Quantifying the Impact of Real-Time Information on Transit Ridership

Candace Brakewood, City College of New York Kari Watkins, Georgia Tech July 21, 2015

Outline

- Motivation
- Research Approach
- Results
 - New York City, NY
 - Tampa, FL
 - Atlanta, GA
- Comparison & Conclusions

Motivation

• Public transit can be unreliable.

• Improving reliability can be expensive.

• Providing real-time transit information to riders via personal devices can help.



Image: NYC Bus Time Mobile Website

Key Prior on the Impacts of Real-Time Information



Watkins, K. E., Ferris, B., Borning, A., Rutherford, G. S., & Layton, D. (2011). Where Is My Bus? Impact of mobile real-time information on the perceived and actual wait time of transit riders.
 Zhang, F., Shen, Q., & Clifton, K. J. (2008). Examination of Traveler Responses to Real-Time Information About Bus Arrivals Using Panel Data. Transportation Research Record. 2082, 107–115.
 Tang, L., & Thakuriah, P. (Vonu). (2012). Ridership effects of real-time bus information system: A case study in the City of Chicago. Transportation Research Part C: Emerging Technologies, 22, 146–161.

Research Approach: OneBusAway

- Evaluation of real-time information focusing on OneBusAway, which is an open source system that relies on open data
- Where is OneBusAway used?
 - Seattle,WA
 - New York, NY
 - Tampa, FL
 - Atlanta, GA
 - Others
- See <u>http://onebusaway.org/</u>





Study Locations

	New York City	Tampa	Atlanta
Transit Agency	New York City Transit	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
Primary Data Sources	nary Data Sources Route-level ridership counts Web-based surveys		Web-based survey combined with smart card data
Methodology	Natural experiment with panel regression	Behavioral experiment with a before-after control group design	Before-after analysis of transit trips

* Unlinked bus trips are 2012 Statistics from the National Transit Database



STUDY I: NEW YORK CITY

Full Manuscript: Brakewood, Candace, Gregory Macfarlane, and Kari Watkins (2015). The Impact of Real-Time Information on Bus Ridership in New York City. Transportation Research Part C: Emerging Technologies, Volume 53, pp. 59-75

Roll-out of Bus Time in New York City

MTA 📮 Bus Time®

Text / Mobile About Contact Developers Help

TIP: Enter an intersection, bus route or bus stop code.

Try these example searches:

Route: <u>B63</u> <u>S62</u> <u>X1</u> Intersection: <u>Main St and Craig Ave</u> Stop Code: <u>200884</u> Location: <u>10304</u> <u>Hylan Blvd</u>

Click here for a list of available routes.

Bus Time modeled with the following dates:

- Feb 2011: B63
- Jan 2012: All Staten Island Routes
- Apr 2012: M34
- Jul 2012: B61
- Nov 2012: All Bronx Routes; M100

Google

Oct 2013: All Manhattan Routes



Route-level Ridership

The dependent variable of interest is monthly route-level ridership over a 3 year panel (t=36 months). All NYCT operated routes were included in the analysis (i=185* routes).

NYCT Average Weekday Ridership per Month (2011-2013) By Borough



Month

* Ridership statistics for a small number of NYCT routes were combined due to joint scheduling/counts (e.g. M101/2/3, BX40/42, etc.)

Data Sources & Variables

Many factors affect transit ridership, including transit-related variables (e.g., fares) and external factors (e.g., weather). The following variables were considered in the analysis.

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

Methodology: Panel Regression

• OLS* regression is insufficient: $y_{it} =$

$$\alpha + \beta x_{it} + \varepsilon_{it}$$

where

y = ridership

i = bus route

t = month

x = *explanatory variables*



Two types of panel regression were evaluated

- Random Effects: $y_{it} = \alpha_i + \beta x_{it} + \varepsilon_{it}$
- Fixed Effects: $y_{it} \overline{y}_i = \beta(x_{it} \overline{x}_i) + \varepsilon_{it}$

