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Joseph M. POGODZINSKI
San Jose State University, j.m.pogodzinski@sjsu.edu

John S. NILES
San Jose State University, john.niles@sjsu.edu

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Joseph M. POGODZINSKI*, John S. NILES
San Jose State University, Mineta Transportation Institute
1 Washington Sq., CA 95192-0114, San Jose, California, USA
**Corresponding author*. E-mail: j.m.pogodzinski@sjsu.edu

IMPACT OF PARK-AND-RIDE ON PUBLIC TRANSIT RIDERSHIP

Summary. We examine the relative impact of increased housing vs. increased parking availability on ridership of public transit. The approach sheds light on the trade-off in alternative land uses near transit stops: park-and-ride (PnR) vs. transit-oriented development (TOD). In the example of one city studied here, econometric analysis suggests that PnR provides more transit ridership than housing. However, the transit agency may choose the alternative of reducing PnR and partnering with housing developers as a source of new non-fare revenue that creates vibrant, walkable growth in station areas, which is considered to be just as important as ridership.

1. THE POLICY ISSUES

Typically, park-and-ride (PnR) facilities in the United States are intended to reduce traffic congestion on the corridors to and on the roads in central cities, reduce emissions by reducing vehicle miles traveled (VMT), and increase public transit use. PnR facilities, which are frequently located on the periphery of central cities, reduce congestion on corridors to central cities by moving commuters from low-occupancy vehicles to public transit, reducing the need for parking facilities in central cities. PnR facilities also tend to increase ridership on public transit vehicles and the boardings per hour of vehicle service [1]. Equitable access to transit for non-car-owning people is a policy issue associated with PnR, and so is access for low-income, disabled, or elderly people who do not want to drive or who cannot. Many low-income, non-car-owning people are workers who live at a great distance from their work because housing is more affordable in remote locations beyond the reach of the transit network. Elderly and disabled people are also working in greater numbers in the U.S. and may not be able to use personal transportation [2-4].

Increasing ridership on public transit may be a mixed blessing for public transit agencies. Public transit is heavily subsidized in the U.S. Farebox recovery of operating expenses was 33% in 2019 [5], before the pandemic reduced fare revenue by half. Increased ridership increases net revenues for a public transit agency if the increased ridership can be accommodated on existing vehicles on scheduled routes. Increased ridership may decrease net revenues if the additional ridership necessitates more frequent service or larger vehicles on a given route. Irrespective of the budgetary impact, increased ridership is an important goal for public transit agencies.

Ridership on transit is measured by vehicle boardings (the number of people who board a transit vehicle), also known as unlinked person trips, which are reported by U.S. public transit agencies every month to the United States Department of Transportation, the Federal Transit Administration [6]. Transit professionals and urban leaders are very interested in finding new ways to increase boardings, since transit use in the U.S. has been decreasing in recent years, even before the 2020 pandemic.

PnR facilities are most often owned and operated by public agencies, which are often units of state or local government (state departments of transportation, county, or municipal (city) governments). Sometimes, the transit agencies that provide public transit services and own and operate PnR facilities are public agencies independent of county or municipal governments (so-called special districts). This is the case for the Santa Clara Valley Transportation Authority (VTA), which is the focus of this paper. VTA operates principally in Santa Clara County (the county that includes the City of San Jose, California, and other Silicon Valley cities), but some stops associated with the agency are located in adjacent counties (Alameda County and Santa Cruz County). All the PnR facilities discussed in this paper are located in Santa Clara County.

The policy issue at the heart of this paper – whether land in the vicinity of a transit center should be devoted to PnR or to additional housing or both – is affected by the ownership/governance structure of the transit agency and, also, by some other considerations. Typically, PnR spaces are offered at no or very low cost to the commuter – actually, at no or very low cost to the parker, whether commuter or not. On the other hand, independent special districts like VTA can decide to lease or sell land that they own to private developers, usually to build housing. Land adjacent to a transit center has a high value when used for housing – especially in areas like Santa Clara County, which have high housing prices. The idea of building high-density housing near transit centers is called transit-oriented development (TOD). Transit agencies that convert PnR facilities into housing can greatly benefit their budgets, which is increasingly important in the post-financial crisis, post-pandemic world.

