

1                   **A DIRECT-DEMAND MODEL FOR BICYCLE COUNTS:**  
2                   **THE IMPACTS OF LEVEL OF SERVICE AND OTHER FACTORS**

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20                  The following paper is a pre-print, the final publication can be found in *Environment and*  
21                  *Planning B: Planning and Design* 43 (1): 93-107, 2016.

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23                  **Keywords:** Transportation Planning, Bicycle, Cycling, Bike Lanes, Traffic Counts, Level of  
24                  Service

25  
26                  **ABSTRACT**

27  
28                  Transportation planning in the US has traditionally focused on automotive traffic but is  
29                  increasingly turning towards a multi-modal approach in order to accommodate all users. This  
30                  shift in focus is particularly crucial for cyclists, as 630 were killed and 51 thousand injured on  
31                  America's roadways in 2009 alone. Unfortunately, most municipalities do not conduct  
32                  comprehensive bicycle counts to determine where cyclists are riding, though some do seek a  
33                  scatter of spot-counts. This investigation uses Seattle metropolitan area cyclist count data from  
34                  251 locations to develop a direct-demand model for estimating peak-period cyclist counts based  
35                  on trip generation and attraction factors (such as site-based population and employment  
36                  densities), as well as cycling-relevant roadway conditions. Roadway condition variables were  
37                  chosen from the 2010 *Highway Capacity Manual's* Chapter 17 on urban street segments  
38                  (including factors like traffic volumes and bike lane width), as well as other physical features  
39                  like bridge presence and access to bicycle trails. Model results show greatest practical  
40                  significance for the City of Seattle indicator variable and curb lane width (both of which are  
41                  correlated with higher counts) and roadway speed (which shows quadratic impacts, with  
42                  expected counts highest around 35 mph and decreasing as speed becomes higher or lower). The  
43                  model is implemented in the community of Shoreline, Washington, just north of Seattle, to  
44                  demonstrate its applicability. As such, the evaluation examines both segment-based bicycle level  
45                  of service and expected intersection-based counts. Model application findings indicate that

1 segment-based bicycle level of service shows little correlation with expected counts, though such  
2 information may be used to target new cycling infrastructure improvements.

### 3 4 **INTRODUCTION**

5  
6 States and municipalities are tasked with annually counting the number of motor vehicles  
7 traveling their roads through the federally mandated Highway Performance Monitoring System  
8 (HPMS). Permanent Automatic Traffic Recorders (ATRs) employing inductive-loop detectors  
9 and temporary pneumatic road tubes are typically used to collect vehicle counts at a sample of  
10 locations throughout local and state networks (FHWA 2011). This information is then used by  
11 transportation planners, designers and policymakers when weighing crucial decisions such as  
12 anticipated funding, future needs, and design requirements for proposed projects.

13  
14 Unfortunately, few states and municipalities have formal procedures for counting bicyclists (Eco  
15 Counter 2012). Without a federal mandate, most agencies forego tracking non-motorized forms  
16 of travel, other than perhaps conducting a limited assortment of spot-counts at intersections or  
17 trail segments. This approach can result in substantial unmet needs and inappropriate  
18 investments and policies, as decision-makers rely on minimal demand data for bike routes. To  
19 address such shortcomings, this research develops a direct demand model based on bicycle count  
20 data in the Seattle, Washington region in combination with other, geo-spatial data in order to  
21 estimate peak-hour cyclist counts at urban intersections. While these efforts fall short of a full  
22 bicycle count program, they remain a useful way to estimate cyclist counts in locations where  
23 direct counts are not available.

### 24 25 **BACKGROUND**

26  
27 The direct-demand model used here is a suitability model, intended to identify the locations  
28 where the presence of cyclists is anticipated to be the greatest, based on roadway conditions and  
29 a number of other factors. These methods are similar to those used by Davis (1995) to generate  
30 suitability models and maps for cyclists. The model developed here differs from many other  
31 bicycle suitability models in several key respects. For example, the San Antonio, Texas  
32 (SABCMPO 2011), Syracuse, New York (SMTCMPO 2003), and Atlanta, Georgia (Atlanta  
33 Bicycle Coalition 2010) models focus on locations that are most conducive to bicycling, such as  
34 areas where motorized-vehicle speeds and counts are low, road shoulders are wide, and  
35 dedicated lanes often present. While these factors are valuable flow predictors, our model's goal  
36 is to determine not where cyclists *should be riding*, but rather where they *are riding*. Thus, the  
37 model specified here is much more similar to (though less complicated than) KTU&A's (2011)  
38 model and map for the City of Chula Vista, California. KTU&A's model employed bike-trip  
39 attractors (parks, schools, retail, neighborhood civic facilities, etc.) and generators (residential  
40 population), along with additional demographic and attraction details, in order to produce a  
41 three-stage generation-attraction-routing model. This paper's investigation is also informed by  
42 Griswold et al.'s (2011) similar investigation, using two-hour cyclist counts across 81 sites in  
43 Berkeley, California, and by McNeil's (2011) exploration of neighborhood "bikeability" in  
44 Portland, Oregon, on the basis of infrastructure provision and destination details.

1 Cycling suitability models are quite valuable. They can be used by transportation agencies to  
2 generate maps for informing cyclists of the most suitable (and safe) routes, as demonstrated by  
3 Hochmair and Fu (2009) for Broward County, Florida. They can be used to identify “missing  
4 links” in cycling networks, to better plan for new facilities (KTU&A 2011), and/or improve  
5 cycling safety (Allen-Munley et al. 2004). This last need is particularly pressing: the National  
6 Highway Transportation Safety Agency (2010) reported that 630 cyclists were killed and 51  
7 thousand injured in 2009 on U.S. roadways. To put this in context, given BTS’ (2004) estimate  
8 that about 0.2% of total miles traveled are by bicycle travel, on a per-mile basis cyclists  
9 experience fatality rates nearly 30 times higher than passenger car occupants, which is even  
10 higher than that of motorcyclists (NHTSA 2010). The cyclist count estimation model  
11 investigated here supports such efforts to improve bicycle safety and planning.

