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Private Shuttles and Public Transportation: Effects of Shared Transit Stops on Travel Time and Reliability in Seattle

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Abstract

An Employer Shared Transit Stop (ESTS) pilot was introduced in April, 2017 by the Seattle Department of Transportation (SDOT) and King County Metro (KCM). Eleven bus stops within the City of Seattle were identified for stop-sharing with private shuttles that serve employees of and are operated by Microsoft and Seattle Children's Hospital, respectively. This study utilizes real-time transit performance data that was generated by KCM, then collected and aggregated by the company Swiftly to assess the impacts of the ESTS program on bus transit reliability. Data analyses based on visualization tools on the Swiftly Insights platform of route-level schedule adherence as well as fixed panel regressions at the mean and at the 0.90 and 0.95 quantile of stop-level schedule adherence are considered. On average, bus transit reliability has not been affected by the ESTS pilot program. Statistically significant results indicating a potential delay in bus arrival times as a result of ESTS stop-sharing were found at only one of the nine stops considered in the study. An increase in participating companies and stops is recommended.

As a city with significant geographical constraints and a rapidly growing population (*1*), the City of Seattle looks for ways to manage roadway congestion and maintain equitable, quality access for citizens (*2*). To these ends, goals for reducing drive-alone rates during commute hours have been adopted at a state level through the Commute Trip Reduction (CTR) Law (*3*). CTR requires cities and counties in Washington State "to reduce the number and length of drive-alone commute trips" by working with major employers in their jurisdictions to develop and implement employee commute programs (*3*). Such measures include, but are not limited to, shuttle services for employees, particularly shuttle services for first mile/last mile links to transit and for routes underserved by transit. Additionally, public transit service providers such as King County Metro (KCM) that share the congested streets of Seattle with personal vehicles have established service guidelines to measure and pursue the goal of quality transportation alternatives for all Seattle residents (*4*).

In an attempt to improve private shuttle services provided by major employers for their employees in the City of Seattle, the Seattle Department of Transportation (SDOT) and KCM began the Employer Shared Transit Stop (ESTS) pilot to "test the feasibility of allowing employer-provided shuttles to use public transit stops while minimizing impacts to public transit operations" (*5*). On April 24th, 2017 the pilot began, allowing private shuttles operated by Microsoft and Seattle Children's Hospital (SCH) to share nine of eleven bus stops throughout the city of Seattle that were identified for the pilot program (*5*). Employers pay a monthly fee for each stop in exchange for special signage and permission to use of the public right of way (ROW) as a pick-up and drop-off for employees (*6*).

Microsoft and SCH both provide private shuttles to employees through their CTR programs. Shuttle fleets are comprised of community buses and motor coaches as defined by the Transportation Capacity and Quality of Service Manual (TCQSM) (*7*). Microsoft Connector Buses provide an alternative to personal vehicle commuting to their campus in Redmond, Washington located 13 miles from downtown Seattle (*8*). SCH's 22-shuttle system provides both first mile/last mile connections to the University of Washington (UW) LINK light rail transit hub as well as along underserved routes (*9*). SCH's CTR program has been particularly aggressive, earning multiple awards for excellence (*10*).

The ESTS pilot program was met with mixed public opinion. The potential positive benefits include: (1) cost-sharing in the maintenance and upgrades to transit stops, which could result in better quality stops overall; (2) employees using

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shuttle buses can more easily transfer between private and public transit; (3) formal loading and unloading is safer for all users of the public ROW; (4) existing transit facilities would have higher overall utilization and improve pedestrian-oriented investments nearby; and (5) sharing facilities could put less pressure on limited curb space throughout the transportation network (*11, 12*). Negative concerns are mostly related to the existence of such shuttles in general, namely their potential to enable gentrification (*13, 14*). Beyond this, concerns about the shuttles' impact on transit have also been raised in response to the announcement of the ESTS pilot program specifically (*6*).

The ESTS pilot is a trial to determine what the impacts of allowing private shuttles to utilize public transit ROW will have on transit services. In a review of literature related to bus transit service reliability, reliability was consistently held as a critical passenger priority, arguably only second in importance to "arriving safely at destinations," and passenger patronage of bus transit is directly correlated to service reliability (*15*). Moreover, from an operator's perspective, low reliability not only affects patronage but can contribute "to increased operating costs" as it "impacts the schedule recovery component of cycle time" (*7*).

Reliability, however, is an ambiguous attribute that is consequently difficult to quantify and measure. In current practice, reliability is typically quantified as on-time performance (OTP). However, while OTP is an easy metric to calculate, it does not adequately represent reliability as perceived from a passenger's perspective. The TCQSM recognizes not only reliability explicitly in its five key concepts but that it also identifies it as a passenger-perspective quality of service performance measure (*7*). To address this, recent efforts by innovative transit agencies are currently seeking to identify more effective ways to measure reliability from a passenger's perspective (*16*).

Though identifying a single metric for reliability is difficult, it generally relates to time (*15*). Many agencies nationally, including KCM, maintain access to General Transit Feed Specification (GTFS) and APIs of real-time transit performance data (*17*). The company Swiftly has collected this data and aggregated it into a format that can be easily queried by tools through its advanced analytics platform as well as downloaded in CSV format for further analysis.

