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NATIONAL CENTER FOR TRANSPORTATION SYSTEMS PRODUCTIVITY AND MANAGEMENT

# Evaluating the Impact of Real-time Transit Information on Ridership and Mode Share

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**Principal Investigator: Dr. Kari Edison Watkins, PhD, PE**

**National Center for Transportation Systems Productivity and Management**
O. Lamar Allen Sustainable Education Building
788 Atlantic Drive, Atlanta, GA 30332-0355
P: 404-894-2236 F: 404-894-2278
nctspm@ce.gatech.edu nctspm.gatech.edu

Georgia Institute of Technology · FIU Florida International University · UAB The University of Alabama at Birmingham · University of Central Florida

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**Brakewood, C.**, G. Macfarlane, and K. Watkins, "The Impact of Real-time Information on Bus Ridership in New York City", *Transportation Research Part C,* Vol. 53, pp. 59-75, 2015.

**Brakewood, C.**, S. Barbeau and K. Watkins, "An experiment validating the impacts of transit information on bus riders in Tampa, Florida", *Transportation Research Part A,* Vol. 69, pp. 409-422, 2014.

Readers are encouraged to seek out these publications for final edited versions of the work for the purpose of referencing.

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# SUMMARY

Public transit agencies often struggle with service reliability issues; when a bus or train does not arrive on time, passengers become frustrated and may be less likely to choose transit for future trips. To address reliability problems, transit authorities increasingly provide real-time vehicle location and arrival information to riders via web-enabled and mobile devices. Although prior studies have found several benefits of offering this information to passengers, researchers have had difficulty determining if real-time information affects ridership levels. Therefore, the objective of this dissertation is to quantify the impact of real-time information on public transit ridership.

Statistical and econometric methods were used to analyze passenger behavior in three American cities that share a common real-time information platform: New York City, Tampa, and Atlanta. New York City was the setting for a natural experiment in which real-time bus information was gradually launched on a borough-by-borough basis over a three year period. Panel regression techniques were used to evaluate route-level bus ridership while controlling for changes in transit service, fares, local socioeconomic conditions, weather, and other factors. In Tampa, a behavioral experiment was performed with a before-after control group design in which access to real-time bus information was the treatment variable and web-based surveys measured behavior changes over a three month period. In Atlanta, a methodology to combine smart card fare collection data with web-based survey responses was developed to quantify changes in transit travel of individual riders in a before-after study. In summary, each study

utilized different data sources and quantitative methods to assess changes in transit ridership.

The results varied between cities and suggest that the impact of real-time information on transit travel is greatest in locations that have high levels of transit service. These findings have immediate implications for decision-makers at transit agencies, who often face pressure to increase ridership with limited resources.

# CHAPTER 1

# INTRODUCTION

## Background and Motivation

Public transit plays an important role in metropolitan transportation systems. Transit can help to reduce carbon dioxide emissions, decrease gasoline consumption, and combat roadway congestion in urban areas (Schrank, Eisele, & Lomax, 2012). It is one of the safest modest of passenger transport, as evidenced by low passenger fatality rates (Federal Transit Administration, 2009). Other benefits of transit include providing personal mobility options for those who cannot or choose not to drive (American Public Transportation Association, 2014) and positive public health impacts associated with active lifestyles (Besser & Dannenberg, 2005). Despite these benefits, transit agencies in many American cities struggle to increase (and in some cases, maintain) ridership levels as they compete with other modes of passenger transportation, particularly single-occupancy motor vehicles.

To meet the mobility needs of passengers, transit service must be fast, frequent, and reliable, among other things (Walker, 2012). Reliability can be improved in many ways, including: increasing levels of right of way, such as providing a dedicated lane; using service planning approaches, such as adding slack to scheduled running times; or implementing control strategies, such as holding vehicles that are ahead of schedule. While supply-side strategies can be effective at improving reliability, they often come at a substantial cost.

Recently, a body of literature has emerged that presents a demand-side strategy to improving (the perception) of reliability of transit service. Carrel et al. (2013) have demonstrated that providing real-time transit information helps passengers adapt when service is unreliable (Carrel, Halvorsen, & Walker, 2013). Real-time transit information can also help riders feel more in control of their trip, particularly their time spent waiting for transit vehicles (Watkins, Ferris, Borning, Rutherford, & Layton, 2011). Moreover, it can be provided to transit passengers in an increasingly cost-effective manner via web-enabled and mobile devices (Schweiger, 2011). Consequently, many transit agencies in the United States have begun to provide real-time transit information to riders (Schweiger, 2011).

Given this trend, transit providers want to understand if these new customer information systems increase ridership. Because transit travel is affected by numerous factors, such as macroeconomic conditions and weather, previous studies have had difficulty isolating changes in transit trip-making that may have been caused by providing real-time information. Therefore, this research aims to quantify the impact of real-time information on transit travel.

## Research Approach

Transit systems differ significantly from city to city, including characteristics of the transit network that affect rider behavior as well as the data available for analysis. Therefore, this research utilized mixed methods in a multi-city approach to assess changes in transit ridership. The overall approach was quantitative analysis of three different transit systems (New York City, Tampa and Atlanta) that share a common real-time transit information system, known as OneBusAway.

**Overview of OneBusAway**

The OneBusAway transit traveler information system was originally developed in 2008 at the University of Washington to provide real-time bus arrival information for riders in greater Seattle. OneBusAway provides multiple interfaces to access automatic vehicle location (AVL) data, including a website (Figure 1), a website optimized for internet-enabled mobile devices, and native applications for iPhone, Android and Windows smartphones (OneBusAway, 2014). Since OneBusAway was originally created over five years ago, it has realized a significant increase in utilization, and it currently hosts more than 100,000 unique users per week. Notably, OneBusAway was developed as an open-source system, which enables the code to be used in other cities.

The Metropolitan Transportation Authority (MTA) in New York City became the first transit agency to reuse the OneBusAway code base, which they adapted for their real-time bus customer information system. Beginning in 2011 and continuing through 2014, the MTA gradually rolled-out real-time information on all MTA bus routes in New York City. While this system is branded as Bus Time (instead of OneBusAway) and has some modifications to the user interface (see Figure 1), it is similar in functionality and feel to the OneBusAway system in Seattle.

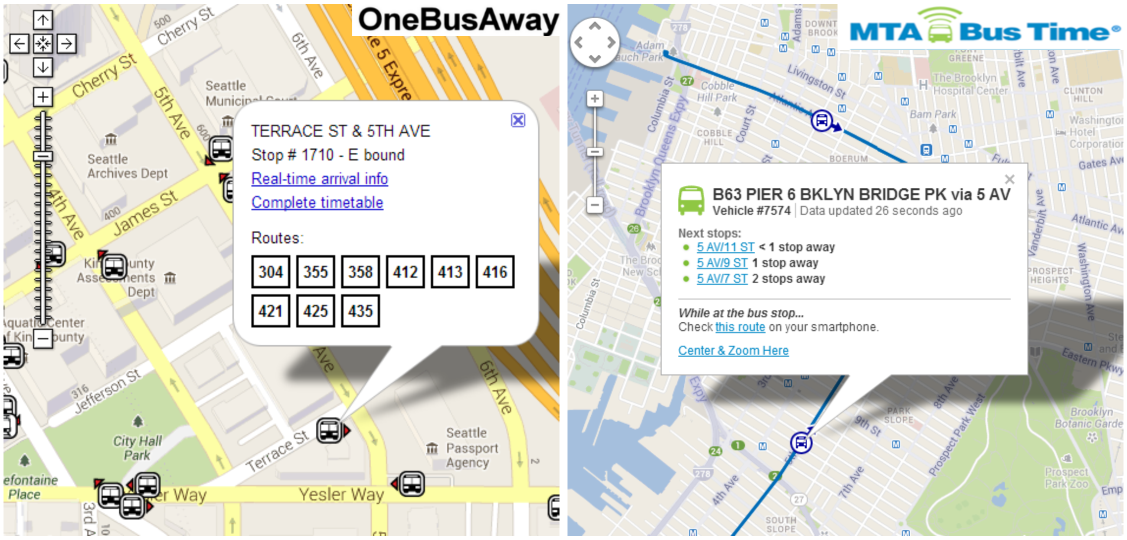


Figure 1: OneBusAway Website for Seattle and Bus Time Website for New York City

The third instance of OneBusAway was deployed in Tampa, Florida. Researchers at the University of South Florida worked in coordination with Hillsborough Area Regional Transit (HART) and Georgia Tech (including the author) to deploy OneBusAway in a small-scale pilot program for all HART operated bus routes in early 2013. A full-scale public instance was deployed in Tampa in the summer of 2013 (Hillsborough Area Regional Transit, 2013).

In Atlanta, Georgia Tech (including the author) worked to deploy OneBusAway for transit service operated by the Metropolitan Atlanta Rapid Transit Authority (MARTA). A “beta” version of OneBusAway with real-time MARTA bus information became available in the spring of 2013, which was primarily used by a small number of Georgia Tech students and staff. A public deployment with MARTA bus and train real-time information and Georgia Tech shuttle real-time information occurred almost one year later in February 2014. In the time between the beta launch and the full-scale deployment, MARTA developed their own real-time information smartphone applications in-house and released them in the fall of 2013, which became important for the evaluation of real-time information in Atlanta.

In summary, four major American cities have similar real-time transit information systems, providing a unique opportunity to study rider impacts in a multi-city approach. Because there have been numerous studies of the rider benefits of real-time information in Seattle, Washington (Ferris, Watkins, & Borning, 2010; Watkins, Ferris, Borning, Rutherford, & Layton, 2011; Gooze, Watkins, & Borning, 2013), this research focuses on the three newest deployments of OneBusAway: New York City, Tampa, and Atlanta. While these cities share a similar real-time information platform, they differ in the characteristics of the transit systems themselves, the way in which real-time information was launched, and the data available for analysis. Therefore, a different methodology has been utilized to study each city, and this is briefly delineated in the following sections.

**Study 1: New York City**

In New York City, most bus service is operated by New York City Transit (NYCT) under the umbrella organization of the Metropolitan Transportation Authority (MTA). NYCT operates the largest bus system in the country with an annual ridership of approximately 805 million unlinked passenger trips (Federal Transit Administration, 2012) and approximately 200 fixed bus routes (Metropolitan Transportation Authority, 2014).

As was previously noted, Bus Time was gradually rolled out on bus routes in New York City, which allowed for a natural experiment in which routes with real-time information could be compared to those without real-time information. Route-level ridership was the primary variable of interest over the multi-year period in which the real-time information system was deployed. To assess if real-time information increased ridership, other factors that affect transit ridership must also be accounted for. Therefore, panel regression was chosen as an econometric approach to modeling bus ridership over time while controlling for changes in transit service, fares, weather, and other factors.

NYCT monitors average weekday route-level ridership on all bus routes for planning and reporting purposes, so this was the primary unit of analysis. Unfortunately, the agency does not have some more advanced technologies, such as smart card fare collection systems, that measure ridership at more refined levels. The data for this analysis was therefore constrained by availability.

**Study 2: Tampa**

In the Tampa Bay region, most bus service is operated by the Hillsborough Area Regional Transit (HART). This small-sized bus system has an annual ridership of approximately 14 million unlinked bus trips (Federal Transit Administration, 2012) and approximately 40 fixed bus routes.

In 2012, HART granted the University of South Florida (and research partner Georgia Tech) special access to their real-time bus data in order to develop an instance of OneBusAway. Since previously there were no other means for HART riders to access real-time information through web-enabled or mobile devices, this was a unique opportunity to expose a controlled population to real-time information and compare them to riders without access to real-time information. Therefore, a behavioral experiment was selected as the methodology for this study. The specific method was a before-after control group research design in which the treatment was access to OneBusAway over a study period of approximately three months (Campbell & Stanley, 1963).

The data used to measure behavior change was from two web-based surveys: one administered before and another after the completion of the study period. The surveys measured changes in transit trips, as well as other possible benefits of real-time information, such as wait times and satisfaction with transit service. Again, the transit agency lacked some newer methods of transit data collection, such as smart cards.

**Study 3: Atlanta**

In Atlanta, the Metropolitan Atlanta Rapid Transit Authority (MARTA) operates the fifteenth bus largest system in the United States with an annual ridership of approximately 61.6 million unlinked bus trips (Federal Transit Administration, 2012) and approximately 95 fixed bus routes.

Real-time information became available for all MARTA bus routes via a beta version of OneBusAway in the late spring of 2013. MARTA's apps became available with real-time information for all buses and trains in the fall of 2013, and OneBusAway was publicly launched in February 2014 for all MARTA buses and trains. In light of the gradual increase in real-time information options in Atlanta, a before-after analysis was selected to evaluate changes in transit travel by MARTA riders between the spring of 2013 and the spring of 2014.

Atlanta was the only one of the three cities with both a contactless smart card ticketing system and real-time transit information, which presented a unique opportunity to examine changes in trip-making patterns using smart card data. In order to understand which smart card users were also real-time users, a short online survey was conducted in which respondents were asked about their use of real-time information and for their unique 16-digit smart card ID number. The smart card ID number was then used to link the survey response to the corresponding smart card trip history; and this joint smart card/survey dataset allowed for a disaggregate before-after analysis of transit trips in which users of real-time information were compared with non-users.

**Comparison**

Table 1 presents a summary of the three studies, including the size of the transit system, the real-time information deployment timeline, the methodology, and the data sources. In summary, this research utilized mixed methods in a multi-city approach to assess changes in transit ridership attributable to providing real-time information.

Table 1: Comparison of Three Studies

| | **New York City** | **Tampa** | **Atlanta** |
|---|---|---|---|
| Transit Agency | NYCT | HART | MARTA |
| Size of Ridership *Annual Unlinked Bus Trips** | Large 805,381,461 | Small 14,314,610 | Medium 61,596,727 |
| Real-Time Information Deployment | Bus Time deployed on groups of routes between 2011 and 2014 | OneBusAway spring 2013 (pilot); OneBusAway full deployment in summer 2013 | OneBusAway spring 2013 (beta); MARTA apps in fall 2013; OneBusAway full deployment in February 2014 |
| Methodology | Natural experiment with panel regression | Behavioral experiment with a before-after control group design | Before-after analysis of transit trips |
| Primary Data Sources | Route-level ridership counts | Web-based surveys | Web-based survey combined with smart card data |
| **2012 statistics from the National Transit Database.* | | | |

## Results

The following is a brief summary of the results of each study. In New York City, two fixed effects panel regression models with robust standard errors were presented. The first model, which included real-time information as a single binary variable, showed an average increase of approximately 118 rides per route per weekday (median increase of 1.7% of weekday route-level ridership) attributable to the availability of real-time information. The second model, which divided the real-time information variable based on quartiles of bus service per route, suggests that the ridership increase occurred on the largest routes. This increase was approximately 340 rides per weekday on the largest routes (median increase of 2.3% of route-level ridership). These results suggest that real-time information may have the greatest impact on routes with higher levels of service.

In Tampa, the frequency of bus trips per week was evaluated before and after the availability of real-time information, but the change in transit trips over the study period did not differ significantly between real-time information users and non-users. This was not surprising since the majority of bus riders in Tampa are transit-dependent, meaning they lack other transportation alternatives. Analysis of "usual" wait times revealed a significantly larger decrease (nearly 2 minutes) for real-time information users compared to the control group during the study period. Additionally, real-time information users had significant decreases in levels of anxiety and frustration when waiting for the bus compared to the control group. These findings provide strong evidence that real-time information significantly improves the passenger experience of waiting for the bus, which is notoriously one of the most disliked elements of transit trips (Mishalani et al. 2006).

Finally, in Atlanta, smart card trip histories were combined with survey results in order to compare changes in monthly transit trips from April 2013 to April 2014 for real-time information users versus non-users. Difference of mean tests and regression analysis of before-after differences in monthly trips suggest that real-time information was not associated with a significant change in monthly transit trips; however, the final sample size that resulted from the data cleaning methodology was very small.

In summary, two of the three studies (Tampa and Atlanta) did not find a substantial change in transit travel associated with use of real-time information, but the methodologies used to study Tampa and Atlanta did not consider completely new transit riders. However, the New York City study did show an increase in ridership associated with the availability of real-time information, and this likely occurred on the routes with the greatest level of preexisting transit service. Since New York City has substantially more bus service than Atlanta or Tampa in terms of the number of routes, the span of service, and the frequency of service on most (if not all) routes, this suggests that the potential for ridership gains due to real-time information may be greatest in areas that already have high levels of existing transit service.

## Contributions

This research makes a number of important contributions. The New York City study compared various panel regression techniques, some of which are not commonly used in the transit literature. The Tampa study included a behavioral experiment, which is a methodology rarely found in the transportation literature. While there are a few recent examples in the transit literature (Fujii & Kitamura, 2003; Rodriguez & Rogers, 2014), to the best of the authors knowledge, there are no existing examples of controlled experiments evaluating smartphone applications and websites in transportation systems. The Atlanta study uses an emerging data source (smart cards) combined with web-based survey data to study the behavior of individual transit riders. This combination of data is a novel approach to studying traveler behavior over time, and it could be more broadly applied for transit marketing and travel behavior analyses.

Last, this research aims to understand if real-time information increases transit ridership, which is a critical question asked by decision-makers at the country's transit operators. Many transit agencies face pressure to increase ridership under tight budget constraints, and they must make difficult choices between investments in infrastructure, service changes, and new technologies. Therefore, this research has immediate implications for leaders in the transit industry making important decisions on how to improve America's public transportation systems.

## Dissertation Structure

This dissertation is structured in a three paper format. Each chapter is a separate study about the respective city (New York City, Tampa, and Atlanta) and each chapter is in preparation for submission to a journal or is already under review. Chapters begin with an abstract, and this is followed by background and motivation, a literature review, discussion of the methodology, conclusion and suggestions for future research. Additionally, each chapter has a separate list of referenced literature. The three manuscripts are followed by a conclusions chapter, which includes a brief comparison of studies, concluding remarks, areas for future research, and a master reference list that includes all of the literature cited in this dissertation.

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# CHAPTER 2

# NEW YORK CITY

Brakewood, C., Macfarlane, G., and Watkins, K. (2014). The Impact of Real-Time Information on Bus Ridership in New York City. In preparation for submission to *Transportation Research Part C: Emerging Technologies*.


## Abstract

In the past few years, numerous mobile applications have made it possible for public transit passengers to find routes and/or learn about the expected arrival of their transit vehicles. Though these services are widely used, their impact on overall transit ridership remains unclear. The objective of this research is to assess the effect of real-time information provided via web-enabled and mobile devices on public transit ridership. An empirical evaluation is conducted for New York City, which is the setting of a natural experiment in which a real-time bus tracking system was gradually launched on a borough-by-borough basis beginning in 2011. Panel regression techniques are used to evaluate bus ridership over a three year period, while controlling for changes in transit service, fares, local socioeconomic conditions, weather, and other factors. A fixed effects model of average weekday bus ridership per month reveals an increase of approximately 118 rides per route per weekday (median increase of 1.7% of weekday route-level ridership) attributable to providing real-time information. Further refinement of the fixed effects model suggests that this ridership increase may only be occurring on larger routes; specifically, the largest quartile of routes defined by revenue miles of service realized approximately 340 additional rides per route per weekday (median increase of 2.3% per

route). While the increase in weekday route-level ridership may appear modest, aggregate impacts – particularly on large routes – demonstrate a substantial effect on overall ridership. The implications of this research are critical to decision-makers at the country's transit operators who face pressure to increase ridership under limited budgets, particularly as they seek to prioritize investments in infrastructure, service offerings, and new technologies.

## Introduction

Public transit plays an important role in urban transportation systems. Transit can help to combat roadway congestion, decrease gasoline consumption, and reduce carbon dioxide emissions in metropolitan areas (Schrank et al., 2012). Other benefits of transit include providing personal mobility options for those who cannot or choose not to drive (American Public Transportation Association, 2014) and supporting active mobility and its subsequent positive health impacts (Besser & Dannenberg, 2005). Despite these benefits, transit agencies in many American cities struggle to increase (and in some cases, maintain) ridership levels as they compete with other modes of passenger transportation, particularly single-occupancy motor vehicles.

In order for public transit to be a viable option for travelers, it must be reliable, accessible, and presented in an understandable manner, among other things (Walker, 2012). These factors can potentially be improved with new customer information systems, which transit agencies are rapidly implementing. The widespread adoption of mobile devices by transit passengers has led to growing reliance on these devices and increased expectations for transportation information provided in personalized formats. Moreover, these applications are frequently more cost-effective to deploy than infrastructure displaying this information, such as dynamic message signs. Consequently, the availability of web and mobile "apps" providing transit information – particularly real-time vehicle location/arrival information – is increasing at an unprecedented pace over the last decade (Schweiger, 2011).

Given the rapid increase in availability of transit apps, quantifying the impact of real-time transit information on actual travel behavior is essential for transit operators to make responsible decisions regarding the implementation of these systems and for planning agencies to properly plan for future scenarios. Because transit travel is affected by numerous factors, such as macroeconomic conditions and the weather, previous studies have had difficulty isolating changes in transit ridership due to real-time information.

This paper relies on a natural experiment that occurred in New York City beginning in 2011, when the MTA began to gradually deploy real-time information on its buses operating in each borough of New York City on a by-borough basis. This deployment pattern enables use of regression techniques that control for unobserved route-level and time-dependent effects. The results of this analysis indicate that real-time information is associated with an increase of approximately 118 rides per route on an average weekday, although this appears to be occurring primarily on the largest bus routes.

This paper proceeds as follows. First, prior research into the effects of traveler information systems on transit passengers is presented to provide a basis for the contribution of this research. Next, the methodology for data collection and econometric analysis is discussed, with results presented thereafter. Finally, areas for improvement, future research, and concluding remarks are presented.

## Prior Research

Real-time information (RTI) refers to the tracking of transit vehicle locations and/or predicted arrival times for vehicles at stops and/or stations, which is typically updated every minute or so. As the practice of providing RTI to transit riders via web-enabled and mobile devices has become increasingly ubiquitous, the body of literature assessing the impacts on passengers has also grown. Studies of transit riders using RTI have found many benefits, including adapting to unreliability by choosing alternative transit service (Carrel, Halvorsen, & Walker, 2013), reducing waiting times (Watkins, Ferris, Borning, Rutherford, & Layton, 2011), increasing perception of personal security (Ferris, Watkins, & Borning, 2010; Gooze, Watkins, & Borning, 2013; Zhang, Shen, & Clifton, 2008), and increasing satisfaction with transit service (Ferris et al., 2010; Gooze et al., 2013; Zhang et al., 2008). If RTI users can adapt to unreliable service more easily, spend less time waiting, feel safer, and/or are more satisfied with overall service, it follows that they may make more trips on the transit system, either by choosing transit over alternative modes or making trips that they would not have made otherwise.

A number of recent studies have aimed to understand the impacts of RTI on transit travel. A few studies utilize simulation modeling techniques and/or stated preference data, where researchers propose hypothetical scenarios to survey participants as opposed to directly observing their behavior, and these include Tang & Thakuriah (2010), Fries, Dunning, & Chowdhury (2011), and others. This brief literature review focuses on research that evaluates actual transit rider behavior (as opposed to simulation or stated preference methods) because these studies are most likely to provide the concrete conclusions needed for decision-makers at transit agencies.

A panel study conducted from 2006 to 2007 on the University of Maryland campus measured changes before and after the implementation of an RTI system on the university shuttle bus network (Zhang et al., 2008). Based on a fixed effects ordered probit model of individual travelers' monthly shuttle trips, the authors concluded that RTI did not significantly affect shuttle bus trip frequency. One possible explanation the authors identify is that the number of shuttle trips was measured only two weeks after an extensive marketing campaign of the new RTI system, and there may have been insufficient time for adjustments of travel behavior (Zhang et al., 2008). Another possibility is that the population under study was an academic community with potentially inelastic travel behavior; class and activity schedules may be relatively fixed, and would not therefore be substantially affected by new information.

Conversely, two studies of bus riders in Seattle, Washington provide some evidence that use of mobile RTI may lead to an increase in trips made on transit. In 2009, Ferris et al. (2010) conducted a web-based survey of over 400 RTI users and asked respondents if their average number of transit trips per week changed as a result of RTI. Approximately 31% of users reported increases in non-commute trips (1 trip, 2 trips, or 3+ trips per week), while a smaller percentage reported increases in commute trips on transit. A follow-up web-based survey of RTI users in 2012 found similar results (Gooze et al., 2013). However, the authors identified two important caveats for these studies: the survey results were all self-reported and did not include a control group of non-RTI users.

The most relevant prior study in the context of this paper is an empirical evaluation of the real-time bus tracking system in Chicago (Tang & Thakuriah, 2012). The authors modeled average weekday route-level bus ridership for each month from 2002 until 2010, during which time Chicago's real-time vehicle tracking system was incrementally rolled out between August 2006 and May 2009. Controlling for unemployment levels, weather, gas prices, population, and transit service attributes (such as fares and frequency of service), Tang and Thakuriah showed a "significant" but "modest" increase of 126 average weekday rides per route attributable to RTI, which was an increase of approximately 1.8-2.2%. However, the authors identified a number of limitations to their study that could have contributed (favorably or otherwise) to their results:

1. **Number of Real-Time Information Interfaces**: The ways riders received information from the original RTI system changed greatly since the basic technology was implemented in 2006, which began with a simple web interface and later expanded to include smartphone applications.
2. **Technology Adoption**: RTI was only available to those who had the devices needed to access it (e.g., computers or handheld devices with internet); thus, riders who did not have these technologies could not use it. This is noteworthy in the beginning of the study period, when levels of mobile technology adoption were lower. For comparison, the Apple iPhone debuted in June 2007 (Apple Computer, 2007), and a public release of Google's Android software followed in late 2008 (Morrill, 2008); only near the end of the study period had modern smartphones achieved widespread market penetration.

3. **Awareness of Real-Time Information**: It is possible that many travelers were unaware of RTI during the period of analysis.

This leads to three noteworthy items that could be improved in future research. The quasi-experimental design used in the Chicago study would be more suitable in a transit system launching RTI under the following three conditions: (1) a simultaneous launch on multiple interfaces (i.e. website, SMS, and smartphone applications), (2) a passenger population with high levels of technology adoption (particularly mobile devices), and (3) a coordinated marketing campaign to increase awareness. These three characteristics describe another major metropolitan area that recently launched a real-time bus customer information system: New York City.

## Methodology

This section describes the methodology used to evaluate the ridership impacts of the bus RTI system in New York City. First, some background information about the New York City transit system and the launch of the bus RTI system is presented. This is followed by the results of an on-board survey supporting the assumptions of high levels of awareness and adoption of RTI. Next, a description of the data used in the ridership analysis is provided, and finally, the specific modeling approach, panel regression, is discussed.

### Background on New York City Transit

In New York City, most local bus service is operated by New York City Transit (NYCT) under the umbrella organization of the Metropolitan Transportation Authority (MTA). NYCT operates both the largest heavy rail system (the Subway) and bus system in the country with an annual ridership of approximately 2.50 billion unlinked rail trips and approximately 800 million unlinked bus trips, respectively (Neff & Dickens, 2013). The bus system, which is the focus of this analysis, includes approximately 200 fixed routes that serve the five boroughs of New York City: Manhattan, Queens, Brooklyn, Staten Island and the Bronx (Metropolitan Transportation Authority, 2014a).

**Roll-out of Real-Time Bus Information**

In 2009, the MTA executive leadership team made providing RTI a strategic priority, and the agency rapidly began to roll-out real-time bus information through a platform known as Bus Time (Rojas, Weil, & Graham, 2012). Bus Time was initially launched on a single bus route in Brooklyn (the B63) on February 1, 2011 (Metropolitan Transportation Authority, 2011). After this 'pilot' route, Bus Time was (mostly) expanded on a borough-by-borough basis. On January 11, 2012 Bus Time was launched on all NYCT bus routes operating in the borough of Staten Island (Metropolitan Transportation Authority, 2012a). This was followed by the availability of Bus Time on a single route in Manhattan (the M34) in April 2012 and another route in Brooklyn (the B61) in July 2012. The second borough-wide launch occurred in the Bronx on November 9, 2012, and nearly one year later, on October 7, 2013, Bus Time became available for all routes in Manhattan (Metropolitan Transportation Authority, 2013). On March 9, 2014, Bus Time was launched on all remaining bus routes in Queens and Brooklyn (Metropolitan Transportation Authority, 2014c). The gradual roll-out of Bus Time is summarized in Figure 2; notably, this launch timeline creates a natural experiment in which routes with RTI can be compared to routes without RTI during an equivalent time period, while simultaneously controlling for other factors that could affect ridership.

