Residential Land Use Regulation and the Spatial Mismatch between Housing and Employment Opportunities in California Cities

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Executive Summary

Spatial mismatches between housing and employment opportunities have received considerable attention over the past half-century. Such mismatches contribute to higher commute burdens and limited access to high-opportunity employment areas, particularly for racial or ethnic minorities and low-income residents. To date, however, there is little evidence regarding the relationship between spatial mismatches and residential land use regulation.

In this paper, I use data from the Terner California Residential Land Use Survey, the American Community Survey, and the Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics to examine whether cities that have adopted differing land use regulations also have differences in the spatial mismatch between housing and employment opportunities.

My analysis suggests that cities that prohibit high-density development tend to have residents whose earnings are markedly higher than those of their workforce. I also find that cities that offer more affordable housing incentives and those that do not impose minimum lot size restrictions on accessory dwelling units (ADUs) tend to have a better balance between the number of residents and the number of workers and have a better fit between the number of affordably-priced housing units and the number of low-income workers. These policies, along with the use of urban growth boundaries and more lenient parking restrictions, also appear to reduce the commute burden experienced by workers.

Introduction

A considerable body of research has examined the spatial mismatch between housing and employment opportunities—imbalances between the location of jobs and housing—and its impact on low-wage and minority workers' commute burden and subsequent access to high-opportunity employment areas (see, for example: Horner & Mefford, 2007; Ihlanfeldt, 1994; Ihlanfeldt & Sjoquist, 1998). Although the topics of spatial mismatch, job-housing balance, and commuting behavior have received considerable attention over the past five decades, little attention has been paid to the potential role of land use regulation in contributing to the problem. For example, in a 2004 review of the literature on exclusionary land use regulation, Ihlanfeldt (2004, p. 272) noted that "restrictive land-use regulations may have important effects on the intraurban geography of economic opportunity among lower-skilled workers. However, it remains unknown just how important these effects might be."

Much of the recent research on land use regulation has focused on its impact on the rate of housing production, sprawl, housing prices (Anthony, 2004; Paulsen, 2014; Pendall, 1999; Quigley & Rosenthal, 2005; Saiz, 2010; Schill, 2005), or patterns of residential segregation by race and income (Lens & Monkkonen, 2016; Rothwell & Massey, 2009). To the extent that land use regulation shapes these factors, it may also contribute to greater commute burdens and mismatches between the location of housing and employment opportunities in urban areas. To my knowledge, however, this has yet to be examined in detail.

In the fifteen years since Ihlanfeldt's (2004) review of the academic literature on the exclusionary effects of land use regulations, there have been relatively few attempts to examine their impact on patterns of spatial mismatch. Three recent analyses suggest that the overall strictness of land use regulation may contribute to spatial mismatch by decreasing household mobility in response to changes in the location of employment (Hong & Geoffrey, 2013), by increasing the number of commuters who must leave their place of residence to get to their place of work (Ogura, 2010), or by increasing commute time (Shoag & Muehlegger, 2015). However, all three of these studies examine the relationship between an aggregate measure of land use regulation and a limited set of potential indicators of spatial mismatch.

In this study I examine the relationship between a number of types of residential land use regulation and the spatial mismatch between housing and employment in California cities. To do so, I use a recent survey of residential land use regulation in California cities conducted by the Terner Center for Housing Innovation at the University of California, Berkeley. This survey of 252 cities (more than 50 percent of the cities in the state) measured detailed characteristics of the regulatory environment across cities. I pair data from the Terner California Residential Land Use Survey (TCRLUS) with data from the American Community Survey (ACS) and the Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics (LODES) to examine the relationship between various regulatory tools and six indicators of spatial mismatch. After describing each of these indicators and the land use regulations derived from the TCRLUS, I conduct regression analyses to examine the relationship between land use regulation and spatial mismatch and present the findings and implications of those analyses.

Methodology

Spatial Mismatch Indicators

In this study I examine the relationship between land use regulation and six indicators of spatial mismatch. Three of these indicators measure imbalances between employment and housing opportunities, and three measure the commute burden experienced by workers. I begin by first describing the indicators that measure imbalance, including resident-worker mismatch, low-income housing fit, and resident-worker earnings mismatch. I then describe the indicators that capture commute burdens, including the percentage of workers who reside within the same city in which they work and the percentage of workers who commute more than 10 minutes or more than 30 minutes from home to work.

Resident-Worker Mismatch

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The first indicator of spatial mismatch that I examine is resident-worker mismatch. This variable measures whether the number of employed residents residing within the city (regardless of where they work) is larger or smaller than the number of workers employed within the city (regardless of where they live). I hypothesized that residential land use regulation may contribute to the creation, or maintenance, of bedroom communities—that is, cities containing disproportionate amounts of housing but relatively few places of employment. To measure resident-worker mismatch, I compared the total number of jobs held by residents in city i, derived from 2015 census block level data from the LODES Residence Area Characteristics files, with the total number of jobs located in city i, derived from 2015 LODES Work Area Characteristics files. I then identified which city contains each census block.[1]

Specifically, I calculated the ratio of employed residents-to-workers in each city[2] and then took the natural log to normalize the distribution, as follows:

$$\text{Resident-Worker Mismatch} = \ln\left(\frac{\text{Employed Residents}_i}{\text{Workers}_i}\right)$$

This indicator of spatial mismatch is centered around zero, as shown in Figure 1 and Table 1, giving it a relatively intuitive interpretation: Any city with a resident-worker mismatch close to zero has a relatively equal number of workers and working residents; cities with positive values have more employed residents than workers; those with negative values have more workers than employed residents.

Figure 1. Resident-Worker Mismatch

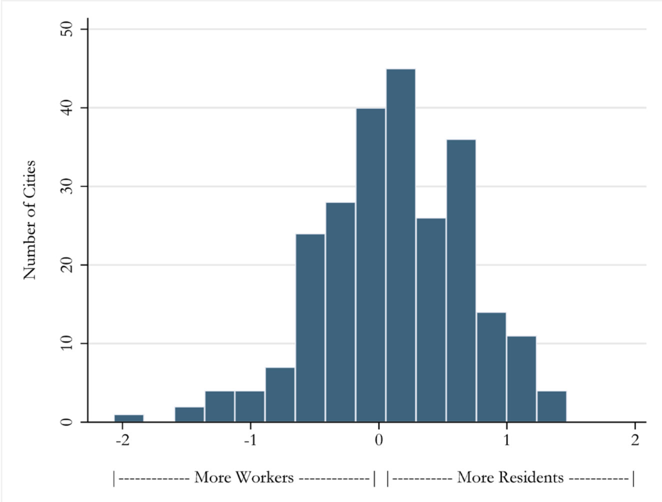


Table 1: Descriptive Statistics: Mismatch Metrics

Variable	Mean	Std. Dev.	Min	Max
Resident-Worker Mismatch	0.11	0.58	-2.07	1.47
Low-Income Housing Fit	0.00	1.00	-3.66	3.03
Resident-Worker Earnings Mismatch	0.15	0.28	-0.41	1.07
Percentage of Workers who Reside in the City	18.74	12.14	0.58	57.34
Percentage of Workers with > 10-Minute Commute	85.59	8.75	48.96	98.02
Percentage of Workers with > 30-Minute Commute	34.65	11.06	9.90	62.90

[1] I did so by identifying whether the centroid of a census block was located within a city.

[2] In the literature on spatial mismatch, scholars use a variety of ways to measure imbalances between jobs and housing. For a helpful review, and for justifications for the use of the approach used here, see Wu, Zhang, and Yang (2015).

Take, for example, the City of Los Angeles, where in 2015 there were 1.75 million workers and 1.61 million employed residents, as shown in Table 2. On the whole, the number of workers and employed residents is fairly balanced, as indicated by a resident-worker mismatch of -.08. Rancho Palos Verdes, on the other hand, located along the coast south of Los Angeles (see Figure 1), has nearly four times as many employed residents (20,262) as it does workers (5,342), giving it a resident-worker mismatch of 1.33. Santa Fe Springs, with a resident-worker mismatch of -2.07, has many more workers (61,055) than employed residents (7,729).[3]

Table 2. Spatial Mismatch Indicators for Five Cities in Los Angeles County

	Rancho Palos Verdes	Long Beach	Los Angeles	Pasadena	Santa Fe Springs
Resident-Worker Mismatch	1.33	0.16	-0.08	-0.60	-2.07
Workers	5,342	167,422	1,751,347	112,512	61,055
Employed Residents	20,262	196,811	1,614,135	61,603	7,729
Low-Income Housing Fit	1.69	0.09	-0.38	-1.34	-2.63
Workers Earning < $1,250 per Month	1,459	41,234	432,426	24,124	8,293
Housing Units with Costs < $800	3,039	31,998	250,266	7,732	1,193
Resident-Worker Earnings Mismatch	0.80	-0.01	-0.12	0.13	-0.05
Median Earnings of Workers	$30,953	$35,960	$34,834	$37,356	$37,303
Median Earnings of Employed Residents	$68,672	$35,477	$30,992	$42,405	$35,475
Percentage of Workers who Reside in the City	12.39	26.69	47.58	12.95	1.59
Workers who Reside in the City	658	44,473	827,902	14,521	963
Workers	5,342	167,422	1,751,347	112,512	61,055
Percentage of Workers with > 10-Minute Commute	89.85	92.48	94.07	92.41	95.45
Workers who Travel more than 10 Minutes to Home	5,424	165,647	1,857,312	106,517	47,999
Workers	6,037	179,111	1,974,458	115,263	50,286
Percentage of Workers with > 30-Minute Commute	38.18	43.80	56.72	46.06	52.89
Workers who Travel more than 30 Minutes to Home	2,305	78,447	1,119,894	53,093	26,598
Workers	6,037	179,111	1,974,458	115,263	50,286

[3] The spatial mismatch indices for each city are shown in the Appendix.

Figure 2. Five Cities in Los Angeles County, California

Low-Income Worker-Housing Fit

As prior research (Benner & Karner, 2016) has illustrated, a specific city may have relatively balanced numbers of workers and residents but still experience mismatches between housing and employment opportunities due to a poor fit between the incomes of workers and the cost of housing. For example, cities may rely heavily on lower-income workers but may provide housing for predominantly higher-income residents. To examine this possibility, I use a modified version of a housing fit metric developed by Benner and Karner (2016) that compares the number of low-income workers (those earning $1,250 per month or less), derived from 2015 LODES Work Area Characteristics data, and the number of affordable housing units (those for which the owner or tenant spends less than, or for which the contract rent is less than, $800 per month), derived from 2013-2017 5-Year Estimates from the American Community Survey (ACS).

