The Causal Effect of Bus Rapid Transit on Changes in Transit Ridership

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Abstract

Numerous studies have reported ridership increases along routes when Bus rapid transit (BRT) replaces conventional bus service, but these increases could be due simply to broader temporal trends in transit ridership. To address this limitation, we compared changes in ridership among routes where BRT was implemented to routes where BRT was planned or already existed in King County, Washington. Ridership was measured at 2010, 2013, and 2014. Ridership increased by 35% along routes where BRT was implemented from 2010 to 2013 compared to routes that maintained conventional bus service. Ridership increased by 29% along routes where BRT was implemented from 2013 to 2014 compared to consistent existing BRT service. These results provide stronger evidence for a causal relationship between BRT and increased transit ridership and a more accurate estimate of the independent effect of BRT on ridership.

Keywords: *Longitudinal study, quasi-experimental, transportation system change, land use*

Introduction

Metropolitan areas across the world are working to increase transit ridership to improve mobility and economic vitality. Bus rapid transit (BRT) is a particularly attractive method to add transit capacity and potentially increase ridership (Currie and Delbosc 2013). BRT promises the speed and reliability of rail while retaining the operating flexibility and lower cost of conventional bus service (Deng and Nelson 2011). This is achieved by running high-capacity buses with streamlined boarding systems along prioritized surface routes at frequent intervals. BRT was pioneered as a "surface metro" in Curitiba, Brazil, in the early 1970s and has since expanded to at least 204 cities worldwide (Across Latitudes and Cultures - Bus Rapid Transit 2016; Cervero 1998).

The exact mix of BRT components varies widely from system to system (Cervero 2013), yet studies consistently suggest that the increased service, reduced travel times, and improved facility identity that occur when BRT replaces conventional bus service result in increases in ridership (Kittelson & Associates Inc. et al. 2007; Levinson et al. 2003; Peak et al. 2005; US Government Accountability Office 2012). Increases in corridor-level ridership over one year can reach 80% (US Government Accountability Office 2012). Furthermore, transit surveys show that new BRT service attracts choice transit riders—those who previously made the trip by a non-transit mode—as well as new transit riders who previously did not make the trip at all (Peak et al. 2005).

Despite these positive findings, there is limited evidence for a causal relationship between BRT implementation and increases in transit ridership for three main reasons. First, most studies only evaluate ridership along routes where BRT was implemented and fail to account for potential increases in ridership among nearby non-BRT routes due to transfers to or from BRT or potential decreases in ridership to nearby routes due to shifts to the BRT route. Second, there is a degree of variability in transit ridership from stop to stop along a corridor, and few studies apply inferential statistics to determine if observed changes in ridership are beyond what may be due to chance by this stop-to-stop variation in ridership. Finally and most important, transit ridership along corridors where BRT was implemented could have increased to the same extent under continued conventional bus service. This counterfactual scenario is impossible to observe, but it can be approximated by comparing corridors where BRT was implemented to similar control corridors where no changes in transit service occurred over the same time period. This concept is illustrated in two studies of Adelaide, Australia, and Oakland, California, which respectively observed 76% and 66% increases in ridership along corridors where BRT was implemented during a time when the overall transit system experienced a decline in ridership (Kittelson & Associates Inc. et al. 2007; Peak et al. 2005). The entirety of a transit system, however, may not be a good basis for comparison. BRT may be implemented along certain corridors *because* these same corridors are experiencing increased demand for transit. Hence, projected increases in transit use may cause the BRT to be implemented rather than the BRT causing the increased transit use.

This study took advantage of an incremental roll-out of BRT in King County, Washington, to compare changes in ridership at stops along traditional bus corridors where BRT was implemented to corridors where BRT was either planned but not yet implemented or already existed. These comparison groups are appropriate because they consist of valid candidates for BRT intervention. We further added to the rigor of the assessment by measuring ridership at all transit stops serving a corridor where BRT was implemented. This helped account for increases in ridership at other routes due to transfers to or from BRT or decreases at other routes due to ridership shifting to the BRT route. Finally, we applied a longitudinal regression model to estimate differences in changes in ridership among corridors where BRT was implemented and corridors where no changes occurred. This model accounted for correlation among stops to provide a robust estimate of changes in ridership and to estimate if these changes are beyond the realm of chance (Locascio and Atri 2011). This study was intended to strengthen the evidence for a causal association between BRT and changes in transit ridership.