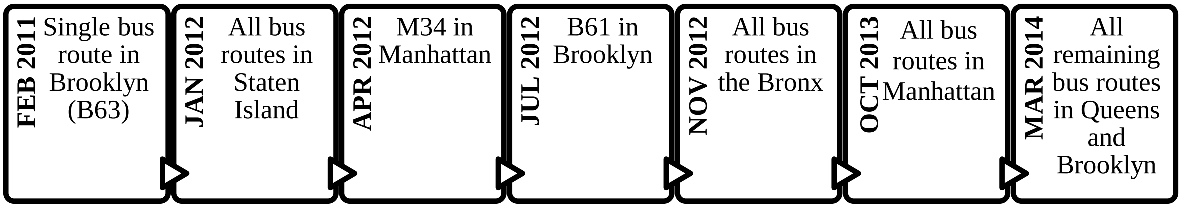


Figure 2: Timeline of the Real-time Information System Launch in New York City

**Real-Time Information Interfaces, Technology Adoption, and Marketing**

New York City advantageously has three characteristics that may improve upon the natural experiment previously used by Tang and Thakuriah (2012) in Chicago: (1) a simultaneous launch of RTI on multiple interfaces, (2) a transit riding population with high levels of technology adoption, particularly mobile, and (3) a coordinated marketing campaign to increase awareness of RTI.

The first characteristic – a simultaneous launch of RTI on multiple interfaces – occurred in New York City in two primary ways. First, each Bus Time launch included three MTA-managed interfaces: a desktop website, a mobile website, and SMS/text messaging (Metropolitan Transportation Authority, 2014c). Additionally, the MTA freely released the real-time bus tracking data to software developers in parallel to the launch of the MTA-managed interfaces since the initial pilot route launched in Brooklyn. This "open data" approach resulted in the availability of numerous smartphone and web applications created by independent third party developers (Metropolitan Transportation Authority, 2014d).

The second characteristic – a transit riding population with high levels of technology adoption – is important to assure that passengers have access to the digital tools necessary to use RTI. The MTA invested significant efforts in customer research to understand levels of technology adoption by transit riders prior to the first borough-wide launch of real-time information in Staten Island. In December 2011, approximately one month prior to the launch, the MTA conducted an on-board rider survey on both local and express bus routes in Staten Island, in which a total of 1,536 paper surveys were collected. Riders were asked which technologies or devices they had used in the last 30 days, and of the 1,304 replies to this question, 62% stated that they had used text messaging, 62% had used internet on a computer, 52% had used a smartphone, and 51% had used the internet on a mobile phone. These survey results indicate that a majority of riders had one or more means to access real-time information prior to its first borough-wide launch.

Third, the MTA conducted a targeted marketing campaign to increase awareness of RTI in coordination with each launch. This included posting instructions about how to use Bus Time on the poles at hundreds of bus stops (known as Guide-a-Rides) to alert riders of this new service as they wait for the bus. In summary, the combination of these three characteristics is likely to have led to high levels of RTI utilization, and consequently, may also result in ridership impacts in a relatively short time period.

**Awareness and Utilization of Real-Time Information in Staten Island**

To understand actual levels of rider awareness and utilization, an on-board survey was conducted a few months after the first borough-wide launch of real-time information in Staten Island. The MTA administered an on-board paper survey for local bus routes in

Staten Island in mid-May 2012 and for express routes in early June 2012.[1] A total of 1,496 surveys were collected, and the results are shown in Table 2. Of the 1,404 respondents who answered the survey question about awareness, 73% stated that they had read about or heard about Bus Time in Staten Island. Two thirds (66%) of respondents who were aware of Bus Time had used it, which equates to nearly half (44%) of all riders surveyed. A total of 30% of Staten Island survey respondents used Bus Time on the day that they were surveyed, either on that specific trip (25%) or on another bus trip (7%). Last, riders who said they had used Bus Time were asked how frequently they use it, and 55% of them stated that they use Bus Time on "most or all" of their Staten Island Bus trips (not shown in the table). In summary, only a few months after the first borough-wide launch, there were high levels of awareness and utilization of real-time information in Staten Island, and it is likely that other boroughs achieved similar (if not greater) levels of awareness and utilization because similar outreach campaigns were used with each launch.

[1] The data from the May/June 2012 Staten Island bus rider survey were provided by the MTA to the lead author.

Table 2: Awareness and Utilization of Real-Time Information in Staten Island

| Topic | Question** | Answers | Count | Responded %* | Total %* |
|---|---|---|---|---|---|
| **Awareness** | Have you read or heard about MTA Bus Time in Staten Island, a new way for riders to get information about how many stops or miles aware the next bus is? | Yes | 1028 | 73% | 69% |
| | | No | 278 | 20% | 19% |
| | | Not sure | 98 | 7% | 7% |
| | | *Total Respondents* | *1404* | *100%* | *94%* |
| | | No Answer | 92 | - | 6% |
| **Utilization** | Have you ever used Bus Time in Staten Island? | Yes | 658 | 66% | 44% |
| | | No | 343 | 34% | 23% |
| | | *Total Respondents* | *1001* | *100%* | *67%* |
| | | Unaware/Not sure/No Answer | 495 | - | 33% |
| | Did you use MTA Bus Time today? | Yes, for this bus trip | 372 | 38% | 25% |
| | | Yes, for another bus trip | 103 | 10% | 7% |
| | | *Yes (this trip or another trip)* | *442* | *45%* | *30%* |
| | | No | 547 | 55% | 37% |
| | | *Total Respondents* | *989* | *100%* | *66%* |
| | | Unaware/Not sure/No Answer | 507 | - | 34% |
| | | All Respondents | 1496 | 100% | 100% |

** All percentages rounded to the nearest whole percent.*
*** Question wording is exactly as it appeared on the survey instrument.*

## Data Collection and Assembly

The primary variable of interest in this analysis is bus ridership. Because real-time information was rolled out on different routes at different times (typically in the same borough), bus ridership was assessed at the route level. Average weekday route-level bus ridership per month was selected as the unit of analysis because this is regularly tabulated by NYCT using data from the fare collection system and is commonly used for long term transportation planning analyses. A total of 185 bus routes (or groups of routes) operated by NYCT were considered in the analysis. Routes operated by the MTA Bus Company were not included in the analysis because the data was not available to the authors. A small number of routes were grouped due to joint scheduling/counts, which occasionally occurs for routes operating in the same corridor (e.g. M101/2/3, BX40/42, etc.).[2]

Average weekday route-level ridership was compiled for each month during a three year period from January 2011 until December 2013 (36 months), which begins shortly before the launch of real-time information on the pilot route in Brooklyn and continues through the borough-wide launches in Staten Island, the Bronx, and Manhattan. Notably, there were no major service changes during the study period, though a major service cut occurred approximately six months earlier in June 2010 (Grynbaum, 2010).

Figure 3 shows the average weekday bus ridership per month with routes aggregated by borough. Borough designation was based on the MTA route name. Routes that begin in B were assigned to Brooklyn, BX to the Bronx, M to Manhattan, S to Staten Island, and Q to Queens.[3] As can be seen in Figure 3, Brooklyn has the highest overall average weekday ridership and Staten Island has the lowest. The data also exhibit strong seasonal trends, with the highest levels of ridership typically occurring in March and May and the lowest usually in August.

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[2] Five NYCT operated routes, which each had less than 500 average weekday rides, were excluded from the analysis. These five routes were either added or removed during the study period, and eliminating these very small routes allowed for a balanced panel.
[3] Express routes (X routes) shown in Figure 3 were assigned a borough for the following analysis based on their origin, since most express routes originate in one of the four outer boroughs and terminate in Manhattan.

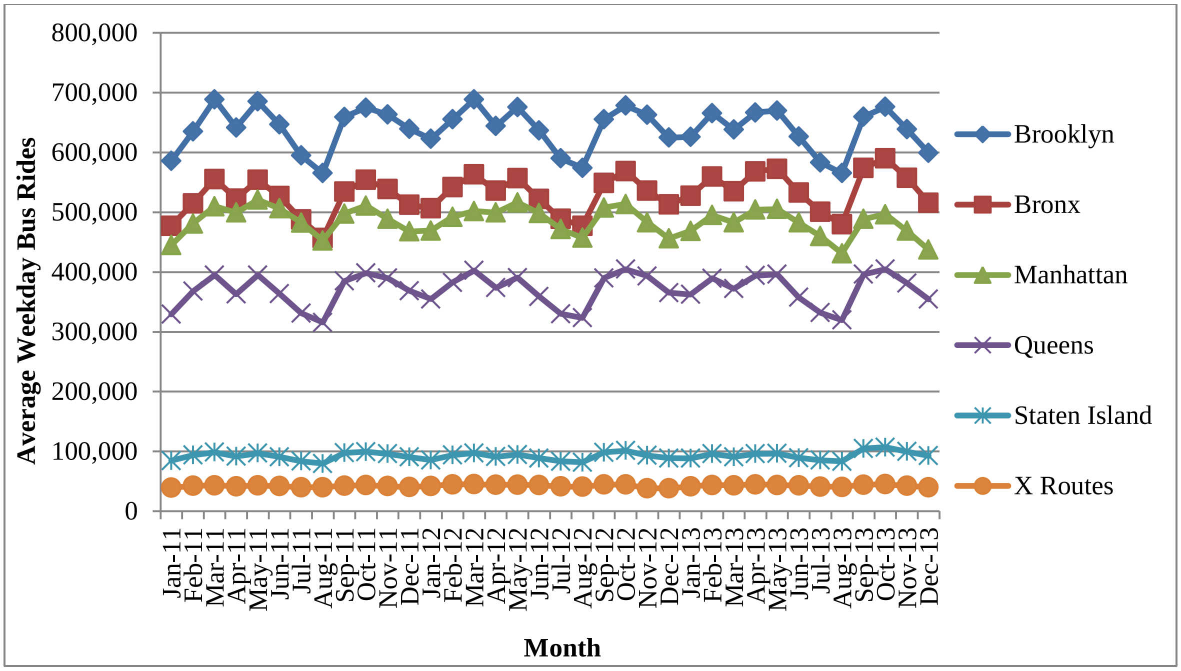


Figure 3: Average Weekday NYCT Bus Ridership by Borough per Month, 2011-2013

To isolate the effect of real-time information on ridership, other factors that may have also affected NYCT bus ridership during the three year study period were taken into account.  Table 3 provides a brief description of each variable considered in the analysis. The explanatory variables were classified into two groups, transit-related and external factors, based on the categorization used by Tang & Thakuriah (2012).  Transit-related variables were those that were largely under the control of the transit agency (such as fares, service provision, etc.), whereas external factors were mostly outside the influence of the transit provider.  To the right of the categorization, a brief description, geographic unit, and source of data of each variable are provided.

Table 3: Variables and Data Sources

| Category | Variable Description | Geographic Unit | Variable Type | Data Source |
|---|---|---|---|---|
| Dependent Variable | Average Monthly Weekday Bus Ridership | Route | Continuous | New York City Transit |
| Explanatory Variables (Transit-related) | Bus Time Real-Time Information Available | Route | Binary | MTA Press Releases |
| | Bus Average Weekday Scheduled Revenue Miles | Route | Continuous | New York City Transit |
| | Select Bus Service | Route | Binary | MTA Press Releases |
| | Bus and Rail Base Fare ($) | City | Continuous | MTA Press Releases |
| | Rail Actual Vehicle Revenue Miles | City | Continuous | New York City Transit |
| | Rail Scheduled Vehicles Operating in Maximum Service | City | Continuous | New York City Transit |
| Explanatory Variables (External Factors) | Bike-sharing | Borough | Binary | Citi Bike Website |
| | Population (only annual estimates available; linear interpolation per month) | Borough | Continuous | US Census Bureau |
| | Gas Price ($/gallon) | City | Continuous | US Energy Information Administration |
| | Unemployment Rate (percent) | City | Continuous | US Bureau of Labor Statistics |
| | Weather (Average temperature, snowfall, precipitation; measurement at Central Park) | City | Binary (Temperature); Continuous (Snow/rain) | National Oceanic & Atmospheric Administration |
| | Hurricane Sandy | City | Binary | NYU Rudin Center Report |

The first transit-related explanatory variable listed in Table 3, real-time information, was modeled as a binary variable for any routes with real-time information during each month in the three year study period.  Initially in January 2011, no routes had real-time information, and this gradually changed until all routes in Staten Island, the Bronx, and Manhattan had real-time information.  Most routes in the remaining two boroughs (Brooklyn and Queens) simply function as controls for the entire study period.

The second transit-related independent variable listed in Table 3 is average weekday scheduled revenue miles per bus route, and this was provided directly by the transit agency.[4] This variable is commonly used in the transit literature (see, e.g., Evans, 2004) and is intended to represent the total amount of service on each bus route because it takes into account differences in frequency, span of service, and route length. Because NYCT bus schedules are modified approximately once per quarter, a total of twelve changes in scheduled revenue miles were included in the three year panel dataset.

Next, the availability of Select Bus Service (SBS) on a route was considered. SBS service includes bus rapid transit (BRT) features, such as off-board fare collection. A total of six bus routes either began as SBS or were upgraded to SBS during the three year study period, and this was modeled with a binary variable.

The literature commonly cites price as a factor that can cause changes in transit ridership (e.g., McCollom & Pratt, 2004). Hence, the base full fare is included as an independent variable. There was only one fare change during the period of analysis, which occurred in March 2013 and was an increase from $2.25 to $2.50 in the base bus and rail fare (Metropolitan Transportation Authority, 2012b).

Two variables to represent the level of service on the rail system were also included: monthly system-wide rail revenue miles and the number of vehicles operated in maximum service. These variables were included because bus riders might be choosing between rail and bus service, and consequently, significant changes in the provision of rail service might result in changes in bus ridership (Tang & Thakuriah, 2012a). The effect of rail might differ from the peak periods compared to the off-peak, and for that reason, the second variable pertaining to maximum service was included.

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[4] Specifically, this was weekday revenue miles when schools were open.

Numerous factors external to the transit system were also considered in the analysis. First, a new bike-sharing program, known as Citi Bike, was introduced in two boroughs (Manhattan and Brooklyn) during the last six months of the study period. Because this represents a new form of transportation not previously available in New York City, it was hypothesized that this could influence bus ridership in areas where bike-share facilities were available. Consequently, the availability of bike-sharing was modeled as a binary variable for all bus routes in Manhattan and Brooklyn after the program commenced.

Prior research has shown that transit ridership can be dependent on changes in population (see, e.g., Taylor & Fink, 2003). To account for this, annual estimates of borough-level population were gathered from the US Census Bureau for 2010 and 2012, and monthly estimates were created by linear interpolation. Similarly, gas prices can influence transit demand, although the short run cross-elasticity of transit and gas price is typically low (Litman, 2014). Regardless, monthly average retail gasoline price in New York City was included, and this was obtained from the US Energy Information Administration.

Research has also shown that variance in daily weather can impact transit ridership (e.g., Arana, Cabezudo, & Peñalba, 2014; Stover & McCormack, 2012). Therefore, weather data were gathered from the National Oceanic and Atmospheric Administration (NOAA) for New York, NY. The measurements at Central Park were used as city-wide measurements, and temperature, precipitation, and snowfall were considered. Temperature was modeled as a binary variable to represent hot and cold months, where a hot month was defined as one with an average temperature above 20 degrees Celsius (68 degrees Fahrenheit) and a cold month was one with an average temperature below 10 degrees Celsius (50 degrees Fahrenheit). Precipitation was modeled as the total monthly precipitation in millimeters, and total monthly snowfall in millimeters was also included.

Last, a special variable was included to account for the effects of Hurricane Sandy, which occurred during the last week of October 2012 and significantly affected transit service in early November 2012. Hurricane Sandy was modeled as a binary variable for all bus routes regardless of their location for November 2012. It should be noted that the hurricane was also taken into account in the route-level bus ridership figures. On the day the hurricane struck, transit service was suspended. Approximately 24 hours after the hurricane stuck, bus service resumed and was provided free of charge (Kaufman, Qing, Levenson, & Hanson, 2012). The MTA did not include these days in the average weekday ridership data, since the method of tabulating average weekday ridership is based upon fare collection data. A few days after the hurricane (in early November 2012), bus service resumed with usual fare collection while some subway service remained suspended; these days are included in the average weekday ridership calculations.

**Modeling Approach**

Average weekday route-level ridership per month ($y$) is considered as a function of the route- and time-level attributes ($x$) described in the previous sections. Using $it$ as an indicator of the route ($i$) at time ($t$), a linear regression model was estimated by ordinary least squares (OLS):

$$y_{it} = \alpha + \beta x_{it} + \epsilon_{it} \qquad [1]$$

where $\beta$ is a vector of estimated coefficients, and $\epsilon_{it}$ is an error term assumed to be independently and identically distributed (IID) with a normal distribution of mean 0 and variance $\sigma$.

The estimates resulting from this model may be inconsistent due to unobserved route-level effects (thus violating the IID assumption). For example, routes passing through neighborhoods of greater density or socioeconomic activity will consistently have higher ridership than routes in less dense or active areas. In this case, the error term $\epsilon_{it}$ is actually composed of two unobservable pieces, an individual effect $u_i$ and an idiosyncratic error $\mu_{it}$. There are two common econometric techniques that attempt to separate $u_i$ from $\epsilon_{it}$. The first is the random effects (RE), or random intercept, model:

$$y_{it} = \alpha_i + \beta x_{it} + \mu_{it} \qquad [2]$$

In the RE model, separate estimates of the variance in individual effects $\sigma_u$ and idiosyncratic error $\sigma_\epsilon$ are obtained; this allows for route-level intercepts $\alpha_i = \alpha + u_i$, where $u_i$ is distributed according to $\sigma_u$ (Wooldridge, 2009).

A potential weakness of the RE model is that estimates obtained in this manner are inconsistent if the route-level effects $u_i$ are correlated with the route-level attributes $x_{it}$. For example, if high ridership routes are more or less affected by changes to fare, weather, or RTI, then RE estimates are potentially unreliable. A consistent but less efficient model in this case is the fixed effects (FE) model,

$$y_{it} - \overline{y}_i = \beta(x_{it} - \overline{x}_i) + \mu_{it} \qquad [3]$$

where the route-level unobserved effects $u_i$ are deleted entirely from the model by demeaning the data. The model is less efficient as a result of sacrificing $N$ degrees of freedom to estimate the individual means $\bar{y}_i$ and $\bar{x}_i$, and no interference from unobserved route-level effects remains.

To assess which of the RE or FE models is appropriate for the situation, a Hausman test can be used (Hausman and Taylor, 1981). This formally tests the differences in the coefficients of the FE and RE model; if the coefficients are sufficiently different from each other, then the RE model is inconsistent and the FE model should be used. On the other hand, if the estimates are similar then the RE model is both consistent and efficient.

Another potential threat to model inference is the possibility that the error terms $\mu_{it}$ are serially correlated, which commonly occurs in time series analyses. If this is the case, then hypothesis tests on the significance of the $\beta$ estimates will be invalid. There are multiple ways to account for serial correlation if it exists, and three commonly used methods were considered. First, an autoregressive AR(1) term can be introduced into the error generating process:

$$\mu_{it} = \rho\mu_{i,t-1} + \nu_{it} \qquad [4]$$

where $\rho$ is an estimated coefficient of the first order autoregressive process, and $\nu_{it}$ is a residual error term assumed IID normal. The significance of $\rho$ can indicate the necessity of an AR structure, as a finding that $\rho = 0$ suggests that there is no autocorrelation.

A second, similar method is the introduction of an autoregressive moving average (ARMA 1,1) term, and this was used by Tang and Thakuriah (2012) in their random effects model. The error generating process in this case has the following structure:

$$\mu_{it} = \rho\mu_{i,t-1} + \nu_{it} + \theta\nu_{i,t-1} \qquad [5]$$

where $\theta$ is another estimable coefficient.

There remains a risk, however, that serially correlated residuals from an RE or FE model follow neither an AR nor an ARMA data generating process. In such a case, hypothesis tests would be invalid. Perhaps a more natural method of addressing issues of serial correlation in panel regression models is to use robust standard errors, such as those calculated using the Huber/White/sandwich estimator (StataCorp, 2013); these standard errors are robust to serial correlation within the panel, as well as heteroskedasticity.

## Results

In this section, the process to identify a statistically preferred model is discussed, and this is used to infer the relationship between RTI and observed route-level bus ridership. The estimated models are presented in Table 4, Table 5, and Table 6.

### Model Identification

First, an elementary OLS model was estimated, which is shown in the leftmost column of Table 4. The results of a Lagrange multiplier test indicated that the error term in the OLS model exhibited systematic effects, and consequently it is necessary to account for route-level effects using either a RE or FE model.

Guided by the methodology of Tang and Thakuriah (2010), RE models were estimated, including two that incorporate defined patterns of serial correlation. Specifically, an AR(1) and ARMA(1,1) error generation process were considered, and the model estimates are shown in Table 4. The RE models were estimated in R (R Core Team, 2013) using the package nlme (Pinheiro, Bates, DebRoy, & Sarkar, 2014). The results of a likelihood ratio test indicate that the RE ARMA(1,1) model is preferred to the simple RE model.

The models in Table 4 seek to replicate as close as was feasible the specifications of the Chicago model, though some changes were necessitated by constraints of data availability. For example, in the Chicago model, weighted hourly frequency of bus service per route was included, but in New York City, revenue miles on each route were more readily accessible to measure transit service provision. Other variables deemed necessary to adapting the framework from Chicago to New York City, such as Hurricane Sandy and the introduction of bike-sharing, were also included. In summary, the model shown in the rightmost column of Table 4 is intended to follow that estimated for the city of Chicago in light of unavoidable constraints.

Table 4: Ordinary Least Squares and Random Effects Regression Results

| | **OLS Estimate** (SE) | **RE Estimate** (SE) | **RE AR(1) Estimate** (SE) | **RE ARMA(1,1) Estimate** (SE) |
|---|---|---|---|---|
| Real-Time Information | -582.17$^{**}$ | 104.99$^{***}$ | 59.84 | 70.53 |
| | (261.23) | (35.56) | (52.86) | (49.34) |
| Bus Service (Revenue Miles) | 5.51$^{***}$ | 3.36$^{***}$ | 3.92$^{***}$ | 3.57$^{***}$ |
| | (0.06) | (0.11) | (0.13) | (0.13) |
| Select Bus Service | 13008.62$^{***}$ | -473.38$^{***}$ | -877.71$^{***}$ | -682.37$^{***}$ |
| | (594.20) | (165.24) | (250.60) | (234.13) |
| Fare ($) | -3380.71$^{***}$ | -1670.53$^{***}$ | -2711.14$^{***}$ | -2880.50$^{***}$ |
| | (92.71) | (200.39) | (219.60) | (206.28) |
| Rail Revenue Miles (thousands) | 0.04 | 0.06$^{***}$ | 0.07$^{***}$ | 0.08$^{***}$ |
| | (0.20) | (0.02) | (0.02) | (0.02) |
| Rail Vehicles Operated in Maximum Service | -6.14$^{*}$ | -2.84$^{***}$ | -4.23$^{***}$ | -5.22$^{***}$ |
| | (3.49) | (0.49) | (0.56) | (0.54) |
| Citi Bike | 1233.57$^{***}$ | -471.84$^{***}$ | -284.69$^{***}$ | -278.74$^{***}$ |
| | (345.81) | (46.21) | (65.24) | (61.45) |
| Unemployment Rate | -227.23 | -368.81$^{***}$ | -446.63$^{***}$ | -484.69$^{***}$ |
| | (241.45) | (49.69) | (51.43) | (49.45) |
| Population (thousands) | 1.73$^{***}$ | 2.55$^{***}$ | 2.66$^{***}$ | 2.51$^{***}$ |
| | (0.14) | (0.60) | (0.65) | (0.65) |
| Gas Price ($) | -523.63 | -219.15$^{**}$ | -318.52$^{***}$ | -264.02$^{**}$ |
| | (768.91) | (104.74) | (104.12) | (104.82) |
| Cold Month | -150.51 | -270.90$^{***}$ | -187.16$^{***}$ | -145.72$^{***}$ |
| | (483.44) | (59.25) | (43.70) | (40.52) |
| Hot Month | -214.94 | -237.38$^{***}$ | -135.18$^{**}$ | -101.51$^{*}$ |
| | (619.71) | (76.12) | (56.45) | (54.85) |
| Total Monthly Snowfall (mm) | -0.76 | -0.84$^{***}$ | -0.60$^{***}$ | -0.45$^{***}$ |
| | (0.69) | (0.09) | (0.07) | (0.07) |
| Total Monthly Precipitation (mm) | -0.06 | -0.04$^{**}$ | -0.04$^{***}$ | -0.05$^{***}$ |
| | (0.14) | (0.02) | (0.01) | (0.01) |
| Hurricane Sandy | 83.9 | 198.77$^{**}$ | 44.94 | -75.1 |
| | (828.02) | (101.05) | (71.03) | (64.88) |
| $R^2$ | 0.62 | | | |
| Adj. $R^2$ | 0.62 | | | |
| AIC | | 108876.69 | 107160.24 | 106943.78 |
| BIC | | 109073.88 | 107364.23 | 107154.57 |
| Log Likelihood | | -54409.34 | -53550.12 | -53440.89 |

*$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$*

*Balanced panel with i=185 routes, t=36 months and N=6660 total observations.*

*Monthly dummy variables are shown in the appendix.*

The next analysis departs considerably from the previous work by also considering the FE model. Recall from the previous econometric presentation that RE estimates are inconsistent when unobserved route level effects are correlated with predictor variables, and that a Hausman test can be used to identify the proper model. Table 5 presents a RE model (with no adjustments for serially correlated errors) in the leftmost column and a FE model with identical variables adjacent. Estimates were obtained using the application Stata. It should be noted that some minor specification changes from the RE models shown in Table 4 were made to better fit this dataset, including dividing the coefficients of bus service and bike-sharing by borough.

A Hausman test on the two models in Table 5 rejects that the RE model is consistent, and therefore the FE model should be selected. To account for residual serial correlation, the robust standard errors (RSE) were estimated for each of the models shown in Table 5. Since the robust standard errors differ from the regular standard errors, the robust standard errors are relied on for statistical inference on the model. In summary, econometric theory and statistical tests advise that an FE model with robust standard errors (RSE) is preferred to the other models previously estimated in terms of statistical reliability and validity. Therefore, the FE models with RSEs are relied on to draw conclusions about the impact of real-time information on ridership.

The models shown in Table 5 include the availability of real-time information as a single binary variable. Because the 185 bus routes in this dataset varied greatly in terms of average weekday ridership from smaller local routes to major trunk routes, the FE model shown in Table 6 was also estimated, which divides the real-time information variable into four quartiles based on the level of bus service per route. All other variables were estimated in the same manner for the FE models shown in Table 5 and Table 6.