The issue is further complicated by consideration of the different effects of TOD and PnR on VMT. The State of California (along with other states) has adopted legislation that mandates a reduction in VMT to meet specific target levels [7]. The rationale for this policy is that reducing VMT will reduce emissions of green-house gasses (GHG). However, the correlation between VMT and GHG is not perfect. It is affected by the automobile and fuel technology. As newer (and lower polluting) internal combustion-powered vehicles supplant older ones, as electric vehicles supplant internal combustion-powered vehicles, and as fuel mixtures are adjusted, the correlation between VMT and GHG generation begins to break down. However, the official policy is still in place: VMT reduction targets must be met.

The issue we address in this paper is the relative size of the effect of more housing near transit stops vs. more parking near transit stops. Addressing this question is a step toward determining whether more PnR or more TOD (or some combination of both) is the best policy for increasing public transit use, but it does not provide the whole answer.

The present study tested and confirmed that both parking and residential density are significant and strong positive influences on transit use (as measured by boardings) and marginal additions of parking spaces near transit stops are a stronger influence on transit use than marginal additions of housing. In addition, the present study found some support for the proposition that the influence of parking on boardings wanes for stops close to parking that are closer to the city center.

2. OVERVIEW OF VTA

The Santa Clara Valley Transportation Authority (VTA) serves the City of San Jose and surrounding communities. The San Jose Metropolitan Statistical Area has the highest median household income in the U.S. ($122,478); the U.S. median household income is $65,712 [8]. Housing prices are correspondingly high in the region, with the ratio of median house price to the median household income standing at 8.5 in San Jose compared to 4.2 in Moscow, Russia, and 11.9 in Vancouver, Canada [9].

As described in the 2019 VTA Congestion Management Plan, “VTA maintains 41 PnR lots in twelve different cities throughout Santa Clara County. The lots connect commuters with VTA’s light rail system, Caltrain, Capitol Corridor, Altamont Commuter Express, and several express bus routes.” [10] The capacity of these facilities is approximately 11,700 spaces, with 41% average utilization.

3. ECONOMETRIC ANALYSIS OF RIDERSHIP INFLUENCES

3.1. Model motivation

Boardings at a stop during the morning commute depend on demographic, economic, and transit-systemic factors, among others. The relevant business, economic, and demographic variables are estimated within the catchment area (which is taken to be walking distance) of the stop. The demographic factors include the number of housing units within walking distance of the stop. The business and economic variables include the number of jobs in the catchment area and the median household income in the catchment area. The main transit-systemic factors examined are the proximity of the stop to a PnR facility, the distance of a PnR facility from the central business district (identified as city hall [11]), and whether the stop is associated with a light rail line. Analysis did not include several potentially significant variables (such as the number of lines serving a stop or the speed of a particular bus) due to data limitations.

3.2. Data

3.2.1. VTA GIS and Related Files

The authors obtained GIS files of lines and stops (including, where relevant, light rail lines and stops) from the Santa Clara Valley Transportation Authority [VTA]. Additionally, we obtained data on the location and capacity of PnR facilities in the agency's service area [12-13]. We obtained data on boardings at a stop identified by weekday service and commute times from VTA. We used data for October 2017 in the analysis.

3.2.2. Census Data

We obtained demographic and economic statistics (such as median household income and number of housing units) from the American Community Survey (ACS) [14] at the Census tract level, as well as business statistics (such as the number of jobs) at the ZIP Code Tabulation Area (ZCTA) [15] level from the Census ZIP Code Business Patterns dataset. (The ZCTA level was chosen for the business statistics because this is the lowest aggregation level at which these data are available.) Additionally, Census mapping data were used to identify the boundaries of cities and related governmental entities.