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### 13 DATA ASSEMBLY

15 In order to predict bicyclist counts at intersections, suitability attributes for the major roadway  
16 approaches at each intersection were developed. These attributes are based on the *Highway*  
17 *Capacity Manual’s* (TRB 2010) Chapter 17 procedures for Bicycle Level of Service (BLOS) at  
18 the individual segment-link level, and include a series of 17 equations requiring 6 conditional  
19 evaluations (i.e. “if/else” statements). A segment approach is used here, rather than an  
20 intersection approach, since the intersection BLOS methodology emphasizes control delay<sup>1</sup> and  
21 requires signal phasing and turning movement information that is often not available. Key  
22 (adjustment) factors influencing segment BLOS include cross-section information, motorized  
23 vehicle volumes and speeds, and pavement conditions; their required inputs include the number  
24 of segment through lanes, outside lane width, outside shoulder width, bike lane width, proportion  
25 of occupied on-street parking during the evaluation period, share of heavy vehicles, mid-segment  
26 flows, motor vehicle running speeds, and pavement condition information. Other meaningful  
27 demand factors were also collected, including population and jobs densities and a residential land  
28 use indicator (for predicting trip generation); adjacency to the major cycling trails (e.g. the  
29 Interurban Trail and Burke Gilman Trails), and indicator variables for proximity to recreational  
30 areas and bridges, as well as other geometric, topographic and roadway features (like the  
31 presence of separated bike paths and shared lane use traffic markings, or “sharrows”, as shown in  
32 Figure 1).

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<sup>1</sup> Control delay is average time spent waiting at an intersection before proceeding.

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Figure 1: Roadways with Bike Lanes, Separated Bicycle Facilities and Sharrows  
(Seattle Department of Transportation 2007)

Bicyclist count data was obtained from the Puget Sound Regional Council (PSRC), which conducted extensive counts at intersections (PSRC 2010a) in October 2010, collecting over 340 three-hour counts that month. Data collection was conducted all over the region, though the areas with greater populations were emphasized, with approximately one third of all counts taken within Seattle’s city limits. Counts occurred Tuesdays through Thursdays, with each count collected during the hours of 6 AM – 9 AM or 3 PM – 6 PM. Additional information collected at the time of the counts reflected precipitation levels, day of week and mean temperature, but their values did not vary substantially, since all counts were taken during a single month and only one location experienced more than 0.32 inches of precipitation in the 3-hour observation period. All bicycle trail counts were removed, since they do not offer roadway BLOS values and so could not appear in the sample cycling demand regression equations. Similar future efforts could be conducted to develop a suitability model for these trail segments, though this was not conducted in the investigation described here.

Average Annual Daily Traffic (AADT) volumes (for automotive traffic) had to be obtained from numerous sources, covering the cities of Auburn (2009), Bellevue (2010), Bothell (2010), Bremerton (2011), Federal Way (2011), Kent (2009), Kirkland (2008), Lakewood (2010), Lynwood (2005), Puyallup (2008), Redmond (2010), Renton (2010), Seattle (2012), Tacoma (2011), and Kitsap County (2010). While AADT counts spanned several years due to the patchwork jurisdictions, each with their own count program, when multiple count dataset were available for a given location, the dataset closest to October 2010 was chosen. Bike-count locations in Burien, Silverdale, Snohomish, Tukwila and a handful of single-count locations where traffic counts were unavailable had to be excluded from the analysis. In cities with AADT data but missing AADT values for the specific bike-count locations, auto traffic was estimated at 5,000 AADT on the major roadway and 3,000 AADT on the minor roadway within Seattle. Outside Seattle, 3,000 AADT was assumed on the major roadway and 2,000 AADT on the minor roadway. About 12% of volumes were assigned in this way, with 25 of 32 locations in the City of Seattle.

Year 2010 population data was obtained from the U.S. Census at the census tract level, which was used to compute tract-level population density values. Since many count locations lie on borders between tracts (since important roadways regularly divide census tracts), each site’s

1 population density estimate was an average from all adjacent tracts. Similarly, employment data  
 2 (and associated shape files) were obtained from the PSRC for larger Forecast Analysis Zones  
 3 (FAZs), where are typically on the order of one to 15 square miles in area. As with population  
 4 density estimates, employment estimates were averaged when count locations fell along the  
 5 border of two or more FAZs.

6  
 7 Google Earth’s satellite photos were used to identify other factors, such as the number of lanes,  
 8 parking presence, and bicycle lane details at individual locations, as noted above. Curb lane  
 9 width (for the lane closest to the curb) and bicycle lane-plus-shoulder widths were estimated  
 10 using Google Earth’s measuring tool, taking measurements from the middle of the painted  
 11 lines/edge striping to the edge of traveled way or gutter-pan (if present). Widths for bike lanes  
 12 and shoulders with no parking present were combined into a single category (referred to in Table  
 13 1 and hereafter as “bike lane width”), since it was often difficult to distinguish the two from  
 14 satellite photos. While modelers wishing to conduct similar investigations using these methods  
 15 may use HPMS data to possibly better assess these features, such values were not available here  
 16 (and they may not be meaningful for cyclists, who do not know what values engineers have  
 17 logged in the HPMS data set: they only know what they see on the road, as visible in Google  
 18 Earth images). Speed limits were estimated based on a combination of factors, including  
 19 roadway functional classification, intersection density, roadway width, on-street parking, and  
 20 land use, as well as comparisons to similar streets in Shoreline (the city used later for model  
 21 application) for which speed data was available (City of Shoreline 2012b). A bridge indicator  
 22 for crossing the region’s water bodies was included to account for impacts of limiting possible  
 23 route choices. Also, a residential land use indicator was used based on adjacent development,  
 24 with the requirement that all corners must be residential land use for the location to be counted as  
 25 residential. Each location was counted either during the AM peak or PM peak, though not both.  
 26 Table 1 summarizes the collected data for all count locations, with subsections separating factors  
 27 impacting cyclist trip generation and attraction from factors impacting the roadway environment,  
 28 and temporal factors (precipitation, time of day, and temperature).