To determine the ESTS pilot impacts, this paper first reviews practical metrics and analysis methods for reliability, then applies these methods to the Swiftly data set of KCM bus schedules and adherence. The three analyses presented in this paper include a standard OTP runtime performance assessment per KCM guidelines, a fixed effects panel regression of schedule adherence at the stop level, and a quantile regression of schedule adherence at the stop level.

Measuring Reliability

While the definition of reliability varies, it consistently involves time, from how actual bus times relate to scheduled times, to consistency of travel time and minimized waiting times (*15*). The most basic and most commonly used metric for reliability is on-time performance (OTP) (*15*). While "most agencies define reliability in terms of OTP," the exact time ranges that constitute an on-time bus arrival/departure vary widely depending on the operator, though, on average, operators consider a bus on-time if it arrives within the window of 1 min early to 5 mins late (*18*). At KCM, schedule reliability is measured with an OTP window that only considers late bus arrivals; routes that experience arrivals >5 min late 35% of the time during PM peak periods or 20% of the time on average are considered non-compliant (*19*). Any early arrivals are considered on-time. In a 2016 OTP service review, KCM found 60 routes that needed "service-hour investments to improve reliability" (*19*).

Percent on-time OTP, though widely used by operators, is considered a sub-par metric throughout the research literature because it does not adequately capture time reliability from a passenger perspective. For passengers, waiting time at bus stops is valued "more than any other time component of their trip" (*15*). In fact, studies have found that passengers can value waiting time at a rate of 3–5 times their time in-vehicle and that the quality of waiting locations can also be valued in in-vehicle time equivalents up to 1.3 min for a stop shelter (*7*). Furthermore, passengers tend to overestimate waiting time, particularly if that waiting time is unpredictable (*15*). Therefore, beyond seeking to reach a set percentage of trips/arrivals that are on-time, looking at the arrivals that fall outside of the "on-time" range and the severity of deviation better captures the passenger's perception of reliability. Additionally, analyzing schedule adherence at the stop level rather than at the route runtime level further focuses on the most critical time component of the trip from a passenger's perspective of reliability.

Based on this, multiple analyses of reliability were considered to determine the impact of the ESTS pilot on KCM service reliability. These methods attempt to capture the impact of company shuttles on transit performance not only from a planning perspective, but also from a user perspective. In a percent on-time OTP analysis (based on KCM standards), the dependent variable is schedule adherence of runtime for each of the affected routes. For the panel regression comparisons, the dependent variable is schedule adherence at the stop level.

Data

Swiftly's Data and Analytics Platform

Swiftly, Inc. is a software company that specializes in developing accurate real-time passenger information and robust data analytics for transit operators. Swiftly Insights is a cloud-based platform that processes and archives GPS data from the computer-aided dispatch (CAD) and automated vehicle location (AVL) systems of transit agencies. The

Table 1. Treated Stops and Routes Identification and Labeling for the Study

Study label	KCM ID#	Stop identification KCM Street	KCM cross-street	Direction of travel	Company shuttle	Implem. date	Routes that utilize the stop				
A	2180	Queen Anne Ave N	W Harrison St	S	Microsoft	24/04/2017	1	2	8	13	32
B	10562	Sand Point Way NE	40th Ave NE	N	SCH	24/04/2017	75				
C	11420	15th Ave E	E Mercer St	S	Microsoft	24/04/2017	10				
D	12340	E Madison St	25th Ave E	SW	Microsoft	24/04/2017	8	11			
E	13250	19th Ave E	E Harrison St	S	Microsoft	24/04/2017	12				
F	~~25200~~	~~NE 45th St~~	~~Union Bay Pl NE~~	~~W~~	~~SCH~~	~~Later~~	~~31~~	~~32~~	~~67~~	~~75~~	~~78~~
G	25765	Montlake Blvd NE	NE Pacific Pl	N	SCH	24/04/2017	65	78			
H	29720	NW Market St	20th Ave NW	W	Microsoft	24/04/2017	44				
~~I~~	~~29920~~	~~NE 45th St~~	~~Mary Gates Memorial~~	E	~~SCH~~	~~Later~~	~~65~~	~~75~~			
J	31970	California Ave SW	SW Spokane St	S	Microsoft	24/04/2017	50	55	128		
K	37920	NE 65th St	39th Ave NE	W	Microsoft	24/04/2017	62	71	76		

platform allows transit agencies, planners, and researchers to quickly access and analyze GPS data points, both for real-time monitoring and for analysis of historical data.

Swiftly Insights generates aggregate variables such as schedule adherence in addition to presenting the basic data pulled from the agency AVLs. Schedule adherence is calculated as the difference between scheduled and actual bus departure times. These variables can then be analyzed either through the visualization tools provided within the Swiftly Insights dashboard or through analyses of CSV downloads of the data.

Data-Set Development

To determine appropriate date and time ranges for the data, KCM press releases and route revisions since the start of Swiftly data records (3/23/2016) were reviewed to determine potential scheduling/routing impacts. For analyses considering before and after effects of the ESTS program, data was considered from the Monday of 3/13/17 after the implementation of a 3/11/17 semi-annual KCM schedule change and until 6/04/17, providing six weeks of data on either side of the 4/24/17 pilot start date. Multiple study stops fall near the UW Seattle campus, so it should be noted that classes were in session throughout the study period with the exception of week 2 of the study when classes were out for spring break.