Methods

This study used a quasi-experimental stepped wedge study design to assess changes in ridership, as King County Metro replaced conventional bus service with BRT along six transit corridors over a four-year period. Stepped wedge studies involve the sequential roll-out of an intervention to all participants over a number of time periods and often are used for ethical reasons when there is a good reason to believe that the intervention will do more good than harm and for practical reasons when it is impossible to deliver the intervention simultaneously to all participants (Handley et al. 2011). Analysis in stepped wedge studies involves comparing outcomes among those who received the intervention and those who did not at a given time (Brown and Lilford 2006). In this study, changes in ridership at transit stop locations that were upgraded to BRT service were compared to transit stop locations where no changes occurred during the same time period. The evaluation is considered quasi-experimental because the location of BRT service and timing of the roll-out of BRT to the six bus corridors was not chosen at random.

Study Setting

King County Metro implemented "RapidRide" branded BRT service in the Seattle metropolitan area starting in October 2010. RapidRide service replaced existing traditional bus service along six existing corridors:

- RapidRide A line replaced bus route 174 starting on October 2, 2010
- RapidRide B line replaced bus routes 230 and 253 starting on October 1, 2011
- RapidRide C line replaced bus routes 54 and 54 express starting on September 29, 2012
- RapidRide D line replaced bus routes 15 and 18 starting on September 29, 2012
- RapidRide E line replaced bus route 358 express starting on February 15, 2014
- RapidRide F line replaced bus routes 110 and 140 starting on June 7, 2014

RapidRide BRT implementation featured changes to vehicles, stops, routes, and service (King County Metro 2016). RapidRide buses were designed to minimize boarding time through three doors, interiors that enable riders to quickly move to seats, and wheelchair restraints that do not require assistance from the bus driver. RapidRide "stations," which account for 48% of RapidRide stops, feature shelters, lighting, pre-pay kiosks, and real-time information systems indicating when the next bus will arrive. RapidRide routes use a combination of transit priority features, including high-occupancy vehicle (HOV) and business access and transit (BAT) lanes, bus bulbs, queue jumps, and signal prioritization. Service was changed from a fixed schedule for traditional buses to BRT 10-minute headways during peak periods and 15-minute headways during off-peak periods. The RapidRide system features distinct branding from the conventional King County Metro bus system. Compared to other BRT systems, RapidRide qualifies as a BRT "lite" primarily because routes comprise varying levels of priority lanes rather than exclusive transit ways and stations are more similar to traditional bus stops as opposed to rail station platforms (Cervero 2013). A 2014 performance evaluation found that route-level travel time had generally decreased and ridership had generally increased along RapidRide corridors compared to times immediately prior to implementation (Parametrix 2014). This prior evaluation, however, did not assess changes to ridership at connecting or competing bus routes, compare changes along RapidRide routes to other similar routes where no service changes occurred, nor attempt to determine if observed changes were beyond the realm of chance.

