Measuring the Determinants of Bus Dwell Time

New Insights and Potential Biases

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Dwell time is a major component of bus travel time and travel time variability. In turn, the distribution of bus travel times affects transit operators' costs and customer satisfaction. Previous research used dwell time from bus stop–level data to understand the key factors that contribute to dwell time duration. However, bus stop–level data have significant shortcomings when bus stops are located near intersections or at time points. Regression results show that the use of only stop-level data can significantly bias estimation of boarding and alighting coefficients. This research complements bus stop data with bus GPS trajectory data around bus stops to prevent estimation bias and to measure better the key factors that determine dwell time. Regression results from individual and pooled bus stop models are compared to provide new insights into the impacts of traffic conditions, signalized intersections, bus bays, and time points on dwell times. The impacts of nearside, midblock, and farside bus stops are included in the analysis. The number of passengers boarding and alighting has a nonlinear effect with economies or efficiencies of scale.

Transit travel times and performance metrics for buses and routes have always been important to both transit authorities and passengers. As stated in 1983, "Transit travel times and operating speeds influence service attractiveness, costs, and efficiency. [These factors] also provide important descriptions of system performance for use in the transportation planning process" (*1*). Today, it is possible to use large data sets that were unavailable 30 years ago. The Tri-County Metropolitan Transportation District of Oregon (TriMet), the transit agency of Portland, Oregon, started collecting bus GPS trajectory data in 2014. Although most transit agencies do not collect trajectory data, more agencies are likely to store trajectory data as sensors and data archival systems become more economical.

Previous research efforts used only stop-level data to understand the key factors that contribute to dwell time lengths. Stop-level data have major shortcomings for bus stops located near signalized intersections because red signals and vehicle queuing may increase dwell times, but there is no variable in the data set that can be used to account for these delays. Several previous research efforts did not analyze bus stop dwell times near signalized intersections, even though these stops have longer dwell times and higher levels of passenger boardings and alightings. The recent introduction of high-resolution bus GPS trajectory data allows researchers to overcome stop-level data shortcomings and revisit factors that affect dwell times.

The goals of this research are to understand the factors that affect dwell times in all types of bus stops and to quantify without statistical bias the relative contribution of each factor. A comparison of regression results using stop-level data and GPS data sets indicates that previous regression results may be biased. The finer granularity of the new data provides new insight into the impact of traffic conditions, signalized intersections, time points, and locations of bus stops on dwell times.

BACKGROUND AND LITERATURE REVIEW

TriMet has been archiving automatic vehicle location and automatic passenger count data for all bus trips at the stop level since 1997, as part of the bus dispatch system. That same year, TriMet began phasing out all high-floor buses (*2*). Currently, all high-frequency routes use low-floor buses; thus, in this research all buses are low-floor (*3*). Two years ago, TriMet started collecting 5-s-interval GPS data for every bus in operation.

The *Transit Capacity and Quality of Service Manual* indicates that dwell time is a major source of bus delay and travel time unreliability (*4*). Traditionally, studies aiming to predict dwell time were bound by stop-level data sets or video (*5*). Most previous studies used regression models. One study found dwell time for Route 14 in Portland to be related only to passenger boardings and alightings. However, that analysis made no distinction between stop types and did not included records with lift usage; other factors that affect bus stops, such as signal timing and the location of intersections, were not discussed (*6*). Using data from Madrid, Spain, researchers separated passenger boardings by access door and found that door use was not a significant variable (*7*). Using data from Montreal, Quebec, Canada, researches also separated boardings and alightings by door use (linear and square terms) and added variables for times of day, bus type, passenger load, and snow cover. Unlike the Madrid study, the different door movements remained significant. Additionally, the statistically significant square values for passenger movement demonstrated nonlinearity in the relationship between passenger movements and dwell times (*8*).

Many studies have used dwell time to determine the effectiveness of various payment methods (*9*). For example, using data from Sydney, Australia, researchers analyzed dwell time and boarding times when passengers pay by cash or card (*10*). In Singapore, researchers added bus characteristics to analyze the impact of bus

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TABLE 1 Summary of Previous Research

Study	City	Year	Observations	Bus Stops	Stop Type	Variables	R^2
Bertini and El-Geneidy (*6*)	Portland, OR	2004	255 111 459 459	64	All types (aggregated)	ons offs (ons + offs)[b] ons, offs	.45 .49 .15 .47
Rajbhandari et al. (*12*)	Newark, NJ	2002	1,349–8,346[a] 1,350–8,346[a] 1,351–8,346[a]	135	All types along each of eight routes (aggregated by route)	(ons + offs)[b] ons, offs (ons + offs)[b], standees	.567–.642[a] .582–.718[a] .568–.643[a]
Dueker et al. (*13*)	Portland, OR	2004	2,347		All types for all buses (aggregated)	Ons, offs, lift, on-time, friction, and dummy variables	.2848
Li et al. (*14*)	Changzhou City, China	2012	5,938		All types (aggregated)	Ons, offs, passenger load, standees, and conflict factor	.421

