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UNIVERSITY OF CALIFORNIA,
IRVINE

**Impacts of Smartphone Transit Applications on Transit Ridership
Applications to Los Angeles County and Berlin**

THESIS

submitted in partial satisfaction of the requirement
for the degree of

MASTER OF SCIENCE

in Civil Engineering

MASTER OF URBAN AND REGIONAL PLANNING

by

Priyoti Ahmed

Thesis Committee:
Professor Jean-Daniel Saphores, Chair
Associate Professor Wenlong Jin
Assistant Professor Doug Houston

2015

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Abstract of the Thesis

Impacts of Smartphone Transit Applications on Transit Ridership

Applications to Los Angeles County and Berlin

By

Priyoti Ahmed

Master of Science in Civil Engineering and Urban and Regional Planning

University of California, Irvine 2015

Professor Jean-Daniel Saphores, Chair

This research investigates the influence of smart phones applications on transit ridership and transit riders' behavior in Los Angeles and in Berlin. In Los Angeles County, monthly ridership is observed before and after the emergence of smartphone applications (apps). A fixed effects panel model is estimated to explain monthly ridership using variables that likely affect monthly ridership to estimate the impact of smartphone apps. I find that, train ridership increased by 0.02 due to the emergence of smartphone apps but that bus ridership was not impacted. In Berlin, the effect of smartphone application is captured through various interviews and a survey of students and faculty of Humboldt University. An analysis of the results shows that transit riders mostly seek and value information related to bus, transfer connectivity, and leisure activities.

Keywords: transit; ridership; smart phone application; panel data; survey.

1. INTRODUCTION

In 2007, the launch of the iPhone radically changed the way people communicate and get information. This device introduced features such as touch screens, Internet connection and “applications,” which became a medium for firms to connect with costumers to sell their products and services. The iPhone started popularizing smart phones, not only from Apple but from many other manufacturers including Samsung, LG, Motorola, HTC, or Sony to name a few. As of March 2015, 187.5 million people in the United States owned smartphones (comScore, 2015).

The availability of smartphones has changed many aspects of people’s lives, including how they travel. Today some of the popular transportation apps provide information about navigation, current traffic conditions, real-time bus/rail arrival times, transit planning, and ticket purchasing options. Apps also allow travelers to compare the travel time (time spent in traffic congestion vs. waiting time for transit) and travel cost (gas prices vs. fare) of different modes, making it easier to find the shortest and cheapest travel options.

The availability of this information has the potential to change people’s attitudes toward public transit and to boost ridership (Waktins, 2010). Public transit offers many benefits to society, including enhanced accessibility to education, jobs, and leisure activities, as well as reductions in traffic congestion, gasoline consumption and carbon footprint (Taylor *et al.*, 2008). Many public transit systems have not reached their full potential because of potential riders are concerned about the variability and the

uncertainty of arrival time, limited connectivity, in addition to safety and comfort. To address the first set of concerns, public transit companies have strived to collect more information about the location of their vehicles and to provide this information to their patrons. The availability of global positioning system (GPS) data was a necessary first step for addressing reliability concerns, but it was only part of the solution because location information had to be communicated in real time to the public. Smart phone apps can provide that missing link.

To-date, the impact of smart phone apps on transit ridership seems to have received relatively little attention in the transportation literature. The purpose of this thesis is therefore to start filling this gap. More specifically, this thesis investigates how the availability of real-time transit information received via smart phones affects the number and the behavior of transit riders. These questions are examined in two case studies.

The first case study analyzes the impact of smart phone transit apps on the ridership of trains and buses in Los Angeles County, California. Even though the Los Angeles County Metropolitan Transportation Authority (Metro) is the second largest public transit agency, the share of public transit in Los Angeles County is only approximately 11%, which is far behind the mode share of automobiles (Freemark, 2010). Currently, the transit system is growing (with 2 new rail lines under construction) and changing rapidly. Given the high penetration rate of smartphones in Los Angeles, it is therefore of interest to find out if smartphone transit apps could help enhance transit ridership.

The purpose of the second case study is to understand how smartphone apps influence people's perception and use of public transit in a world city when transit has reached a mature stage, with an application to Berlin, Germany. Currently, the share of

transit in Berlin is approximately 26%, which is more than double the share of Los Angeles (Passenger Transport Mode Shares in World Cities, 2011). Information about perceptions of transit and smartphone apps were collected via 10 interviews and a survey of Humboldt University students, faculty, and staff conducted during winter of 2015.

Overall, this thesis considers the following questions:

1. In Los Angeles, did transit ridership increase as a result of the introduction and use of transit smartphone apps?
2. In Berlin, is mode choice influenced by the availability of transit information? Is there a difference in perceived wait-time between smartphone and non-smartphone users?

This thesis is organized as follows. Section 2 summarizes selected papers dealing with technology and transit ridership. Section 3 presents the Los Angeles case study, and Section 4 analyzes the Berlin case study. Finally, conclusions and ideas for future research are presented in Section 5.

2. LITERATURE REVIEW

The impact of technology on transit ridership has received some attention in the transportation literature going back at least to the 1990s but the analysis of the impact of mobile applications is still in its infancy because this technology only emerged seven years ago. This chapter presents an overview of selected papers, which are further summarized in Table 1.

The transit ridership literature shows that ridership levels depend on a number of economic and social characteristics, including urban geography, metropolitan economic activity, and population characteristics (e.g., see Taylor *et al.*, 2003). Employment levels, population growth, and system fares also matter (i.e., see Kuby, *et al.*, 2004; or Kain, *et al.*, 1999). An extensive study by the Canadian Urban Transit Association found that ridership declines as fares increase and transit service hours decline, with impacts dependent on the city considered (Kohn, 1999).

In a recent study of the Metropolitan Tulsa Authority, Chiang *et al.* (2011) reported a statistically significant travel elasticity of fare, which suggests that Tulsa Transit will lose 50,000 passengers if trip fares increase by \$1 per day. In an extensive literature review of transit ridership factors, Talyor *et al.* (2008) found that the quality of service is more important than the quantity of the service. Reliability and a sense of security are equally important as frequency and accessibility. Most importantly for this work, results from a survey conducted in Sacramento and Santa Clara, California, show that 58.6% of riders would likely take transit if more information were available (i.e., Talyor *et al.*, 2008).

Smartphone technology, which processes GPS data and displays information about

travel time, traveling cost, route update on a user-friendly device, only emerged in the last 5 years (Google Map Achieve, 2009). Thus, few published papers focus on the link between mobile use and transit ridership. However, a number of papers have analyzed the impact of real time information on ridership (Hickman *et al.*, 1995). Bachok (2007) analyzed the information travelers need to navigate through public transportation based on a survey of 537 passengers of the commuter-rail serving Klang Valley in Malaysia. Bachok (2007) reported that travelers find system updated information especially useful if it is given before they travel.

Using a mixed effect model, Tang *et al.* (2012) concluded that bus trackers implemented in Chicago resulted in ridership increases of 1.8 to 2.2% depending on the line considered. Their explanatory variables include population, bus fare increases, service frequency, unemployment rate, extreme weather indicators, and gas price.

The availability of real-time information is also impacting travelers' perception of public transit. For example, the ShuttleTrac system implemented at the University of Maryland resulted in increases of two psychological indicators among riders (Zhang *et al.*, 2007). The ShuttleTrac system shows real-time bus arrival times, and it includes an interactive system at an activity center, an interactive telephone system and a website. Zhang *et al.* (2007) developed two-fixed effects model and five-random-ordered probit model estimated on 1679 students of the University of Maryland. Their two behavioral models (monthly shuttle trips and monthly campus-based shuttle trips) included five psychological behaviors: feeling of security during the day and after dark, the perception of on-time performance of the shuttle service, the anxiety level while waiting for a shuttle, and the overall level of satisfaction. Results show that increases in security perception and

in overall system satisfaction (psychological behavior) are significantly correlated with use of the ShuttleTrac system.

Along with increases in security perception and satisfaction, real-time information reduces the perceived waiting time. The research on OnebusAway application in the Seattle area (Watkins *et al.*, 2011) investigated the link between app use and perceived waiting time of riders based on 655 interviews of riders at bus stops near the University of Washington. They found that passengers who depend on real time information are waiting 2 minutes less than passengers who depend only on published schedules. Another study at the University of Ohio (Mishalani *et al.*, 2006) investigated differences between perceived and actual wait-times. Over a year, 83 students were surveyed about actual and perceived wait-times. Based on linear regression models, Mishalani *et al.* (2006) found that perceived wait-time is greater than actual time. The perceived wait-time becomes closer to actual wait-time when time constraints are few.