To determine the routes needed for analysis, the OneBusAway online browser was used to identify affected stops and related routes based on the SDOT press release announcing the ESTS pilot program (summarized in Table 1). According to this release, all but two Children's stops were introduced on the 4/24/2017 pilot start date (*5*). These two stops were removed from the study (as shown by the strike-throughs in Table 1), resulting in a total of nine shared stops considered as the treatment stops in the study. As shown in the Table 1 summary of treated stop and route information for the study, all of the study stops are low-volume, with only one initial stop (A) serving five routes. The majority (7/9) of study stops only serve one or two routes and all of the study stops are simple curb-side (rather than bus bay) stops.

To develop the control group, schedule adherence reports from the previous year were avoided given the rapid growth in Seattle. Instead, two types of stops were identified as potential control stops: upstream (US) stops and different route (DR) stops. US stops are stops located upstream (or before) a treated stop whereas DR stops are located in the same geographic area but not along the same route as a treated stop. US stops were selected because, among a wide variety of factors that have been found to affect bus reliability, many are directly tied to a given route; factors include driver experience, length and complexity of route, operating environment, and other route conditions such as on-street parking, signalized intersections, and direction of travel (*20*). For both control group stop types, only low-volume, curb-side bus stops were considered.

While stops along nearby streets with comparable surrounding land use and parking patterns as well as number and type of routes utilizing the stops were held as the ideal for DR control stop selection, such stops exist for only two of the nine treated stops. As a result, the majority of DR stops identified were nearby stops in the opposite direction of travel of treated routes/stops, that is, stops across the street from treated stops. To try to control for the impact of the differing directionality, DR stops in the opposite direction of travel from treated stops were only selected if they experienced similar weekday peak congestion per the Google Maps Typical Traffic™ function.

Based on these requirements, the CSV data download feature in the Swiftly Insights platform was used to extract the historical KCM data for all potentially affected routes. The data was disaggregated into AM and PM peak sets per KCM guidelines: AM peak from 6 AM to 9 AM and PM peak from 3:30 PM to 6:00 PM (*21*). All routes in the vicinity of the treated stops operate within mixed traffic environments as defined by the TCQSM (*7*). Cumulative Distribution Function

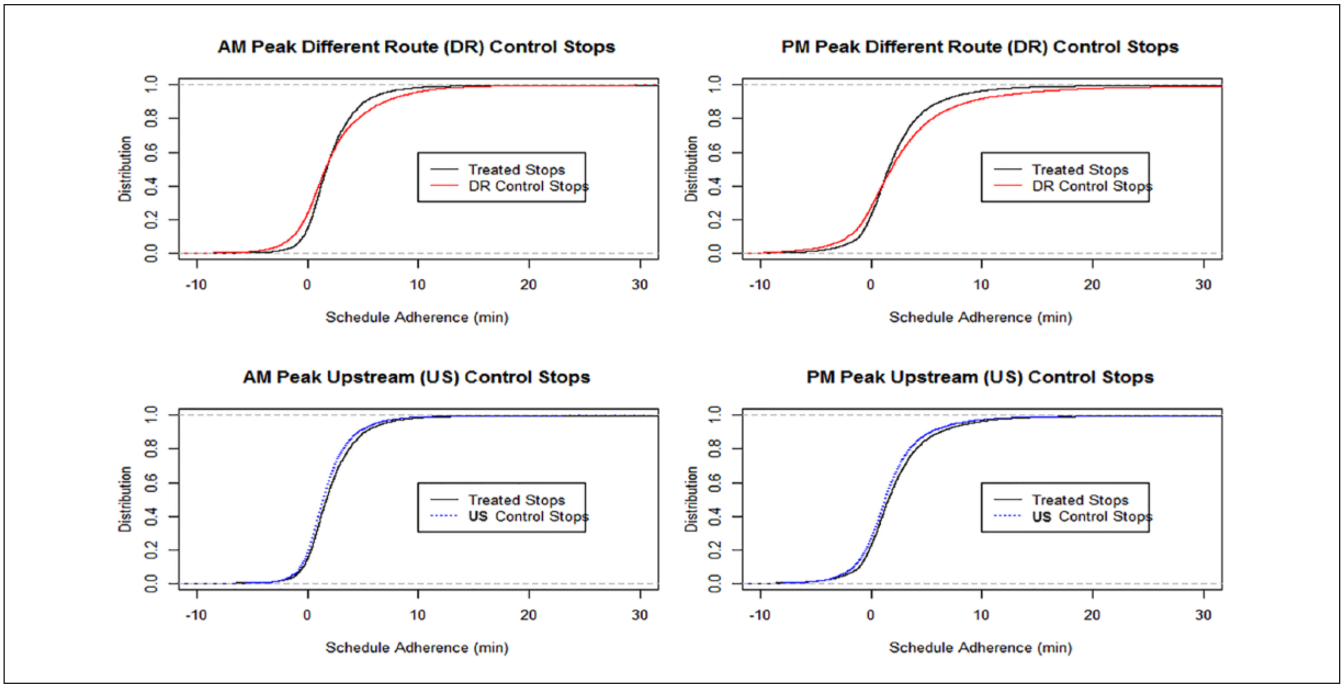

Figure 1. CDF plots comparing the schedule adherence distributions of potential collections of control stops upstream (US) or along different routes (DR) to treated stops before the ESTS program began.