I make a number of modifications to Benner and Karner's (2016) housing fit measure. Whereas Benner and Karner use only rental units in their measure of housing fit, I use estimates for owner-occupied units as well. Similarly, whereas Benner and Karner use a $750 housing cost threshold for affordability, I use an $800 threshold.[4] Moreover, I invert the ratio, thus dividing the number of affordable rental units by the number of workers to allow for ease of interpretation in the regression analyses that follow. This ensures that land use regulations that are associated with increases in the ratio of affordable housing units to low-income workers lead to increases in the housing fit index. I then take the natural log of the ratio to ensure that a one-unit change in the numerator has the same impact on the index regardless of whether the numerator is larger or smaller than the denominator and I standardize the index so that it has a mean of zero and standard deviation of one.

In this study, housing fit is therefore calculated as follows:

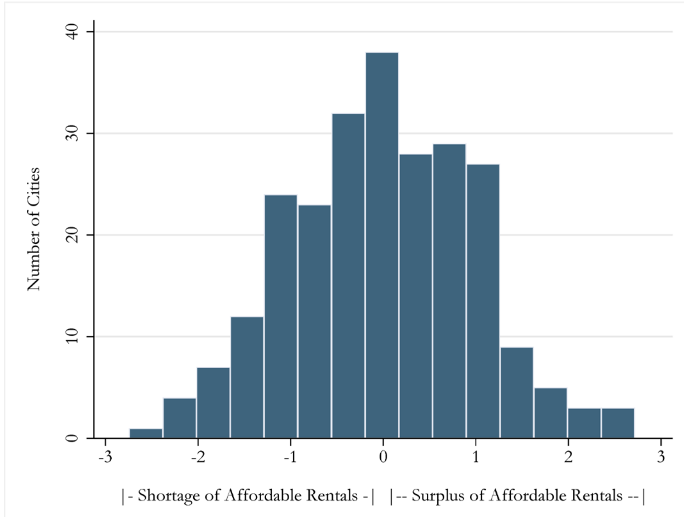
$$\textbf{Low-Income Housing Fit} = \frac{\bar{X}\text{-}ln\left(\dfrac{\textit{Housing Units with Costs} < \$800_i}{\textit{Workers with Earnings} < \$1{,}250 \textit{ per month}_i}\right)}{s}$$

[4] Benner and Karner (2016) calculate the sum of the number of occupied rental housing units with gross rent of $750 or less and the number of unoccupied rental units with contract rent of less than $750. As they note, the use of the cost threshold for affordable housing units is a somewhat subjective decision. The specific threshold for affordability may vary by the number of earners per household, their actual incomes, and their total housing costs. Moreover, because estimates of the number of housing units below the selected housing cost threshold are subject to sampling error, there is also additional measurement error in the housing fit index. In the housing fit index that I calculate here, I use an $800 threshold. I also include owner-occupied units with owner costs below that threshold. In the case of owners, housing costs are also dependent upon whether or not they have a mortgage and its interest rate and amortization schedule. I tested the use of different housing cost thresholds, ranging from $400 to $1,500; the housing fit index based on the $800 threshold had the highest r-squared (0.08) when regressed on the land use regulations described below. It thus appeared to be the threshold that was most closely related to the land use regulations studied here. I also used regression analysis to compare my housing fit index based on both owner and rental units at the $800 threshold with Benner and Karner's version of the housing fit index (i.e., with only rental housing units) at various housing cost thresholds from $400 to $1,500. The r-squared (0.039) for the rental housing fit index with the $750 threshold was the highest, but it was considerably lower than that of the index that I use here (0.08). It therefore appeared that an index based on all housing units, regardless of tenure, was more appropriate.

where the ratio in parentheses is the inverse of the modified Benner and Karner (2016) housing fit metric using units with housing costs below $800 per month as the threshold for affordability, ln normalizes the housing fit ratio using the natural log, and $\overline{X}$ and s represent the average and standard deviation of the log housing fit for the sample of cities surveyed.

Figure 3 shows the distribution of the housing fit indicator for the cities in the TCRLUS. Cities with housing fit indices less than zero have lower housing fit indices than the average city—thus, they likely have a shortage of affordable housing. Cities with housing fit indices greater than zero have higher housing fit indices than the average city and thus likely have a surplus of affordable housing relative to the number of low-income workers. To illustrate how housing fit differs from resident-worker mismatch, Table 2 again compares five cities in Los Angeles County. Although there is some variation between resident-worker mismatch and housing fit, most cities are relatively similar: Rancho Palos Verdes, for example, has an oversupply of affordable housing units relative to the number of low-income workers, as indicated by a housing fit index of 1.69; this parallels the resident-worker mismatch index of 1.33. Similarly, Long Beach and Los Angeles have low-income housing fit indices that are fairly close to zero (0.09 and -0.38, respectively), suggesting relative balance between the number of low-income workers and the number of affordable housing units; again, this largely parallels the findings from the resident-worker mismatch index. Lastly, Pasadena and Santa Fe Springs have negative low-income housing fit indices, suggesting that both cities have a limited supply of affordable housing relative to the number of low-income workers; this mirrors their resident-worker mismatch indices as well.

Figure 3. Low-Income Housing Fit



Resident-Worker Earnings Mismatch

Because prior research suggests that areas with a better match between worker and resident incomes have larger shares of residents who live and work in the same area (Stoker & Ewing, 2014), I also examine differences between the median earnings of employed residents (those who live in the city, regardless of where they work) and workers (those who work in the city, regardless of where they live). I calculate the resident-worker earnings mismatch as follows:

$$\text{Resident-Worker Earnings Mismatch} = ln\left(\frac{\textit{Median Earnings of Employed Residents}_i}{\textit{Median Earnings of Workers}_i}\right)$$

Once again, I take the natural log of the ratio of employed resident earnings to worker earnings, both of which are derived from 2013-2017 5-Year Estimates from the ACS,[5] in order to normalize the distribution. After doing so, the metric has an intuitive interpretation: In cities with a resident-worker earnings mismatch of zero, employed residents and workers have identical median earnings; in cities with positive mismatches, employed residents have higher earnings than workers; in those with negative mismatches, employed residents have lower earnings than workers. As is shown in Figure 4, the distribution is highly skewed to the right; this is due to the fact that there are many cities in the sample in which employed residents have dramatically higher earnings than workers. I suspected that this might be attributable to exclusionary land use regulations that increase the cost of housing and reduce housing opportunities for low-income workers, a hypothesis I test below.

Figure 4. Resident-Worker Earnings Imbalance

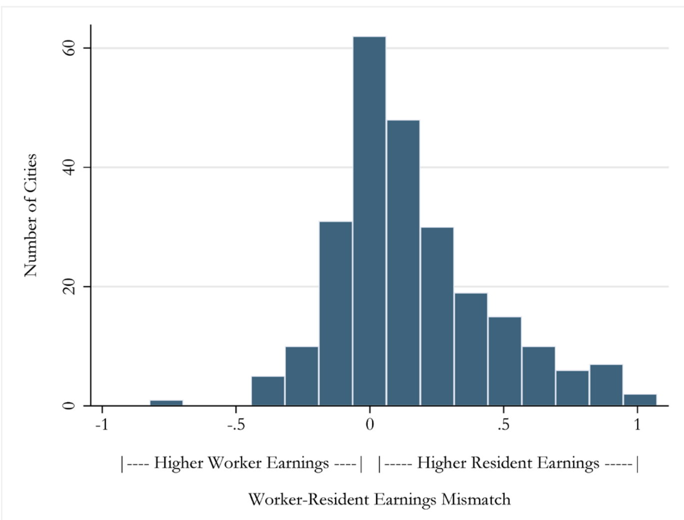


Table 2 presents the resident-worker earnings mismatch for the same five cities in Los Angeles County. As is clear, these five cities have relatively comparable median earnings among workers, ranging from a low of $30,953 in Rancho Palos Verdes and a high of around $37,356 in Pasadena. In some cities, such as Long Beach, Los Angeles, and Santa Fe Springs, the median earnings of employed residents are actually lower than that of workers employed in the city—though in all three cases the differences are not large. This results in resident-worker earnings mismatches of close to zero. In Rancho Palos Verdes, however, the median earnings of employed residents ($68,672) is more than double that of workers ($30,953), resulting in a resident-worker earnings mismatch of 0.80.

Percentage of Workers who Reside in the City

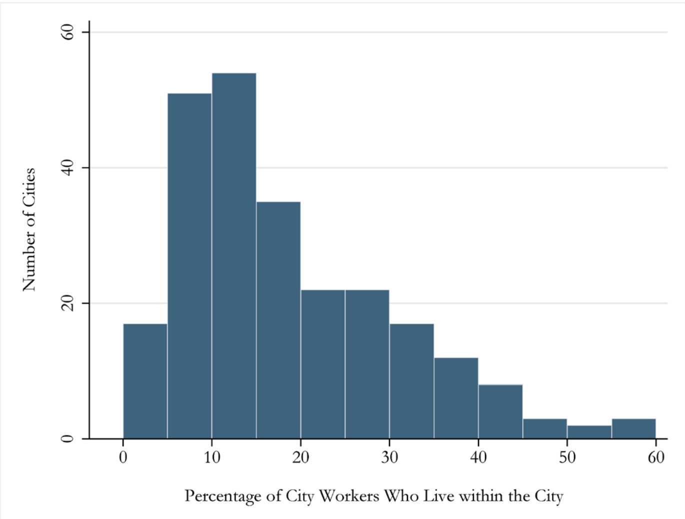
I now turn to a discussion of the three indicators that measure commute patterns for workers in each city. I begin with a discussion of the internal capture of workers, or the percentage of workers who reside in the same city in which they work. I use 2015 Origin-Destination files from LODES to identify the place of work and place of residence for each worker. I begin by identifying workers in each city, i, using census block FIPS codes for Work Area Characteristics. I then identify the share of these workers who reside within the same city, i, using census block codes for Residence Area Characteristics. I multiply the ratio by 100 to convert it to a percentage, as follows:

$$\text{Percentage of Workers Who Reside in the City} = \left(\frac{\textit{Workers Residing within the City}_i}{\textit{Workers}_i}\right) * 100$$

[5] To measure median earnings for employed residents, I use earnings data for the place of residence (Table B08121); to measure median earnings for workers, I use earnings data for the place of work (i.e., workplace geography, Table B08521).

As shown in Figure 5, most cities in the sample have a relatively low degree of internal capture of workers. In more than half of the 252 cities that responded to the TCRLUS, fewer than 15 percent of city workers lived within the same city in which they worked. As is fairly clear in Table 2, cities with large populations of employed residents, such as Los Angeles, have a high degree of internal capture of workers (47.5 percent of workers in Los Angeles also reside within the city), while those with a smaller population of employed residents, such as Santa Fe Springs, have a low degree of internal capture (1.5 percent).