Several studies have analyzed the ability of cell phones to provide real time information about transit thanks to apps that allows riders to track the location of buses and underground trains thanks to their motion detectors, GPS, and accelerometers. For example, Thiagarajan *et al.* (2010) show that knowing the location of transit vehicles can help reduce wait time by 2 minutes with 5% riders using these tracking apps.

Common models in the papers reviewed include linear regression and Poisson count models, where ridership is explained using multiple factors. In this work, I rely instead on a simple panel data model to identify changes in ridership behavior (Tourangeau *et al.*, 1997).

Table 2-0-1: Summary of Selected Papers

Authors & Year	Area & Data	Methodology	Main Findings
Bachhok, 2007	Effectiveness of Passenger Information (PSI) for commuter rail in Klang Valley, Malaysia. Researchers surveyed 583 users.	Survey question analysis	Long-term rail information is preferred compare to the short-term service updated information.
Hickman and Wilson, 1995	Massachusetts Bay Transportation Authority (MBTA) transit riders origin and destination choices based on real-time information.	Path choice model which includes travel time and real-time information	Real-time information does not benefit transit ridership in any major way.
Kain and Liu, 1999	Factors of transit ridership in Houston “(all bus) and San Diego (bus and light rail) including fare, employment, population and annual transit ridership over 16 years	Cross-sectional dataset of transit ridership, employment and population growth.	Transit increases happens due increase in population growth and employment and reduction in employment.
Kohn, 1999	Through Canadian Urban Transit Association members various transit related factors were evaluated over 7 years.	Multiple regression analysis were used to evaluate among fare, ridership and revenue	Increase in fare and decrease in service hours have negative impact on transit ridership but positive impact in revenue.
Kuby, Barranda, and Upchurch, 2004	Nine US cities’ 268 stations are evaluated to find factors which affect transit ridership. The ridership data include average weekday boardings over a year.	Multiple regressions is applied on various socio economic, location factor and average weekday ridership.	Variable were significant in these cities are employment, population, and percent renters within walking distance, bus lines, and park-and-ride
Mishalani et al., 2006	In Campus Area Bus Service (CABS) in Ohio State University 83 students were survey. The survey asked question regarding their perceived wait-time	Linear regression model was applied to actual and perceived wait-time and its socio-economic variables.	No evidence found that additional perceived wait-time varies with actual-time within the range of 3-15 minutes. Additionally, time-constraints bring actual and perceived wait-time closer.

Thaigarajan <i>et al.</i> , 2010	Chicago transit network is used to check for travelers wait-time in bus and train.	Development of an application where users report their location and application predict their arrival time.	With 5% of transit riders using this application expected wait-time is reduced by 2 minutes in Chicago.
Tourangeau, Zimowski, and Ghadialy, 1998	Survey design and appropriate methodology.		
Taylor and Fink, 2003	National analysis of transit ridership and their associated control variables.		Quality of service and pricing are more important than the offered quantity of service; the latter becomes important when there is built-up demand.
Zhang, Shen, and Clifton, 2007	Riders' behavior and psychology through the use of ShuttleTrac at the University of Maryland. The data are gathered through 3 types of surveys.	Two fixed and five random-effects ordered probit models.	The finding shows that real-time information increases rider's feeling of security after dark and boosted their overall satisfaction however, also finds that there no increase of transit ridership due to real-time information
Taylor <i>et al.</i> , 2008	The research data is gathered from National Transit Database (NTD) in year 2000.	Ordinary least squares	The researchers estimated the effect of transit ridership due to change in service or frequency.
Watkins <i>et al.</i> , 2010	Impact of mobile real-time information on the perceived and actual wait time of transit riders in Seattle area. Researchers interviewed 856 riders of the bus stops near University of Washington for their research design.	These surveys were used to develop 3 hypothesis which was estimated through statistical analysis	The study finds that usage of mobile application not only reduces the perceived waiting time but it reduced the actual wait time. Real-time information users wait 2 minute less than traditional schedule.
Ferris, Watkins, and Borning, 2010	The research investigates the experience of the Seattle transit	The evaluations of the measures were determined	The survey found that transit riders walked more.

	riders with the system and usage of OneBusAway application.	by the conducting two surveys.	
Chiang <i>et al.</i> , 2011	Forecasting Ridership for a Metropolitan Transit Authority	Variants of regression model- linear regression model and logarithmic regression model	A significant travel elasticity of fare (-0.3), which suggests that Tulsa Transit will lose 50,000 passengers if trip fares increase by \$1 per day
Tang and Thakuriah, 2012	Real-Time information affecting transit ridership in Chicago from 2002 through 2010.	This longitudinal data was applied in a mixed model to determine the transit ridership of before and after bus trackers	Bus-tracker increase the CTA ridership but it is modest and inconclusive due to geographical variations.

3. CASE STUDY 1: LOS ANGELES

3.1 Introduction

Setting the stage for this case study requires introducing the Los Angeles (LA) County Metropolitan Transportation Authority (LACMTA), which operates transit services in Los Angeles County, which is most populous county in the United States with a 2010 population of over 9.8 million people. In 1993, the California State Legislature created LACMTA through a merger of the Los Angeles County Transportation Commission and Southern California Rapid Transit District. Currently, this is the third largest agency responsible for operating the clean air CNG powered Metro fleet, Rapid Bus lines and Metro Rail Lines. Today, LAMATA serves in 170 bus routes and 87 miles of rail throughout Los Angeles County (Los Angeles Transit History). The tables below provide summaries the agencies' services throughout Los Angeles county. The frequency of the buses are more spread out on from 5-10 minutes during peak hour where the rail have more set schedule from 5-8 minutes during peak hour.

Table 3-1: Metro Rail Service Summary

Stations	80
Miles of Service	87
Number of Lines	4 Light Rail, 2 Subway

Table 3-2: Metro Bus Service Summary

Bus Stops	15,967
Square Miles in Service Area	1,433
Number of Bus Routes	170
Total Metro Bus Fleet	2,228
Buses leased to contractors to provide service on Metro routes (Included in total)	173

3.2 Emergence of Mobile Applications (Apps)

In 2009, LA Metro signed a public private partnership with Google Inc. to include Metro bus and rail lines on their transit map planner. Metro gave Google access to all 170-buses and five rail lines scheduled arrival times so it could report that information in its transit planner (“L.A. Metro Transit System Now on Google Maps, Los Angeles).

Real time information started becoming in 2010, when LA Metro contracted with NextBus, to use its patented technology to process data obtained from all buses in LA Metro’s fleet equipped with GPS devices. Nextbus in turn provided real-time or predictive bus arrival information to users by interfacing with various media including website-based traveler information service, LA Metro’s own public website, the nextbus.com website, as well as cell and smartphone text messaging. Note, however, that since GPS trackers only equip Metro buses; travel times for rail lines are still based on scheduled time. Since then NextBus has worked with LA Metro to create mobile transit apps, which includes function like trip planner, real-time bus arrival and locators (Metro-the Magazine, WebTech Wireless' NextBus Awarded L.A. Metro Contract, Los Angeles).

Figure 3-1: Study Area



3.3 Model Overview

This section introduces the statistical models estimated to assess the influence of smartphone transit apps on transit ridership in Los Angeles County. My starting hypothesis is that smartphone transit apps in LA could impact ridership level because LA's transit system is still growing and changing. For that reason, the models considered in this chapter explain transit ridership for buses and trains using a number of explanatory variables selected based on a review of selected papers and microeconomic considerations. Models are estimated separately for buses, trains, and for the combined ridership to tease out the impact of smartphone transit app on each mode because this information could help LA Metro operate its system better.

More specifically, three models were developed that explain the following dependent variables:

1. Monthly Weekday Bus Ridership
2. Monthly weekday train ridership
3. Monthly weekday train and bus ridership

The datasets are panel data of both ridership and socio-economic data and mobile apps usage from January of 2009 to December of 2013 in a monthly base, or roughly one year before the introduction of transit mobile apps (2010) to three year after. This enables the model to capture any seasonal changes over this time period.

In order to isolate the impact of transit mobile apps on ridership, it is important to control for other factors that may have influenced ridership levels during the study period,

including additions or cancellations of lines, reconfiguration of existing routes, strikes by transit workers, and impact of holidays.

During the study period, 7 bus lines were added and 21 lines were cancelled. To account for these changes, the ridership from added and canceled bus lines was subtracted from the dataset for consistency. Likewise, the ridership from the Expo rail line, which opened in 2012, was subtracted from the aggregate rail ridership.

Although some bus routes experienced some changes during the study period, these changes were minor. Unfortunately, they could not be accounted for because of limited available information.

There was no strike in LA Metro system between 2009 and 2013. Since the dependent variables are monthly average weekday ridership, it was important to account for holidays that fall during a weekday. These holidays were counted as Sunday when aggregated ridership is reported.

