PUBLIC POLICY INSTITUTE OF CALIFORNIA

Technical Appendix

Making the Most of Transit

Density, Employment Growth, and Ridership around New Stations

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Contents

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Appendix

This appendix provides more technical detail about the research methodology and findings.

Density, Centralization, and Transit Usage at the Metropolitan Level

This section provides more detail on the relationship between land use patterns and transit usage at the metropolitan level. We use ordinary least squares (OLS) regression to estimate the effect of several land use measures on transit's share of commutes. The land use measures are tract-weighted population and employment densities, as described in the main text, and population and employment centralization. Centralization is a measure of how concentrated population or employment is around downtown. A simple measure is the share of metropolitan population or employment within a given distance of the central business district (CBD) (Kneebone 2009). We use a richer measure, the "density gradient," which is the slope of the relationship between density of a Census tract and its distance from the CBD (Kim, 2007; Glaeser and Kahn, 2004). If density were uniform across all tracts in a metropolitan area, there would be no relationship between density and distance from the CBD, and the centralization measure would be zero. In nearly all metropolitan areas, both population and employment densities are highest near the CBD, yielding negative density gradients for population and employment: multiplying by -1 results in a higher score reflecting greater centralization. For each metropolitan area, therefore, we have measures of population density, employment density, population centralization, and employment centralization. Population data are from the 2000 Census, and employment data are from the 2000 NETS, and transit share is from the 2000 CTPP.

Including all measures together, transit ridership is higher in metropolitan areas with higher population density, higher employment density, higher employment centralization, and *lower* population centralization. In other words, ridership is highest in where employment is densely concentrated in downtown and population is dense but more dispersed. These patterns describe a traditional downtown-centered city, in which large numbers of workers commute into the center. All four coefficients are statistically significant at the 1 percent level, as shown in Table A1, and a one standard-deviation increase in tract-weighted density is associated with more than a half-standard-deviation increase in transit ridership. The relationship between employment density and transit ridership is twice as large as that between residential density and transit ridership, and both centralization measures have smaller effects than the density measures do.

TABLE A1
Metropolitan-area transit ridership and land use patterns

Dependent variable: share of commuters riding transit	Coefficient and standard error	Standardized coefficient
Log tract-weighted population density	.0090***	.28
	(.0018)	
Log tract-weighted employment density	.0129***	.56
	(.0012)	
Population centralization (inverse of slope of population density gradient)	-.0129***	-.23
	(.0034)	
Employment centralization (inverse of slope of employment density gradient)	.0104***	.18
	(.0036)	
R-squared	.62	
N	275	

NOTES: *** denotes statistical significance at 1 percent level. Standardized coefficients represent the change in the number of standard deviations in the dependent variable associated with a one-standard-deviation change in the independent variable.

This analysis includes only land use measures as explanatory variables. Transit system characteristics, like travel speed, frequency of service, and geographic reach of the transit system, may also affect transit ridership, but these transit system characteristics are themselves influenced by expected ridership demand, which in turn are influenced by the land use measures we include.

Data and Methods: Transit Stations and Employment Growth

The original contribution of this report is to assess the extent of employment growth around new transit stations in California between 1992 and 2006. The set of transit stations includes all newly operational stations on fixed-line routes in the state, including subway, streetcar, rail, and dedicated bus-rapid-transit lines — but not express or local bus lines that lack dedicated lanes or rights-of-way. The transit stations that opened in California between 1992 and 2006 were in numerous systems throughout the major metropolitan areas of the state. In all, 217 stations opened, including extensions to BART in the San Francisco Bay Area, the Sacramento light rail system, the San Jose light rail system, San Francisco MUNI, and LA Metro Rail, and new or largely new systems like the Altamont Commuter Express, Coaster San Diego, the Harbor Transitway, and Metrolink Southern California. The only new stations excluded from this analysis were those that overlapped with pre-existing stations on other routes. The main instance of this overlap was the Market Street portion of the San Francisco MUNI F-line streetcar, which runs directly above MUNI Metro lines and BART trains. The F-line portion along the San Francisco wharves, however, does not overlap with older fixed-line transit routes and therefore was included. Information on these stations, including exact address and opening date, were gathered from the National Transportation Atlas Database of the Bureau of Transportation Statistics and from transit systems' websites.