(CDF) plots were used to compare the distributions before the implementation of the ESTS program of the potential control stops versus the treated stops to determine the best control group for the study. As shown in Figure 1, the DR stops have a different distribution of schedule adherence compared to the treated stops, especially in the PM peak. In contrast, the US stops have a similar distribution before the start of the ESTS stop sharing pilot in both the AM and PM peak as shown in Figure 1. Based on this, US stops at a ratio of 3:1 control:treated stops were selected as control stops for the analysis with one exception.

As shown in Figure 2, treated stop B is downstream of treated stop G. Additionally, stops along the west and southwest edges of the UW serve as major transfer hubs for buses within the region. As a result, control stops for either stop B or G could not be identified immediately upstream. Control stops for treated stop G were selected from US stops west (or further upstream of) the transfer hubs that border the University campus. Because stop B is located near the start of route 75, a route that runs through multiple bus transfer hubs on UW's campus, only one US stop could be identified. As a result, stop B has a ratio of 1:1 control:treated stops. However, because the US control stop serves a second route in addition to the 75, observations are roughly 2:1 control stop:stop B.

Analysis Methods

Four analysis methods were selected to determine ESTS impacts on KCM reliability from the Swiftly schedule adherence data set. The first analysis most closely adheres to the KCM guidelines for reliability measurement. It considers the route runtime and analyzes the data using the tools provided by the Swiftly platform. From this, the percentage of late run times along each route before and after the ESTS start date is identified.

The second analysis method utilizes panel regression which considers all treated stops, along with US control stops, along the same affected route. Panel regression is a widely used method in social sciences and econometrics to analyze a data set in terms of identity and time to consider cross-sectional and longitudinal relationships and impacts (*22*). Specifically, a fixed effects panel regression was utilized to determine the average difference between treated and control stop types, between weeks within the study, and between stops affected by the ESTS pilot shuttles and non-treated stops. A total of 12 study weeks were considered with the ESTS pilot beginning at the start of the seventh study week. Stops affected by the ESTS pilot shuttles are the treated stops during weeks 7–12, and non-treated stops are all stops in the control group and stops in the treated stop group during weeks 1–6. This model ultimately identifies the average waiting time at the stop caused by the introduction of ESTS pilot shuttles. Given that "unreliable transit service will increase average waiting time," the model provides a good metric to determine whether the ESTS pilot affected transit reliability (*7*).

The third analysis method considers quantile panel regressions of the 0.90 and 0.95 quantile of schedule adherence. Because quantile regression focuses on a user-specified

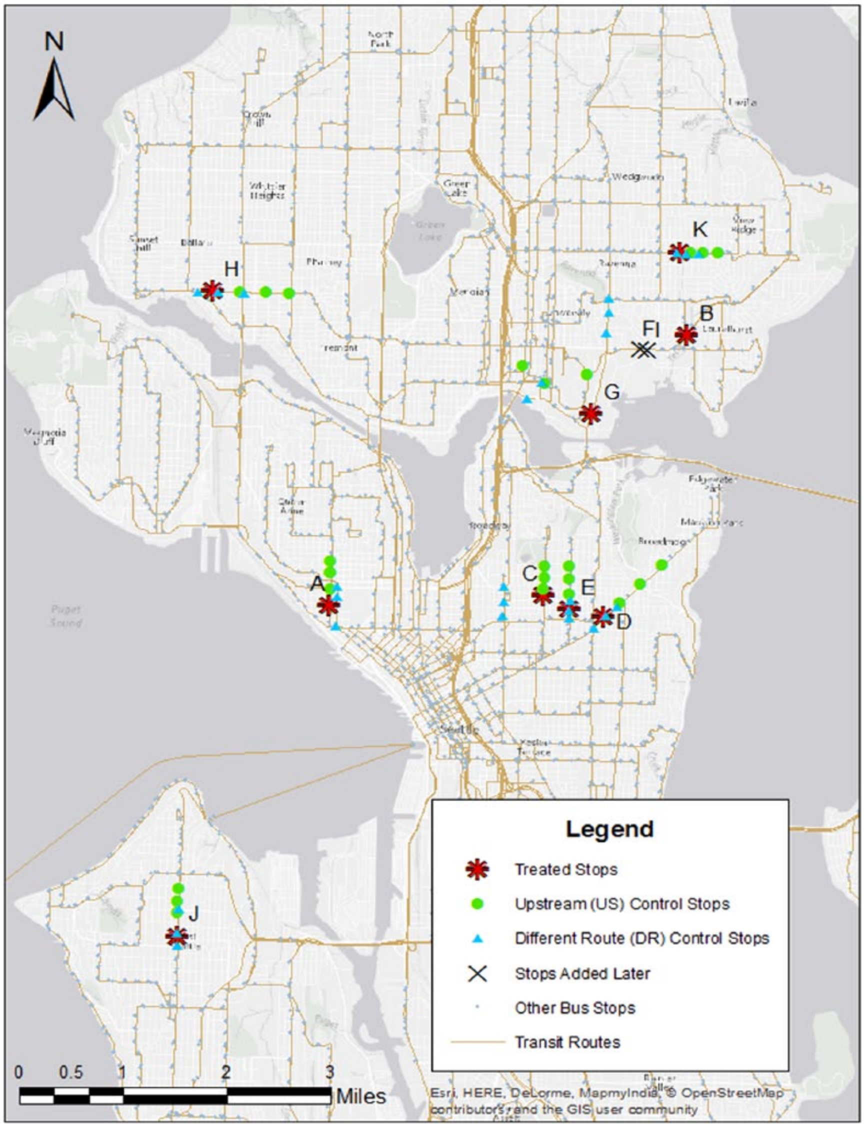

Figure 2. ESTS pilot study stops and control stops considered within the analysis.