Finally, note that although bus routes GPS trackers were implemented at different times, when Nextbus was contracted all the bus routes were equipped with GPS so real time information was reported at the same time. Since rail lines do not have GPS, reported train arrival times are based on scheduled times.

3.4 Data Overview

In this research, transit ridership is assumed to be a function of fares, unemployment / employment, extreme weather events, gas prices, and transit app mobile downloads. Let us examine each variable in turn.

3.4.1 Depended Variables

The dependent variables in my models are monthly average weekday bus and train boardings from January 2009 to December 2013, taking holidays into account. Models were estimated separately for buses, trains, and for their combined ridership.

Bus ridership data were recorded by “automatic passenger counters aboard”, which are implemented in every bus and count passengers as they pass through narrow doorways. The bus ridership is then processed internally to check if the ridership was recorded and transmitted properly. The trains do not benefit from such a technology. Train ridership is recorded by human counters and a sampling method is applied to calculate average monthly train ridership.

Figures 1 to 3 show respectively average monthly train, bus, and combined ridership. Ridership has been increasing slowly over time and exhibits monthly fluctuations. For example, between December and January ridership typically decreases, which is not unexpected given the holiday season, and it increases in May due to tourism.

Figure 3-2: Average Monthly Train Ridership

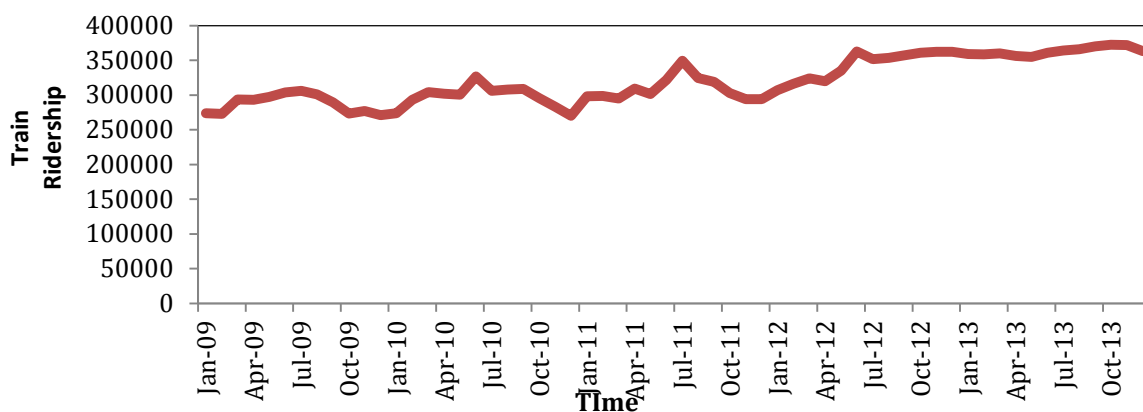


Figure 3-3: Average Monthly Bus Ridership

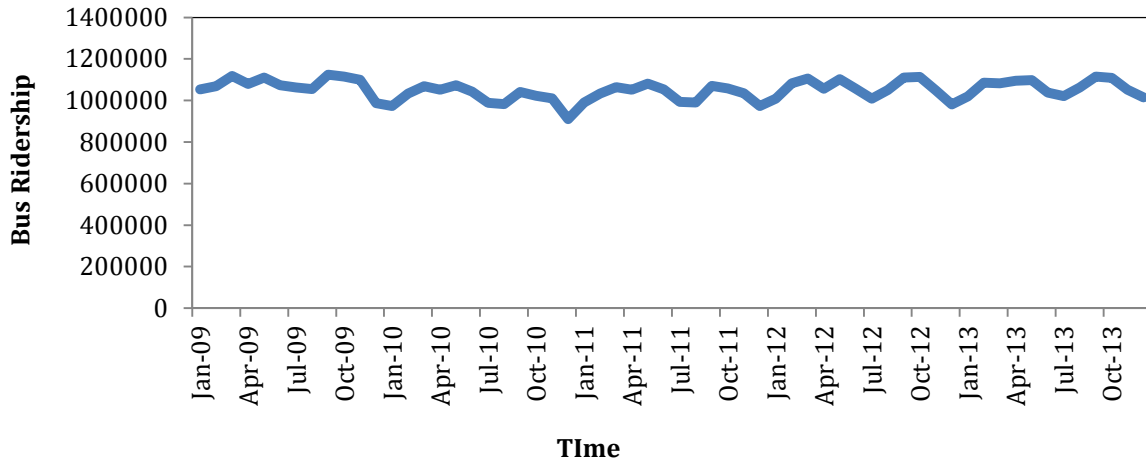
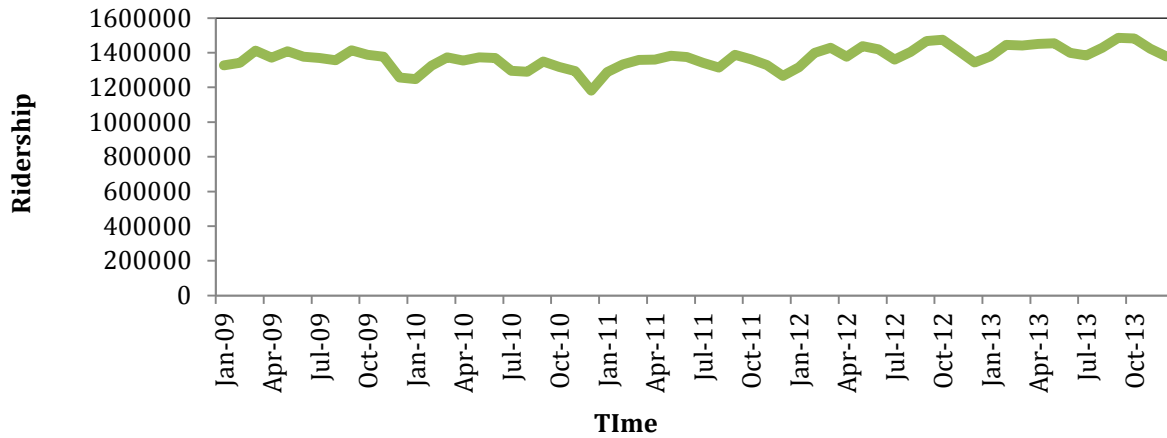


Figure 3-4: Average Monthly Bus and Train Ridership



3.4.2 Independent Variables

Explanatory variables for this research are factors that may affect transit ridership. They include unemployment rates, gas prices, fare changes and extreme weather events, all compiled on a monthly basis during weekdays. It would have been useful to also include population but this is not available on a monthly basis but population in LA County was relatively stable during the study period.

3.4.2.1 Mobile Application Visits

The variable of most interest for this research is mobile application visits. Currently available mobile apps for Los Angeles include NextBus, LA Metro and LA Metro Tracker. Mobile app visits counts are recorded by each of these entities and reported to LA Metro. These mobile app visit statistics take into account all mobile apps available to riders, and they represent the number of times transit apps are opened. Although there is a possibility of redundancy as travelers may visit pages more than once, especially for more complex trips, this inflation is consistent throughout the study period and it is currently the best way to measure mobile app usage.

Figure 3-5: Application Index

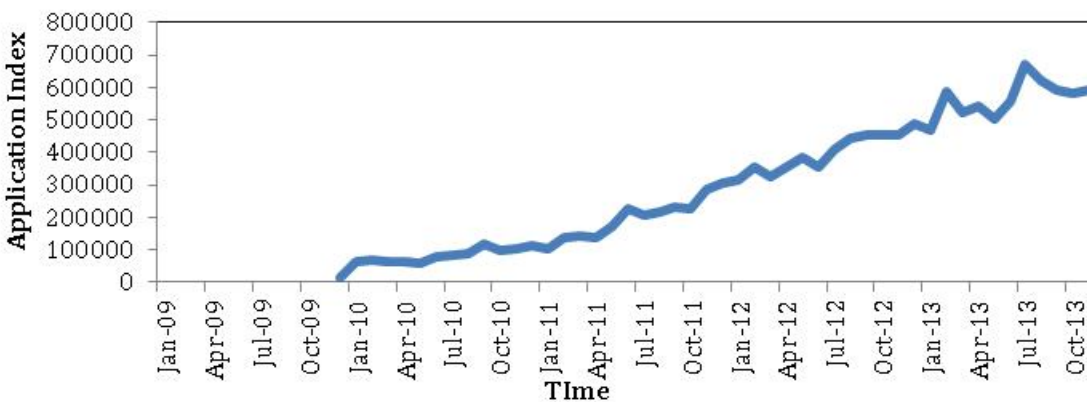
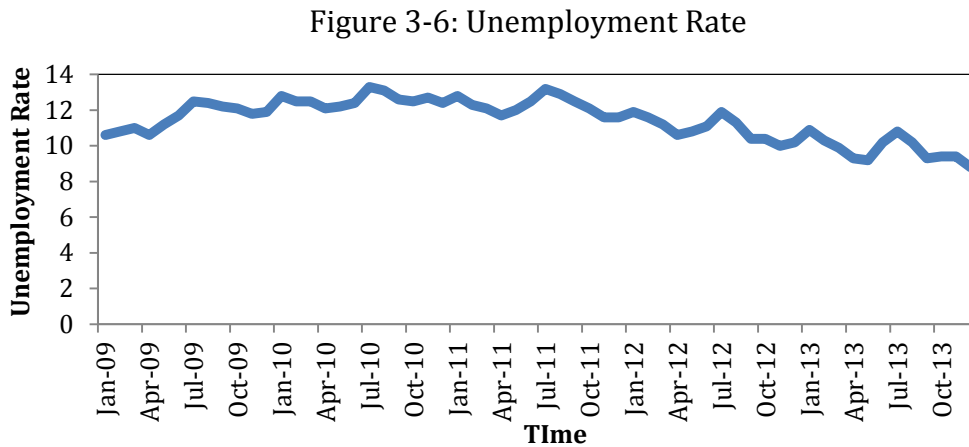


