Title
The Half-Mile Circle: Does It Best Represent Transit Station Catchments?

Authors
Guerra, Erick
Cervero, Robert
Tischler, Daniel

Publication Date
2011-08-01

University of California Transportation Center
UCTC-FR-2011-09

The Half-Mile Circle:
Does It Best Represent Transit Station Catchments?

Erick Guerra, Robert Cervero and
Daniel Tischler
University of California, Berkeley
August 2011

Abstract

One-half mile has become the accepted distance for gauging a transit station's catchment area in the U.S. It is the de facto standard for planning TODs (transit oriented developments) in America. Planners and researchers use transit catchment areas not only to make predictions about transit ridership and the land use and socioeconomic impacts of transit, but also to prescribe regulations, such as the relaxation of restrictive zoning, or carve out TOD financial plans. This radius is loosely based on the distance that people are willing to walk to transit, but this same reasoning has been used to justify other transit catchment areas. Using station-level variables from 1,449 high-capacity American transit stations in 21 cities, we aim to identify whether there is clear benchmark between distance and ridership that provides a norm for station-area planning and prediction. For the purposes of *predicting* station-level transit ridership, we find that different catchment areas have little influence on a model's predictive power. This suggests that transit agencies should use the easiest and most readily available data when estimating direct demand models. For *prescribing* land-use policy, by contrast, the evidence is less clear. Nevertheless, we find some support for using a quarter-mile catchment area for jobs around transit and a half-mile catchment for population. While these distances will likely vary from place to place and depending on the study purpose, they are a good starting point for considering transit-oriented policy or collecting labor-intensive data, such as surveys, about transit-adjacent firms or households.

INTRODUCTION

One-half mile has become the accepted distance for gauging a transit station's catchment area in the U.S. It is the de facto standard for the planning of TODs (transit oriented developments) in America. The Center for Transit Oriented Development provides a web interface with maps and data on 3,776 existing and 833 proposed American transit stations. They aggregate publicly available data on population, demographics, and employment using quarter and half-mile radii transit sheds. The half-mile radius is the default and a partner organization, Reconnecting America, has even named its blog Half-Mile Circles. This radius is loosely based on the distance that people are willing to walk to transit, but this same reasoning has been used to justify other transit catchment areas. Planners and researchers use transit catchment areas not only to make predictions about transit ridership and the land use and socioeconomic impacts of transit, but also to prescribe regulations, such as the relaxation of restrictive zoning, or carve out TOD financial plans.

A particularly intimate relationship has evolved between the half-mile circle and TOD planning. One-half mile corresponds to the distance over which someone from the edge of the circle can reach a station within 10 minutes walking at 3 mph. At a little more than 500 acres in size, the area within the half-mile ring represents the spatial extent of most TOD planning. Indeed, the principal justification for TOD is the promise of increasing ridership – notably, getting motorists to switch to trains and buses (*1*). Is there empirical evidence that demonstrates one-mile to be a norm – i.e., the appropriate catchment for station-area planning and policy-making?

In this paper, we run regression equations that predict the average of weekday boardings and alightings at 1,449 high-capacity American transit stations using a variety a radial transit catchment areas. Our aim is to see, statistically at least, whether there is clear benchmark between distance and ridership that provides a norm for station-area planning. We find strong evidence that, for the purposes of estimating station-level transit ridership, changing the radius has very little influence on a model's predictive power. A quarter-mile radius explains variation in transit ridership across the United States just as well as a half-mile radius, which itself performs similarly to a three-quarter mile radius. This suggests that transit agencies should use the easiest and most readily available station-area data when estimating direct demand models. For making causal inferences or developing land-use policy, we find some support for using a quarter-mile catchment area when looking at jobs around transit stations and a half-mile catchment when looking at population. While these distances will likely vary from place to place and depending on the study purpose, they are a good starting point for considering transit-oriented policy or collecting labor-intensive data, such as surveys, about transit-adjacent firms or households.

TRANSIT STATION CATCHMENT AREAS

The distance of origins and destinations from transit stations has a strong influence on whether people use transit to get to and from them. In a recent meta-analysis of the influence of the built environment on travel behavior, Ewing and Cervero (*2*) found that a one percent decrease in household's distance to transit corresponded with a 0.29 percent increase in transit use. Cervero (*3*) found that Californians living within one half mile (0.8 kilometers) of a transit station were four time more likely to use transit than those living between one half mile and three miles (4.8 kilometers) of transit and that dense jobs around destination stations significantly influenced the likelihood of transit use. In another Californian study, Cervero (*4*) found that 52.3

percent of previous automobile commuters switched to transit after moving within a half mile of transit stations. Where individual-level studies do not include a variable accounting for proximity to transit, transit access times capture the effect. Both stated preference surveys and observed behavior indicate that time spent walking is significantly more onerous than time spent in a car or transit vehicle (*5, 6*). Researchers have also found that many light, commuter, and heavy rail investments have significant impacts on surrounding land uses and property values *(7, 8, 9, 10, 11, 12, 13, 14*). Bus rapid transit investments have also influenced land use and land values around stations (*15, 16*).