Employment data come from the National Establishment Time-Series (NETS), as described briefly in the main report. Using the exact street address provided in the NETS, we geocoded all California businesses and calculated the level of employment within ¼ mile and within ½ mile of each transit station, as well as total employment in each blockgroup in California, from 1992 to 2006.[1] Population and land area by blockgroup came from the 2000 Census SF3 file; 1990 Census data were available for the 2000 blockgroup boundaries in the "1990 Long Form in 2000 Boundaries" data product by Geolytics. All analysis, therefore, used consistent geographic definitions over the entire study period.

The estimation approach is a standard difference-in-differences approach. The difference in employment growth around a transit station before and after it became operational (hereafter, "turned on") is compared with the difference in employment growth for the same before-and-after time period for a comparable control area. This method hinges on selecting a comparison area as similar as possible to the treatment area—the area surrounding the new transit station—but without a transit station opening that same year. A natural candidate for control areas is the area around transit stations that opened in different years: these areas should be quite similar because they were also selected as locations for new transit stops. However, this approach requires variation in the opening dates of different stations, and often many stations—particularly stations in the same region within the same transit system—open simultaneously, such as when a new line is opened or extended to several new stations at once.

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[1] All distances were calculated aerially, using the formula for distance between two points defined by latitude and longitude.

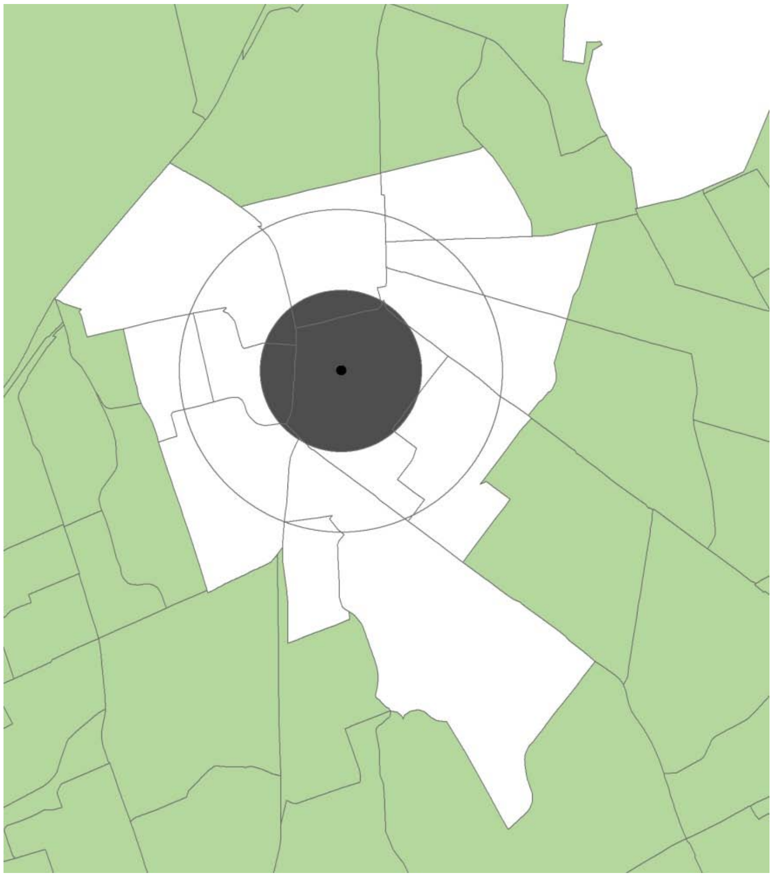
A second candidate for a control area is older transit stations since these, too, were once selected as sites for new transit stops. Yet the areas around older transit stations could be affected by new transit station openings if the extended reach of the transit system changes demand for land around the older stations. This potential for spillovers also applies to other new nodes with staggered opening dates. Because employment changes around other stations—whether old or new—might be directly affected by new station openings, they are not ideal control areas.