29  
 30 Table 1: Cyclist Count Location Attribute Summary

Variable	Mean	Min.	Max.	Std. Dev.
<b>Bicycle Count (in 3-hour period)</b>	36.3	0	578	75.4
<b>Seattle</b>	0.363	0	1	0.48
<b>Pop. Dens. (1000 / sq. mi.)</b>	2.29	0.123	10.0	1.83
<b>Empl. Dens. (1000 / sq. mi.)</b>	8.58	0.279	70.2	13.0
<b>Bike Trail Access</b>	0.036	0	1	0.19
<b>Bridge</b>	0.032	0	1	0.18
<b>Recreational Area Access</b>	0.092	0	1	0.29
<b>AADT (1000s)</b>	14.6	0.538	59.3	11.5
<b>Median Present</b>	0.06	0	3	0.29
<b># Lanes</b>	3.49	1	8	1.38
<b>Curb Lane Width (ft.)</b>	11.22	8.20	19.65	1.61
<b>Bike Lane Width (ft.)</b>	0.89	0	6.96	1.94
<b>Sharrows</b>	0.084	0	1	0.28
<b>Separated Path</b>	0.020	0	1	0.14

<b>Speed (mph)</b>	32.5	25	50	4.57
<b>Parking Present</b>	0.215	0	1	0.41
<b>Residential</b>	0.175	0	1	0.38
<b>Precipitation (in.)</b>	0.07	0	8.06	0.51
<b>AM Period</b>	0.530	0	1	0.50
<b>Mean Temp. (deg. F)</b>	52.89	44	58	3.18

$n_{\text{obs}} = 251$

This summary data show that 36% of all counts were collected within the City of Seattle, and employment density was higher than population density in 76% of all count locations. Motorized-vehicle traffic volumes were typically moderate (averaging 14,620 AADT), as were traffic speeds (averaging 32 mph). About 18% of all count locations featured bike lanes, which averaged 4.9 feet in width when present. A scattering of count locations were on bridges (3.2%), near bike trails (3.6%), near recreational areas like parks or arenas (9.2%), or in residential areas (17.5%); but most count locations were in commercial areas, with none of these features.

While the data collection for this analysis was extensive, it can be improved. For example, heavy vehicle shares and pavement conditions appear in BLOS equations, as noted above, but were not included here due to data availability issues and difficulties in assessing pavement conditions using satellite images. This is made even more difficult since two or more years often separated the Google Earth images from cyclist counts. Only motor vehicle AADTs and major-street geometric features were assembled, due to frequently missing traffic volumes.

## DIRECT-DEMAND MODEL

Using the cyclist count data and location-specific explanatory variables noted above, three cyclist count estimation models were developed. These models included a preliminary Poisson regression count model (P1), a secondary Poisson regression count model (P2) that permits heteroskedasticity in error terms by using robust error terms, and a negative binomial model (NB). The negative binomial model (NB) takes the following form, as noted in Greene (2011):

$$Y \sim \text{Poisson}(\lambda + \varepsilon), \text{ where } E[Y|\mathbf{x}, \varepsilon] = \exp(\boldsymbol{\beta}'\mathbf{x} + \varepsilon) = h\lambda,$$

$$h = \exp(\varepsilon) \sim \text{Gamma}(\theta, \theta), \lambda = \exp(\alpha + \boldsymbol{\beta}'\mathbf{x}), \text{ and}$$

$$\text{Prob}(y_i = j|\mathbf{x}_i) = \frac{\exp(-h_i\lambda_i)(h_i\lambda_i)^j}{j!}, \text{ for } j = 0, 1, \dots$$

The gamma error term ( $\varepsilon$ ) has a unit mean and variance  $1/\theta$ , where  $\theta$  is called the dispersion parameter. The Poisson-gamma interaction results in a negative binomial distribution for cyclist counts, conditioned on an individual's explanatory factors  $\mathbf{x}$ . The vector of parameters  $\boldsymbol{\beta}$  was estimated using weighted maximum-likelihood regression, in Stata software.

Transformations and interactions of various covariates were also investigated, as potential explanatory variables (e.g., natural log and squared transformations of the density variables, traffic volumes (AADT), speed, and curb and bike lane widths). Count-specific indicator variables were also tested, along with Seattle- and Tacoma- specific indicator variables. These location-specific indicator variables served two purposes: they served as a proxy for the larger

1 population (for trip generation) and employment/destinations (for trip attraction) that can most  
 2 easily access the count location, and they helped identify whether the populations' latent  
 3 propensity for cycling was stronger in some areas than others.

4  
 5 The model was then first estimated using all potential explanatory variables, then dropping  
 6 variables using stepwise elimination until all remaining explanatory variables were statistically  
 7 significant at the 5% level. As expected, due to its behavioral flexibility, the NB model is  
 8 preferred, though all results are shown in Table 2, and used in later discussion. For the preferred  
 9 NB model, elasticity values were also estimated by perturbing coefficient values by 1% and  
 10 observing the resulting impact on estimated cyclist counts. For example, if curb lane widths  
 11 uniformly increase by 1%, a resulting 0.56% increase in regional counts could be expected.