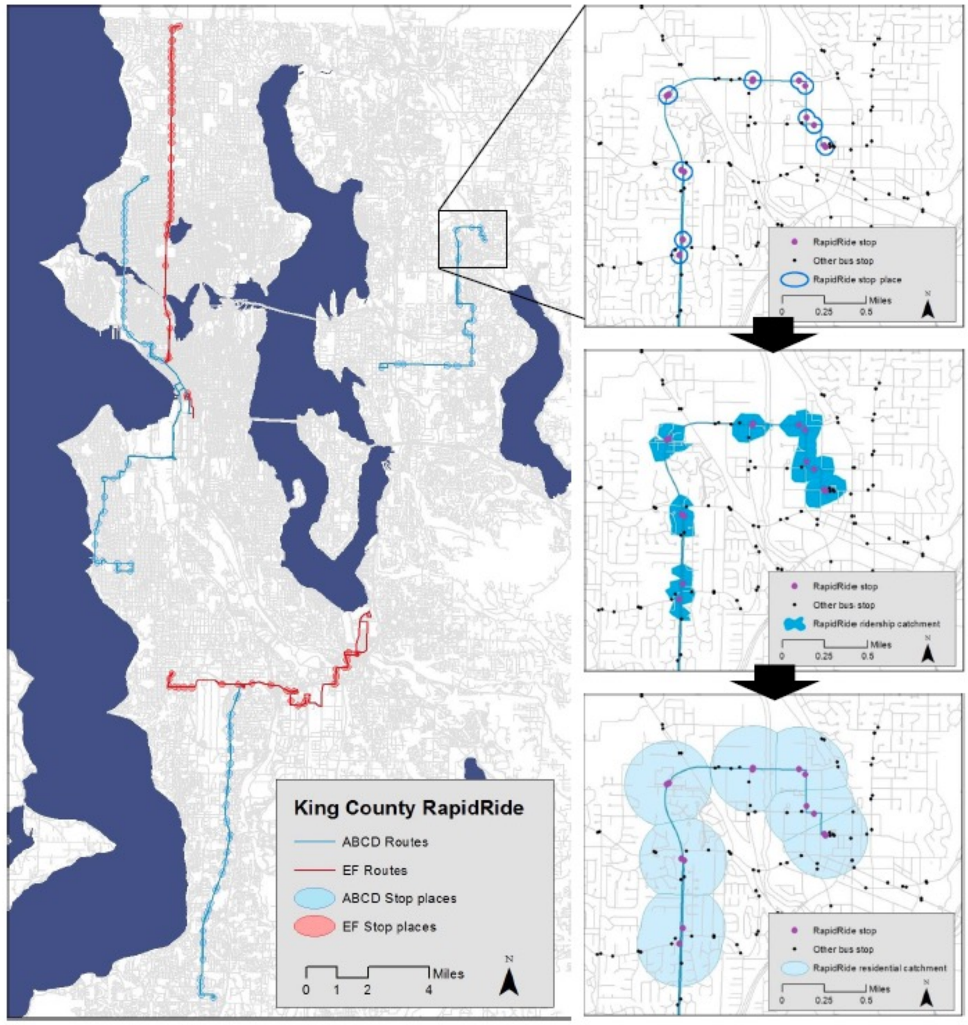
Unit of Analysis: RapidRide Stop Places

This analysis used geocoded bus stop locations and corresponding stop-level total boarding and alightings (ridership) collected by King County Metro during three time periods to assess changes in ridership. Analyzing longitudinal changes in ridership at the bus-stop level can be problematic. Individual stops are sometimes closed and replaced by new stops with new IDs in similar locations, which makes it difficult to track changes in ridership across minor bus stop relocations or upgrades. Such changes often occurred as part of RapidRide implementation. Analyzing all bus ridership within a buffer of each stop is one solution to this problem. However, multiple stops often are very near one another; for example, stops across the street may serve different directions of the same route, which results in very similar measurements of ridership and violates the assumption of independent observations required for most regression models. Conceptually, individual bus stops (or buffers around them) also may not be the most appropriate unit of analysis. Because of transfers to nearby bus stops serving different routes and round trips with origins and destinations at the same place, broader "catchment areas" around groups of bus stops may more appropriately capture how riders interact with the transit system. Thus, for this analysis, the unit of analysis was the location of groups of nearby RapidRide stops, or "RapidRide stop places," that were present in Fall 2014 after all RapidRide lines were in service. These RapidRide stop places were applied retrospectively to take measurements over the study period of 2010 to 2014.

To delineate RapidRide stop places, RapidRide stops within 500 Euclidean feet of one another were grouped together. This effectively combined RapidRide stops for the same route in the same service location, but serving different directions (e.g., northbound and southbound) and which may be used for the same round trip. The 500-foot threshold was chosen assuming that "paired" RapidRide stops would be no further than about a block apart. Five hundred feet is roughly the sum of a downtown Seattle city block (300 feet) plus two street widths (100 feet). A visual review of the data showed that this worked well in most locations (Figure 1, top right panel).

FIGURE 1.
Map of RapidRide routes and stop places by BRT A, B, C, and D lines (implemented from 2010 to 2013) and E and F BRT lines (implemented from 2013 to 2014)

The inset illustrates how stop places were defined by grouping nearby RapidRide stops, then attributing bus stop ridership ≤1/8 network mile and residential units ≤1/4 Euclidean mile.



Stop Place Measures of Ridership and Residential Access

For each RapidRide stop place, weekday ridership was summed for King County Metro bus stops within 1/8 mile (660 feet) along the street network from any individual RapidRide stop that comprised the stop place (Figure 1, middle right panel). If a bus stop was within 1/8 mile of two or more RapidRide stop places, its ridership was assigned to the closest. Operationally, this was executed in ArcGIS 10.2 using the Network Analyst OD cost matrix function to measure the distance from each bus stop to all RapidRide stops within 1/8 mile, then joining the closest bus stops to each RapidRide stop and summing the ridership for all joined stops by RapidRide stop place. Ridership was measured as average weekday boardings and alightings during Spring 2010, Fall 2013, and Fall 2014. The 1/8-mile ridership catchment area was used to capture ridership at bus stops closed or relocated by RapidRide, as well as changes in ridership at bus stops serving nearby routes that may be due to transfers or displacement to RapidRide stops.