Table 5: Single Real-Time Information Variable Regression Results

| | **Random Effects Estimate** | | **Fixed Effects Estimate** | |
|---|---|---|---|---|
| | (SE) | (Robust SE) | (SE) | (Robust SE) |
| Real-Time Information | 104.954 | | 118.278 | |
| | (35.760)*** | (52.029)** | (35.162)*** | (52.695)** |
| Bus Service in Brooklyn | 5.804 | | 5.381 | |
| | (0.188)*** | (0.543)*** | (0.241)*** | (0.693)*** |
| Bus Service in Bronx | 6.059 | | 5.073 | |
| | (0.227)*** | (0.865)*** | (0.263)*** | (0.935)*** |
| Bus Service in Manhattan | 5.819 | | 3.051 | |
| | (0.264)*** | (1.088)*** | (0.374)*** | (1.227)** |
| Bus Service in Queens | 3.127 | | 2.765 | |
| | (0.159)*** | (0.926)*** | (0.179)*** | (1.275)** |
| Bus Service in Staten Island | 0.574 | | 0.212 | |
| | (0.183)*** | (0.254)** | -0.238 | -0.301 |
| Select Bus Service | -331.617 | | -262.039 | |
| | (166.210)** | -443.946 | -165.009 | -461.757 |
| Fare ($) | -1,030.88 | | -862.884 | |
| | (164.240)*** | (103.282)*** | (184.457)*** | (121.641)*** |
| Rail Revenue Miles (thousands) | 0.079 | | 0.072 | |
| | (0.021)*** | (0.009)*** | (0.021)*** | (0.008)*** |
| Rail Vehicles in Maximum Service | -2.925 | | -2.566 | |
| | (0.452)*** | (0.428)*** | (0.453)*** | (0.398)*** |
| Citi Bike in Manhattan | -467.602 | | -556.237 | |
| | (62.827)*** | (126.536)*** | (62.135)*** | (143.921)*** |
| Citi Bike in Brooklyn | -376.546 | | -375.308 | |
| | (54.936)*** | (97.277)*** | (53.857)*** | (96.701)*** |
| Unemployment Rate | -275.806 | | -243.379 | |
| | (45.289)*** | (41.964)*** | (48.215)*** | (40.208)*** |
| Cold Month | -249.481 | | -249.223 | |
| | (58.040)*** | (30.536)*** | (56.868)*** | (30.778)*** |
| Hot Month | -258.168 | | -246.906 | |
| | (75.470)*** | (38.447)*** | (73.991)*** | (35.622)*** |
| Total Monthly Snowfall (mm) | -0.833 | | -0.819 | |
| | (0.081)*** | (0.071)*** | (0.079)*** | (0.070)*** |
| Total Monthly Precipitation (mm) | -0.387 | | -0.366 | |
| | (0.158)** | (0.063)*** | (0.155)** | (0.060)*** |
| Hurricane Sandy | 212.891 | | 206.319 | |
| | (100.157)** | (51.822)*** | (98.172)** | (51.793)*** |
| $\sigma_u$ | 3569.71 | | 6425.35 | |
| $\sigma_\mu$ | 758.52 | | 758.52 | |
| $R^2$ | 0.47 | | 0.47 | |

**p<0.1; **p<0.05; ***p<0.01; Monthly dummy controls in appendix; Huber-White robust standard error.*

Table 6: Quartiles of Bus Service Real-Time Information Variable Regression Results

| | Fixed Effects Estimate | |
|---|---|---|
| | (SE) | (Robust SE) |
| Real-Time Information on Small Routes (Q1) | 16.256 | |
| | (61.568) | (62.551) |
| Real-Time Information on Smaller Medium Routes (Q2) | 147.101 | |
| | (61.415)** | (106.412) |
| Real-Time Information on Larger Medium Routes (Q3) | -35.114 | |
| | (64.971) | (106.778) |
| Real-Time Information on Large Routes (Q4) | 340.466 | |
| | (63.655)*** | (124.803)*** |
| Bus Service in Brooklyn | 5.376 | |
| | (0.240)*** | (0.693)*** |
| Bus Service in Bronx | 5.017 | |
| | (0.263)*** | (0.945)*** |
| Bus Service in Manhattan | 3.153 | |
| | (0.375)*** | (1.229)** |
| Bus Service in Queens | 2.762 | |
| | (0.179)*** | (1.274)** |
| Bus Service in Staten Island | 0.03 | |
| | -0.243 | -0.329 |
| Select Bus Service | -326.825 | |
| | (165.544)** | -458.593 |
| Fare ($) | -868.031 | |
| | (184.201)*** | (123.463)*** |
| Rail Revenue Miles (thousands) | 0.073 | |
| | (0.021)*** | (0.008)*** |
| Rail Vehicles in Maximum Service | -2.564 | |
| | (0.453)*** | (0.393)*** |
| Citi Bike in Manhattan | -535.102 | |
| | (62.646)*** | (152.800)*** |
| Citi Bike in Brooklyn | -375.586 | |
| | (53.781)*** | (96.759)*** |
| Unemployment Rate | -244.935 | |
| | (48.153)*** | (40.397)*** |
| Cold Month | -247.74 | |
| | (56.788)*** | (30.635)*** |
| Hot Month | -245.322 | |
| | (73.890)*** | (35.529)*** |
| Total Monthly Snowfall (mm) | -0.82 | |
| | (0.079)*** | (0.070)*** |
| Total Monthly Precipitation (mm) | -0.366 | |
| | (0.155)** | (0.061)*** |
| Hurricane Sandy | 204.454 | |
| | (98.027)** | (51.790)*** |
| $\sigma_u$ | 6393.18 | |
| $\sigma_\mu$ | 757.37 | |
| $R^2$ | 0.47 | |

** p<0.1; ** p<0.05; *** p<0.01*
*Monthly dummy controls presented in appendix. Huber-White robust standard error.*

## Model Inference

In this section, the information revealed by the preferred model specifications is discussed. As shown in Tables 5 and 6, the variable of interest, real-time information, was significant to some degree in both models. The coefficient of the real-time information variable can be interpreted as the number of additional bus trips per route on an average weekday attributable to the deployment of real-time information. The coefficient of 118 in the single variable FE model indicates that real-time information yields, on average, an increase of approximately 118 daily rides on routes where real-time information was available, which is a median increase of 1.7% of route-level ridership.

However, the quartile model's robust standard errors reveal that real-time information only caused a significant increase in ridership on large routes, but that the improvement was larger than the single variable model indicated. On the largest quartile of routes (defined as having more than 1,900 revenue miles of service on an average weekday), real-time information increased ridership, on average, by about 340 rides per weekday. This represents a median increase of 2.3% of route-level ridership on the largest routes. This finding is intuitive for a few reasons: routes with lots of service may see a larger change simply because the existing level of service is highest, and they are more likely to attract "choice" trips (such as non-commute trips). Another explanation may be that the ridership numbers are simply high enough to actually realize a quantifiable change; on small routes, a 1-2% change may only be a handful of rides per day, which may be lost to measurement error or overcome by statistical noise.

As can be seen in Tables 5 and 6, most of the transit-related independent variables were significant in the FE model. The level of bus service per route was significant, and it can be interpreted as the change in average weekday ridership resulting from an increase in revenue miles of service. The coefficients for bus service per route were separated into five different variables based on the borough of each route, and these coefficients indicate significantly different effects on ridership by borough. Staten Island had the only insignificant coefficient in the FE models. This may be because it has the lowest current availability of transit service; therefore, changing the level of service may have little impact on ridership in this more automobile dependent borough.

The dummy variable for Select Bus Service (SBS) was not significant in the FE models when robust standard errors are observed. It should be noted that SBS routes were modeled as having joint ridership with their corresponding local route (e.g. the B44 and B44SBS were modeled as a single route) due to data constraints, and this may have been one reason why there was little predicted impact on ridership.

The coefficient for the fares variable was significant. The value of the coefficient (-862.884 in the single variable model and -868.031 in the quartile model) can be interpreted as the change in average weekday route-level ridership associated with a one dollar increase in fares.

The two variables representing system-wide rail service were both significant. The total number of rail revenue miles operated per month had a coefficient of approximately 0.07, and this positive value suggests that as the level of overall rail service increases, bus ridership increases. Perhaps this can be interpreted as overall rail service having a complementary relationship with bus service; for example, as rail service increases, travelers in New York City become more reliant on transit, and consequently, increase both their rail and bus trips.  On the other hand, the variable for system-wide peak rail service, which was vehicles operated in maximum service, had a negative coefficient of approximately -2.56.  This suggests that increasing rail service in the peak hour may decrease bus ridership.  This substitution effect may be because commuters choose rail service over bus in peak periods.

For the external factors, the Citi Bike bike-sharing program had a significant, negative effect on route-level bus ridership.  The availability of bike-sharing may have decreased route-level bus ridership by over 500 rides per route in Manhattan, which has more bike-sharing stations, and approximately 375 rides per route in Brooklyn on an average weekday.  The decrease may be because bike-sharing provides an alternative mode of transportation to bus service, particularly for short trips that might be made on local bus routes.  However, the magnitude of this coefficient appears to be unrealistically large.  Performing a back of the envelop calculation to assess if all NYCT bus routes in Manhattan and Brooklyn experienced this level of ridership decrease reveals that a very large percentage (almost all) of Citi Bike's ridership on an average weekday in 2013 would be from former bus riders.  Therefore, further study is recommended to better understand the complex relationship between buses and bike-sharing.

Three commonly used socioeconomic variables were included in the analysis: unemployment rate, population and gas prices.  The unemployment rate had a significant negative effect on bus ridership.  Both models suggest that as unemployment rate increases 1%, route-level bus ridership decreases by approximately 244 rides on an average weekday.  This aligns with previous research that suggests as unemployment increases, travelers make fewer trips on a whole, and this can have a negative impact on transit ridership. The two other socioeconomic variables, gas prices and population, did not have a significant impact on bus ridership in the fixed effects model results, and consequently, they were removed from the final specification. The cross price elasticity of gas prices in the short run is inelastic, so it is unsurprising that this variable was insignificant in the model (Litman 2014). In terms of population, the data available was not at a granular level (only annual estimates by borough were available), and if there were more accurate reflections of population changes, this could have a more substantial impact on ridership.

Numerous weather variables were included in the model. Both cold and hot temperatures appear to have caused declines in ridership, with a decrease of approximately 240-250 rides per route on an average weekday if the month were either cold or hot. Perhaps this is because transit riders forgo unnecessary trips if the weather is particularly hot or cold, or they instead use other modes (such as a taxi or private automobile) to ensure that the entire trip was air conditioned or heated. Both total monthly snowfall and total monthly precipitation had a negative impact of ridership, which aligns with previous literature. The last weather variable, Hurricane Sandy, had a significant positive coefficient. The two models indicate that the occurrence of the hurricane increased route-level bus ridership by approximately 205 to 206 rides per route on average weekdays in November 2012. This is likely because sections of the rail system remained shut down in the immediate aftermath of the disaster, and transit riders instead used the bus system to travel (Kaufman, Qing, Levenson, & Hanson, 2012).

Finally, the goodness-of-fit across all models is comparable, as shown by the similar R-squared values. It should also be noted that monthly dummy variables were included in the model since transit ridership exhibited strong seasonal trends, and these variables are shown in the appendix.

**Areas for Improvement and Future Research**

There are a number of notable limitations to this study. One of the most challenging aspects of this research design was controlling for all of the factors that affected route-level bus ridership during the three year study period. For example, Hurricane Sandy significantly affected transit service in November 2012, but there could have been important lingering effects that were not captured in the model. Similarly, minor changes to the transportation network in New York City (e.g. road closures, bridge repairs, etc.) could have influenced the level of bus ridership.

An interesting avenue for future research that emerged from the regression models pertains to the impact of bike-sharing programs on public transit ridership. In this analysis, the availability of bike-sharing was simply modeled as a binary variable, despite varying levels of bike-sharing service along bus routes (in terms of station location and number of bikes), and the magnitude of the impact of the bike-sharing program on bus ridership appears to be unrealistically large. Therefore, further research in this area is recommended, and additional studies could also evaluate the impacts on rail ridership, which may differ from that on bus service.

In terms of the modeling approach, there could be opportunities to utilize more sophisticated emerging techniques that consider both temporal and spatial autocorrelation. Routes that intersect or parallel each other may see their ridership counts move together as a result of transferring passengers or unobserved changes in local activity patterns. Controlling for these endogenous or unobserved effects will be an important challenge.

This analysis focused on the overall impacts of bus real-time information on route-level bus ridership, but there are many interesting areas for additional analysis in the future. For example, future research could segment ridership impacts between high and low frequency routes or peak and off-peak periods. Additionally, expansions to understand the impact of real-time information on train ridership could be conducted, since real-time information also became available for most of the rail system during the study period (Mann, 2012). Last, the impact of additional ridership from real-time information on farebox revenue could be assessed, and this could be compared to the costs of deploying and maintaining the real-time information system.

## Conclusions

In this study, an empirical analysis of the ridership impacts of real-time bus information in New York City was conducted. Panel regression techniques were used to evaluate bus ridership over a three year period, while controlling for changes in transit service, fares, local socioeconomic conditions, weather, and other factors. Two fixed effects models with robust standard errors were selected for final presentation. The first model, which included real-time information as a single binary variable, showed an average increase of approximately 118 rides per route per weekday (median increase of 1.7% of weekday route-level ridership) attributable to providing real-time information. The second model, which divided the real-time information coefficient based on quartiles of bus service per route, suggests that the ridership increase occurred on the largest routes, which have 1900 revenue miles or more of average weekday service. Specifically, the model implied that real-time information increased ridership by about 340 rides per weekday on the largest quartile of routes, which is a median increase of 2.3% of route-level ridership.

Although both models present plausible results, the second model is preferable for two reasons. One possible explanation why the largest routes experience a significant increase in ridership is that they may be more likely to attract “choice” trips (such as trips to go shopping or to recreational activities). For example, when a traveler is considering taking a bus trip versus an alternative mode, checking real-time information for the bus routes with the highest service levels may reveal that a vehicle is only a few minutes away, and consequently, the traveler chooses to take that extra trip on the bus. On bus routes with lower levels of service, the traveler may be presented with the information that he or she would have to wait for a longer period of time, and in that situation, the traveler may choose an alternative mode or forgo the unnecessary trip. An alternative explanation may be that the ridership numbers are simply high enough to realize a quantifiable change; on small routes, a change less than 2% may only be a handful of rides per day, which may escape data capture or significance in the model.

While the second model presents a somewhat more plausible explanation of what is occurring in the real world, the striking similarity that the first model (with a single real-time information variable) has with the results of the Chicago study should be noted. The same unit of analysis for the dependent variable in the regression model (monthly average weekday bus ridership per route) was utilized, which allows for direct comparison between this model and the Chicago model. Tang and Thakuriah (2012) found a significant increase of 126 average weekday rides per route (approximately 1.8-2.2% of route-level ridership) attributable to RTI. The single real-time information variable fixed effects model showed an average increase of approximately 118 rides per route per weekday (median increase of 1.7% of weekday route-level ridership). While a few limitations of the natural experiment in Chicago were previously noted, this study of New York City also had limitations; for example, the study period was only three years, and extending the panel – particularly to include the launch of real-time information in the remaining two boroughs – could potentially impact the final results. Perhaps the similarity in these findings, despite limitations in each of the studies, suggests that bus ridership may increase one or two percent (holding all else equal) when passengers are provided with real-time information via web-enabled and mobile devices. In light of the finding regarding greater impacts on bus routes with high levels of service, the potential generalization of this result could be limited to large bus systems, since NYCT and the CTA are the first and third largest bus systems, respectively, in the country based on unlinked passenger trips (Neff & Dickens, 2013).

These results, concurrent with the previous findings in Chicago, suggest that investments in customer information systems have had a significant impact on bus ridership levels, particularly for two of the country's largest bus systems. Therefore, this research has immediate implications for leaders in the transit industry making important decisions on how to improve America's public transportation systems, particularly those agencies that face pressure to increase ridership under tight budget constraints.

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# CHAPTER 3

# TAMPA

Brakewood, C., Barbeau, S. and Watkins, K. (2014). An Experiment Evaluating the Impacts of Real-Time Transit Information on Bus Riders in Tampa, Florida. Submitted to *Transportation Research Part A: Policy and Practice* on February 7, 2014.


## Abstract

Public transit agencies often struggle with service reliability issues; when a bus does not arrive on time, passengers become frustrated and may be less likely to choose transit for future trips. To address reliability issues, transit authorities have begun to provide real-time information (RTI) to riders via mobile and web-enabled devices. The objective of this research is to quantify the benefits of RTI provided to bus riders. The method used is a behavioral experiment with a before-after control group design in which RTI is only provided to the experimental group. Web-based surveys are used to measure behavior, feeling, and satisfaction changes of bus riders in Tampa, Florida over a study period of approximately three months.

The results show that the primary benefits associated with providing RTI to passengers pertain to waiting at the bus stop. Analysis of "usual" wait times revealed a significantly larger decrease (nearly 2 minutes) for RTI users compared to the control group. Additionally, RTI users had significant decreases in levels of anxiety and frustration when waiting for the bus compared to the control group. Similarly, they had significant increases in levels of satisfaction with the time they spend waiting for the bus and how often the bus arrives at the stop on time. Taken together, these findings provide

strong evidence that RTI significantly improves the passenger experience of waiting for the bus, which is notoriously one of the most disliked elements of transit trips. The frequency of bus trips and bus-to-bus transfers were also evaluated during the study period, but there were no significant differences between the experimental and control groups. This is not surprising since the majority of bus riders in Tampa are transit-dependent and lack other transportation alternatives.

The primary contribution of this research is a comprehensive evaluation of the passenger benefits of RTI conducted in a controlled environment. Moreover, this research has immediate implications for public transit agencies – particularly those serving largely transit-dependent populations – facing pressure to improve service under tight budget constraints.

## Introduction

Public transit plays a vital role in urban transportation systems. Transit helps to reduce carbon dioxide emissions, decrease gasoline consumption, and combat roadway congestion in metropolitan areas (Schrank, Eisele, & Lomax, 2012). It is one of the safest modes of passenger transport, as evidenced by low passenger fatality rates (Neff & Dickens, 2013). Other benefits of transit include providing mobility options for those who cannot or choose not to drive (American Public Transportation Association, 2014) and public health benefits associated with active lifestyles (e.g. Besser & Dannenberg, 2005).

Despite its benefits, transit agencies in many American cities struggle to compete with other modes of passenger transportation, especially single-occupancy motor vehicles. To be a viable option when compared to alternatives, transit service must be fast, frequent, and reliable, among other things (Walker, 2012). Reliability can be improved in many ways, including: increasing levels of right of way, such as providing a dedicated lane; using service planning approaches, such as adding slack to scheduled running times; or implementing control strategies, such as holding vehicles that are ahead of schedule. While these supply-side strategies can be effective at improving reliability, they often come at a substantial cost.

Recently, a demand-side strategy has emerged that can improve the perception of reliability: providing real-time vehicle location and/or arrival information helps passengers adapt to unreliability of transit service (Carrel et al., 2013). Moreover, real-time information (RTI) can be provided to passengers in an increasingly cost-effective manner, particularly when agencies take an “open data” approach. “Open data” means that the transit authority makes their service information freely available to the general public in a computer-readable format (Barbeau, 2013; Wong, Reed, Watkins, & Hammond, 2013). This information can be used by third-party software developers to create transit “apps,” often at little-to-no additional cost to the agency. The rapid adoption of mobile devices makes this third-party information dissemination channel directly accessible to an increasing number of riders (Schweiger, 2011). This trend has occurred so rapidly in the United States that, in December of 2012, the president of the American Public Transportation Association said that “the proliferation of transit apps is one of the most exciting things to happen to this industry” (Mann, 2012).

In light of this, decision-makers at the country’s transit providers want to understand the impacts of RTI, and this research aims to provide a comprehensive controlled study of the benefits of providing RTI to riders via web-enabled and mobile devices.

## Literature Review

There is a growing body of research that aims to understand the rider benefits of RTI. An early segment of this research focused on the impacts of RTI displayed on signage at stops or in stations (e.g., Hickman & Wilson, 1995; Dziekan & Kottenhoff, 2007; Politis, Papaioannou, Basbas, & Dimitriadis, 2010). Recently, the literature has expanded to include the provision of RTI through web-enabled and/or mobile devices. Many of the initial studies of RTI provided via personal devices relied heavily on stated preference and/or simulation methods to evaluate possible impacts (e.g., Caulfield & Mahony, 2009; Tang & Thakuriah, 2010). Given the recent widespread availability of RTI applications throughout the country, there is a growing subset of the literature that uses actual behavioral data to understand rider benefits, and it is the focus of this review. Based on prior behavioral studies, the following key benefits of RTI were identified: (1) decreased wait times, (2) increased satisfaction with transit service, and (3) increased ridership. The following review includes discussion of each one of these impacts, a summary of the rider benefits of RTI, and a brief review of behavioral experiments in public transit.

### Decreased Wait Times and Feelings Experienced While Waiting

When passengers utilize RTI, they can time their departure from their origin to minimize their wait time at stops or stations; moreover, RTI can reduce their perception of the length of wait times. In Seattle, Washington, a recent study found that bus riders with RTI had actual wait times that were almost two minutes less than those of non-users, and perceived wait times of RTI users were approximately 30% less than those who did not use RTI (Watkins, Ferris, Borning, Rutherford, & Layton, 2011).

Because passengers spend less time waiting at stops and stations, RTI may increase passenger perceptions of personal security when riding transit, particularly at night. A panel study conducted at the University of Maryland measured changes before and after the implementation of a RTI system on the university shuttle bus network, and the results revealed that passengers reported increased levels of perceived personal security at night attributable to RTI (Zhang, Shen, & Clifton, 2008). Two web-based surveys of RTI users conducted in Seattle, Washington provide additional evidence that RTI may increase self-reported levels of personal security. In the first survey, conducted in 2009, 18% of respondents reported feeling "somewhat safer" and another 3% felt "much safer" as result of using RTI (Ferris, Watkins, & Borning, 2010). In 2012, a follow-up web-based survey in Seattle found over 32% of RTI users had a positive shift in their perception of personal security (Gooze, Watkins, & Borning, 2013).

In addition, prior studies have aimed to assess changes in other feelings while waiting for the bus, including aggravation, anxiety and relaxation. The previously mentioned University of Maryland panel study evaluated levels of anxiety while waiting for the bus but did not find a significant decrease associated with the use of RTI (Zhang et al., 2008). Similarly, the Seattle study of wait times evaluated passenger levels of aggravation and relaxation while waiting, but the results showed no significant difference between the RTI users self-reported aggravation levels and that of those without RTI (Watkins et al., 2011).

**Increased Satisfaction with Transit Service**

In theory, if transit passengers spend less time waiting (or perceive waiting time to be less), it follows that they may feel more satisfied with overall transit service. The University of Maryland study found a significant increase in overall satisfaction with shuttle bus service attributable to RTI (Zhang et al., 2008). Additionally, in the 2009 web-based survey of RTI users in Seattle, 92% of respondents stated that they were either "somewhat more" satisfied or "much more" satisfied with overall transit service, and the follow-up 2012 survey of RTI users found similar results (Ferris et al., 2010; Gooze et al., 2013).

**Increased Ridership and Transfers**

If passengers spend less time waiting and/or are more satisfied with overall transit service, then the provision of RTI may also cause an increase in the frequency of transit trips by existing riders or potentially attract new riders to transit. In Seattle, the two web-based surveys of RTI users previously discussed found that approximately one third of riders reported an increase in the number of non-work/school trips per week made on transit because of RTI (Ferris et al., 2010; Gooze et al., 2013). On the other hand, the University of Maryland study also evaluated frequency of travel on the university shuttle bus system but concluded that RTI did not cause an increase in shuttle bus trips (Zhang et al., 2008). Last, an empirical evaluation of Chicago bus ridership found a "modest" increase in overall route-level ridership (precisely 126 rides per route per day, which is 1.8-2.2% of average route-level weekday bus ridership) attributable to real-time bus information (Tang & Thakuriah, 2012).

If passengers take more trips on transit, they may also increase the number of transfers they make between transit routes. Similarly, if RTI reduces the perception of the length of wait times, it could also reduce the perception of transfer times, potentially leading to an increased willingness to transfer. In a follow-up study in Chicago, the impacts of bus RTI on rail ridership were evaluated, and the results showed a small increase in rail ridership (0.3% of the average weekday train station-level ridership) attributable to bus RTI. The authors argue that this increase in rail ridership may be due to increased intermodal transfer efficiency between buses and trains, which suggests a complementary effect of the provision of bus RTI on connected rail service (Tang, Ross, & Han, 2012).

**Summary of the Rider Benefits of Real-Time Information**

Based on this literature review of studies evaluating transit rider behavior, several potential benefits of providing RTI to transit riders were identified. First, RTI may be associated with a decrease in the wait times (both actual and perceived) of riders. Second, riders using RTI may report increased levels of personal security while riding transit, likely because they can reduce their wait times at bus stops. Third, RTI use may be associated with changes in levels of aggravation, anxiety and/or relaxation while waiting for the bus, although most prior studies have not found significant changes in these feelings. RTI use may also result in higher levels of satisfaction with overall transit service. Last, RTI users may increase their frequency of transit trips, as well as their frequency of transferring.

It should be noted that the majority of these behavioral studies of RTI were conducted in two large American cities (Seattle and Chicago) that have extensive bus systems. The Chicago Transit Authority and King County Metro in Seattle operate the second and seventh largest American bus systems, respectively, based on passenger miles (Neff & Dickens, 2013). Given the sheer size of these networks, they differ from many other American bus systems in their level of service provision (namely frequency of service and/or origin-destinations served), as well as the demographics of transit riders that include relatively high level of "choice" riders (ORC, 2011; Zhao, Webb, & Shah, 2014). Evaluation of the benefits of RTI in a mid- or small-sized transit system may find different levels of benefits.

Finally, it should be noted that there may be other rider benefits associated with the use of RTI (e.g. route choice to minimize travel time), but prior research has largely relied on stated preference or simulation methods (e.g., Cats et al., 2011; Fonzone & Schmöcker, 2014). Therefore, this study focuses on the benefits grounded in actual behavioral studies to provide a framework for evaluation of RTI in a controlled environment.

**Controlled Behavioral Experiments Involving Transit Riders**

Controlled behavioral experiments are an established methodology in the social sciences to understand the impact of a treatment variable on study participants while controlling for other environmental effects (Campbell & Stanley, 1963). Despite this, the practice of performing true behavioral experiments to evaluate traveler behavior is somewhat limited. A few recent studies that specifically evaluate transit traveler behavior include Fujii & Kitamura (2003), who evaluated drivers' habits and attitudes toward public transit before and after giving them a treatment of a free one month bus pass, and Rodriguez & Rogers (2014), who conducted an experiment involving information about accessibility to transit and its effects on university student housing location choices. To the best of the authors' knowledge, there have not been any prior controlled behavior studies evaluating the impacts of RTI or mobile applications providing transit information to travelers.

## Methodology

A controlled behavioral experiment was conducted in Tampa, Florida to evaluate the benefits of providing RTI to transit riders. Tampa was selected as the location for this study for two reasons. First, the transit provider in Tampa, the Hillsborough Regional Transit Authority (HART), operates a bus service of approximately 27 local and 12 express bus routes (HART, 2013a) and had a FY2013 annual ridership of approximately 14.6 million bus trips (HART, 2013b). Therefore, this small-sized transit system differs from the prior studies of larger systems (Seattle and Chicago). Notably, the demographics of HART's ridership are largely transit-dependent users; their most recent system-wide survey showed that 56% of riders do not have a valid driver's license and 66% live in households without cars (Tindale-Oliver & Associates, 2010).

More importantly, Tampa offered a unique opportunity to provide RTI to only a controlled subset of transit riders. HART outfitted all of their buses with automatic vehicle location (AVL) equipment in 2007, but initially implemented the system for operational purposes only and did not share RTI with riders. In 2012, the agency granted the authors special access to their real-time bus data in order to develop a RTI system for riders. Since there were no other means for HART riders to access RTI, a controlled environment was available for experimentation.[5] The transit agency and the authors decided to pursue a small-scale launch of the RTI system, which provided a limited time to conduct a research study that restricted access of RTI to a small group of participants. In light of the opportunity to expose a controlled population to RTI without other interference (i.e. the launch of other transit agency developed applications or the public release of open real-time data), a behavioral experiment was selected as the methodology for this study.

**Experimental Design**

The specific method utilized was a before-after control group research design (Campbell & Stanley, 1963). The treatment in this experiment was access to RTI over a study period of approximately three months. The method of measuring rider behavior, feeling, and satisfaction changes was two web-based surveys: one administered before RTI and another after the completion of the study period.

**Recruitment**

The "before" survey was conducted in February 2013 during a two week period. HART bus riders were recruited to participate in the study through a link posted on the homepage of the transit agency website, as well as through the transit agency email list and other local email lists. Interested riders could enter a publically accessible link to the web-based survey software, and on the pre-wave survey, all respondents were asked to

[5] In 2012, HART installed a small two-line LED sign system for estimated arrival information that was intermittently functional. To the best of the authors' knowledge, the LED signs were only operational at one stop (Marion Transit Center) during the experiment.

provide an email address in order to contact them for follow-up and the “after” survey. An incentive of a free one day bus pass was provided to all pre-wave survey participants to help increase the response rate. Respondents were then randomly assigned to the control group and the experimental group. Then, the experimental group was emailed instructions explaining how to use RTI, and they were instructed not to share RTI with anyone during the study period. After approximately three months, the after survey was administered during the last two weeks of May 2013. A second incentive of a free one day bus pass was provided to all participants (both the control and experimental groups) to help increase the response rate of the post-wave survey.

**Treatment**

The treatment in this experiment was exposure to RTI. RTI was provided to riders through a transit traveler information system known as OneBusAway. OneBusAway was originally developed in 2008 at the University of Washington to provide real-time bus arrival information for riders in greater Seattle. Over its five years in existence in the Puget Sound region, OneBusAway has increased in utilization to become a proven platform, currently hosting more than 100,000 unique users per week. More importantly, OneBusAway was developed as an open-source system, which allows others to adapt the code for their own transit systems.