12  
 13 Table 2: Poisson Regression Bicycle Count Estimation Model

Variable	Poisson (P1)		Poisson w/ RSE (P2)		Neg. Bin. (NB)		
	Coef.	Std. Dev.	Coef.	Std. Dev.	Coef.	Std. Dev.	Elasticity
<b>Constant</b>	-14.55	1.04	-9.412	3.363	-4.185*	2.019	-4.10
<b>Seattle</b>	1.782	0.045	1.842	0.225	1.64	0.152	1.27
<b>Pop. Dens. (1000 / sq. mi.)</b>	0.070	0.011	-	-	-	-	-
<b>Empl. Dens. (1000 / sq. mi.)</b>	0.012	0.003	-	-	-	-	-
<b>Ln (Empl. Dens.)</b>	0.134	0.022	0.204	0.06	0.175	0.042	0.34
<b>Pop. D. * Empl. D. / 1000</b>	-2.090	0.688	-	-	-	-	-
<b>Bike Trail Access</b>	1.327	0.038	1.281	0.261	1.255	0.32	0.21
<b>Bridge</b>	1.302	0.054	1.477	0.209	1.117	0.256	0.25
<b>Recreational Area Access</b>	0.208	0.042	-	-	-	-	-
<b>Curb Lane AADT (1000s)</b>	-0.070	0.008	-	-	-	-	-
<b>AADT (1000s)</b>	-0.050	0.010	-0.012*	0.006	-	-	-
<b>Ln (AADT)</b>	0.475	0.081	-	-	-	-	-
<b>AADT<sup>2</sup> / 1000</b>	0.556	0.101	-	-	-	-	-
<b>Median Present</b>	-0.426	0.066	-	-	-	-	-
<b>Curb Lane Width (ft.)</b>	4.557	0.791	-	-	0.558	0.256	0.58
<b>Curb Lane Width<sup>2</sup> (ft.)</b>	-0.509	0.105	-	-	-	-	-
<b>Bike Lane Width (ft.)</b>	0.240	0.072	-	-	0.597*	0.282	0.11
<b>Sharrows</b>	-0.447	0.044	-	-	-	-	-
<b>Separated Path</b>	1.209	0.043	0.916	0.245	1.163	0.352	0.24
<b>Speed (mph)</b>	0.733	0.056	0.678	0.197	0.357	0.119	12.17 (0.42)
<b>Speed<sup>2</sup> / 1000 (mph)</b>	-	0.857	-9.536	2.898	-5.269	2.017	-5.35 (0.42)
<b>Residential</b>	-0.482	0.046	-0.544	0.169	-0.397	0.135	-0.03
<b>AM Period</b>	-0.527	0.038	-0.484*	0.222	-0.56	0.103	-0.41
<b>Mean Temp.</b>	0.014	0.005	-	-	-	-	-
<b>Over-dispersion Param. (θ)</b>	-	-	-	-	0.427	0.046	-

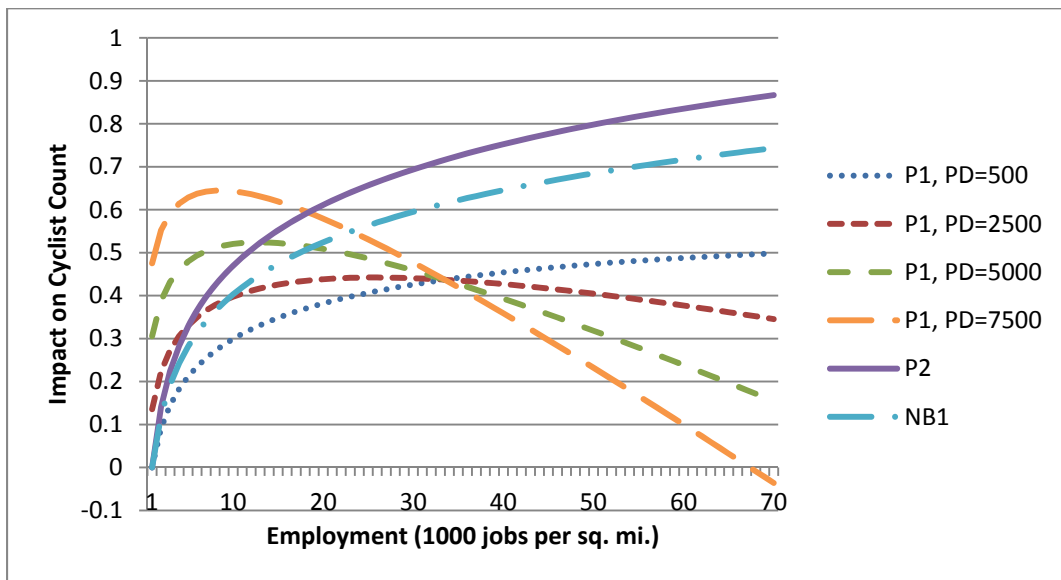
<b>Pseudo R<sup>2</sup></b>	0.7585	0.7369	0.506
<b>Log-Likelihood</b>	-2280.1	-2484.3	-971.09

1  $N_{obs} = 251$ , RSE = robust standard errors.  
2 \* indicates statistical significance at the 5% level; all other covariates statistically significant at the 1% level.  
3 Parentheses indicate the joint elasticity effects of both Speed and Speed<sup>2</sup> covariates  
4

## 5 MODEL ANALYSIS AND ASSESSMENT

6  
7 The model results suggest many things. First, the natural log of employment density, bike trail  
8 access and Seattle indicator variables have positive coefficients. These coefficients are  
9 intuitively consistent since all three covariates serve as bicycle trip attractors, with the Seattle  
10 indicator variable also representing a trip generator. The Seattle variable by far exhibited the  
11 greatest elasticity (and practical significance) outside of the decoupled speed covariates, and  
12 employment also showed notable practical significance. Population density (for trip generation)  
13 and recreational area proximity (for trip attraction) also appear with positive coefficients in the  
14 P1 model, though their absence in the other two models suggests a weaker connection to cyclist  
15 counts. As expected, the bridge-variable's coefficient is estimated to be positive, since bridges  
16 tend to funnel travelers from many routes into a single crossing route.