portion of a data distribution rather than fitting an average to the distribution as a whole, it generates models that more robustly estimate the effect of outliers in a data set (*23*). It is therefore ideal for assessing the frequency of severe bus delays and thus more closely approximates the frequency of low reliability from a passenger perspective. The quantile regression R package is "quantreg" (*24*).

Finally, to separate and further investigate individual treated stops, CDF plots were utilized to identify different distributions of schedule adherence before and after the ESTS pilot start date. First, the quantiles of schedule adherence at each of the treated stops before and after the ESTS pilot start date were compared to identify a subset of stops with increased arrival delays after the start of the ESTS pilot. Quantile regression at the median (0.50 quantile) as well as in the 0.90 and 0.95 quantiles were fitted to the subset of stops to determine if the increase in bus delays was the result of the ESTS shuttles or some other factor.

Discussion of Results

The results of the four analysis methods are discussed below.

Analysis 1: OTP Measurement Following KCM Guidelines

KCM guidelines for reliability identify routes experiencing >35% late arrivals (i.e., arrivals more than 5 mins past the scheduled time) in PM peak as unreliable and in need of

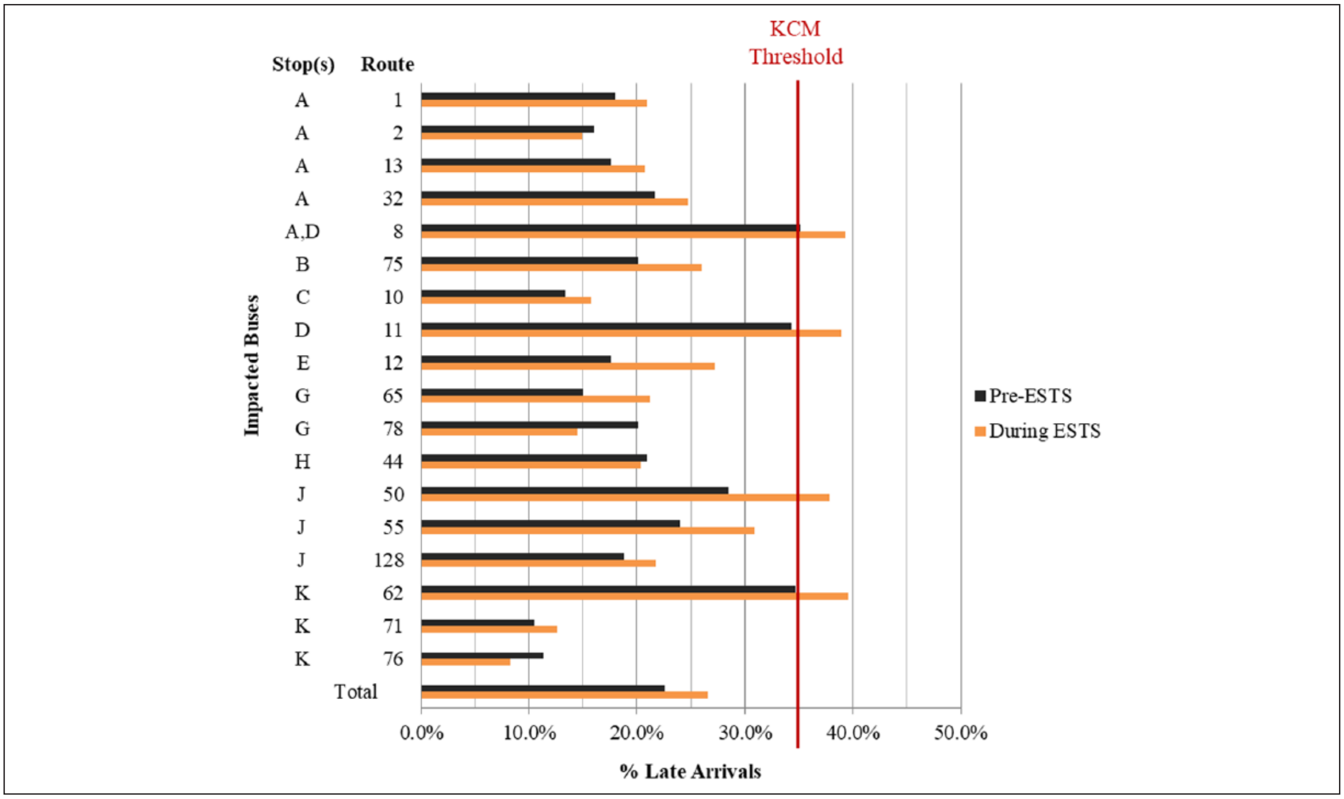

Figure 3. Schedule adherence by route for routes with shared stops before and after the ESTS pilot start date during the PM peak.

remedial attention (*19*). Per these guidelines, Figure 3 was generated using the Schedule Adherence by Route feature on the Swiftly Insights platform to look at the percent on-time OTP of routes affected by ESTS shuttle stops before and after the pilot start date (4/24/17). As Figure 3 shows, the percentage of late arrivals increased in most study routes with four (rts 8, 11, 50, 62 which stop at A and D, D, J, and K, respectively) of the 18 routes passing the KCM threshold of 35% late arrivals. Comparatively, only one (rt 8 which stops at A) of the 18 routes passed the 35% threshold before the ESTS start date.