Transit catchment areas are broadly based on an understanding of how far people are willing to walk to take transit. In addition to supporting the half-mile radius, the same general explanation has also been used to justify using quarter-mile (*17*) and two-fifths-of-a-mile (*18*) catchment areas (0.40 and 0.64 kilometers). Looking at 17 transit agencies with light rail service, O'Sullivan and Morral (*19*) found transit walking distance guidelines that ranged from 300 to 900 meters (0.19 to 0.56 miles). Given that road networks do not emanate radially from transit stations, some researchers define transit catchment areas based on road network distances (*20, 21*). Willingness-to-walk also varies by person, trip purpose, gender, age, land use, safety, weather, and the cost and availability of parking. Furthermore, there is no reason to expect that the impacts of a transit investment are limited to the average or even maximum walking distance. Many transit users access stations by car, bike, or bus. The half-mile transit catchment area, whether radial or network-based, is more an artifact of historical precedent than a statistical or analytical construct. In the case of individual- or parcel-level data, land use changes or probability of using transit can be measured partly as a function of actual distance between a household or office and a station. When data are aggregated within geographic areas, however, researchers generally must choose what area falls within a transit stations primary zone of influence. When data, computing power, and Geographic Information System (GIS) software are readily available, it is relatively simple to estimate a variety of models, using different assumptions about transit catchment areas. For example, several recent station-level direct demand models use multiple transit catchment bands to estimate transit ridership (*22, 23*). Similarly, studies on land use change and property values can divide treatment effects into various catchment bands (*16*).

When collecting primary data, as in a survey of households living near transit or site inspections, simplifying ridership predictions, as in direct demand models, or using the geography outside of the primary impact area as a statistical control, it is useful to have a better understanding of what distance delimits a transit catchment area. While this distance is likely to vary across locations and study purposes, current practice often assigns the catchment area somewhat arbitrarily. Through an analysis of station-level transit ridership in American cities, we hope to contribute to general knowledge about what catchment areas are most appropriate for what kinds of studies. This follows the work of others who have used statistical fits over different distance bands to set spatial benchmarks, such as for the planning of jobs-housing balances (*24*).

RESEARCH APPROACH AND DATASET

We collected data on 832 heavy rail, 589 light rail, and 36 bus rapid transit stations and their surroundings from twenty American transit agencies. We then estimated several dozen station-level direct demand models of transit ridership. Using direct demand models—essentially a statistical regression based on observed ridership—is a simple alternative to full-blown travel models to predict transit ridership on transit stations, corridors, and systems (*25*).

The advantages of direct demand models stem from the ease of estimating them using data that are readily available to transit agencies. A personal computer equipped with basic GIS software and statistical analysis software and access to the internet are the only critical prerequisite materials. For early stage transit scenario testing this means that a large number of potential transit alignments or alternatives can be tested with a relatively light investment of effort. These models not only provide order of magnitude ridership potential with greater ease than by using traditional regional transportation planning models, but they may also have superior predictive power in certain respects *(26*). Direct demand models are also attractive for transit planning purposes since the pedestrian scale dynamics that are considered to be important in determining transit ridership are often too fine grained to show up in regional travel models (*25*). By focusing on an area defined within a radius or access distance of a transit station, direct demand models reflect actual land use characteristics in the specific area most likely to be most influential in determining actual transit ridership. They are also the areas where land use is most likely to be influenced by transit. By relying on direct demand modeling, we were able to collect data on the majority of non-commuter-rail fixed guideway transit in the United States. This gives us greater confidence in making generalizations about other American transit systems.

We compiled average weekday ridership, station park-and-ride spots, transit schedules, and bus connections from the online documents, websites, and unpublished records for the 20 different transit agencies included in the study. Station-level ridership is the average of weekday alightings and boardings, or one or the other, when transit agencies were unable to provide both counts. The majority of counts came from September 2009. Several agencies, however, could not provide counts for this month, and we instead relied on the most recent non-summer figures or average annual weekday ridership. While seasonality and annual trends influence ridership, there is no reason to believe that this variation is correlated with any of the other variables we include. Any differences will be captured by the error term and city-level dummy variables, resulting in slightly larger standard errors, but not in biased estimates.