• Fixed Effects panel regression was selected

Model I: Fixed Effects Regression Single Bus Time Variable

Variable	Estimate	Robust Standard Error					
Bus Service by Borough (Revenue Miles)							
Brooklyn	5.381	(0.693)***					
Bronx	5.073	(0.935)***					
Manhattan	3.051	(1.227)**					
Queens	2.765	(1.275)**					
Staten Island	0.212	(0.301)					
Other Transit-Related Variables							
Select Bus Service	-262.039	(461.757)					
Fare (\$)	-862.884	(121.641)***					
Rail Revenue Miles (thousands)	0.072	(0.008)***					
Rail Vehicles in Max. Service	-2.566	(0.398)***					
Other External Factors							
Citi Bike in Manhattan	-556.237	(143.921)***					
Citi Bike in Brooklyn	-375.308	(96.701)***					
Unemployment Rate	-243.379	(40.208)***					
Cold Month	-249.223	(30.778)***					
Hot Month	-246.906	(35.622)***					
Total Monthly Snowfall (mm)	-0.819	(0.070)***					
Total Monthly Precipitation (mm)	-0.366	(0.060)***					
Hurricane Sandy	206.319	(51.793)***					
Real-Time Information	118.278	(52.695)**					
Monthly Dummy Variables (see paper)							
R ² 0.47							

Interpretation

- Bus service increases →
 bus ridership increases
- Availability of bike-sharing → bus ridership decreased
- Hurricane Sandy → bus ridership increased
- Bus Time real-time information → increased route-level ridership ~118 rides per route per weekday (median of 1.7%),

Model 2: Fixed Effects Regression with Real-Time Information by Route Size

Variable	Estimate	Robust Standard Erro
Bus Service by Borough (Revenue Miles)		
Brooklyn	5.376	(0.693)***
Bronx	5.017	(0.945)***
Manhattan	3.153	(1.229)**
Queens	2.762	(1.274)**
Staten Island	0.03	(0.329)
Other Transit-Related Variables		
Select Bus Service	-326.825	(458.593)
Fare (\$)	-868.03 I	(123.463)***
Rail Revenue Miles (thousands)	0.073	(0.008)***
Rail Vehicles in Maximum Service	-2.564	(0.393)***
Other External Factors		
Citi Bike in Manhattan	-535.102	(152.800)***
Citi Bike in Brooklyn	-375.586	(96.759)***
Unemployment Rate	-244.935	(40.397)***
Cold Month	-247.74	(30.635)***
Hot Month	-245.322	(35.529)***
Total Monthly Snowfall (mm)	-0.82	(0.070)***
Total Monthly Precipitation (mm)	-0.366	(0.061)***
Hurrisans Sandy	204.454	(51.700)***
Real-Time Information		
Small Routes (QI)	16.256	(62.551)
Smaller Medium Routes (Q2)	147.101	(106.412)
Larger Medium Routes (Q3)	-35.114	(106.778)
Large Routes (Q4)	340.466	(124.803)***
Monchly Dummy Variables (see paper)	-	
R∠	0	.47

ror Interpretation

- Bus service increases \rightarrow bus ridership increases
- Availability of bike-sharing \rightarrow bus ridership decreased
- Hurricane Sandy → bus ridership increased
- Bus Time on Large Routes→ increased ridership by ~340 rides per weekday on the largest quartile of routes (median of 2.3%)

New York City Conclusions

Conclusions

- Model I: Average increase of ~118 trips per route per weekday (median of 1.7%), which is similar to Chicago
- Model 2: Average increase of ~340 trips per weekday on the largest quartile of routes (median of 2.3%)
- Weekday farebox revenue from these additional trips was also investigated (\$5.6-\$6.3 million over three years).

Limitations

- Short Timescale: Study period had only 3 months of Bus Time in Manhattan and was prior to the Brooklyn and Queens launch
- Unit of Analysis: Only considered weekday trips (not weekend)



STUDY II: TAMPA

Full Manuscript: Brakewood, Candace, Sean Barbeau, and Kari Watkins (2014). An Experiment Evaluating the Impacts of Real-Time Transit Information on Bus Riders in Tampa, Florida. Transportation Research Part A: Policy and Practice, Volume 69, pp. 409-422.