While this suggests a potential impact on routes, it does not indicate whether these increased delays are the result of the ESTS shuttles or some additional factors. For example, the 8 is the only bus that runs along a highly congested east-west thoroughfare near the Amazon campus with a portion of the roadway under construction during the study dates. Additionally, the 62 has been receiving remedial attention since it was created as a combination of two routes discontinued after the LINK light rail extension in March of 2016. The 50, however, has remained constant in schedule with no published concerns since early 2016, as has the 11, beyond minor routing changes in September 2016. Therefore, while this percent on-time OTP route-level analysis suggests the possibility that ESTS shuttles are affecting OTP, additional analysis is necessary.

Analysis 2: Fixed Effects Panel Regression

To better identify whether the ESTS shuttles affect bus performance, this second analysis not only focuses more acutely on the point of impact (the stops), but also introduces a set of control observations. Additionally, both AM and PM peak periods are considered. Once US control stops were identified (as explained in the "DATA" section), control and treated stops were compared in a fixed effects panel regression as specified in Equation 1.

$$\begin{gathered} y_{iwt} = \alpha_i + \gamma_w + \beta D_{iw} + \epsilon_{iwt} \\ i = \text{stops} \\ w = \text{weeks} \\ t = \text{observations} \end{gathered} \tag{1}$$

The model specification includes fixed effects both for stops ($\propto_i$) and for weeks (γ_w). The stop-level fixed effects capture average schedule adherence at each stop, while the week-level fixed effects capture area-wide variations between weeks such as those caused by seasonality and UW sessions. A treated dummy variable (D_{iw}) is used to specify when treated stops are subjected to the ESTS pilot program treatment, and the coefficient β represents the average treatment effect. The dummy variable D_{iw} has a value of 1 from weeks 7 to 12 at the treated stops (since week 7 marks the start of the ESTS pilot program) and is 0 otherwise. Table 2 shows

Table 2. Fixed Effects Panel Regression of Schedule Adherence in the AM and PM Peak at All ESTS Study Stops

	Dependent variable: Schedule adherence (min)	
	AM peak	PM peak
Week 2	−0.256** (0.063)	−0.582** (0.094)
Week 3	−0.116 (0.066)	0.542** (0.091)
Week 4	−0.015 (0.066)	−0.107 (0.092)
Week 5	−0.653** (0.066)	−0.837** (0.092)
Week 6	−0.365** (0.067)	−0.016 (0.093)
Week 7	−0.270** (0.069)	−0.401** (0.095)
Week 8	−0.063 (0.070)	1.235** (0.098)
Week 9	−0.246** (0.069)	0.016 (0.096)
Week 10	−0.227** (0.068)	0.174 (0.096)
Week 11	−0.054 (0.069)	0.532** (0.097)
Week 12	−0.245** (0.070)	0.426** (0.100)
Treated dummy	0.001 (0.060)	0.102 (0.087)
Constant	2.534** (0.069)	1.880** (0.095)
Stop fixed effects	Yes	Yes
Observations	37,477	37,155
R^2	0.1	0.077
Adjusted R^2	0.099	0.076
Residual std. error	2.641 (df = 37431)	3.763 (df = 37109)
F statistic	92.904** (df = 45; 37431)	69.227** (df = 45; 37109)

Note: *$p < .05$; **$p < .01$.

Table 3. Fixed Effects Quantile Regression in the AM and PM Peak for All ESTS Study Stops

	Dependent variable: Schedule adherence (min)			
	AM peak		PM peak	
	0.9	0.95	0.9	0.95
Treated dummy	−0.147 (0.085)	−0.141 (0.135)	−0.376* (0.171)	−0.226 (0.229)
Constant	5.846** (0.142)	7.314** (0.164)	5.512** (0.186)	7.798** (0.240)
Weekly fixed effects	Yes	Yes	Yes	Yes
Stop fixed effects	Yes	Yes	Yes	Yes
Degrees of freedom	140116 total; 140041 residual		149170 total; 149095 residual	

Note: *$p < .05$; **$p < .01$.

the results of the regression analysis. The estimated treatment effects of the ESTS pilot program are small and not statistically significant. This suggests that, on average, sharing stops with private shuttles did not affect schedule adherence for KCM buses at the studied stops. Further, the "Constant" for the models represents the average schedule adherence in the data set; for both AM and PM peaks, the average arrival time for buses occurs on-time, only ~2 mins after the scheduled arrival time.