Five OneBusAway interfaces were developed for Tampa and made available to the experimental group: a website, two mobile websites for internet-enabled mobile devices (one text-only and the other optimized for smartphones), a native Android application, and a native iPhone application (see screenshots in Figure 4). For the three websites, access was limited by only providing the web address to the experimental group. For the two smartphone applications, participants in the experimental group were instructed to download the OneBusAway application from Seattle and change the settings for the OneBusAway server application programming interface (API) from Seattle to Tampa. An example of the setting change is shown in the rightmost screenshot in Figure 4.

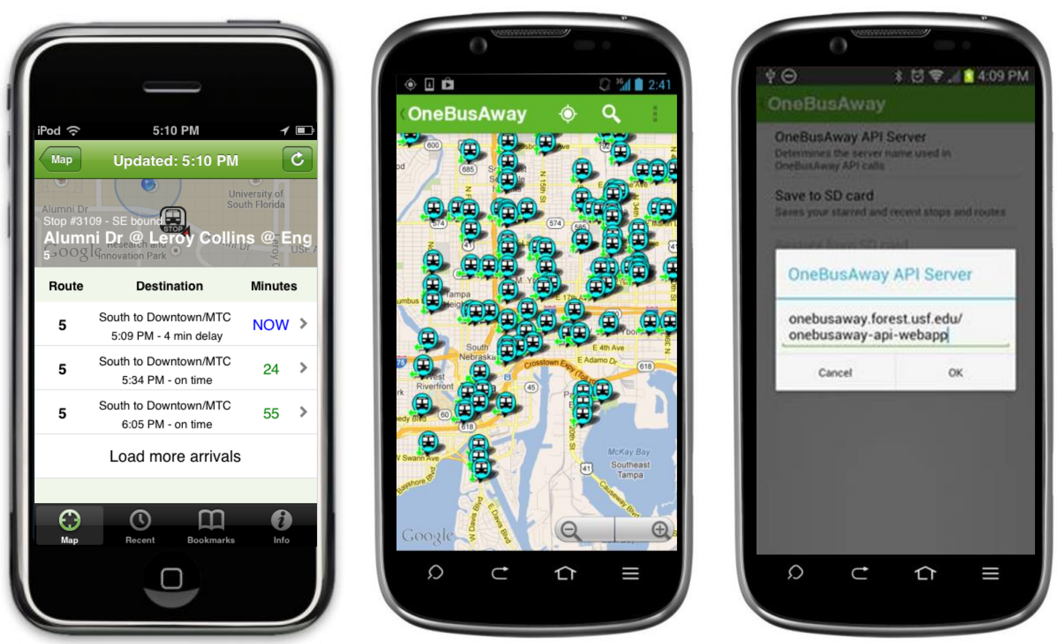


Figure 4: Screenshots of the OneBusAway Tampa iPhone Application, Android Application, and Setting Changes to Limit Access (shown for Android)

### Survey Content

To measure behavior, feeling, and satisfaction changes, the survey instruments contained identical questions in the pre-wave and the post-wave surveys for both the control and experimental groups. Transit travel behavioral questions included the number of trips on HART buses in the last week and the number of transfers between HART bus routes in the last week. To assess wait times, respondents were asked about their “usual” wait time on the route that they ride most frequently. Participants were also asked questions about eight feelings while waiting for the bus, and they rated them on a five point Likert scale. Specifically, they were asked about three feelings discussed in the prior literature (relaxed, anxious and safety at night and during the daytime), and a minor alteration was made to a fourth (aggravation was changed to frustration). Additionally, three feelings were included that could change due to the availability of RTI: bored, productive and embarrassed. It was hypothesized that riders may feel bored or unproductive while waiting for the bus, but those who checked RTI could experience decreases in these feelings; similarly, passengers might be embarrassed to stand on street corners waiting for the bus for extended periods of time and, if this were the case, those who use RTI may experience a decrease in this feeling. To assess satisfaction, all participants were asked to rate their level of satisfaction with overall transit service on a five point Likert scale. Because the transit customer research literature typically breaks down satisfaction ratings into specific elements of service provision (e.g., Eboli & Mazzulla, 2007), five indicators of certain elements of transit service were also included. One of these indicators was specifically targeted at passenger wait times: “how long you have to wait for the bus.” Two indicators aimed to capture reliability of the transit service: “how often the bus arrives at the stop on time” and “how often you arrive at your destination on time.” The last two indicators represented frequency of service and transferring, respectively: “how frequently the bus comes” and “how often you have to transfer buses to get to your final destination.”

In addition to the questions that were asked of both the control and experimental groups in the before and after surveys, a series of questions was added to the post-wave survey of the experimental group to assess if RTI users perceived a change in their travel behavior, satisfaction, and feelings.  This was specifically done because two prior studies in the Seattle area asked RTI users to self-report changes (Ferris et al., 2010; Gooze et al., 2013), and asking these perception questions allows for comparison with the previously mentioned questions asked on both the pre-wave and post-wave surveys.

It should also be noted that standard socioeconomic characteristics were asked to understand the representativeness of the survey participants; similarly, participants were asked which information and communication technologies they use.  Finally, after composing the survey instruments, they were pre-tested on a group of a dozen students and staff at Georgia Tech and reviewed by customer research employees at HART.

**Sample Size**

The sample sizes for the before and after surveys are shown in Table 7.  A total of 534 people initially entered the link to the survey software, and of these, 452 responses included a unique email address, which was necessary to contact participants for the post-wave survey.  These 452 usable responses were then divided into the control and experimental groups using a random number generator.  59% of the usable experimental group and 60% of the usable control group sufficiently completed the post-wave survey, which resulted in a final sample size of 268 participants.

A key challenge to conducting this controlled behavioral experiment was limiting access of OneBusAway to only the experimental group.  As can be seen in Table 7, some contamination of the control group occurred because 24 participants figured out how to access OneBusAway, mostly by searching the internet sufficiently to find the website (14/24) or receiving instructions from family/friends (8/24).  Similarly, there were some members of the experimental group (27 total) that never used OneBusAway during the study period. The most common reason for not using OneBusAway was not having a smartphone (12/27), and other common reasons included not riding the bus, not needing it, and not having time to read instructions. Due to their deviation from random assignment, the contaminated control group and experimental non-user group were not given the complete post-wave survey. Therefore, the results presented in the following sections include only the clean control group (107) and the clean experimental group (110). Last, the socioeconomic characteristics of the clean control and experimental groups were compared to assure that the usable sample remained equivalent after attrition. As shown in Table 8, the groups were not statistically different in age, annual household income, gender, employment status, household car ownership, and having a driver's license, but they differed in ethnicity (*p=0.002).*

Table 7: Sample Size

| | **Before Survey*** | | **After Survey**** | | | |
|---|---|---|---|---|---|---|
| | *Began Survey* | *Usable Sample Size* | *Sample Size of OneBusAway Users* | *Sample Size of Non-Users* | *Sample Size Total* | *Percent of Before Usable Sample* |
| Experimental Group | 534 | 229 | 110 | 27 | 137 | 59% |
| Control Group | | 223 | 24 | 107 | 131 | 60% |
| Total | 534 | 452 | 134 | 134 | 268 | 59% |

**Only participants who provided a unique email address and were 18+ years of age were deemed usable*
***Only participants responding to at least 50% of the questions were included in the final sample*

Table 8: Socioeconomic Characteristics of the Control and Experimental Groups

| | | Control Group | | Experimental | | Total | |
|---|---|---|---|---|---|---|---|
| **Category** | **Variable** | **#** | **%*** | **#** | **%*** | **#** | **%*** |
| *Total* | *All Respondents* | *107* | *100%* | *110* | *100%* | *217* | *100%* |
| Age | Age 18-24 | 10 | 9% | 11 | 10% | 21 | 10% |
| | Age 25-34 | 24 | 22% | 23 | 21% | 47 | 22% |
| | Age 35-44 | 24 | 22% | 29 | 26% | 53 | 24% |
| | Age 45-54 | 27 | 25% | 30 | 27% | 57 | 26% |
| | Age 55-64 | 16 | 15% | 15 | 14% | 31 | 14% |
| | Age 65-74 | 5 | 5% | 1 | 1% | 6 | 3% |
| | Age 75 and over | 1 | 1% | 0 | 0% | 1 | 0% |
| | No Answer | 0 | 0% | 1 | 1% | 1 | 0% |
| | *Wilcoxon Sum Rank Test: W=6124.5, p-value=0.514* | | | | | | |
| Annual Household Income | Under $5,000 | 9 | 8% | 10 | 9% | 19 | 9% |
| | $5,000 to $9,999 | 9 | 8% | 11 | 10% | 20 | 9% |
| | $10,000 to $19,999 | 23 | 21% | 13 | 12% | 36 | 17% |
| | $20,000 to $29,999 | 14 | 13% | 28 | 25% | 42 | 19% |
| | $30,000 to $39,999 | 13 | 12% | 14 | 13% | 27 | 12% |
| | $40,000 to $49,999 | 8 | 7% | 10 | 9% | 18 | 8% |
| | $50,000 or more | 27 | 25% | 18 | 16% | 45 | 21% |
| | No Answer | 4 | 4% | 6 | 5% | 10 | 5% |
| | *Wilcoxon Sum Rank Test: W=5599, p-value=0.568* | | | | | | |
| Household Car Ownership | No cars | 53 | 50% | 59 | 54% | 112 | 52% |
| | 1 car | 30 | 28% | 27 | 25% | 57 | 26% |
| | 2 cars | 19 | 18% | 18 | 16% | 37 | 17% |
| | 3 or more cars | 4 | 4% | 6 | 5% | 10 | 5% |
| | No Answer | 1 | 1% | 0 | 0% | 1 | 0% |
| | *Wilcoxon Sum Rank Test: W=5971.5, p-value=0.737* | | | | | | |
| License | Has a valid license | 71 | 66% | 83 | 75% | 154 | 71% |
| | No license | 35 | 33% | 27 | 25% | 62 | 29% |
| | No Answer | 1 | 1% | 0 | 0% | 1 | 0% |
| | *Kruskal-Wallis Test: Chi-squared=1.885, p-value=0.170* | | | | | | |
| Gender | Male | 53 | 50% | 45 | 41% | 98 | 45% |
| | Female | 54 | 50% | 64 | 58% | 118 | 54% |
| | No Answer | 0 | 0% | 1 | 1% | 1 | 0% |
| | *Kruskal-Wallis Test: Chi-squared=1.475, p-value=0.225* | | | | | | |
| Employ-ment Status | Employed Full Time | 57 | 53% | 63 | 57% | 120 | 55% |
| | Employed Part Time | 17 | 16% | 14 | 13% | 31 | 14% |
| | Not Employed | 7 | 7% | 11 | 10% | 18 | 8% |
| | Retired | 6 | 6% | 4 | 4% | 10 | 5% |
| | Student | 13 | 12% | 13 | 12% | 26 | 12% |
| | Other (disabled, etc.) | 4 | 4% | 2 | 2% | 6 | 3% |
| | No Answer | 3 | 3% | 3 | 3% | 6 | 3% |
| | *Kruskal-Wallis Test: Chi-squared=0.377, p-value=0.542* | | | | | | |
| Ethnicity ** | White | 75 | 70% | 54 | 49% | 129 | 59% |
| | Black/African American | 19 | 18% | 26 | 24% | 45 | 21% |
| | Hispanic or Latino | 5 | 5% | 19 | 17% | 24 | 11% |
| | Asian | 0 | 0% | 1 | 1% | 1 | 0% |
| | Other | 8 | 7% | 9 | 8% | 17 | 8% |
| | No Answer | 0 | 0% | 1 | 1% | 1 | 0% |
| | *Kruskal-Wallis Test: Chi-squared=9.546, p-value=0.002* | | | | | | |
| **Figures rounded to the nearest percent. **Multiple responses included in Other.* | | | | | | | |

# Results

The results of this behavioral experiment are divided into four sections. The first three sections evaluate changes in behavior, feeling, and satisfaction using identical questions posed on both the pre-wave and post-wave surveys. The fourth section assesses the questions that were only asked of the experimental group in the post-wave survey.

## Behavior Changes

Three measures of behavior change were evaluated: trip frequency, transfer frequency and wait time. To measure differences in transit trip frequency associated with RTI use, all respondents were asked how many trips on HART buses they made in the last week. Similarly, to measure changes in transit transfer frequency, respondents were asked how many of their trips in the last week included a transfer from one HART bus route to another bus route. Riders were also asked which HART bus route they traveled on most frequently and what their "usual" wait time was on that route. Then, for each of the three measures, the gain score, or difference (D), from the before survey ($Y_1$) to the after survey ($Y_2$) was calculated for each individual as follows: $D = Y_2 - Y_1$. The mean (M) and standard deviation (SD) of the before survey, after survey, and gain scores for the number of trips per week, number of transfers per week, and "usual" wait times are shown in Table 9 for the control group and the experimental group.

Table 9 shows that all three variables had, on average, a decrease from the before to the after survey for both the control and experimental groups. The difference in the mean gain scores between the control group and the experimental group was not significant for bus trips per week ($t$=0.66, $p$=0.512) nor was it significant for transfers per week ($t$=0.37, $p$=0.715). On the other hand, the mean gain score of the usual wait time for the experimental group (-1.79 minutes) was significantly different ($t$=2.66, $p$=0.009 < 0.01) from the control group (-0.21 minutes). This implies that the experimental group experienced a decrease in "usual" wait times approximately 1.5 minutes greater than they would have without RTI.

In theory, the research design should control for other changes affecting travel behavior, since such changes could be expected to occur similarly for members of both the experimental and control groups. This assumption was directly investigated to understand potential threats to internal validity. Differences in the frequency of transit trips and transfers may be caused by changes in automobile ownership, availability of a driver's license, household and work location, among other things. Therefore, all participants were asked if they bought/sold a car, got/lost a driver's license, moved household locations, or changed work/school locations during the study period. A total of 50 participants (24 in the control group; 26 in the experimental group) had one or more of these socioeconomic changes during the study period. Then, participants who had these changes (plus 3 who did not answer the questions) were removed from the calculations. The difference of mean gain scores between the remaining participants in the control group and experimental group was again not significant for bus trips per week ($t$=-0.37, $p$=0.712) or transfers per week ($t$=0.36, $p$=0.721). These results support the previous results shown in Table 9.

Similarly, prior transit research has shown that expected wait times are a function of the frequency and reliability of the transit service (Furth, Hemily, Muller, & Strathman, 2006). Therefore, participants were asked what bus route they ride most often. 38 participants (20 in the experimental group; 18 in the control group) reported changing their usual route during the study period. When the participants who changed bus routes were removed from the usual wait time calculations (plus 9 who did not answer the question), the difference between the mean gain scores of the usual wait time for the experimental group (-1.97 minutes) and the control group (-0.01 minutes) was nearly 2 minutes and was significantly different ($t$=3.02, $p$=0.003 < 0.01).[1]

A few caveats about this analysis should be made. First, the difference of means test assumes that the variables (difference in trips/week, transfers/week, and usual wait time) are continuous. To lessen the burden of survey participation on the respondents, these questions were posed with multiple choice answers that were capped on the high end (trips/week ranged from 0 to 11 or more trips; transfers/week from 0 to 11 or more transfers; usual wait time from 0 to more than 15 minutes). Therefore, this analysis decreases the impact of extreme values (trips/transfers more than 12 per week and usual wait times above 15 minutes).

Additionally, it is important to note that the one positive finding (usual wait time) relied completely on self-report data, but prior research has shown that self-reported wait times may not align with actual wait times due to the perception of time (Watkins et al., 2011a). Accordingly, the finding that the usual wait times of RTI users were less than the usual wait times of non-users could be interpreted as either a change in actual wait time

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[1] Regression models of the gain scores of trips/week, transfers/week, and usual wait time were also created to understand the extent to which the experimental design “controlled” for other factors. The results do not differ substantially from the simple t-statistics. The regression models are included in the appendix.

or a change simply in the perception of wait time attributable to RTI. The proportion of the reported change in wait time attributed to perceived or actual changes in wait time cannot be known without independent observations of passenger wait times.

**Feelings Experienced While Waiting**

Identical questions were posed to participants in the pre-wave and post-wave surveys to evaluate potential changes in feelings while waiting for the bus. These questions quantify the frequency that a respondent experienced specific feelings while waiting for the bus on the following five-point scale: never, rarely, sometimes, frequently, and always. Eight different indicators were used: bored, productive, anxious, relaxed, frustrated, embarrassed, safe at night and safe during the day. Similar to the previous section, the gain score, or difference (D), from the before survey ($Y_1$) to the after survey ($Y_2$) was calculated for each individual as follows: $D = Y_2 – Y_1$. Since each feeling was rated on a five-point scale, the differences ranged from -4 to 4. The gain scores were then used in a Wilcoxon rank sum test to evaluate any differences between the control group and the experimental group, and the results are shown in the rightmost column of Table 10. Additionally, the percent of respondents experiencing these feelings more than average (either "frequently" or "always") for the control group and the experimental group on the before survey and the after survey is shown in Table 10.

Table 10 shows that four feelings (productive, anxious, frustrated, and safe during the day) had significant differences from the pre-wave to the post-wave survey between the control group and the experimental group. Feeling "productive" while waiting for the bus increased from 10% of the experimental group in the pre-wave survey to 17% in the post-wave survey (combined total of "frequently" and "always"), and this was significantly different from the control group (*p*=0.051). This may be because RTI users have better knowledge of how long they will be waiting, which helps them to choose an activity (e.g. reading, sending emails) that is a good fit for the amount of time they will be waiting, as opposed to simply passing the time idly. Second, the experimental group had a small decrease in the frequency with which they feel "anxious" while waiting for the bus, which was somewhat different from the control group (*p*=0.082). Providing RTI to passengers may help them to feel as if they have more control over their trip (Watkins et al., 2011) and reduce their level of anxiety when waiting for the bus. Notably, the experimental group decreased their frequency of feeling "frustrated" when waiting for the bus (from 25% to 18%; combined total of "frequently" and "always"), and this was significantly different from the control group (*p*=0.006). One possible explanation of this is that RTI decreases the perception of unreliability of transit service and enables riders to adjust their behavior when service is delayed. This may be particularly important for riders who are dependent on the transit system and do not have other alternatives readily available.

Additionally, feelings of safety during the daytime significantly increased for the experimental group compared to the control group (*p*=0.035). This may be because passengers spend less time waiting on street corners where they feel exposed to passing traffic or personal crime. Furthermore, at less popular stops, passengers may find themselves waiting alone, and feel unsafe compared to when they are on a transit vehicle with other passengers. It is interesting to note that feelings of safety at night did not have a significant difference between the two groups. There are two likely explanations for why this may not have occurred. First, the pre-wave survey was conducted in February, when daylight hours are short, whereas the post-wave survey was conducted in May, when days are much longer and the evening peak commute occurs in daylight. Because of the seasonal differences, regular commuters may not have experienced as many trips during darkness, and therefore may not have had the opportunity to perceive a change in feelings of safety at night. An alternative explanation is that most RTI users are carrying a smartphone, which is a common item targeted by thieves (even resulting in the term "Apple-picking" as a common crime in most transit systems). Therefore, RTI users may feel more susceptible to petty theft if they use their smartphones to check RTI at night.

The three remaining feelings (bored, relaxed and embarrassed) did not have a significant difference between the mean gain scores of the control and experimental groups. Regarding levels of relaxation, it was originally hypothesized that those who decreased their levels of frustration or anxiety would have similar increases in levels of relaxation while waiting, but this did not occur.

Table 9: Mean (M), Standard Deviation (SD), and Difference of Mean Gain Scores for Trips, Transfers and Wait Time

| | Control Group | | | | Experimental Group | | | | Diff. of Mean Gain Scores | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Sample n | Before M (SD) | After M (SD) | Difference M (SD) | Sample n | Before M (SD) | After M (SD) | Difference M (SD) | Two-tailed t-stat | p-value | |
| Trips/Week | 107 | 7.03 (3.79) | 6.63 (4.09) | -0.40 (2.63) | 110 | 7.09 (3.94) | 6.40 (3.71) | -0.69 (3.76) | 0.66 | 0.512 | |
| Transfers/Week | 88 | 4.53 (4.15) | 4.35 (3.90) | -0.18 (3.77) | 94 | 4.26 (3.93) | 3.87 (3.33) | -0.38 (3.63) | 0.37 | 0.715 | |
| Usual Wait Time (minutes) | 102 | 10.71 (3.88) | 10.50 (4.25) | -0.21 (4.42) | 107 | 11.36 (4.06) | 9.56 (4.68) | -1.79 (4.21) | 2.66 | 0.009 | *** |
| *Significance: * p<0.10; ** p<0.05; *** p<0.01* | | | | | | | | | | | |

Table 10: Percent Frequently or Always and Wilcoxon Rank Sum Test for Change in Feelings while Waiting for the Bus

| | Control Group | | | Experimental Group | | | Diff. in Gain Scores | | |
|---|---|---|---|---|---|---|---|---|---|
| | Sample | Before | After | Sample | Before | After | Wilcoxon Test | | |
| | n | % Frequently + Always | % Frequently + Always | n | % Frequently + Always | % Frequently + Always | W | p-value | |
| Bored | 103 | 49% | 45% | 107 | 31% | 30% | 4864 | 0.112 | |
| Productive | 102 | 11% | 10% | 106 | 10% | 17% | 6201 | 0.051 | * |
| Anxious | 99 | 18% | 19% | 106 | 26% | 25% | 4547.5 | 0.082 | * |
| Relaxed | 101 | 34% | 34% | 105 | 27% | 25% | 5518 | 0.592 | |
| Frustrated | 103 | 24% | 26% | 104 | 25% | 18% | 4240.5 | 0.006 | *** |
| Embarrassed | 100 | 3% | 7% | 103 | 3% | 7% | 4808.5 | 0.346 | |
| Safe at night | 97 | 36% | 35% | 105 | 24% | 24% | 5104.5 | 0.976 | |
| Safe during the day | 103 | 73% | 67% | 104 | 72% | 73% | 6185 | 0.035 | ** |
| *Significance: * p<0.10; ** p<0.05; *** p<0.01* | | | | | | | | | |

**Satisfaction**

Six indicators asked about specific aspects and overall service of HART buses, and each indicator was rated on the following five-point scale: very dissatisfied, somewhat dissatisfied, neutral, somewhat satisfied, and very satisfied. Again, the gain score, or difference (D), from the before survey ($Y_1$) to the after survey ($Y_2$) was calculated for each individual as follows: $D = Y_2 - Y_1$. Since the indicators were rated on a five-point scale, the differences ranged from -4 to 4. The gain scores were then used in a Wilcoxon rank sum test to evaluate any differences between the control group and the experimental group, and the results are shown in the rightmost column of Table 11. Additionally, the percent satisfied (either "somewhat" or "very") for the control group and the experimental group is shown for the before survey and the after survey in Table 11.

Two of the variables (how long you have to wait for the bus and how often the bus arrives at the stop on time) increased significantly from the before to the after survey between the control group and the experimental group. This may be because RTI users are able to time their arrival at the bus stop to decrease how long they have to wait for the bus, which may also lead to increased levels of satisfaction with how long they have to wait for the bus. Additionally, RTI may also change a passenger's perception of a vehicle arriving on time at the stop. Because passenger with RTI know when the vehicle is running late, they may not perceive the bus as being "late" and may be more satisfied with how often the bus arrives at the stop according to the posted schedule. These two variables directly support the "usual" wait time analysis discussed in a previous section.

Both the indicators for frequency of service and arriving at a final destination on time did not have significant changes between the experimental group and the control group.  Since the frequency of HART bus service did not change over the study period, it is reasonable that there were not changes in satisfaction with frequency.  Similarly, RTI should not, in theory, impact the final time that passengers arrive at their destination, unless they change routes/paths, which is unlikely in a sparse transit network like Tampa's.  It is therefore logical that this indicator did not change.  Similarly, there was not previously a difference in the number of transfers associated with using RTI, and therefore, it also is reasonable that satisfaction with the number of transfers did not change.

Finally, it was surprising that the analysis of overall HART bus service did not show a significant change between the control and experimental groups.  It was envisioned that since passengers are more satisfied with waiting times – which are notoriously one of the most onerous parts of riding transit (e.g., Hess, Brown, & Shoup, 2004) – their overall ratings of service might increase.  Similarly, since HART is piloting a new technology and catering to the changing demographics of transit riders, this could reinforce their overall satisfaction with transit.  The results of the Wilcoxon rank sum test did not support this hypothesis.  One possible reason why this may be the case is that a five-point Likert scale is a very simple approximation to estimating changes in satisfaction, and therefore, if the changes were slight, then the unit of measurement may not have been sufficient to capture it.

Table 11: Percent Satisfied and Wilcoxon Rank Sum Test for Changes in Satisfaction

| | **Control Group** | | | **Experimental Group** | | | **Difference in Gain Scores** | | |
|---|---|---|---|---|---|---|---|---|---|
| | Sample n | Before % Satisfied | After % Satisfied | Sample n | Before % Satisfied | After % Satisfied | Wilcoxon Test W | p-value | |
| How frequently the bus comes | 103 | 37% | 41% | 107 | 40% | 44% | 5812 | 0.459 | |
| How long you have to wait for the bus | 103 | 39% | 34% | 106 | 36% | 46% | 6425 | 0.020 | ** |
| How often the bus arrives at the stop on time | 103 | 54% | 45% | 107 | 45% | 59% | 7094 | 0.0001 | *** |
| How often you arrive at your destination on time | 101 | 57% | 53% | 106 | 55% | 63% | 5835 | 0.236 | |
| How often you transfer to get to your final destination | 100 | 44% | 42% | 106 | 38% | 36% | 4916 | 0.342 | |
| Overall HART bus service | 102 | 63% | 59% | 106 | 57% | 58% | 5717 | 0.410 | |

*Significance: * p<0.10; ** p<0.05; *** p<0.01*

## Perceived Changes

In addition to the measures of behavior, feeling, and satisfaction discussed above, the post-wave survey also included questions to the experimental group to directly measure perceived changes due to using RTI, including three questions about behavior (frequency of HART bus trips, frequency of making transfers, and wait time), three questions about feelings while waiting (relaxed, safety at night, and safety during the day), and one question about overall satisfaction with transit service. These questions were specifically included to help assess if participants perceived changes and to test if these perceived changes aligned with the actual (self-reported) differences from the before survey to the after survey. Additionally, these questions were similar to two prior studies of RTI users in Seattle, which also relies on OneBusAway for transit traveler information (Ferris et al., 2010; Gooze et al., 2013), so responses between the two studies could be compared. It is important to note that these questions were placed after all of the previously discussed questions (but prior to questions on changes in demographics) to avoid influencing the responses to the other post-wave survey questions.

Figure 5 shows that 39% of the experimental group reported that they make HART bus trips more often (combined total of "somewhat" or "much" more often), while the majority (60%) stated that they ride HART buses "about the same" amount. This result is similar to the findings of the Seattle surveys; approximately one third of RTI users said that they make more non-work/school trips per week (Ferris et al., 2010a; Gooze et al., 2013a). To compare this question with the results of previous analysis of gain scores from the pre-wave to post-wave surveys, each gain score of self-reported trips per week was categorized as an increase, decrease, or no change, and the correlation coefficient with “perceived” changes (more often, the same, less often) was calculated. The results indicate that there was limited correlation between the perceived change in trips and actual difference in self-reported trips per week over the study period (Pearson’s R=0.129).[1]

Figure 5 also shows that 16% of RTI users believe that they transfer more often (combined total of “somewhat” or “much” more often), whereas over three quarters (79%) of stated that they transfer “about the same” number of times. Again, there is limited correlation between the stated question and the actual change (increased, decreased or same number) in transfers per week from the before to the after survey (Pearson’s R=0.138).

Importantly, 64% of RTI users reported that they spend less time waiting at the bus stop, which is in alignment with the previous analysis of “usual” wait times. This result is notably smaller than for a similar question posed of Seattle RTI users, which found that 91% reported spending less time waiting (Ferris et al., 2010a). Also, when this question is compared to the change in self-reported usual wait times from the before to the after survey, there was very little correlation (Pearson’s R=0.009). This low level of correlation was likely due to two groups: one group who reported actual decreases in “usual” wait times but stated that they wait “about the same” (14% of the experimental group) and another group who reported identical “usual” wait times from the before to the after survey but stated that they wait less (21%). This may be caused by differences in the perception of wait time.

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[1] Analysis shown in Appendix.