Counts of residential units within walking distance of RapidRide stop places were used to control for increased development that often corresponds with BRT implementation.

This variable was measured as the count of residential units within ¼ mile of the closest RapidRide stop place. Operationally, this was executed in ArcGIS 10.2 using hybrid Euclidean-Thiessen buffers to identify the area within ¼ mile of the closest RapidRide stop place (Figure 1, bottom right panel). Euclidean-Theissen buffers were ¼-mile Euclidean buffers clipped by Theissen Polygons, whose boundaries defined the area closest to each RapidRide stop relative to all other RapidRide stops. A ¼-mile residential catchment area was used because it is commonly used as a "rule of thumb" walking distance to bus transit (Kittelson & Associates Inc. et al. 2013). Euclidean distances rather than network distances were used because the formal street network may be an incomplete representation of the informal paths that exist for pedestrians to most directly access transit in suburban areas served by high-capacity transit (Moudon et al. 1998). Residential unit data were derived from the King County Assessor's parcel data for the years 2010, 2013, and 2014. These data included counts of residential units for all residential land uses, including multi-family dwellings such as apartments, condominiums, and mixed-use buildings. Residential units were summed for all parcels that intersected each stop place residential catchment buffer. If a parcel partially intersected a buffer, the proportion of units equal to the proportion of area inside the buffer was counted.

Analysis

A total of 167 RapidRide stop places along the A, B, C, D, E, and F lines were identified. Stop places with no ridership data for any of the three time points were excluded (n=11) because they likely represented places newly served by RapidRide rather than areas where RapidRide replaced existing service. Stop places serving multiple RapidRide lines were also excluded (n=6), because they experienced RapidRide interventions at multiple time points, which would make analysis difficult. Also, however, they represented unique transit hubs (e.g., the downtown bus corridor and the Tukwila International Boulevard Link light rail station), where the effects of RapidRide service could be diluted by other changes to the transit system.

The remaining analytic sample of 150 RapidRide stop places was divided into two groups according to when RapidRide service began (Figure 1, left panel). The first group consisted of stop places serving the A, B, C, and D lines, which all opened between 2010 and 2013. The second group consisted of stop places serving the E and F lines, which opened between 2013 and 2014. Mean stop place ridership and residential units are presented for each group and for each RapidRide line by time period. Absolute and percent changes in mean ridership and residential units were calculated for each of the two time intervals, 2010 to 2013 and 2013 to 2014.

Statistically significant ($p<0.05$) differences in longitudinal changes in ridership between the two groups were assessed using a mixed effects negative binomial regression model. This model treats ridership at each time period as the dependent variable. The mixed effects component of the regression model accounts for correlation in observations among each stop place over the three time periods. The negative binomial link in the regression model accounts for overdispersion in the distribution of ridership count data (i.e., count data with many small values but also some very large values, which results in a standard deviation greater than the mean) and results in coefficients that, when exponentiated, take the form of incident rate ratios (IRRs). In this case, IRRs can be interpreted as ratios of ridership among groups that differ by one unit of the dependent variable. Dependent variables include a dummy variable representing group membership (ABCD group = 0, EF group = 1), a categorical time variable (values of 2010, 2013, and 2014), and a categorical interaction term of group by time. Thus, the group membership IRR represents the ratio of ridership among the EF group compared to the ABCD group at 2010; the time IRRs represent the ratio of ridership among ABCD groups at 2013 and 2014 compared to 2010; the group by 2013 interaction term IRR represents the ratio of the change in ridership from 2010 to 2013 among the EF group compared to the ABCD group; and the group by 2014 interaction term IRR represents the ratio of the change in ridership from 2010 to 2014 among the EF group compared to the ABCD group.