Areas not near old or new transit stations are yet another candidate for control areas. Among the different Census geographies, blockgroups in urban areas are the most similar in land area to the ¼- or ½-mile circle around a transit station; tracts tend to be larger than those circles, and individual Census blocks much smaller (long-form Census data are unavailable at the block level but available at the blockgroup level, furthermore). Including all blockgroups in the state, or even restricting to blockgroups only in counties served by transit, would result in control areas containing blockgroups quite dissimilar from the treatment areas, since transit stations are not located randomly, as demonstrated below.

Two methods could be used to select similar blockgroups. One is propensity-score matching: by estimating the predicted likelihood that a blockgroup could be selected as the location for a transit station based on characteristics that actually predict transit-station selection, blockgroups (and transit station themselves) can be given a propensity score. Imbens and Wooldridge (2009) and Crump et al. (2009) suggest that a propensity-score-trimmed model that drops control and treatment areas with extreme propensity score values produces a control area more similar to the treatment area and improves the precision of regression estimates. However, this method can drop some treatment areas and therefore estimates the effect only on treatment areas with non-extreme values of the propensity score. Furthermore, the propensity-score-trimming method selects blockgroups most similar to transit stations exhibiting typical transit-station characteristics, and transit stations tend to be heterogeneous in their location, density, and other characteristics. A better alternative, therefore, is to match each transit station to the blockgroups most similar to itself. This process, nearest-neighbor matching, selects N control areas for each treatment area based on similarity of matching variables' values.

For each new transit station in the state, the candidate blockgroups for matching were all blockgroups in the same regions as the transit station, excluding any blockgroups containing any land area within ½ mile of any transit node in the state (either pre-1992 or part of the 1992–2006 sample). Figure A1 illustrates a transit station (Concord BART), the ¼-mile circle (shaded black), the ½-mile circle (unshaded), blockgroups containing land area within the 1/2-mile circle (white); all other blockgroups, in green, are candidates for matching the dark circle surrounding the transit station.

FIGURE A1
Transit station and blockgroups illustration: Concord BART



Black center point: Concord BART

Solid gray circle: ¼ mile radius

Outlined outer circle: ½ mile radius

All other lines are blockgroup boundaries

Unshaded blockgroups are “buffers” and not eligible to be comparison areas for the gray circle

Green blockgroups are eligible to be comparison areas for the gray circle

Five regions across the state were defined to reflect local economies and to avoid, as best as possible, splitting transit systems into multiple regions.[2] The seven matching variables included:

- distance to CBD, nearest freeway, and nearest pre-1992 transit station, in order to achieve similarity of access to other features;
- population density (1990) and employment density (1992), in order to achieve similarity of land use; and
- centroid latitude and longitude, to minimize physical distance in order to reflect localized employment shocks.

Each transit station was paired with the twenty best-matching blockgroups. Because matching was “with replacement,” some blockgroups matched to multiple transit stations, which raises econometric issues addressed below.

$$\Delta Y_{it} = \alpha + \beta on_{it} + \lambda everon_i + \sum_{g'=1}^{G} \sum_{t'=1}^{T} D_{g't'} \theta_{g't'} + \Omega X_i + \varepsilon_{it}$$

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[2] The regions consisted of (1) San Francisco, San Mateo, Alameda, Contra Costa, and San Joaquin counties; (2) Santa Clara county; (3) Sacramento county; (4) San Diego county; and (5) Los Angeles, Orange, Riverside, San Bernardino, and Ventura counties.

The baseline empirical specification pools all transit stations and their associated matching blockgroups. The unit of observation is the ¼-mile area surrounding the transit station (a "node") or a matched blockgroup, both indexed *i*, at year *t*. Together, a node and its twenty matched blockgroups constitute a "pair" (referring to a treatment-control pair), indexed *g*. The dependent variable, Y_{it}, is employment growth for node/blockgroup *i* in year *t* (the log of the ratio of employment at *t+1* and employment at *t*). Within each "pair," a standard difference-in-difference model in which a treatment turns on in year 0 includes three dummy variables: (1) a dummy that equals 1 for all *it*, *t*>=0 (omitted); (2) a dummy that equals 1 only for treatment nodes *i,* for all years *t* (*everon*); and (3) a dummy that equals 1 only for treatment nodes *i* and only for years *t*>=0 (*on*)—in other words, only in the years when the new transit station is operational. This last dummy has the coefficient of interest, designated in the model above as β. The model includes year-pair fixed effects. A dummy that equals 1 for all *it* in pair *g* for *t*>=0 is constant for all observations in a year-pair; this dummy is therefore redundant in the model with year-pair fixed effects and is omitted.

