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Quantifying the Impact of Real-Time Information on Transit Ridership

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Abstract This research aims to understand if real-time information increases transit ridership, a critical question asked by decision-makers facing pressure to increase ridership under tight budget constraints. Mixed research methods were utilized in a multi-city approach to assess changes in transit ridership attributable to providing real-time information. Two of the three cities studied, Tampa and Atlanta, did not have a significant change in transit travel associated with use of real-time information; however, real-time information did positively impact riders in other ways, such as reducing wait times or the perception thereof. The third study, of New York City, revealed an increase in ridership associated with the availability of real-time information, and this likely occurred on the routes with the greatest level of pre-existing transit service. 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.

Keywords: Real-Time Information · Bus Ridership · Behavioral Experiment · Panel Regression · Smart Cards

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1 Background and Motivation

Transit can help to reduce carbon dioxide emissions, decrease gasoline consumption, combat roadway congestion (Schrank, Eisele, & Lomax, 2012), provide personal mobility options for those who cannot drive (American Public Transportation Association, 2014), and impact public health positively because of associated active lifestyles (Besser & Dannenberg, 2005). Despite these benefits, transit agencies in many American cities struggle to increase ridership levels as they compete with other modes of passenger transportation.

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 these supply-side strategies can be effective at improving reliability, they often come at a substantial cost.

Providing transit real-time information (RTI) has recently emerged as a demand-side strategy to improving the perception of reliability of transit service. RTI helps passengers adapt when service is unreliable (Carrel, Halvorsen, & Walker, 2013) and can 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).

As they consider providing such information, transit agencies 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 RTI. Therefore, this research aims to quantify the impact of RTI on transit travel. Mixed methods are used in a multi-city approach to assess changes in transit ridership in three American cities (New York City, Tampa, and Atlanta) that share a common RTI system, known as OneBusAway.

This paper proceeds as follows. First, prior research about transit RTI is reviewed. The next section provides background information about the OneBusAway system. The impact of OneBusAway on ridership is assessed in three different cities (New York City, Tampa, and Atlanta), and for each city, the method used to evaluate RTI and the results are discussed. This is followed by a comparison of the three studies, conclusions, and areas for future research.

2 Literature Review

There is a growing body of research that aims to understand the rider impacts 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, et al., 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. 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). This review focuses on the benefits grounded in actual behavioral studies, and it includes discussion of each one of these impacts (decreased wait times, increased satisfaction, and increased ridership.

2.1 Decreased Wait Times

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, et al., 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, et al., 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, more than 20% of respondents reported feeling safer as result of using RTI (Ferris, et al., 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, et al., 2013).

2.2 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).

2.3 Increased Ridership

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).

3 OneBusAway Real-Time Information System

This research focuses on a specific RTI system known as OneBusAway, which is now available in a number of major American cities. OneBusAway was originally developed in 2008 at the University of Washington for riders in greater Seattle and has grown to host more than 100,000 unique users per week. 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). It 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. From 2011 to 2014, the MTA gradually rolled-out RTI on all MTA bus routes. While this system is branded as Bus Time and has some modifications to the user interface (see Figure 1), it is similar in functionality and feel to the OneBusAway system in Seattle.

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 to deploy a small-scale pilot program for all HART operated bus routes in early 2013 and a full-scale public instance in summer 2013 (Hillsborough Area Regional Transit, 2013).

In Atlanta, researchers at Georgia Tech worked to deploy OneBusAway for transit service operated by the Metropolitan Atlanta Rapid Transit Authority

(MARTA). The instance was introduced in “beta” in spring 2013 and a public deployment with MARTA bus and train and Georgia Tech shuttle information occurred in February 2014. Additionally, MARTA developed their own RTI smartphone applications in-house and released them in fall 2013, which became important for the evaluation of RTI in Atlanta.