Figure 5. Percentage of Workers who Reside in the City



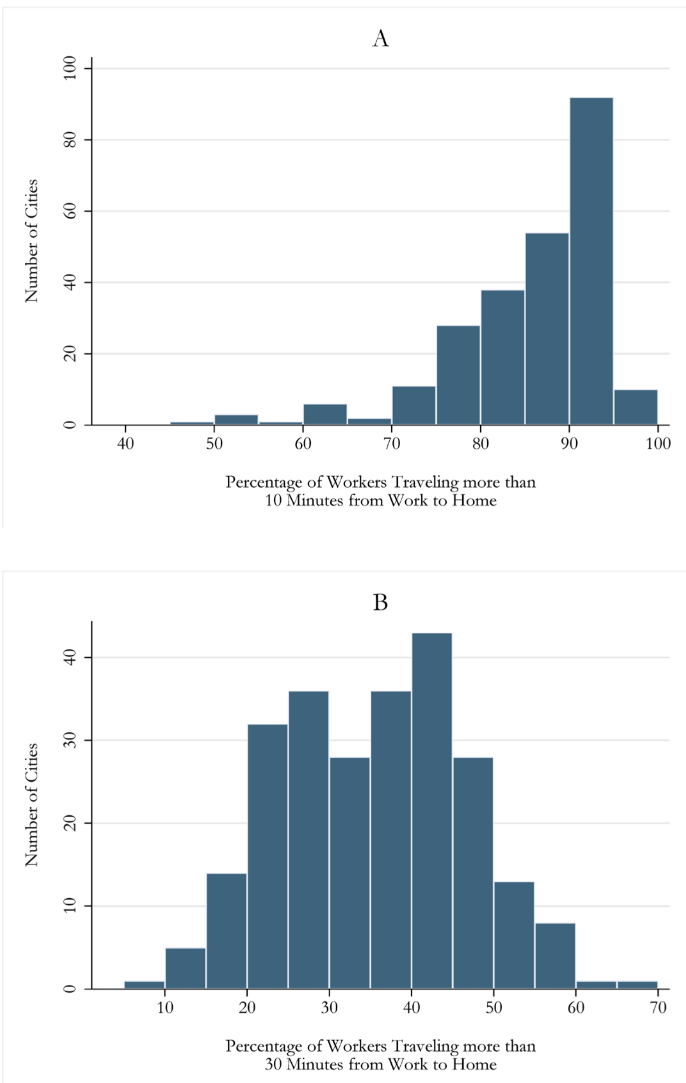
Worker Travel Time to Home

I also sought to measure the travel burden of workers in each city. To do so, I calculated the share of workers in each city who travel more than 10 minutes or more than 30 minutes from work to home, derived from 2013-2017 5-Year Estimates from the ACS, as follows:

$$\textbf{Worker Travel Time to Home} = \left(\frac{\textit{Workers who Travel more than X Minutes to Home}_i}{\textit{Workers}_i}\right) * 100$$

I tested various thresholds, X, from five minutes to one hour. Ten minutes and 30 minutes were selected as the thresholds for further analysis for two reasons. I selected the 10-minute threshold because it had the highest r-squared when regressed on the land use regulations discussed below; I selected the 30-minute threshold due to its intuitive interpretation: A 30-minute commute equates to an hour of lost productivity due to travel. As shown in Figures 6.A and 6.B, there is wide variation in commute times across the sample, for both the 10-minute and 30-minute thresholds. For the 10-minute threshold, shown in Figure 6.A, the distribution is centered around 90 percent—thus, in the typical city, 90 percent of workers travel more than 10 minutes from work to home. For the 30-minute threshold, shown in Figure 6.B, the index is more normally distributed, with the center around 35 percent.

Figure 6 A/B. Worker Travel Time to Home



The results in Table 2 suggest that approximately 90 percent or more of workers in all five of the sample cities from Los Angeles County have commutes of more than 10 minutes. This is higher than the average city in California, as shown in Table 1, where 86 percent of workers, on average, commute more than 10 minutes. Similarly, as shown in Table 2, all five cities in the Los Angeles sample had shares of workers with 30-minute commutes (between 38 percent and 58 percent) that were larger than that of the average city in the TCRLUS sample (35 percent), shown in Table 1. This suggests that commute patterns may vary from region to region and that such differences should be controlled for in the regression analyses that follow.

Land Use Regulations

I now turn to a discussion of data on land use regulations derived from the TCRLUS. I chose to focus specifically on land use regulations rather than on perceptions of housing constraints, opposition to housing development, the frequency of applications for development projects, or other factors measured by the TCRLUS. As shown in Table 3, I use measures of zoning for non-residential uses, the strictness of residential density zoning, the number of parking restrictions imposed by the city, the use of urban growth boundaries, the number of affordable housing incentives provided by the city, and whether the city had a minimum lot size requirement for accessory dwelling units (ADUs).

Only one question on the TCRLUS asked about policy related to non-residential land use regulations. Respondents to the TCRLUS were asked the following question: "Roughly how much land is zoned to allow non-residential uses (commercial, industrial, agricultural, etc.)? Please include zoning that also allows residential uses." As shown in Table 4, responses were recorded as categories ranging from 0 to 5 percent up to 96 to 100 percent. I recoded this variable as a percentage, using the midpoint of the category as the percentage of land zoned for non-residential uses. More than half of cities reported that between 26 percent and 50 percent of the land was zoned for non-residential uses; an additional third of cities reported that between 6 percent and 25 percent was zoned for non-residential uses.

Table 3. Descriptive Statistics: Land Use Regulations and Selected Controls

Variable	Mean	Std. Dev.	Min	Max	Source
Percentage of Land Zoned to Allow Non-Residential Uses	33.65	16.75	15.00	97.50	TCRLUS
Residential Zoning Index	0.06	0.90	-4.13	3.26	TCRLUS
Minimum Lot Size for ADUs	0.49	0.50	0.00	1.00	TCRLUS
Number of Parking Restrictions	2.83	1.48	0.00	6.00	TCRLUS
Urban Growth Boundary	0.35	0.48	0.00	1.00	TCRLUS
Number of Affordable Housing Incentives	1.95	1.49	0.00	6.00	TCRLUS
Median Value (Natural Log)	12.99	0.58	11.70	14.51	ACS 2013-2017
Median Worker Earnings (Natural Log)	10.43	0.25	9.87	11.44	ACS 2013-2017
Percentage of Workers Using Public Transit	2.24	2.48	0.00	18.41	ACS 2013-2017
Number of Workers (Natural Log)	9.67	1.15	6.83	14.27	LODES 2015

Table 4. Non-Residential Land Uses as a Share of Land Area

Original Categorical Response	Recoded Percentage	Number of Responses	Percentage of Responses
0-5%	2.5	5	1.99
6-25%	15	85	33.86
26-50%	37.5	131	52.19
51-75%	62.5	25	9.96
76-95%	85	3	1.2
96-100%	97.5	2	0.8

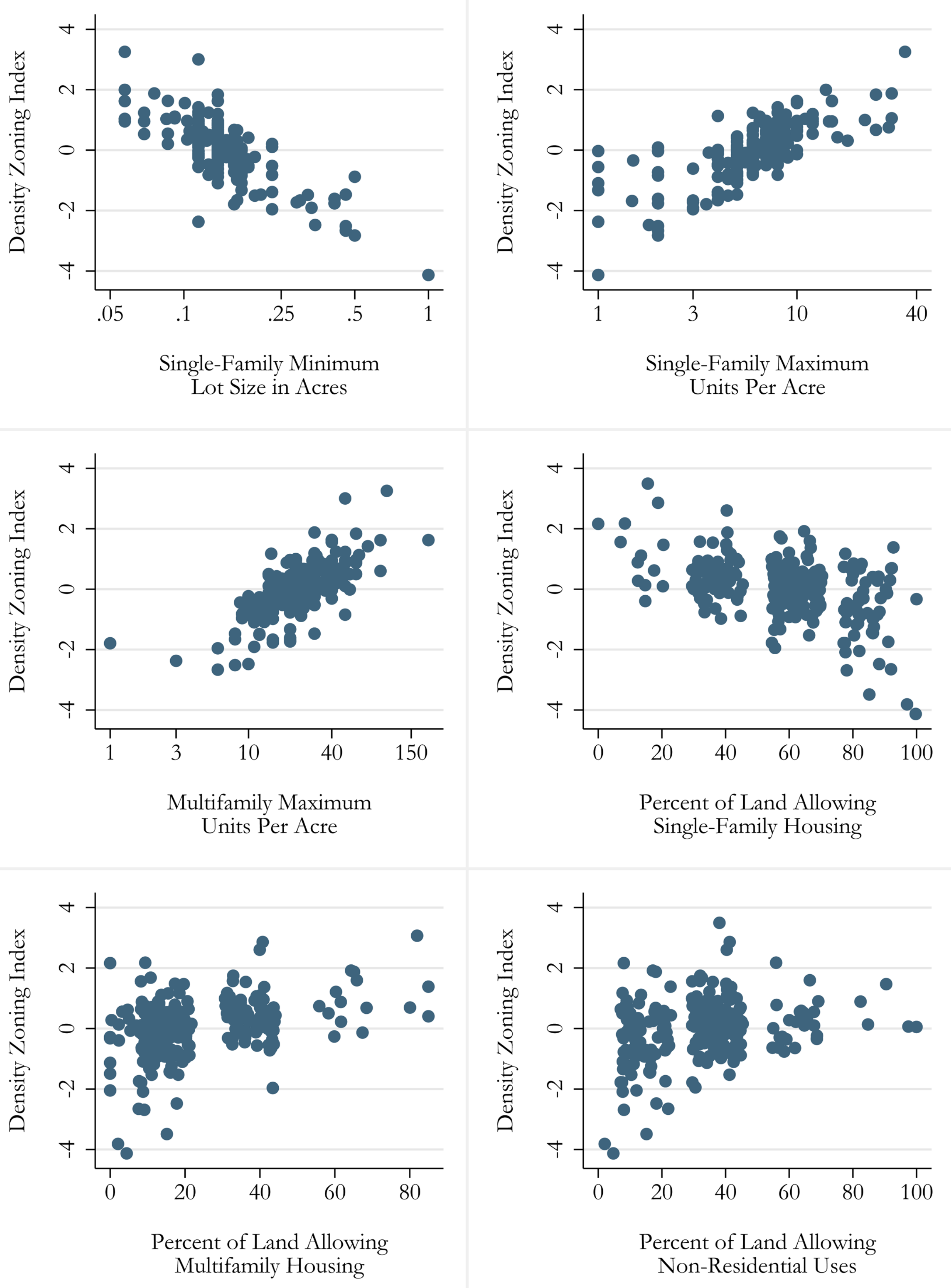
The TCRLUS asked respondents a series of questions on residential zoning that directly touched on the issue of housing density. I selected five factors that I believed would directly shape the density of housing developed in each city in order to create a single index that would capture the typical residential density zoning standards for each city: single-family minimum lot sizes; single-family and multifamily maximum housing units per acre, respectively; and the percentage of land zoned to allow single-family and multifamily housing, respectively. I began by taking the natural log of the minimum lot size and density variables to normalize their distribution. I then converted the TCRLUS variables documenting the share of land zoned for single-family and multifamily housing, respectively, from a categorical variable (measured identically to non-residential land uses, as shown in Table 4) to percentages, again using the midpoint of each category as an estimate of the share of land in each city on which specific types of housing are allowed.