[a]Regression model for eight routes.
[b](ons + offs) is total passenger movement at stop.

types on times (*11*). A study in Newark, New Jersey, added variables to more accurately predict dwell times; the number of standing passengers was statistically significant but barely increased the adjusted R^2 of the model (*12*). A study in Portland that focused on dwell time used additional variables for time of day, bus type, loading, and passenger friction; however, it separated the data into cases in which the lift was activated and when it was not. Without the lift, the boarding coefficient was 3.5 s per person, the alighting coefficient was 1.7 s per person, and the adjusted R^2 was .35. With the lift, coefficients for boardings and alightings were 10.21 and 0.513 s, respectively. The R^2 of the estimated models was relatively low and equal to .28 (*13*). Using data from Changzhou City, China, researchers added variables to estimate friction such as passenger load and a conflict factor that takes into account the number of standing passengers; the addition of these variables increased the R^2 of the model from .294 to .421 (*14*).

Previous studies aggregated all data for all buses in the study areas (Table 1). Among previous studies, only one paper noted that there are difficulties when working near intersections or at time points (*13*). As later shown, unless trajectory data are also included, the estimation of boarding or alighting coefficients at near- or far-side stops may be significantly biased if only bus stop–level data are used.

DATA SOURCES

In 2013, TriMet implemented a new system to collect 5-s bus GPS data. The new GPS data were intended to augment the existing stop-level data sets. Unlike the stop-level data, the new GPS data set collects information between bus stops, which allows the estimation of bus trajectory and speeds between stops. However, unlike the stop-level data, GPS data do not provide information about passenger movements, doors, or other factors that occur at stops themselves; this type of information is found only in the original stop-level data.

The GPS data are recorded only when the bus is not stationary for more than 5 s, that is, there are no consecutive points that have different time stamps and the same GPS coordinates. It is possible to augment the original stop-level data set by matching the time and location of the GPS coordinates before and after a bus stop; this matching can be done with algorithms that compare dates, bus numbers, and times for each stop event in the stop-level data. For each stop event, two high-resolution points before and two after were extracted and used to create three segments centered on the stop. Information (e.g., speed) was then added to the stop-level data for each segment.

Three weeks of weekday bus data for November 2013 were used in this study. The fourth week of November, Thanksgiving week, was excluded from the analysis because of holiday bus scheduling and passenger activity. The stop-level data may occasionally contain errors associated with the passenger counting equipment aboard the buses. The data were carefully parsed and analyzed to remove obvious outliers; for example, a stop record may show 70 people boarding and 10 people alighting a bus that already has 30 passengers and a capacity of 60 passengers. This type of error was rare, far less than 0.5% of the data records.

Statistics that describe dwell times per bus stop are presented in Table 2. For many bus stops, the dwell time 15th percentile is zero when the bus skips a stop more than 15% of the time; that is, for many bus trips there is no bus stop activity and the bus does not pull off and service the stop. From the values of the percentiles, it is possible to observe that dwell times generate asymmetric distributions that are right-skewed (positive skewedness). In addition, some stops show long dwell times that last more than 4 min, whereas at other stops maximum dwell times do not reach 1 min.

The stops shown in Table 2 were selected to represent high and low utilization levels for bus stops. These bus stops have different levels of boardings and alightings per day, as shown in Table 3, and different location characteristics (nearside, farside, and so on) and the presence of a bus bay or shelter. There is a clear correlation between longer dwell time statistics and bus stop activity. Farside stops tend to be time points (i.e., locations where early buses can wait to be on time, as indicated in their schedules) and have higher utilization than other stops located midblock or away from traffic signals. For simplicity in tables and graphs, the variable "ons" indicates the number of boardings, and "offs" indicates the number of alightings. The variable "lift" indicates the operation of the wheelchair lift.

The route chosen for this study, TriMet Route 9, runs from NE Kelly Avenue and 5th Street to Northwest 6th Avenue and Flanders

TABLE 2 Dwell Statistics per Bus Stop

Stop	Nearest Intersection	Dwell Statistics (s) Min.	15th	Median	85th	Average	SD	Max.
Stop Near Signalized Intersection								
Farside								
Eastbound	39th, TP	0	16	30	67	39.2	29.6	196
	82nd, TP	0	21	41	102	57.5	45.7	270
	86th	0	0	13	25	12.7	13.6	82
Westbound	39th, TP	0	19	31	64	39.9	29.4	230
	82nd, TP	0	22	43	118	61.8	48.2	286
Nearside								
Eastbound	42nd	0	0	10	32	13.2	16.8	84
Westbound	87th	0	0	13	33	15.0	17.1	94
No Signal Near Bus Stop								
Eastbound	34th	0	0	12	22	12.2	12.1	78
	36th	0	0	0	16	6.7	9.3	62
	79th	0	0	11	23	11.3	14.6	88
	90th	0	0	0	18	7.5	12.1	70
Westbound	34th	0	0	13	26	14.0	14.6	81
	36th	0	0	0	17	8.4	10.3	57
	40th	0	0	0	17	7.5	9.8	78
	79th	0	0	10	21	9.8	11.3	60
	84th	0	0	11	28	14.1	19.5	113

NOTE: TP = time-point stop.