We combined these data with spatial point files from the National Transit Atlas Database and individual transit agencies. Using these points, we generated cropped one-quarter mile bands of transit-station catchment areas with assigned Zip-code-level job counts from the US Census' 2007 County Business Patterns and Esri's 2007 block-group population estimates (*26, 27*). We found these data to fit our models better than 2000 Census population counts. Figure 1 shows the quarter-mile catchment bands for several stations in Boston, MA. We opted to use cropped area, since they better reflect a station's catchment area, relative to the location of other stations, and also tend to provide better model fits (*28, 23*). While we also cropped station-area based on network distances for several systems, we opted to rely on a radial based approach for two reasons. First, the majority of direct demand models rely on a radial area. Second, the network calculations add significantly to the data collection efforts with little to no benefit in terms of predictive power. Many stations are surrounded by parks, paths, and parking lots which provide pedestrian access but do not show up in available road network files. Adding these manually is labor-intensive and counterintuitive to the direct demand models objective of simplifying predictions.

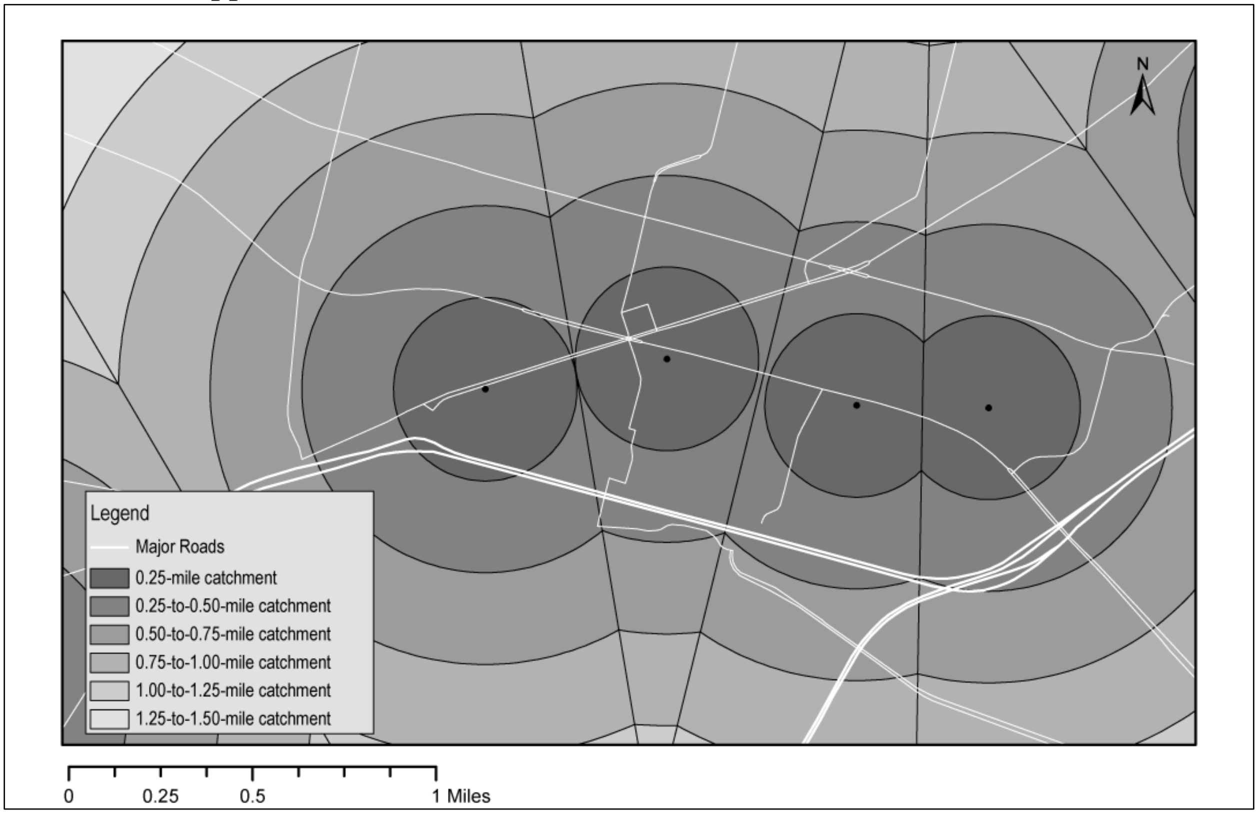
Table 1 provides descriptive statistics and sources for the variables included in the analysis. While we also tested and included system-level and metropolitan-area statistics, because they provided superior model fits, we used city-level dummy variables to capture these larger system effects.