Because the matching procedure selects control areas—blockgroups—that are as similar as possible but still not identical on the matching characteristics, the matching characteristics (excluding latitude and longitude) are included in X_i as time-invariant controls: the three distance measures and the two density measures. Controls also include two summary measures of industrial composition in 1992: average earnings, measured as the national average industry earnings weighted by node/blockgroup *i*'s industry mix, and predicted growth, measured as national average industry growth (excluding California) weighted by node/blockgroup *i*'s industry mix. Although neither of these variables should predict the location of transit stations, making them unsuitable matching variables, both could plausibly affect subsequent employment growth. The last control variable is the number of local growth regulations affecting commercial and industrial development, out of a maximum of five, based on a 1992 survey of local officials in California described in Glickfeld et al. (1999). Because the nature and stringency of local land-use regulation is hard to quantify and incorporates numerous components, this zero-to-five scale is a simple and imperfect proxy. Yet, to our knowledge, it is the only measure available specifically of commercial or industrial land-use regulation—other measures commonly used in land-use research focus on residential regulation. Also, it has the advantage of pre-dating the time period our analysis covers, so it does not reflect regulatory changes that accompanied or followed transit station openings.

Some blockgroups are replicated in the dataset because they match multiple transit stations. This replication could affect both the coefficient estimates, because the replication gives extra weight to those blockgroups, and the standard errors, because the replicated blockgroups do not have independent errors. Accordingly, observations are weighted by 1/p, where p equals the number of transit stations a that blockgroup matches; all transit stations and unreplicated blockgroups have weight 1 (following Addison et al. 2009). Also, standard errors are multi-way clustered, by "pair" *g* and by node/blockgroup *i* (following Dube et al. forthcoming).[3]

The basic specification models the treatment effect as a one-time, permanent shift in the employment growth rate. The variable on_{it} equals 1 in the year that the transit station becomes operational and all subsequent years. Alternative specifications include:

1. Adding a dummy that equals 1 ONLY in the year that the transit station becomes operational: this allows the growth rate to have both a one-time and permanent change.

[3] The latest version of the stata command xtivreg2 handles fixed effects with weighting and multi-way clustering.

2. Adding a fuller set of leads and lags.
3. Interacting the control variables with the treatment effect estimator to test explanations for heterogeneous effects across transit stations. (Note that, with interactions, the dummy variable that equals 1 for both the treatment and control in the "pair" for all t>=0 is no longer constant within the pair-year when interacted.)
4. Estimating the treatment effect for each transit node separately with its own matched blockgroups only.

In addition, specification checks include adjusting the number of matched blockgroups per transit station; using employment within ½-mile of a transit station instead of ¼-mile; and using alterative control areas, as will be described below.

Results: Transit Stations and Employment Growth

The first results examine the location of new transit stations in California. We use a probit model where the observations are the ¼-mile circles around new transit stations, 1992–2006, and all blockgroups excluding (1) those within ½-mile of old or new nodes, as illustrated in Figure A1, and (2) those outside the 13 California counties with transit stations. The dependent variable is whether the observation is a transit station or a blockgroup outside the area around a transit station, so in effect the dependent variable is whether the area is in the treatment group (a transit node) or not (blockgroups away from transit stations). County fixed-effects are included as well. The regression results in Table A2 show that new transit nodes in California tended to be located in areas with higher employment density, lower population density, and closer to freeways. Many of these measures—like population density, employment density, and distance from CBD—are themselves highly correlated. Although population density is negatively associated with the location of new transit nodes, holding other variables constant, a univariate regression reveals that new transit nodes tend to be located in areas with higher population density.

TABLE A2
Regression results: location of new nodes and density (and other factors)

Dependent variable: transit station = 1, blockgroup = 0	
Distance from nearest freeway	-0.00287***
	(0.000430)
Distance from nearest pre-1992 transit station	3.19e-05
	(3.71e-05)
Log population density, 1990	-0.00126***
	(0.000253)
Log employment density, 1992	0.00272***
	(0.000469)
Distance from central business district (CBD)	-2.63e-06
	(3.22e-05)
N	14011

NOTE: Uses probit model. Dependent variable is new node; observation is area around nodes plus all other blockgroups in region, excluding blockgroups around pre-1992 nodes.