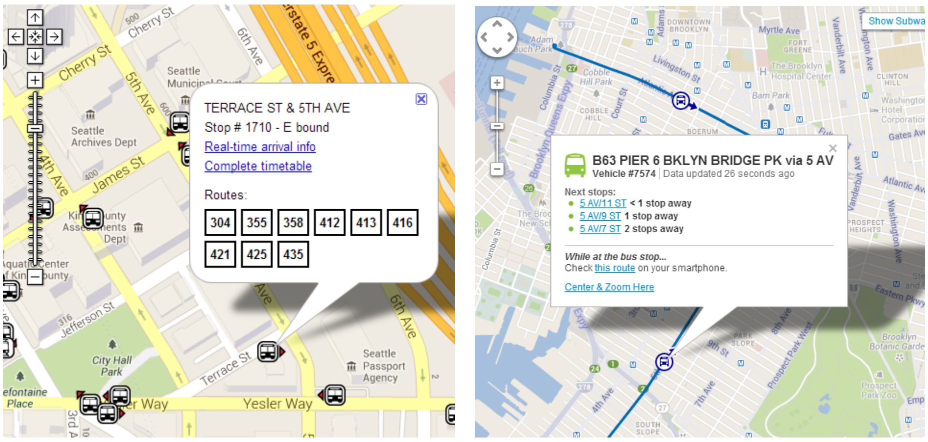

Figure 1: OneBusAway Website for Seattle and Bus Time Website for New York

In summary, four major American cities have similar RTI 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 RTI in Seattle, Washington (Ferris, et al., 2010; Watkins, et al., 2011; Gooze, et al., 2013), this research focuses on the three newest deployments of OneBusAway: New York City, Tampa, and Atlanta. While these cities share a similar RTI platform, they differ in the characteristics of the transit systems themselves, the way in which RTI was launched, and the data available for analysis. Therefore, a different methodology has been utilized to study each city. The following sections provide a summary of the method and results for each study, beginning with New York City.

4 New York City Study

The largest bus system in the United States is operated by New York City Transit (NYCT) under the umbrella organization of the Metropolitan Transportation Authority (MTA). The bus real-time information system in New York City is known as Bus Time, and it was gradually rolled out on bus routes primarily on a borough-by-borough basis. Bus Time was initially launched on a single bus route in Brooklyn (the B63) in February 2011. After this ‘pilot’ route, Bus Time was expanded by borough with a few strategic single routes between major borough releases. In January 2012, Bus Time was launched on all routes in Staten Island. The second borough-wide launch occurred in the Bronx in November 2012, and in October 2013, Bus Time became available for all routes in Manhattan. In March 2014, Bus Time was launched on all remaining bus routes in Queens and Brooklyn. The gradual roll-out of Bus Time 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.

4.1 New York City Methodology

To assess if RTI increased ridership, 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 over the multi-year period. Specifically, average weekday route-level unlinked bus trips per month was selected as the dependent variable in the regression models. Ridership data were 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. A total of 185 bus routes (or groups of routes) operated by NYCT were considered in the analysis.

In the panel regression models, the independent variable of interest, RTI, was modeled as a binary variable for any route with RTI during each month in the three year study period. To isolate the impact of RTI on ridership, other factors that may have affected NYCT bus ridership during the three year study period were taken into account. Average weekday scheduled revenue miles per bus route was in included as an independent variable, and it represents the total amount of service on each bus route because it takes into account differences in frequency, span of service, and route length. 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, and this was modeled with a binary variable. The base full fare was also included as an independent variable. Two variables to represent the level of service on the subway system were also considered: monthly system-wide rail revenue miles and the number of vehicles operated in peak 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.

Numerous factors external to the transit system were also considered as control variables in the regression analysis. A new bike-sharing program, known as Citi Bike, was introduced in sections of two boroughs (Manhattan and Brooklyn) during the last six months of the study period, so the availability of bike-sharing was modeled as a binary variable for all bus routes in Manhattan and Brooklyn after the program commenced. 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. Gas prices can influence transit demand, so monthly average retail gasoline price in New York City was included. Weather data were gathered from the National Oceanic and Atmospheric Administration (NOAA) for New York, NY, and temperature, precipitation, and snowfall were considered. Additionally, 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. Last, monthly dummy variables were included to account for seasonality.