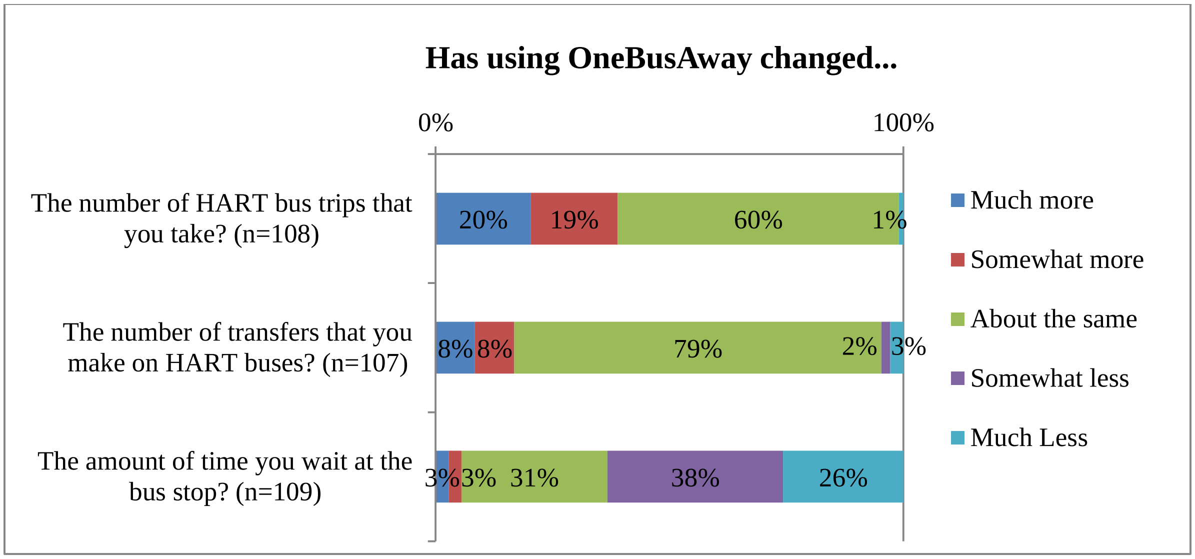


Figure 5: Perceived Behavior Changes of Real-Time Information Users

Members of the experimental group were also asked to agree or disagree (on a five-point Likert scale from strongly disagree to strongly agree) with statements about increases in feelings of safety at night, safety during the day, and relaxation while waiting for the bus. Figure 6 shows that 52% were "neutral" about feeling safer at night and the remainder was split almost equally between agreeing (strongly or somewhat) and disagreeing (strongly or somewhat). When asked about safety during the daytime, 40% agreed that they feel safer since they began using OneBusAway. These results are similar to the 2012 survey in Seattle, which found that approximately 32% of RTI users had a positive shift in the perception of personal security (Gooze et al., 2013). However, while these results appear to support the previous analysis of changes in perceptions of personal security from the before to the after survey, the correlation between those who had changes in ratings of safety (net increase, decrease or same) with those who perceived that they did was very limited (Pearson's R=0.011).

As can be seen in Figure 6, 68% of the experimental group agreed that they feel "more relaxed" since they started using RTI. While the previous analysis of feelings did not reveal a statistically significant difference between the experimental group and the control group in relaxation, this could in part be captured by reductions in levels of frustration and anxiousness.

Last, members of the experimental group were asked (on a five-point Likert scale from strongly disagree to strongly agree) about increases in their satisfaction with overall HART bus service. As can be seen in Figure 6, 70% of the experimental group agreed (somewhat or strongly) with the statement that they are more satisfied with overall transit service since they began using RTI. This is notably less than the 2009 study in Seattle, which found that 92% of OneBusAway users were either somewhat or much more satisfied with overall transit service (Ferris et al., 2010a). Comparing this question to the changes in ratings of overall satisfaction from the before to the after survey shows no correlation (Pearson's R=-0.010), but there is some limited correlation with the changes in satisfaction with "how long you have to wait for the bus" (Pearson's R=0.134) and "how often the bus arrives at your stop in-time" (Pearson's R=0.100).

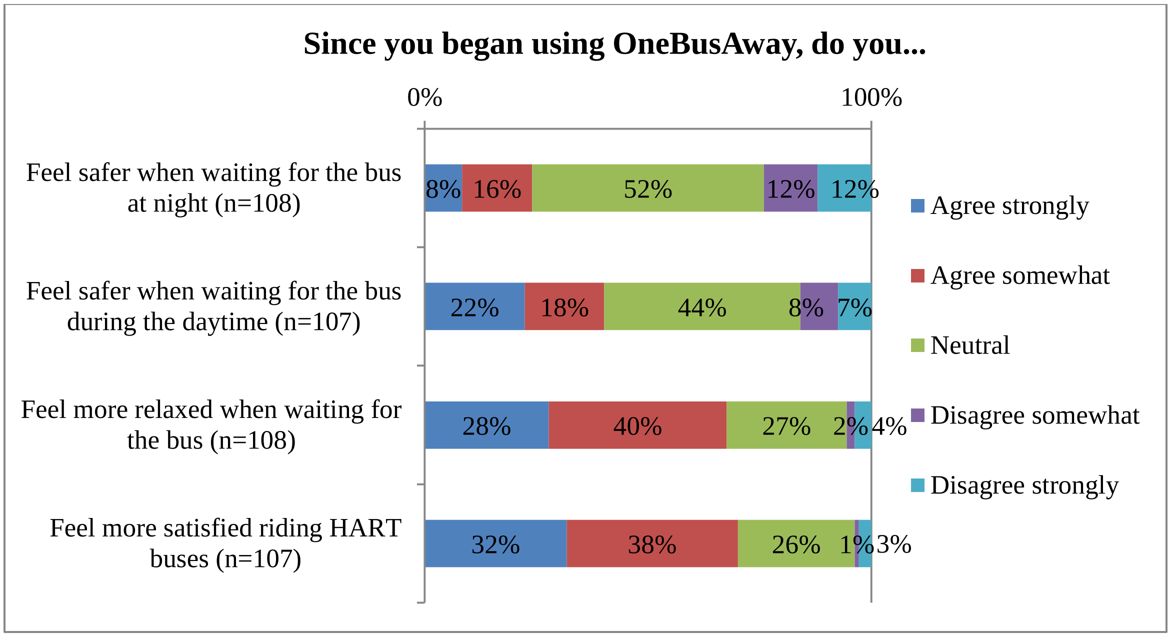


Figure 6: Perceived Feeling and Satisfaction Changes of Real-Time Information Users

The analysis discussed in this section presents mixed results, since many of the questions about user perceptions did not align with the self-reported changes from the before to the after survey. One possible reason for this discrepancy is that the questions posted on both the before and after surveys suffered from an insufficient scale of measurement. For example, the use of trips per week to measure transit travel frequency could be insufficient if a person only makes one or two additional trips per month attributable to RTI. A more reliable way to measure this would be to record trips over an extended period of time (e.g. respondents report their number of trips per week for all the weeks over the study period). It is also important to note that this question was a multiple choice question with answers that were capped on the high end (trips/week ranged from 0 to 11 or more trips). Many respondents (12% of the experimental group) selected the maximum category in the pre-wave survey (11 or more trips/week), and then stated that they increased their trips in the post-wave survey, but the surveys did not capture this change.

A second plausible explanation is bias on behalf of the survey respondents. The survey methods literature has shown that respondents often have an affirmation bias, also known as the demand characteristic, and will give the response that he or she thinks the researchers want to hear (Stopher, 2012). When asked directly about changes (as opposed to those changes inferred from before and after self-reported measures), participants may have selected answers that they felt would make RTI or their participation in the study look more favorable.

## Limitations

There are four notable caveats that may limit the results of this study: the length of time of the study, participant difficulties using the smartphone applications, representativeness of the sample, and applicability to a larger population beyond Tampa.

One important limitation of the study was the time at which the post-wave survey was conducted. In June 2013, HART opened its first Bus Rapid Transit (BRT) route in central Tampa. Because this was a significant change to the transit network, the post-wave survey was conducted approximately two weeks before the opening of the BRT route. In theory, the before-after control group design should mitigate such external events (e.g. opening of a new route/line) because the experimental group can be compared to the control group. Despite this, the study was concluded sooner than desired to avoid potentially muddying the effect of the treatment by this significant change in transit service. This resulted in a total study period of slightly less than three months, which may not have been sufficiently long to capture changes in travel behavior, feelings, or satisfaction.

A second limitation pertains to the manner in which the treatment (access to RTI) was limited to only the experimental group. As was previously noted, in order to use the native smartphone applications for Androids and iPhones, participants were instructed to download the publically available Seattle OneBusAway smartphone applications and then change a setting to re-direct the application programming interface from Seattle to Tampa. In the post-wave survey, the experimental group was asked how difficult this setting change process was, and 64% stated that it was easy. However, 5% of the sample agreed with the statement that it was “so difficult that I did not use the Android/iPhone apps.” Therefore, there could be a non-response bias in which those that found this process overly complicated dropped out of the experimental group. If this was the case, these participants were likely less tech-savvy or possibly less patient than remaining participants, which could, for example, bias feelings while waiting for the bus.

Since the use of a before-after control group research design helps to protect against many threats to interval validity, other noteworthy concerns include threats to external validity (Campbell & Stanley, 1963). First, the representative of the sample to overall bus ridership in Tampa could be a concern since non-probability sampling was used to recruit participants. To investigate this, socioeconomic questions were asked on the pre-wave survey, and whenever possible, questions were worded in an identical manner to the last system-wide HART bus ridership survey, which was conducted in 2009 (Tindale-Oliver & Associates, 2010). The participants in this study differed from the 2009 system-wide survey on three noteworthy socioeconomic characteristics:

ethnicity, income, and automobile ownership. This study had a total of 59% white participants and 21% African American respondents, whereas the 2009 system-wide survey had only 29% white respondents and 49% African Americans.[2] Similarly, this study had only 18% of respondents with annual household incomes less than $10,000, but the 2009 ridership survey found that 45% of riders had annual household incomes less than $10,000. Finally, this study had 52% of respondents without cars in their household, whereas the 2009 survey had 66% of respondents without cars in their household. Additionally, due to institutional review board regulations, participants under age eighteen were not included in this study, which biased the sample away from younger riders. Therefore, it appears that certain groups were oversampled, including those with slightly higher incomes, somewhat increased levels of automobile ownership, older age groups, and Caucasians. Despite these differences, this sample was primarily composed of transit-dependent, low-income participants.

A related concern is that those who were oversampled may be more likely to have higher levels of technology adoption (i.e. web-enabled and mobile devices). Unfortunately, prior survey data on transit rider use of information and communication technologies in Tampa was not available for comparison. Despite this, in the pre-wave survey, respondents were asked which information and communication technologies they use. A total of 78% of participants stated that they used smartphones, and the most commonly used smartphones were Androids (52% of all participants). Since the before

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[2] This survey question in this study allowed respondents to select more than one ethnicity, but the 2009 system-wide survey did not. Therefore, the two ethnicity questions are not perfectly equivalent.

and after surveys were conducted through web-based survey software, all participants had, at a minimum, a means to access the internet and could therefore try OneBusAway through the web or mobile web interfaces.

Finally, with respect to the limited gains in trips per week associated with RTI, there are two important notes. First, many bus riders in Tampa are dependent on transit and have limited ability to increase their trips, as they are already using transit for all or a majority of their trips. Also, the participants in this study were recruited from among people already in the sphere of influence of the transit provider; thus, there was no opportunity to analyze the potential of RTI for attracting entirely new riders. For these reasons, a substantial change in existing ridership associated with RTI was not anticipated in this study of Tampa, which may differ from previous research in transit-dense cities such as Seattle or Chicago. For these reasons, it is important to continue to use experimental studies to gauge the impacts of RTI in a variety of locations.

## Conclusions

This study conducts a comprehensive analysis of the benefits of RTI provided to bus riders in Tampa, Florida. Based on the results of a before-after control group research design, the primary benefits associated with providing RTI to passengers pertain to waiting at the bus stop. A difference of means analysis of gain scores of "usual" wait times revealed a significantly larger decrease (nearly 2 minutes) for the experimental group than the control group. Moreover, analysis of the gain scores of feelings while waiting for the bus revealed significant decreases in levels of anxiety and frustration and increases in levels of productivity and safety during the daytime associated with the use of RTI. This is further supported by significant increases in satisfaction with "how long you have to wait for the bus" and "how often the bus arrives at your stop on time" for the experimental group compared to the control group. Taken together, these three analyses provide strong evidence that RTI significantly improves the passenger experience of waiting for the bus, which aligns with prior studies of RTI in other cities. Two respondents summed up these benefits in the open-ended question at the end of the post-wave survey by writing the following:

*"Brilliant tool! ... Often when catching busses along their route, I felt like it was the 'wild, wild, west' with times, busses not showing, etc. OneBusAway helped make everything much more sensible and relaxing!! (sic)"*

*"Please put the OneBusAway program into affect (sic) as soon as possible. There is nothing more frustrating than waiting on a bus that is running real late or not going to show at all. And the whole time you're stuck out in the street just waiting and waiting."*

While the experience of waiting for the bus appears to have been significantly improved by using RTI, evidence supporting changes in the number of transit trips associated with RTI was limited for this sample of existing transit riders. The difference of mean gain scores in weekly trips showed that the experimental group did not have a significant change compared to the control group. A largely transit-dependent population of riders in Tampa could be contributing to this limited increase. Despite this, a sizable percentage (39%) of the experimental group stated that they ride the bus more frequently since they began using RTI. This is likely due to either an affirmation bias on behalf of the respondents and/or an insufficient scale of measurement used by the researchers.

In addition to these findings, a key contribution of this research is demonstrating that controlled behavioral experiments can be used to evaluate web and mobile applications used by transit travelers. This experiment was particularly distinctive in its ability to (largely) limit the use of the smartphone applications to the experimental group. Hopefully, the successful implementation of this behavioral experiment will lead to the increased use of before-after control group research designs to evaluate new information and communications technologies used by travelers in the future.

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# CHAPTER 4

# ATLANTA

Brakewood, C. and Watkins, K. (2014). A Method for Linking Transit Smart Card Data and Survey Responses to Evaluate Travel Behavior and its Application to a Before-After Analysis of Real-Time Information. In preparation for submission to *Transport Policy*.


## Abstract

Transit agencies often struggle to provide reliable service, and to address this, they increasingly provide real-time vehicle location and arrival information to riders via web-enabled and mobile devices. However, researchers have had difficulty determining if the provision of this new information source causes travelers to ride transit more. Therefore, the objective of this research is to develop a new methodology to quantify potential changes in the number of transit trips by real-time information users.

The method combines data from a smart card ticketing system with web-based survey responses to study the behavior of individual transit riders before and after the availability of real-time information. First, three conditions were imposed on the joint smart card/survey dataset to assess if each record accurately reflected an individual's travel behavior. The first condition necessitated that the respondent began using real-time information in the appropriate timeframe and had the smart card sufficiently long to be used in the before-after analysis. The second condition tested if one smart card actually represented one traveler, and the third condition verified that the smart card number trip history corresponded to the respondent's stated travel behavior. Then, difference of means tests and regression analysis were used to assess differences in

monthly transit trips between real-time information users and non-users. The results suggest that real-time information did not have a significant effect on the number of trips made by users in the study, but the final sample size used in this analysis was very small.

The primary contribution of this research is the methodology, which may be more broadly applied for transit marketing and travel behavior analyses.

## Introduction

Maintaining a high level of reliability is a substantial operational challenge for many public transit agencies. To address reliability issues, transit authorities increasingly provide real-time vehicle location or arrival information to riders via web-enabled and mobile devices (Schweiger, 2011; Rojas, Weil, & Graham, 2012). Studies of transit riders using real-time information have found many benefits, including passengers adapting to unreliability by choosing alternative transit service (Carrel, Halvorsen, & Walker, 2013), reducing wait times (Watkins, Ferris, Borning, Rutherford, & Layton, 2011), increasing the perception of personal security (Ferris, Watkins, & Borning, 2010b; Gooze, Watkins, & Borning, 2013; Zhang, Shen, & Clifton, 2008), and increasing satisfaction with transit service (Ferris et al., 2010; Gooze et al., 2013; Zhang et al., 2008). Despite these benefits, researchers have had difficulty answering a question that managers and planners at transit agencies commonly ask: does real-time information cause travelers to ride transit more? Because transit ridership is affected by numerous factors, previous studies have had difficulty isolating changes in transit trip-making caused by providing real-time information.

To explore this, another increasingly common transit technology is used: smart card ticketing systems. While contactless smart card systems were installed with the primary purpose of revenue collection, the data created from these systems can be used to evaluate travel behavior (Bagchi & White, 2005; Pelletier, Trépanier, & Morency, 2011). In this case, smart card data are used to conduct a disaggregate analysis of the frequency of transit trips before and after the availability of mobile real-time information. In order to understand which smart card users are also real-time information users and which are not, the smart card data are combined with the responses from a web-based survey asking about use of real-time information. To link the two data sets, a survey question requested the unique 16-digit smart card number of each respondent. This method was applied to the case study of Atlanta, Georgia.

This paper is divided into seven sections. First, prior research about real-time information and smart card systems is briefly reviewed. The second section provides background information on Atlanta, and the third section describes the survey data collection process. Next, the methodology is described and three key conditions are applied to the combined smart card/survey dataset. The fifth section is an application of the combined smart card/survey dataset to evaluate the impacts of real-time information in Atlanta. This is followed by a discussion of areas for improvement and future research, and last, conclusions are presented.

## Prior Research

This brief literature review is divided into two parts. The first section summarizes prior studies of the impact of real-time information on passenger behavior, with a focus on changes in transit trip-making. The second section provides a review of the uses of transit smart card data to study traveler behavior.

**Real-Time Information Literature**

Real-time information (RTI) refers to up-to-the-minute tracking of transit vehicle locations, and it often includes predicted arrival times for stops and/or stations. Mobile RTI is increasingly used by passengers as they travel in transit systems due to the widespread adoption of web-enabled and mobile devices (Schweiger, 2011). In light of this trend, a growing body of literature aims to assess the benefits of providing RTI to transit riders. Prior studies have found many benefits, including riders adapting to unreliability by choosing alternative transit service (Carrel et al., 2013), reducing waiting times (Watkins et al., 2011), increasing perceptions of personal security (Ferris et al., 2010; Gooze et al., 2013; Zhang et al., 2008), and increasing satisfaction with transit service (Ferris et al., 2010; Gooze et al., 2013; Zhang et al., 2008). If RTI users can adapt to unreliable service more easily, spend less time waiting, feel safer, and/or are more satisfied with overall service, it follows that they may make more trips on the transit system, either by choosing transit over alternative modes or making trips that they would not have made otherwise. A small number of studies have aimed to understand this, and this literature review focuses on research that evaluates actual transit rider behavior (as opposed to simulation or stated preference methods).

A panel study conducted on the University of Maryland campus measured changes before and after the implementation of an RTI system on the university shuttle bus network (Zhang et al., 2008). Based on the results of a fixed-effects ordered probit model of shuttle trips, the authors concluded that RTI did not significantly increase travelers' transit trip frequency. The authors noted that they evaluated the number of shuttle trips only two weeks after an extensive marketing campaign of the new RTI system, and consequently, there may have been insufficient time for adjustments of travel behavior. The authors also stated that "further research on the long-term effects of real-time transit information systems is necessary to understand how travelers may gradually change their behaviors and perceptions as they make more use of real-time transit information" (Zhang et al., 2008).

Two studies of bus riders in Seattle, Washington provide some evidence that use of mobile RTI may lead to an increase in the number of trips made on transit. In 2009, a web-based survey of over 400 RTI users asked respondents if their average number of transit trips per week changed as a result of RTI. Approximately 31% of users reported increases in non-commute trips (1 more trip, 2 more trips, or 3+ trips per week), while a smaller percentage reported increases in commute trips on transit (Ferris et al., 2010). A follow-up web-based survey of RTI users in 2012 found similar results (Gooze et al., 2013). The authors identified two important caveats for these studies: the survey results were all self-reported and did not include a control group of non-users (Ferris et al., 2010).

Perhaps the most relevant reference to this study is an empirical evaluation of Chicago's real-time bus tracking system (Tang & Thakuriah, 2012). The authors created a linear mixed regression model of monthly average weekday route-level bus ridership from 2002 to 2010, during which time RTI was gradually rolled out on groups of bus routes. After controlling for many factors including transit service attributes, unemployment, gas prices, and weather, the authors found a "modest" increase in bus ridership of approximately 126 weekday rides per route attributable to RTI. A noteworthy limitation of the study design is that only route-level changes in trips were assessed because the availability of RTI was modeled as a binary variable for each bus route in the regression model. Therefore, the modeling framework could not clearly differentiate between additional trips made by users of RTI versus non-users of RTI.

In summary, two of the three locations studied (Chicago and Seattle) provide some evidence that use of RTI may cause an increase in transit travel. To improve upon the prior research, this study has the following three enhancements: (1) a sufficiently long period of time after the launch of RTI; (2) a more reliable method of measuring travel than self-reported data; and (3) differentiation between the travel patterns of users and non-users of RTI. To do this, smart card data were used to assess transit traveler behavior, and a brief review of literature pertaining to smart card datasets is provided in the following paragraphs.

**Smart Card Literature**

While smart card systems are designed for the purpose of revenue collection, they can also provide a rich source of data about transit use (Bagchi & White, 2005; Pelletier et al., 2011). Passengers with contactless smart cards pay their fares by "tapping" their cards on fareboxes or faregates, and with each tap, a record is created that includes the date and time, the type of transaction (boarding/entering, transfer, etc.), fare type, route/line ID, route/line direction, station/stop ID, a unique card ID number (similar to a credit card number), among other things (Pelletier et al., 2011). Some transit agencies also allow smart card users to register their cards, typically for the purpose of refunding the value of lost/stolen cards or for using autoload features; registration can include a limited amount of personal information, such as contact information.

A growing body of research takes advantage of this automatically collected dataset, and Pelletier et al. (2011) provide a thorough literature review of the uses of transit smart card data, which they divide into three groups: operational-level, tactical-level, and strategic-level applications. Operational-level studies use smart card data to measure various transit supply-and-demand indicators and performance indicators, such as calculating schedule adherence for a given run, route, or day. Tactical-level studies most commonly focus on service adjustments, while strategic level studies are typically related to long-term network planning, demand forecasting, and traveler behavior analysis. In this case, a strategic-level analysis of transit traveler behavior was conducted.

As Bagchi & White (2005) note, there are some advantages of using smart card data compared to traditional methods of studying transit travel behavior. Public transit providers have typically found it difficult to examine travel behavior over the long term due to a lack of suitable temporal data. In contrast, smart card records can be stored for years and accessed as needed over time (Bagchi & White, 2005). Another advantage of using smart card data to study travel behavior is that the data are automatically collected, and consequently may not be subjected to the biases commonly found in self-reported travel data.

Pelletier et al. (2011) point out that one disadvantage of using smart card data for studying travel behavior is a lack of socioeconomic attributes about the cardholder. While some smart card systems collect a limited amount of registration information (Utsunomiya, Attanucci and Wilson 2006), most lack basic demographic information about the cardholders and none include highly specific attributes, such as the use of real-time information.

One possible solution to obtaining information about the individual cardholder is a method recently used by Riegel and Attanucci (2014). The authors worked with the London Travel Demand Survey, which is a single day household travel diary for the London region. The 2011-2012 survey questionnaire asked respondents to provide up to two smart card (Oyster card) numbers used by travelers in the household. Then, the Oyster card journey histories were compared to the corresponding respondent's self-reported public transport trips for the day of the travel diary. The authors concluded that combining the survey responses with Oyster data for specific households greatly enhanced the validity of the single day travel diary.

For this research, the procedure of asking for a unique smart card ID number in the survey instrument was expanded upon by also asking other questions beyond the simple travel diary to evaluate items not directly measurable using smart card data. This method of linking smart card data with detailed survey responses can be used to evaluate transit trips over an extended period of time, without relying on self-report data to measure travel behavior, while also including specific attributes of the individual traveler (in this case, if they are a user or non-user of real-time information). This method was applied to an empirical analysis of trips on Metropolitan Atlanta Rapid Transit Authority (MARTA).

## Background

Atlanta was selected for this analysis for two primary reasons. First, MARTA operates the 16$^{th}$ largest bus system and the 6$^{th}$ largest heavy rail system in the country based on passenger miles (Neff & Dickens, 2013) and provides mobile real-time information for all fixed route bus and train service. Because most of the prior research of RTI systems focused on urban buses, this provides a more multimodal approach to the evaluation of real-time transit information. Second, MARTA has a smart card ticketing system that was installed before the availability of real-time information, which is a necessary condition for a before-after analysis of real-time information. Additional details about the smart card system and real-time information systems are provided in the following paragraphs.

**Smart Cards in Atlanta**

MARTA's smart card ticketing system, known as Breeze, was launched in 2006 (Hong, 2006). Fare media include a plastic contactless Breeze card and a coated paper contactless Breeze ticket, which is primarily used for student tickets, group tickets, and special events. A single ride can also be paid directly with cash at bus fareboxes (MARTA, 2014b). According to a recent system-wide survey of MARTA passengers, over 99% of riders have one or more plastic Breeze cards (MARTA, 2013).

The Breeze system requires tap-in on all buses and both tap-ins and tap-outs on MARTA rail, but this study includes tap-in data only. MARTA riders do have the option of registering their Breeze cards for balance protection and reloading value online. The personal information included in these processes is kept strictly confidential by the transit agency for privacy reasons, and consequently, was not considered in this analysis.

**Real-Time Information in Atlanta**

Mobile real-time transit information is available in Atlanta in a number of different ways. First, MARTA has developed Android and iPhone smartphone applications, which are known as “On-the-Go.” While these apps were originally developed with static schedule information, real-time bus and train tracking information was added in the fall of 2013. Georgia Tech launched the OneBusAway real-time information suite of tools in Atlanta, with real-time bus information launched in “beta” in the spring of 2013 and both train and bus real-time information launched publically in February 2014. These two platforms provide the basis for the analysis provided in the following sections, but it is noted that a few other apps were created within a similar timeframe.[3]

## Data Collection

To assess which riders use RTI applications, a short rider survey was conducted. The data were collected via a web-based survey, primarily to allow for questions with images (such as a Breeze Card with the 16-digit number circled and screenshots of the RTI smartphone applications). Survey responses were collected during a one week period in early May 2014.[4] Participants were primarily recruited through online channels, including an electronic message sent via the OneBusAway platform, MARTA’s social media, the Atlanta Regional Commission email list, and other similar email lists. Additionally, flyers were distributed in a small number of train stations to advertise the

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[3] There were some limited ways of accessing real-time information prior to the launch of these commonly used apps. In the fall of 2012, MARTA openly released their real-time bus tracking data, and a small number of other apps were created shortly thereafter, although usage appears to be small based on the results of the survey. Additionally, MARTA had a web-based system called “web watch” that provided some access to real-time bus tracking.

[4] Data collection was completed before a MARTA service change went into effect on May 19, 2014.

survey. An incentive of a $5 Starbucks gift card was provided to all participants who completed the survey.

**Survey Content**

The survey was titled "Georgia Tech's Survey of Technologies Used by MARTA Riders" to recruit both users and non-users of RTI, and the survey instrument was divided into five sections. The first section included questions about paying for transit, such as use of a Breeze Card and the corresponding Breeze Card number. In this section, the respondent was also asked if they share their Breeze Card(s) and if they use other ways to pay for MARTA (such as occasionally using a paper Breeze Ticket). The second section contained transit travel behavior questions, including how many transit trips the respondent made in the last week. The third part of the survey instrument included questions about the use of RTI via smartphone applications. The next section asked a few questions about recent service changes on MARTA. The last section was composed of socioeconomic questions, including how these characteristics may have changed over the past year. It should be noted that detailed personal information (such as email address, home address, etc.) was not collected in the survey to protect anonymity of participants at MARTA's request. Last, the survey instrument was reviewed by a dozen Georgia Tech students and staff, as well as a MARTA customer research employee.

**Response Rate**

A total of 669 participants entered the online survey during the one week recruitment period, and of these, 651 respondents answered the first question, which asked how they typically pay for MARTA. Of the 651 respondents, 11 (2%) respondents said that they use a paper Breeze Ticket, 7 (1%) stated that they pay using cash, and 1

(0%) respondent was not sure of the fare media that s/he typically uses. This left 632 survey respondents who use one or more Breeze Cards, and of those, 538 provided a 16-digit smart card number. The 16-digit smart card numbers were provided to MARTA, and 497 matched active Breeze Card numbers. Three additional participants were removed due to restrictions (i.e. under age 18), and consequently, the remaining sample size was 494, or 74% of all those who entered the survey. The transit trip histories for the 494 eligible participants were then combined with their corresponding survey response using the unique smart card number. It should be noted that transit trip histories were aggregated to the number of trips per day per mode (bus/rail), and disaggregate data about the complete trip history (i.e. time-stamped tap-in locations) was not provided as a safeguard to protect the privacy of respondents at MARTA's request. Last, to assure that the transit trip histories from the Breeze Card database were accurate, the smart card trip histories of a few researchers were requested and assessed.