Furthermore, new transit stations vary considerably in their location and characteristics. Some, like the Pershing Square station on the LA Metro Rail and the Washington/Embarcadero stop on the MUNI F Wharves line in San Francisco, are near the CBD and in high density areas; some are primarily "origin" nodes, in areas with high residential and low employment density, like the North Concord/Martinez BART and Avalon LA Metro Rail stations; and some are in low density areas, like the Hazel station on Sacramento light rail and the Vincent Grade/Acton Metrolink station. Some run in a freeway median, such as portions of the LA Metro Rail green line and the Harbor Transitway, whereas most of the Altamont Commuter Express and the MUNI F Wharves line are not adjacent to a freeway. The variation among transit nodes argues in favor of matching blockgroups to each individual station, rather than using a propensity-score matching model to identify the blockgroups most similar to a transit station with typical characteristics.

As mentioned above, the matching process identifies the twenty blockgroups most similar to each new transit station, on the variables included in Table A2 as well as latitude and longitude. By construction, therefore, the transit stations and the matched blockgroups will have similar average values for these measures, unless even the best-matching blockgroups are still quite different on some measures than the transit stations. Table A3 shows the means for each variable for the transit stations and the matched blockgroups. (As noted above, some blockgroups are matched to multiple transit stations, and these blockgroups are included multiple times in constructing the descriptive statistics in Table A3.)

TABLE A3
Descriptive statistics for transit stations and matched blockgroups

	Transit stations	Matched blockgroups
Distance from CBD (miles)	11.78	12.18
Distance from nearest pre-1992 node (miles)	10.71	10.98
Distance from nearest highway (miles)	0.57	0.72
Employment density (per sq km), 1992	6643	3416
Population density (per sq km), 1990	1265	1351
Predicted cumulative employment growth, 1992 industry mix	17.4%	20.5%
Average pay, 1992 industry mix	$25,720	$24,861
Employment growth, when station is operational (log ratio n+1/n)	.0019	-.0006
Employment growth, before station is operational (log ratio n+1/n)	.0145	.0032
Employment growth (standard deviation)	.25	.24
N (each station/blockgroup—year is an observation)	3038	60760

For the five matching variables (excluding latitude and longitude), the matched blockgroups are similar in distance from CBD and from older transit stations and in population density; they are somewhat farther from a highway and have much lower employment density. These differences warrant including these variables as controls in the baseline regression specification because these variables could affect employment growth. For the two industry-composition variables included as controls, the matched blockgroups have industries that, on average, would subsequently grow faster in the U.S. (outside of California) and that, on average, have slightly lower pay than industries near new transit stations. The table also shows the means for employment growth—the dependent variable of the baseline specification—for stations and blockgroups. Employment growth in the ¼-mile circle where transit stations opened in 1992–2006 was 1.45 percent annual before the station came into operation and only 0.19 percent afterward. For matched blockgroups, employment growth was 0.32 percent annually before the matching transit station came into operation and -0.06 percent afterward. The decline in employment growth before-and-after for the area around transit stations is larger than the analogous decline for the matched blockgroups, so the difference-in-difference is -0.0088, a slower growth rate by 0.88 percentage points.

The baseline regression specification, as described above, includes fixed effects, controls, and corrections to account for the replication of some matched blockgroups. Results are presented in Table A4, column 1. The difference-in-difference estimator, the coefficient on the variable *on* that equals 1 only for transit nodes and only in years when they are operational, is -0.0091 (a decline in growth rate of 0.91 percent) and not statistically significant (and about the same magnitude as the simple difference-in-difference estimate from the descriptive statistics in Table A3). The coefficient on *everon* is 0.015 and statistically significant, meaning that employment growth in areas around transit stations before they became operational was higher than employment growth in matched blockgroups in the same years, which corresponds to the higher growth rate for transit stations before they are operational, in Table A3. Note that only stations opening between 1993 and 2005, inclusive, are included; for stations opening in 1992 or in 2006, employment was not observed both before and after station opening.