4.2 New York City Results

Regression was used to assess the relationship between route-level bus ridership and the previously discussed independent variables over the three year panel. Numerous specifications were considered, and a fixed effects (FE) model with robust standard errors (RSE) was preferred and used to draw conclusions about the impact of RTI on ridership. The model shown in Table 1 includes the availability of RTI 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, a second FE model was also estimated, which divides the RTI variable into four quartiles based on the level of bus service (in revenue miles) per route.

The first model, which included RTI 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 RTI. The second model, which divided the RTI 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 RTI may have the greatest impact on routes with higher levels of service.

More detailed results of this study can be found in Brakewood, Macfarlane and Watkins (2015).

Table 1: New York City Bus Ridership Panel Regression Results

	Single Bus Time Variable Fixed Effects Estimate		**Quartiles of Bus Service** Fixed Effects Estimate	
	(SE)	(Robust SE)	(SE)	(Robust SE)
Bus Time Real-Time Information	118.278		-	
	(35.162)***	(52.695)**		
Bus Time on Small Routes (Q1)	-		16.256	
			(61.568)	(62.551)
Bus Time on Smaller Medium Routes (Q2)	-		147.101	
			(61.415)**	(106.412)
Bus Time on Larger Medium Routes (Q3)	-		-35.114	
			(64.971)	(106.778)
Bus Time on Large Routes (Q4)	-		340.466	
			(63.655)***	(124.803)***
Bus Service in Brooklyn	5.381		5.376	
	(0.241)***	(0.693)***	(0.240)***	(0.693)***
Bus Service in Bronx	5.073		5.017	
	(0.263)***	(0.935)***	(0.263)***	(0.945)***
Bus Service in Manhattan	3.051		3.153	
	(0.374)***	(1.227)**	(0.375)***	(1.229)**
Bus Service in Queens	2.765		2.762	
	(0.179)***	(1.275)**	(0.179)***	(1.274)**
Bus Service in Staten Island	0.212		0.03	
	-0.238	-0.301	-0.243	-0.329
Select Bus Service	-262.039		-326.825	
	-165.009	-461.757	(165.544)**	-458.593
Fare ($)	-862.884		-868.031	
	(184.457)***	(121.641)***	(184.201)***	(123.463)***
Rail Revenue Miles (thousands)	0.072		0.073	
	(0.021)***	(0.008)***	(0.021)***	(0.008)***
Rail Vehicles in Maximum Service	-2.566		-2.564	
	(0.453)***	(0.398)***	(0.453)***	(0.393)***
Citi Bike in Manhattan	-556.237		-535.102	
	(62.135)***	(143.921)***	(62.646)***	(152.800)***
Citi Bike in Brooklyn	-375.308		-375.586	
	(53.857)***	(96.701)***	(53.781)***	(96.759)***
Unemployment Rate	-243.379		-244.935	
	(48.215)***	(40.208)***	(48.153)***	(40.397)***
Cold Month	-249.223		-247.74	
	(56.868)***	(30.778)***	(56.788)***	(30.635)***
Hot Month	-246.906		-245.322	
	(73.991)***	(35.622)***	(73.890)***	(35.529)***
Total Monthly Snowfall (mm)	-0.819		-0.82	
	(0.079)***	(0.070)***	(0.079)***	(0.070)***
Total Monthly Precipitation (mm)	-0.366		-0.366	
	(0.155)**	(0.060)***	(0.155)**	(0.061)***
Hurricane Sandy	206.319		204.454	
	(98.172)**	(51.793)***	(98.027)**	(51.790)***
Sigma_u	6425.35		6393.18	
Sigma_e	758.52		757.37	
Rho	0.99		0.99	
R^2	0.47		0.47	

** p<0.1; ** p<0.05; *** p<0.01.*
Robust standard errors calculated using the Huber/White/sandwich estimator.
Monthly dummy variables can be found in Brakewood, Macfarlane and Watkins (2015).