I then used these transformed variables to create an index. To reduce loss of information and degrees of freedom, I chose not to use factor analysis.[6] Instead, I calculated a density zoning index by standardizing each variable to ensure that each was given equal weight in the index. To ensure that increases in each variable would correspond to increases in housing density, I then multiplied the standardized measures of single-family minimum lot sizes and the share of land within the city on which single-family housing is allowed by negative one. I then averaged each city's standardized response for the five density zoning variables, omitting missing responses from the calculation of the average.[7] The final index is shown in Figure 7 alongside the original variables from which it was derived. As is clear in Figure 7, the index is highly correlated with single-family minimum lot size restrictions, restrictions on the maximum units per acre in areas zoned for single-family housing, and the share of land that allows single-family housing. The index is also correlated, though to a lesser extent, with restrictions on the maximum units per acre in areas

[6] I initially used factor analysis to identify a single index that could capture the zoning regulation in each city. However, due to many non-responses for the five density zoning questions, this led to the omission of data for 51 cities (approximately 20 percent of the data set). I compared my analysis in Tables 6 and 7 with those using the density zoning index created from factor analysis, and the results were largely unchanged when the index derived from factor analysis was used.

[7] In total, one city had missing responses on four of the five variables; three cities had missing responses on three of the five variables; 16 had missing responses on two of the five variables; and 39 cities had missing responses on one of the five variables.

Figure 7. Components of the Density Zoning Index



zoned for multifamily housing and the share of land that is zoned to allow multifamily housing. Notably, the density zoning index is also correlated with the share of land zoned for non-residential uses, although the latter was not used to derive the index. This correlation is likely attributable to the fact that cities that allow high-density residential development are more likely to allow non-residential uses, possibly in the form of mixed-use development.

I also thought it would be useful to measure policy related to ADUs, which offer an additional supply of housing by allowing infill on undeveloped parts of single-family lots. This hidden form of density may ameliorate jobs-housing imbalances by expanding the supply of housing without dramatically altering the look and feel of a city. I thus sought to measure the strictness of ADU policies. Deciding on how best to do so was not easy. The TCRLUS asked respondents to "enter the typical standards and fees in your jurisdiction for ADUs," including how many parking spaces were required for ADUs, whether the city had minimum lot size requirements, whether there was a maximum unit size for ADUs, and whether the city required ADU fees. The TCRLUS also asked respondents whether the city was in the process of adopting or had already adopted a local ADU ordinance, as shown in Table 5. A large number of cities did not respond to these questions. It is unclear whether this means the respondents skipped this question or whether the cities did not have the specific policy in place.[8] There is also additional ambiguity due to the fact that a number of cities that reported not having an ADU ordinance or that were still in the process of developing one also reported specific requirements regarding minimum lot sizes, maximum unit sizes, off street parking requirements, or ADU fees, as shown in Table 5.

I suspected that cities with exclusionary, low-density zoning might also be opposed to ADUs, and that this might provide insight into how best to measure ADU policies. I therefore conducted additional analyses to examine whether any of the four ADU policies were correlated with the density zoning index discussed earlier. To illustrate, Figure 8 plots each ADU policy alongside the density zoning index.[9] Minimum lot sizes for ADUs show a clear negative relationship with the density zoning index; regressions of the ADU minimum lot size requirement on the density zoning index produced an r-squared of 0.3. The maximum unit size, total amount of fees charged, and number of off-street parking spaces required for ADUs, however, show only a slight relationship with density zoning (although the density zoning index has a statistically significant association with maximum unit size and off-street parking requirements, only 2.4 percent and 3.6 percent of the variation in these variables, respectively, is explained by the density zoning index). It is unclear how, precisely, this should be interpreted. The most likely explanation, I think, is that the specific minimum lot size threshold adopted by each city largely reflects the zoning standards in place in that city—in other words, cities that require large lots for single-family zones also typically require large lots for ADUs in those same zones. Thus, once each city's broader density zoning index is held constant, a more relevant means of measuring the impact of ADU minimum lot size requirements on spatial mismatch may be to simply distinguish those cities that reported a minimum lot size for ADUs from those that did not. As shown in Tables 3 and 5, approximately half of cities reported having minimum lot size requirements for ADUs. I therefore include a dichotomous variable equal to one if the city reported a minimum lot size requirement for ADUs.

[8] In the section of the TCRLUS on single-family and multifamily zoning standards, the respondent was prompted to leave the field blank if the city does not utilize a specific standard; this was not the case in the section on ADUs.

[9] In these plots I removed three cities with minimum ADU lot size restrictions of less than 2,000 square feet and three cities with ADU maximum unit sizes of less than 400 square feet or more than 4,000 square feet. These appeared to be outliers.

Figure 8. Accessory Dwelling Unit Regulations and the Density Zoning Index

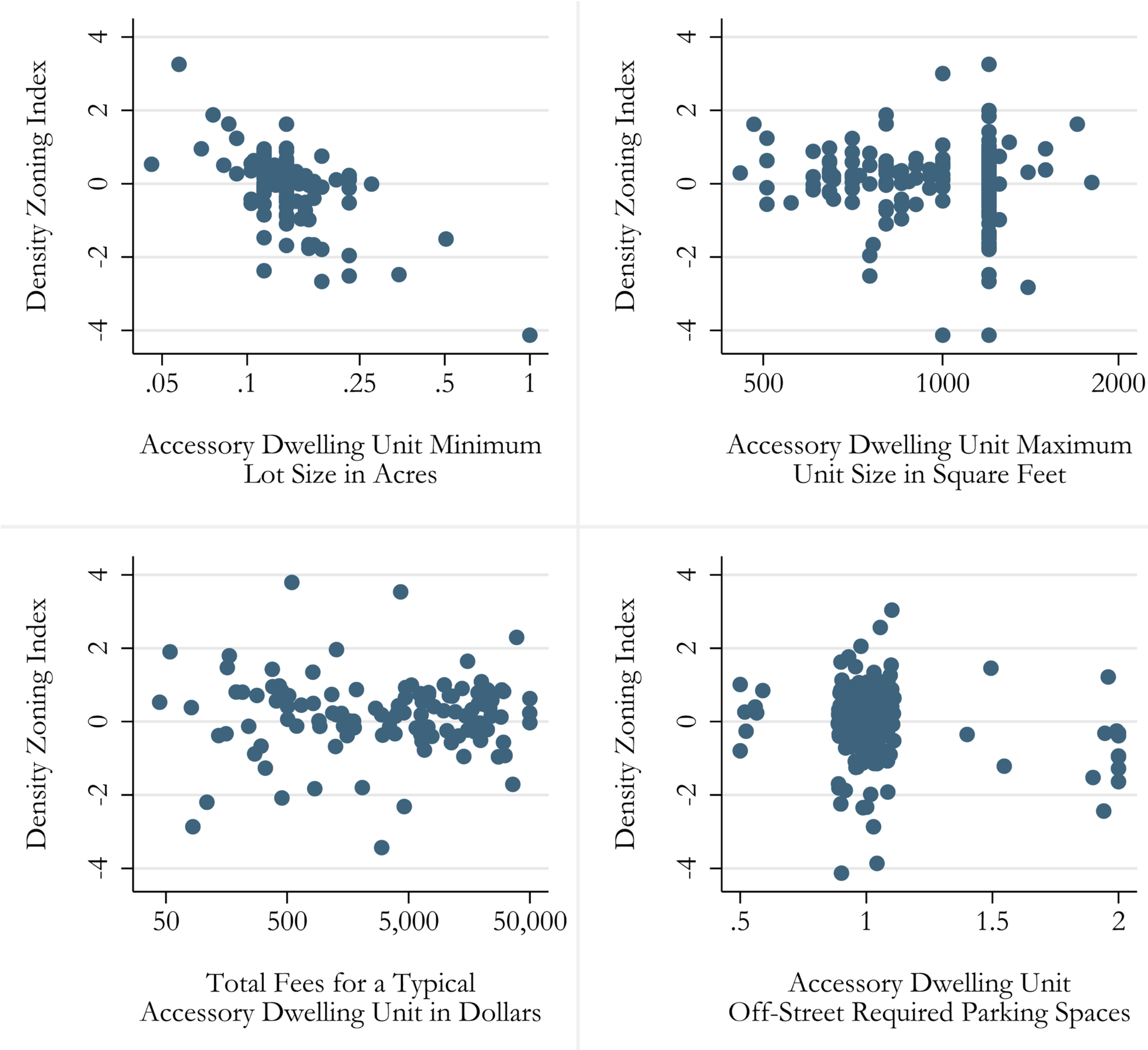


Table 5. Accessory Dwelling Unit (ADU) Regulations

	Mean	Number of Non-responses (% of Total)	Number of Non-responses for Cities with No Adopted Ordinance
Minimum lot size where ADUs are allowed (square feet)	6,457	130 (52%)	42 (17%)
Maximum ADU size (square feet)	1,118	46 (18%)	54 (21%)
Off street parking (spaces)	1.05	87 (35%)	51 (20%)
Total fees for a typical ADU (dollars)	9,249	119 (52%)	33 (13%)
In process of adopting an ADU ordinance	N/A	59 (23%)	N/A
Adopted an ADU ordinance	N/A	168 (67%)	N/A

I also control for the total number of incentives provided to “ease regulatory impacts on applicants proposing projects with an affordable housing aspect,” as recorded by the TCRLUS, including expedited permit review, the easing of height, parking, or transportation mitigation requirements, and the reduction of impact or permit fees. As shown in Table 3, the average city provided approximately two of these incentives, although some cities provided none of them and others provided all six.