3.3. Methodology

First, the ridership data related to the morning weekday commute boardings were associated with stops in the system. Then, the catchment areas of those stops were identified. The catchment areas selected for this study are quarter mile (402.3 meters) buffers around each stop. In U.S. planning practice, a quarter mile is taken as acceptable walking distance to reach a bus stop, and a half-mile is used for rail stations and buses with the route designated for faster service with dedicated lanes and signal pre-emption [16, 17]. Since most of the stops for this study are associated with ordinary bus service, a quarter-mile buffer was deemed appropriate.

The economic and demographic statistics that applied to a catchment area were estimated based upon the proportion of the quarter-mile buffer around a stop that overlapped a Census geographic area (such as a Census tract or ZCTA). The methodology differed slightly depending on whether the variable being estimated was measured in absolute terms or as an average that applied to the entire Census geographic area. If the variable was measured as an average that applied to the entire Census geographic area (such as the median household income), the average variable was estimated as the weighted mean of each Census geographic area that the catchment area intersected. If the variable was measured in absolute terms, the amount that applied to the catchment area was estimated as the ratio of the catchment area intersecting the Census geographic area to the total area of the Census geographic area. Formulae for both types of computations are shown below. For variables measured as averages, one set of weights is used; for variables measured in absolute terms, a different set of weights is used.

The first set of weights comprises the fraction of the catchment area that falls in each Census geographic area. These weights are denoted by w_j and defined by

$$w_j = \frac{A_j}{Area_{catchment}^{stop}}$$

for j=1, 2,…,k, where k is the number of Census geographic areas that the buffer intersects. The sum of these weights over all Census geographic areas that the catchment area intersects is 1, i.e.,

$$\sum_{j=1}^{k} w_j = 1 \sum_{j=1}^{k} w_j = 1$$

The second set of weights is the fraction that the catchment area intersecting a particular Census geographic area is of that Census geographic area. These weights are denoted by f_j, and they are defined by

$$f_j = \frac{A_j}{Area_j^{CG}}$$

for j=1,2,…,k, where k is the number of Census geographic areas that the catchment area intersects.

These weights are positive, but do not sum to a constant.

For variables measured as averages, the estimated variable in the catchment area is given by expression (1) below (involving only the w_j weights). For variables measured in absolute terms, the estimated variable in the catchment area is given by expression (2) below (involving only the f_j weights). In these expressions, V_j is the value of the average variable (e.g., median household income) in Census geography j and N_j is the absolute number (e.g., of jobs, workers, or housing units) in Census geographic area j.

$$(1)\ V_{stop}^{estimate} = \sum_{j=1}^{k} w_j V_j \ V_{stop}^{estimate} = \sum_{j=1}^{k} w_j V_j$$

$$(2)\ N_{stop}^{estimate} = \sum_{j=1}^{k} f_j N_j \ N_{stop}^{estimate} = \sum_{j=1}^{k} f_j N_j$$

The variables in the analysis along with their expected sign and significance in the regressions are discussed below. The descriptive statistics of the entire sample are given in the Appendix.

3.3.1. Dependent Variable: Morning Weekday Boardings

The approach in this research is *cross-sectional* (covering a single time period, e.g., a month) and *stop-level* (namely, the variables are observed for specific stops or the catchment areas around specific stops). The dependent variable, *AM_Boardings*, is the morning boardings at a stop on a weekday aggregated for the month of October 2017.

3.3.2. Independent Variables: Economic, Demographic, and Business Variables

The following demographic, economic, and business variables, measured in absolute amounts, are used in the analysis:

EMP_stop: an estimate of the total number of jobs in the catchment area around a stop; the expected sign is positive, but weakly significant;

HU_stop: an estimate of the total number of housing units in the catchment area around a stop; the expected sign is positive and strongly significant.

To estimate the number of jobs or the number of housing units in the catchment area around a stop, the authors determined (using the Tabulate Intersection tool in ArcGIS) the intersection of the quarter-mile buffers with the Census geographic areas at which the economic, demographic, or business variable was observed. Data of housing units in the catchment area come from Census tract-level ACS data. For employment, the authors relied on Census ZIP Code Business Patterns data. The ZCTA is the lowest level of aggregation at which jobs data are observed.

