Riding in Real-Time: Estimating Ridership Effects of the Adoption of Mobile Real-Time Transit Tracking Applications

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Executive Summary

Advances in technology, and declining costs of adoption have permitted local transit agencies to provide real-time tracking information to their customers. The customers through the use of a mobile phone can find up-to-the-minute wait times for transit stops. This is enabled through the use of GPS technology and modern mapping software to account for networked distance and traffic impedance. This technology is a service upgrade in strict economic terms, but it is important to inquire whether such an improvement would have an effect on service utilization. This study analyzes the relationship between ridership and adoption of this service upgrade.

The study uses a panel of 27 medium sized transit agencies, queried ten times over as many years in a fixed effect framework to evaluate the effect of the adoption of these trackers on ridership. Ridership is measured in terms of both passenger trips (unlinked passenger trips) and aggregate length of passenger trips (passenger miles traveled). Control variables for population, city density, unemployment, congestion and fuel prices are included.The results indicate that the adoption of this technology does not have an effect on ridership in either measure. This is likely the result of the captive nature of most of these markets.

The same model was used to examine the aggregate farebox revenue received after the adoption of the technology. It found that agencies could expect an increase of nearly three million dollars in fare revenue on average. In light of the previous results, the relationship is likely reverse-causal as agencies which are increasing fare prices may offer to adopt the service in order to assuage customers.

Further research will be necessary to break down the various types of markets in an attempt to isolate the effect for different transit markets. If the panel data approach is used this will require the collection of more specific time variant data regarding transportation networks and urban form. This information will be important for agency decision makers considering the adoption of this technology on public subsidy. The fact that ridership increases are unlikely should be considered in the development of plans to pay for and politically justify the adoption of tracker systems.

Introduction

As personal technology has advanced, the amount of information available to the consumer has advanced comparably. Smartphones, characterized by their connection to the internet and the utilization of mobile "applications" or "apps," may be a game-changer in the distribution of information to consumers. Users have access to data in real time and on the go, which stands to revolutionize a variety of industries. Smartphones are reaching greater levels of adoption in the U.S. By 2013, 91 percent of Americans used some kind of mobile phone; 56 percent of respondents reported having adopted smartphones. Adoption among adults aged 25-34 rises is 81 percent, and this trend is expected to continue as the millennial population ages. [1]

This technology, paired with global positioning system (GPS) technology, has allowed for the creation of real time transit tracker (RTTT) apps. As a subset of the larger Intelligent Transportation System (ITS) field, these apps provide users with the information on bus and train arrival to the minute at a growing number of transit agencies around the nation and the world. The bus is fitted with a GPS transponder that facilitates the calculation and data delivery; more advanced systems use other ITS technology to factor in traffic flow rather than a rote estimation based on network bounded distance.

The arrival information is supposed to alleviate what is known as transit anxiety. Busses are notoriously late on many routes. This leaves many riders concerned as to the bus' arrival time or if the bus is inbound at all. This anxiety

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[1] Arron Smith, "Smartphone Ownership 2013," *Pew Research Center* June 5 2013. http://www.pewinternet.org/Reports/2013/Smartphone-Ownership-2013/Findings.aspx

results from a perceived (sometimes this perception is based in reality) unreliability in transit. This manifests itself in very real stress for riders waiting for transit; many of these riders perceive their waits to be as much as 13 percent longer than their real wait times.[2] These perceived additional minutes are likely indicative more of psychological stress than the feeling of additional minutes of actual wait time. The upgrade of a transit system to RTTT is clearly a kind of service upgrade, but it is important to discover whether this upgrade is sufficient to allow for increased ridership or if it only helps riders that would have boarded otherwise. If uncertainty from transit presents marginal potential riders with psychological distress, a form of negative utility, it follows that some riders would choose to take to transit if some of its uncertainty was removed.

Research specific to the real time transit tracking apps is still very new and surprisingly absent within the policy field. Researchers studying the Chicago Transit Authority -an agency which had a staggered rollout of RTTT on its routes allowing for comparative analysis- found that the technology had resulted in a modest but significant increase in ridership.[3] The research is mostly either reserved to single system analyses or to the intersection of transit and psychology research. Both of these are interesting and valid pursuits, but a national comparative perspective of many systems could add to the literature.

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[2] Watkins, Kari; Ferris, Brian; Borning, Alan; Rutherford, Scott; Layton, David. “Where is my Bus? Impact of mobile real-time information on the perceived and actual wait time of transit riders.” *Transportation Research Part A: Policy and Practice 45 no. 8* (Oct 2011).

[3] Tang, Lie and Piyushimita (Vonu) Thakuriah. “Ridership effects of real-time bus information system: A case study in the City of Chicago.” *Transportation Part C 22* (2012): 146-161.

Perhaps most relevantly, the connection between ridership and RTTT installation is a calculation of taxpayer expenditure. Local transit across the nation is taxpayer funded via matching grants from the federal level. State and local governments often levy taxes to match these funds, as fare revenue generally makes up a relatively small portion of the agency's budget. Increased ridership means increased revenue from the fare box. Answering whether transit agencies are getting enough for the expenditure to warrant adoption relative to ridership is a crucial policy question due to the expenditure of taxpayer revenue.