5 Tampa Study

In the Tampa Bay region, most bus service is operated by the Hillsborough Area Regional Transit (HART), and this is a small-sized bus system. In 2012, HART granted researchers 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 RTI through web-enabled or mobile devices, this was a unique opportunity to expose a controlled population to RTI and compare them to riders without access to RTI.

5.1 Tampa Methodology

A before-after control group research design was selected as the methodology (Campbell & Stanley, 1963) in which the treatment was access to OneBusAway over a study period of approximately three months. 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. 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.

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. The data used to assess behavior change was from “before” and “after” web-based surveys asking about transit trips, as well as other possible benefits of RTI, such as wait times and satisfaction with transit service. The “before” survey was conducted in February 2013 during a two week period. After the pre-wave survey was completed, respondents were randomly assigned to the control and experimental groups. 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. An incentive of a free one day bus pass was provided to all participants (both the control and experimental groups) to help increase the survey response rates. The final sample sizes were 107 in the control group and 110 participants in the experimental group.

The survey instruments contained identical questions in the pre-wave and the post-wave surveys for both the control and experimental groups to measure behavior, feeling, and satisfaction changes. 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. To assess satisfaction, all participants were asked to rate their level of satisfaction with overall transit service on a five point scale, and five indicators of certain elements of transit service were also included.

5.2 Tampa Results

As can be seen in Table 2, the frequency of bus trips per week was evaluated before and after the availability of RTI, but the change in transit trips over the study period did not differ significantly between RTI 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. Table 2 shows that analysis of "usual" wait times revealed a significantly larger decrease (nearly 2 minutes) for RTI users compared to the control group during the study period. Table 3 reveals that RTI users had significant decreases in levels of anxiety and frustration when waiting for the bus compared to the control group. Finally, Table 4 shows the results of satisfaction with overall transit service and five indicators of certain elements of service. Two 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 wait time. 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 (Mishalani et al., 2006).

More detailed results of this study can be found in Brakewood, Barbeau and Watkins (2014).

Table 2: Mean (M), Standard Deviation (SD), and Difference of Mean Gain Scores for Trips, Transfers, and Wait Time in Tampa

	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-test 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 3: Percent Frequently or Always and Wilcoxon Rank Sum Test for Change in Feelings while Waiting for the Bus in Tampa

	Control Group			**Experimental Group**			**Diff. in Gain Scores**		
	Sample n	Before % Frequently +	After % Frequently +	Sample n	Before % Frequently +	After % Frequently +	Wilcoxon Test 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*									

Table 4: Percent Satisfied and Wilcoxon Rank Sum Test for Changes in Satisfaction in Tampa

	Control Group			**Experimental Group**			**Difference in Gain Scores**		
	Sample n	Before %	After %	Sample n	Before %	After %	Wilcoxon Rank Sum 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*									

6 Atlanta Study

The Metropolitan Atlanta Rapid Transit Authority (MARTA) operates the fifteenth largest bus system in the United States. RTI became available for all MARTA bus routes via a beta version of OneBusAway in late spring 2013. MARTA launched their own smartphone applications that were developed in-house for all buses and trains in fall 2013, and OneBusAway was publicly launched in February 2014 for all MARTA buses and trains. In light of the gradual increase of RTI options in Atlanta, a before-after analysis was selected to evaluate changes in transit travel by MARTA riders between the spring of 2013 and 2014 (specifically, April 2013 and April 2014).

6.1 Atlanta Methodology

Atlanta was the only one of the three cities with both a contactless smart card ticketing system and RTI, 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 RTI 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 a total of 494 smart card records were successfully merged to the corresponding survey response.

This joint smart card/survey dataset allowed for a disaggregate before-after analysis of transit trips in which users of RTI were compared with non-users. To do this, the combined smart card/survey dataset was first evaluated on a number of dimensions. First, the use of RTI was considered to divide participants into RTI user and non-user groups. Next, three conditions were investigated to assess if each record in the smart card/survey dataset accurately reflected an individual's travel behavior.