17  
18 It is also interesting to understand the interactions of population and employment in the P1  
19 model, as compared to the other two models, as shown in Figure 2. This figure illustrates how  
20 cyclist counts rise with employment density, but eventually taper off (and may actually fall off, if  
21 both employment and population density levels are high, presumably as trip distances shorten,  
22 streets congest, and travelers can turn to walking). It should be noted the high end of these x-axis  
23 values are rarely seen in Seattle: employment density exceeds 30,000 jobs per square mile in just  
24 5% of the count sizes, and in only one of those observations was population density at least  
25 5,000 persons per square mile.  
26



27  
28 Figure 2: Model-Predicted Impacts of Employment and Population Density on Cyclist Counts  
29 Notes: PD = Population density per sq. mi. Chart normalized for P1 so intercept = 0 at PD=500 & ED = 0.  
30



1 In addition to trip generation and attraction, the roadway environment was found to significantly  
 2 impact cyclist counts across locations. It is meaningful to compare the impacts of BLOS-  
 3 estimated values with those of the count models developed here, as shown in Table 3. Here,  
 4 model results are compared against the HCM BLOS formula values using roadway  
 5 characteristics contained in both sets of models. Table cells list whether the key measures  
 6 positively or negatively impact cyclist counts and HCM BLOS, as well as their functional  
 7 relationship to the key measures. Lower scores on the HCM BLOS index represent better  
 8 cycling conditions, so any positive impacts noted in Table 3 should be taken to represent lower  
 9 HCM BLOS values.

10  
 11 Table 3: Comparison of Cyclist Count Models and HCM BLOS

Parameter	Impact on Cyclists			Agreement
	Model P2	Model NB	HCM BLOS	
<b>Bike Lane Width</b>	-	Linear, Positive	Square, Positive	Partial
<b>Curb Lane Width</b>	-	Linear, Positive	Square, Positive	Partial
<b>Curb Lane AADT</b>	-	-	Log, Negative	Partial
<b>Segment AADT</b>	Linear, Negative	-	-	Partial
<b>Speed</b>	Lin./Sq., Mixed	Lin./Sq., Mixed	Log, Negative	Possible

12  
 13 As Tables 2 and 3 indicate, increased bike lane widths and curb lane widths are correlated with  
 14 higher cyclist counts in the NB model, with bike lane widths exhibiting a slightly stronger impact  
 15 than curb lane widths. This is consistent with the HCM BLOS formulations, though the  
 16 estimated impacts are linear, rather than quadratic/squared. In terms of practical effects, curb  
 17 lane width has a relatively high elasticity value (when compared to bicycle lane width as well as  
 18 other values), due in part to the presence of curb lanes at all count locations.

19  
 20 While the NB model specification does not suggest that automotive traffic volumes impact  
 21 cyclist counts in any statistically significant way (given the relatively small data set used here),  
 22 statistically significant impacts were estimated in the P1 and P2 models. Both models showed  
 23 generally negative impacts of rising AADT on estimated cyclist counts (in agreement with the  
 24 HCM BLOS), though some key differences emerge, as shown in Figure 3.

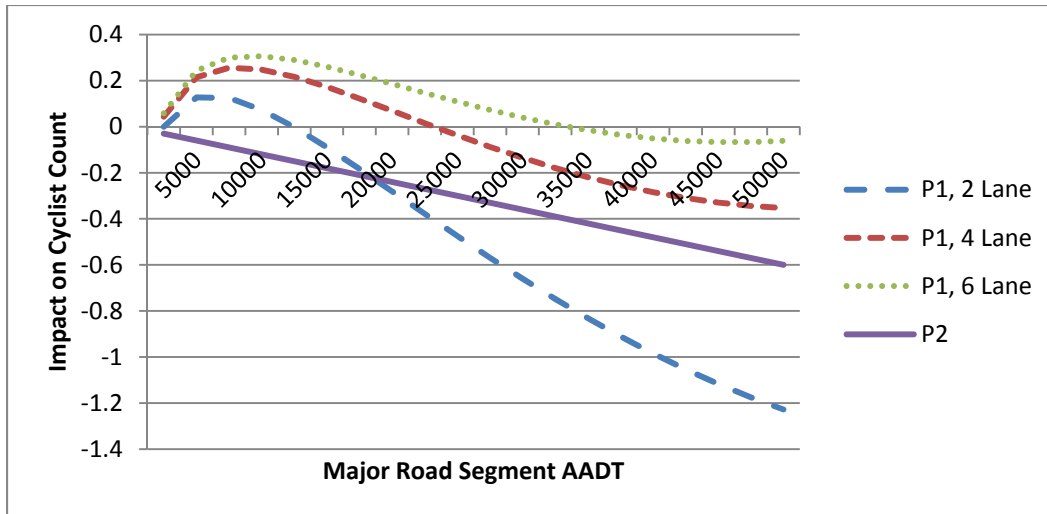


Figure 3: Impacts of Major Road Segment AADT on Cyclist Counts

Note: Chart normalized for P1 so intercept = 0 at AADT = 2500 with 2 lanes.

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Model P1 exhibits consistency with the HCM BLOS formulas in both the logarithmic functional component and the use of curb lane traffic volumes, rather than just road segment AADTs. However, at low traffic volumes model P1's application will continue to generate higher predicted cyclist counts until curb lane volumes reach about 2500 vehicles per day. While the P2 model suggests linear impacts and relies on segment AADTs rather than curb lane volumes, this model and its overall impacts are preferred to those of P1, thanks to its greater functional flexibility, helping avoid the issues encountered in the P1 model in the presence of low AADT values.

Speed limit impacts in the cyclist count model offer both positive and negative impacts, thanks to the presence of a squared speed limit term with a negative coefficient estimate. The resulting concave response prediction exhibits its greatest positive impacts at roughly 35 mph (slightly below 35 mph in model NB and slightly above in P1 and P2), as illustrated in Figure 4.