For many systems the increased ridership may be irregular trips (rather than daily commuting trips) that would have otherwise been made by automobile. Each trip shifted from automobile to fixed route transit has environmental benefits.[4] While unique carbon and fuel would be expended by the automobile trip, the fuel and carbon costs are sunk in a fixed route transit as the bus or train will make the trip whether empty or full.

Information regarding the effect of RTTT is essential for the transit agencies that have yet to adopt this technology and for those that have and need to forecast revenues into the future. Though outside the scope of this study, this information could be a crucial first step in constructing a benefit-cost model for the adoption of RTTT. Pricing the ridership gains for factors relating to the environment, congestion,

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[44] A fixed route transit system is a transit system that takes a predesigned and timed route on a typical schedule like that found in most urban areas. This contrasts with many rural transit systems often used for non-emergency medical transportation.

government revenue (fares), while factoring in changes in perceived and actual wait times, could allow for a formal BCA assessment of the technology.

Literature Review

Literature on the effect of RTTT systems can be broadly divided into two types: ridership studies and behavioral studies. As demonstrated below, the behavioral studies have established that this technology decreases wait times, but the literature on ridership in connection to RTTT is much more limited.

Ridership Studies

A great deal of research on RTTT was conducted on systems prior to its current incarnation in the mobile phone. During this period, findings suggest varying level of positive effects of RTTT systems on transit ridership.[5][6][7][8] Other studies show a more muted impact of RTTT systems on ridership.[9] Earlier RTTT systems relied on conveying information to riders via screens at the stop itself. While seemingly minor in focus, this difference affects the whole trip planning process. While perceived wait times may decline, this should have no effect on trip planning and therefore no effect

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[5] Abdel-Aty, M. and P. Jovanis. "The effect of ITS on transit ridership." *ITS Quarterly 3 no. 2*, (1995): 21–25.

[6] Abdel-Aty, M. "Using ordered probit modeling to study the effect of ATIS on transit ridership." *Transportation Research, Part C, Emerging Technologies* 9 no. 4 (2001): 265–277.

[7] Cham, L., Darido, G., Jackson, D., Laver, R., Booz, A.H., and D. Schneck. "Real-time Bus Arrival Information Systems Return-on-Investment Study – Final Report." *National Technical Information Service, Federal Transit Administration, Washington, DC.* 2006.

[8] Peng, Z., Beimborn, E.A., Octania, S., and R.J. Zygowicz. "Evaluation of the Benefits of Automated Vehicle Location Systems in Small and Medium Sized Transit Agencies." Center for Urban Transportation Studies, University of Wisconsin-Milwaukee. 1999. <http://www4.uwm.edu/cuts/its/avl1-29.pdf>.

[9] Zhang, F., Shen, Q., Clifton, K.J., "Examination of traveler responses to real-time information about bus arrivals using panel data." *Transportation Research Record 2082* (2008): 107–115.

on actual wait times because the riders wouldn't receive information regarding arrival times until riders arrived at the stop.

Tang and Thakuriah found that there was a modest increase in ridership after the implementation of real-time bus information in the Chicago area, but found that some of these gains were modest at best with 126 added trips on the lines which used bus tracker. More importantly the authors found that the effect of the introduction was more noticeable in the later stages and routes of the implementation process. The authors took into account unemployment levels, gas prices, local weather conditions, transit service attributes, and socioeconomic characteristics during the study period (Tang and Thakuriah 2012).

Wait Time Studies

Ferris et al. 2010, initially hypothesizing minor changes in rider behavior, examined the interaction between consumer behavior and real time transit tools.[10] Survey data reveal that the Seatle based tracking service, OneBusAway, increased rider satisfaction and that change in satisfaction negatively correlated with age. The multidisciplinary team found that the younger the rider, the more satisfaction gained from using OneBusAway. Survey data also shows that 91 perccent of respondents reported shorter wait times, 18 percent reported feeling personally safer (p>10-15) and 78 percent reported that they were likely to walk to a different stop in order to change the overall plan for their route. The study is limited by self reporting and the

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[10] Ferris, Brian; Watkins, Kari; Borning, Alan. 2010. "OneBusAway: Results from Providing Real-time Arrival information for Public Transit." *Computer Human Interaction.* (2010).

lack of a control population, but established an early estimate of consumer reactions to this new information offered by transit entities.

Other authors have analyzed the relationship between perceived and actual wait times. This body of research is specifically important for understanding some of the behavior of passengers before and after the installation of RTTT apps. As discussed above, having actual information not only helps fit the psychological experience of waiting for a bus to the reality of doing so, it also facilitates better planning, thus reducing actual wait times. In a pure study of rider perception at stops without RTTT, Mishani et al. found that that perceived wait time positively correlated with both actual wait time and walking times. They also found that the perceived wait time was negatively correlated with an imposed time constraint, or strictly scheduled appointment.[11] To summarize, they assert that perceived wait times were generally longer than but correspondent to actual wait times. The sheer fact that there is a difference in perceived and actual wait times for some users led Mishani et al. to suggest RTTT as a possible remedy for this issue.