Lastly, I control for two other regulatory tools that I suspected might contribute to or ameliorate mismatches between housing and employment opportunities by impacting commuting patterns. First, I calculated the number of parking restrictions imposed by each city. To do so, I summed the following requirements: whether 1) garages or 2) covered parking spaces were required for multifamily buildings; whether tandem parking was prohibited for 3) single-family and 4) multifamily buildings; 5) whether the city required more than two total off-street parking spaces for a three-bedroom single-family unit; and 6) whether the city required two or more resident parking spaces for a two-bedroom apartment in a multifamily building. As shown in Table 3, the average city in the sample imposed approximately three of these restrictions, but some imposed none while others imposed all of them. Lastly, I include a dichotomous variable indicating whether the city is subject to an urban growth boundary; as shown in Table 3, this was the case for 35 percent of the cities in the sample.

Analytical Method

To examine the relationship between various forms of land use regulation and measures of spatial mismatch, I estimate two series of models. The first set of models is estimated as follows:

$$\mathbf{Y = \beta_0 + \beta_1 X_{1i} + \varepsilon_i}$$

where Y represents each of the five measures of spatial mismatch described above and X1 represents a vector of land use regulations in city i, including the percentage of land zoned to allow non-residential uses, the residential density zoning index described earlier, a dichotomous variable indicating whether or not the city reported having a minimum lot size for ADUs, the total number of parking restrictions enforced by the city, whether or not the city is subject to an urban growth boundary, and the total number of affordable housing incentives offered by the city. I exclude all cities (six in total) with a population of workers or employed residents of less than five hundred, derived from 2015 LODES data; these cities had such low populations that their mismatch or commute burden metrics differed substantially from all other cities in the sample.

I then replicate these preliminary models as follows:

$$\mathbf{Y = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + u_j + \varepsilon_i}$$

where X2 represents a series of additional economic characteristics of each city’s housing market or the characteristics of each city’s workforce, including the median value of owner-occupied housing (natural log), the percentage of workers employed in each city who use public transit to commute to work, the total number of workers employed in the city (natural log), and the median earnings of workers employed in the city (natural log).[10] As shown in Table 6, these data are derived from either 2013–2017 ACS 5-Year Estimates or 2015 LODES data. I also control for metropolitan and micropolitan fixed effects, as indicated by u, to account for any regional differences in the housing market, labor market, and transit systems or commute patterns.

It is important to note that my analysis does not imply a causal relationship between the land use regulations examined here and patterns of spatial mismatch between housing and employment. Indeed, there are a number of reasons to interpret these findings with caution. First, there may be variables that have been omitted from this analysis that are associated with both land use regulation and spatial mismatch. The omission of these variables may bias the estimates from the regression models. Second, due to the timing

[10] In alternative models, I also controlled for the average size of households in each city in order to account for the fact that low-income housing fit compares the number of workers with the number of housing units and some households may have more than one worker. The results were largely unchanged.

of data collection, the date of measurement for the dependent variables (either 2015 for variables derived from LODES data or 2013–2017 for variables derived from ACS data) precedes that of the measurement of land use regulations from the TCRLUS (collected in 2018). This complicates causal inference due to, among other things, reverse causality: Thus, it is possible that any statistical association identified here would represent not the causal effect of the land use regulation in question but rather the propensity of cities with specific patterns of spatial mismatch to adopt specific types of land use regulation. That said, I believe the analysis that follows still provides considerable insight into how patterns of spatial mismatch differ across cities with distinct regulatory tools.

Findings

Estimates of the relationship between land use regulations and the imbalance metrics are shown in Table 6, while those examining the relationship between land use regulations and commute burdens are shown in Table 7. For comparative purposes, and to center the discussion around each regulatory approach, I discuss each land use regulation individually, moving vertically down Tables 6 and 7.

Table 6: Regressions of Imbalance Metrics

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
	Resident-Worker Mismatch	***Resident-Worker Mismatch***	***Low-Income Housing Fit***	***Low-Income Housing Fit***	***Resident-Worker Earnings Mismatch***	***Resident-Worker Earnings Mismatch***
Percentage of Land Zoned to Allow Non-Residential Uses	-0.008**	-0.006*	-0.003	-0.003	-0.004**	-0.001
	(0.002)	(0.002)	(0.004)	(0.003)	(0.001)	(0.001)
Residential Zoning Index	-0.105*	-0.098+	-0.265**	-0.195**	-0.072**	-0.036**
	(0.042)	(0.050)	(0.080)	(0.065)	(0.024)	(0.013)
Number of Parking Restrictions	0.052*	0.032	-0.043	0.001	0.002	0.005
	(0.025)	(0.031)	(0.040)	(0.037)	(0.012)	(0.007)
Urban Growth Boundary	0.150*	0.081	0.234+	0.139	-0.006	0.007
	(0.073)	(0.056)	(0.130)	(0.112)	(0.041)	(0.033)
Number of Affordable Housing	0.045*	0.058*	0.054	0.049*	-0.011	0.010
	(0.023)	(0.023)	(0.040)	(0.020)	(0.013)	(0.010)
Minimum Lot Size for ADUs	-0.021	-0.097	-0.066	-0.164*	-0.009	0.006
	(0.069)	(0.072)	(0.123)	(0.067)	(0.034)	(0.027)
Median Value (Natural Log)		-0.397**		-1.216**		0.519**
		(0.083)		(0.136)		(0.032)
Percentage of Workers Using Public Transit		0.002		0.050**		-0.011**
		(0.004)		(0.007)		(0.003)
Number of Workers (Natural Log)		-0.142**		-0.318**		-0.038*
		(0.030)		(0.066)		(0.018)
Median Worker Earnings (Natural Log)		-0.902**		-0.116		-0.556**
		(0.196)		(0.270)		(0.048)
Y-intercept	0.117	16.067**	0.093	20.035**	0.301**	-0.409
	(0.132)	(1.220)	(0.215)	(1.934)	(0.065)	(0.875)
N	241	240	241	240	241	240
R-sq	0.134	0.425	0.08	0.451	0.139	0.598
Metro/micro Fixed Effects	No	Yes	No	Yes	No	Yes
Standard errors in parentheses						
*+ p<.1, *p<.05, ** p<.01*						

Table 7. Regressions of Commute Burden

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	Percentage of Workers who Reside in the City	*Percentage of Workers who Reside in the City*	*Percentage of Workers with > 10-Minute Commute*	*Percentage of Workers with > 10-Minute Commute*	*Percentage of Workers with > 30-Minute Commute*	*Percentage of Workers with > 30-Minute Commute*
Percentage of Land Zoned to Allow Non-Residential Uses	-0.004	-0.082*	0.050	0.030*	0.031	0.056*
	(0.055)	(0.032)	(0.036)	(0.013)	(0.049)	(0.023)
Residential Zoning Index	-0.655	-1.187+	1.152	-0.417	1.458	-0.327
	(0.891)	(0.699)	(0.702)	(0.351)	(1.014)	(0.398)
Number of Parking Restrictions	-1.623**	-0.990+	0.787*	0.647+	0.844+	0.397
	(0.492)	(0.561)	(0.398)	(0.372)	(0.501)	(0.391)
Urban Growth Boundary	5.021**	4.894**	-4.045**	-2.246*	-3.576*	-0.689
	(1.669)	(1.685)	(1.312)	(0.941)	(1.584)	(0.795)
Number of Affordable Housing Incentives	1.371*	0.389	-0.058	0.138	-0.864	-0.369*
	(0.566)	(0.554)	(0.446)	(0.272)	(0.539)	(0.155)
Minimum Lot Size for ADUs	-1.206	-2.305*	1.374	2.330**	0.347	1.904**
	(1.474)	(1.077)	(1.101)	(0.484)	(1.403)	(0.506)
Median Value (Natural Log)		-7.286*		1.564		4.235**
		(3.341)		(1.880)		(1.407)
Percentage of Workers Using Public Transit		0.399**		0.024		0.533*
		(0.132)		(0.079)		(0.221)
Number of Workers (Natural Log)		2.503*		2.803**		1.625**
		(1.129)		(0.599)		(0.505)
Median Worker Earnings (Natural Log)		-6.501		7.151**		14.381**
		(4.101)		(2.437)		(2.467)
Y-intercept	19.698**	160.339**	82.328**	-39.939*	34.393**	-189.754**
	(3.051)	(36.024)	(2.422)	(18.503)	(3.036)	(22.729)
N	241	240	241	240	241	240
R-sq	0.132	0.279	0.095	0.465	0.063	0.502
Metro/micro Fixed Effects	No	Yes	No	Yes	No	Yes

Standard errors in parentheses
*+ p<.1, *p<.05, ** p<.01*

Cities that allocate more land to non-residential uses tend to have more workers than residents, and those workers are more likely to commute in from outside the city, often more than 30 minutes away.

I begin by first discussing the relationship between non-residential zoning and the six measures of spatial mismatch. As shown in the first and second columns in Table 6, cities that allocate more of their land to non-residential uses tend to have more workers than residents. This makes intuitive sense: allowing for more non-residential development expands employment opportunities within the city, thus reducing the number of residents relative to the number of workers and attracting workers from other parts of the metropolitan region. For example, as shown in Table 7, cities that allocate more of their land to non-residential uses have lower shares of workers who reside within the city (Model 2) and larger shares of workers who commute more than 10 or 30 minutes from work to home (Models 4 and 6). All three results likely illustrate the fact that cities that allocate large amounts of land to non-residential uses serve as employment hubs for the broader metropolitan or micropolitan area. They therefore attract workers who live outside the city, and often more than a 30-minute commute away.

Compared to cities that zone for lower residential density, jurisdictions that allow for higher density tend have a better match between resident and worker incomes; however, they also have a lower share of workers who reside within the city, disproportionately low numbers of residents relative to the number of workers, and disproportionately low numbers of affordable housing units relative to the number of low-income workers.

I now turn to a discussion of the relationship between residential land use regulation and the imbalance and commute burden metrics. I begin by first discussing density zoning. Recall that cities that allow for higher-density residential development have higher values of the residential zoning index. My analysis suggests that higher-density zoning may alleviate mismatches between employed residents' earnings and workers' earnings, as shown in columns 5 and 6 in Table 6. Cities that allow for higher-density zoning have greater balance between the incomes of residents and the incomes of workers; thus, cities with high-density zoning are more likely to have resident populations whose earnings are comparable to those of their workforce. Conversely, these results suggest that cities with low-density residential zoning serve as residential enclaves where residents' earnings are markedly higher than those of their workforce. This relationship is attenuated once housing and labor market characteristics of cities and metro/micro fixed effects are controlled for, but remains statistically significant at the .01 level.