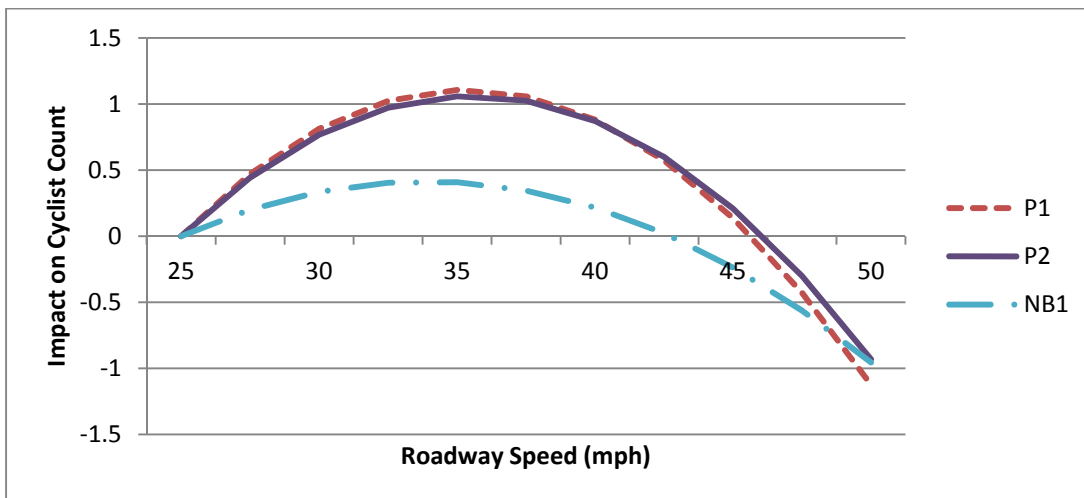


Figure 4: Impacts of Roadway Speed on Cyclist Counts

Note: Chart normalized so intercept = 0 at 25 mph in all models.

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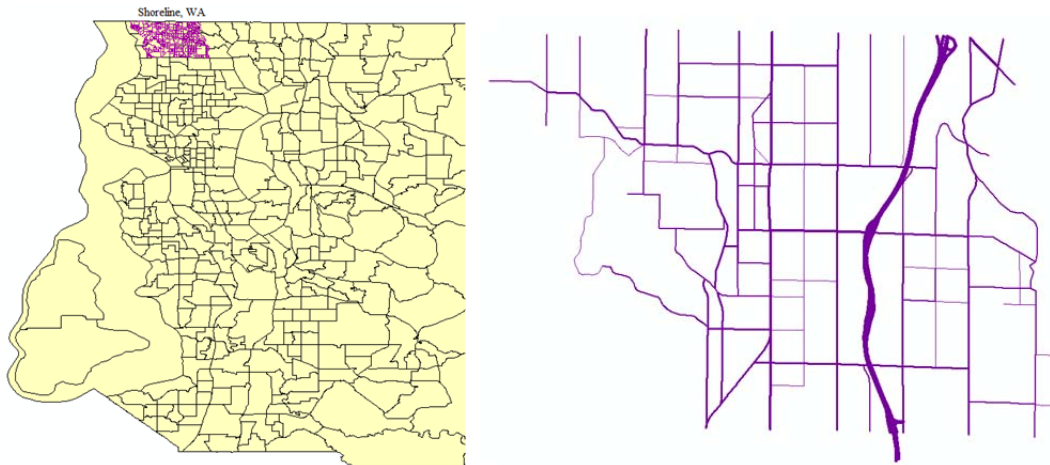
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2 Cyclist utility may be the driving factor here, explaining the discrepancy between the count-  
3 model predictions and those from HCM BLOS formulae. Locations with low speeds are less  
4 likely to like along more popular cycling routes, with bike trips concentrating on higher-speed  
5 collectors and arterials, much like car traffic concentrates on higher-order roadway facilities.  
6 Lower speeds (and speed limits) may also come with high intersection density, creating  
7 additional cyclist conflicts with autos and stops. However, the model predictions suggest that  
8 cyclists tend to avoid the highest speed roads and seek other routes. (Recall that the data set's  
9 speed values are estimates, so trends may vary a bit, if true speed limits and actual traffic speeds  
10 are controlled for throughout.) When taken individually, the speed-related covariate elasticities  
11 dominate other factors. However, even jointly speed is the third most influential input for  
12 predicting cyclist counts, with elasticity values indicating that slight increase in system-wide  
13 speeds would lead to a corresponding increase in cyclist counts.

14  
15 Other estimates' signs are also readily explained. For example, the presence of separated paths  
16 comes with significantly higher cyclist counts across all models, which may simply come from  
17 designers working to provide separated paths at high-demand/high-use locations; and, once  
18 constructed, they are likely to attract even more cyclists. Residential areas are regularly on road  
19 systems enjoying less network connectivity (e.g., those having cul de sacs), and offer fewer trip  
20 attractors than commercially developed areas, which may explain the negative coefficient across  
21 all three models. Cyclists were also predicted to prefer afternoon riding to morning, which is  
22 consistent with motorized traffic counts. (More trips are made in the afternoons, right after  
23 school and work.)

24  
25 Three other explanatory variables emerged in the P1 model, but not in the P2 or NB model, so  
26 their associated implications should be examined with some caution. In the P1 model, the  
27 presence of a median is associated with lower roadway cycling suitability, perhaps due to  
28 restrictions on bike maneuverability (as well as higher traffic flows, but this variable was  
29 controlled for already). Non-intuitively, sharrows were estimated to have a negative impact on  
30 cycling suitability, perhaps because such measures were taken as interim measures (in lieu of  
31 providing dedicated bicycle lane)s; or it could simply be a false-positive arising in the model  
32 (due to the Poisson specification's less flexible structure). Finally, warmer temperatures  
33 appeared generally preferred, within the observed 44 to 58 degrees (Fahrenheit) range.