Street in Portland. Route 9 was chosen because the researchers have an excellent knowledge—from previous studies—of traffic patterns, bus operations, and the geometry of the roadways and bus stops. The selected bus stops are located along Powell Boulevard, a major urban arterial in the Portland metropolitan area, which connects the city of Gresham to downtown Portland and carries more than 40,000 vehicles daily. Bus stop locations are shown in Figure 1.

Other demographic and operational factors may affect dwell times. For example, boardings and alightings may be slower at stops near senior housing. In this research model, demographic passenger data were not readily available and so not included in the regression models.

TABLE 3 Bus Stop Activity Statistics

Stop	Nearest Intersection	Stops (per day)	Ons (per day)	Offs (per day)	Lift[a] (per week)	Bus Bay	Shelter
Stop Near Signalized Intersection							
Far side							
Eastbound	39th, TP	63	162	283	9.0	x	x
	82nd, TP	64	256	266	15.0	x	x
	86th	40	32	55	1.0	x	x
Westbound	39th, TP	64	268	110	6.0		x
	82nd, TP	63	226	155	5.3	x	x
Near side							
Eastbound	42nd	33	12	40	0.3		x
Westbound	87th	38	48	30	1.0	x	
No Signal Near Bus Stop							
Eastbound	34th	45	35	70	2.0		
	36th	29	11	35	0.3		
	79th	35	8	63	1.0	x	
	90th	22	10	26	0.3		x
Westbound	34th	45	76	32	2.7		x
	36th	32	41	16	0.3		
	40th	31	15	42	1.3		
	79th	35	54	7	0.0	x	x
	84th	34	16	71	2.3	x	

NOTE: x indicates that bus stop has bus bay or shelter.
[a]5-day workweek (Monday–Friday).

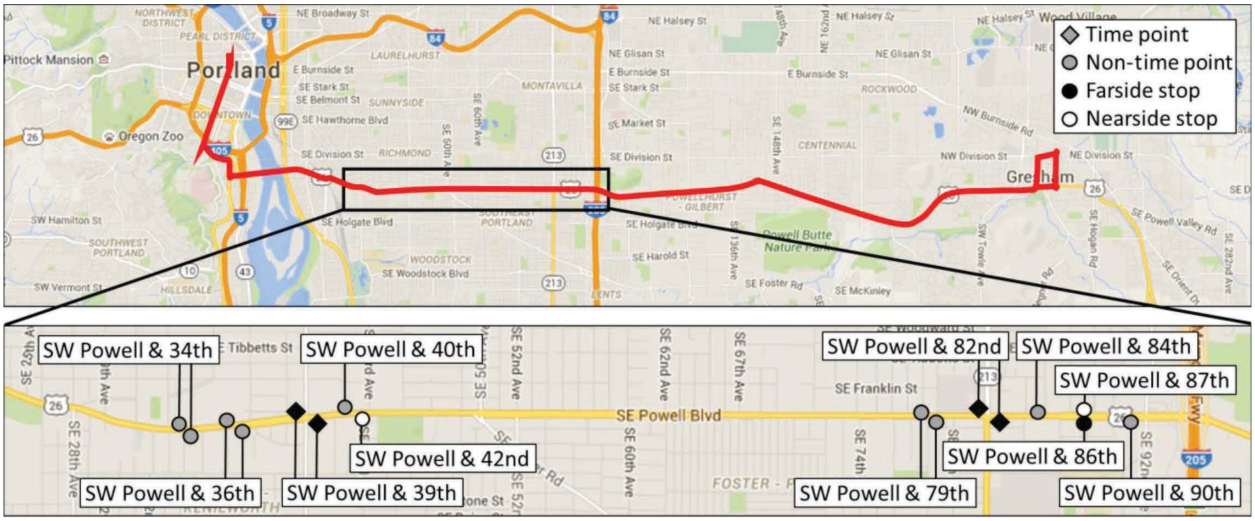

FIGURE 1 Route 9 (in red) and westbound and eastbound stops above and below Southeast Powell.