The interaction terms are used to test the hypothesis that changes in ridership were greater among stop places that experienced RapidRide intervention compared to stop places that had no change during the same time period. The group by 2013 interaction term directly tests whether the change in ridership from 2010 to 2013 was different among the EF group, which had traditional bus service during this time, compared to the ABCD group, which experienced RapidRide implementation. The linear combination of the group by 2014 interaction term minus the group by 2013 interaction term tests whether the change in ridership from 2013 to 2014 was different among the EF group, which experienced RapidRide implementation during this time period, compared to the ABCD group, which had existing RapidRide service. For interpretability, IRR are presented comparing the group that experienced RapidRide implementation compared to the group that experienced no change.

Models were repeated including residential units as a time-varying control variable to assess whether any changes in ridership were due to corresponding changes in the number of residential units served by each stop place.

Exploratory analyses were conducted to determine if the effect of RapidRide was different for lines serving downtown Seattle compared to lines serving outlying communities. Analyses were repeated separately for the CDE lines serving downtown Seattle and the ABF lines serving the outlying communities. All analyses were conducted using Stata 13.0.

Results

Mean stop place ridership increased along all RapidRide corridors from Spring 2010 to Fall 2013 and, with the exception of the B line, from Fall 2013 to Fall 2014 (Table 1). Both absolute and percent changes in mean ridership from 2010 to 2013 were greater among the ABCD group, during which time RapidRide was implemented, compared to the EF group, which had consistent conventional bus service during that time period. Similarly, both absolute and percent changes in mean ridership from 2013 to 2014 were greater among the EF group, during which time RapidRide was implemented, compared to the ABCD group, during which time had consistent existing RapidRide service.

TABLE 1.
RapidRide Stop Place Ridership (Average Weekday Boardings and Alightings) by Time

Line(s)	N (stop places)	2010	2013	2014	Change, 2010–2013		Change, 2013–2014	
		Mean (SD)	*Mean (SD)*	*Mean (SD)*	*Absolute*	*Percent*	*Absolute*	*Percent*
A	32	326 (542)	667 (893)	693 (902)	342	105%	26	4%
B	23	562 (1223)	1217 (2802)	1197 (2681)	655	98%	-20	-2%
C	16	422 (523)	763 (958)	903 (1075)	341	81%	140	18%
D	22	862 (967)	1289 (1355)	1439 (1424)	427	50%	150	17%
ABCD Total	93	528 (871)	967 (1671)	1030 (1653)	439	83%	64	7%
E	31	1229 (2856)	1569 (2866)	1945 (3124)	340	28%	377	24%
F	26	641 (1325)	904 (2113)	973 (2139)	264	41%	68	8%
EF Total	57	960 (2289)	1266 (2550)	1502 (2740)	305	32%	236	19%

Mean residential units within ¼ mile were slightly greater among the ABCD lines stop places than the EF lines (Table 2). However, changes in residential units were similar among both groups—about a 6% increase from 2010 to 2013 and a 1% increase from 2013 to 2014.

TABLE 2.
RapidRide Stop Place Residential Units within ¼ Mile by Time

Line(s)	N (stop places)	2010	2013	2014	Change, 2010–2013		Change, 2013–2014	
		Mean (SD)	*Mean (SD)*	*Mean (SD)*	*Absolute*	*Percent*	*Absolute*	*Percent*
A	32	316 (210)	324 (219)	324 (219)	8	3%	0	0%
B	23	429 (430)	476 (482)	476 (483)	47	14%	0	0%
C	16	598 (339)	641 (353)	641 (352)	43	7%	0	0%
D	22	902 (833)	946 (903)	963 (927)	44	5%	17	2%
ABCD Total	93	531 (537)	563 (580)	567 (591)	32	6%	4	1%
E	31	663 (503)	718 (532)	730 (551)	54	8%	12	2%
F	26	218 (246)	228 (262)	227 (260)	10	5%	-1	0%
EF Total	57	460 (461)	494 (493)	500 (507)	34	7%	6	1%

Results from the longitudinal regression model showed no differences in 2010 rates of ridership among the EF group compared to the ABCD group (IRR: 0.94; 95% CI: 0.73, 1.23; p=0.664) (Table 3). Rates of ridership among the ABCD group increased by 88% from 2010 to 2013 (IRR: 1.88; 95% CI: 1.73, 2.05; p<0.001). During the same time period, changes in ridership among the EF group were significantly lower, only 70% that of the change in the ABCD ridership (IRR: 0.70; 95% CI: 0.61, 0.81; p<0.001). From 2010 to 2014, rates of ridership among the ABCD group increased by 107% (IRR: 2.07; 95% CI: 1.90, 2.25; p<0.001), which were not significantly different from changes in ridership among the EF group from 2010 to 2014 (IRR: 0.92; 95% CI: 0.80, 1.06; p=0.232). This is explained by the 31% greater change in ridership from 2013 to 2014 among the EF group compared to the ABCD group (IRR: 1.31; 95% CI: 1.16, 1.49; p<0.001). Controlling for residential units only slightly attenuated the observed changes in ridership.