The first condition necessitated that the person began using RTI in the appropriate timeframe and had the smart card sufficiently long for the before-after analysis, and this was referred to as ***panel eligibility***. Some participants began using RTI during the "after" period of analysis (April 2014), and therefore, these participants did not meet the condition of ***panel eligibility of the intervention*** (referred to as Condition 1A). Similarly, some participants did not have smart cards during the "before" period of the analysis (April 2013), so they did not meet the condition of ***panel eligibility of the smart card*** (Condition 1B). A total of 305 of the 494 participants (62%) met Conditions 1A and 1B.

The second condition tested if one smart card represented one traveler, which was referred to as ***complete and unique***. A smart card record 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 would be captured in the smart card record. Participants who used more than one smart card did not meet the condition of ***complete with one smart card*** (Condition 2A). Similarly, participants who occasionally pay for transit with other forms of fare media (such as a paper ticket) did not meet the completeness condition known as ***complete with no other fare media*** (Condition 2B). A smart card was considered ***unique*** if it was only used by a single person. Participants who stated that they share their smart card did not meet ***unique*** condition (Condition 2C). Only 159 of the 494 participants (32%) met the conditions of panel eligible, complete, and unique.

The third condition verified that the smart card record corresponded to the respondent's stated travel behavior and was named ***congruence***. This was assessed by comparing each smart card record to a self-reported travel behavior survey question and was used to identify potential errors when the respondent entered his smart card number in the survey or possible errors in the smart card system. The specific method was comparing the number of MARTA train trips made in the last week from the smart card record to a self-reported survey question. Participants who had self-reported trips that matched the respective smart card trip history within two train trips were deemed to be ***closely congruent*** (Condition 3A). Respondents whose survey responses perfectly matched the respective smart card record for train trips in the last week were deemed ***perfectly congruent*** (Condition 3B). After imposing all three conditions, only 100 of the original 494 records (20%) remained.

6.2 Atlanta Results

Statistical analysis was used to assess differences in monthly trips on MARTA before (April 2013) and after (April 2014) the availability of RTI. Table 5 shows the before-after analysis of monthly MARTA trips using difference of means tests. This analysis suggests that RTI 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 because only 100 of the original 494 participants met all three conditions. Regression models were also created using the same data, which did not show a significant impact associated with use of RTI.

In addition to the questions used for the before-after analysis, the survey also asked respondents about perceived changes in their behavior or feelings. RTI users were asked if using an app with RTI changed the number of trips that they take on MARTA trains or buses. Participants 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 buses, and the results for trains are shown in Figure 2. Figure 2 shows that 76% of RTI users 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" and another 18% spend "much less" time waiting for the train. Additionally, 47% of RTI users are "somewhat more" and another 13% are "much more" satisfied with overall MARTA train service. However, the sample size in Figure 2 was small because it includes only those RTI users who met all three conditions, which was 38 respondents. More detailed results of this study are currently under review (Brakewood and Watkins).

Table 5: Before-After Analysis of Transit Trips in Atlanta

Dataset		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 Use		**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
Apr-13	M	10.2	4.7	10	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
	Med	0	0	0	0	2	0	2	0	3	0	5	1	3	0	0.5	0
	SD	20.2	14.5	19.1	14.5	20.1	16.5	20.3	18	21.2	18.9	22	20	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
Apr-14	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
	Med	8.5	1	6	1	5	1	6	1	9	1	12	1	7.5	1	3	0
	SD	29.3	22.4	29.7	22.4	31.1	23.8	27.4	26.6	26.9	26.5	27.6	27	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	6.1	2.2	8.3	1
	Med	2	0	1	0	0	0	0	0	0	0	0	0	0	0	0.5	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*	