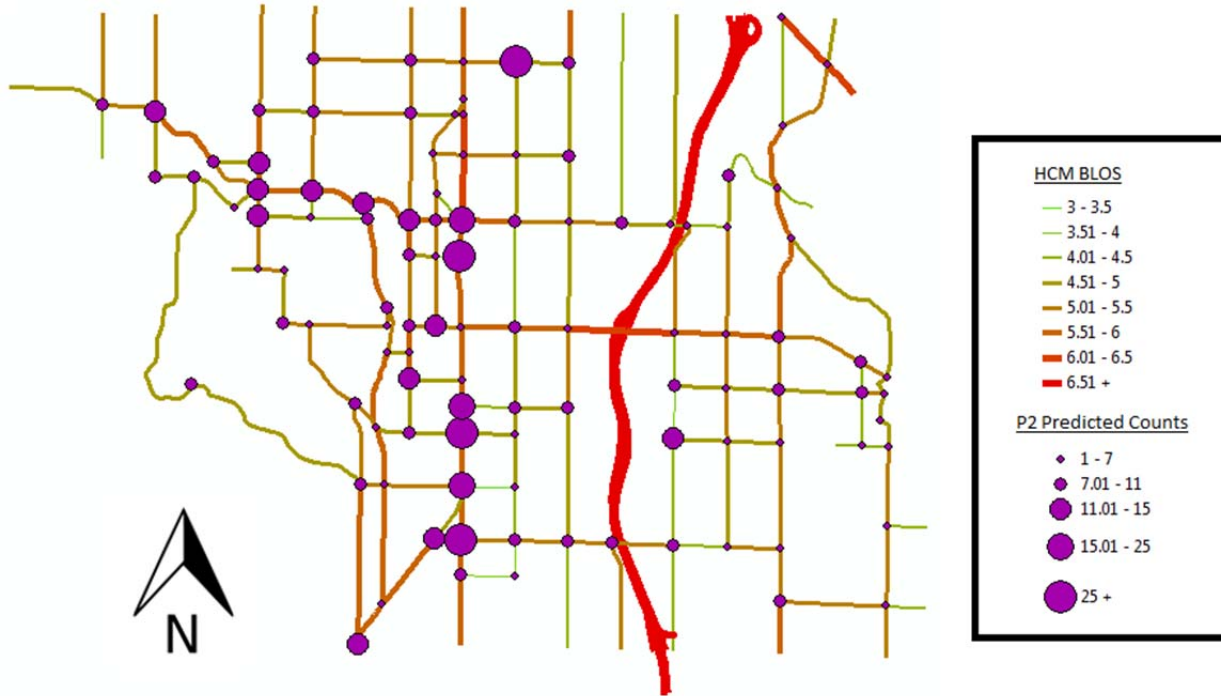
## 34 35 **MODEL APPLICATION**

36  
37 Both models P2 and NB were applied to the City of Shoreline, Washington, a small municipality  
38 of 53,000 persons within a 12.3 square mile area (City of Shoreline 2012a), located just north of  
39 Seattle in the northwest corner of King County as shown in Figure 5.  
40

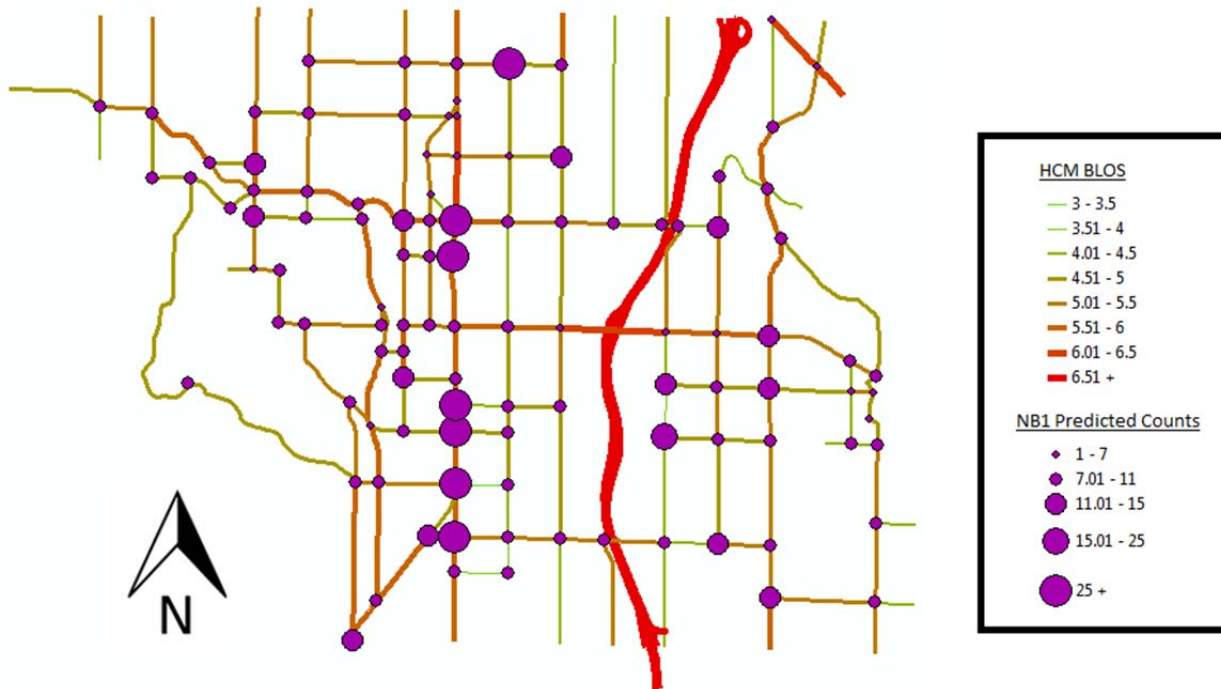


1  
2 Figure 5: Shoreline, WA Location in the Northwest Corner of King County (Left) and Shoreline  
3 Roadway Transportation Network (Right) with Line-weights Representing Auto Traffic Flows  
4

5 Roadway traffic counts (AADTs) and 24-hour average weekday speeds were obtained from the  
6 City of Shoreline (2012b). All roadway links with less than 1,000 AADT were eliminated, to  
7 ensure a reasonable number of sample links while eliminating cul-de-sacs and minor residential  
8 streets that should expect very low levels of cyclist traffic. This resulted in a final sample of 182  
9 (bi-directional) segment links and 106 intersections. Shoreline is covered by two FAZs and is  
10 composed of 13 census tracts, providing some variation and diversity in model inputs/site  
11 attributes. Once traffic, speeds, employment, population and roadway characteristics were  
12 compiled, the HCM BLOS model was applied to the City of Shoreline's links and cyclist  
13 estimation count models were applied to Shoreline's intersections, resulting in Figure 6's two  
14 maps (both using model P2) and Figure 7's two maps (using the NB specification). These  
15 figures both assume an afternoon count, and estimate intersection cyclist counts based on major  
16 (higher AADT) road characteristics. Each individual road link also shows the HCM BLOS score  
17 (where high values represent poor level of service), assuming constant values for reasonably  
18 good pavement condition (scoring 4 out of 5) and 5% heavy truck volumes.  
19