## Methodology

The following section details the methodology used to evaluate the validity of the combined smartcard/survey dataset for a before-after analysis of the impact of RTI. First, the use of RTI by survey respondents was considered. Next, three key conditions were investigated. The first condition necessitates that the respondent began using RTI in the appropriate timeframe and had the smart card sufficiently long to be used in the before-after analysis. The second condition tests if one smart card actually represents one traveler. The third condition verifies that the smart card number trip history corresponds to the respondent's stated travel behavior.

### Use of Real-Time Information

To assess the use of real-time information, the survey contained questions in which the respondent was presented with images of the most popular RTI applications ("apps") in Atlanta and was asked if he or she has used real-time transit information. A total of 302 of the 494 eligible participants (61%) have used one or more apps to access RTI. Next, respondents who had used real-time information were asked which app they use most frequently. The majority of participants typically use MARTA's On the Go app (225/301 = 75%), and another 56 (18%) usually use OneBusAway. Respondents were then asked how often they use RTI apps. 30% of RTI users stated that they use an RTI app every time they ride MARTA trains and 31% said every time they ride MARTA buses.

### Condition 1: Panel Eligibility

Next, a series of conditions were imposed on the joint smart card/survey dataset to assess if each record accurately reflects an individual's travel behavior. The first condition was that of *panel eligibility*. For the before-after analysis of RTI, the smart card trip histories were compared for April 2013 and April 2014. Because the intervention (the launch of various RTI apps) occurred at different times in 2013 and 2014, a month before the main release of RTI in Atlanta (April 2013) and the same month one year later (April 2014) were selected. Since there was the possibility that respondents began using RTI during the before period (April 2013 or earlier) or in the middle of the after period (April 2014), respondents were asked to recall when they began using RTI to test their panel eligibility. Similarly, to ensure that the smart card was in use for the entire study period, respondents were asked to recall when they began using their smart card in a second test of panel eligibility.

Condition 1A: Panel Eligibility of the Intervention

First, respondents were asked to recall approximately when they started using an app that provides real-time information (i.e. the intervention), and the results are shown in Table 12. The majority of respondents who use RTI began within the last year, since most apps were released within the last twelve months (see discussion in the Background section). A total of 201 respondents began using the apps between May 2013 and March 2014, and these respondents were deemed panel eligible. Another 36 could not recall when they began using RTI, and 2 did not answer the question, and it was assumed that they began within the last year. In summary, a total of 239 respondents were deemed panel eligible real-time information users, and they could be compared to the 192 non-users. This resulted in a sample size of 431 respondents meeting Condition 1A.

Table 12: Condition 1A (Panel Eligibility of the Intervention)

| **When did you start using an app with RTI?** | **#** | **%** | **Met Condition 1A** |
|---|---|---|---|
| Began using RTI before April 2013 | 37 | 7% | No |
| Began between May 2013 and March 2014 | 201 | 41% | Yes |
| April 2014 or later | 26 | 5% | No |
| Cannot remember | 36 | 7% | Yes |
| No Answer | 2 | 0% | Yes |
| Total | 302 | 61% | 239 |
| Non-users | 192 | 39% | Yes |
| Grand Total | 494 | 100% | 431 |

Condition1B: Panel Eligibility of the Smart Card

Panel eligibility was also assessed by asking respondents if they got their Breeze Card within the last year or more than a year ago, and the results are shown in Table 13. Of the 431 respondents meeting Condition 1A, a total of 264 of the respondents (61%) stated that they have had their Breeze Card for more than a year, and consequently, they met the second requirement of panel eligibility. Another 41 respondents (10%) could not recall when they acquired their Breeze Card, and it was assumed that these respondents were also panel eligible. This resulted in a total of 305 participants who met Condition 1B. These survey responses were also compared to the trip history from the smart card in April 2013, as shown in Table 13. Last, it should be noted that this condition excludes any person(s) who began riding transit in Atlanta within the last year, since they did not have a Breeze Card a year ago.

Table 13: Condition 1B (Panel Eligibility of the Smart Card)

| | **Breeze Card History** | | | | |
|---|---|---|---|---|---|
| **Self-Reported Card Acquisition** | No Trips in April 2013 | 1 or More Trips in April 2013 | Total | % Total | Met Condition 1B |
| Within the last year | 111 | 15 | 126 | 29% | No |
| One year or more ago | 111 | 153 | 264 | 61% | Yes |
| I'm not sure | 29 | 12 | 41 | 10% | Yes |
| Total | 251 | 180 | 431 | 100% | 305 |

**Condition 2: Completeness and Uniqueness (i.e. One Smart Card = One Person)**

Next, a respondent's smart card/survey response was tested for the conditions of *completeness* and *uniqueness*. A Breeze Card trip history was considered *complete* if the respondent did not use any other form of payment when riding MARTA; consequently, all of the respondent's transit trips on MARTA would be captured in the trip history of his or her smart card. A Breeze Card was considered *unique* if it is only used by a single person. A Breeze Card trip history could be complete if the person uses it for all of their MARTA trips, but it would not be unique if it is shared with others and consequently represents the travel behavior of more than one person. If both the conditions of completeness and uniqueness are met, it was assumed that one smart card represents one person. The conditions of completeness and uniqueness were assessed using the survey responses to three questions; consequently, this test relies solely on self-reported information.

Condition 2A: Complete with One Breeze Card

The first survey question pertaining to completeness asked if a respondent had one Breeze Card or two or more Breeze Cards. As is shown in Table 14, a total of 86 (71+15) respondents have two or more Breeze Cards and therefore, their trip histories may not be complete.[5] The remaining 219 (193+26) participants were assumed to meet Condition 2A.

Condition 2B: Complete with No Other Fare Media

As a second measure of completeness, all participants were asked if they pay for MARTA in other ways (such as cash or a paper Breeze Ticket). A total of 26 of the 219 respondents who met Condition 2A also used other fare media, and consequently, their

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[5] Respondents with 2 or more Breeze Cards were asked to provide the number of the card that they use most frequently. Future research could aim to gather the number of all smart cards that respondents possess. Additional Breeze Card numbers were not requested in this analysis to lessen the burden on the respondent.

smart card trip history cannot be considered complete. Table 14 shows that a total of 193 participants met both Conditions 2A and 2B and can be deemed complete (shown in the lower left box in Table 14).

<u>Condition 2C: Unique</u>

Finally, to understand uniqueness, survey participants were asked if they share their Breeze Card, and to what extent they share their card (e.g. occasionally, often). A total of 159 respondents met the uniqueness condition because they never share their single Breeze Card (shown in the upper left box in Table 14). Consequently, it was assumed that the smart card numbers provided by those 159 respondents accurately represents the transit travel of only those respondents.

Table 14: Conditions 2A, 2B, and 2C (Completeness and Uniqueness)

<table>
<tr><td colspan="2" rowspan="3"></td><td colspan="5">Complete</td></tr>
<tr><td colspan="2">1 Breeze Card</td><td colspan="2">2+ Breeze Cards</td><td rowspan="2">Total</td></tr>
<tr><td>Uses only Breeze Card</td><td>Uses other media</td><td>Uses only Breeze Card</td><td>Uses other media</td></tr>
<tr><td rowspan="8">Unique</td><td>I never share my Breeze Card (1 or 2 cards)</td><td>159</td><td>20</td><td>42</td><td>8</td><td>229</td></tr>
<tr><td>I have shared my Breeze Card once or twice</td><td>25</td><td>4</td><td>14</td><td>3</td><td>46</td></tr>
<tr><td>I occasionally share my Breeze Card</td><td>3</td><td>2</td><td>13</td><td>4</td><td>22</td></tr>
<tr><td>I often share my Breeze Card</td><td>4</td><td>0</td><td>1</td><td>0</td><td>5</td></tr>
<tr><td>I'm not sure</td><td>1</td><td>0</td><td>0</td><td>0</td><td>1</td></tr>
<tr><td>Other</td><td>1</td><td>0</td><td>1</td><td>0</td><td>2</td></tr>
<tr><td>Total</td><td>193</td><td>26</td><td>71</td><td>15</td><td>305</td></tr>
<tr><td>Percent Total</td><td>63%</td><td>9%</td><td>23%</td><td>5%</td><td>100%</td></tr>
</table>

**Condition 3: Congruence (i.e. That Smart Card = That Person)**

Last, the responses in the combined survey/smart card dataset were tested for the condition of *congruence* by comparing each smart card trip history to a self-reported travel behavior survey question. The primary purpose of this assumption was to identify errors when the respondent entered his or her 16-digit Breeze Card number in the online survey or potential errors in the Breeze Card system. A Breeze Card trip history was considered *congruent* with a survey response if it aligned with a question about transit travel, and if it did, it was assumed that the particular smart card trip history represents that particular person.

The specific method to assess congruence in this analysis was comparing the number of MARTA train trips made in the last week from the smart card trip histories to an equivalent survey question. The survey respondent was instructed to begin counting train trips from the previous day and continuing back seven days. Because the online survey response included a time and date of completion, the self-reported number of trips was compared to the same seven days of smart card trip history to tabulate the numbers of MARTA train trips. Respondents were also instructed to count train-to-train transfers as single trips, but transfers that involved bus modes (bus and train) were counted separately. This was to assure that the number of "taps" in the smart card database aligned with self-reported trips, since bus-to-train transfers involving tapping the smart card at the transfer point whereas train-to-train transfers do not require an second tap (since one stays within the fare gates).

Condition 3A: Closely Congruent

As is shown in Table 15, a total of 135 (of unique, complete, and panel eligible respondents) self-reported trips from the survey matched the respective smart card trip history within two train trips. These survey responses were deemed to be "closely congruent" with the respective smart card and meet Condition 3A. "Close" congruence was considered because self-reported travel behavior questions are often subject to error, particularly recall bias in which respondents cannot correctly remember their transit trip-making patterns (Stopher, 2012, p. 142). Similarly, there is the possibility that a transaction was missing from the smart card dataset, since prior research by Utsunomiya, Attanucci and Wilson (2006) identified this as a possible flaw with smart card datasets.

Condition 3B: Perfectly Congruent

Table 15 shows that a total of 100 respondents (of those who were unique, complete, and panel eligible) had self-reported survey results that perfectly matched the respective smart card trip history. These survey responses were deemed to be "perfectly congruent" and met Condition 3B.

Table 15: Condition 3A and 3B (Closely or Perfectly Congruent)

| | **Number of Breeze Card Trip Histories** | | |
|---|---|---|---|
| **Self-Reported Train Trips in the Last 7 Days** | Closely Congruent (Within 2 Trips) | Perfectly Congruent | All Responses |
| 0 trips | 63 | 62 | 63 |
| 1 trips | 11 | 7 | 11 |
| 2 trips | 17 | 8 | 18 |
| 3 trips | 0 | 0 | 0 |
| 4 trips | 10 | 5 | 13 |
| 5 trips | 2 | 0 | 4 |
| 6 trips | 0 | 0 | 1 |
| 7 trips | 0 | 0 | 2 |
| 8 trips | 4 | 3 | 7 |
| 9 trips | 0 | 0 | 0 |
| 10 trips | 16 | 7 | 21 |
| 11 trips or more | 12 | 8 | 19 |
| Total | 135 | 100 | 159 |
| Percent Total | 85% | 63% | 100% |

**Summary**

Three key conditions were imposed on the linked survey/smart card dataset, and this resulted in a total of 100 (20%) of the 494 eligible participants whose records were deemed panel eligible, complete, unique, and congruent. Table 16 shows the sample size as each assumption was applied. Since the sample size decreased substantially, all assumptions were considered and compared in the following analysis.

Table 16: Summary of Conditions and Sample Sizes

| Number | Condition | Sample Size | Percent Total |
|---|---|---|---|
| - | Full Survey/Smart Card Dataset | 494 | 100% |
| 1A | Panel Eligibility of the Intervention | 431 | 87% |
| 1B | Panel Eligibility of the Smart Card | 305 | 62% |
| 2A | Complete with One Breeze Card | 219 | 44% |
| 2B | Complete with No Other Fare Media | 193 | 39% |
| 2C | Unique | 159 | 32% |
| 3A | Closely Congruent | 135 | 27% |
| 3B | Perfectly Congruent | 100 | 20% |

## Application to Evaluate Use of Real-Time Information

The next section uses the joint smart card/survey dataset to conduct a before-after analysis of the impacts of real-time information on transit trip-making. This analysis is divided into three parts. The first section presents simple statistics to compare the number of transit trips by RTI users with non-users. The second section uses regression analysis to control for other factors that may be influencing participants' levels of transit travel. The third section presents the results of additional survey questions that assess changes in perception for RTI users.

**Difference of Mean Differences**

The first analysis uses simple statistics to compare the number of transit trips before and after the availability of RTI for users and non-users. The period of analysis was four weeks in April beginning with the first Tuesday of the month to ensure the same number of days and the same type of days (i.e. 4 Mondays, 4 Tuesdays, etc.) in both April 2013 and April 2014. Conveniently, April also includes typical school trips (the local universities are all in session) and no major holidays.

Table 17 shows the mean (M), standard deviation (SD), minimum (Min), and maximum (Max) number of transit trips for the four weeks in April 2013 and the comparable number in 2014 broken down by RTI users versus non-users. The difference between 2013 and 2014 was calculated for each individual, and this difference was used in a difference of means test between RTI users and non-users. The results are shown for the entire dataset (n=494) in the leftmost column of Table 17. Each condition (Conditions 1A through 3B) was progressively applied moving toward the right of the table and a comparable analysis was conducted.

When the full dataset (n=494) is considered (the leftmost column in Table 17), the results suggest that RTI users increased MARTA trips significantly more than non-users from April 2013 to April 2014 (*mean difference* $_{RTI\text{-}users}$*=11.7 trips, mean difference* $_{non\text{-}users}$*=4.9 trips, two-tailed p-value=0.0006).* There are similar findings when Condition 1A (Panel Eligibility of the Intervention) is applied, which excludes any RTI user who may have begun using RTI before May 2013 or after March 2014.

When Conditions 1B, 2A-2C, and 3A-3B are applied, the mean difference in trips for the RTI user group is still greater than the mean difference in trips from April 2013 to

April 2014 for the non-user group; however, this difference is not statistically different between the two groups. This could be in part because the more filtered datasets have smaller sample sizes and therefore have larger variances of the estimator, making it more difficult to detect a difference. It may also be because the RTI user group consistently took more trips in April 2013 than the group of non-users, which suggests that those who use transit more were more likely to adopt RTI.

Difference of means tests were run for each mode (bus, rail) separately, and similar results were found in which RTI was only significant for the full dataset and for the dataset meeting Condition 1A.

Table 17: Before-After Analysis of Transit Trips

| | | All Data (Matches) | | Condition 1A (Panel Eligible) | | Condition 1B (Panel Eligible) | | Condition 2A (Complete) | | Condition 2B (Complete) | | Condition 2C (Unique) | | Condition 3A (Congruent) | | Condition 3B (Congruent) | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | RTI | No | RTI | No | RTI | No | RTI | No | RTI | No | RTI | No | RTI | No | RTI | No |
| Count | | 302 | 192 | 239 | 192 | 166 | 139 | 114 | 105 | 99 | 94 | 77 | 82 | 60 | 75 | 38 | 62 |
| April 2013 | M | 10.2 | 4.7 | 10.0 | 4.7 | 12.9 | 6.2 | 14.1 | 6.8 | 15.8 | 7.4 | 17.5 | 8.4 | 15.6 | 5.7 | 12.8 | 4.1 |
| | SD | 20.2 | 14.5 | 19.1 | 14.5 | 20.1 | 16.5 | 20.3 | 18.0 | 21.2 | 18.9 | 22.0 | 20.0 | 21.7 | 12.3 | 22.2 | 9.4 |
| | Min | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | Max | 113 | 138 | 113 | 138 | 91 | 138 | 91 | 138 | 91 | 138 | 91 | 138 | 91 | 59 | 91 | 46 |
| April 2014 | M | 21.9 | 9.6 | 21.4 | 9.6 | 21.2 | 10.1 | 21.4 | 11.9 | 21.7 | 12.2 | 22.8 | 12.5 | 21.7 | 7.9 | 21.1 | 5.1 |
| | SD | 29.3 | 22.4 | 29.7 | 22.4 | 31.1 | 23.8 | 27.4 | 26.6 | 26.9 | 26.5 | 27.6 | 27.0 | 27.5 | 14.7 | 29.8 | 10.6 |
| | Min | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | Max | 212 | 205 | 212 | 205 | 212 | 205 | 112 | 205 | 112 | 205 | 112 | 205 | 112 | 70 | 112 | 40 |
| Difference | M | 11.7 | 4.9 | 11.4 | 4.9 | 8.3 | 3.9 | 7.3 | 5.1 | 5.9 | 4.8 | 5.2 | 4.0 | 6.1 | 2.2 | 8.3 | 1.0 |
| | SD | 27.8 | 15.8 | 28.3 | 15.8 | 29.1 | 15.7 | 24.6 | 17.9 | 23.2 | 16.3 | 24.3 | 14.7 | 25.4 | 11.3 | 25.1 | 8.9 |
| | Min | -51 | -32 | -51 | -32 | -51 | -32 | -44 | -32 | -44 | -32 | -44 | -32 | -24 | -32 | -17 | -32 |
| | Max | 174 | 95 | 174 | 95 | 174 | 95 | 112 | 95 | 112 | 80 | 112 | 67 | 112 | 45 | 112 | 40 |
| | | *t = -3.478 p=0.0006* | | *t = -3.016 p=0.003* | | *t = -1.69 p=0.092* | | *t = -0.7524 p=0.453* | | *t = -0.369 p=0.713* | | *t = -0.3728 p=0.710* | | *t = -1.097 p=0.276* | | *t = -1.732 p=0.0905* | |

## Regression Analysis

Since changes in an individual's monthly transit trips could be attributed to factors other than the use of RTI, survey respondents were asked a series of retrospective questions to understand possible changes that may have influenced their travel behavior between April 2013 and April 2014. This included questions about changes in household size, automobile ownership, job location, and household location over the last year. Additionally, a few short questions about awareness of MARTA's minor service changes that occurred in December 2013 were included in the survey instrument, since this could have also caused changes in transit travel during the study period. The results of these questions were then included in a regression model to assess the impact of real-time information while controlling for these other factors. The dependent variable in the regression was the difference in monthly trips (precisely, four weeks) from 2013 to 2014 from the smart card trip history, and the independent variables included the previously mentioned retrospective survey questions, as well as standard socioeconomic characteristics (e.g. ethnicity, age, etc.).

Various regression models were assessed, and the regression models selected for presentation are shown in Table 18. This set of regression models contains only those variables that were significant in either the full dataset or the congruent conditions (3A and 3B); a regression table showing all variables that were considered can be found in the appendix. As shown in Table 18, the variable of interest, real-time information, was only significant in the regression models using the full dataset and the dataset in which Condition 1A was met. When the additional assumptions were applied, use of real-time information was no longer significant. The other variables that were consistently significant as the sample size decreased were having a valid driver's license, which caused a decrease in MARTA trips from 2013 to 2014, and being African American, which was associated with an increase in transit trips. However, both of these variables were to some extent collinear with the intercept: only 9% of the final sample was African American and 96% had a driver's license. Two other variables were significant in some of the models. Increasing the number of cars in a household over the one year study period was associated with a decrease in MARTA trips in the full dataset and when condition 1A was applied. On the other hand, awareness of MARTA's recent (minor) service change was associated with an increase in trips in the models when the congruence conditions (3A and 3B) were applied. This could suggest that the minor service changes in December 2013 positively impacted the number of trips riders made on MARTA, although further study of this is recommended. Last, the goodness of fit was an R-squared of 0.15 for the full dataset, and this increased to 0.30 when all of the conditions were applied.

Table 18: Regression Analysis of Difference in Transit Trips

| **Condition** | **Full** | **1A** | **1B** | **2A** | **2B** | **2C** | **3A** | **3B** |
|---|---|---|---|---|---|---|---|---|
| (Intercept) | 20.89*** | 20.79*** | 25.68*** | 34.22*** | 40.49*** | 37.47*** | 37.11*** | 36.15*** |
| | (4.13) | (4.39) | (5.96) | (6.61) | (6.19) | (6.45) | (6.98) | (7.93) |
| Use Real-Time Information | 6.61*** | 6.49*** | 4.05 | 1.55 | 0.33 | -0.67 | -0.66 | 2.65 |
| | (2.20) | (2.30) | (2.74) | (2.74) | (2.61) | (2.91) | (3.01) | (3.33) |
| Has a License | -18.63*** | -18.18*** | -25.36*** | -34.28*** | -40.96*** | -38.44*** | -38.94*** | -38.44*** |
| | (3.88) | (4.18) | (5.69) | (6.37) | (5.99) | (6.22) | (6.74) | (7.82) |
| African American | 16.54*** | 13.72*** | 15.50*** | 19.67*** | 15.73*** | 17.59*** | 18.47*** | 10.81** |
| | (3.34) | (3.60) | (4.07) | (4.35) | (4.48) | (4.83) | (5.03) | (5.29) |
| Increased Cars in Household | -8.21** | -8.01** | -6.78 | -3.57 | -1.07 | -2.16 | -4.24 | -2.16 |
| | (3.66) | (3.77) | (4.40) | (4.56) | (4.56) | (5.03) | (4.95) | (5.59) |
| Aware of MARTA Service Changes | 0.01 | -0.08 | 1.96 | 4.22 | 4.60* | 4.57 | 6.23** | 6.65** |
| | (2.15) | (2.31) | (2.74) | (2.75) | (2.61) | (2.91) | (2.98) | (3.22) |
| $R^2$ | 0.15 | 0.13 | 0.16 | 0.26 | 0.32 | 0.33 | 0.35 | 0.30 |
| Adj. $R^2$ | 0.14 | 0.12 | 0.15 | 0.24 | 0.30 | 0.30 | 0.32 | 0.27 |
| No. Observations^ | 477 | 416 | 296 | 214 | 189 | 155 | 131 | 98 |

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

^ Number of observations reduced from previous sample sizes due to missing responses.

**Perceived Changes**

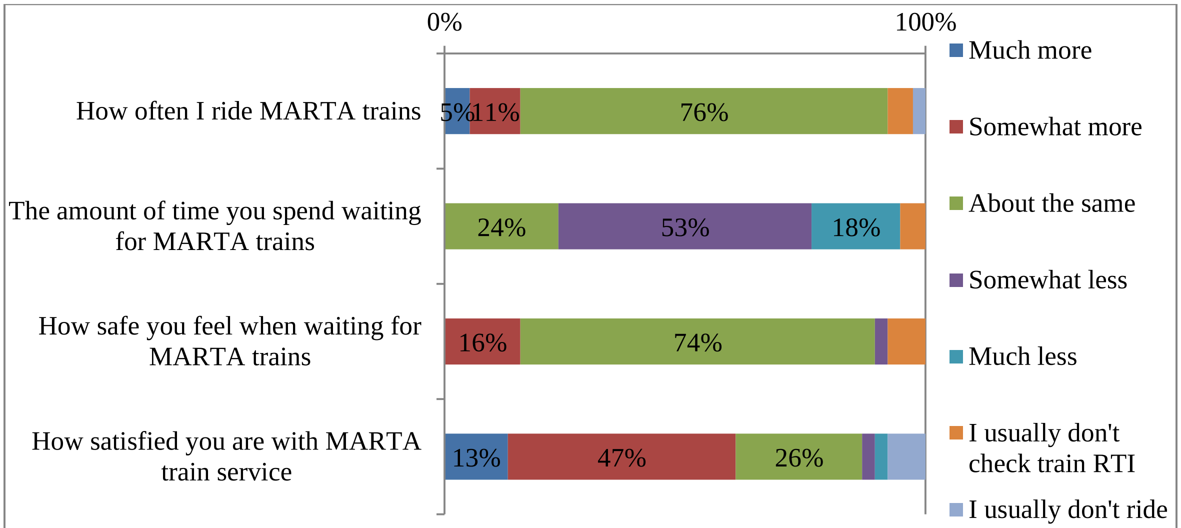
In addition to the questions used in the smart card trip history analysis, the survey also included questions to directly measure if RTI users perceived a change in their transit travel since they began using RTI. RTI users were asked if using an app with real-time information changed the number of trips that they take on MARTA trains or buses. In addition, riders were also asked about three other possible benefits of using RTI, including the amount of time they spend waiting, how safe they feel when waiting, and how satisfied they are with overall MARTA service. Each of these four possible benefits (number of trips, waiting time, personal security, and satisfaction) were asked separately for MARTA trains and MARTA buses. These questions were similar to two prior studies of RTI users in Seattle (Ferris et al., 2010; Gooze et al., 2013).

The results of perception questions for RTI users who met all of the conditions (1A-3B) are shown in Figure 7 for questions about MARTA trains and Figure 8 for MARTA buses.[1] As can be seen in Figure 7, 76% of respondents said that they ride MARTA trains "about the same" number of times since they began using RTI. However, 53% of RTI users stated that they spend "somewhat less" time waiting for the train, and another 18% stated that they spend "much less" time waiting for the train. Additionally, 47% of RTI users that they are "somewhat more" satisfied with overall MARTA train service, and another 13% are "much more" satisfied. As can be seen in Figure 8, most (50%+) of the "perfectly congruent" RTI users in the study did not regularly ride the bus.

[1] The results of the perception questions for the full dataset (n=494) are presented in the appendix.

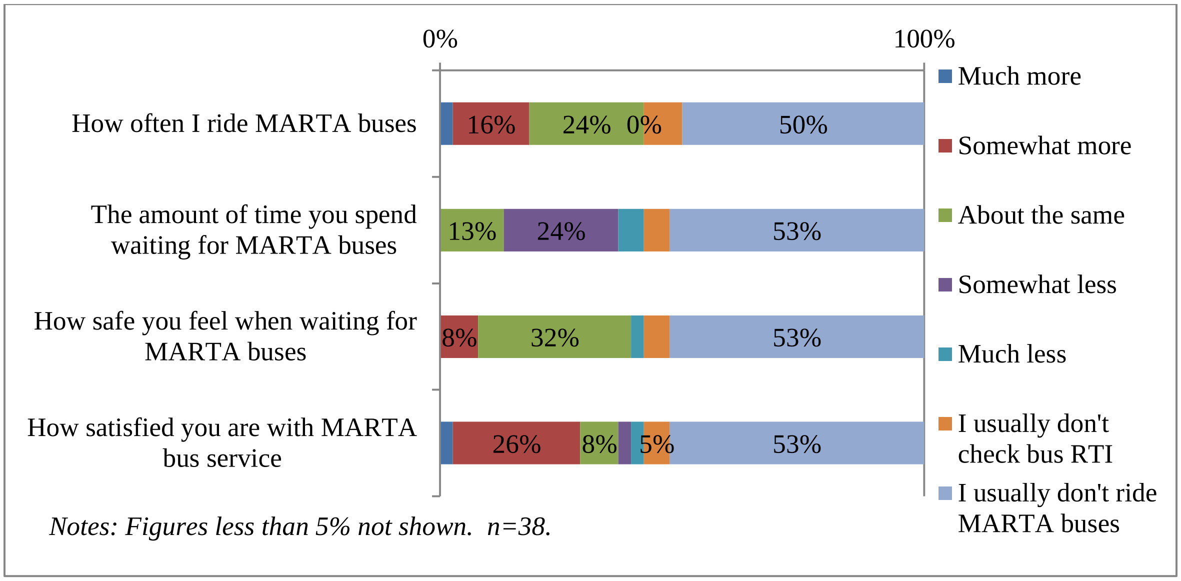
Similar to the train responses, the most pronounced perceived benefits appear to pertain to reductions in wait times (24% stated that they wait "somewhat less") and satisfaction with MARTA bus service (26% are "somewhat more" satisfied). Last, it should be noted that the sample size of "perfectly congruent" RTI users was only 38 respondents for both train and bus questions.