REGRESSION VARIABLES

Stop level combined with GPS data are called combined data in this study. Three types of regressions were run to estimate dwell time determinants:

1. Use of dwell time (stop-level data) as the dependent variable. This is the difference between bus stop arrive time and leave time. Only passenger activity variables are included.
2. Use of dwell time (stop-level data) as the dependent variable. This is the difference between bus stop arrive time and leave time. All available dependent variables are included.
3. Use of interval time (combined data) as the dependent variable. Interval time is defined as the time elapsed between the closest GPS coordinate before the stop and the closest GPS coordinate after the stop. All available dependent variables are included.

The independent variables obtained from the stop-level data are the following:

- Ons. Number of passengers boarding a bus at a specific stop (passengers board only from front door),
- Offs. Number of passengers alighting a bus at a specific stop (passengers alight from both doors),
- Lift. Number that indicates wheelchair lift operation (seconds),
- Early. Time ahead of schedule at a time point (seconds), and
- Stop. Binary variable that is 1 if a bus stopped to serve passengers and 0 otherwise (seconds).

The independent variables obtained from the combined data are the following:

- Length. Distance between consecutive GPS coordinates before and after the bus stop (feet);
- Avg. Speed. Average speed in the segment immediately before and immediately after the bus bay (miles per hour);
- Intersection. Binary variable that is 1 if a GPS point is located on the other side of a signalized intersection with respect to a bus stop; this variable has nonzero values only for nearside or farside stops;
- Int-far. Binary variable that is 1 if a GPS point is located on the nearside of a farside bus stop; and
- Int-near. Binary variable that is 1 if a GPS point is located on the farside of a nearside bus stop.

The regressions were estimated with the MASS R package, which uses a stepwise function to remove insignificant variables one at a time; the RELAIMPO R package was used to estimate the relative importance of each variable.

COMPARISON OF ADJUSTED R^2 VALUES

A comparison of three types of regressions is shown in Table 4, where (*a*) the first column of numbers shows the adjusted R^2 values when dwell time is regressed against stop activity variables, (*b*) the second column shows the adjusted R^2 values when dwell time is regressed against stop activity variables plus variables that can be obtained from the GPS data, and (*c*) the third column shows the adjusted R^2 values when interval time is regressed against all the combined data variables. The shaded cells show the highest adjusted R^2 values for the row.

The results in Table 4 show that a simple regression model type (Type 1) appears to produce good results for stops that have relatively few boardings and alightings and that are not located near a traffic signal, for example, eastbound Powell and 36th. However, Model 1 produces very low adjusted R^2 values for time-point stops such as Powell and 82nd. A regression model type (Type 2) does not improve on the simple model (Type 1) at low-activity stops, but it does produce better results at time-point stops. Finally, the Type 3 model produces superior results for all time-point stops and very good adjusted R^2 values for regular stops. (The main difference between Models 3 and 2 is the dependent variable.)

ANALYSIS OF REGRESSION COEFFICIENTS

Adjusted R^2 values are important, but a good regression model must also have sound coefficients. Table 5 presents the coefficients estimated with Model 3 for regular—that is, without time points—bus

TABLE 4 Comparison of Adjusted R^2 Values per Bus Stop

Stop	Bus Stop Location	Dwell ~Stops + Ons + Offs + Lift	Dwell ~Stops + Ons + Offs + Lift + Avg. Speed + Early + Intersection	Interval ~Stops + Ons + Offs + Lift + Avg. Speed + Early + Intersection + Length
Time-Points				
Eastbound	Powell & 39th, FS	.165	.499	.600
	Powell & 82nd, FS	.135	.414	.574
Westbound	Powell & 39th, FS	.189	.431	.476
	Powell & 82nd, FS	.122	.250	.471
Regular Stops				
Eastbound	Powell & 34th	.670	.671	.666
	Powell & 36th	.787	.787	.578
	Powell & 42nd, NS	.553	.553	.522
	Powell & 79th	.611	.623	.587
	Powell & 86th, FS	.737	.737	.737
	Powell & 90th	.731	.733	.699
Westbound	Powell & 34th	.719	.719	.693
	Powell & 36th	.847	.848	.729
	Powell & 40th	.811	.814	.842
	Powell & 79th	.795	.795	.788
	Powell & 84th	.554	.561	.533
	Powell & 87th, NS	.687	.701	.684

NOTE: NS = nearside bus stop; FS = farside bus stop.