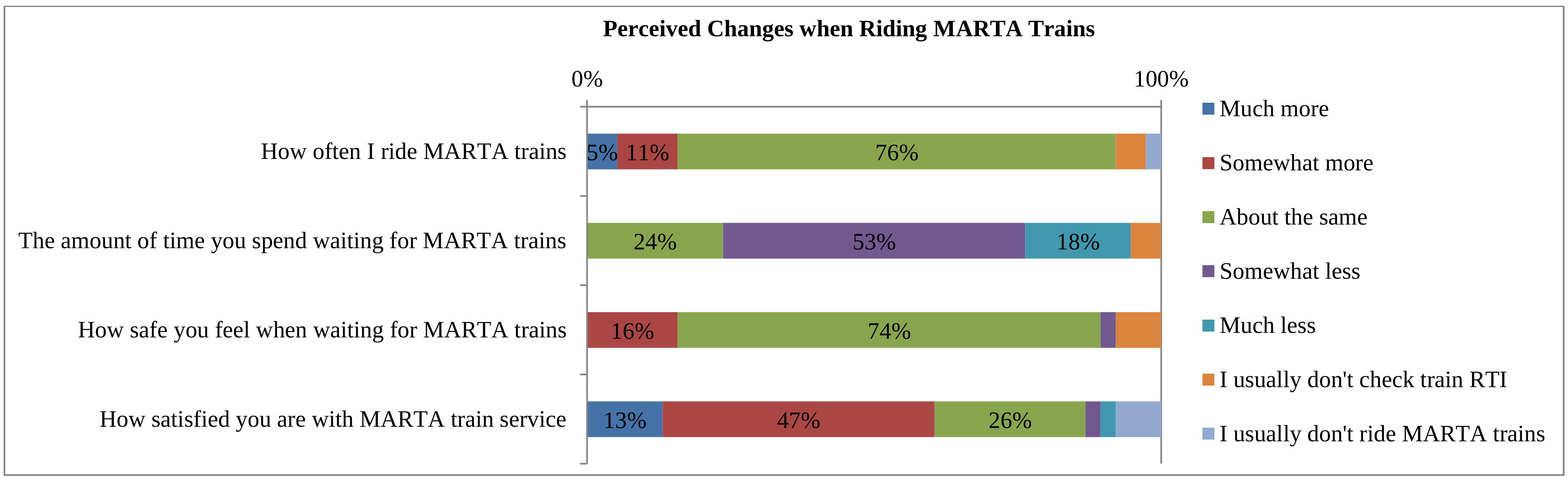

Figure 2: Perceived Changes when Riding MARTA Trains in Atlanta

7 Comparison and Conclusions

This study presents a meta-analysis of the impacts of RTI on transit ridership in three American cities (New York City, Tampa, and Atlanta) that share a common RTI system, known as OneBusAway. While these cities share a similar RTI platform, they differ in the characteristics of the transit systems themselves, the way in which RTI was launched, and the data available for analysis. Therefore, a different methodology has been utilized to study each city. Table 6 presents a summary of the three studies, including background on the transit system, the way that RTI was deployed, the methodology, and the key findings.

Table 6: Comparison of Case 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
Method	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
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
Key Findings	Route-level ridership increased by approximately 118 rides on an average weekday; 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; 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
**2012 statistics from the National Transit Database: www.ntdprogram.gov/ntdprogram/*			

The results shown in Table 6 reveal that two of the three studies (Tampa and Atlanta) did not find a substantial change in transit trips associated with use of RTI. However, one study (New York City) did show an increase in ridership likely attributable to providing RTI 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 routes, this suggests that the potential for ridership gains due to RTI may be greatest in areas that already have high levels of pre-existing transit service.

One possible explanation for these findings is that RTI 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 RTI 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 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, RTI 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 RTI.

8 Areas for Future Research

Many interesting avenues for future research emerged from this research. First, additional research is recommended to evaluate other cities with high levels of transit service to better understand when and where RTI is affecting ridership. For example, future studies could examine the impact of varying headways coupled with RTI on ridership; perhaps on routes with high to medium frequencies (e.g. headways less than 20 minutes), RTI has greater potential to increase ridership since RTI 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 RTI 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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