Figure 7: Perceived Changes when Riding MARTA Trains




*Notes: Figures less than 5% not shown. n=38.*

Figure 8: Perceived Changes when Riding MARTA Buses




**Areas for Improvement and Future Research**

This exploratory analysis sheds light on some possible improvements and potential challenges for further applications of this method. First, the survey responses used in this analysis were collected via non-probability sampling, and consequently, they are not representative of all MARTA riders. This survey substantially differed from MARTA's last system-wide survey in two ways: there were more Caucasian respondents and higher levels of income than those of typical MARTA riders. A detailed breakdown of the socioeconomic status of this survey participants and a comparison to MARTA's last system-wide survey are presented in the appendix. Even though regression analysis was performed to help control for differences in socioeconomic characteristics, future research could use probability sampling to increase the generalizability of descriptive statistics.

Another important improvement regarding the sampling methodology is incorporating assumptions pertaining to the "shrinking" sample size into the survey sampling methodology. The original dataset began with 494 linked survey/smart card responses, and this decreased significantly to 100 (20%) after strictly imposing the three conditions to perform the before-after analysis. Future applications of this methodology should aim to increase the sampling rate in anticipation of this.

A third area for improvement in the data collection process is to include an additional survey question asking if a person began riding transit in the last year. In this analysis, new riders were not considered, since these respondents did not have smart cards in the "before" period of analysis. However, it is possible that they may have begun using transit because of the availability of real-time information, and this should be explored in future research.

Another area for improvement pertains to the condition of congruence. This was assessed using the number of train trips in the last week for each respondent by comparing each self-reported number of transit trips to the corresponding smart card trip history. As was previously noted, self-reported travel behavior questions are often subject to error, particularly recall bias in which respondents cannot correctly remember their transit trip-making patterns (Stopher, 2012, p. 142). Perhaps a better measure of congruence is "home" station, since respondents are likely able to recall this easier. Another possible improvement is requesting a respondent's Breeze Card number twice on the survey instrument to avoid unintentional errors by the respondent when entering the 16-digit number.

An extension of using smart card data to evaluate disaggregate transit travel is to understand the revenue implications for transit agencies. In this before-after analysis, the fare type used for each trip (e.g. monthly pass, full fare pay as you go, student pass) was not considered, but future applications may want to evaluate this important attribute. This could be used to calculate the farebox revenue impact of the intervention under analysis.

A potential challenge to applying this methodology in the future is consistency in using smart card "taps" to measure transit trips over time if there are fare policy changes. The study period for this analysis was selected during a timeframe when there were no known changes in fare policy. Shortly after the study period, MARTA changed their bus open door policy at transfer locations, which could impact the number of "taps" in future analyses.

Last but not least, a noteworthy challenge to applying this methodology more broadly may be privacy concerns on behalf of the transit agency pertaining to the use of smart card data (e.g. Dempsey 2008). Transit agencies may be hesitant (or unwilling) to share their data with researchers, particularly if they have stringent privacy policies.

## Conclusions

In this study, a methodology was developed to combine smart card fare collection data with survey responses to evaluate changes in transit travel behavior over time. This method was applied to an empirical analysis of real-time information in Atlanta. The initial linked smart card/survey dataset began with 494 eligible participants, and conditions of panel eligibility, completeness, uniqueness and congruence were sequentially applied, resulting in 100 (20%) responses in the final dataset. Difference of mean tests and regression analysis were used to compare each individual's monthly transit trips from April 2013 to April 2014. The results for the complete dataset (n=494) and Condition 1A (Panel Eligibility of the Intervention) suggest that real-time information led to an increase in the overall number of trips made on transit. However, when the remaining conditions were applied and the sample size was reduced, the difference in trips from April 2013 to April 2014 was not significantly different between the RTI user group and non-user group. This may because the RTI user group consistently took more trips in April 2013 than the group of non-users, which suggests that those who use transit more were more likely to adopt RTI.

A primary contribution of this research is the methodology to combine smart card data with survey responses to evaluate changes in transit travel. Traditional surveys lack a method of accurately measuring travel behavior over extended periods of time (unless surveys are repeated), and the smart card dataset advantageously provides a record of transit trips needed for before-after or panel analyses. Similarly, the survey instrument can be used to gather socioeconomic information and other characteristics of the respondent, which would otherwise be unavailable in a smartcard dataset. This methodology could be used to evaluate other attributes – beyond use of real-time information – and more broadly applied for transit marketing and travel behavior analyses in the future. Transit planners and market researchers conducting regular transit customer satisfaction surveys could include a few additional questions about smart cards – particularly the smart card number – and apply this methodology to evaluate how future policy or planning changes impact transit travel.

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# CHAPTER 5

# CONCLUSIONS

This chapter presents a brief comparison of the key findings from the three studies presented in this dissertation: New York City, Tampa, and Atlanta. This meta-analysis is followed by concluding remarks and areas for future research.

## Comparison of Case Study Findings

This section presents a comparison of the results of the three studies. First, New York City was the setting for a natural experiment in which real-time bus information was gradually launched on a borough-by-borough basis over a three year period. Panel regression techniques were used to evaluate route-level bus ridership for 185 bus routes while controlling for changes in transit service, fares, local socioeconomic conditions, weather, and other factors. Two fixed effects models with robust standard errors were presented. The first model, which included real-time information as a single binary variable, showed an average increase of approximately 118 rides per route per weekday (median increase of 1.7% of weekday route-level ridership) likely attributable to providing RTI. This result is very similar to a prior study conducted in Chicago (Tang and Thakuriah 2012) that found an increase of 126 average weekday rides per route (approximately 1.8-2.2% of route-level ridership). The second model, which divided the real-time information variable based on quartiles of bus service per route, suggests that the ridership increase occurred on the largest routes, and this increase was approximately 340 rides per weekday on the largest routes (median increase of 2.3% of route-level ridership). One plausible explanation of why the largest routes experienced a significant increase in ridership is that they may be more likely to attract “choice” trips (such as non-commute trips). These results suggest that RTI may have the greatest impact on routes with higher levels of service.

In Tampa, a behavioral experiment was performed with a before-after control group design in which access to real-time bus information was the treatment variable. Web-based surveys measured behavior changes over a three month study period for 217 eligible study participants. The frequency of bus trips per week was evaluated before and after the availability of RTI, but there were no significant differences between the RTI user group and the control group. This was not surprising since the majority of bus riders in Tampa are transit-dependent, meaning they lack other transportation alternatives. Notably, this study also considered other possible benefits to riders, and the results suggest that the primary benefits associated with providing RTI to passengers pertain to waiting at the bus stop. Analysis of “usual” wait times revealed a significantly larger decrease (nearly 2 minutes) for RTI users compared to the control group, and RTI users had significant decreases in levels of anxiety and frustration when waiting for the bus compared to the control group. These findings provide strong evidence that RTI significantly improves the passenger experience of waiting for the bus, which is notoriously one of the most disliked elements of transit trips.

Finally, in Atlanta, a methodology to combine smart card fare collection data with web-based survey responses was developed to quantify changes in transit travel of individual riders in a before-after study. After joining the smart card data to the survey responses, three conditions were imposed to assess if each record accurately reflected an individual’s travel behavior. The first condition necessitated that the respondent began using real-time information in the appropriate timeframe and had the smart card sufficiently long to be used in the before-after analysis. The second condition tested if one smart card actually represented one traveler, and the third condition verified that the smart card number trip history corresponded to the respondent's stated travel behavior. After imposing all three conditions, the dataset was reduced in size from 494 initial participants to 100 (20%) usable responses. Then, difference of means tests and regression analysis were used to assess differences in monthly transit trips between real-time information users and non-users from April 2013 to April 2014. The results show that there was not a significant difference in the change in monthly transit trips between the RTI user group and non-user group; however, the final sample size was very small. These results, as well as those from the New York City and Tampa studies, are summarized in Table 19.

Table 19: Comparison of Case Study Findings

| | **New York City** | **Tampa** | **Atlanta** |
|---|---|---|---|
| Agency | NYCT | HART | MARTA |
| Methodology | Natural experiment with panel regression | Behavioral experiment with a before-after control group design | Before-after analysis of transit trips |
| Key Findings | Route-level ridership increased by approximately 118 rides on an average weekday;<br>A second model suggests the ridership increase only occurred on large routes | Comparison of bus trips before and after does not suggest a change in weekly transit travel;<br>The primary benefits pertain to the passenger waiting time and experience | Difference of mean tests and regression analysis of changes in monthly transit trips do not suggest a change in transit trips among current riders |
| Unit of Analysis | Route-level bus ridership | Individual (transit passenger) | Individual (transit passenger) |
| Final Sample Size | 185 bus routes | 217 eligible study participants | 100 eligible study participants |

## Concluding Remarks

The results shown in Table 19 reveal that two of the three studies (Tampa and Atlanta) did not find a substantial change in transit trips associated with use of real-time information. However, one study (New York City) did show an increase in ridership likely attributable to providing real-time information and was most significant on the routes with the greatest level of transit service (measured in revenue miles). Since New York City has substantially more bus service than Atlanta or Tampa in terms of the number of routes, the span of service, and the frequency of service on most (if not all) routes, this suggests that the potential for ridership gains due to real-time information may be greatest in areas that already have high levels of preexisting transit service.

One possible explanation for these findings is that real-time information could help increase ridership by attracting “choice” trips in areas with high levels of transit service. When a traveler is considering taking a bus trip versus an alternative mode, checking real-time information in locations with high transit service levels may reveal that a bus stop is located nearby and that a transit vehicle is only a few minutes away, and consequently, the traveler chooses to take that extra trip on the bus. On the other hand, in locations with lower levels of transit service, the traveler may be presented with the information that he or she is far from a transit stop or would have to wait for a long period of time, and in that situation, the traveler may choose an alternative mode or forgo the unnecessary trip.

Additional analysis from the Tampa and Atlanta study suggests that, even in locations with low levels of transit service provision, real-time information positively impacts riders in other ways, such as reducing wait times or the perception thereof. While transit agencies serving this type of market may not experience significant ridership gains, they are likely to improve the transit riding experience by providing passengers with real-time information.

## Future Research

Many interesting avenues for future research emerged from this dissertation. First, additional research is recommended to evaluate other cities with high levels of transit service to better understand when and where real-time information is affecting ridership. For example, future studies could examine the impact of varying headways coupled with real-time information on ridership; perhaps on routes with high to medium frequencies (e.g. headways less than 20 minutes), real-time information has greater potential to increase ridership since consulting real-time information reveals relatively short wait times. Another possible refinement is comparing the ridership impacts of RTI on weekdays (as in the New York City study) with weekends, since weekend travel typically includes more discretionary trips. Yet another possible stratification for future research is differentiating the ridership impacts of real-time information between peak and off-peak trips.

Looking ahead, there are many areas for future research evaluating new and emerging transit information sources beyond real-time vehicle location and arrival information. Attributes of transit alternatives that were previously not readily available – such as crowding levels – may soon be provided to riders via smartphone applications, and this trend is likely to increase as riders become more connected and demand higher levels of personalized, dynamic information. By providing relevant information on key issues, operators may enable flexible travelers to make informed decisions that better suit their needs, which will hopefully lead to more travelers choosing transit for future trips.

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## APPENDIX A: ADDITIONAL NEW YORK CITY ANALYSES

Table 20 shows the monthly dummy variables that were estimated with the OLS and RE models shown in Table 4. The reference month is January.

Table 20: Monthly Dummy Variables from the OLS and RE Regression Results

| | **OLS Estimate** (SE) | **RE Estimate** (SE) | **RE AR(1) Estimate** (SE) | **RE ARMA(1,1) Estimate** (SE) |
|---|---|---|---|---|
| February | 744.53 | 706.79*** | 774.11*** | 811.06*** |
| | (640.37) | (78.28) | (60.19) | (58.69) |
| March | 1076.22* | 646.66*** | 815.46*** | 844.82*** |
| | (570.99) | (70.57) | (64.06) | (64.43) |
| April | 663.62 | 81.81 | 302.26*** | 355.29*** |
| | (832.57) | (105.10) | (90.36) | (87.42) |
| May | 1329.86 | 660.09*** | 939.16*** | 1028.32*** |
| | (830.87) | (101.74) | (90.29) | (87.97) |
| June | 770.25 | 434.44*** | 625.67*** | 721.30*** |
| | (1014.96) | (124.70) | (103.01) | (99.18) |
| July | 272.74 | -148.05 | 82.97 | 154.39 |
| | (993.82) | (122.90) | (101.67) | (97.11) |
| August | -147.05 | -660.82*** | -449.21*** | -387.24*** |
| | (1041.86) | (127.96) | (111.74) | (109.28) |
| September | 1043.73 | 684.66*** | 928.22*** | 1031.84*** |
| | (871.50) | (106.37) | (90.37) | (88.46) |
| October | 1108.38 | 794.12*** | 1023.56*** | 1116.95*** |
| | (776.68) | (95.96) | (78.03) | (75.84) |
| November | 364.43 | 192.50* | 340.52*** | 414.82*** |
| | (773.06) | (102.08) | (84.85) | (83.32) |
| December | -257.32 | -405.88*** | -365.85*** | -352.98*** |
| | (558.03) | (78.53) | (66.31) | (64.63) |
| Constant | 42783.04** | 23030.54*** | 32491.99*** | 38721.18*** |
| | (19330.38) | (3570.31) | (3786.93) | (3589.77) |

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 21 shows the monthly dummy variables that were estimated with the RE and FE models shown in Table 5 and Table 6. The reference month is January.

Table 21: Monthly Dummy Variables from the FE and RE Regression Results

| | **Single Bus Time Variable** | | | | **Quartiles of Bus Service** | |
|---|---|---|---|---|---|---|
| | Random Effects Estimate | | Fixed Effects Estimate | | Fixed Effects Estimate | |
| | (SE) | (Robust SE) | (SE) | (Robust SE) | (SE) | (Robust SE) |
| February | 741.475 | | 736.343 | | 737.328 | |
| | (74.529)*** | (55.784)*** | (73.070)*** | (56.152)*** | (72.961)*** | (56.023)*** |
| March | 604.792 | | 620.926 | | 620.633 | |
| | (66.222)*** | (60.433)*** | (65.399)*** | (59.805)*** | (65.305)*** | (60.115)*** |
| April | 112.587 | | 134.889 | | 135.545 | |
| | (104.011) | (63.608)* | (102.918) | (62.220)** | (102.775) | (62.375)** |
| May | 648.763 | | 656.287 | | 656.884 | |
| | (97.725)*** | (66.094)*** | (96.181)*** | (64.769)*** | (96.041)*** | (65.111)*** |
| June | 445.53 | | 425.23 | | 423.84 | |
| | (123.115)*** | (75.221)*** | (120.694)*** | (71.749)*** | (120.524)*** | (71.886)*** |
| July | -133.344 | | -182.398 | | -185.548 | |
| | (120.411) | (77.207)* | (118.156) | (79.564)** | (117.990) | (79.556)** |
| August | -642.912 | | -681.253 | | -685.116 | |
| | (121.834)*** | (80.790)*** | (119.454)*** | (85.440)*** | (119.287)*** | (85.354)*** |
| September | 718.078 | | 707.926 | | 708.024 | |
| | (105.453)*** | (68.256)*** | (103.349)*** | (65.809)*** | (103.196)*** | (65.955)*** |
| October | 851.279 | | 855.124 | | 857.67 | |
| | (95.326)*** | (73.605)*** | (93.647)*** | (71.535)*** | (93.518)*** | (71.536)*** |
| November | 311.315 | | 331.713 | | 333.744 | |
| | (96.351)*** | (58.463)*** | (95.460)*** | (54.847)*** | (95.332)*** | (55.224)*** |
| December | -305.317 | | -275.612 | | -275.687 | |
| | (76.273)*** | (56.841)*** | (77.226)*** | (54.415)*** | (77.121)*** | (54.546)*** |
| Constant | 22,769.29 | | 21,721.07 | | 21,771.18 | |
| | (2568.7)*** | (2770.7)*** | (2626.5)*** | (2312.1)*** | (2624.7)*** | (2302.7)*** |

** p<0.1; ** p<0.05; *** p<0.01*

*Robust Standard errors calculated using the Huber/White/sandwich estimator.*

# APPENDIX B: ADDITIONAL TAMPA ANALYSES

Regression models of the gain scores of trips/week, transfers/week, and usual wait time were created to understand the extent to which the experimental design controlled for other factors that may influence travel behavior. The dependent variable in each model was the gain score of trips/week, transfers/week and usual wait time, respectively. Unless otherwise noted, the independent variables were from categorical survey questions and were modeled as binary variables. The independent variables included the following:

- used real-time information (RTI),
- age,
- annual household income,
- gender,
- employment status,
- ethnicity (multiple ethnicities and Asian included in "other"),
- household size (continuous variable from 1 to 6)
- household automobile ownership (continuous variable from 0 to 3),
- having a valid license,
- sold a car during the study period,
- bought a car during the study period,
- got a license during the study period,
- lost a license during the study period,
- moved household or job/school locations during the study period, and

- changed usual bus routes during the study period (only in the usual wait time model).

The results of the three regression models are shown in Table 22. In the regression model for the difference in trips per week shown in the leftmost column, the variable representing use of RTI was not significant. The only variable that was statistically significantly to the 1% confidence level was the binary variable for having a valid driver's license. The interpretation of this coefficient implies that study participants with valid driver's license decreased their bus travel by 1.28 trips per week, holding all else equal, over the study period.

The regression model for the difference in transfers per week is shown in the middle column of Table 22, and again, the variable representing the use of RTI was not statistically significant. Only one variable was statistically significant to the 1% confidence level, and this was the binary variable for participants between 25 and 34 years of age. It is unclear why this group significantly decreased their transit travel over the study period.

The regression model for the difference in usual wait times (in minutes) is presented in the rightmost column of Table 22. This model has one more independent variable than the previous two models, and this variable is for participants who changed the bus route that they ride most frequently during the study period (shown at the bottom). The noteworthy result from this model is that the use of RTI significantly decreased the usual wait time by approximately 2.19 minutes, holding all else equal. Three other variables were statistically significant: gender, participants age 45 to 54 and those age 55 to 64. It is unclear why these groups had significant changes in self-reported usual wait times over the course of the study. In summary, the three regression results did not differ substantially from the conclusions presented in previous sections.

Last, the perceived behavior, feeling, and satisfaction changes of the experimental group were compared to the actual (self-reported) differences from the before survey to the after survey. Tables 23, 24 and 25 show the results of this analysis for behavior changes, feeling changes, and satisfaction changes, respectively.

Table 22: Regression Models for Difference in Trips, Transfers and Usual Wait Time

| **Ordinary Least Squares (OLS) Regression Results** | | **Difference in Trips/Week** | | **Difference in Transfers/Week** | | **Difference in Usual Wait Time (minutes)** | |
|---|---|---|---|---|---|---|---|
| Category | Variable | Beta | T-stat | Beta | T-stat | Beta | T-stat |
| | Intercept | -1.09 | -0.76 | 1.16 | 0.63 | 3.07 | 1.55 |
| Used RTI | Used RTI | 0.05 | 0.09 | 0.29 | 0.44 | -2.19 | -3.17 |
| Age | Age 18-24 (reference) | - | - | - | - | - | - |
| | Age 25-34 | 0.04 | 0.04 | -2.47 | -2.00 | -2.63 | -1.96 |
| | Age 35-44 | -0.47 | -0.47 | -1.91 | -1.56 | -2.54 | -1.88 |
| | Age 45-54 | 0.75 | 0.70 | -1.43 | -1.08 | -3.11 | -2.11 |
| | Age 55-64 | 0.66 | 0.55 | -1.78 | -1.15 | -3.70 | -2.21 |
| | Age 65 and over | 0.87 | 0.47 | -0.92 | -0.37 | -1.96 | -0.74 |
| Annual Household Income | Under $5,000 (reference) | - | - | - | - | - | - |
| | $5,000 to $9,999 | 1.92 | 1.76 | 1.23 | 0.90 | 0.80 | 0.54 |
| | $10,000 to $19,999 | 0.99 | 1.01 | 0.20 | 0.16 | -0.99 | -0.74 |
| | $20,000 to $29,999 | 1.35 | 1.29 | 1.17 | 0.89 | 1.24 | 0.87 |
| | $30,000 to $39,999 | 0.95 | 0.83 | 0.30 | 0.20 | 0.26 | 0.16 |
| | $40,000 to $49,999 | 0.02 | 0.01 | -0.39 | -0.22 | -0.99 | -0.55 |
| | $50,000 or more | 2.20 | 1.85 | 2.17 | 1.44 | 0.89 | 0.54 |
| Employment Status | Employed Full Time (reference) | - | - | - | - | - | - |
| | Employed Part Time | 0.62 | 0.78 | 0.78 | 0.79 | -0.65 | -0.60 |
| | Unemployed | -1.07 | -1.04 | -0.41 | -0.32 | -0.86 | -0.61 |
| | Retired | 0.69 | 0.54 | 0.52 | 0.29 | 1.35 | 0.70 |
| | Student | 0.81 | 0.92 | 1.07 | 0.98 | -1.59 | -1.31 |
| | Other (disabled, etc.) | 0.17 | 0.11 | -1.01 | -0.56 | 0.53 | 0.26 |
| Ethnicity | White (reference) | - | - | - | - | - | - |
| | Black or African American | 0.34 | 0.52 | -0.47 | -0.56 | -1.80 | -1.94 |
| | Hispanic or Latino | 0.33 | 0.39 | -0.14 | -0.14 | 1.11 | 0.97 |
| | Other (Includes Asian & Mixed Race) | -0.33 | -0.36 | -0.25 | -0.21 | 2.15 | 1.73 |
| Household Size | Number People in Household | -0.04 | -0.16 | 0.31 | 1.09 | -0.47 | -1.55 |
| Cars | Number of Cars in Household | -0.43 | -1.21 | -0.68 | -1.38 | 0.43 | 0.87 |
| License | Has a Valid License | -1.28 | -2.24 | -1.29 | -1.83 | -0.52 | -0.66 |
| Gender | Female | 0.58 | 1.17 | -0.22 | -0.35 | 1.41 | 2.06 |
| Changes During the Study Period | Got a Car | -2.08 | -1.93 | -3.31 | -1.96 | 0.09 | 0.06 |
| | Sold a Car | -2.24 | -1.14 | -2.95 | -1.26 | 1.86 | 0.69 |
| | Got a Driver's License | -0.68 | -0.59 | -0.97 | -0.70 | -1.11 | -0.70 |
| | Moved Household/Job Location | -0.11 | -0.16 | 0.39 | 0.43 | 0.33 | 0.34 |
| | Switched Usual Bus Route | Not included | | Not included | | 1.20 | 1.31 |
| Summary Statistics | Degrees of Freedom | 172 | | 144 | | 165 | |
| | F-statistic | 1.182 | | 0.926 | | 1.183 | |
| | R-squared | 0.161 | | 0.153 | | 0.172 | |
| | Adjusted R-squared | 0.025 | | -0.012 | | 0.027 | |

Table 23: Comparison of Perceived and Before-After Changes in Behavior

| ***Perceived Changes: Has using OneBusAway changed…** | **Before-After (Self-Reported) Change** | | | | **Statistics**** |
|---|---|---|---|---|---|
| **The number of HART bus trips that you take?** | Decreased | Same | Increased | Total | Sample Size |
| I ride HART buses (much or somewhat) more often | 15% | 10% | 14% | 39% | 108 |
| I ride HART buses about the same | 25% | 22% | 13% | 60% | Pearson's R |
| I ride HART buses (much or somewhat) less | 1% | 0% | 0% | 1% | 0.129 |
| Total | 41% | 32% | 27% | 100% | |
| **The number of transfers that you make on HART buses?** | Decreased | Same | Increased | Total | Sample Size |
| I transfer (much or somewhat) more often | 5% | 4% | 9% | 18% | 93 |
| I transfer about the same | 23% | 24% | 31% | 77% | Pearson's R |
| I transfer (much or somewhat) less | 3% | 1% | 0% | 4% | 0.138 |
| Total | 31% | 29% | 40% | 100% | |
| **The amount of time you wait at the bus stop?** | Decreased | Same | Increased | Total | Sample Size |
| I spend (much or somewhat) more time waiting | 4% | 2% | 0% | 6% | 107 |
| I spend about the same time waiting at the bus stop | 14% | 10% | 7% | 31% | Pearson's R |
| I spend (much or somewhat) less time waiting | 34% | 21% | 8% | 64% | 0.009 |
| Total | 51% | 34% | 15% | 100% | |

**Values rounded to the nearest whole percent.*
***Sample sizes may differ from previous figures/tables due to varying response rates to multiple questions.*

Table 24: Comparison of Perceived and Before-After Changes in Feelings

| *Perceived Changes: Since you began using OneBusAway, do you… | Before-After (Self-Reported) Change | | | | Statistics** |
|---|---|---|---|---|---|
| **Feel safer when waiting for the bus at night** | Decreased | Same | Increased | Total | Sample Size |
| Agree (somewhat or strongly) | 6% | 10% | 8% | 23% | 105 |
| Neutral | 11% | 27% | 14% | 52% | Pearson's R |
| Disagree (somewhat or strongly) | 9% | 11% | 5% | 25% | 0.115 |
| Total | 26% | 48% | 27% | 100% | |
| **Feel safer when waiting for the bus during the daytime** | Decreased | Same | Increased | Total | Sample Size |
| Agree (somewhat or strongly) | 8% | 18% | 13% | 39% | 104 |
| Neutral | 5% | 28% | 12% | 44% | Pearson's R |
| Disagree (somewhat or strongly) | 3% | 9% | 5% | 16% | 0.011 |
| Total | 15% | 55% | 30% | 100% | |
| **Feel more relaxed when waiting for the bus** | Decreased | Same | Increased | Total | Sample Size |
| Agree (somewhat or strongly) | 18% | 33% | 17% | 69% | 105 |
| Neutral | 5% | 12% | 9% | 26% | Pearson's R |
| Disagree (somewhat or strongly) | 3% | 2% | 1% | 6% | 0.008 |
| Total | 26% | 48% | 27% | 100% | |

**Values rounded to the nearest whole percent.*

***Sample sizes may differ from previous figures/tables due to varying response rates to multiple questions.*

Table 25: Comparison of Perceived and Before-After Changes in Satisfaction

| *Perceived Changes: Since you began using OneBusAway, do you… | Before-After Satisfaction Change | | | | Statistics** |
|---|---|---|---|---|---|
| | **Overall HART Bus Service** | | | | |
| **Feel more satisfied riding HART buses?** | Decreased | Same | Increased | Total | Sample Size |
| Agree (somewhat or strongly) | 11% | 47% | 11% | 70% | 105 |
| Neutral | 3% | 18% | 6% | 27% | |
| Disagree (somewhat or strongly) | 1% | 3% | 0% | 4% | Pearson's R |
| Total | 15% | 68% | 17% | 100% | -0.010 |
| | **How Long You Have to Wait** | | | | |
| **Feel more satisfied riding HART buses?** | Decreased | Same | Increased | Total | Sample Size |
| Agree (somewhat or strongly) | 14% | 28% | 28% | 70% | 104 |
| Neutral | 6% | 13% | 7% | 26% | |
| Disagree (somewhat or strongly) | 2% | 1% | 1% | 4% | Pearson's R |
| Total | 22% | 42% | 36% | 100% | 0.134 |
| | **How Often the Bus Arrives at Stop On Time** | | | | |
| **Feel more satisfied riding HART buses?** | Decreased | Same | Increased | Total | Sample Size |
| Agree (somewhat or strongly) | 9% | 33% | 27% | 70% | 106 |
| Neutral | 4% | 15% | 8% | 26% | |
| Disagree (somewhat or strongly) | 0% | 4% | 0% | 4% | Pearson's R |
| Total | 13% | 52% | 35% | 100% | 0.100 |

**Values rounded to the nearest whole percent.*

***Sample sizes may differ from previous figures/tables due to varying response rates to multiple questions.*

# APPENDIX C: ADDITIONAL ATLANTA ANALYSES

This appendix includes four additional MARTA analyses. First, a set of regression models with all of the independent variables considered in the analysis is shown in Table 26. The dependent variable was the difference in monthly trips (precisely, four weeks) from 2013 to 2014 from the smart card trip history, and the independent variables included retrospective survey questions, such as awareness of service changes and socioeconomic changes, as well as many other socioeconomic characteristics of the respondent. Only two variables (African American and having a driver's license) were consistently significant when all of the conditions were applied.

In Table 27, the socioeconomic characteristics of the study participants are shown for each of condition, and these statistics were also compared to the 2013 system-wide survey conducted by MARTA, which is shown in the rightmost column of Table 27. There are two noteworthy differences between the two surveys: ethnicity and income.