TABLE 5 Regular Bus Stops Interval, Model Type 3

Stop	Adjusted R^2	Intercept	Stops	Ons	Offs	Lift	Avg. Speed	Length	Early
Eastbound									
34th		−7.47***	14.58***	4.43***	1.15***	28.85***	.24***	.01	.03***
n = 935	.666		26.2%	19.5%	8.4%	5.4%	4.6%	2.4%	0.2%
36th			12.25***	3.22***	0.48			.03***	
n = 977	.578		35.0%	8.5%	10.6%			3.9%	
42nd, NS		5.02**	20.08***	3.72***	1.59**	29.12**	−0.15	.02***	
n = 898	.522		30.7%	5.7%	10.0%	0.4%	3.9%	1.9%	
79th		11.25***	13.82***	3.00***	1.54***	15.52	−.45***	.03***	
n = 964	.587		27.7%	3.0%	12.4%	0.2%	13.2%	2.4%	
86th, FS		4.13**	15.43***	4.16***	1.03***	39.01***	−.20***	.03***	
n = 970	.737		35.2%	16.3%	9.2%	2.6%	8.2%	2.3%	
90th		6.98***	15.47***	3.59***	1.40***	49.20***	−.28***	.03***	
n = 890	.699		37.8%	9.0%	13.3%	2.6%	6.2%	1.2%	
Westbound									
34th		3.23*	14.18***	3.26***	2.05***	36.30***	−.16**	.03***	
n = 1,006	.693		26.5%	20.3%	5.8%	7.3%	7.4%	2.3%	
36th		7.00***	11.79***	2.34***	1.37***		−.27***	.03***	
n = 963	.729		33.8%	16.6%	4.7%		14.1%	3.9%	
40th		5.19***	12.54***	2.91***	1.45***	17.60***	−.22***	.03***	
n = 1,027	.842		39.8%	10.3%	15.9%	2.8%	12.2%	3.3%	
79th		4.07**	14.62***	2.82***	1.57***	na	−.17**	.03***	
n = 1,025	.788		34.6%	21.8%	1.9%		16.5%	4.0%	
84th		10.41***	15.68***	4.90***	2.19***	23.25***	−.45***	.02***	.02*
n = 941	.533		23.1%	6.8%	11.9%	1.9%	8.5%	.1%	1.2%
87th, NS		10.31***	17.84***	4.27***	1.21**	38.59***	−.39***	.02***	
n = 981	.682		30.1%	16.7%	4.5%	3.2%	11.1%	2.4%	

NOTE: % = relative explanatory power; na = not applicable.
* $p < .05$, ** $p < .01$, *** $p < .001$.

TABLE 6 Time-Point Bus Stops

Direction	Stop	Adjusted R^2	Variables: Intercept	Stops	Ons	Offs	Lift	Avg. Speed	Early	Intersection	Length
Model 2–Dwell											
Eastbound	39th		8.48	18.63***	3.31***	.66**	24.08***	−.49*	.33***	46.33***	na
	$n = 966$	.499		2.0%	8.3%	2.3%	3.7%	0.6%	18.2%	15.3%	
	82nd		11.75	34.64***	2.64***	2.03***	27.30***	−1.22**	.41***	55.31***	na
	$n = 982$	.414		2.0%	5.1%	4.2%	2.9%	2.0%	19.4%	6.3%	
Westbound	39th		4.80	23.83***	2.82***	1.32**	29.33***	−.54*	.33***	29.85***	na
	$n = 994$	.431		4.1%	12.1%	1.2%	2.6%	0.7%	18.9%	3.8%	
	82nd		16.03	32.61***	3.18***	4.16***	20.33*	−0.94	.32***	57.71***	na
	$n = 978$	.250		2.6%	4.0%	5.3%	0.4%	0.7%	7.9%	4.5%	
Model 3–Interval											
Eastbound	39th		10.71	16.35***	3.37***	.47*	24.50***	−.50*	.30***	43.05***	.03*
	$n = 828$	.600		2.2%	9.8%	2.2%	3.8%	1.1%	19.3%	17.2%	4.7%
	82nd		−2.00	31.52***	2.77***	.80**	30.09***	−0.51	.36***	60.13***	.04*
	$n = 793$	.574		2.9%	7.3%	2.0%	3.7%	1.6%	25.5%	12.8%	1.9%
Westbound	39th		0.75	25.72***	2.46***	.99*	30.25***	−.45*	.30***	28.50***	.04***
	$n = 901$	.476		5.5%	10.4%	0.9%	3.7%	0.4%	20.5%	5.6%	1.1%
	82nd		−5.65	29.90***	2.30***	0.74	40.10***		.37***	66.13***	.03
	$n = 723$	.471		4.2%	3.1%	1.7%	2.6%		22.4%	12.5%	1.2%

* $p < .05$, ** $p < .01$, *** $p < .001$.

stops. As expected, the variable with the highest explanatory power in the model was stops (i.e., if bus stopped to serve passengers), followed by ons, offs, and lift (i.e., passenger movements). When the number of boardings per day is higher, the explanatory value of the variable ons increases and likewise for offs and lift (compared with daily values in Table 3). Average speed is negative, which indicates that during the times of day when speeds are high or there is no congestion, bus times are shorter. Length is always positive and accounts for the distance between GPS points. As expected, in stops that are not time points, there is a very small explanatory value for early buses.