TABLE 3.
Mixed Effects Negative Binomial Regression Model of Stop Place Ridership

	Crude		Adjusted*	
	IRR (95% CI)	*p value*	*IRR (95% CI)*	*p value*
EF (reference = ABCD)	0.94 (0.73, 1.23)	0.664	1.00 (0.78, 1.27)	0.984
Time: 2010	Reference		Reference	
2013	1.88 (1.73, 2.05)	<0.001	1.76 (1.62, 1.91)	<0.001
2014	2.07 (1.90, 2.25)	<0.001	1.90 (1.75, 2.07)	<0.001
Residential units (100)			1.08 (1.06, 1.10)	<0.001
EF X 2013	0.70 (0.61, 0.81)	<0.001	0.74 (0.65, 0.85)	<0.001
EF X 2014	0.92 (0.80, 1.06)	0.232	0.96 (0.84, 1.09)	0.537
EF X 2014 - EF X 2013	1.31 (1.16, 1.49)	<0.001	1.29 (1.15, 1.45)	<0.001

* *adjusted for residential units*

Translating the model results to directly compare changes in ridership among stop place catchment areas where RapidRide was implemented to those where no change occurred resulted in an estimated 43% increase in ridership compared to consistent traditional bus service and a 31% increase in ridership compared to consistent RapidRide existing service (Table 4). Controlling for the effect of concurrent residential development only slightly reduced these estimates to 35% and 29% increases, respectively. When the sample was stratified by routes serving downtown Seattle and routes serving outlying communities, a stronger effect was observed among routes serving outlying communities.

TABLE 4.
Mixed Effects Negative Binomial Regression Model Results Modified to Compare RapidRide Intervention Group to No Change Group

Location	Intervention	Comparison	Comparator	Crude		Adjusted*	
				IRR (95% CI)	*p value*	*IRR (95% CI)*	*p value*
All	ABCD line BRT implementation	EF line bus service prior to BRT implementation	Change in ridership from 2010 to 2013	1.43 (1.24, 1.65)	<0.001	1.35 (1.17, 1.55)	<0.001
	EF line BRT implementation	ABCD lines existing BRT service	Change in ridership from 2013 to 2014	1.31 (1.16, 1.49)	<0.001	1.29 (1.15, 1.45)	<0.001
Inside Seattle	CD line BRT implementation	E line bus service prior to BRT implementation	Change in ridership from 2010 to 2013	1.16 (1.00, 1.35)	0.045	1.17 (1.01, 1.34)	0.034
	E line BRT implementation	CD lines existing BRT service	Change in ridership from 2013 to 2014	1.14 (1.01, 1.29)	0.040	1.16 (1.02, 1.30)	0.019
Outside Seattle	AB line BRT implementation	F line bus service prior to BRT implementation	Change in ridership from 2010 to 2013	1.73 (1.33, 2.26)	<0.001	1.61 (1.24, 2.09)	<0.001
	F line BRT implementation	AB lines existing BRT service	Change in ridership from 2013 to 2014	1.55 (1.24, 1.94)	<0.001	1.53 (1.23, 1.90)	<0.001

* *adjusted for residential units*

Discussion

We estimated that implementation of BRT service leads to a 35% increase in transit ridership compared to continued conventional bus service. This estimate more accurately captures the causal effect of BRT on ridership than simple before/after comparisons of ridership along conventional bus routes where BRT is implemented, which appears to be the industry standard (Kittelson & Associates Inc. et al. 2007; Levinson et al. 2003; Parametrix 2014; Peak et al. 2005; US Government Accountability Office 2012). The estimate accounts for temporal trends in ridership, shifts in ridership due to BRT-related service changes, and nearby residential development that may accompany BRT service.