1  
2 Figure 6: Bicycle Counts for Shoreline, Washington, using HCM BLOS on Links and P2 Model  
3 Forecasts for Intersection Counts



4  
5 Figure 7: Bicycle Counts for Shoreline, Washington, using HCM BLOS on Links and NB Model  
6 Forecasts for Intersection Counts  
7

8 Important inferences may be made when comparing the two maps and count model applications.  
9 First, the NB model estimated consistently higher intersection counts (of cyclists) than the P2  
10 model did. NB model predictions ranged from 5.4 to 49.2 cyclists (per 3-hour afternoon period),

1 averaging 10.2 with a standard deviation of 6.7, in contrast to the 3.4- to 31.8-cyclists range, 8.6-  
2 cyclist average, and 5.0-cyclist standard deviation under the P2 model.

3  
4 Despite these minor differences, however, the two models generated very similar results. Both  
5 models showed strong agreement regarding locations with the greatest number of cyclists. These  
6 intersections ran north-south along Aurora, cutting slightly east at the far northern end. These  
7 locations aligned with access to the Interurban (bicycle) Trail, though it should be noted that the  
8 trail skews slightly east of a few intersections, which the map clearly shows as having lowered  
9 count estimates. When excluding these seven intersections, the two models remain in relative  
10 agreement when identifying higher-usage locations. For example, model NB identifies another  
11 14 locations with more than 11 cyclists and model P2 another 12 locations, of which 7 are in  
12 agreement. For the remainder, all five of the locations that P2 predicted as having 11 or more  
13 cyclists (in the 3-hour peak period) had 10 or more cyclists in the NB model, and model P2  
14 shows counts similarly close to the 10-cyclist threshold, though to a lesser degree. Moreover,  
15 estimated counts at just 18 of the 106 intersections differed by more than 3 cyclists, with an  
16 average discrepancy of 5.1 cyclists among these intersections, and those discrepancies  
17 attributable to bike trail access, bike lane presence, and/or large curb lane widths (i.e., greater  
18 than 4 meters). All this agreement is to be expected: both models relied on the same data set and  
19 have just three dissimilar parameters (AADTs in P2, and curb and bike lane widths in NB).

20  
21 Additional insights can be gleaned by comparing intersection cyclist count model results to the  
22 HCM BLOS values for segments leading into those intersections. HCM BLOS values for the  
23 modeled segments varied from 3.2 to 6.6 cyclists (for a 3-hour weekday, afternoon period),  
24 averaging 5.1, with a standard deviation of 0.54. HCM BLOS values ultimately appeared to  
25 offer minimal impact on intersection count predictions, with other factors having greater  
26 influence on count model forecasts. Many intersections with intersecting streets having low  
27 HCM BLOS values had high counts, and many intersections that had favorable HCM BLOS had  
28 low counts. Overall, there appeared to be little correlation, likely due to the previously noted  
29 parabolic speed impacts, and the negative sign on the residential indicator coefficient.  
30 Nevertheless, merging these datasets does present valuable opportunities: areas with low HCM  
31 BLOS and high predicted cyclist counts may be strong candidates for further cycling  
32 infrastructure enhancements.

## 33 34 **CONCLUSIONS**

35  
36 This investigation developed a series of direct demand cyclist count models to estimate the  
37 number of cyclists on roadway segments in the Seattle Metropolitan area. The models were  
38 compared to the HCM's BLOS index, which estimates cyclist suitability and comfort based on  
39 roadway characteristics. Consistencies between the count models and the HCM BLOS index  
40 show that wider bike lanes and curb lanes, along with lower traffic volumes, create favorable  
41 conditions for higher numbers of cyclists. While the two preferred models developed here  
42 indicate either the use of curb lane width or bike lane width or automotive traffic volume be  
43 used, it is likely that all three variables would become statistically significant if more data points  
44 were available.

1 The model estimates primarily diverge from HCM BLOS in cases where a roadway feature has  
2 positive impacts for cyclist comfort, but suggests little destination attractiveness (such as  
3 residential neighborhoods and location with driving speed limits 30 mph and lower). These new  
4 models also feature trip generation and attraction terms that provide a more complete and  
5 accurate characterization of locations with numerous cyclists. When the cyclist count models  
6 and HCM BLOS indices were both applied to Shoreline's roadway network, the two most  
7 preferred cyclist count models showed very close predictions to one another, though little  
8 correlation with HCM BLOS values for intersecting streets, which is largely due to the  
9 residential covariate's effects, and the concavity of speed-limit impacts, on estimated cyclist  
10 counts.

11  
12 In summary, the cyclist count models developed in here show significant promise for forecasting  
13 bicycle demand in the Seattle metro area and beyond. While this exploration showed that the  
14 count models are still imperfect, it possesses significant utility and may be used by transportation  
15 planners to inform decision making, promote cycling, improve safety, and accommodate cyclists  
16 within their neighborhoods and regions. Moreover, by combining estimated cyclist counts with  
17 the actual levels of service that they are experiencing, locations with the greatest need and/or  
18 potential for cycling enhancement may be quickly identified. After all, most cities do not  
19 conduct comprehensive bicycle count programs and so lack reliable information as to where  
20 cyclists really are. While this model falls short of a comprehensive count program, it gives  
21 analysts the tools to generate cyclist count predictions based on readily available roadway  
22 characteristics and population and employment information, thus enabling more informed  
23 planning and decision making.

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