Table 6 presents the coefficients estimated with Models 2 and 3 for time-point bus stops. As expected, at these stops the early variable has a high explanatory value. The relative contribution of stops is less important because many passengers are boarding and alighting and because there are significant delays caused by delays at the nearby intersection or by buses arriving ahead of schedule, the later captured by the variable "early."

The comparison of regression coefficients shows a striking difference between some ons, offs, and lift coefficients—for example, at the westbound 82nd stop. These large differences are caused by a biased estimation of the bus activity coefficients when dwell time is used as a dependent variable; this factor is extensively discussed in the next section.

POTENTIAL STOP-LEVEL DATA BIAS

Several studies in the literature used a cutoff dwell time value to separate outliers to obtain reasonable results; however, they did not include results that show the impact of different cutoff values on estimated regression coefficients. This section analyzes the impact of the cutoff time on the estimation of regression coefficients. Tables 7 and 8 show the coefficients for the westbound bus stop at Powell and 82nd estimated with Models 2 and 3, respectively. The first column contains values using all the records, and the subsequent columns use a more restrictive dwell time or interval cutoff value, from 180 to 90 s; as expected, the number of observations decreases from right to left. In Table 7, regression-standard errors decrease steadily as the right tail of the time distribution is shortened. The change in the value of coefficients for ons and offs is notable. The coefficient for ons decreases from 3.18 to 1.68 s, whereas the coefficient for offs decreases from 4.16 to 1.33 s when the data are restricted to dwell times below 90 s. Furthermore, the offs variable is highly significant and has a higher explanatory value (5.3%) than the ons variable (4%); the coefficients and the explanatory values are counterintuitive because at this bus stop the average number of boardings is significantly larger than the number of alightings (Table 3).

In Table 8, regression standard errors also decrease steadily as the right tail of the time distribution is shortened. However, the values for the ons coefficients are fairly steady, ranging from 2.3 to 2.09 s. The values of the offs coefficients are also more stable, and the explanatory value of the offs variable is significantly smaller than the explanatory value of the ons variable, which is as expected given the number of boardings and alightings at this stop.

Further analysis of the regression results shows that in Table 7 dwell time values are inflated by intersection delays, and, as a result, ons and offs coefficients are inflated as well. The problem is caused by the way in which stop-level data are collected near signalized intersections. Around a bus stop, there is a circle of approximately 50-ft (15.2-m) radius that is used to determine bus arrival and departure times (Figure 2). If a stop is too close to the intersection, the bus may already have left (or arrived at) the stop, but the departure (arrival) time is not recorded until the bus crosses the circle. Thus, traffic and signal delays can inflate dwell times. Finally, all signalized intersections along the route, except 82nd Street, have transit signal priority. However, previous research showed that the average impact of transit signal priority per intersection is small (less than 2 s) and mostly useful to reduce lateness and travel time

TABLE 7 Regression Results for Westbound Powell and 82nd, Model Type 2

Value and Variable	All	<180 (s)	<150 (s)	<120 (s)	<105 (s)	<90 (s)
R^2	.255	.274	.257	.259	.251	.281
Adjusted R^2	.250	.270	.251	.252	.244	.275
Standard error	41.8	35.7	32.7	25.4	21.3	17.2
Observations	n = 978	n = 958	n = 926	n = 834	n = 779	n = 726
Intercept	16.03	–4.05	15.88	18.51*	10.14	14.46*
Stops	32.61***	35.28***	31.78***	30.29***	30.01***	26.68***
	2.6%	3.5%	3.7%	5.3%	7.2%	9.2%
Ons	3.18***	2.70***	2.53***	1.63***	1.57***	1.68***
	4.0%	4.0%	4.3%	2.9%	3.6%	5.9%
Offs	4.16***	4.12***	3.65***	2.46***	1.74***	1.33***
	5.3%	6.7%	6.2%	4.7%	3.5%	3.4%
Lift	20.33*	16.57	19.04*	20.51**	23.20***	18.68**
	0.4%	0.4%	0.7%	1.0%	1.4%	1.3%
Avg. speed	–0.94		–.88*	–.99**	–0.58	–.76**
	0.7%		0.9%	1.5%	1.1%	2.1%
Early	.32***	.28***	.23***	.22***	.18***	.15***
	7.9%	7.8%	5.8%	8.1%	6.6%	6.3%
Intersection	57.71***	52.72***	47.92***	38.86***	45.65***	
	4.5%	4.8%	3.9%	2.3%	1.8%	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

variability (*15–17*); however, unlike the Early variable, the Late variable was not significant in the regression models.