Figure 4 shows the application index (i.e., the number of transit page visits) for the study period. It shows a steep increase in page visits, starting in 2010 when that service was introduced, until later in 2013, which saw a dip in transit page visits.

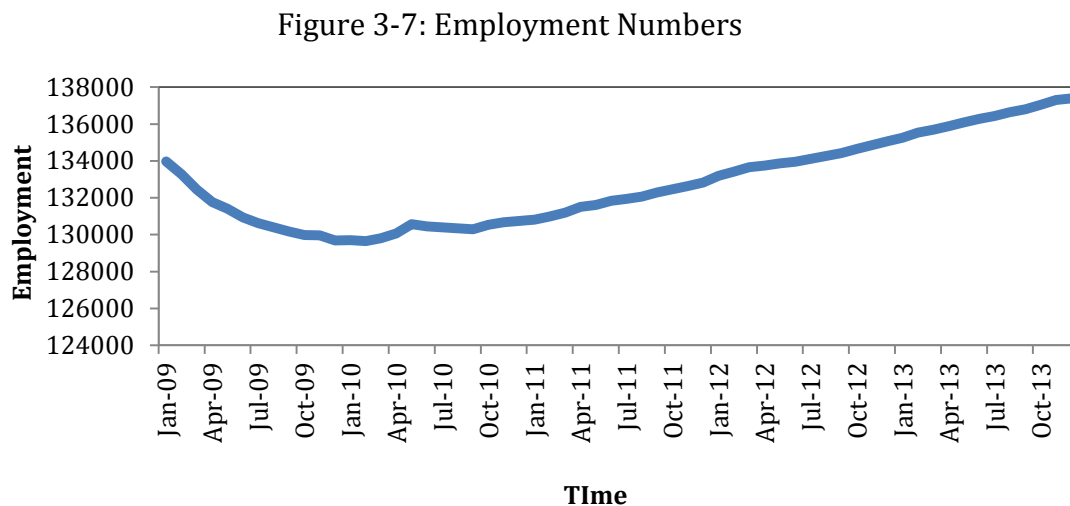
3.4.2.2 Unemployment

The unemployment rate data for 2009-2013 for Los Angeles County comes from the US Census Bureau. It is depicted on Figure 5.



3.4.2.3 Population: Employment

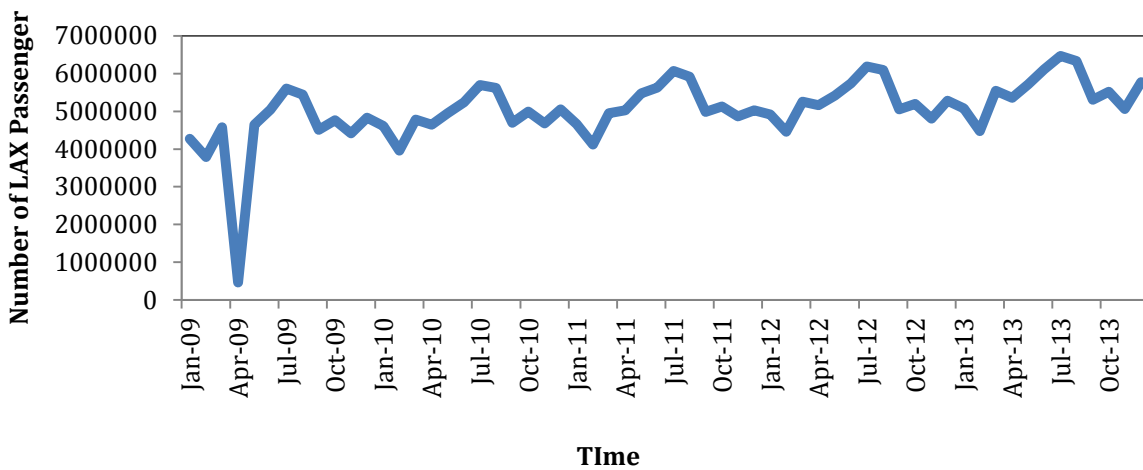
Employment data for Los Angeles County for 2009 to 2013 were gathered from the United States Bureau of Labor statistics. These data are seasonally adjusted. Employment numbers decreased substantially in July 2009 and increased steadily after October 2011.



3.4.2.4 Population: Tourism

Tourism is variable gathered from Los Angeles Tourism organization. It represents number of passengers arriving at the Los Angeles Airport. Even though not all travelers land at LAX are tourist however, it does include seasonal change in number of people who travel through LAX.

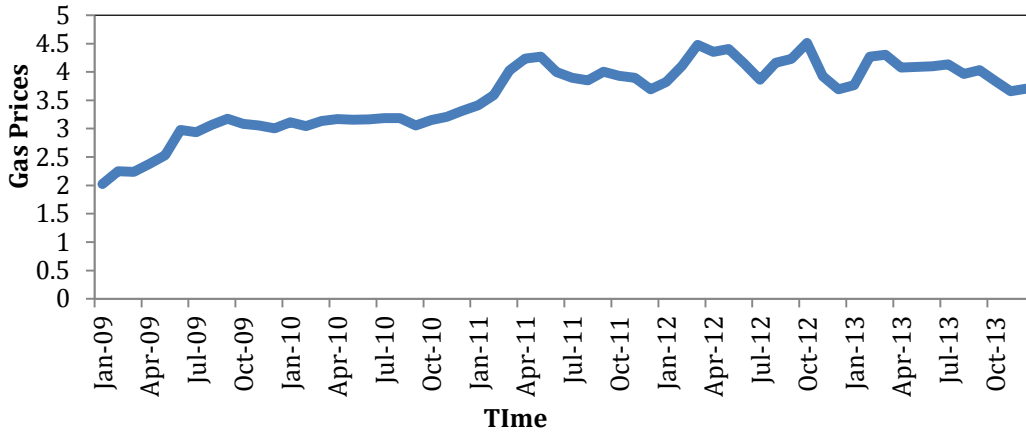
Figure 3-8: Tourism



3.4.2.5 Gas Prices

Monthly gas prices include all grades and formulations. They were obtained from the through US Energy Information Administration. Figure 8 shows substantial variations over the study period.

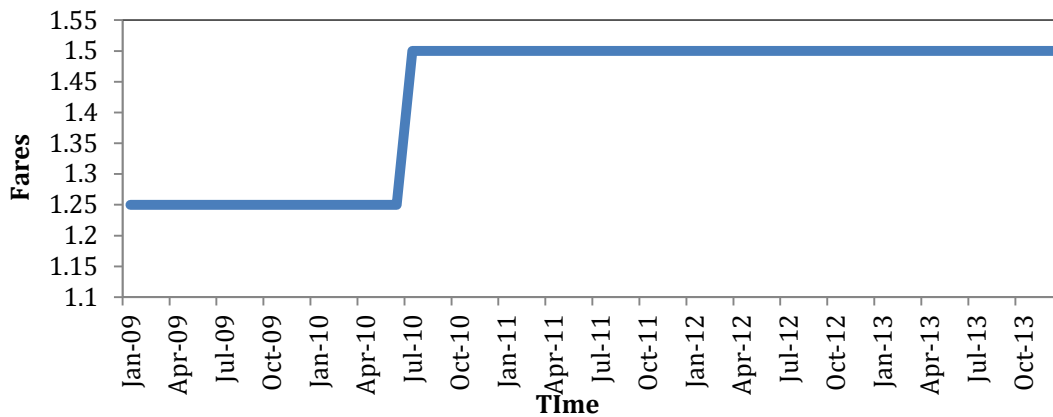
Figure 3-9: Gas Prices (Dollars)



3.4.2.6 Fares

Monthly fares for LA Metro varied only once during the study period. In 2009, the one trip fare was 1.25 dollars, and it increased in June of 2010 to 1.50 dollars. (New Metro Fare Structure Starts July 1, 2007, Los Angeles).