If the quarter-mile buffer around a stop fell within a single Census tract or ZCTA, the proportion of the Census tract or ZCTA within the quarter-mile buffer was determined, as was the proportion of jobs, or housing units, or labor force in that Census tract or ZCTA. If the quarter-mile buffer around a stop fell within several Census tracts or ZCTAs, the proportion of each Census tract or ZCTA within each buffer was used, and the fraction of the buffer contained in each Census tract or ZCTA was computed as a weighted average of the proportional amounts of jobs, or housing units, or labor force that correspond to that fraction. In addition, the median household income in the catchment area around a stop, measured as an average for the Census geographic area, is used in the analysis. Data of the median household income are Census tract-level ACS data.

3.3.3. Independent Variables: Variables Related to Park-and-Ride

Three characteristics of PnR facilities are incorporated into the analysis:

- Distance to a PnR facility to a stop – the expected sign is negative and strongly significant;
- The capacity (number of spaces) in the PnR facility – the expected sign is positive and strongly significant; and
- The distance of the PnR facility to the central business district – the expected sign is positive and there is no expectation of significance.

The first two characteristics are incorporated by constructing several variables related to the size of the nearest PnR facility and its proximity to a stop. The third characteristic arises from the construction of another variable. These PnR-related variables are explained below.

To investigate influence on ridership at a stop of proximity to a PnR facility in a way that promotes comparison to housing, employment, and income effects, three kinds of variables were constructed to capture the size and proximity of a park-and-ride facility to a stop.

First, a variable is constructed for each stop that is equal to the size of the nearest PnR facility if there is a PnR facility within a quarter mile of the stop and zero otherwise. For this variable, the value associated with most stops is zero because most stops are not within a quarter mile of any PnR facility.

Second, variables are constructed corresponding to proximity of a stop to a PnR facility within a specific capacity (number of spaces) range. A PnR facility is classified as “small” if it is between the 0^{th} and 25^{th} percentile of PnR facilities for the sample. “Medium”-sized facilities were between the 25^{th} and 75^{th} percentile. “Large” facilities were those above the 75^{th} percentile. The *PnR_small* variable is 1 if there is a small park-and-ride facility within a quarter mile of a stop and 0 otherwise. Similarly, the *PnR_medium* variable is 1 if there is a medium-sized park-and-ride facility within a quarter mile of a stop and 0 otherwise. The *PnR_large* variable is 1 if there is a large park-and-ride facility within a quarter mile of a stop and 0 otherwise. Again, for these variables, most stops are associated with a zero value because most stops are not within a quarter mile of any park-and-ride facility.

Third, a distance-decay specification (related to a gravity model) is used. For each stop, a variable *Size_Near_PnR* represents the size of the nearest PnR facility and *Dist_PnR* represents distance to the nearest PnR facility. In this specification, no stop has a zero value for either variable.

There is also evidence in the literature that suburban PnR facilities impact ridership more than PnR facilities closer to the city center. A constructed variable (*Dist_CityHall*) measures the distance of a PnR facility from City Hall (treated as the location of the Central Business District) if the stop is within a quarter mile of a park-and-ride facility. The variable is 0 if the stop is not within a quarter mile of any PnR facility and is equal to the straight-line distance between City Hall and the associated PnR facility if the stop is within a quarter mile of that PnR facility.

3.3.4. Independent Variables: Transit-System-Specific Variable

The variable *LightRailDummy* is one if the stop is a light rail stop and zero otherwise.

3.4. Econometric Specifications

Three alternative econometric specifications are used, differing by the PnR variables used (as detailed above). These alternative specifications are intended to test the robustness of the main conclusions about the relative impact of PnR variables and housing density variables.

The first specification uses absolute values of business, economic, and demographic variables (income, jobs, and housing units) to measure the impact of the demographic, economic, and business variables (*EMP_stop*, *HU_stop*, *MedHHInc_Lo*, *MedHHInc_Hi*), the interaction between quarter-mile dummy variables and size of the nearest PnR facility to measure the PnR effect (*Size_wi_QMi*), the interaction between the quarter-mile dummy and the distance of the PnR facility from city hall to measure the "suburban" effect (*Dist_CityHall*), and a dummy variable to measure the light rail effect (*LightRailDummy*).