TABLE 1 Variables Included in Ridership Models

	Mean	St. Dv.	Min.	Max.	Year	Source
Average of weekday boardings/alightings	6,020	11,318	46	189,507	2009	(a)
Frequency (trains during AM peak hour)	23	19	4	269	2009	(a)
Park-and-ride spaces	187	518	0	5,821	2009	(a)
Regional Rail Connection Dummy	0.06	0.24	0	1	2009	(a)
Bus lines servings station area	3.49	4.50	0	35	2009	(a)
Terminal station dummy	0.10	0.30	0	1	2009	(a)
Airport station dummy	0.01	0.11	0	1	2009	(a)
Linear distance (yards) to central business district	9,944	8,026	0	51,283	2009	(a)
Linear distance (yards) to nearest station	1,042	980	19	15,514	2009	(a)
Population within 0.25 miles	3,687	4,318	0	28,237	2007	(b)
Population in 0.25-to-0.50-mile band	3,930	4,068	0	36,322	2007	(b)
Population in 0.50-to-0.75-mile band	2,877	3,560	0	39,782	2007	(b)
Population in 0.75-to-1.0-mile band	2,362	3,221	0	25,639	2007	(b)
Jobs within 0.25 miles	2,463	5,673	0	86,102	2007	(c)
Jobs in 0.25-to-0.50-mile band	2,091	4,073	0	64,216	2007	(c)
Jobs in 0.50-to-0.75-mile band	1,341	2,448	0	46,950	2007	(c)
Jobs in 0.75-to-1.0-mile band	977	1,397	0	16,428	2007	(c)
Observations	1449					

Notes. (a) Transit agencies and GIS calculations, (b) Esri 2007 population block group estimates and GIS calculations; (c) U.S. Census Zipcode County Business Patterns

FIGURE 1 Cropped Station Catchment Areas



FINDINGS

Our first set of models test the predictive power of direct demand models using different radial catchment areas. Each increment increases in one quarter mile bands and excludes geographic areas that are closer to another transit station. Each model includes the full list of station controls from table 1, as well as modal and city dummy variables to capture variation across mode types and specific cities. Table 2, which models different radii population counts, includes a full range job counts in quarter-mile-catchment bands out to 1.5 miles (2.4 kilometers). Table 3 reverses the jobs and population counts to see if the best predictive catchment area differs for jobs and population counts. We ran both sets of models using ordinary least squares regressions with standard errors clustered by city. Northern New Jersey cities were clustered together and given the same city-level dummy.

The most notable finding is that the chosen station catchment area has little to no influence on the predictive power of the models. For the six radii catchment areas, the adjusted r-square ranges from 0.742 to 0.746 for population and from 0.723 to 0.745 for jobs. This suggests that, for the purposes of direct demand modeling, discussions about the appropriate walking distance or type of catchment area (radial, diamond, or network) are largely irrelevant. Nevertheless, the best fitting models are the half-mile and three-quarter-mile radii for population counts and, more noticeably, the quarter-mile radius for job counts. The declining parameter estimates with increasing radius distance follow expectations. An additional person within a quarter mile of a station correlates with 0.338 more average weekday trips; within one half-mile, 0.249 more.

TABLE 2 Ordinary Least Squares Regressions of the Influence of Catchment-Area Population on the Average of Weekday Boardings and Alightings[a]

	(1)	(2)	(3)	(4)	(5)	(6)
Population within 0.25 miles	0.338*** (6.02)					
Population within 0.50 miles		0.249*** (4.62)				
Population within 0.75 miles			0.183** (3.52)			
Population within 1.00 miles				0.146** (3.00)		
Population within 1.25 miles					0.122* (2.67)	
Population within 1.50 miles						0.104* (2.38)
Observations	1449	1449	1449	1449	1449	1449
Adjusted R-squared	0.7402	0.7463	0.7463	0.7454	0.7445	0.7436

Notes: (a) For a list of the included control variables, see Table 1. The regression also includes six job count variables in quarter-mile bands out to 1.5 miles.
(b)Robust clustered t statistics in parentheses; (c) * p<0.05, ** p<0.01, *** p<0.001

TABLE 3 Ordinary Least Squares Regressions of the Influence of Catchment-Area Jobs on the Average of Weekday Boardings and Alightings[a]

	(1)	(2)	(3)	(4)	(5)	(6)
Jobs within 0.25 miles	0.685*** (4.25)					
Jobs within 0.50 miles		0.421*** (4.88)				
Jobs within 0.75 miles			0.342*** (4.80)			
Jobs within 1.00 miles				0.317*** (4.29)		
Jobs within 1.25 miles					0.301*** (3.89)	
Jobs within 1.50 miles						0.287** (3.55)
Observations	1449	1449	1449	1449	1449	1449
Adjusted R-squared	0.7448	0.7405	0.7333	0.7287	0.7255	0.7225

Notes: (a) For a list of the included control variables, see Table 1. The regression also includes six population count variables in quarter-mile bands out to 1.5 miles.
(b)Robust clustered t statistics in parentheses; (c) * p<0.05, ** p<0.01, *** p<0.001

To assess how jobs and population concentrations at different distances from transit influence ridership and to try to determine an optimal catchment-area radius, we reran the models including counts in quarter mile bands out to one mile. What one is looking for is a precipitous drop in coefficients from one distance band to the next – i.e., a clear inflection point or step function that can serve as a benchmark.