The 35% increase in transit ridership due to BRT implementation compared to continued conventional bus service from Spring 2010 to Fall 2013 was greater than the 29% increase observed when BRT implementation was compared to continued BRT service from Fall 2013 to Fall 2014. This could be due to the longer interval during which BRT implementation was compared to continued conventional bus service (3.5 vs. 1 year). It also could be due to continued gains in ridership during the 2013 to 2014 interval among the BRT lines that were implemented during the 2010 to 2013 interval. In either event, this suggests that major ridership gains from BRT implementation occur immediately, but also continue to accrue years after the service change. Residual longer-term gains in ridership associated with BRT may be due to residential or commercial development that occurs after BRT implementation (US Government Accountability Office 2012) and as people who wish to use transit move closer to the BRT corridor to take advantage of the service. Unfortunately, this analysis cannot pinpoint the precise temporal changes in ridership associated with BRT due to the limited number of time periods during which ridership was observed.

Unsurprisingly, the number of residential units within ¼ mile of stop places was positively associated with ridership. Controlling for change in residential units in the longitudinal analysis attenuated somewhat the effect of BRT implementation on increased ridership. This suggests that some of the increased ridership due to BRT was the result of increased residential density along BRT corridors. Transit planners who wish to get the most out of BRT implementation should work with land use planners to focus transit-oriented development (TOD) along the corridors (Cervero and Dai 2014), as it appears that the increased capacity of BRT is capable of handling the increased residential demand for transit service. The study was limited due to its inability to control for changes in employment density. Employment data at a spatial and temporal resolution suitable for this analysis were not available. It is possible that much of the effect of RapidRide on ridership could be due to employers choosing to locate along these BRT lines.

A stronger effect of BRT implementation was observed for the ABF lines outside of Seattle than for the CDE lines serving downtown Seattle. Ridership for routes outside Seattle were estimated to increase 61% with BRT implementation compared to conventional bus service, whereas ridership for routes serving downtown Seattle were estimated to increase 17%. It may be that BRT is more effective in attracting riders in places where transit use is less common or in areas where the initial improvement in service frequency and span was more substantial.

The stepped wedge design employed in this study is a robust alternative to randomized controlled trials—the gold standard study design for estimating a causal effect—when the timing of the intervention is assigned randomly (Bonell et al. 2011). BRT implementation in this quasi-experimental study was not assigned randomly and, therefore, the timing of BRT implementation across corridors could have biased the estimate if BRT was rolled out to correspond with increases in ridership due to exogenous events. This is unlikely, as there were no major commercial developments or infrastructure projects completed in the vicinity of the BRT corridors during this time, and the analysis controlled for residential development.

This analysis used data from King County, Washington, and evaluated RapidRide BRT implementation that rolled out between 2010 and 2014. It may be of limited generalizability to other metropolitan area, BRT systems, or time periods. King County is a major metropolitan area that is largely reliant on bus service for transit. The RapidRide BRT service does not compete with rail transit for riders; in fact, all but one of the RapidRide corridors provide transfer service to the single light rail corridor in the region. Similar increases in ridership may not be realized in major metro areas where BRT must compete with existing, extensive rail transit systems or in smaller cities where transit is less competitive with driving. The RapidRide service includes many of the features commonly found in BRT systems worldwide, such as frequent service and a streamlined entry system, yet it qualifies as BRT lite only due to the lack of dedicated travel lanes and subway-like transit platforms (Cervero 2013). More or less extensive BRT systems may result in greater or lesser changes in ridership. Finally, during the study period King County's population increased by an estimated 86,000 from 1.93 million to 2.02 million (Office of Financial Management 2016), and median housing prices increased by 16%, from $349,000 to $406,000 (Zillow 2016). BRT that is implemented during periods of slower growth may see smaller changes in ridership.

This study also was limited to the use of average weekday ridership as its single evaluation metric. RapidRide service changes were most dramatic during weekend service periods, and any resulting changes in weekend ridership were not captured in this study. We also did not capture changes in service quality. The increases in ridership associated with RapidRide BRT implementation we observed during weekdays likely were due to a combination of more spacious buses, shorter headways, extended service hours, and more welcoming stop infrastructure—all for the same fare price as traditional bus service. These enhancements would conceivably result in a quicker and more comfortable trip, even for an individual who would have ridden the bus anyway.

Finally, during the study period, King County Metro changed automatic passenger count systems. The older system under-counted by about 3% and the newer system over-counted by about 4%. This means that the changes in ridership over time presented in Table 1 are slightly inflated. However, the primary analysis compared the changes in ridership over time between routes with and without RapidRide implementation, which would be subject to the same measurement errors over time and thus still result in a robust estimate.