The second specification uses the same absolute values of business, economic, and demographic variables and the same measure of the "suburban" effect, but uses the interaction between quarter-mile dummy variables and size categories to measure the PnR effect (*PnR_small, PnR_medium, PnR_large*).

The third specification also uses the same absolute values of business, economic, and demographic variables and the same measure of the "suburban" effect but uses the size of the nearest PnR facility (*Size_Near_PnR*) and the distance to the nearest PnR facility (*Dist_PnR*) to measure the PnR effect.

Negative binomial regression is used in this analysis because the outcome variable is a count variable that exhibits overdispersion.

Negative binomial regression is a generalization of Poisson regression. Poisson regression coefficients are determined in the course of estimating the negative binomial regression; the values of the log-likelihood statistics can be used to determine which technique is more appropriate. The dependent variable, weekday morning boardings, exhibits overdispersion—the variance of the variable is greater than the mean. (Overdispersion is commonly observed in empirical datasets.) Therefore, negative binomial regression is the appropriate technique as opposed to Poisson regression [18]. The Poisson regression technique is particularly robust [19].

4. ECONOMETRIC RESULTS

In each of the three specifications estimated, the dependent variable is weekday morning boardings. The econometric results for each of the three specifications tell similar stories and are generally in line with expectations. The specifications differ by how PnR is represented. In the first specification, the effects of PnR are gauged by a single dummy variable that examines whether there is a PnR facility within a quarter mile of a stop. In the second specification, the effects of PnR are gauged by defining three categorical variables to examine the effects of the size as well as the proximity of a PnR facility. In the third specification, we use a distance-decay formulation that treats both size and proximity as continuous variables.

The estimated coefficients of the negative binomial regression are reported as well as the values of these coefficients converted into *incidence rate ratios* (*IRR*). The coefficient estimates, when exponentiated, give the IRRs. Robust standard errors are used to determine whether the coefficient estimates are statistically significant.

Poisson and negative binomial regressions estimate *expected boardings* as a function of the independent variables, including proximity to and size of a PnR facility; the number of workers or housing units or jobs within walking distance of a stop; and the median household income within walking distance of a stop. These variables appear in some form in the regression specifications.

Following Cameron and Trivedi [20], the coefficient estimate of a negative binomial regression can be interpreted as a semi-elasticity. The incidence rate ratio has a multiplicative interpretation. The semi-elasticity interpretation states that one more unit of, say, housing results in a (coefficient*100) = x% increase (decrease) in expected boardings.

The semi-elasticity interpretation is rooted in the fundamental mathematics of the Poisson distribution and the maximum likelihood estimation method. The Poisson distribution posits that the expected value of the dependent count variable conditional on the independent variables is the exponent of the dependent variables multiplied by the true coefficient values. The results for Specification 1 are presented in Table 1.

For Specification 1 (Table 1), the signs of *MedHHInc_Lo* and *MedHHInc_Hi* are negative and positive, respectively, which is consistent with the idea that public transit is an inferior good. The number of housing units in the catchment area of a stop, *HU_wgt*, is strongly positive, as expected. The coefficient on the variable *Size_wi_QMi*, which is the size of the park-and-ride lot if there is a park-and-ride lot within a quarter mile of a stop, is also strongly positive and roughly twice the size of the coefficient estimate on the number of housing units in the catchment area of a stop.

Table 1

Specification One Results

Specification 1					
Negative binomial regression	Number of obs	=	3,034		
	LR chi2(7)	=	1659.91		
Dispersion = mean	Prob > chi2	=	0		
Log likelihood = -14964.666	Pseudo R2	=	0.0525		
AM_Boardings	Coef.	IRR	Std. Err.	z	P>z
1.MedHHInc_Lo	0.3740284	1.453578	0.058325	6.41	0
1.MedHHInc_Hi	-0.3975839	0.6719416	0.058299	-6.82	0
HU_wgt	0.0011078	1.001108	0.0000968	11.45	0
EMP_wgt	0.0001194	1.000119	0.0000237	5.04	0
1.LRDummy	2.448883	11.57541	0.1209959	20.24	0
Size_wi_QMi	0.0025563	1.00256	0.0002876	8.89	0
Dist_CityHall	0.0000368	1.000037	7.72E-06	4.77	0
_cons	3.114155	22.5144	0.0643585	48.39	0
/lnalpha	0.4731313		0.0224241		
alpha	1.605012		0.035991		