Model 1 in Table 4 includes all catchment bands for job and population counts. For population counts, the quarter-mile and quarter-to-half-mile bands are highly significant and provide reasonable and expected results. The quarter-mile counts for jobs also provide reasonable, significant, and expected results. More distant bands, however, result in some unexpected signs and parameter estimate magnitudes. For example, it is somewhat unexpected that the half-to-three-quarter-mile band is insignificant, while the three-quarter-to-one-mile band has an expected sign and magnitude for population counts. The model, however, suffers from high multicollinearity. Variance inflation factors (VIF) for job and population counts range from 2.55 to 8.18. While there is no strict rule on acceptable VIF scores, scores above 5, combined with irregular parameter estimates suggest that the model is over-fitting the data and that bands should be dropped. Models 2 through 4 drop additional bands to evaluate the impacts on the model. The quarter-mile band provides the best model fit for job counts and, when included with other bands, is the most statistically significant. The case for the best population count band is less clear. Three of the bands are statistically significant in the first model. However, based on the insignificance of the third band in model 1 and the results of Table 2, there is some limited evidence that the half-mile band performs best. Model 4 includes the first two distance bands for population. The parameter estimates are statistically different, but surprisingly higher for the second band than the first. A chi-squared test of the model's power when assuming the estimates are equal, however, suggests that it is appropriate to combine the two into a single parameter, the half-mile radius (Model 5).

TABLE 4 Ordinary Least Squares Regressions of the Influence of Catchment-Area Jobs and Population on the Average of Weekday Boardings and Alightings[a]

	(1)	(2)	(3)	(4)	(5)
Population within 0.25 miles	0.209**	0.214**	0.196**	0.201**	-
	(0.0684)	(0.0689)	(0.0617)	(0.0609)	
Population in 0.25-to-0.50-mile band	0.258***	0.244***	0.286***	0.322***	-
	(0.0590)	(0.0602)	(0.0595)	(0.0561)	
Population in 0.50-to-0.75-mile band	-0.0109	0.0626	-	-	-
	(0.0848)	(0.0763)			
Population in 0.75-to-1.0-mile band	0.117*	-	-	-	-
	(0.0543)				
Jobs within 0.25 miles	0.634**	0.633**	0.616**	0.680***	0.681***
	(0.186)	(0.186)	(0.177)	(0.157)	(0.159)
Jobs in 0.25-to-0.50-mile band	0.0471	0.0685	0.132	-	-
	(0.111)	(0.109)	(0.0682)		
Jobs in 0.50-to-0.75-mile band	0.249*	0.132	-	-	-
	(0.106)	(0.100)			
Jobs in 0.75-to-1.0-mile band	-0.316**	-	-	-	-
	(0.106)				

Population within 0.50 miles	-	-	-	-	0.269***
					(0.0465)
Observations	1449	1449	1449	1449	1449
Adjusted R-squared	0.746	0.746	0.746	0.745	0.745

Notes: (a) For a list of the included control variables, see Table 1;
(b)Robust clustered t statistics in parentheses; (c) * $p<0.05$, ** $p<0.01$, *** $p<0.001$

In addition to linear specifications, direct demand models are often estimated using a power function. This models the log of the dependent variable against the log of all continuous dependent variables. To avoid taking the log of zero, we added marginally to continuous independent variables. Table 5 presents the results of the preferred linear model against a log-linear and log-log specification. It also provides parameter estimates for the control variables. The log-log model fits the data best and furthermore corrects an unexpected sign from the linear model; we expect ridership to decrease rather than increase as a function of distance from the central business district. We also reran the models from tables 2, 3, and 4 using a log-log specification. We prefer, however, to report the linear estimations since multicollinearity was even more problematic with power functions; VIF scores ranged from 4 to 14 with all bands included.

TABLE 5 Ordinary Least Squares Regressions of the Average Of Weekday Transit Station Boardings and Alightings

	(1) Linear	(2) Log-linear	(3) Log-log
Population within 0.50 miles	0.269***	0.0000342***	0.0922*
	(5.79)	(15.17)	(2.27)
Jobs within 0.25 miles	0.681***	0.0000266***	0.198***
	(4.29)	(6.60)	(3.88)
Frequency (trains during AM peak hour)	360.7***	0.0208***	0.875***
	(6.73)	(6.02)	(17.70)
Park-and-ride spaces	1.092**	0.000279***	0.0136***
	(3.33)	(4.33)	(4.20)
Regional Rail Connection Dummy	4113.6*	0.177*	0.296**
	(2.13)	(2.21)	(3.37)
Bus lines servings station area	162.9**	0.0640***	0.0375***
	(3.44)	(8.33)	(7.79)
Terminal station dummy	1482.9***	0.0731	0.340**
	(4.26)	(0.91)	(3.59)
Airport station dummy	3000.6**	0.687***	0.755***
	(3.78)	(5.08)	(3.98)
Linear distance (yards) to central business district	0.108*	-0.0000145***	-0.0204*
	(2.40)	(-4.82)	(-2.74)
Linear distance (yards) to nearest station	0.195	0.00000969	0.00971
	(1.38)	(0.31)	(0.40)
Light rail dummy	-2861.8*	-1.064***	-1.098***