POOLED RESULTS

Because interval models of Type 3 were the most unbiased, the next research step involved pooling all the observations into a single model type (Type 4). Because each stop had a different number of observations, a weighted regression model was estimated; observation weights were inversely proportional to the number of observations per stop to ensure that each stop had the same influence in the final model. In addition, because the model included different bus stops, some characteristics related to the location and geometry of the bus stop were included.

The results of the pooled model are shown in Table 9. The pooled model has a good adjusted R^2 value. The estimated coefficients, signs, and relative importance provide new insights:

1. The highest relative contribution is provided by stops, almost 13%.
2. Both ons and offs have a significant linear and square term.

TABLE 8 Regression Results for Westbound Powell and 82nd, Model Type 3

Value and Variable	All	<180 (s)	<150 (s)	<120 (s)	<105 (s)	<90 (s)
R^2	.476	.476	.462	.445	.401	.399
Adjusted R^2	.471	.471	.457	.438	.394	.392
Standard error	25.7	25.0	21.8	17.4	15.2	13.2
Observations	n = 723	n = 720	n = 702	n = 668	n = 645	n = 622
Intercept	–5.65	–6.37	1.22	8.49	7.46	4.96
Stops	29.90***	29.67***	27.19***	24.98***	24.36***	25.00***
	4.2%	4.4%	5.2%	7.2%	9.4%	12.4%
Ons	2.30***	2.32***	2.40***	2.38***	2.32***	2.09***
	3.1%	3.2%	4.7%	7.3%	9.6%	11.2%
Offs	0.74	0.87	0.88*	0.65	0.75*	0.54*
	1.7%	2.0%	2.0%	1.7%	2.2%	1.9%
Lift	40.10***	31.88***	32.36***	29.85***	25.43***	23.92***
	2.6%	1.7%	2.6%	3.7%	2.8%	3.2%
Avg. speed				–0.58	–0.47	–0.39
				1.3%	1.1%	1.0%
Early	.37***	.36***	.32***	.26***	.21***	.16***
	22.4%	21.6%	20.0%	17.4%	13.7%	9.6%
Intersection	66.13***	66.01***	61.05***	45.96***	35.87**	
	12.5%	13.3%	11.6%	5.4%	1.0%	
Length	0.03	0.04		.03*	.03*	.04**
	1.2%	1.4%		0.5%	0.3%	0.6%

* $p < .05$, ** $p < .01$, *** $p < .001$.

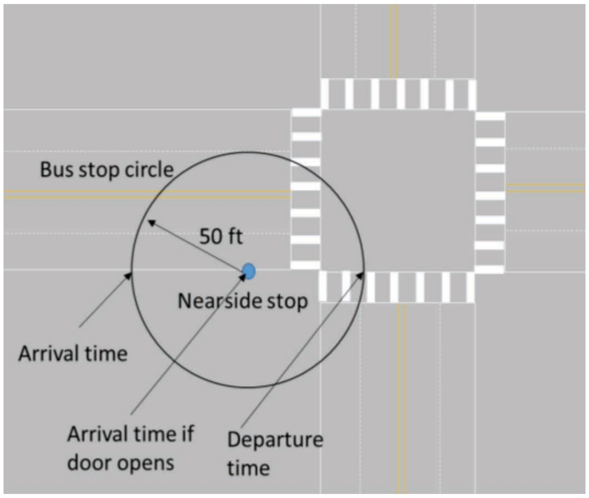

FIGURE 2 Bus stop area of influence near intersections (*15*).

3. The combined contribution of ons and ons^2 is the highest, almost 14%.

4. With respect to the baseline stop, a midblock stop with no bus bay, the nearside and farside variables show a significant positive contribution.

To verify the correctness of the pooled model with respect to Insights 2 and 3, Figure 3 shows the relationship between the estimated coefficients for ons and offs estimated in the individual models (Tables 5 and 6). Figure 3 shows that as a bus stop has more activity, the estimated coefficient tends to decrease, that is, there are efficiencies or boarding or alighting time economies of scale. This fact explains that both ons^2 and offs^2 are highly significant and have negative coefficients. Figure 3 strongly suggests that there are efficiencies of scale; stops with more boarding or alighting activity tend to have lower boarding or alighting times per passenger. To put the boarding numbers in context, the coefficients of Table 9 are used to show that the estimated average time for one boarding is approximately 4.0 s per passenger, and for four boardings it is approximately 3.5 s per passenger. These numbers are within the range of coefficients shown in Figure 3*a.*