Figure 3-10: Fares (Dollars)



3.4.2.7 Weather

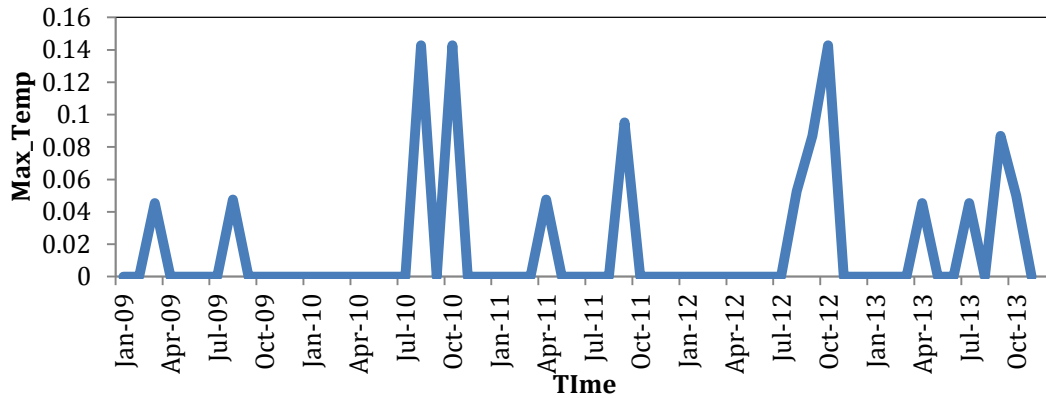
Extreme weather data may also impact transit ridership. This work focused on extreme temperatures and precipitation.

Data come from the National Weather and Forecasting website. Maximum daily temperatures were obtained and for weekdays, the number of maxima over a threshold was counted and divided by the number of weekdays in the corresponding month (see Figure 10). Maximum temperature and its frequency determined the threshold over each year.

Table 3-3: Threshold for Maximum Temperature

Year	2009	2010	2011	2012	2013
Temperature	90	86	86	88	90

Figure 3-11: Maximum Temperature Index

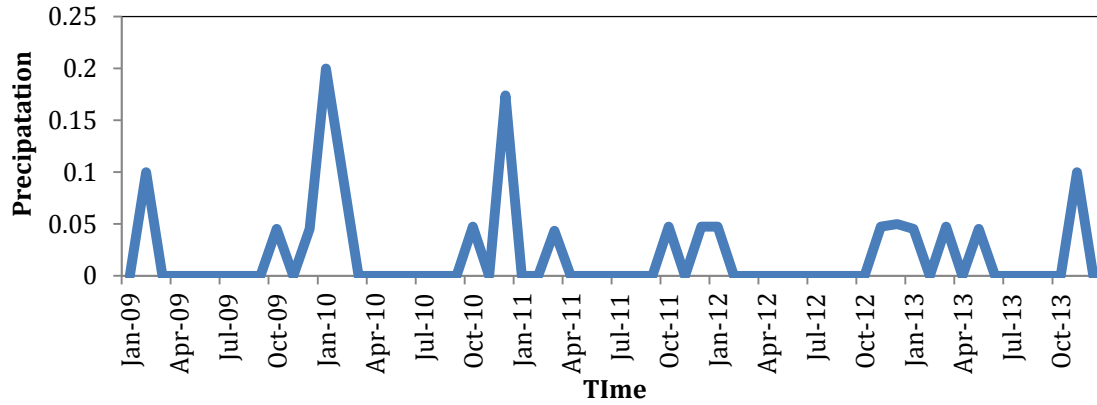


The precipitation data were processed similarly (see Figure 11).

Table 3-4: Threshold for Precipitation

Year	2009	2010	2011	2012	2013
Precipitation (in)	1	0.75	0.65	0.65	0.75

Figure 3-12: Maximum Precipitation Index



3.5 Models

To estimate the impact of mobile transit app page visits (the application index) on transit ridership, fixed effect models were estimated on our panel datasets. Fixed effect models explain changes in a dependent variable (here transit ridership) with variations in explanatory variables.

$$Y_t = \beta * X_t + u + \epsilon_t \quad t = 1, \dots, 300,$$

where:

- X_t is a vector of explanatory variables;
- β is a vector of unknown coefficients to estimate;
- u is an unknown fixed effect that is differenced out;
- ϵ_t is an error term; and
- $t=1, \dots, 300$ spans the number of months in the dataset.

Fixed effects models allow controlling for omitted variables when these variables do not change over time (Stock and Watson, 2007).

3.6 Results

Results were estimated using Stata. They are presented and discussed below. All three models have the same explanatory variables. Note that the employment variable was excluded from all the models since it was highly correlated with unemployment rate.

3.6.1 Model 1: Monthly Weekday Bus Ridership

This model evaluates how bus ridership is being affected by smart phone applications.

Results are shown in Table 6

Table 3-5: Model 1—Bus Ridership

Monthly Weekday <u>Bus</u> Ridership			
		R ² (overall)	0.610
Variable	Coefficient	Std. Err.	P> t
Unemployment Rate	-21.950	8.730	0.015
Gas Prices	63.865	16.229	0.000
Fares	-216.500	73.949	0.005
Maximum Temperature	251.810	121.408	0.043
Precipitation	-401.230	98.714	0.000
Smartphone App Index	-0.113	0.109	0.307
Tourism	-0.007	0.007	0.340
Constant	1445.788	131.177	0.000

Model 1 has the lowest R² of the 3 models presented here, although it is still relatively high for a transportation model.

First, we note that several variables are significant: unemployment rate, gas prices, fares, and the weather variables. As the unemployment rate increases, bus ridership decreases, which makes sense intuitively. Likewise when gas prices increase, bus ridership

increases, which again conform to expectations, just like a fare increase decreases ridership. Interestingly, both extreme weather variables are significant here, but they act in opposite directions. When temperatures are high enough, bus ridership increases probably because buses are air-conditioned. Conversely, weekdays with heavy downpours see sharp decreases in ridership, possibly because walking in the rain is not appealing to Angelinos.

Second, we see that two variables are not significant. The first one is tourism, which is somewhat surprising since I expected tourism to impact bus ridership after talking with LA Metro officials. Most of interest to this research, we also see that the smartphone app index is not statistically significant. One possibility is that the availability of real time bus information is not enough to sway people to abandon their cars in favor of bus transit.

3.6.2 Model 2: Monthly Weekday Train Ridership

This model evaluates monthly train boarding with smart phone application. In this model, the dependent variable is monthly weekday train boarding.

Table 3-6: Model 2—Train Ridership

Monthly Weekday <u>Train</u> Ridership			
		R ² (overall)	0.743
Variable	Coefficient	SE.	P> t
Unemployment Rate	5.373	3.136	0.093
Gas Prices	-5.635	5.830	0.339
Fares	-59.308	26.566	0.030
Maximum Temperature	23.546	43.616	0.592
Precipitation	-154.928	35.463	0.000
Smartphone App Index	0.113	0.039	0.006
Tourism	0.002	0.002	0.393
Constant	320.486	47.125	0.000

Results are presented in Table 7. First, we note that Model 2 has the highest R^2 of the 3 models discussed here, so it has better explanatory power.

Interestingly, a different set of explanatory variables is statistically significant. In this model, a higher unemployment rate increases train boarding, which is slightly surprising. As expected, however, a fare increase decreases train boarding, and just as for the bus model, heavy downpours lead to ridership decreases.

In this model, however, gas prices are not significant. The train ridership mostly consists of commuters (Metro 2013 Quarterly Survey) but changes in gas prices during the study period may not have been sufficient to create a mode shift in favor of trains. For this model, we also note that extreme temperatures do not affect train ridership probably because people who were already driving have nothing to gain then by taking the train, which will likely require walking in the heat to reach a destination (the density of bus stops is much higher than for train stations). As before the tourism variable is not significant.

Another important difference with the previous model is that smartphone usage is statistically significant, with more transit app page downloads leading to a higher train ridership. The coefficient of the smartphone app variable also shows positive impact on train ridership. One possible explanation in this case is that smartphone transit apps help train travelers commute with other modes to reach their destination.