	(-2.83)	(-5.68)	(-9.69)
Bus rapid transit dummy	-6505.0***	-1.553***	-1.876***
	(-17.72)	(-6.05)	(-13.13)
City-level dummy variables	Yes	Yes	Yes
Constant	-6179.9**	7.408***	3.907***
	(-3.15)	(74.47)	(7.23)
Observations	1449	1449	1449
Adjusted R-squared	0.745	0.789	0.798

Notes: (a)Robust clustered t statistics in parentheses;
(b) * p<0.05, ** p<0.01, *** p<0.001

To test the robustness of our estimates and provide additional evidence for the large and growing literature on the influence of job and population concentrations around transit, we ran several additional model specifications. Table 6 provides parameter estimates of the influence of jobs and population around transit, ranging respectively from 0.20 to 0.47 and 0.09 to 0.345. Model 1, the preferred model from Table 5, includes variables on transit technology and service frequency. While these factors likely generate transit ridership, they are also influenced by demand. Service variables, as shown in models 1 and 2, appear to exert a strong and statistically significant influence on station-level transit ridership. At an elasticity of over 0.80, our estimates of the influence of service levels on ridership are within the range of previous estimates, but higher than average (*29*).

Agencies, however, only build high capacity subway or run frequent service where demand is high. Removing these endogenous variables nearly doubles the estimated impact of jobs and population on transit ridership. The true elasticity likely lies within the bounds of the parameter estimates from models 1 and 3. Since coefficients of log-log models represent elasticities, the results also show that ridership is more strongly influenced by jobs within ¼ mile than population within ½ mile. While TOD planning tends to focus on residences, these results reinforce the findings of others that non-residential development can have an even bigger impact on transit ridership (*30, 3, 31*). This suggests that transit-oriented development policies focus on jobs, in addition to housing.

Finally, we remove the city-level dummy variables. This significantly reduces the predictive power of the models and again increases the importance of jobs and population on ridership. This indicates that, in a national model of transit ridership, system-level variation is as important, or more important, than station-level variation. Some cities have developed driving or transit cultures over time, or have other attributes, such as more significant parking constraints, that lead to higher or lower ridership. It is important to note, however, that the signs and magnitudes of these effects are sensitive to which variables are included in the model. They absorb the average effects of all excluded but relevant predictor variables. For example, when modal dummy variables are included, Portland has higher ridership than would otherwise be expected. However, when not accounting for Portland's light rail technology, ridership levels are lower than otherwise expected. New Jersey Transit systems have lower ridership than otherwise predicted in all models, while Washington D.C. subway has higher than expected ridership. Contrary to what one might expect, high concentrations of jobs and people around transit do a good job of predicting New York City transit ridership; there does not appear to be some excluded variable that drives the city's high ridership. Although we tested several system-level attributes that influence ridership, these did not provide better fits than the city-level dummy variables.

TABLE 6 Log-Log Ordinary Least Squares Direct Models of U.S. Transit Ridership

	(1)	(2)	(3)	(4)	(5)
Population within 0.50 miles	0.0922*	0.140**	0.137**	0.147**	0.345***
	(2.27)	(2.99)	(3.15)	(3.00)	(5.18)
Jobs within 0.25 miles	0.198***	0.257***	0.374**	0.370**	0.466***
	(3.88)	(3.89)	(3.73)	(3.78)	(4.61)
Park-and-ride spaces	0.0136***	0.0137***	0.0145**	-	-
	(4.20)	(4.06)	(3.09)		
Regional Rail Connection Dummy	0.296**	0.292*	0.446**	-	-
	(3.37)	(2.67)	(3.62)		
Bus lines servings station area	0.0375***	0.0401***	0.0479***	-	-
	(7.79)	(5.68)	(8.60)		
Terminal station dummy	0.340**	0.359***	0.322***	-	-
	(3.59)	(3.96)	(4.26)		
Airport station dummy	0.755***	0.788***	0.753**	-	-
	(3.98)	(3.90)	(3.31)		
Linear distance (yards) to central business district	-0.0204* (-2.74)	-0.0256* (-2.46)	-0.0343* (-2.16)	-	-
Linear distance (yards) to nearest station	0.00971 (0.40)	0.0932* (2.47)	0.0589 (1.22)	-	-
Frequency (trains during AM peak hour)	0.875*** (17.70)	0.817*** (13.24)	-	-	-
Light rail dummy (1=LRT)	-1.098***	-	-	-	-
	(-9.69)				
BRT dummy (1=BRT)	-1.876***	-	-	-	-
	(-13.13)				
City-level dummy variables					
Baltimore	-0.203*	-0.922***	-1.197***	-1.383***	-
Boston	-0.0115	-0.629***	-0.367***	-0.730***	-
Buffalo	0.388**	-0.689***	-1.044***	-1.191***	-
Chicago	-0.506***	-0.491***	-0.347***	-0.605***	-
Dallas	0.279*	-0.814***	-0.908***	-0.961***	-
Denver	-0.0396	-1.113***	-1.211***	-1.271***	-
Los Angeles	0.303**	-0.785***	-0.695***	-0.776***	-
Miami	-0.765***	-0.792***	-0.835***	-0.747***	-
Minneapolis	0.432**	-0.607***	-0.733***	-1.071***	-
New York	0.0935	-0.0107	0.289*	-0.106	-
Newark/Jersey City	-0.914***	-1.965***	-1.970***	-2.197***	-
Phoenix	-0.0278	-1.115***	-1.303***	-1.443***	-