The relationship between density zoning and the other measures of imbalance and commute burden are more complex. As shown in the first and second columns in Table 6, cities that zone for higher density also tend to have a lower resident-worker mismatch than do cities that zone for lower density (i.e., they have more workers than residents). This relationship remains relatively unchanged, though is less precise, after controlling for selected economic characteristics of cities and metro/micro fixed effects (coefficient of 0.098; $p<.1$; see Model 2 in Table 6). Similarly, cities that zone for higher density also have lower housing fit indices—thus, lower numbers of affordably priced housing units relative to the number of low-income workers—than cities that zone for lower density (coefficient of -0.195; $p<.01$; see Model 4 in Table 6). Moreover, my analysis also suggests that cities that allow high-density residential development also have lower shares of workers who reside within the city (coefficient of -1.187; $p<.05$; as shown in Model 2 in Table 6).

Residents in cities with more parking restrictions are more likely to work elsewhere and face longer commute times, while the opposite is true in places that impose urban growth boundaries.

Parking restrictions for single-family and multifamily units show no consistent relationships with the mismatch metrics but relatively consistent relationships with commute burdens. For example, there appears to be no relationship between parking restrictions and the imbalance metrics: although, as shown in Model 1 in Table 6, cities that impose a larger number of parking restrictions tend to have higher resident-worker mismatches—that is, they tend to have more residents than workers—this relationship is attenuated and insignificant after including controls for housing and labor market characteristics and metro/micro fixed effects. Moreover, the number of parking restrictions do not appear to be associated with differences in low-income housing fit or resident-worker mismatch.

However, the relationship between parking restrictions and commute burdens is more consistent, if imprecise. For example, as shown in the first column of Table 7, each additional parking restriction imposed by cities is associated with a 1.6 percentage point reduction in the share of workers who reside in the city. After including expanded controls, this relationship declines to 1 percentage point and is marginally significant ($p<.1$). Similarly, each additional parking restriction imposed by the city is associated with a 0.79 percentage point increase in the share of workers with a commute of 10 minutes or longer ($p<.05$); this relationship is attenuated slightly and is significant only at the .1 level after the inclusion of expanded controls. Finally, cities that impose more parking restrictions also have higher shares of residents with commutes of 30-minutes or more (0.84; $p<.1$), but this estimate declines by more than half and is insignificant after including expanded controls.

The use of urban growth boundaries also appears to be associated with reduced commute burdens but not with the imbalance metrics. As shown in Models 1 and 3 in Table 6, cities subject to urban growth boundaries have higher numbers of residents relative to workers (i.e., higher resident-worker mismatches) and higher numbers of affordable rental units relative to the number of low-income workers (i.e., higher housing fit indices), but these estimates are attenuated and insignificant after the inclusion of additional controls and metro/micro fixed effects (see Models 2 and 4 in Table 6). Moreover, there is no relationship between the use of urban growth boundaries and resident-worker earnings mismatch. However, the use of urban growth boundaries does appear to be closely associated with differences in the commute burden experienced by workers. Cities subject to urban growth boundaries have 5 percentage points greater shares of workers residing within the city limits ($p<.01$; see columns one and two in Table 7); between 2 and 4 percentage points lower shares of workers with a commute of ten minutes or more ($p< .05$ and .01; see columns 3 and 4 in Table 7); and lower shares of workers with a commute of 30 minutes or more (see column

5), although the latter is attenuated and is insignificant after the inclusion of expanded controls.

Cities that offer more affordable housing incentives tend to have more balanced resident-worker populations, better low-income housing fit, and fewer workers with commutes of more than 30 minutes.

There is some evidence that cities that provide more affordable housing incentives differ in regards to measures of imbalance or commute burdens. For example, cities that offer more affordable housing incentives have larger shares of residents relative to workers (thus, higher resident-worker mismatch indices). This relationship persists even after controlling for expanded housing and labor market characteristics and metro/micro fixed effects (coefficient of 0.058; $p<.05$; see Model 2 in Table 6). Similarly, cities that offer more affordable housing incentives also have better housing fit, meaning they have more affordably priced housing units relative to the number of low-income workers in the city (coefficient of 0.049; $p<.05$; see Model 4 in Table 6). As shown in Table 7, there is also some evidence that the provision of affordable housing development incentives is associated with differences in commute burdens. The first model in Table 7 suggests that each additional incentive provided by the city is associated with a 1.37 percentage point increase in the share of workers who reside in the city, although this relationship is attenuated and insignificant after the inclusion of additional controls (see Model 2). Lastly, there is a small association between the use of affordable housing incentives and commute times, as shown in the last model in Table 7; each additional affordable housing incentive is associated with a 0.37 percentage point decrease in the share of workers who commute more than 30 minutes ($p<.05$).

Cities that impose minimum lot size restrictions on ADUs have worse low-income housing fit and greater commute burdens.

As for ADU-related policies, there appears to be no relationship between the use of minimum lot size restrictions and resident-worker mismatch or resident-worker earnings mismatch (Models 1, 2, 5, and 6 in Table 6). There is, however, some evidence that cities that impose a minimum lot size restriction on ADUs have fewer affordably priced housing units relative to the number of low-income workers in the city, and thus worse low-income housing fit, as illustrated in Model 4 in Table 6. There is also clear evidence that cities with minimum lot size restrictions for ADUs have greater commute burdens for workers. For example, as shown in Model 2 in Table 7, cities that impose minimum lot size restrictions have 2.3 percentage points lower shares of workers residing within the city ($p<.05$), 2.3 percentage points higher shares of workers with commutes of more than 10 minutes, and 1.9 percentage points higher shares of workers with commutes over 30 minutes.

Policy Implications and Conclusion

Although both spatial mismatch and residential land use regulation have received considerable attention in the academic literature, few empirical studies have examined their relationship and none that I am aware of has examined them in detail. This study illustrates the myriad of ways in which land use regulation is closely associated with both imbalances between housing and employment opportunities and the commute burdens experienced by workers. Although this study cannot provide direct evidence of the causal impact of land use regulation on spatial mismatch or commute burdens, it does point toward potential policy levers that cities might consider when seeking to address issues of sustainability, equity, and inclusion in regards to local opportunities for housing and employment.

My analysis illustrates that cities in California that allocate more land to non-residential uses have higher numbers of workers relative to the number of residents and larger shares of workers who live outside the city or who commute more than 10 or more than 30 minutes from home to work. These cities therefore appear to serve as employment hubs for the broader metropolitan or micropolitan area in which they are located.

For cities that are interested in expanding affordable housing opportunities for, or reducing the commute burden experienced by, their local workforce, my analysis also points toward a number of nuanced policy options. For example, my findings suggest that cities that do not impose minimum lot size restrictions on ADUs and those that offer more affordable housing incentives—such as expedited permit review, the easing of height, parking, or transportation mitigation requirements, and the reduction of impact or permit fees—have greater balance between the number of residents and the number of workers and have a better fit between the number affordably priced housing units and the number of low-income workers. There is also evidence that these policies may contribute to lower commute burdens for workers by allowing more workers to reside within the city and by reducing their commute time. Cities that are subject to urban growth boundaries and those that impose fewer parking restrictions—for example, those that allow tandem parking, require fewer parking spaces, or do not require garages or covered parking spaces for multifamily buildings—also tend to have workers who are more likely to live in the city and are less likely to have a commute of 10 minutes or more.

This study also adds to existing research on density zoning and its impact on the segregation of high-income households (Lens & Monkkonen, 2016) by illustrating the way in which low-density zoning may exacerbate mismatches between the incomes of residents and the incomes of workers within cities. For example, I find that cities that prohibit high-density residential development have the highest resident earnings relative to worker earnings. In other words, California cities that zone for low-density housing effectively serve as predominantly high-income residential enclaves despite their dependence upon moderate- to low-income workers. My analysis suggests that allowing higher-density residential development in these cities may reduce resident-worker earnings mismatch by allowing more low- and moderate-income workers to reside in the city in which they are employed. That said, there is limited evidence that changes to density zoning will ameliorate broader mismatches in the location of jobs and housing or the location of low-income jobs and low-income housing. Indeed, as my regression models illustrate, compared with cities that prohibit high-density residential development, those that zone for higher density actually have lower numbers of residents relative to workers and lower numbers of affordably priced housing relative to the number of low-income workers (low-income housing fit). This is likely attributable to the fact that high-density residential areas often allow mixed-use development that accommodates both residential and non-residential uses. Thus, although high-density residential development may allow for a larger supply of housing in general and more affordably priced housing in particular, it may also accommodate a larger number of jobs, many of which may be low-paying jobs. This, in turn, means that cities may not be able to ameliorate broader resident-worker mismatches or low-income housing fit simply by addressing density zoning. Instead, the policies discussed earlier—removing minimum lot size restrictions for ADUs and offering additional affordable housing incentives—may be needed to address imbalances between the location of housing and employment opportunities.