Conclusion

This study used a quasi-experimental stepped wedge study design to assess the effect of incremental RapidRide BRT implementation in King County, Washington. The analysis was intended to add to the evidence for a causal association between BRT implementation and increased transit ridership by accounting for temporal changes in ridership, shifts in ridership to or from other bus routes, and residential development that may correspond with BRT implementation. Independent of these factors, BRT implementation was associated with a 35% increase in ridership compared to consistent conventional bus ridership and a 29% increase in ridership compared to consistent existing BRT service. These estimates should help transit planners develop more reliable estimates of ridership changes due to planned BRT systems and make a stronger argument for the ability of BRT to increase transit ridership and contribute to the mobility and vitality of the urban population they serve.

References

Across Latitudes and Cultures – Bus Rapid Transit (ALC-BRT). 2016. BRT Data, http://brtdata.org, retrieved April 11, 2016.

Bonell, C. P., J. Hargreaves, S. Cousens, D. Ross, R. Hayes, M. Petticrew, and B. R. Kirkwood. 2011. "Alternatives to Randomisation in the Evaluation of Public Health Interventions: Design Challenges and Solutions." *Journal of Epidemiology Community Health*, 65(7): 582-587.

Brown, C. A., and R. J. Lilford. 2006. "The Stepped Wedge Trial Design: A Systematic Review." *BMC Medical Research Methodology*, 6: 54.

Cervero, R. 1998. *The Transit Metropolis: A Global Inquiry*. Island Press, Washington, DC.

Cervero, R. 2013. "Bus Rapid Transit (BRT): An Efficient and Competitive Mode of Public Transport." Berkeley Institute of Urban and Regional Development, Berkeley, CA.

Cervero, R., and D. Dai. 2014. "BRT TOD: Leveraging Transit Oriented Development with Bus Rapid Transit Investments." *Transport Policy*, 36: 127-138.

Currie, G., and A. Delbosc. 2013. "Exploring Comparative Ridership Drivers of Bus Rapid Transit and Light Rail Transit Routes." *Journal of Public Transportation*, 16: 47-65.

Deng, T., and J. Nelson. 2011. "Recent Developments in Bus Rapid Transit: A Review of the Literature." *Transport Reviews*, 31(1): 69-96.

Handley, M. A., D. Schillinger, and S. Shiboski. 2011. "Quasi-experimental Designs in Practice-based Research Settings: Design and Implementation Considerations." *Journal of the American Board of Family Medicine*, 24(5): 589-596.

King County Metro. 2016. RapidRide, http://metro.kingcounty.gov/travel-options/bus/rapidride/, retrieved April 11, 2016.

Kittelson & Associates Inc., Herbert S. Levinson Transportation Consultants, and DMJM+Harris. 2007. *Bus Rapid Transit Practitioner's Guide*. Transportation Research Board, Washington, DC.

Kittelson & Associates Inc., Parsons Brinckerhoff, KFH Group, Texas A&M Transportation Institute, and Arup. 2013. "Chapter 4: Quality of Service Concepts." In *Transit Capacity and Quality of Service Manual, 3rd Ed.* Transportation Research Board, Washington, DC.

Levinson, H., S. Zimmerman, J. Clinger, S. Rutherford, R. L. Smith, J. Cracknell, and R. Soberman. 2003. "Bus Rapid Transit, Volume 1: Case Studies in Bus Rapid Transit." Transportation Research Board, Washington, DC.

Locascio, J. J., and A. Atri. 2011. "An Overview of Longitudinal Data Analysis Methods for Neurological Research." *Dement Geriatr Cogn Dis Extra*, 1(1): 330-357.

Moudon, A. V., P. M. Hess, M. C. Snyder, and K. Stanilov. 1998. "Effects of Site Design on Pedestrian Travel in Mixed-Use, Medium-Density Environments." *Transportation Research Record*, 1578: 48-55.

Office of Financial Management. 2016. Official Population Estimates, http://www.ofm.wa.gov/pop/april12, retrieved April 12, 2016.

Parametrix. 2014. King County Metro RapidRide Performance Evaluation Report.

Peak, M., C. Henke, and L. Wnuk. 2005. "Bus Rapid Transit Ridership Analysis." Federal Transit Administration, Washington, DC.

US Government Accountability Office. 2012. "Bus Rapid Transit: Projects Improve Transit Service and Can Contribute to Economic Development." Washington, DC.

Zillow. 2016. King County Home Prices & Values, http://www.zillow.com/king-county-wa/home-values/, retrieved April 12, 2016.

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