3.6.3 Model 3: Monthly Weekday Bus and Train Ridership

This model evaluates monthly bus and train boarding with smart phone application. In this model all the dependent variables are the same as other models and dependent variable is monthly bus and train boarding.

Results for Model 3 (see Table 8) are similar to those for Model 1 (monthly bus ridership), which is not surprising because bus ridership is much higher than the train ridership and dwarfs train boardings.

Table 3-7: Model 3—Bus and Train Ridership

Monthly Weekday Train and Bus Ridership			
		R ² (overall)	0.707
Variable	Coefficient	SE	P> t
Unemployment Rate	-16.577	9.457	0.086
Gas Prices	58.230	17.580	0.002
Fares	-275.808	80.106	0.001
Maximum Temperature	275.355	131.516	0.042
Precipitation	-556.158	106.933	0.000
Smartphone App Index	0.000	0.118	0.998
Tourist	-0.004	0.007	0.548
Constant	1766.274	142.098	0.000

4. CASE STUDY 2: BERLIN

Public transit is the bloodline of Berlin. Its landmarks, attractions, and seasonal activities are closely associated with transit stations. To foster tourism, Berlin is striving to have a well-kept transit system. Moreover, maps and information about Berlin's multiple transit systems are ubiquitous and make the city easy to navigate.

4.1 A Brief History of Public Transit in Berlin

In 1838, the first public transport system opened to connect Berlin to the city of Potsdam. Six lines followed, linking Berlin with Koethen, Stettin, Frankfurt, Breslau, Hamburg and Magdeburg. However, the six terminals of these lines were not connected in Berlin. This led to the first public transit line in Berlin, the "Ringbahn," which opened in 1850 to connect these six terminals. Its construction was the source of many controversies about high fare prices, traffic congestion, and vibrations of adjacent buildings. In 1882, following strong demand for public transport to link East and West Berlin, the 12-km long Stadtbahn or S-bahn was completed. It runs from Schlesischer Bahnhof to Charlottenburg, went through the Ringbahn and connected different parts of Berlin. After its opening, the S-bahn started running at capacity, which led to electrifying the line to increase its capacity. Subsequently, encouraged by the success of the S-bahn, the underground rail line, U-bahn was introduced for shorter trips and to connect the inner city. In 1902, a 34-km long underground train line entered service to link Schelsischer Bahnhhof to Zoologischer Garten. The success of this line fostered the addition of a north-south line and a second line running from east to west (Fabian, 2009).

4.2 Current System

Unlike other major European cities such as London and Paris, Berlin has multiple centers. The S-ban connects different parts of the city (e.g., East to West) and the U-ban links different neighborhoods. This structure enables Berlin residents to travel longer distances from East to West and to take shorter trips within the city.

Table 4-1: Berlin System Summary

System	Stations	Lines	Net Length (KM)	Passengers/ year
U-Bahn	173	10	145	457 million
S-Bahn	133	15	294	376 million
Tram	398	24	192	171 million
Bus	2,869	162	1,626	407 million
Ferry	14	6		

Currently, there are 5 public transport modes in Berlin: S-ban, U-ban, tram, bus, and ferry. The S-ban mostly runs above ground around Berlin in a “ring” and branches out toward the outskirts. S-ban trains are used for both short and long distance trips. The U-ban mostly runs underground within the city. It typically serves people who are traveling shorter distances. Trams were built to connect S-ban and U-ban stations and they primarily run in eastern Berlin. Buses follow route patterns similar to those of trams especially in areas not served by trams, where they connect U-ban and S-ban stations. In

addition, Berlin is served by 6 ferry lines operated by Verkehrsverbund Berlin-Brandenburg (VBB).

Table 7 presents summary statistics for Berlin’s transit system and Figure 12 shows a map of Berlin’s public transportation system. Figure 12 presents ridership statistics by mode for Berlin’s public transit system.

Figure 4-1: Berlin Transit Map

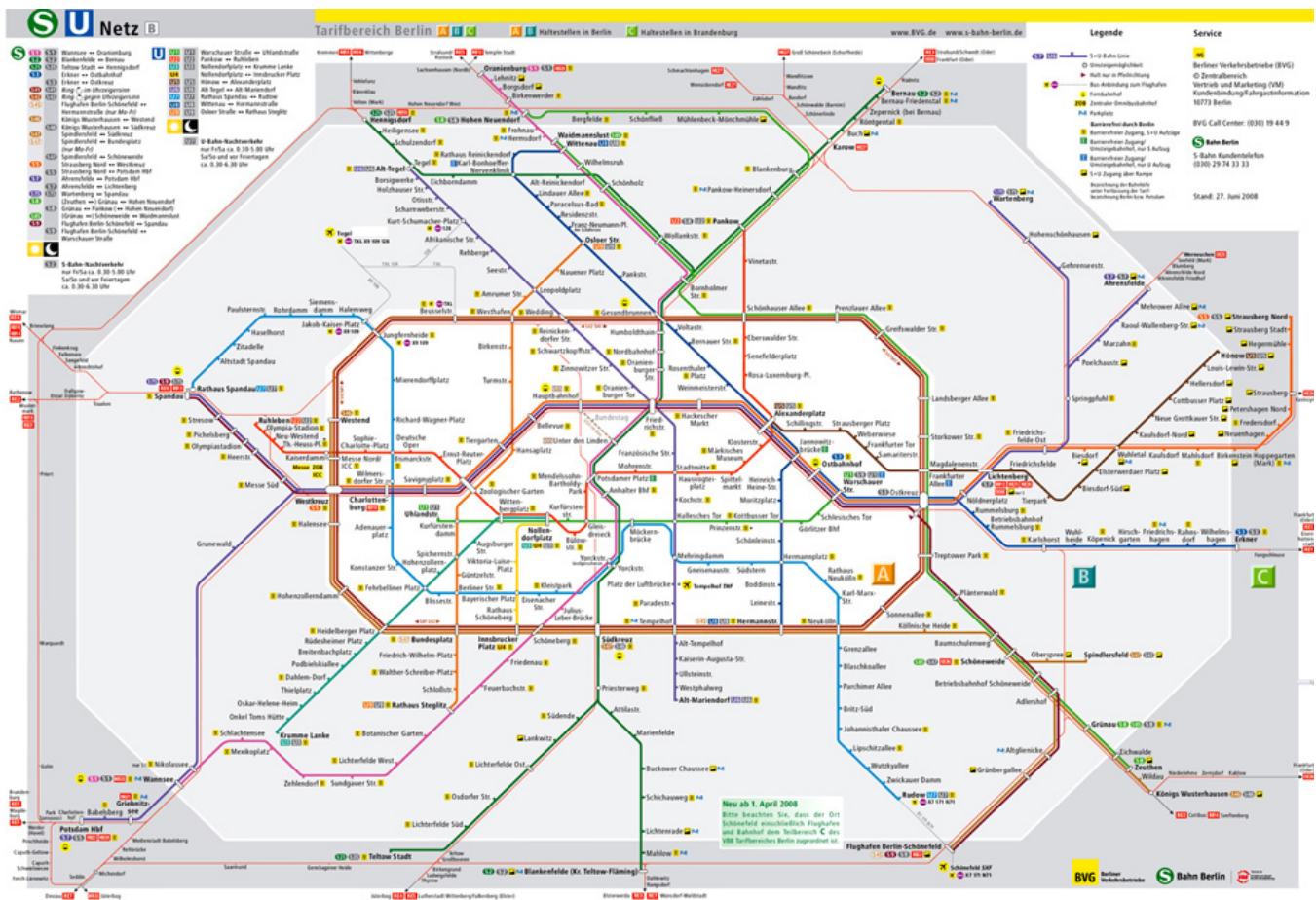
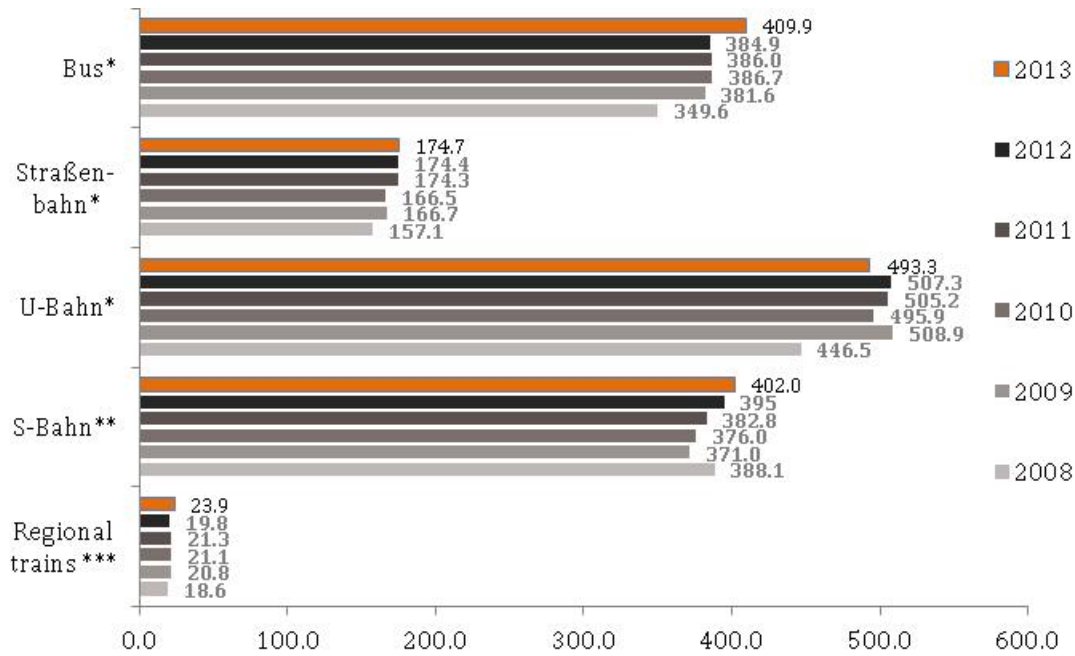
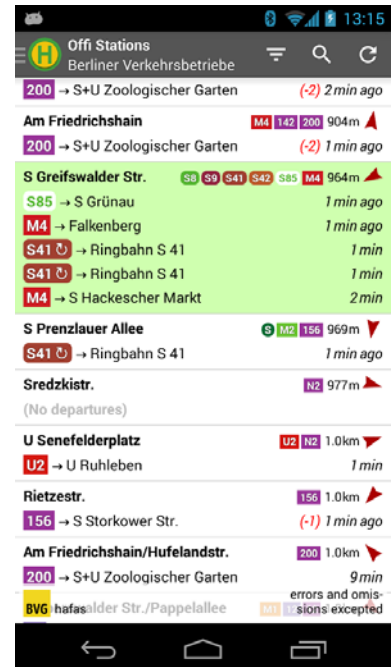