Appendix 1: Spatial Mismatch Indices

City	County	Resident-Worker Mismatch	Low-Income Housing Fit	Resident-Worker Earnings Mismatch	Percentage of Workers who Reside in the City	Percentage of Workers with > 10-Minute Commute	Percentage of Workers with > 30-Minute Commute
Alameda	Alameda	0.35	0.14	0.22	18.66	2.40	43.28
Albany	Alameda	0.65	-0.39	0.55	11.76	1.96	37.31
American Canyon	Napa	0.98	0.95	0.14	10.92	2.67	30.72
Anaheim	Orange	-0.08	-1.28	-0.01	14.72	2.51	47.04
Anderson	Shasta	0.11	1.27	0.09	16.17	2.19	15.36
Antioch	Contra Costa	0.77	0.72	0.12	23.86	2.71	29.25
Apple Valley	San Bernardino	0.69	1.58	0.17	29.60	2.15	27.18
Arcadia	Los Angeles	-0.21	-1.14	0.45	8.94	2.38	43.49
Arcata	Humboldt	-0.50	0.29	-0.32	25.77	1.85	14.76
Arroyo Grande	San Luis Obispo	0.17	0.61	0.24	16.06	2.40	16.82
Atascadero	San Luis Obispo	0.42	0.70	0.03	35.57	2.41	21.89
Atherton	San Mateo	0.08	-0.97	0.70	4.53	2.12	46.18
Avalon	Los Angeles	-0.15	-0.74	-0.02	42.81	3.65	13.78
Avenal	Kings	0.01	2.21	-0.82	17.31	3.91	59.27
Bakersfield	Kern	0.08	0.42	0.10	50.87	1.84	20.32
Baldwin Park	Los Angeles	0.41	0.26	-0.18	11.90	2.47	43.09
Beaumont	Riverside	1.09	1.47	0.38	22.23	2.66	30.71
Bell	Los Angeles	-0.20	-0.68	-0.39	3.63	2.31	52.74
Bellflower	Los Angeles	0.47	-0.07	0.13	8.54	2.25	36.63
Belmont	San Mateo	0.58	0.11	0.81	8.58	2.66	44.59
Benicia	Solano	0.06	0.27	0.29	16.07	2.74	36.88
Berkeley	Alameda	-0.36	-0.13	-0.03	17.65	2.16	45.76
Beverly Hills	Los Angeles	-1.22	-3.15	0.47	4.09	2.15	62.90
Bishop	Inyo	-0.67	-0.05	0.01	20.83	1.00	9.90
Blythe	Riverside	0.00	1.91	-0.04	44.72	4.34	21.39
Brentwood	Contra Costa	0.69	-0.43	0.48	24.10	2.43	24.40
Brisbane	San Mateo	-0.97	-0.33	0.13	2.22	2.42	51.74
Buena Park	Orange	0.20	-0.83	0.14	7.95	2.34	40.86
Burlingame	San Mateo	-1.08	-2.26	0.45	4.40	2.66	45.56
Calistoga	Napa	0.13	0.45	0.26	33.02	2.61	35.38
Camarillo	Ventura	-0.03	-0.42	0.44	17.29	2.38	37.04
Capitola	Santa Cruz	-0.49	-1.55	0.47	6.14	2.41	27.58
Carlsbad	San Diego	-0.44	-1.31	0.32	14.71	2.51	38.15
Carson	Los Angeles	-0.28	-0.40	0.05	5.66	2.36	47.79
Chico	Butte	-0.19	0.32	-0.04	45.98	2.09	21.02
Chino	San Bernardino	-0.21	-1.10	0.15	8.60	2.66	45.45
Chula Vista	San Diego	0.55	0.06	0.18	30.89	1.97	23.84
Citrus Heights	Sacramento	0.75	0.83	0.27	13.21	2.23	29.58
Clayton	Contra Costa	1.17	0.33	0.65	11.03	2.38	30.78
Cloverdale	Sonoma	0.83	1.14	0.02	38.84	2.95	30.26
Coachella	Riverside	0.72	0.94	-0.16	26.26	2.01	26.45
Colma	San Mateo	-1.38	-3.29	0.32	0.58	2.54	27.78
Colton	San Bernardino	0.04	0.95	-0.03	7.02	2.44	39.17
Concord	Contra Costa	0.03	-0.05	0.03	15.22	2.76	42.75
Corona	Riverside	-0.07	-0.94	0.20	14.17	2.90	45.36
Costa Mesa	Orange	-0.58	-1.69	0.09	8.26	2.64	43.18
Covina	Los Angeles	0.01	-0.97	0.21	6.91	2.46	37.60
Culver City	Los Angeles	-1.32	-3.66	0.24	2.99	2.48	57.89
Cupertino	Santa Clara	-0.47	-0.56	0.12	6.80	2.41	49.71
Cypress	Orange	-0.08	-0.26	0.10	5.48	2.36	46.32
Daly City	San Mateo	1.05	0.51	0.13	19.04	1.92	35.54
Danville	Contra Costa	0.51	-0.50	0.79	11.38	2.54	38.12
Davis	Yolo	0.55	0.43	0.07	29.27	2.71	27.70
Del Mar	San Diego	-0.88	-1.93	0.85	3.56	2.68	52.66
Desert Hot Springs	Riverside	1.22	2.54	0.10	32.23	2.21	33.80
Dinuba	Tulare	0.30	1.14	-0.09	25.47	2.56	28.26
Dixon	Solano	0.59	0.24	0.05	26.09	2.79	29.69
Downey	Los Angeles	0.26	-0.45	-0.02	9.14	2.35	44.94
Duarte	Los Angeles	-0.14	0.34	0.00	7.34	2.47	43.21
Dublin	Alameda	0.14	-1.72	0.54	8.82	2.96	50.95
El Cajon	San Diego	0.09	-0.37	-0.09	16.89	2.14	24.34
El Centro	Imperial	-0.08	0.59	0.06	34.17	1.90	14.92
El Cerrito	Contra Costa	0.91	0.76	0.61	8.59	2.40	38.29
El Monte	Los Angeles	0.31	0.47	-0.19	13.44	2.19	45.10
Elk Grove	Sacramento	0.76	-0.02	0.44	26.71	2.40	29.73
Emeryville	Alameda	-1.40	-1.94	0.14	2.20	2.56	56.33
Encinitas	San Diego	0.07	-0.72	0.64	16.71	2.50	39.78
Escondido	San Diego	0.31	-0.05	-0.04	25.95	2.58	36.75
Eureka	Humboldt	-0.49	0.58	-0.05	30.36	1.60	16.21

City	County	Resident-Worker Mismatch	Low-Income Housing Fit	Resident-Worker Earnings Mismatch	Percentage of Workers who Reside in the City	Percentage of Workers with > 10-Minute Commute	Percentage of Workers with > 30-Minute Commute
Fairfax	Marin	0.87	0.55	0.36	21.75	1.77	37.21
Fairfield	Solano	0.17	-0.07	0.00	25.32	2.59	27.75
Farmersville	Tulare	0.75	1.26	-0.04	15.05	2.17	16.51
Fillmore	Ventura	1.20	0.98	0.01	33.30	2.49	23.57
Firebaugh	Fresno	0.71	2.51	-0.16	40.93	2.65	29.63
Fontana	San Bernardino	0.44	-0.06	0.03	14.53	2.63	40.82
Fort Bragg	Mendocino	-0.18	0.07	-0.08	38.26	0.97	16.05
Fountain Valley	Orange	-0.11	-0.24	0.12	6.93	2.25	43.86
Fullerton	Orange	0.06	-0.54	0.10	11.47	2.40	40.80
Galt	Sacramento	1.03	0.93	0.47	32.30	2.52	26.76
Garden Grove	Orange	0.42	-0.06	0.00	14.78	2.05	38.39
Gilroy	Santa Clara	0.32	-0.66	0.36	26.73	3.05	33.87
Glendale	Los Angeles	-0.07	-1.56	-0.01	22.42	2.23	45.29
Gonzales	Monterey	-0.49	-1.82	0.01	6.87	2.86	22.54
Grass Valley	Nevada	-0.74	0.26	-0.21	17.09	1.98	20.29
Grover Beach	San Luis Obispo	0.60	0.85	0.06	15.41	2.31	15.35
Half Moon Bay	San Mateo	0.17	-0.03	0.53	23.13	2.64	32.19
Hayward	Alameda	0.04	-0.34	-0.13	15.63	2.60	47.59
Healdsburg	Sonoma	-0.18	-0.23	0.18	17.16	2.64	28.15
Hesperia	San Bernardino	0.86	1.37	0.21	30.71	1.97	25.69
Hillsborough	San Mateo	0.76	-1.23	0.87	5.76	2.68	40.35
Huntington Beach	Orange	0.20	-0.10	0.29	18.62	2.37	40.63
Imperial	Imperial	0.68	0.89	0.13	22.14	1.80	18.53
Imperial Beach	San Diego	1.31	0.85	0.14	21.12	1.67	23.20
Indian Wells	Riverside	-1.02	-0.37	0.98	1.49	2.03	22.69
Inglewood	Los Angeles	0.46	0.18	-0.03	10.38	2.17	48.38
Irvine	Orange	-1.03	-1.54	0.18	10.14	2.68	47.78
Jackson	Amador	-0.34	0.81	-0.15	10.03	2.65	35.64
Kerman	Fresno	-0.37	-0.96	0.26	13.92	3.82	33.82
Kingsburg	Fresno	-0.06	0.33	0.30	14.49	2.68	29.93
La Canada Flintridge	Los Angeles	0.37	-1.16	0.86	7.51	2.39	30.82
La Habra	Orange	0.74	-0.03	0.27	10.42	2.41	41.31
La Mesa	San Diego	0.05	-0.08	0.19	8.83	2.05	21.81
La Palma	Orange	0.09	0.69	-0.11	2.80	2.45	45.66
La Quinta	Riverside	0.22	0.60	0.47	17.27	1.84	27.69
Laguna Beach	Orange	-0.11	-0.69	0.84	11.39	2.46	47.89
Laguna Hills	Orange	-0.30	-1.54	0.13	4.36	2.69	37.33
Laguna Niguel	Orange	0.59	0.06	0.35	11.80	2.86	32.03
Lake Elsinore	Riverside	0.55	-0.23	0.30	17.13	2.78	33.11
Lakeport	Lake	-0.60	0.28	0.03	18.84	2.50	30.97
Lakewood	Los Angeles	0.72	0.08	0.50	7.46	2.27	37.60
Lancaster	Los Angeles	0.30	0.68	0.08	37.19	2.21	23.31
Lathrop	San Joaquin	0.07	-0.23	0.07	7.21	2.84	42.35
Lindsay	Tulare	0.25	1.36	-0.22	24.56	2.32	27.63
Livermore	Alameda	-0.04	-0.42	0.11	21.89	3.04	50.41
Livingston	Merced	0.01	0.92	-0.09	18.81	2.53	23.52
Loma Linda	San Bernardino	-0.62	0.55	-0.12	12.36	2.48	36.15
Lomita	Los Angeles	1.21	1.16	0.43	8.52	1.96	35.54
Long Beach	Los Angeles	0.16	0.09	-0.01	26.69	2.26	43.80
Los Altos	Santa Clara	0.12	-0.26	0.91	6.24	2.49	45.04
Los Altos Hills	Santa Clara	0.49	0.55	0.59	4.59	2.57	55.79
Los Angeles	Los Angeles	-0.08	-0.38	-0.12	47.58	2.37	56.72
Los Banos	Merced	0.61	1.28	0.26	45.65	2.71	16.54
Los Gatos	Santa Clara	-0.24	-1.26	0.67	6.79	2.24	38.96
Mammoth Lakes	Mono	-0.72	-0.62	0.04	31.23	3.77	16.16
Manhattan Beach	Los Angeles	-0.25	-1.37	1.07	6.70	2.32	44.43
Manteca	San Joaquin	0.53	0.23	0.35	23.61	2.77	28.15
Marina	Monterey	0.78	1.08	0.08	19.11	2.27	28.44
Menifee	Riverside	0.92	1.36	0.39	20.60	2.56	29.33
Merced	Merced	0.07	1.05	-0.05	38.59	2.03	20.48
Mill Valley	Marin	0.03	-0.86	0.90	9.62	2.43	45.27
Millbrae	San Mateo	0.59	0.05	0.65	9.64	2.20	42.87
Milpitas	Santa Clara	-0.28	-0.95	-0.10	8.51	2.39	49.00
Mission Viejo	Orange	0.35	-0.20	0.46	13.92	2.66	30.75
Modesto	Stanislaus	-0.01	0.45	0.05	35.72	2.22	25.68
Monrovia	Los Angeles	-0.07	-0.66	0.14	8.26	2.59	46.38
Montclair	San Bernardino	0.05	-0.27	0.03	5.49	2.68	34.94
Monterey	Monterey	-0.83	-1.48	-0.01	13.50	2.68	28.23
Moorpark	Ventura	0.29	-0.60	0.17	15.99	2.83	36.10
Moraga	Contra Costa	0.49	-0.32	0.82	10.29	2.34	44.72
Moreno Valley	Riverside	0.73	0.00	0.13	27.81	2.66	37.88