Methodology

Before-After Control Group Research Design

- Motivation: HART provided USF & Georgia Tech special access to real-time data
- **Recruitment:** HART website/email list (Incentive of I day bus pass)
- **Measurement:** Web-based surveys
- **Group Assignment:** Random number generator
- **Treatment:** 5 interfaces of OneBusAway (3 websites & 2 smartphone apps)

Limiting the Treatment: iPhone & Android Apps

				On	eBusAway	→ L2 + L2 = 14,05
d 🙃 Map	5:10 PM Updated: 5:10 PM	1	C	On Deb One	eBusAway API S emines the server no BusAway API calls	lerver ame used in
umni Dr top #3109 Jumni	SE bound R	iversity of ath Florida	ng	Sav	ve to SD card	ecent stops and routes
Route	Destination	Minute	s	0	DneBusAway	API Server
5 ⁸	outh to Downtown/MTC 5:09 PM - 4 min delay	NOW	>	0	onebusaway.fore onebusaway-api	est.usf.edu/ -webapp
5	outh to Downtown/MTC 5:34 PM - on time	24	>		Cancel	ОК
5	outh to Downtown/MTC 6:05 PM - on time	55	>			
	Load more arrivals					
\odot	© m	6				
Мар	Recent Bookmarks	Info				

Analysis of Usual Wait Times

Identical questions about usual wait time on regular route on the before and after surveys

Usual Wait Time	Sample Size Before		After	Difference
(minutes)	n	M <u>ean (S</u> D)	Mean (SD)	Mean
Control Group	102	[10.71]	10.50	
Control Group	102	(3.88)	(4.25)	-0.21
Experimental Group	107	11.36	9.56	1 79
Experimental Group	107	(4.06)	(4.68)	-1.77
Comparison	Difference	of Means: t=2.65,	two-tailed p=0.00	09 < 0.01

• Experimental group post-wave survey only: Has using OneBusAway changed the amount of time you wait at the bus stop?



- I spend much more time waiting
- I spend somewhat more time waiting
- I spend about the same time waiting
- I spend somewhat less time waiting
- I spend much less time waiting

Analysis of Feelings While Waiting for the Bus

• Identical questions about feelings while waiting asked on the before and after surveys

	Control Group		Experiment	tal Group	Diff. in Gain Scores		
	% Frequently +	Always	% Frequently	y + Always	Wilcoxon Test		
Feelings	Before	After	Before	After	W	p-value	
Productive	11%	10%	10%	17%	6201	0.051 *	
Anxious	18%	19%	26%	25%	4548	0.082 *	
Relaxed	34%	34%	27%	25%	5518	0.592	
Frustrated	24%	26%	25%	18%	4241	0.006 ***	
Significance: * p<0.10; ** p<0.05; *** p<0.01							

• Experimental group post-wave survey only asked: Since you began using OneBusAway, do you feel more relaxed when waiting for the bus?



Agree strongly
Agree somewhat
Neutral
Disagree somewhat
Disagree strongly

Analysis of Satisfaction

Identical questions about satisfaction asked on the before and after surveys

	Control % Sati	Control Group % Satisfied		Experimental Group % Satisfied		n Gain Scores ilcoxon Test
	Before	After	Before	After	W	p-value
How frequently the bus comes	37%	41%	40%	44%	5812	0.459
How long you have to wait for the bus	39%	34%	36%	46%	6425	0.020 **
How often the bus arrives at the stop on time	54%	45%	45%	59%	7094	0.0001 ***
How often you arrive at your destination on time	57%	53%	55%	63%	5835	0.236
How often you have to transfer buses to get to your final destination	n 44%	42%	38%	36%	4916	0.342
Overall HART bus service	63%	59%	57%	58%	5717	0.410
Significance: * p<0.10; ** p<0.05; *** p<0.01						

• Experimental group post-wave survey only asked: Since you began using OneBusAway, do you feel more satisfied riding HART buses?



Analysis of Bus Trips/Week

• Identical questions about the number of HART bus trips/week on the before and after surveys

Tring/Mook	Sample Size Before		After	Difference		
Trips/ Week	n	M <u>ean (S</u> D)	Mean (SD)	Mean		
Control Crown	107	(7.03)	6.63			
Control Group	107	(3.79)	(4.09)	-0.40		
Even a vinc an tal Cuaun	110	7.09	6.40	0.49		
Experimental Group		(3.94)	(3.71)	-0.67		
Comparison	Difference of Means: t=0.66, two-tailed b=0.512					
•	11	I	<i>,</i> 1			

• Experimental group post-wave survey only: Has using OneBusAway changed the number of HART bus trips that you take?