TABLE 9 Pooled Regression Model Results

	Model Type 4–Interval		
Variable and Characteristic	Coefficient	Relative Contribution (%)	Variance Inflation Factor
Intercept	−0.501		
Stops	16.43***	13.04	1.450
Ons	4.041***	9.81	1.387
Offs	1.929***	5.16	1.246
Ons^2	−.132***	4.11	1.160
Offs^2	−.107***	2.03	1.093
Lift	24.01***	1.79	1.038
Length	.041***	1.12	1.023
Avg. speed	−.281***	3.90	1.161
Intersection	2.219***	0.47	1.002
Early	0.095***	2.79	1.020
Far side	6.493***	6.52	1.307
Near side	7.252***	0.15	1.003
Int-far	25.67***	2.67	1.053
Int-near	−5.260***	0.13	1.003
Bus bay	.707*	1.65	1.083

NOTE: For pooled model, R^2 = .5533; adjusted R^2 = .5528; and observations = 15,872.
* $p < .05$, ** $p < .01$, *** $p < .001$.

With respect to Insight 4, the interaction between intersection and nearside or farside variables may show a trend. From observations along Powell Boulevard, these variables reflect the impact of traffic or queues that block or do not let buses move freely to or from bus bays or nearside and farside bus stops. If a bus stops before an intersection with a farside stop, it waits on average 25 s (most likely because of a red light). If a bus does not stop at a nearside stop before crossing (most likely because of a green light), it saves 5 s on average. But, after the impacts of traffic signals are removed, the coefficients for nearside and farside variables are nearly the same. This result confirms results of previous research (*15*). Nearside stop efficiency is likely to increase if there are boarding or alighting activities while the bus is stopped at the red light. Hence, the relative efficiency of nearside and farside stops may be mostly

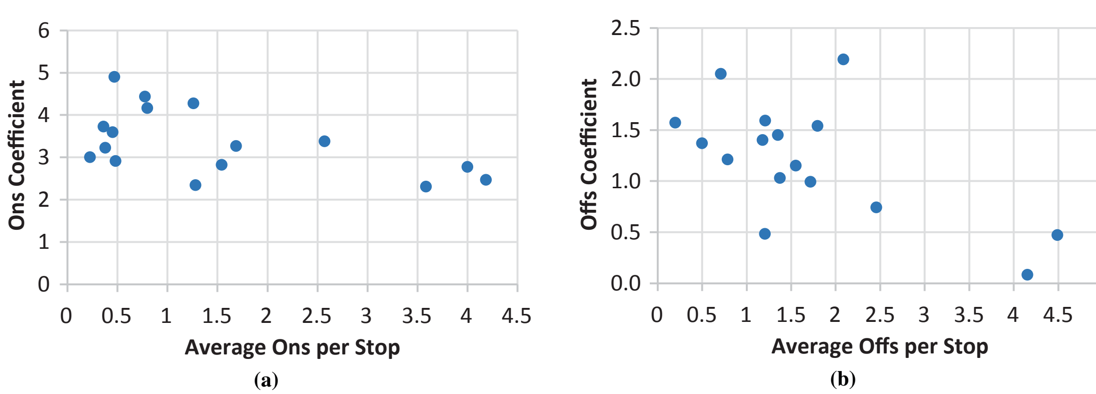

FIGURE 3 Estimated regression coefficients versus average ons and offs per stop.

determined by how often or how long the bus is delayed by red indications and other factors, such as the efficiency of transit signal priority (*15*). These nearside or farside results should be considered with caution because of the low number of observations and because farside stops included in the sample have a higher level of passenger activity (boardings, alightings, and lift usage in Table 3). Additional research is needed to generalize the trends in the pooled regression model.

CONCLUSIONS

This study combined bus stop–level data and trajectory GPS data to provide new insights into the determinant factors of bus dwell time. Results showed that use of only bus stop–level data to estimate dwell time factors can result in estimation of biased regression coefficients for the boarding and alighting variables.

Pooled and individual regression models were compared and analyzed to evaluate the contribution of each variable. Traffic queuing or signalized intersection delay can have a major impact on bus times at stops located at the nearside or the farside compared with midblock stops or stops located away from traffic signals. When a bus stops before the intersection of a farside stop (red indication delay), delays may increase on average as much as when a lift is activated. For nearside stops, intersection delay may be reduced if the bus uses a green indication after servicing passengers during a red light. In this research, farside stops were time points with high passenger movements located after major cross streets with longer red times than minor cross streets; hence, additional research is needed to generalize the trends in the regression models. The results also show that boardings and alightings show clear economies or efficiencies of scale. The average time per passenger per boarding or alighting decreases as the number of total passengers boarding or alighting increases.

Dwell time is a major component of bus travel time and travel time variability. In turn, the distribution of bus travel times affects transit operators' costs and customer satisfaction. The results presented in this study have major implications for efforts to reduce bus travel times, and these results are being used in an ongoing study analyzing bus stop removal. The presented insights and results are also valuable for bus consolidation or removal analysis as well as for dwell time estimation.

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