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Mount Shasta	Siskiyou	-0.34	0.53	-0.12	24.63	1.96	12.95
Mountain View	Santa Clara	-0.58	-0.71	-0.13	8.75	2.52	55.99
Napa	Napa	0.22	-0.19	0.13	38.91	2.45	32.43
National City	San Diego	0.02	-0.32	-0.02	10.43	1.90	24.29
Newark	Alameda	0.27	0.01	0.21	9.27	2.60	50.16
Norwalk	Los Angeles	0.54	0.03	0.01	11.46	2.24	44.99
Novato	Marin	0.10	0.17	0.04	19.22	2.93	44.17
Oakland	Alameda	-0.06	0.35	-0.15	25.62	2.47	52.10
Oakley	Contra Costa	1.47	1.29	0.47	26.45	1.74	23.71
Oceanside	San Diego	0.56	0.73	0.08	29.19	2.41	31.65
Ontario	San Bernardino	-0.51	-1.35	-0.03	9.20	2.79	44.20
Pacific Grove	Monterey	0.53	0.81	0.26	20.82	1.70	25.45
Pacifica	San Mateo	1.47	1.05	0.59	31.24	1.89	28.16
Palm Desert	Riverside	-0.46	0.04	0.23	14.55	2.30	31.20
Palm Springs	Riverside	-0.54	0.90	0.04	19.51	2.42	33.64
Palo Alto	Santa Clara	-1.31	-0.95	0.25	7.61	2.65	58.57
Paramount	Los Angeles	0.09	-0.15	-0.14	8.71	2.15	37.00
Pasadena	Los Angeles	-0.60	-1.34	0.13	12.95	2.48	46.06
Paso Robles	San Luis Obispo	0.03	-0.15	0.17	30.94	2.43	23.88
Pico Rivera	Los Angeles	0.36	0.43	0.17	9.65	2.27	44.46
Pinole	Contra Costa	0.55	0.13	0.67	8.29	2.70	31.29
Pittsburg	Contra Costa	0.67	0.77	-0.08	18.45	2.38	33.76
Placentia	Orange	0.49	-0.22	0.29	8.62	2.43	38.62
Pleasanton	Alameda	-0.50	-1.51	0.30	10.39	3.03	45.63
Port Hueneme	Ventura	1.02	0.60	-0.32	10.48	1.94	25.11
Rancho Cordova	Sacramento	-0.53	0.14	-0.26	9.44	2.48	46.76
Rancho Cucamonga	San Bernardino	-0.05	-1.32	0.30	14.04	2.71	40.45
Rancho Palos Verdes	Los Angeles	1.33	1.69	0.80	12.39	2.17	38.18
Rancho Santa Margarita	Orange	0.57	-0.92	0.44	12.37	2.85	39.71
Red Bluff	Tehama	-0.21	1.37	-0.15	25.37	2.51	25.90
Redondo Beach	Los Angeles	0.24	-0.58	0.30	10.17	2.40	42.39
Redwood City	San Mateo	-0.41	-0.61	-0.26	9.34	2.80	53.48
Reedley	Fresno	0.22	0.22	-0.15	24.19	2.31	25.55
Richmond	Contra Costa	0.38	1.14	-0.31	15.55	2.60	49.06
Ridgecrest	Kern	0.20	2.26	-0.01	57.10	0.99	10.39
Riverbank	Stanislaus	1.05	1.12	0.16	16.98	1.94	19.89
Riverside	Riverside	-0.17	-0.33	-0.02	23.02	2.68	42.41
Rohnert Park	Sonoma	0.49	0.00	0.17	16.16	2.23	23.63
Rolling Hills Estates	Los Angeles	0.08	-1.38	0.91	3.49	2.30	35.11
Rosemead	Los Angeles	0.31	0.04	-0.20	12.68	2.16	42.82
Roseville	Placer	-0.30	-0.66	0.20	17.01	2.41	29.44
Sacramento	Sacramento	-0.45	0.42	-0.16	27.30	2.42	43.19
Saint Helena	Napa	-0.75	-0.51	0.01	12.70	2.83	44.82
Salinas	Monterey	0.12	-0.38	-0.14	43.39	2.51	21.74
San Anselmo	Marin	0.53	0.23	0.78	14.91	2.25	39.45
San Bernardino	San Bernardino	-0.36	0.23	-0.27	16.94	2.61	40.32
San Bruno	San Mateo	0.48	0.03	0.10	10.00	2.49	40.77
San Diego	San Diego	-0.24	-0.45	-0.04	50.10	2.43	40.51
San Francisco	San Francisco	-0.43	-0.10	-0.01	40.71	2.26	66.17
San Gabriel	Los Angeles	0.24	-0.32	0.15	12.58	1.67	35.84
San Jacinto	Riverside	0.84	1.73	0.05	23.22	1.72	29.91
San Jose	Santa Clara	0.14	-0.21	-0.05	44.93	2.17	42.81
San Juan Capistrano	Orange	0.13	-0.19	0.03	10.81	2.42	37.59
San Leandro	Alameda	-0.03	0.21	-0.03	10.78	2.64	40.59
San Luis Obispo	San Luis Obispo	-0.53	-0.60	-0.30	24.26	2.69	27.71
San Pablo	Contra Costa	0.75	0.99	0.19	11.22	2.34	34.42
San Rafael	Marin	-0.50	-0.80	-0.02	12.82	2.87	51.04
San Ramon	Contra Costa	-0.13	-1.95	0.23	11.45	2.78	54.45
Sanger	Fresno	0.23	0.35	0.14	21.80	2.47	24.68
Santa Ana	Orange	-0.26	-0.91	-0.37	15.03	2.43	45.60
Santa Barbara	Santa Barbara	-0.31	-0.82	0.03	34.53	2.21	24.35
Santa Clara	Santa Clara	-0.60	-0.99	-0.17	8.80	2.27	51.10
Santa Clarita	Los Angeles	0.19	-0.75	0.32	28.68	2.79	38.93
Santa Cruz	Santa Cruz	-0.22	-0.40	0.02	27.65	2.10	30.51
Santa Fe Springs	Los Angeles	-2.07	-2.63	-0.05	1.59	2.43	52.89
Santa Maria	Santa Barbara	-0.13	-0.28	-0.08	38.92	1.96	19.23
Santa Paula	Ventura	0.92	1.27	0.08	30.95	2.33	26.13
Santa Rosa	Sonoma	0.03	0.01	-0.01	38.56	2.00	23.72
Seaside	Monterey	0.65	0.57	0.02	16.37	2.44	24.73
Sebastopol	Sonoma	-0.32	-0.12	0.48	8.82	1.99	25.71
Shasta Lake	Shasta	0.78	2.26	-0.01	19.23	2.02	18.14
Sierra Madre	Los Angeles	0.71	0.50	0.65	10.90	2.35	41.85

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Simi Valley	Ventura	0.54	0.04	0.36	32.30	2.57	32.25
Solana Beach	San Diego	-0.44	-0.96	0.38	6.11	2.64	43.90
Soledad	Monterey	0.12	-0.17	-0.41	21.28	3.23	39.11
South El Monte	Los Angeles	-0.71	-0.94	-0.07	4.48	2.09	41.09
South Gate	Los Angeles	0.48	0.25	-0.02	8.98	2.17	41.55
South San Francisco	San Mateo	-0.36	-0.34	-0.37	8.63	2.45	51.81
Stanton	Orange	0.80	0.38	-0.07	6.19	2.17	38.07
Stockton	San Joaquin	0.01	0.69	-0.04	39.22	2.46	29.32
Susanville	Lassen	-0.12	1.00	0.03	55.43	2.01	20.02
Temple City	Los Angeles	0.84	0.82	0.40	14.84	1.88	34.37
Torrance	Los Angeles	-0.45	-0.59	0.33	13.07	2.30	44.64
Truckee	Nevada	0.07	-0.36	0.11	57.34	1.81	31.28
Turlock	Stanislaus	0.09	0.41	0.06	31.32	2.36	20.66
Tustin	Orange	-0.10	-1.16	0.06	5.68	2.49	42.53
Twentynine Palms	San Bernardino	0.90	2.73	-0.11	44.54	2.57	20.36
Union City	Alameda	0.17	-0.55	0.19	11.53	2.76	46.41
Vallejo	Solano	0.53	0.58	0.06	27.72	2.79	31.55
Victorville	San Bernardino	0.25	0.47	0.09	25.09	2.18	24.24
Visalia	Tulare	-0.11	0.38	0.12	40.30	2.26	20.81
Vista	San Diego	0.12	0.13	-0.06	16.14	2.23	29.00
Walnut Creek	Contra Costa	-0.64	-0.49	0.22	7.01	2.70	46.72
Watsonville	Santa Cruz	-0.05	-0.15	-0.07	25.50	2.58	24.94
Weed	Siskiyou	-0.32	0.72	-0.12	20.02	2.13	19.44
West Covina	Los Angeles	0.48	-0.41	0.31	10.66	2.46	40.95
West Hollywood	Los Angeles	-0.26	-0.92	0.38	6.44	2.08	59.83
West Sacramento	Yolo	-0.28	0.51	-0.11	11.53	2.61	39.44
Westlake Village	Los Angeles	-1.25	-1.69	0.44	2.32	2.75	46.02
Westminster	Orange	0.56	0.21	0.10	13.46	2.00	32.36
Whittier	Los Angeles	0.37	-0.40	0.27	13.35	2.17	39.17
Woodland	Yolo	0.17	0.70	0.01	33.41	2.95	30.49
Yorba Linda	Orange	1.00	0.05	0.69	10.60	2.64	44.93
Yreka	Siskiyou	-0.37	1.36	-0.19	38.00	2.17	26.35
Yuba City	Sutter	0.23	0.88	0.09	35.82	1.83	19.62
Yucaipa	San Bernardino	1.05	1.90	0.51	33.77	2.20	24.50

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