Bottom graphic: n=108. 0% selected "I ride somewhat less." Figures rounded to the nearest whole percent.

Tampa Conclusions

- Significant improvements in the "waiting experience"
 - Decreases in self-reported usual wait times
 - Decreases in negative feelings, particularly frustration
 - Increases in satisfaction with wait times
- Little evidence supporting a change in transit trips
 - Approx. I/3 of RTI users stated they ride the bus more frequently, perhaps because of:
 - Affirmation bias of respondents
 - Scale of measurement (trips per week)
 - Only riders within sphere of transit agency



STUDY III: ATLANTA

In preparation for submission.

Methodology

- Background on Real-Time Information:
 - MARTA launched apps in November 2013
 - OneBusAway launched in February 2014
- Method: Before-After Analysis of MARTA Trips
 April 2013 to April 2014
- Unit of Analysis: Individual rider
- **Primary Data Source:** Breeze Card smart cards
 - Number of transit trips on bus and train



MARTA's On the Go Apps



Source of Images: itsmarta.com

Smart Card Data

Date: Day determines 'before' & 'after' trips	of: 20-Mar f 3 Transit 0 ted Start an d Operato Sele Selecte Selecte Selected Tonsac Selected Bus Mur	-13 14:44:14 Card: 01600143 d End Dates ar rs: s: tion Types: tion Statuses: nber(s):	T 377218919 nd Times: 01/01/13	ransit Card Trans 00:00:00 to 03/20/13 00:00:0	action Histor	у	Metro	opolitan Atlanta Rapid Tra pr-nl A100 / PN.14-04.2	ansit Authority bms3:nextfare 701.04 / 1108
Mode:	Time e Id Bu	Operator Is ID Cart ID	Facility Grp ID Hi/Lo a	Route One Transaction Description	Value Change \$ Bonus	Value \$ Left \$	Rides Left	Renewed In Advance Transaction Count* Status	Card Seq Num
Bus + Rail		MARTA Rail N/A	Lindbergh Center	/A Pass Entry (Tag On)	0.00	0.00	15	0 Success	2
	02-Jan-13 13:35:24 RVG30717	ARTA Rail	Lenox N/A N/A / N	/A Pass Exit (Tag Off)	0.00	0.00	15	0 Success	3
	02-Jan-13 17:10:36 RVG30715	MARTA Rail N/A	Lenox N/A N/A / N	/A Pass Entry (Tag On)	0.00	0.00	14	0 Success	4
	02-Jan-13 17:25:08 RVG30413	MARTA Rail N/A	Midtown N/A N/A / N	/A Pass Exit (Tag Off)	0.00	0.00	14	0 Success	5
	02-Jan-13 18:50:37 DCU02349 23	MARTA Bus 45 N/A	Perry Garage N/A N/A / N	North De A Pass Transfer	ecatur Road :: N (36) 0.00	0.00	14	0 Success	6
	04-Jan-13 07:05:50 DCU10053 23	MARTA Bus 49 N/A	Perry Garage N/A N/A / N	North De A Pass Entry (Tag On)	ecatur Road :: N (36) 0.00	0.00	13	0 Success	7
	04-Jan-13 16:49:26 DCU02145 23	MARTA Bus 46 N/A	Perry Garage N/A N/A / N	North De A Pass Entry (Tag On)	ecatur Road :: N (36) 0.00	0.00	12	0 Success	8
	07-Feb-13 07:39:04 DCU10053 23	MARTA Bus 49 N/A	Perry Garage N/A N/A / N	North De A Pass Entry (Tag On)	ecatur Road :: N (36) 0.00	0.00	11	0 Success	9
	07-Feb-13 18:24:06 DCU02215 23	MARTA Bus 43 N/A	Laredo Garage N/A N/A / N	North De A Pass Entry (Tag On)	ecatur Road :: N (36) 0.00	0.00	10	0 Success	10
Spatial Uni	11-Feb-13 07:50:56 2330 23 t:	MARTA Bus 60 N/A	Hamilton Garage	North De A Pass Entry (Tag On)	ecatur Road :: N (36) 0.00	0.00	9	0 Success	11

Station (Rail) & Route (Bus)

Survey Data

- Data Collection
 - Web-based survey conducted first week of May 2014
- Recruitment
 - Both real-time information (RTI) users and non-users

• Matching with Smart Cards

- 669 participants entered survey software
- 538 provided a 16 digit smart card number
- 494 matched usable, active smart cards



*3. What is your 16-digit Breeze Card number? Please do not enter spaces or dashes.