Figure 4-2: Berlin Transit System from 2008-2013



4.3 Emergence of Smartphone Applications

Public transit applications first emerged in Berlin in 2007. The transit layer was added to Google maps where it showed different line route options and journey times (scheduled arrival time) (Google Map Achieve, 2009). Berlin transit authorities such as VBB and BVG provided global positioning system (GPS) information to Google, and this information was used to predict the arrival times of different modes. Information from Google transit allowed travelers to find the location of the closest transit stop, arrival times, and directions to their destinations. Since the Google maps app was already



available on smartphones, this new information allowed travelers to check public transit

alternatives side by side with driving options. The availability of GPS information also enabled other developers to create apps with different interfaces and layouts. Currently, the most popular travel apps in Berlin are VBB, BVG, Offi Directions and City Maps.

4.4 Methodology

This section discusses the approach used to analyze the influence of smartphone applications on travel behavior in Berlin. Berlin is a city with an established and comprehensive transit system but since I did not have access to detailed monthly ridership information, I decided to assess the impact of smartphone transit apps on transit riders' confidence and perception.

To gather data, I conducted some interviews and surveyed students and faculty of Humboldt University. My purpose was to understand their daily travel pattern and their use of smartphone apps. I was especially interested in understanding to what degree people depend on their smartphone apps to plan their travel. More specifically, my purpose was to: 1. Understand the link between smartphone apps and public transit mode selection; 2. Assess if there is a perceived difference in waiting time between smartphone transit app users and non-users; and 3. Investigate transit app use for different trip purposes.

4.4.1 Interviews

Ten students and faculty members from Humboldt University were interviewed to gain a preliminary understanding of Berlin residents' dependency on public transit and smartphone applications. Each interview had 3 parts: 1) daily interactions and experience with public transit; 2) smartphone application usage; and 3) questions about dependences

interviewee, Dominik, explained that even though he lived in Berlin all his life and claims to know the system really well smartphone apps still sometime gives him the fastest route to reach places, which is not completely surprising because the system is massive and typically offers many ways to travel to one place. The information given by smartphone applications help trip planning, which shows the fastest route option. Moreover, smartphone apps are not necessarily bringing more riders; instead they are improving their traveling experience.

4.4.1.3 Dependency on Smartphone Application Usage

Having and using a transit smartphone app can have many psychological impacts. First, it can give a sense of saving time. One student of Humboldt University, Antonia, said, “The applications are easy [to use] and [gives you] the feeling of saving time”. She explained that when a smartphone app shows an exact time it makes transit riders more aware of their traveling time. This awareness increases their dependency on their smartphone transit app and reduces perceived waiting and trip times. This motivated me to include a question on perceived wait-time in the survey.

Many interviewees found smartphone apps most helpful at night especially in a new place when the frequency of service is low (i.e., a train every 20 minutes) or when transit options are limited. Another interviewee, Lina, states, “When I go somewhere new I use it since I don’t know how to get there. Also, I check the bus times to plan ahead especially when I am going to different places. [I use it] mostly to optimize the trip”. This quote shows that smartphone apps are used especially when traveling to a new place. So in the case of

Berlin, if smartphone applications are not bringing additional travelers they are helping optimize trips.

The interviews suggested some of the main reasons why Berlin's transit riders use smartphone transit apps:

1. The real-time information provided by smartphones is used to find the arrival/departure times of a mode, especially for buses;
2. Having real-time information reduces the waiting time of a trip; and
3. Smartphone apps are especially appreciated when there are questions about transit frequency, when transit options are limited, and when traveling to new places.

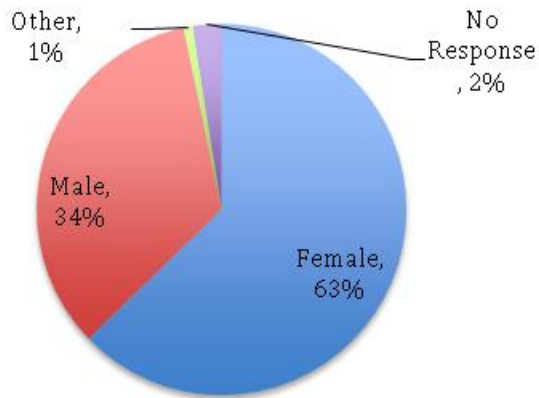
One purpose of the survey is to quantify the importance of these reasons.

4.4.2 Survey

To further understand the impact of smartphone transit apps on travel behavior and perceptions, I designed a survey to gather information from students and faculty members of Humboldt University. After obtaining feedback from faculty at UCI and at Humboldt University, the survey instrument was modified, programmed using Lime Survey HU, and distributed to students, faculty and staff through the Humboldt University email server. The survey was active for a month and a half (from February 17, 2015 to March 30th 2015). During that period, two reminders were sent to potential respondents. A total of 838 answered the survey, of which 728 respondents completed the whole survey and 110 had

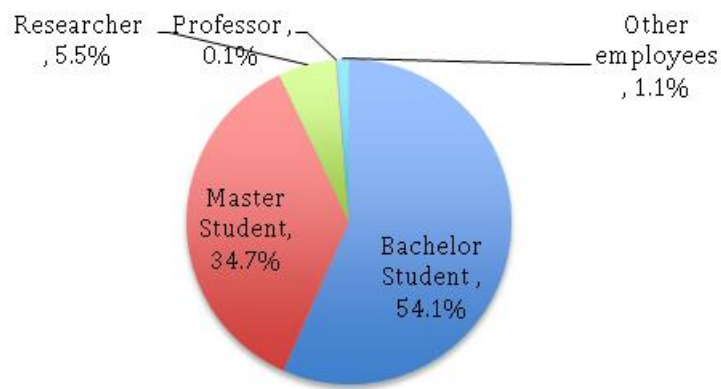
some missing responses (see Figure 14 for a graphical summary). The rest of this chapter focuses on the 728 complete survey questionnaires.

Figure 4-3: Respondents Gender Breakdown



During the 2014-15 academic year, Humboldt University had 33,033 students, 18,959 of which (57% of total students) are female and 14,074 (43% of total students) male. By comparison, 63% of respondents were female, 34% male, 1% other and 2% provided no response.

Figure 4-4: Respondents Education Breakdown



Although the survey was conducted during the 2015 winter semester, the latest enrollment data available was for the 2013-2014 academic year. At that time, 59% of students were pursuing a bachelor or an undergraduate degree, 23% were graduate or master students, and 14% post-graduate students, with 4% were on leave. A look at Figure 15 shows that the survey respondents cover the range of possible academic statuses for students, although faculty and staff are clearly under-represented.