Portland	0.327*	-0.675***	-0.702***	-1.066***	-
Sacramento	0.635***	-0.403***	-0.879***	-1.352***	-
San Diego	0.295*	-0.788***	-1.004***	-1.308***	-
San Francisco	0.0560	-0.0151	0.157*	0.330***	-
San Jose	-0.681***	-1.751***	-2.188***	-2.440***	-
St. Louis	0.557**	-0.481***	-0.737***	-0.879***	-
Trenton	-0.503**	-1.546***	-1.977***	-2.156***	-
Washington D.C.	0.459***	0.500***	1.026***	0.300***	-
Constant	3.907***	2.750**	4.606***	4.778***	1.812
Observations	1449	1449	1449	1449	1449
Adjusted R-squared	0.798	0.734	0.667	0.577	0.334

Notes: (a)Robust clustered t statistics in parentheses; (b) * p<0.05, ** p<0.01, *** p<0.001

CONCLUSION

Our results strongly indicate that, for purposes of predicting ridership, little is gained from using a particular station catchment area or type over another. The marginal gains from using a quarter-mile or half-mile circle are quite small. The benefits from using a diamond shape or network path will be equally small. As a result, direct demand modelers would do well to use whatever catchment is most readily available or easily calculated. The case for the correct catchment area, however, is far from clear. That said, when testing quarter-mile radial bands, we find some indication that the quarter-mile catchment area works best for predicting ridership as a function of jobs, while the half-mile radius works best for population. This is far from definitive and researchers should continue to test the appropriate boundaries when possible. If, however, a researcher lacks the data or resources to model multiple catchment areas or needs to choose an area from which to conduct surveys on transit-adjacent firms or households, our research provides some evidence that firms should be chosen from within a quarter-mile radius and households within a half-mile.

References

(1) Cervero, R., G. Arrington, J. Smith-Heimer, R. Dunphy, and others. *Transit-oriented development in the United States: experiences, challenges, and prospects*. Washington, D.C.: Transportation Research Board of the National Academies, 2004.
(2) Ewing, R., and R. Cervero. Travel and the Built Environment -- A Meta-Analysis. In *Journal of the American Planning Association*, 76, no. 3, 2010, pp. 265-294.
(3) Cervero, R. Transit-oriented development's ridership bonus: a product of self-selection and public policies. In *Environment and Planning A*, 39, no. 9, 2007, pp. 2068–2085.
(4) Cervero, R. Transit-based housing in California: evidence on ridership impacts. *Transport Policy*, 1, no. 3, 1994, pp. 174–183.
(5) Small, K. *Urban transportation economics*. Chur Switzerland: Hardwood Academic Publishers, 1992.
(6) Wardman, M. A review of British evidence on time and service quality valuations. In *Transportation Research Part E: Logistics and Transportation Review*, 37, no. 2, 2001, pp. 107-