TABLE A4
Baseline specifications and alternative time paths

	(1)	(2)	(3)
On	-0.00908	-0.00869	
	(0.00953)	(0.00884)	
Everon	0.0151**	0.0151**	0.0135**
	(0.00657)	(0.00657)	(0.00543)
3 years before on			0.0343
			(0.0374)
2 years before on			0.0114
			(0.0252)
1 year before on			-0.0279
			(0.0192)
Year turning on		-0.00291	-0.00996
		(0.0220)	(0.0212)
1 year after on			-0.0225
			(0.0160)
2 years after on			-0.0328*
			(0.0176)
3+ years after on			9.88e-05
			(0.00765)
N	59,976	59,976	59,976

NOTE: all models include controls, fixed effects, weighting, and 2-way clustering, but no interactions with “on” or “everon.” 20 matches, ¼ mile circle.

Testing alternative time paths of effects, the difference-in-differences estimator for employment growth around transit stations remains statistically insignificant yet negative. Table A4, column 2, adds a dummy variable that equals 1 only in the year that the station becomes operational, corresponding to alternative specification #1 listed above. This coefficient is very small and statistically insignificant, and the coefficient on the change in growth for the entire time the station is operational (*on*) is essentially unchanged from column 1. Table A4, column 3, adds leads and lags, corresponding to alternative specification #2, listed above. In this model, the *everon* variable reflects growth around the transit station relative to growth in matched blockgroups prior to the first lead variable, three years before the station "turns on", and is still positive and statistically significant. Of all leads and lags included, only the two-year lag (equals 1 for employment growth two years after the station turns on) is statistically significant at the 10 percent level, in the negative direction. For all other years immediately before and after station opening, employment growth around new transit stations is not statistically different from employment growth in matched blockgroups, relative to the difference in growth more than three years prior to the station becoming operational.

The results in Table A4 and the descriptive statistics in Table A3 are average effects across all new transit stations in California, but employment growth around new transit stations relative to growth around matched blockgroups is heterogenous. As the main text of the report mentions, of the 204 stations that opened between 1993 and 2005 and therefore allow for before-and-after comparison, the difference-in-differences estimator for employment growth was positive and statistically significant at the 10 percent level for 18 stations and negative and statistically significant at the 10 percent level for 20 stations (this analysis corresponds to alternative specification #3, above). The statistically siginificant effects were not limited to specific systems or routes, but the effects are related to characteristics of individual transit stations. Table A5 presents coefficients from a single regression, following the baseline specification but adding interactions between the *on* variable and the control variables, corresponding to alternative specification #4, above.

TABLE A5
Interactions

	Main effects	Interacted with "on"
From highway	-0.00608*	-0.00818
	(0.00352)	(0.0166)
From older node	0.00123	0.00173**
	(0.000939)	(0.000844)
Population density	-0.0104***	0.0142***
	(0.00248)	(0.00544)
Employment density	-0.0177***	0.0265
	(0.00244)	(0.0161)
Industry avg growth	0.0589***	-0.0432
	(0.0170)	(0.102)
Industry avg pay	6.41e-07	-2.71e-06
	(4.53e-07)	(3.10e-06)
From CBD	-0.00161	0.000618
	(0.00103)	(0.00102)
Growth controls	-0.00322*	-0.00410
	(0.00190)	(0.00767)
N	59,976	

NOTE: N=59.976, include controls, fixed effects, weighting, and 2-way clustering, 20 matches per transit station, ¼ mile circle. Also included in the model were interactions between each control variable and *everon* and between each control variable and a dummy equaling 1 for both the transit station and its matched blockgropus for all years that the station was operational.

The main effects of several variables are statistically significant. Employment growth is higher in areas (around transit stations or matched blockgroups) that are closer to highways; have lower population density in 1990; have lower employment density in 1992; have industries that grew faster nationally between 1992 and 2006; or were in localities with fewer regulatory controls on commercial or industrial growth as of 1992.[4] The interactions of these variables with *on* reveals how the difference-in-differences estimator varies with these characteristics. Employment growth associated with the opening of a transit station was higher for transit stations farther from pre-1992 transit stations or those with higher population density. The magnitude of the interaction with employment density is larger than that with population density, but the standard error is much larger and therefore the level of significance is weaker for the employment density interaction. Although distance from nearest highway, stringency of growth controls, and predicted growth from industry composition all affect employment growth generally, none has a statistically significant effect on the differential growth associated with a transit station opening.