Analysis 3: Quantile Regressions of Stop Schedule Adherence

While the fixed effects panel regression considered the average impact of ESTS shuttles on the treated stops, or impact at the mean, quantile regressions provide a shifted focus. Quantile regressions of the fixed effects panel data were performed on all stops at the 0.90 and 0.95 quantiles (i.e., the 90th and 95th percentiles) to look more closely at the severity of later bus arrivals. Models were fitted per the same specifications given in Equation 1 and the resulting coefficients for the intercept and treatment dummy variable are presented in Table 3. As shown, results in the 0.95 quantile are not statistically significant, while results for the 0.90 quantile have a p-value of .028 in the PM peak. The estimated treatment effect implies that schedule adherence improved as a result of the ESTS pilot. This is an unreasonable causal impact and suggests that additional factors not present in this analysis affected the results. To seek further

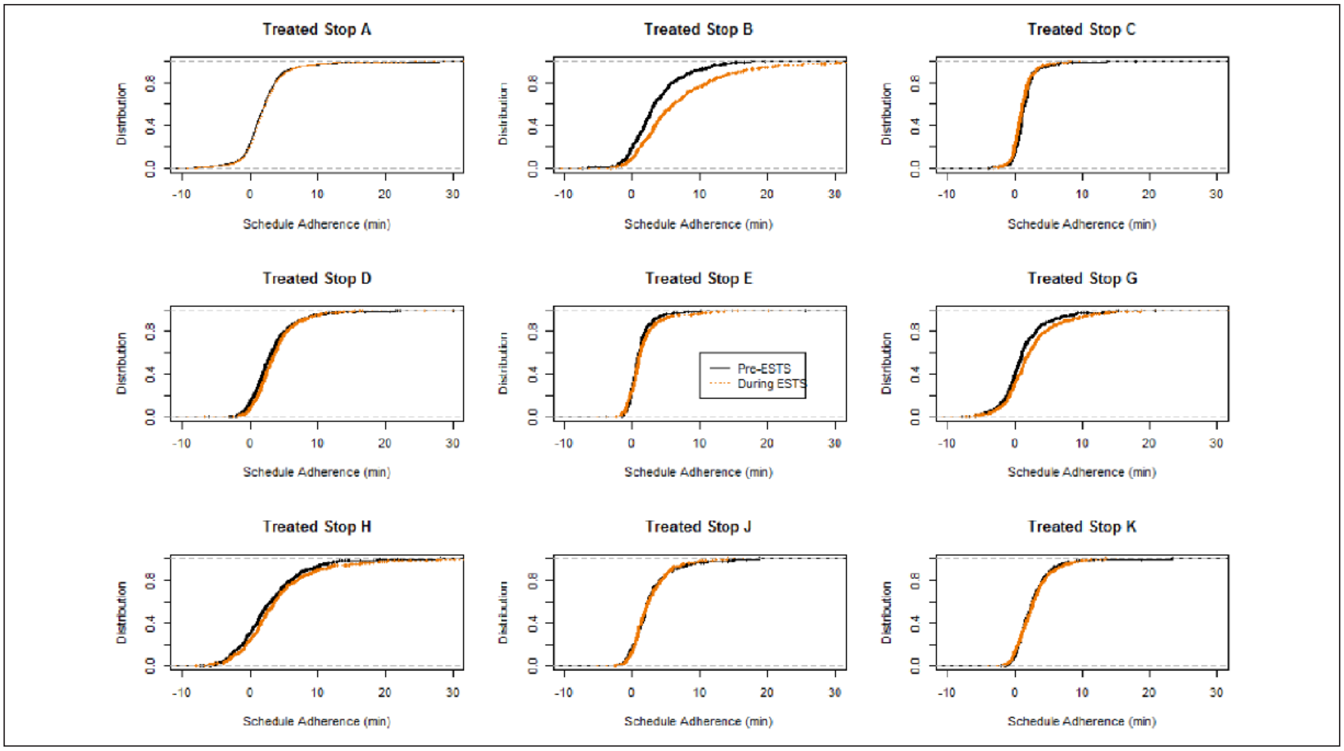

Figure 4. CDF plots of schedule adherence for treated stops before and after the start of ESTS.

clarification, a fourth analysis of each stop individually was considered.

Analysis 4: Quantile Comparisons and Regressions of Individual Stop Schedule Adherence

While the results at both the mid and upper quantiles did not indicate an effect of the ESTS program on transit performance, an additional analysis was conducted to determine whether or not individual stops have been affected. Rather than relying exclusively on the first analysis of an increase in late runtimes after the start of the ESTS program, schedule adherence before and after the start of the ESTS program at the stop level was assessed by comparing distributions. Figure 4 presents the CDF plots of schedule adherence times before and after the start of ESTS at the treated stops. Most of the stops show little to no difference, as the CDF curves overlap almost perfectly. Plots B and G, however, represent the stops that have experienced clear disparities between the distribution of schedule adherence at the stop before and after the start of the ESTS program. At both stops, buses are consistently later after the start of the ESTS program, with significantly later arrivals occurring at stop B after the start of the ESTS program. Based on these variations, treated stops B and G were identified as stops that required additional attention.

To determine whether these disparities are the result of the presence of ESTS shuttles or simply the result of other factors not considered in the analysis, fixed effects panel regressions at the median (0.50), 0.90, and 0.95 quantile comparing the treated stops to their corresponding control stops were considered. Table 4 presents the estimated treatment effects for stops B and G. Quantile regression models for stop G failed to reject the null hypothesis that the ESTS shuttles had no impact on bus schedule adherence during both peak periods and at all quantiles tested.

