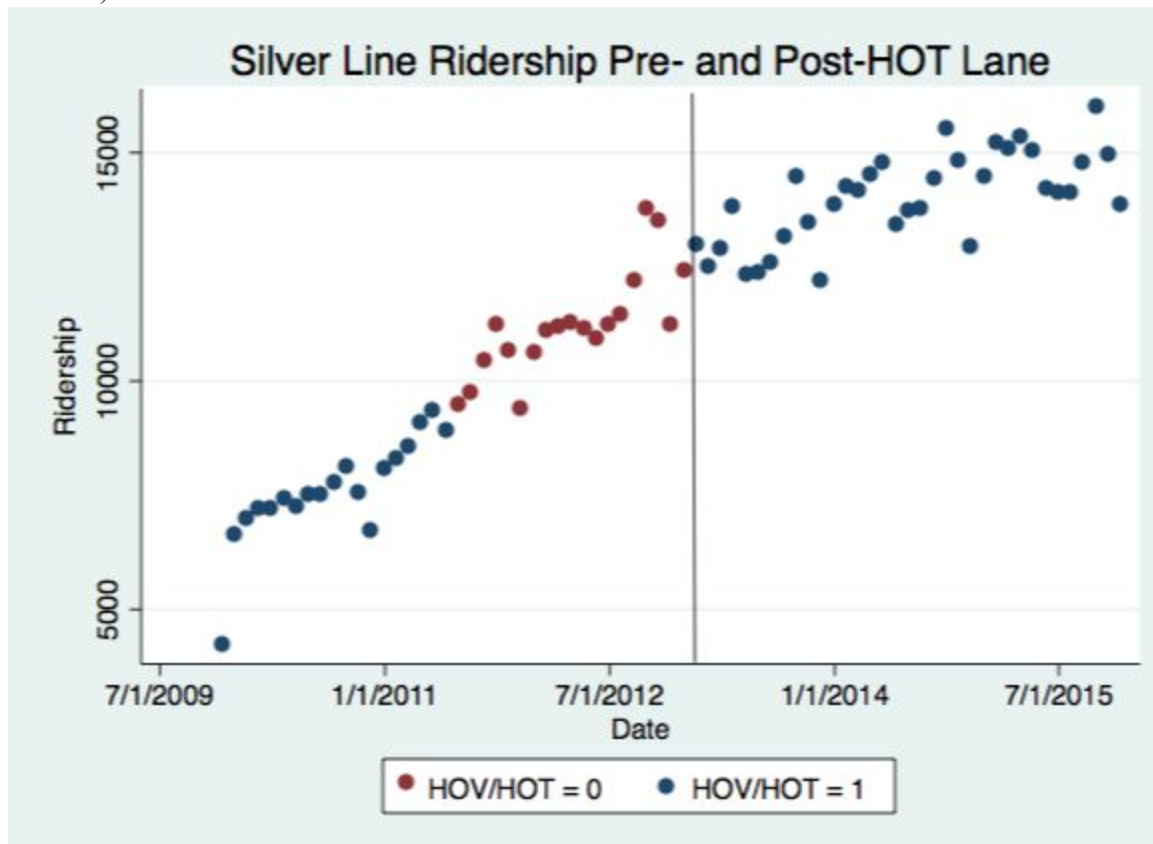
**Figure 7:** Orange Line busway ridership pre- and post-HOT lane ( $hov = 1$  from October 2013 onward).



**Figure 8:** Blue Line rail ridership pre- and post-HOT lane ridership (*hov* = 1 November 2012 onward).



**Figure 9:** Silver Line busway ridership pre- and post-HOT lane (*hov* = 1 February 2013 onward).



## 8 Tables

**Table 1:** Summary statistics for method 1 (full sample) and method 2 (partial Red Line sample).

<b>Lines</b>	<b>Observations</b>	<b>Mean</b>	<b>Std. Dev.</b>	<b>Min.</b>	<b>Max.</b>
Method 1: Full Sample					
<b>Red Line</b>	273	100782.5	51905.54	11430	171163
<b>Orange Line</b>	122	24621.98	3634.196	15491.82	32069
<b>Silver Line</b>	73	11596.89	2864.396	4208	15990
<b>Blue Line</b>	304	62132.77	19259.34	18075	93201
<b>Green Line</b>	243	32438	9053.558	10400	47214
<b>Gold Line</b>	146	29394.5	11713.83	11414.51	47025
<b>All</b>	1,161	53769.58	40922.36	4208	171163
<b>Lines</b>	<b>Observations</b>	<b>Mean</b>	<b>Std. Dev.</b>	<b>Min.</b>	<b>Max.</b>
Method 2: Partial Sample (excluding pre-2006 Red Line data)					
<b>Red Line</b>	119	146144.3	11653.49	118278.9	171163
<b>Orange Line</b>	122	24621.98	3634.196	15491.82	32069
<b>Silver Line</b>	73	11596.89	2864.396	4208	15990
<b>Blue Line</b>	304	62132.77	19259.34	18075	93201
<b>Green Line</b>	243	32438	9053.558	10400	47214
<b>Gold Line</b>	146	29394.5	11713.83	11414.51	47025
<b>All</b>	1,007	51940.44	40307.8	4208	171163



**Table 2:** Table showing the HOV/HOT lane roads, opening dates, and the corresponding treatment group transit lines.

HOV/HOT Lane Road	HOV/HOT Lane Opening	Corresponding Transit Line
I-110 (HOT)	November, 2012	Blue Line
I-10 (HOT)	February, 2013	Silver Line
I-405 (HOV)	October, 2013	Orange Line and Red Line

**Table 3:** Progression table showing the first method's effect of HOV/HOT lane introduction on transit ridership. Standard errors are in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

Variables	Basic Model	Adding Red Line intercept changes, differential trends, and fixed effects	Add gas prices
HOV/HOT Lane	0.192*** (0.0454)	-0.0575*** (0.0180)	-0.0476** (0.0184)
Hollywood extension		0.0144 (0.780)	0.115 (0.779)
Hollywood*trend		0.0379 (0.0758)	0.0273 (0.0758)
N. Hollywood extension		1.855** (0.770)	1.826** (0.768)
N. Hollywood*trend		-0.114 (0.0734)	-0.111 (0.0732)
Purple Line data combination		-0.418*** (0.159)	-0.476*** (0.160)
Purple Line*trend		0.0380*** (0.0103)	0.0412*** (0.0104)
Wilshire extension		1.015*** (0.212)	.998*** (0.211)
Wilshire*trend		-0.102*** (0.0292)	-0.0992*** (0.0291)
ln(gas)			0.0627** (0.0255)
Seasonal Effects	no	yes	yes
Line Effects	no	yes	yes
Line Effects*Line trend	no	yes	yes
Constant	10.56*** (0.0265)	10.39*** (0.0252)	10.35*** (0.0291)
Observations	1,161	1,161	1,161
R-squared	0.016	0.973	0.973

**Table 4:** Progression table showing the second method's effect of HOV/HOT lane introduction on public transit ridership. Standard errors are in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

Variables	Basic Model	Add all fixed effects and differential trends	Add gas prices
HOV/HOT Lane	0.260*** (0.0462)	-0.0574*** (0.0183)	-0.0469** (0.0187)
ln(gas)			0.0665** (0.0268)
Seasonal Effects	no	yes	yes
Line Effects	no	yes	yes
Line Effects*Line trend	no	yes	yes
Constant	10.49*** (0.0290)	10.39*** (0.0257)	10.35*** (0.0299)
Observations	1,007	1,007	1,007
R-squared	0.031	0.971	0.971