Watkins et al. continue this line of research confirming that RTTT has a genuine effect on both perceived and actual wait times. The presence of RTTT reduced the average perceived wait time by 0.7 minutes (13 percent). Real time information users also reduced their actual wait times by an average of 2.4 minutes

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[11] Mishalani, Rabi G; McCord, Mark M.; Wirtz, John. “Passenger Wait Time Perceptions at Bus Stops: Empirical Results and Impact on Evaluating Real-Time Bus Arrival Information.” *Journal of Public Transportation 9 no. 2* (2006).

(30percent).[12] This study of the Seattle area shows that RTTT apps can reduce both perceived and actual wait times, improving the rider experience. Rutherford et al. also looked to the perceived and actual wait time in the Seattle area using Bluetooth technology to better hone estimates of actual wait time. They found that riders using RTTT information did not perceive their wait time to be longer than their actual wait time. The study used Bluetooth technology to map automated passenger wait time data collection, revealing basic trends such as average wait times (7.54 minutes with RTTT and 9.86 without; 31percent different; p=0.00).[13]

Reactions to these systems appear to be very positive both in the US and around the world. Dziekan and Kottenhoff utilized a meta-analytic framework to examine seven main effects from 11 studies of 9 transit systems.[14] The authors considered the effects of at-stop real-time displays including reduced wait time, positive psychological factors (reduced uncertainty, increased ease-of-use and a greater feeling of security), increased willingness-to-pay, adjusted wait time behavior, modal choice effects, higher customer satisfaction and "better image". The study finds that perceived wait times can be reduced by 20percent by employing RTTT technology. The study also presents the effects of RTTT technology on adjusted

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[12] Watkins, Kari; Ferris, Brian; Borning, Alan; Rutherford, Scott; Layton, David. "Where is my Bus? Impact of mobile real-time information on the perceived and actual wait time of transit riders." *Transportation Research Part A: Policy and Practice 45 no. 8* (Oct 2011).

[13] Rutherford, G Scott; Wang, Yinhai; Watkins, Kari Edison and Yegor Malinovskiy. "Perceived and Actual Wait Time Measurement at Transit Stops Using Bluetooth." *Transportation Northwest Research Report* TNW2012-09 (June 2011).

[14] Dziekan, Katrin and Karl Kottenhoff. "Dynamic at-stop real-time information displays for public transport: effects on customers" *Transport Research Part A: Policy and Practice* 41 no. 6 (July 2007): 489-501.

walking speeds by observing passengers as they approach the stops. . The authors conclude that many of these factors increased in most of the studies and that RTTT technology had distinct effects on rider behavior.

Brian Ferris' doctoral dissertation on the OneBusAway RTTT system revealed a number of positive features including increased (92 percent) satisfaction with public transit via survey data. 38 percent of respondents agreed that "OneBusAway alleviated the uncertainty and frustration of not knowing when a bus is really going to arrive."[15] Ten percent of survey respondents responded that the OneBusAway interface was more convenient than existing tools. Consistent with other research, the positive responses were significantly negatively correlated with age, with younger riders finding more utility with the system than the average older rider. Ninety-one percent reported shorter waiting times. Most importantly for a transit company's bottom line, Ferris found that OneBusAway saw an increase in the number of trips reported, especially those reported for non-commute trips.

Specific to the issue of user adoption, Maclean and Dailey researched the earliest of mobile phone and internet interfaces as early as 2002. These systems were quite simplistic by today's standards, as they operated on phones which lacked today's modern operating systems and designed interface. The author studied the daily variation in usage by both web-based and mobile-based platforms, again in the Seattle area. They found that the web-based service was many times more popular,

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[15] Ferris, B. "OneBusAway: Improving the Usability of Public Transit." PhD thesis, Department of Computer Science and Engineering, University of Washington, 2011. 116.

likely due to drawbacks of the mobile platform at the time.[16] Additionally, the web-based data usage was far more stable throughout the day whereas mobile-based data usage spiked higher at morning and afternoon rush hours compared to a lower baseline.

Research Design

For this study, I utilize data from the National Transit Database, Census, Bureau of Labor Statistics, in addition to data from the Texas Transportation Institute's annual congestion survey. The data span a ten year period and represent 27 transit agencies which began utilizing this technology prior to 2011. All of these agencies could be described as "medium" sized; I exclude the major transit systems of the northeast and Chicago for two reasons. First, these systems did not have a hard start date, making the use of dummy variables to describe the program impossible. Secondly, I exclude systems which have a significant multimodal element to their operations in order to study the unique phenomena surrounding the relatively rapid expansion of RTTT technology in bus systems. This additionally should limit the potential endogeneity between ridership and level of service as riders in these systems are either captive or convenience riders. A list of transit agencies and selected ridership figures is available in Appendix 1.

I will use the following fixed effect model, where observations are repeated for each transit agency in order to study each agency before and after the model:

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[16] Maclean, S. D.; Dailey, D. J. "Wireless Internet Access to Real Time Transit Information." *Transportation Research Board: Journal of the Transportation Research Board 1791* (2002): 92-98.

$$\text{UPT/PMT/FareRevenue}_{it} = \text{program}_{it} + \text{laggedprogram}_{it}$$

$$\text{pop}_{it} + \text{pop\_dense}_{it} + \text{Unemp}_{it} + \text{CDH}_{it} + \text{Fuel}_{it} + \text{DRM}_{it} + e$$

I measure ridership as both unlinked passenger trips (UPT) and passenger miles traveled (PMT). These variables describe the number of trips made by users and the aggregate distance of those trips respectively. In addition to ridership, I use the same technique for estimating the impact of the program on fare revenue directly. The program is marked by a dummy variable for the use of real time transit tracking (RTTT) applications (and a one year lagged variable to indicate the effect of the year following the introduction of the program). The model uses control variables for the transit agencies and their service areas in a year. This includes controls for local population, population density, unemployment, congestion delay hours, the local cost of gas, and a measure of supply: directional route miles (DRM). The DRM variable describes the distance that an entire transit system covers in a given day. A list of variables, their descriptions and their sources is available in Appendix 2.