Table 28 and Table 29 present additional analysis of survey questions that were asked of real-time information (RTI) users in order to understand perceived changes in behavior and feelings. Toward the end of the survey questionnaire, RTI users were asked about potential behavior and feeling changes since they began using RTI, including the following: the number of trips they make on MARTA, their waiting time, their perception of safety, and their overall satisfaction with MARTA service. These questions were asked separately for MARTA bus service (shown in Table 28) and MARTA train service (shown in Table 29). Last, it should be noted that these questions were similar to the perception questions from the Tampa study.

Table 26: Regression Analysis of Difference in Transit Trips with All Independent Variables

| **Regression of Difference in Trips** | **Full** | **1A** | **1B** | **2A** | **2B** | **2C** | **3A** | **3B** |
|---|---|---|---|---|---|---|---|---|
| Intercept | 19.65$^{**}$ | 23.60$^{***}$ | 34.34$^{***}$ | 34.27$^{***}$ | 42.16$^{***}$ | 36.75$^{***}$ | 31.07$^{**}$ | 18.89 |
| | (8.31) | (8.67) | (10.66) | (10.65) | (9.64) | (11.43) | (12.53) | (18.88) |
| Use Real-Time Information | 5.09$^{**}$ | 4.24$^{*}$ | 2.31 | -0.44 | -0.67 | -2.14 | -1.82 | 0.37 |
| | (2.35) | (2.47) | (3.00) | (2.94) | (2.74) | (3.29) | (3.40) | (4.14) |
| Aware of MARTA Service Changes | 0.60 | 0.20 | 0.41 | 4.15 | 4.85$^{*}$ | 6.19$^{*}$ | 7.73$^{**}$ | 7.49$^{*}$ |
| | (2.27) | (2.47) | (2.91) | (2.90) | (2.69) | (3.29) | (3.40) | (4.12) |
| Employed Part Time | 3.04 | 2.32 | -2.51 | 0.11 | 0.46 | 2.33 | 0.64 | -0.74 |
| | (3.64) | (3.91) | (5.14) | (4.95) | (4.60) | (6.08) | (6.72) | (9.48) |
| Unemployed | -8.82 | -11.62$^{*}$ | -13.37$^{*}$ | 0.10 | -1.58 | 2.02 | 9.42 | 3.39 |
| | (6.04) | (6.72) | (7.53) | (7.41) | (7.42) | (8.01) | (7.84) | (9.51) |
| Student | -3.04 | -3.57 | -4.12 | -4.76 | -1.02 | -2.70 | 2.61 | -1.41 |
| | (3.43) | (3.68) | (4.61) | (4.64) | (4.44) | (5.24) | (5.77) | (7.74) |
| Retired | 1.24 | 0.65 | 2.08 | 1.70 | 0.59 | 0.27 | 4.92 | 6.93 |
| | (11.50) | (11.50) | (14.45) | (12.26) | (10.89) | (11.78) | (11.35) | (13.79) |
| Other Employment | -4.56 | -5.43 | -4.94 | -4.46 | 1.39 | 3.25 | 4.96 | 6.45 |
| | (11.56) | (11.52) | (11.60) | (11.23) | (12.13) | (12.85) | (12.10) | (14.02) |
| Has a License | -16.95$^{***}$ | -16.35$^{***}$ | -25.75$^{***}$ | -32.14$^{***}$ | -42.75$^{***}$ | -43.25$^{***}$ | -48.55$^{***}$ | -40.54$^{***}$ |
| | (4.62) | (4.91) | (6.69) | (7.14) | (6.69) | (7.71) | (8.70) | (10.35) |
| Number of Cars in Household | -2.32 | -4.33$^{**}$ | -4.01$^{*}$ | -3.54 | -0.69 | 0.51 | 1.07 | 1.88 |
| | (1.84) | (1.98) | (2.39) | (2.28) | (2.18) | (2.66) | (2.99) | (3.80) |
| Household Size | -1.02 | -0.18 | 0.47 | -0.13 | -1.31 | -1.17 | -0.13 | 0.41 |
| | (1.31) | (1.40) | (1.68) | (1.67) | (1.64) | (1.90) | (1.99) | (2.87) |
| Increased Household Size | 5.17 | 6.24 | 3.83 | 5.46 | 6.35 | 6.98 | -2.77 | -2.06 |
| | (4.54) | (4.63) | (5.10) | (4.99) | (4.67) | (5.85) | (6.06) | (7.35) |
| Decreased Household Size | -11.87 | -9.83 | -11.03 | -9.37 | -7.90 | -6.25 | -9.97 | -3.69 |
| | (11.26) | (11.26) | (12.40) | (10.45) | (9.33) | (12.04) | (11.76) | (14.00) |
| Increased Cars in Household | -9.74$^{**}$ | -9.05$^{**}$ | -6.22 | -5.30 | -2.72 | -4.48 | -4.97 | -2.72 |
| | (4.17) | (4.30) | (5.09) | (4.93) | (4.87) | (5.75) | (5.66) | (7.39) |

Table 26 (continued): Regression Analysis of Difference in Transit Trips with All Independent Variables

| **Regression (Continued)** | **Full** | **1A** | **1B** | **2A** | **2B** | **2C** | **3A** | **3B** |
|---|---|---|---|---|---|---|---|---|
| Decreased Cars in Household | 0.95 | 2.46 | 2.70 | 2.51 | 3.25 | 2.85 | 2.19 | 1.93 |
| | (5.18) | (5.51) | (6.95) | (6.28) | (6.98) | (8.15) | (8.56) | (10.99) |
| Changed Household Location | 3.42 | 3.29 | -1.59 | 1.87 | 0.64 | -0.15 | 0.66 | 5.00 |
| | (2.65) | (2.85) | (3.56) | (3.66) | (3.68) | (4.44) | (4.58) | (5.52) |
| Changed Jobs | 3.67 | 1.63 | -2.17 | -0.15 | 1.86 | -0.24 | 1.27 | -1.36 |
| | (2.64) | (2.87) | (3.62) | (3.78) | (3.56) | (4.46) | (4.54) | (6.00) |
| Got a License | 1.83 | -0.95 | -5.54 | -15.21 | -16.73 | -14.09 | -20.33 | - |
| | (9.20) | (9.99) | (13.39) | (13.70) | (12.10) | (12.80) | (18.37) | - |
| Lost a License | 9.81 | 10.85 | - | - | - | - | - | - |
| | (15.99) | (16.06) | - | - | - | - | - | - |
| Male | -0.61 | 0.81 | -0.98 | 1.73 | 0.97 | 1.73 | 0.75 | 3.66 |
| | (2.26) | (2.43) | (2.98) | (2.95) | (2.78) | (3.32) | (3.35) | (4.05) |
| Age 18 to 24 | 13.79* | 13.83* | 14.10 | 9.27 | 4.84 | 6.97 | 12.74 | 9.92 |
| | (7.12) | (7.36) | (9.09) | (8.41) | (7.78) | (9.27) | (10.01) | (14.97) |
| Age 25 to 34 | 4.15 | 2.54 | 1.08 | 6.05 | 4.02 | 7.96 | 15.61* | 12.26 |
| | (6.33) | (6.56) | (7.75) | (7.35) | (6.63) | (8.20) | (8.38) | (13.79) |
| Age 35 to 44 | 3.99 | 0.26 | 0.65 | 1.33 | 3.32 | 4.37 | 10.44 | 11.64 |
| | (6.47) | (6.75) | (7.91) | (7.52) | (6.76) | (8.38) | (8.74) | (14.08) |
| Age 45 to 64 | 2.68 | -1.03 | -2.86 | -2.27 | -0.38 | 2.53 | 10.47 | 9.65 |
| | (6.82) | (7.21) | (8.33) | (8.02) | (7.41) | (8.94) | (9.17) | (14.39) |
| Hispanic | 2.41 | 4.38 | 6.24 | 5.54 | 7.98 | 6.57 | 1.72 | 2.28 |
| | (5.81) | (6.00) | (6.89) | (7.00) | (6.74) | (7.71) | (8.85) | (11.38) |
| African American | 17.76*** | 15.95*** | 14.50*** | 20.83*** | 16.79*** | 19.35*** | 24.73*** | 17.33** |
| | (3.77) | (4.10) | (4.83) | (4.97) | (5.06) | (6.02) | (6.19) | (7.20) |
| Asian | -2.12 | -5.27 | -6.71 | -5.06 | -4.37 | -7.04 | 0.57 | 1.38 |
| | (4.07) | (4.37) | (5.03) | (4.59) | (4.29) | (5.65) | (6.05) | (7.67) |
| Other Race | 0.41 | -0.17 | -2.36 | 7.27 | 8.54 | 12.19 | 2.74 | 3.39 |
| | (7.70) | (7.73) | (10.69) | (10.13) | (9.06) | (9.89) | (11.25) | (12.56) |

Table 26 (continued): Regression Analysis of Difference in Transit Trips with All Independent Variables

| Regression (Continued) | Full | 1A | 1B | 2A | 2B | 2C | 3A | 3B |
|---|---|---|---|---|---|---|---|---|
| Household Income Less than $30,000 | 2.91 | 1.03 | 6.24 | 1.47 | 1.32 | 0.00 | -3.09 | 0.05 |
| | (3.87) | (4.13) | (5.17) | (4.79) | (4.60) | (5.70) | (6.10) | (7.46) |
| Household Income $30,000-$50,000 | -3.45 | -4.69 | -3.67 | -2.62 | -3.92 | -2.13 | -1.71 | 0.48 |
| | (3.47) | (3.72) | (4.53) | (4.51) | (4.28) | (5.13) | (5.34) | (7.03) |
| Household Income $50,000-$75,000 | -0.15 | -0.98 | -3.06 | -0.72 | 0.36 | 2.85 | 5.49 | 6.99 |
| | (3.19) | (3.43) | (4.12) | (4.00) | (3.65) | (4.41) | (4.54) | (5.59) |
| Number of Observations# | 452 | 393 | 277 | 203 | 179 | 146 | 122 | 93 |
| $R^2$ | 0.23 | 0.22 | 0.27 | 0.37 | 0.44 | 0.44 | 0.49 | 0.38 |
| Adj. $R^2$ | 0.17 | 0.16 | 0.18 | 0.27 | 0.33 | 0.30 | 0.33 | 0.12 |

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$, (standard error), #Number of observations reduced from previous sample sizes due to missing responses

Table 27: Socioeconomic Characteristics of Survey Participants

| | | **All Data** | | **1A** | | **1B** | | **2A** | | **2B** | | **2C** | | **3A** | | **3B** | | **System** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | # | % | # | % | # | % | # | % | # | % | # | % | # | % | # | % | % |
| | Grand Total* | 494 | 100% | 431 | 100% | 305 | 100% | 219 | 100% | 193 | 100% | 159 | 100% | 135 | 100% | 100 | 100% | 100% |
| Household Income | Under $10,000 | 20 | 4% | 16 | 4% | 8 | 3% | 8 | 4% | 5 | 3% | 4 | 3% | 3 | 2% | 3 | 3% | *20%* |
| | $10,000 to $19,999 | 28 | 6% | 25 | 6% | 13 | 4% | 10 | 5% | 8 | 4% | 8 | 5% | 7 | 5% | 4 | 4% | *19%* |
| | $20,000 to $29,999 | 48 | 10% | 45 | 10% | 31 | 10% | 24 | 11% | 21 | 11% | 17 | 11% | 13 | 10% | 12 | 12% | *21%* |
| | $30,000 to $39,999 | 34 | 7% | 32 | 7% | 19 | 6% | 9 | 4% | 8 | 4% | 7 | 4% | 4 | 3% | 2 | 2% | *13%* |
| | $40,000 to $49,999 | 40 | 8% | 34 | 8% | 24 | 8% | 18 | 8% | 14 | 7% | 10 | 6% | 10 | 7% | 7 | 7% | *7%* |
| | $50,000 to $74,999 | 83 | 17% | 72 | 17% | 52 | 17% | 34 | 16% | 34 | 18% | 28 | 18% | 23 | 17% | 20 | 20% | *9%* |
| | Over $75,000 | 212 | 43% | 181 | 42% | 138 | 45% | 105 | 48% | 92 | 48% | 75 | 47% | 65 | 48% | 45 | 45% | *11%* |
| | No Answer | 29 | 6% | 26 | 6% | 20 | 7% | 11 | 5% | 11 | 6% | 10 | 6% | 10 | 7% | 7 | 7% | - |
| Ethnicity | Amer. Indian | 2 | 0% | 2 | 0% | 0 | 0% | 0 | 0% | 0 | 0% | 0 | 0% | 0 | 0% | 0 | 0% | *0%* |
| | Asian** | 40 | 8% | 36 | 8% | 26 | 9% | 22 | 10% | 19 | 10% | 13 | 8% | 10 | 7% | 8 | 8% | *3%* |
| | Black | 57 | 12% | 50 | 12% | 39 | 13% | 24 | 11% | 17 | 9% | 14 | 9% | 11 | 8% | 9 | 9% | *76%* |
| | White | 368 | 74% | 318 | 74% | 226 | 74% | 165 | 75% | 150 | 78% | 125 | 79% | 108 | 80% | 78 | 78% | *15%* |
| | Other | 12 | 2% | 12 | 3% | 7 | 2% | 5 | 2% | 4 | 2% | 4 | 3% | 3 | 2% | 3 | 3% | *5%* |
| | No Answer | 15 | 3% | 13 | 3% | 7 | 2% | 3 | 1% | 3 | 2% | 3 | 2% | 3 | 2% | 2 | 2% | - |
| Spanish | Not Hispanic | 461 | 93% | 401 | 93% | 285 | 93% | 207 | 95% | 183 | 95% | 150 | 94% | 128 | 95% | 95 | 95% | *94%* |
| | Hispanic | 20 | 4% | 19 | 4% | 13 | 4% | 8 | 4% | 7 | 4% | 6 | 4% | 4 | 3% | 3 | 3% | *6%* |
| | No Answer | 13 | 3% | 11 | 3% | 7 | 2% | 4 | 2% | 3 | 2% | 3 | 2% | 3 | 2% | 2 | 2% | - |
| Gender | Female | 232 | 47% | 207 | 48% | 133 | 44% | 91 | 42% | 81 | 42% | 59 | 37% | 51 | 38% | 39 | 39% | *49%* |
| | Male | 246 | 50% | 211 | 49% | 163 | 53% | 123 | 56% | 107 | 55% | 95 | 60% | 79 | 59% | 59 | 59% | *51%* |
| | No Answer | 16 | 3% | 13 | 3% | 9 | 3% | 5 | 2% | 5 | 3% | 5 | 3% | 5 | 4% | 2 | 2% | - |
| Age | Under 24*** | 62 | 13% | 57 | 13% | 25 | 8% | 20 | 9% | 16 | 8% | 13 | 8% | 11 | 8% | 10 | 10% | *23%* |
| | 25 to 34 | 229 | 46% | 204 | 47% | 141 | 46% | 99 | 45% | 88 | 46% | 72 | 45% | 61 | 45% | 46 | 46% | *26%* |
| | 35 to 44 | 113 | 23% | 96 | 22% | 79 | 26% | 61 | 28% | 54 | 28% | 44 | 28% | 37 | 27% | 27 | 27% | *18%* |
| | 45 to 54 | 56 | 11% | 43 | 10% | 38 | 12% | 24 | 11% | 20 | 10% | 17 | 11% | 14 | 10% | 10 | 10% | *18%* |
| | 55 to 64 | 19 | 4% | 18 | 4% | 15 | 5% | 11 | 5% | 11 | 6% | 9 | 6% | 8 | 6% | 4 | 4% | *12%* |
| | 65 or older | 3 | 1% | 3 | 1% | 1 | 0% | 1 | 0% | 1 | 1% | 1 | 1% | 1 | 1% | 1 | 1% | *3%* |
| | No Answer | 12 | 2% | 10 | 2% | 6 | 2% | 3 | 1% | 3 | 2% | 3 | 2% | 3 | 2% | 2 | 2% | - |

*System-wide numbers in the rightmost column from MARTA's 2013 Quality of Service Report.*

**Percentages rounded to whole numbers. ** MARTA's Asian category includes Asian Indian. ***Georgia Tech survey did not include those under age 18.*

Table 28: Perceived Changes when Riding MARTA Buses

| | | All Data | | 1A | | 1B | | 2A | | 2B | | 2C | | 3A | | 3B | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *Grand Total* | *302* | *100%* | *239* | *100%* | *166* | *100%* | *114* | *100%* | *99* | *100%* | *77* | *100%* | 60 | *100%* | 38 | *100%* |
| Bus Trips | I ride MARTA buses much more often | 19 | 6% | 15 | 6% | 10 | 6% | 6 | 5% | 5 | 5% | 5 | 6% | 3 | 5% | 1 | 3% |
| | " somewhat more often | 52 | 17% | 44 | 18% | 31 | 19% | 21 | 18% | 18 | 18% | 15 | 19% | 9 | 15% | 6 | 16% |
| | " about the same | 83 | 27% | 61 | 26% | 39 | 23% | 26 | 23% | 21 | 21% | 15 | 19% | 13 | 22% | 9 | 24% |
| | " somewhat less often | 1 | 0% | 1 | 0% | 1 | 1% | 0 | 0% | 0 | 0% | 0 | 0% | 0 | 0% | 0 | 0% |
| | " much less often | 0 | 0% | 0 | 0% | 0 | 0% | 0 | 0% | 0 | 0% | 0 | 0% | 0 | 0% | 0 | 0% |
| | I usually don't check bus RTI | 13 | 4% | 13 | 5% | 10 | 6% | 6 | 5% | 5 | 5% | 5 | 6% | 5 | 8% | 3 | 8% |
| | I usually don't ride MARTA buses | 131 | 43% | 102 | 43% | 73 | 44% | 55 | 48% | 50 | 51% | 37 | 48% | 30 | 50% | 19 | 50% |
| | No Answer | 3 | 1% | 3 | 1% | 2 | 1% | 0 | 0% | 0 | 0% | 0 | 0% | 0 | 0% | 0 | 0% |
| Waiting Time | I spend much more time waiting | 2 | 1% | 1 | 0% | 0 | 0% | 0 | 0% | 0 | 0% | 0 | 0% | 0 | 0% | 0 | 0% |
| | " somewhat more | 4 | 1% | 4 | 2% | 2 | 1% | 1 | 1% | 0 | 0% | 0 | 0% | 0 | 0% | 0 | 0% |
| | " about the same | 33 | 11% | 25 | 10% | 16 | 10% | 13 | 11% | 10 | 10% | 9 | 12% | 7 | 12% | 5 | 13% |
| | " somewhat less | 65 | 22% | 50 | 21% | 37 | 22% | 25 | 22% | 22 | 22% | 18 | 23% | 13 | 22% | 9 | 24% |
| | " much less | 48 | 16% | 39 | 16% | 26 | 16% | 14 | 12% | 12 | 12% | 8 | 10% | 5 | 8% | 2 | 5% |
| | I usually don't check bus RTI | 9 | 3% | 9 | 4% | 7 | 4% | 4 | 4% | 3 | 3% | 3 | 4% | 3 | 5% | 2 | 5% |
| | I usually don't ride MARTA buses | 138 | 46% | 108 | 45% | 76 | 46% | 57 | 50% | 52 | 53% | 39 | 51% | 32 | 53% | 20 | 53% |
| | No Answer | 3 | 1% | 3 | 1% | 2 | 1% | 0 | 0% | 0 | 0% | 0 | 0% | 0 | 0% | 0 | 0% |
| Personal Security | I feel much safer when waiting | 10 | 3% | 9 | 4% | 0 | 0% | 0 | 0% | 0 | 0% | 0 | 0% | 0 | 0% | 0 | 0% |
| | " somewhat safer | 21 | 7% | 20 | 8% | 15 | 9% | 10 | 9% | 9 | 9% | 7 | 9% | 5 | 8% | 3 | 8% |
| | " about the same | 119 | 39% | 87 | 36% | 63 | 38% | 41 | 36% | 33 | 33% | 26 | 34% | 19 | 32% | 12 | 32% |
| | " somewhat less safe | 2 | 1% | 2 | 1% | 1 | 1% | 0 | 0% | 0 | 0% | 0 | 0% | 0 | 0% | 0 | 0% |
| | " much less safe | 1 | 0% | 1 | 0% | 1 | 1% | 1 | 1% | 1 | 1% | 1 | 1% | 1 | 2% | 1 | 3% |
| | I usually don't check bus RTI | 10 | 3% | 10 | 4% | 8 | 5% | 5 | 4% | 4 | 4% | 4 | 5% | 3 | 5% | 2 | 5% |
| | I usually don't ride MARTA buses | 136 | 45% | 107 | 45% | 76 | 46% | 57 | 50% | 52 | 53% | 39 | 51% | 32 | 53% | 20 | 53% |
| | No Answer | 3 | 1% | 3 | 1% | 2 | 1% | 0 | 0% | 0 | 0% | 0 | 0% | 0 | 0% | 0 | 0% |
| Satisfaction | I feel much more satisfied | 31 | 10% | 24 | 10% | 13 | 8% | 9 | 8% | 8 | 8% | 6 | 8% | 3 | 5% | 1 | 3% |
| | " somewhat more | 66 | 22% | 53 | 22% | 39 | 23% | 26 | 23% | 23 | 23% | 18 | 23% | 13 | 22% | 10 | 26% |
| | " about the same | 49 | 16% | 37 | 15% | 26 | 16% | 16 | 14% | 11 | 11% | 8 | 10% | 6 | 10% | 3 | 8% |
| | " somewhat less | 8 | 3% | 7 | 3% | 4 | 2% | 2 | 2% | 2 | 2% | 2 | 3% | 2 | 3% | 1 | 3% |
| | " much less | 2 | 1% | 1 | 0% | 1 | 1% | 1 | 1% | 1 | 1% | 1 | 1% | 1 | 2% | 1 | 3% |
| | I usually don't check bus RTI | 8 | 3% | 8 | 3% | 6 | 4% | 4 | 4% | 3 | 3% | 3 | 4% | 3 | 5% | 2 | 5% |
| | I usually don't ride MARTA buses | 135 | 45% | 106 | 44% | 75 | 45% | 56 | 49% | 51 | 52% | 39 | 51% | 32 | 53% | 20 | 53% |
| | No Answer | 3 | 1% | 3 | 1% | 0 | 0% | 0 | 0% | 0 | 0% | 0 | 0% | 0 | 0% | 0 | 0% |

Table 29: Perceived Changes when Riding MARTA Trains

| | | All Data | | 1A | | 1B | | 2A | | 2B | | 2C | | 3A | | 3B | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *Grand Total* | *302* | *100%* | *239* | *100%* | *166* | *100%* | *114* | *100%* | *99* | *100%* | *77* | *100%* | 60 | *100%* | 38 | *100%* |
| Train Trips | I ride MARTA trains much more | 21 | 7% | 16 | 7% | 10 | 6% | 5 | 4% | 4 | 4% | 4 | 5% | 2 | *3%* | 2 | *5%* |
| | " somewhat more often | 32 | 11% | 26 | 11% | 20 | 12% | 16 | 14% | 14 | 14% | 8 | 10% | 7 | 12% | 4 | *11%* |
| | " about the same | 209 | 69% | 163 | 68% | 112 | 67% | 79 | 69% | 71 | 72% | 57 | 74% | 46 | 77% | 29 | *76%* |
| | " somewhat less often | 1 | 0% | 1 | 0% | 0 | 0% | 0 | 0% | 0 | 0% | 0 | 0% | 0 | 0% | 0 | *0%* |
| | " much less often | 1 | 0% | 0 | 0% | 0 | 0% | 0 | 0% | 0 | 0% | 0 | 0% | 0 | 0% | 0 | *0%* |
| | I usually don't check train RTI | 29 | 10% | 24 | 10% | 18 | 11% | 11 | 10% | 8 | 8% | 7 | 9% | 4 | 7% | 2 | *5%* |
| | I usually don't ride MARTA trains | 6 | 2% | 6 | 3% | 4 | 2% | 3 | 3% | 2 | 2% | 1 | 1% | 1 | 2% | 1 | *3%* |
| | No Answer | 3 | 1% | 3 | 1% | 2 | 1% | 0 | 0% | 0 | 0% | 0 | 0% | 0 | 0% | 0 | *0%* |
| Waiting Time | I spend much more time waiting | 3 | 1% | 3 | 1% | 1 | 1% | 1 | 1% | 0 | 0% | 0 | 0% | 0 | 0% | 0 | *0%* |
| | " somewhat more | 3 | 1% | 2 | 1% | 0 | 0% | 0 | 0% | 0 | 0% | 0 | 0% | 0 | 0% | 0 | *0%* |
| | " about the same | 83 | 27% | 57 | 24% | 42 | 25% | 28 | 25% | 26 | 26% | 23 | 30% | 14 | 23% | 9 | *24%* |
| | " somewhat less | 123 | 41% | 100 | 42% | 70 | 42% | 50 | 44% | 43 | 43% | 30 | 39% | 28 | 47% | 20 | *53%* |
| | " much less | 53 | 18% | 46 | 19% | 32 | 19% | 21 | 18% | 20 | 20% | 16 | 21% | 13 | 22% | 7 | *18%* |
| | I usually don't check train RTI | 31 | 10% | 25 | 10% | 18 | 11% | 13 | 11% | 10 | 10% | 8 | 10% | 5 | 8% | 2 | *5%* |
| | I usually don't ride MARTA trains | 3 | 1% | 3 | 1% | 1 | 1% | 1 | 1% | 0 | 0% | 0 | 0% | 0 | 0% | 0 | *0%* |
| | No Answer | 3 | 1% | 3 | 1% | 2 | 1% | 0 | 0% | 0 | 0% | 0 | 0% | 0 | 0% | 0 | *0%* |
| Personal Security | I feel much safer when waiting | 13 | 4% | 11 | 5% | 1 | 1% | 0 | 0% | 0 | 0% | 0 | 0% | 0 | 0% | 0 | *0%* |
| | " somewhat safer | 31 | 10% | 26 | 11% | 15 | 9% | 13 | 11% | 11 | 11% | 7 | 9% | 6 | 10% | 6 | *16%* |
| | " about the same | 215 | 71% | 167 | 70% | 126 | 76% | 85 | 75% | 76 | 77% | 60 | 78% | 48 | 80% | 28 | *74%* |
| | " somewhat less safe | 2 | 1% | 2 | 1% | 1 | 1% | 1 | 1% | 1 | 1% | 1 | 1% | 1 | 2% | 1 | *3%* |
| | " much less safe | 2 | 1% | 1 | 0% | 1 | 1% | 0 | 0% | 0 | 0% | 0 | 0% | 0 | 0% | 0 | *0%* |
| | I usually don't check train RTI | 33 | 11% | 26 | 11% | 19 | 11% | 14 | 12% | 11 | 11% | 9 | 12% | 5 | 8% | 3 | *8%* |
| | I usually don't ride MARTA trains | 3 | 1% | 3 | 1% | 1 | 1% | 1 | 1% | 0 | 0% | 0 | 0% | 0 | 0% | 0 | *0%* |
| | No Answer | 3 | 1% | 3 | 1% | 2 | 1% | 0 | 0% | 0 | 0% | 0 | 0% | 0 | 0% | 0 | *0%* |
| Satisfaction | I feel much more satisfied | 43 | 14% | 32 | 13% | 18 | 11% | 13 | 11% | 13 | 13% | 11 | 14% | 7 | 12% | 5 | *13%* |
| | " somewhat more | 131 | 43% | 105 | 44% | 82 | 49% | 62 | 54% | 53 | 54% | 39 | 51% | 32 | 53% | 18 | *47%* |
| | " about the same | 84 | 28% | 64 | 27% | 40 | 24% | 21 | 18% | 19 | 19% | 16 | 21% | 13 | 22% | 10 | *26%* |
| | " somewhat less | 7 | 2% | 6 | 3% | 4 | 2% | 3 | 3% | 3 | 3% | 2 | 3% | 2 | 3% | 1 | *3%* |
| | " much less | 2 | 1% | 2 | 1% | 1 | 1% | 1 | 1% | 1 | 1% | 1 | 1% | 1 | 2% | 1 | *3%* |
| | I usually don't check train RTI | 29 | 10% | 24 | 10% | 18 | 11% | 13 | 11% | 10 | 10% | 8 | 10% | 0 | 0% | 0 | *0%* |
| | I usually don't ride MARTA trains | 3 | 1% | 3 | 1% | 1 | 1% | 1 | 1% | 0 | 0% | 0 | 0% | 5 | 8% | 3 | *8%* |
| | No Answer | 3 | 1% | 3 | 1% | 2 | 1% | 0 | 0% | 0 | 0% | 0 | 0% | 0 | 0% | 0 | *0%* |