128.
(7) Cervero, R., and J. Landis. Twenty years of the Bay Area Rapid Transit system: Land use and development impacts. In *Transportation Research Part A: Policy and Practice*, 31, no. 4, 1997, pp. 309-333.
(8) Hess, D., and T. Almeida. Impact of Proximity to Light Rail Rapid Transit on Station-area Property Values in Buffalo, New York. In *Urban Studies*, 44, no. 5-6, 2007, pp. 1041-1068.
(9) Lewis-Workman, S., and D. Brod. Measuring the neighborhood benefits of rail transit accessibility. In *Transportation Research Record: Journal of the Transportation Research Board*, no. 1576, 1997, pp. 147–153.
(10) McMillen, D., and J. McDonald. Reaction of House Prices to a New Rapid Transit Line: Chicago's Midway Line, 1983-1999. In *Real Estate Economics*, 32, no. 3, 2004, pp. 463-486.
(11) Nelson, A. Transit stations and commercial property values: a case study with policy and land-use implications. *Journal of Public Transportation*, 2, no. 3, 1999, pp. 77–93.
(12) Voith, R. Changing Capitalization of CBD-Oriented Transportation Systems: Evidence from Philadelphia, 1970-1988. *Journal of Urban Economics*, 33, no. 3, 1993, pp. 361-376.
(13) Weinberger, R. Light Rail Proximity: Benefit or Detriment in the Case of Santa Clara County, California? In *Transportation Research Record: Journal of the Transportation Research Board*, no. 1747, pp. 104-113.
(14) Baum-Snow, N., and M. Kahn. The effects of new public projects to expand urban rail transit. In *Journal of Public Economics*, 77, no. 2, 2000, pp. 241-263.
(15) Rodríguez, D., and F. Targa. Value of accessibility to Bogotá's bus rapid transit system. In *Transport Reviews: A Transnational Transdisciplinary Journal*, 24, no. 5, 2004, pp. 587-610.
(16) Cervero, R., and C. D. Kang. Bus rapid transit impacts on land uses and land values in Seoul, Korea. In *Transport Policy*, 18, no. 1, 2011, pp. 102–116.
(17) Zhao, F., L. Chow, M. Li, I. Ubaka, and A. Gan. Forecasting Transit Walk Accessibility: Regression Model Alternative to Buffer Method. *In Transportation Research Record: Journal of the Transportation Research Board*, no. 1835, 2003, pp. 34-41.
(18) Calthorpe, P. *The Next American Metropolis: Ecology, Community, and the American Dream*. 3rd ed. Princeton, NJ: Princeton Architectural Press, 1993.
(19) O'Sullivan, S. and J. Morrall. Walking Distances to and from Light-Rail Transit Stations. In *Transportation Research Record: Journal of the Transportation Research Board*, no. 1538, 1996, pp. 19-26.
(20) Kuby, M., A. Barranda, and C. Upchurch. Factors influencing light-rail station boardings in the United States. In *Transportation Research Part A: Policy and Practice*, 38, no. 3, 2004, pp. 223-247.
(21) Upchurch, C., M. Kuby, M. Zoldak, and A. Barranda. Using GIS to generate mutually exclusive service areas linking travel on and off a network. In *Journal of Transport Geography*, 12, no. 1, 2004, pp. 23-33.
(22) Walters, G. and R. Cervero. 2003. *Forecasting Transit Demand in a Fast Growing Corridor: The Direct-Ridership Model Approach,* Fehrs and Peers Associates, 2003. http://www.fehrandpeers.com/fp-lib/public/forecast-td-dirRidershp-approach.pdf. Accessed July 1, 2011.
(23) Usvyat, L., L. Meckel, M.Dicarlantonio, and C. Lane. *Sketch Model to Forecast Heavy-Rail Ridership*. Presented at 88th Annual Meeting of the Transportation Research Board, Washington, D.C., 2009.

(24) Cervero, R. and M. Duncan. Which reduces vehicle travel more: jobs-housing balance or retail-housing mixing? In *Journal of the American Planning Association,* 72, no. 4, 2006, pp. 475-490.
(25) Cervero, R. Alternative approaches to modeling the travel-demand impacts of smart growth. In *Journal of the American Planning Association*, 72, no. 3, 2006, pp. 285-295.
(26) U.S. Census Bureau. *County Business Patterns,* 2007, http://www.census.gov/econ/cbp/download/index.htm. Accessed October 12, 2010.
(27) Esri. *ESRI Data & Maps* [DVD]. Redlands, CA: Environmental Systems Research Institute, 2007.
(28) Lane, C., M. DiCarlantonio, and L. Usvyat. Sketch models to forecast commuter and light rail ridership: Update to TCRP report 16. In *Transportation Research Record: Journal of the Transportation Research Board*, 1986, no. 1, 2006, pp. 198–210.
(29) Evans, J. TCRP Report 95: *Traveler Response to Transportation System Changes, Chapter 9: Transit Scheduling and Frequency*. Transportation Cooperative Research Program, Report 95, Transportation Research Board of the National Academies, Washington, D.C., 2004.
(30) Cervero, R. Built Environments and Mode Choice: Toward a Normative Framework. In *Transportation Research* D, Vol. 7, 2002, pp. 265-284.
(31) Kolko, J. *Making the Most of Transit: Density, Employment Growth, and Ridership around New Stations.* Report published by the Public Policy Institute of California, 41pp., 2011. http://www.ppic.org/main/publication.asp?i=947. Accessed July 1, 2011.