For Specification 2 (Table 2), the presence and size of a PnR facility are represented by three dummy variables: a dummy variable representing the presence of a small PnR facility (*PnR_small*) within a quarter-mile of a stop, where small means a PnR facility between the 0th and 25th percentiles of PnR facilities in the sample; a dummy variable representing the presence of a medium-sized PnR facility (*PnR_medium*) within a quarter mile of a stop, where medium means a PnR facility between the 25th and 75th percentiles of PnR facilities in the sample; and a dummy variable representing the presence of a large PnR facility (*PnR_large*) within a quarter-mile of a stop, where large means a facility in the 75th percentile or greater of PnR facilities in the sample. All three variables appear in the regression equation because most stops are not within a quarter mile of any PnR facility.

A "one-unit increase" as applied to the PnR variables in this table should be understood as creation of a small, medium-sized, or large PnR facility within a quarter mile of a stop. The effect of additional housing units is entirely consistent with the results previously shown in Table 2.

Specification 3 (Table 3) is based on a distance-decay model (a type of gravity model). Each stop in the system has a PnR facility associated with it—the PnR facility that is nearest to the stop, even though that might be a very great distance. The size of the nearest PnR facility is also associated with each stop. The effect of PnR is expected to be positively related to the size of the PnR facility and negatively related to distance from the PnR facility. One advantage of the distance-decay model is that every stop has associated PnR characteristics. A potential disadvantage is that the effect of PnR may fall off dramatically with distance: beyond 1,000 meters, the proximity and size of a PnR facility are likely to be irrelevant to boardings. This would make estimating the effects problematic because the vast majority of stops are not within 1,000 meters of a PnR facility.

Table 2

Specification Two Results

Specification 2					
Negative binomial regression	Number of obs	=	3,034		
	LR chi2(9)	=	1726.8		
Dispersion = mean	Prob > chi2	=	0		
Log likelihood = -14931.222	Pseudo R2	=	0.0547		
AM_Boardings	Coef.	IRR	Std. Err.	z	P>z
1.MedHHInc_Lo	0.4016871	1.494344	0.0577647	6.95	0
1.MedHHInc_Hi	-0.3414653	0.7107282	0.0580099	-5.89	0
HU_stop	0.0011622	1.001163	0.0000954	12.18	0
EMP_stop	0.0001237	1.000124	0.0000236	5.23	0
1.LRDummy	2.398476	11.00639	0.1205353	19.9	0
1.PnR_small	1.208337	3.347911	0.1789807	6.75	0
1.PnR_medium	1.314632	3.723381	0.1652427	7.96	0
1.PnR_large	1.839639	6.294268	0.1797722	10.23	0
Dist_CityHall	1.79E-06	1.000002	7.47E-06	0.24	0.811
_cons	3.028254	20.66113	0.064011	47.31	0
/lnalpha	0.4563918		0.0224829		
alpha	1.578369		0.0354862		

The effect of housing units is entirely consistent with the results obtained using the other specifications in this analysis. The effect of the size of the PnR facility is considerably smaller than the estimates for Specification 1 (the closest analog to Specification 3). This is to be expected, because the effects of size of the facility are determined for *all* stops, not just those within a quarter mile. Distance to the PnR facility is expected to be positive if the "suburbanization" effect holds.

Across the three specifications, the marginal influence ratio on VTA transit ridership of 100 parking spaces in an existing PnR facility is seen to be about double the impact of 100 nearby housing units of transit-oriented development. This is shown in the comparison of the coefficient estimates for *HU_wgt* and *Size_wi_QMi* in Table 2 referred to above, and the comparison of the IRRs associated with *HU_wgt* and any of the PnR variables in Table 3.