It should be noted that DRM and ridership variables are difficult to separate that some scholars may recommend the use of a two stage model as a minimum necessity to remove the potential effects of endogeneity. This is not necessary for this dataset due to the size and modal nature of these transit systems. The U.S. urban landscape outside of the excluded major systems is largely automobile bound. Riders in these systems are generally captive and or ride out of convenience of the connection between their origins and destinations. Because the nature of supply and

Information About Included Variables

Variable	Source	Categorized By/Noted In	Expected Effect on Ridership
Unlinked Passenger Trips	National Transit Database	1000s	N/A
Passenger Miles Traveled	National Transit Database	1000s	N/A
Fare Revenue	National Transit Database	1000s	N/A
Program	Survey of Systems	Dummy	Unknown
Population	Census Bureau	1000s	Pos.
Population Density	Constructed	Population/NTD prov. Service Area Statistics	Pos.
Unemployment Rate	Bureau of Labor Statistics	-	Unknown
Congestion Delay Hours	Texas Transportation Institute	1000s	Pos.
Average Fuel Costs	Bureau of Labor Statistics	Regionally Classified, in Dollars	Pos.
Directional Route Miles	National Transit Database	1000s	Pos.

demand in captive transit markets is not akin to that of the free market supply and demand for goods, the potential for endogeneity between ridership and DRM is less concerning. A two-stage model may be ideal for this estimation, but a due to time constraints and limited access to proper time-variant instrumental variables, a one-stage model suffices.

Results

The fixed effect regression model does not cast an overly positive light on the potential relationship between ridership and the adoption of this technology by medium sized transit agencies. This could be because of a number of factors but captive ridership is likely the major culprit. The effect of the program measured as indistinguishable from zero in the models for both unlinked passenger trips and passenger miles traveled. See Tables 1 and 2. Thus, I am unable to reject the null hypothesis.

Table 1: Fixed Effect Regression Model of 27 Transit Systems with Real Time Transit Tracker Applications Independent Variable: Unlinked Passenger Trips(UPT) (1000s)

	Coef.	t-stat	P value		R^2	Within	0.1453
RTTT Intro.	-2566.0	-1.21	0.227			Between	0.0050
RTTT Lagged 1 Year	-2620.5	-1.09	0.276			Overall	0.0036
Population (1000s)	2.0	0.34	0.734				
Population Density	-5.5	-0.75	0.457		F Stat:	4.32	
Unemployment Rate	329.6	1.07	0.288		Prob > F	0.0001	
Congest Del. Hrs (1000s)	-58.3	-1.50	0.136				
Avg Fuel Costs	4667.6	3.22	0.001	***			
Route Miles(1000s)	8.7	3.80	0.000	***			
Constant	70468.5	4.40	0.000	***			

The first model explains a small overall amount of variance for what can be expected in the transportation field. Looking to the differences between the “Within” R squared values and the “Between” R squared values finds that the within reported higher (explain more variance) in each case. The model does a reasonable job (R squared values between .1453 and 4322) of explaining the change of a single system overtime, which is most important to the study. The model does a poorer job explaining difference between systems.

These differences could potentially be captured in α but the differences likely lie in hard-to-collect variables like land use and transportation network type. These variables are being cataloged for researchers in databases like the “Reshaping America Dataset” which reports data on housing, land use and network characteristics. These kinds of datasets are not (or not yet) time series, however, making panel data models difficult. Some of this information is captured by α in the fixed effects model, but the time variant information which would otherwise show how two communities change uniquely during the time period is not included. While models two and three do a better job of explaining the variance between systems, the pursuit of a higher R squared for models like this will require expansive research projects.

Table 2: Fixed Effect Regression Model of 27 Transit Systems with Real Time Transit Tracker Applications Independent Variable: Passenger Miles Traveled(PMT) (1000s)

	Coef.	t-stat	P value		R^2		Within	0.4322
RTTT Intro.	-1875.6	-0.20	0.843				Between	0.2158
RTTT Lagged 1 Year	-8871.2	-0.83	0.410				Overall	0.1902
Population (1000s)	15.3	0.59	0.554					
Population Density	-32.5	-0.99	0.325		F Stat:	19.79		
Unemployment Rate	1661.7	1.20	0.231		Prob > F	0.0000		
Congest Del. Hrs (1000s)	-1279.9	-7.31	0.000	***				
Avg Fuel Costs	17166.1	2.65	0.009	***				
Direct Route Miles (1000s)	78.1	7.60	0.000	***				
Constant	363170	5.07	0.000	***				

Looking to further justify the model, the variables for service delivery (DRM) and fuel costs were both significant and positive (as expected) for the ridership equations. These variables represent strong predictors of transit success, as they represent two of the major costs that go into making transportation decisions. Directional route miles represent the size and frequency level of a system and as expected the systems that are serving larger areas or the similar areas with greater frequency are garnering more riders. As for fuel costs, the declining utility of automobile trips as costs increase creates a push towards alternative modes.