The models for stop B, however, reject the null hypothesis at the median (0.50) and 0.90 quantile during the PM peak. As Figure 5 shows, an increase in delays at the treated stop B compared to the US control stop occurs after the ESTS pilot begins. The differences between stops are very statistically significant, many with p-values $<.0001$. Based on this, the model suggests that, while arrival times at stop B are consistently later than arrival times at the control stop throughout the study period, buses began arriving even later at stop B after the start of the ESTS pilot. In the aggregate, these results suggest that the introduction of ESTS shuttles at stop B may have affected schedule performance.

Conclusions and Recommendations

Many factors affect bus schedule adherence. This study attempts to control for a multitude of factors through a robust control group development effort to study the impact of the introduction of private shuttles sharing bus transit stop ROW through the ESTS program with schedule adherence (time) information. While standard KCM reliability analysis methods looking at OTP at the route level were considered, they

Table 4. Treated Dummy Coefficients for Schedule Adherence at the 0.50 (Median), 0.90, and 0.95 Quantile of Stops B and G during the AM and PM Peak

	Treated dummy values for dependent variable: Schedule adherence (min)					
	AM peak			PM peak		
Models	0.5	0.9	0.95	0.5	0.9	0.95
Stop B	0.395 (0.311)	0.791 (1.130)	1.382 (0.957)	1.864** (0.457)	2.756* (1.386)	1.644
Stop G	−0.165 (0.125)	−0.629 (0.378)	−0.748 (0.585)	0.178 (0.226)	−0.889 (0.764)	−1.874 (1.284)
Weekly fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Stop fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Deg. of freedom stop B	5187 total; 5173 residual			7146 total; 7132 residual		
Deg. of freedom stop G	18039 total; 18023 residual			17946 total; 17930 residual		

Note: *p < .05; **p < .01.

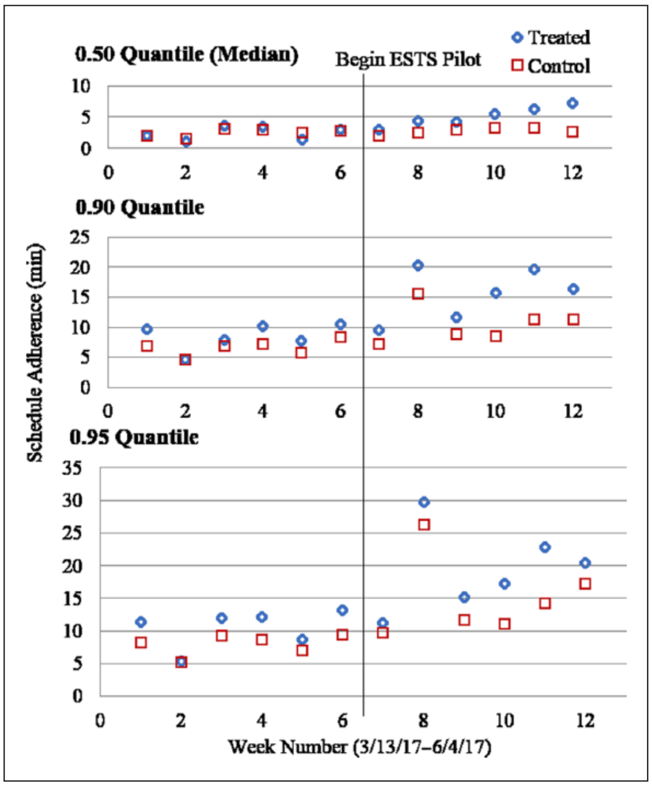

Figure 5. Stop B treated versus control stop schedule adherence in the PM peak by quantile.

were ultimately too zoomed out from the study locations. Moreover, discrepancies were found at the stop level that did not appear at the route level and vice versa. Furthermore, stop-level analysis is more likely to capture the perceived reality of impact caused by ESTS shuttles by better representing what passengers experience and would consider to be unreliable service.

An aggregate analysis of all nine stops selected for the ESTS pilot study paired against control stops and considered at the mean as well as at the 0.90 and 0.95 quantile in fixed effects panel regressions did not suggest a negative impact on public transit performance. At the stop level, however, one model suggested a potential relationship. Stop B that serves only one route (route 75) may have been affected. Stop B is a low capacity bus facility with only one loading area. Given that capacity and reliability are inherently linked, it is possible that the addition of shuttles stopping at this low capacity location is the sole cause of the increased bus arrival delays (cite TCQSM pp. 1–7). However, given that none of the other low-volume, single loading zone stops exhibit statistically significant impacts, the presence of multiple loading areas at a stop should not necessarily be a prerequisite for shared stop selection.

Based on this analysis, further investigation is needed to determine whether ESTS shuttle sharing is the sole cause of these delays, and, if so, why this stop is adversely affected while others are not. Further, because low-volume pilot stops were selected, results from these stops may not provide a clear indication of the potential impacts if a wider-spread program made use of busier stops. However, given the apparent minimal to no impact caused by the ESTS shuttle stops sharing ROW with transit buses at lower-volume stops, an expansion of the program at similar, lower-volume stops is recommended at this time. A more detailed analysis that considers more factors beyond time is necessary to fully isolate and determine impacts from ESTS. However, the potential for positive utilization of public curb space ROW and increased investment in transit services that revenue from a stop-sharing program such as ESTS provides outweigh the minimal negative impacts and warrant further investigation into expansion options.

Acknowledgments

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