5. CONCLUSIONS

The analysis in the previous section reveals that parking near transit stops shows a stronger association with ridership than housing density in the neighborhood of those stops. The public interest in promoting ridership on public transit means that parking for customers is always an important option to consider. This will still be true after the 2020-21 pandemic subsides when the popularity rises again among climate policy advocates for dense, multi-family housing in transit-oriented development projects as a way to encourage reduced motor vehicle use.

Table 3

Specification Three Results

Specification 3					
Negative binomial regression	Number of obs	=	3,034		
	LR chi2(8)	=	1624.93		
Dispersion = mean	Prob > chi2	=	0		
Log likelihood = -14982.158	Pseudo R2	=	0.0514		
AM_Boardings	Coef.	IRR	Std. Err.	z	P>z
1.MedHHInc_Lo	0.379208	1.461127	0.0590722	6.42	0
1.MedHHInc_Hi	-0.5473089	0.5785045	0.0590802	-9.26	0
HU_stop	0.0009869	1.000987	0.0000952	10.36	0
EMP_stop	0.0001448	1.000145	0.0000268	5.4	0
1.LRDummy	2.571153	13.0809	0.1222488	21.03	0
Size_PnR	0.0004374	1.000437	0.0001251	3.5	0
DIST_PnR	0.0000769	1.000077	0.0000104	7.38	0
Dist_CityHall	0.0000999	1.0001	8.77E-06	11.39	0
_cons	2.929211	18.71286	0.0778528	37.62	0
/lnalpha	0.4819529		0.0223913		
alpha	1.619234		0.0362567		

Nevertheless, a transit agency deciding what to do with land near its train and bus stations has more factors to consider than the impact on ridership. In particular, selling that land to developers for housing will most likely generate more revenue for the agency than investing in building parking facilities and collecting usage fees. Transit-oriented development of housing near stations promotes the desirable “smart growth” characterized by transit customers walking to stations rather than driving cars. Suppression of driving is sought as a way to reduce greenhouse gas generation and air pollution. Provisos can be attached to TOD housing development that a portion of the project must offer units at below-market rates to meet a public policy goal of providing a bigger supply of affordable housing in the transit service territory.

However, in the Silicon Valley region served by VTA, there are many potential customers in the suburbs of San Jose who have already decided to live outside the range of walking to reach transit. More of them every year are driving electric cars. Driving to reach transit is the option they are looking for, or else they will drive into the city, adding to traffic. Transit in the U.S. requires the political support of the tax-paying public. Making driving easy and convenient by providing parking facilities with price-managed capacity utilization exclusively for transit customers not only boosts ridership coming from beyond the edges of the transit network, but may do so more cost-effectively than extending rail lines and bus service further outward [21].

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APPENDIX: DESCRIPTIVE STATISTICS OF VTA SAMPLE

Variable	Obs	Mean	Std. Dev.	Min	Max
AM_Boardings	3,034	94.19	328.94	1.0	6460.0
MedHHInc	3,034	107943.50	35010.17	21907.9	244238.8
HU_stop	3,034	555.47	260.71	4.0	1720.9
EMP_stop	3,034	741.65	1022.25	10.7	10132.3
Size_wi_QMi	3,034	24.61	112.94	0.0	1155.0
LRDummy	3,034	0.04	0.19	0.0	1.0
PnR_small	3,034	0.02	0.14	0.0	1.0
PnR_medium	3,034	0.03	0.17	0.0	1.0
PnR_large	3,034	0.03	0.16	0.0	1.0
Dist_CityHall	3,034	886.50	4234.69	0.0	46663.3
QMiDummy	3,034	0.07	0.26	0.0	1.0
Size_Near_PnR	3,034	259.07	209.19	22.0	1155.0
Dist_PnR	3,034	2182.11	1836.54	11.9	16826.1
MedHHInc_Lo	3,034	0.25	0.43	0.0	1.0
MedHHInc_Medium	3,034	0.50	0.50	0.0	1.0
MedHHInc_Hi	3,034	0.25	0.43	0.0	1.0

Note: The boarding count for VTA covered the total of all weekday mornings in October 2017.