As stated above these systems largely cater to captive riders, (those who cannot afford other modal choices) and ultimately the goal of technology like RTTT is to boost the service to whatever population uses the transit service in a given urban area. The RTTT technology appears to be ineffective at increasing the size of this service population. A potential dream of agencies looking to implement RTTT technology was the potential to capture some of the millennial generation which are characterized as bound to their smartphones. This may work in cities like Chicago, where transit is more competitive due to frequency and the higher cost of automobile usage, but not in captive markets.[17]

TABLE 3: FIXED EFFECT REGRESSION MODEL OF 27 TRANSIT SYSTEMS WITH REAL TIME TRANSIT TRACKER APPLICATIONS INDEPENDENT VARIABLE: FARE REVENUE (1000S)

	COEF.	t-stat	P		R^2	Within	0.2891
RTTT	2960.0	2.12	0.035	**		Between	0.2215
RTTT LAG. 1 YEAR	852.2	0.54	0.590			Overall	0.1887
POPULATION (1000S)	0.2	0.06	0.949				
POPULATION DENSITY	-2.1	-0.44	0.661		F Stat:	10.57	
UNEMPLOYMENT RATE	70.1	0.34	0.731		Prob > F	0.0000	
CONGEST DEL. HRS (1000S)	-151.6	-5.91	0.000	***			
AVG FUEL COSTS	1641.8	1.72	0.087	*			
DIRECT ROUTE MILES (1000S)	0.9	0.63	0.535				
CONSTANT	32431.8	3.07	0.002	***			

The appearance of a statistically significant program variable in the revenue equation is problematic given that the other models do not show a relationship between the program and ridership. The revenue is explicitly the dollars which are collected at the farebox. This presents a contradiction in the findings which must be considered. There is a possible reverse causal explanation, having increased farebox revenue from fare hikes may lead agencies to spend some money on RTTT as a means to offer a greater level of service for the increased fare price. This would be easily examined in future research should fare levels and outlays become available.

Other explanations come down to the data itself. This could be a classic type one error due to the fact that it contradicts the program variables from the other

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[17] 3 ibid.

models and the lagged program variable from its own model. Expansion of the dataset or testing a different set of similar agencies will be necessary to explain this potential anomaly.

Discussion and Further Research

The expenditure of funds on public transportation is a serious task that should weigh on all agency directors. The use of money on technological upgrades is popular but not always justified. Costs of technology come down over time as the technology ages making the decision of when to adopt very important. Knowledge of the impact of this technology on ridership can be very important in making this decision. To be clear, the currently established impact of RTTT on large systems was significant but small; a potential ridership effect of zero does not radically change the fiscal or policy picture within this context.

Ridership is not, however, the only concern of a transit system. Many systems focus more on the principle of access than efficiency. This tool has been experimentally proven to save users time and psychological distress associated with transit waiting even if that population is within the captive market.[18] People's time and psychological health is valuable to them and should be measured in future studies for consideration of the costs and benefits of RTTT adoption.

With the lack of clear ridership benefits, these time saving benefits should be compared to the cost of the adoption of the product. The Regional Transportation

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[18] 10 ibid., 11 ibid.

District (RTD) from Sacramento, California provides a reasonable estimation of the cost of implementing this technology to relatively early adopters. When surveyed for a project by the Transit Cooperative Research Program (TCRP) they reported to researchers that they had capital costs of $15,000,000 for the 1,111 vehicles of the fleet.[19] RTD reported an average per vehicle cost of $8,101. This was the upper bounds of what was reported by U.S. systems. King County metro made a similar capital investment for 1,300 busses and had a slightly smaller cost per-vehicle. City Bus had a very low per-vehicle cost of $3,000. The same survey found that many transit agencies had increased staffing needs as a result of the upgrade creating non-trivial operations costs.

Further research will be necessary to establish the precise point at which a system becomes too small or too captive to fail to experience the kinds of ridership gains found in cities like Chicago. Panel data approaches provide a promising way to create a generalizable estimation regarding the impact of single determinants on transit usage. The ability to capture the unique characteristics of a transit system and its surrounding environment through repeated observations can simplify models. The crux of continued research into all transit ridership determinants will be the collection of the time variant data from which to test. The age of big data provides an opportunity to achieve this goal.

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[19] TCRP Synthesis 48: Real-Time Arrival Information Systems. *Transportation Research Board.* 2003. http://onlinepubs.trb.org/onlinepubs/tcrp/tcrp_syn_48.pdf

Like most products, advertising probably has an impact in the use of RTTT transit services. This will be an interesting line of research if variance can be found between agencies regarding the program launch public relations presence. Appendix two shoes the included agencies' social media presence. Presence in the traditional media could be important for the public presence of the launch as well. I also conducted a query of Google news archives, searching for the transit agency name and the words "transit tracker launch." This search did not provide useful results. Further research on the public relations element will be important to determine the impact of media presence on the adoption of RTTT.