Let us now test the main reasons for which Berliners may use smartphone transit apps.

4.4.2.1 Hypothesis 1: Bus riders depends on smartphone applications

In Berlin, four of the five transit modes (S-bahn, U-bahn, tram and ferries) but not buses provide real-time information on overhead information displays. Therefore, I expect bus riders to depend on their smartphone apps information more than other riders.



To assess this hypothesis, I will compare the use of various transit modes with the use of smartphone transit apps. Information about public transit mode use comes from question 3 in the survey, which asks respondents how many times a week on average they take various public transit mode (Bus, S-bahn, U-bahn, and Tram). Answers could fall in 4 categories: 1) 5 or more times; 2) 3-4 times; 3) 1-2 times and 4) less than once. Table 8 shows that 28% of respondents ride buses at least 1-2 times per week, 20% ride it 5 or more times per week, and 31% rarely (less than once). These numbers show that there is

an even breakdown between riders who use buses every day and those who use them occasionally.

Table 4-2: Public Transit Mode Users' Breakdown

Mode	5 or more times	3-4 times	1-2 times	Less than 1	No Response
Bus	20%	16.64%	28.20%	31.22%	3.58%
S-Bahn	52%	23.52%	16.37%	7.02%	1.10%
U-Bahn	50%	22.56%	18.02%	7.57%	2.06%
Tram	17%	11.28%	20.63%	46.08%	4.95%

Table 4-3: Average Weekly Public Transit Frequency

Frequency	Number of Responses	Percentage
Less than 1	39	6.64%
1-2 (A3)	130	22.15%
3-4 (A2)	138	23.51%
5-9 (A5)	145	24.70%
10+ (A4)	128	21.81%
No Responses	7	1.19%

The survey also asked about smartphone transit apps usage. Question 9 on the survey asked how many times a week on average respondents use their smartphone transit apps to check public transit information, with five options to answer: 1-2 times; 3-4 times; 5-9 times; 10 or more times; or less than 1 time. The category with the most respondents was 5 to 9 times a week. Table 9 summarizes survey responses to that question.

4.4.2.2 Hypothesis 2: Smartphone transit app users perceive they are waiting less compared to non-users

The question here is whether or not there is any difference in perceiving transit wait-time between users of smartphone and non-smartphone owners. Survey question number 4

asks about the perceived wait-time of respondents per trip. There are 4 options, which gives respondents a wide range of options to choose their average wait-time per trip. According to survey results, 46% of respondents stated that their perceived wait-time is between 3 and 5 minutes. The second highest percentage is 38% for a perceived wait-time between 6 and 10 minutes (see Table 12).

Table 4-4: Respondents' Perceived Wait-Time

Perceived Wait-Time	Responses	Percentage
1-2 Minutes	13	1.79%
3-5 Minutes	339	46.63%
6-10 Minutes	281	38.65%
More than 10 minutes	91	12.52%
No Answer	3	0.41%

It is also important to know the number of smartphone owners among survey respondents. This information is provided by question number 5. As shown in Table 13, the number of smartphone owners was a large percentage of respondents (87%).

Table 4-5: Respondents' Smartphone Ownership

Smartphone Owner	Responses	Percentage
Yes	639	87.90%
No	84	11.55%
No Answer	4	0.55%

4.4.2.3 Hypothesis 3: Leisure trips benefit from smartphone transit apps

Finally, I hypothesize that smartphone transit apps are more useful for leisure trips than for recurring trips, which are based on some routine choices; in that case, smartphone transit apps may simply be used to validate trips rather than to plan them. However, unusual trips, especially for leisure purposes, can be expected to depend more on smartphone transit apps. For this hypothesis, I will rely on the data collected in survey question 12, which records for which trip purposes respondents used their smartphone transit apps the most.

Table 4-6: Respondents' Trip Purpose and Frequency

Trip Purpose/ Frequency	90-100%	50-90%	10-50%	Less than 10	No Response
Commuting to the university	13.46%	18.57%	20.44%	35.09%	12.44%
Commuting to work	10.39%	9.88%	19.76%	34.41%	25.55%
Traveling to leisure events	40.89%	37.99%	15.16%	3.75%	2.21%

Table 14 summarizes survey responses to question 12. It shows that the trip purpose most depended on smartphone transit apps is traveling to a leisure activity (40.89%). The different functions of smartphone transit apps become most important when traveling to a new place. Also, leisure activities often take place at night when transit options are more limited.

4.4.3 Statistical Tool

To test the hypotheses above, I relied on a Chi-square (χ^2) test, which compares if differences between expected and observed values are statistically different. I selected a significance level of $\alpha = 0.05$. The corresponding test statistic is:

$$\chi^2 = \sum \frac{(\text{Observed Value} - \text{Expected Value})^2}{\text{Expected Value}}$$

If the null hypothesis of no difference between expected and observed values hold, the Chi-square statistic above has a Chi-square distribution with n-1 degrees of freedom, where n is the number of categories.

4.5 Results

This section discusses results of the hypotheses.

4.5.1 Hypothesis 1

The specific hypothesis in this case is that bus riders have a higher usage of smartphone transit apps compared to other transit users. Table 13 shows the frequency of bus ridership with respect to smartphone transit app usage per week. It shows that all bus riders from less than 1 time a week to 5 or more times a week use smartphone transit apps 5 to 9 times a week. All bus riders have high usage of smartphone application.

The p-value for the Chi-square statistic here is 0.02, so we reject the null hypothesis that people who ride buses use smartphone transit apps no more than other transit users; instead, bus users rely more on their smartphone transit app than other transit users.

Table 4-7: Hypothesis 1—Bus Ridership and Smartphone Usage

Bus/Smartphone application Usage	Less 1	1-2 times	3-4 times	5-9 times	10+	Total
Less than 1 time	14	43	36	60	25	178
1-2 times	11	36	34	37	40	158
3-4 times	7	15	28	22	25	97
5 or more times	5	32	31	19	29	116
Total	37	126	129	138	119	549

4.5.2 Hypothesis 2

We would like to know here if perceived wait-time is impacted by the use of smartphone transit apps. For both users and non-users of smartphone transit apps, the most common perception is that their average wait time per trip is 3 to 5 minutes. The p-value for this Chi-square test is 0.08, so we conclude that using smartphone transit apps does not statistically affect the waiting time perception.

Table 4-8: Hypothesis 2—Smartphone Ownership and Perceived Wait-Time

Smartphone Owner/Perceived Wait-Time	Yes	No	Total
1-2 Minutes	12	1	13
3-5 Minutes	293	45	338
6-10 Minutes	245	34	279
More than 10 Minutes	87	4	91
Total	637	84	721

4.5.3 Hypothesis 3

A Chi-square test that smartphone transit apps are more useful for leisure trips than for recurring trips is highly significant (p-value<0.01) so trip purpose matters.

5. CONCLUSIONS

The purpose of this research was to investigate some impacts of smartphone transit apps on transit ridership. Two case studies were conducted. The first one focused on the relatively newer, and changing transit system in Los Angeles County. The second case study evaluated how the perception of users of Berlin's transit system, which is established and stable, may be being affected by smart phone transit apps.

Since the transit system in Los Angeles is still changing, it was assumed that smartphone transit apps could impact the level of ridership, separated by modes, bus and train. This study covered the period extending from January 2009 to December 2013, which corresponds to one year before the emergence of smartphone apps and 3 years after the introduction of the first one. A fixed effect panel dataset model was estimated variations in monthly bus and/or train boardings were explained by unemployment rates, weather extremes, fare changes, gas prices, tourism and a smartphone application index. The statistical analysis found that smartphone application has no effect on bus riders. Results indicate that the introduction of smartphone transit apps did not increase bus ridership but it increased the train ridership. One possible explanation is that bus riders in Los Angeles do not rely on smartphone transit apps as much as train riders. However, the smartphone transit use index in the model does not capture specifically what mode was chosen for each trip, just the number of times a transit app was opened Future work should strive to build a better indicator of transit app use.

The second case study analyzed Berlin's transit system and its riders' use of smart phone transit apps. Interviews and a survey of students, staff, and faculty of Humboldt

University to understand their use of smartphone transit apps, how these apps are used and how they may affect their perceptions. Results showed that bus riders use more smartphone apps than riders of other transit modes. Moreover, there is no statistically significant difference in perceived wait-time between users of smartphone transit apps and non-users. Finally, transit apps are most useful during unusual trips such as leisure trips or at times when transit frequency may be lower. Future studies could evaluate the usefulness for transit apps to present integrated information about various modes such as biking, walking, taking transit buses, taking the train or driving. They could also consider the impact of transit apps on perceptions related to the safety of transit.

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