Returning to the specification without interactions, we perform some sensitivity checks: five matched blockgroups per transit station instead of twenty, and the ½-mile circle around the transit station instead of the ¼-mile circle. With five matches rather than twenty, the average match quality is higher since the best twenty matches to a transit station include fifteen matches all worse than the best five; however, fewer matches should lead to less precision and higher standard errors. With a ½-mile circle rather than a ¼-mile circle, the treatment area adds land less proximate to transit and therefore might include areas where demand for land is unaffected by the transit station opening, but the larger area could improve precision and reduce standard errors. Comparing the original model (Table A6, column 1; repeated from Table A4, column 2) with these alternatives, the difference-in-differences estimator—the coefficient on *on*—remains negative, of similar magnitude, and not statistically significant for the ½-mile circle with twenty matches (Table A6, column 2), with a notable reduction in the standard error relative to the ¼-mile circle. The coefficient on *everon*—the difference in employment growth rates between transit stations and matched blockgroups prior to the stations becoming operational—remains positive, significant, and of very similar magnitude.

TABLE A6
Sensitivity checks

	¼ mile circle Matches=20 (1)	½ mile circle Matches=20 (2)	¼ mile circle Matches=5 (3)	½ mile circle Matches=5 (4)
On	-0.00869	-0.00851	-0.00559	-0.00585
	(0.00884)	(0.00530)	(0.00923)	(0.00617)
Year turning on	-0.00291	0.00717	0.00605	0.0139
	(0.0220)	(0.0135)	(0.0251)	(0.0191)
Everon	0.0151**	0.0148***	0.0146**	0.0145***
	(0.00657)	(0.00379)	(0.00673)	(0.00419)
R-squared	0.006	0.005	0.006	0.004
N	59,976	59,976	17,136	17,136

NOTE: all models include controls, fixed effects, weighting, and 2-way clustering, but no interactions with “on” or “everon.”

A final alternative specification departs from the framework outlined above with matched blockgroups in order to investigate whether the higher employment growth rate around new transit stations prior to becoming

[4] Recall that the sample is transit station areas and blockgroups selected for their similarity to the transit station areas on many of these dimensions.

operational also holds true for transit stations coming into operation prior to 1992. In this specification, all blockgroups in counties with transit stations are included as controls, as well as the areas within ¼-mile of pre-1992 transit stations. In place of the pair-year fixed effects in the baseline specification, this model includes county-year fixed effects as well as the set of earlier control variables. Standard errors are clustered on county, and because no matching is used, no blockgroups are replicated and no weighting is necessary.

The results in Table A7 show that, relative to other blockgroups in the same county, employment growth around pre-1992 transit stations was 1.8 percent higher between 1992 and 2006. Employment growth in transit stations that became operational between 1992 and 2006 was also 1.8 percent higher between 1992 and 2006; although this coefficient is not statistically significant, it is of very similar magnitude to the coefficient on the pre-1992 transit stations. (Even with the different control area, the difference-in-differences estimator—the coefficient on *on*—remains negative and not statistically significant.) Thus, the higher employment growth rate observed for new transit stations prior to their becoming operational is not unique to new stations. The areas surrounding both older and newer transit stations, regardless of whether the stations are operational, experienced higher employment growth than elsewhere in their counties. It is unclear whether this higher growth rate is due to the decision to site transit stations in areas where employment grows faster or due to spillover effects from newly opening transit stations elsewhere in the same system (which could contribute to higher employment growth around the older transit stations).

TABLE A7
Alternative control areas

	(1)	(2)
On	-0.0137	-0.0128
	(0.0131)	(0.0111)
Year turning on		-0.00678
		(0.0196)
Everon (1992–2006)	0.0184	0.0184
	(0.0103)	(0.0103)
Everon (pre-1992)	0.0180***	0.0180***
	(0.00318)	(0.00319)
R-squared	0.007	0.007
N	199,262	199,262

NOTE: Old & new nodes, plus all blockgroups—county/year fixed effects.

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