In general the body of research into real-time transit applications is relatively new. This research specific to smaller systems is also very small but growing. A current but diminishing hurdle in studying this phenomenon is the availability of systems to analyze. Ten of our 27 systems adopted the technology in 2010; another ten systems adopted the technology in 2012. As the number of systems continues to grow so will the size of data sets and the explanatory power of research models.

Works Cited

Abdel-Aty, M. and P. Jovanis. “The effect of ITS on transit ridership.” *ITS Quarterly 3 no. 2*, (1995): 21–25.

Abdel-Aty, M. “Using ordered probit modeling to study the effect of ATIS on transit ridership.” *Transportation Research, Part C, Emerging Technologies* 9 no. 4 (2001): 265–277.

Cham, L., Darido, G., Jackson, D., Laver, R., Booz, A.H., and D. Schneck. “Real-time Bus Arrival Information Systems Return-on-Investment Study – Final Report.” *National Technical Information Service, Federal Transit Administration, Washington, DC.* 2006.

Dziekan, Katrin and Karl Kottenhoff. “Dynamic at-stop real-time information displays for public transport: efforts on customers” *Transport Research Part A: Policy and Practice* 41 no. 6 (July 2007): 489-501.

Ferris, B. "OneBusAway: Improving the Usability of Public Transit." PhD thesis, Department of Computer Science and Engineering, University of Washington, 2011. 116.

Ferris, Brian; Watkins, Kari; Borning, Alan. 2010. “OneBusAway: Results from Providing Real-time Arrival information for Public Transit.” *Computer Human Interaction.* (2010).

Maclean, S. D.; Dailey, D. J. “Wireless Internet Access to Real Time Transit Information.” *Transportation Research Board: Journal of the Transportation Research Board 1791* (2002): 92-98.

Mishalani, Rabi G; McCord, Mark M.; Wirtz, John. “Passenger Wait Time Perceptions at Bus Stops: Empirical Results and Impact on Evaluating Real-Time Bus Arrival Information.” *Journal of Public Transportation 9 no. 2* (2006).

Peng, Z., Beimborn, E.A., Octania, S., and R.J. Zygowicz. “Evaluation of the Benefits of Automated Vehicle Location Systems in Small and Medium Sized Transit Agencies.” Center for Urban Transportation Studies, University of Wisconsin-Milwaukee. 1999. <http://www4.uwm.edu/cuts/its/avl1-29.pdf>.

Rutherford, G Scott; Wang, Yinhai; Watkins, Kari Edison and Yegor Malinovskiy. “Perceived and Actual Wait Time Measurement at Transit Stops Using Bluetooth.” *Transportation Northwest Research Report* TNW2012-09 (June 2011).

Smith, Arron. “Smartphone Ownership 2013.” *Pew Research Center* June 5 2013. http://www.pewinternet.org/Reports/2013/Smartphone-Ownership-2013/Findings.aspx

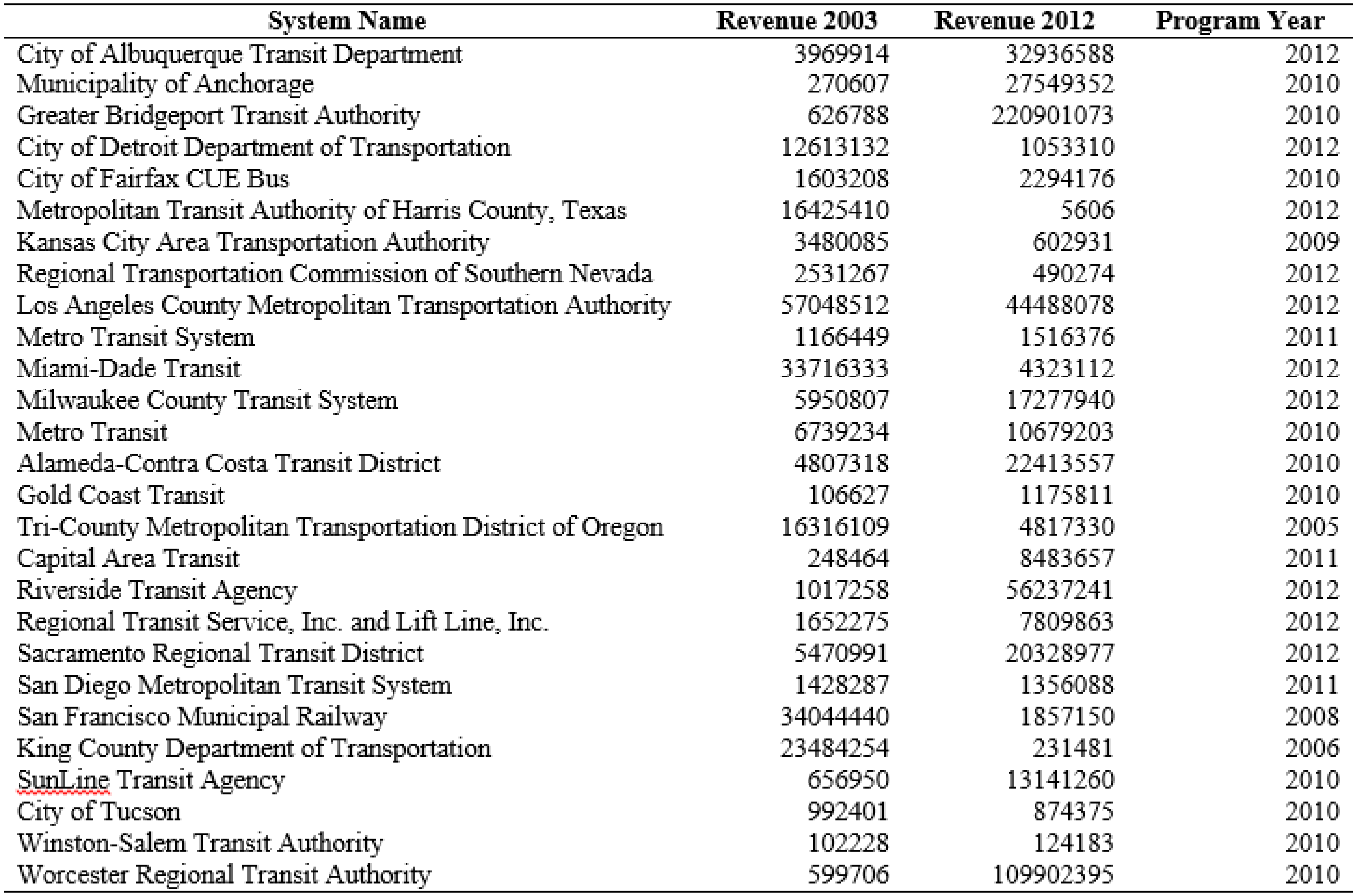
Tang, Lie and Piyushimita (Vonu) Thakuriah. “Ridership effects of real-time bus information system: A case study in the City of Chicago.” *Transportation Part C 22* (2012): 146-161.