Georgia Tech's OneBusAway Apps



Conditions Imposed on the Dataset

- Initial: Combined Survey/Smart Card Dataset (n=494)
- Condition I: Panel Eligibility (April 2013 + April 2014)
 - Real-Time (n=431)
 - Smart Card (n=305)
- Condition 2: Complete & Unique (One Card = One Person)
 - Complete with One Breeze Card (n=219)
 - Complete with No Other Fare Media (n=193)
 - Unique without Sharing Breeze Card (n=159)
- Condition 3: Congruent (That Card = That Person)
 - Closely Congruent (n=135)
 - Perfectly Congruent (n=100)

Before-After Comparison of MARTA Trips

			Data	Closely C	ongruent	Perfectly (Congruent	
Use of Real-Time Information (RTI)		RTI	No	RTI	No	RTI	No	
	Count	302	192	60	75	38	62	
bril 13*	Mean	10.2	4.7	15.6	5.7	12.8	4.1	
20 Ap	SD	20.2	14.5	21.7	12.3	22.2	9.4	
4*	Mean	21.9	9.6	21.7	7.9	21.1	5.1	
Z01 Z01	SD	29.3	22.4	27.5	14.7	29.8	10.6	
e	Mean	1.7	4.9	6.1	2.2	8.3	1.0	
enc	SD	27.8	15.8	25.4	11.3	25.1	8.9	
liffer		t = -3	t = -3.478		t = -1.097		t = -1.732	
		p=0.0006		р=0.276		р =0 .	0905	
Total Sample Size		49	94	13	5		00	

*4 weeks in April 2013 and April 2014 beginning with the first Tuesday of the month.

Perceived Changes: Riding MARTA Trains Perfectly Congruent

Has using an app with real-time information changed the NUMBERS OF TRIPS that you take on MARTA TRAINS?*



Has using an app with real-time information changed the amount of time you spend WAITING for MARTA TRAINS?**



Sample Size is Real-Time Information Users Meeting Conditions IA-3B (n= 38) .

*Zero answers for "I ride somewhat less" or "I ride much less". **Zero answers for "I spend much more time waiting" or "I spend somewhat more time waiting.

Atlanta Conclusions

Conclusions

- Full Dataset (n=494): RTI users increased transit trips
- Datasets with Conditions: No significant difference between RTI users and non-users
- Many RTI users perceived a decreased in wait times and increased satisfaction with MARTA service

Limitations

- Non-probability sampling
- Decreasing sample size

COMPARISON & CONCLUSIONS

Comparison of Key Findings

	New York City	Tampa	Atlanta
Transit Agency	New York City Transit	HART	marta
Methodology	Natural experiment with panel regression	Behavioral experiment with a before- after control group design	Before-after analysis of transit trips
Key Finding	Average weekday route-level increase of ~118 rides (median of 1.7%); Average weekday increase of ~340 rides on the largest routes (median of 2.3%)	Little evidence supporting a change in bus trips; Significant improvements in the waiting experience, particularly wait times	Little evidence supporting a change in bus/train trips; Perceived improvements in wait times and overall satisfaction with MARTA

Concluding Remarks



Perhaps there are increases in ridership where there is the highest level of transit service, attracting "choice" trips.

THANK YOU.

Questions? Email cbrakewood@gmail.com

Acknowledgements:

- The New York City study was co-authored with Gregory Macfarlane and the Tampa study was coauthored with Sean Barbeau; the authors gratefully acknowledge their contributions.
- This work was funded by a US DOT Eisenhower Graduate Fellowship, the National Center for Transit Research (NCTR), the National Center for Transportation Systems Productivity and Management (NCTSPM), and Georgia Tech's GVU Center.
- The authors are very grateful to the MTA in New York City, HART in Tampa, and MARTA in Atlanta for their support of this research.
- Finally, the authors owe a tremendous amount of gratitude to the many people who have contributed to OneBusAway open source project over the years, particularly Brian Ferris.