TCRP Synthesis 48: Real-Time Arrival Information Systems. *Transportation Research Board.* 2003. http://onlinepubs.trb.org/onlinepubs/tcrp/tcrp_syn_48.pdf

Watkins, Kari; Ferris, Brian; Borning, Alan; Rutherford, Scott; Layton, David. "Where is my Bus? Impact of mobile real-time information on the perceived and actual wait time of transit riders." *Transportation Research Part A: Policy and Practice 45 no. 8* (Oct 2011).

Zhang, F., Shen, Q., Clifton, K.J., "Examination of traveler responses to real-time information about bus arrivals using panel data." *Transportation Research Record 2082* (2008): 107–115.

APPENDIX I: System Information



System Name	Revenue 2003	Revenue 2012	Program Year
City of Albuquerque Transit Department	3969914	32936588	2012
Municipality of Anchorage	270607	27549352	2010
Greater Bridgeport Transit Authority	626788	220901073	2010
City of Detroit Department of Transportation	12613132	1053310	2012
City of Fairfax CUE Bus	1603208	2294176	2010
Metropolitan Transit Authority of Harris County, Texas	16425410	5606	2012
Kansas City Area Transportation Authority	3480085	602931	2009
Regional Transportation Commission of Southern Nevada	2531267	490274	2012
Los Angeles County Metropolitan Transportation Authority	57048512	44488078	2012
Metro Transit System	1166449	1516376	2011
Miami-Dade Transit	33716333	4323112	2012
Milwaukee County Transit System	5950807	17277940	2012
Metro Transit	6739234	10679203	2010
Alameda-Contra Costa Transit District	4807318	22413557	2010
Gold Coast Transit	106627	1175811	2010
Tri-County Metropolitan Transportation District of Oregon	16316109	4817330	2005
Capital Area Transit	248464	8483657	2011
Riverside Transit Agency	1017258	56237241	2012
Regional Transit Service, Inc. and Lift Line, Inc.	1652275	7809863	2012
Sacramento Regional Transit District	5470991	20328977	2012
San Diego Metropolitan Transit System	1428287	1356088	2011
San Francisco Municipal Railway	34044440	1857150	2008
King County Department of Transportation	23484254	231481	2006
SunLine Transit Agency	656950	13141260	2010
City of Tucson	992401	874375	2010
Winston-Salem Transit Authority	102228	124183	2010
Worcester Regional Transit Authority	599706	109902395	2010

System Name	UZA Name	Pop 2003	Pop 2012
City of Albuquerque Transit Department	Albuquerque, NM	765381	900464
Municipality of Anchorage	Anchorage, AK	338665	392139
Greater Bridgeport Transit Authority	Bridgeport-Stamford, CT-NY	892776	933733
City of Detroit Department of Transportation	Detroit, MI	2044832	4292832
City of Fairfax CUE Bus	Washington, DC-VA-MD	3954711	4618598
Metropolitan Transit Authority of Harris County, Texas	Houston, TX	5086012	6175466
Kansas City Area Transportation Authority	Kansas City, MO-KS	1902540	2038690
Regional Transportation Commission of Southern Nevada	Las Vegas-Henderson, NV	1570341	1997659
Los Angeles County Metropolitan Transportation Authority	Los Angeles-Long Beach-Anaheim, CA	9801378	9951690
Metro Transit System	Madison, WI	526246	620740
Miami-Dade Transit	Miami, FL	2320649	5763282
Milwaukee County Transit System	Milwaukee, WI	1526411	1566182
Metro Transit	Minneapolis-St. Paul, MN-WI	3077414	3422417
Alameda-Contra Costa Transit District	San Francisco-Oakland, CA	4157602	4454159
Gold Coast Transit	Oxnard, CA	785220	834398
Tri-County Metropolitan Transportation District of Oregon	Portland, OR-WA	2035389	2289038
Capital Area Transit	Raleigh, NC	889078	1188504
Riverside Transit Agency	Riverside-San Bernardino, CA	3617130	4342332
Regional Transit Service, Inc. and Lift Line, Inc.	Rochester, NY	1040259	1082375
Sacramento Regional Transit District	Sacramento, CA	1968902	2193927
San Diego Metropolitan Transit System	San Diego, CA	2927311	3176138
San Francisco Municipal Railway	San Francisco-Oakland, CA	4157602	4454159
King County Department of Transportation	Seattle, WA	3136965	3552591
SunLine Transit Agency	Indio-Cathedral City, CA	785220	834398
City of Tucson	Tucson, AZ	902773	992395
Winston-Salem Transit Authority	Winston-Salem, NC	435045	647221
Worcester Regional Transit Authority	Worcester, MA-CT	772514	923228

System Name	PMT 2003	PMT 2012	UPT 2003	UPT 2012
City of Albuquerque Transit Department	21408432	576535226	7801883	119952268
Municipality of Anchorage	19826784	471450953	3619051	103218538
Greater Bridgeport Transit Authority	11758245	1845573805	4645509	401616849
City of Detroit Department of Transportation	187803922	21597096	38032201	5951650
City of Fairfax CUE Bus	3242351	58809104	985500	22714997
Metropolitan Transit Authority of Harris County, Texas	425061306	3294218	77405265	907498
Kansas City Area Transportation Authority	53654556	33928324	13551201	6908735
Regional Transportation Commission of Southern Nevada	158204833	8169466	47888979	3513549
Los Angeles County Metropolitan Transportation Authority	1818160294	613211863	429804232	107339867
Metro Transit System	35180503	53893760	11183979	14852159
Miami-Dade Transit	395020789	132764542	85082037	45717441
Milwaukee County Transit System	162154141	369321440	58200166	81053506
Metro Transit	284715496	147142115	67235776	33021811
Alameda-Contra Costa Transit District	172496283	534552036	62292979	80891292
Gold Coast Transit	18898694	48244579	3532319	13059274
Tri-County Metropolitan Transportation District of Oregon	414940206	64872418	98502917	16517706
Capital Area Transit	10450901	194937308	3228452	54396776
Riverside Transit Agency	42044977	468707154	7146680	222936607
Regional Transit Service, Inc. and Lift Line, Inc.	50919988	121226088	13601203	26338465
Sacramento Regional Transit District	124659477	385281424	28869962	85235926
San Diego Metropolitan Transit System	121935254	62018259	32801554	8800273
San Francisco Municipal Railway	423856449	84677453	215594583	20464273
King County Department of Transportation	532406507	14545658	98547887	3545026
SunLine Transit Agency	29896197	234746929	3551819	61016792
City of Tucson	62441699	30475671	16872423	4561637
Winston-Salem Transit Authority	6203699	8176553	2760180	3678809
Worcester Regional Transit Authority	11571077	2269365323	4229220	464875164

APPENDIX II: Social Media Presence

SYSTEM NAME	HAS TWITTER	HAS FACEBOOK
CITY OF ALBUQUERQUE TRANSIT DEPARTMENT	X	X
MUNICIPALITY OF ANCHORAGE	X	X
GREATER BRIDGEPORT TRANSIT AUTHORITY	X	X
CITY OF DETROIT DEPARTMENT OF TRANSPORTATION	X	X
CITY OF FAIRFAX CUE BUS		
METROPOLITAN TRANSIT AUTHORITY OF HARRIS COUNTY, TEXAS	X	X
KANSAS CITY AREA TRANSPORTATION AUTHORITY	X	X
REGIONAL TRANSPORTATION COMMISSION OF SOUTHERN NEVADA	X	X
LOS ANGELES COUNTY METROPOLITAN TRANSPORTATION AUTHORITY	X	X
METRO TRANSIT SYSTEM	X	X
MIAMI-DADE TRANSIT	X	X
MILWAUKEE COUNTY TRANSIT SYSTEM	X	X
METRO TRANSIT	X	X
ALAMEDA-CONTRA COSTA TRANSIT DISTRICT		X
GOLD COAST TRANSIT	X	X
TRI-COUNTY METROPOLITAN TRANSPORTATION DISTRICT OF OREGON	X	X
CAPITAL AREA TRANSIT	X	X
RIVERSIDE TRANSIT AGENCY	X	X
REGIONAL TRANSIT SERVICE, INC. AND LIFT LINE, INC.	X	X
SACRAMENTO REGIONAL TRANSIT DISTRICT	X	X
SAN DIEGO METROPOLITAN TRANSIT SYSTEM	X	X
SAN FRANCISCO MUNICIPAL RAILWAY	X	X
KING COUNTY DEPARTMENT OF TRANSPORTATION	X	X
SUNLINE TRANSIT AGENCY		X
CITY OF TUCSON	X	X
WINSTON-SALEM TRANSIT AUTHORITY	X	X
WORCESTER REGIONAL TRANSIT AUTHORITY	X	X