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Abstract

The presence of employment centers provides the potential for reducing commuting distance. However, employment centers have distinctive attributes, which may lead to varied impacts on commuting outcomes. We attempt to examine the effect of distance to the nearest employment center on commuting distance while addressing the heterogeneity of employment centers and workers. We consider multiple attributes of employment centers related to location, persistency, job density, industry diversity, and size. For workers, we mainly focus on low- and high-income groups as they differ in several aspects, such as availability of commute modes, options for housing, and preference for job opportunities. We applied a fixed-effects model using data from 2002 to 2019 to capture within-tract variation. Our analysis of the Los Angeles region shows that increasing proximity to the nearest employment center decreases commuting distance even after controlling for the job attributes located in the neighborhood of workers. The results show that employment centers are not equal in terms of their impact on commute distance and that their impact is different for commuters from different income groups. Our results contribute to the literature by deciphering the location and attributes of employment centers that may exert a greater impact on commuting distances.

1. Introduction

The urban spatial structure of global cities has changed substantially during recent decades. Starting from a monocentric form, the decentralization of employment has occurred with the growth of metropolitan areas. A significant factor for understanding the decentralization process is whether employers co-locate and create agglomeration economies. If employers co-locate, the urban spatial structure will evolve to a polycentric form with multiple employment centers. Otherwise, employment would decentralize, showing a general pattern of dispersion, where the polycentric form is rather viewed as a transitional stage (Glaeser et al., 2001a). Recent studies on the spatial structure of US metropolitan areas are mixed regarding the decentralization process. Based on a comparison between 1990 and 2010, Arribas-Bel & Sanz-Graciz (2014) find that the monocentric form dominates in US metropolitan areas over time. Using the case of the Los Angeles region, Giuliano et al. (2019, 2022) suggest that the polycentric structure is persistent with relatively small changes over time in the boundary and the number of jobs in employment centers. Relatedly, Li (2020) also found that Chinese cities have evolved towards concentration while also showing some trend of decentralization.

The presence of multiple employment centers creates a potential for reducing commuting distance (Wang, 2000). In theory, employees benefit from agglomeration economies by sharing job opportunities, and the decentralization of employment increases the possibility of jobs-housing proximity and balance (e.g., Horner, 2002; Loo & Chow, 2011; Zhao et al., 2011). A few empirical findings also suggest that shorter distances to employment centers (e.g., central business district (CBD), subcenters) are associated with shorter commutes (e.g., Ding et al., 2017; Islam & Saphores, 2022; Zhu et al., 2022). However, the dispersion of employment can sometimes complicate commuting patterns, often leading to long-distance commuting. Evidence of either cross- or inverse-commuting implies that workers do not necessarily commute to the nearest employment center, further suggesting that workers might be influenced by all existing centers as well as the considerable number of jobs not located within employment centers (Koster & Rouwendal, 2013).

Employment centers have distinctive attributes, which may lead to different impacts on commuting outcomes. Employment centers differ in size, density, persistence, the composition of industries, and their geographical location. For instance, Giuliano et al. (2019)

showed that employment centers are specialized in certain industry types, with the composition of industries also related to the peak density of centers. In addition, the heterogeneity in attributes of employees also impacts whether the commuting outcome of a worker is sensitive to the presence of employment centers. Income level, for example, is associated with transportation mobility, residential location constraints, and the industry type of jobs, which leads to a different relationship between the location of employment centers and commuting distance (Hu & Schneider, 2017). To elaborate, the commuting distance of high income workers may be more sensitive to the distance to employment centers as there are more professional jobs clustered in these areas. In contrast, low income workers may easily find substitute employment outside of employment centers, which could weaken the relationship between commuting distance and the distance to employment centers.

In this study, we attempt to examine the effect of distance to the nearest employment center (i.e., either CBD or subcenter) on commuting distance while addressing the heterogeneity of employment centers and workers. We consider multiple attributes of employment centers related to location, persistency, job density, level of industry diversity, and size. For workers, we mainly focus on low- and high-income groups as they differ in several aspects, particularly their ability to have certain housing, job, and commuting options. We apply a fixed effects model, which arguably provides stronger causal evidence given that it estimates how change *within* tracts over time impacts change in our outcome measure, compared to typical regression models that compare across geographic units. Our analysis of the Los Angeles region shows that increasing proximity to the nearest employment center reduces commuting distance even after controlling for the job attributes located in the neighborhood of workers. The results show that employment centers are not equal in terms of their impact on commute distance and that their impact differs across commuters from high or low income groups.

While testing the relationship between employment centers and commuting distance is not new, we revisit the relationship for three reasons. First, existing works have less considered whether the distance to the nearest employment center influences commuting outcomes. We explicitly explore whether the location and attributes of the nearest employment center and the distance to it influences commuting distance. Second, while existing literature reports mixed results on the effect of employment centers on commuting, their analysis typically relies on cross-sectional data. We revisit the hypothesis by using longitudinal data and fixed-effects models that provide a more robust analytical approach. Lastly, the heterogeneity across employment centers is not a focus in the literature. While numerous studies have suggested shorter commuting distances for workers living close to employment centers (e.g., Ding et al., 2017; Islam & Saphores, 2022; Zhu et al., 2022), there is limited understanding of the characteristics of employment centers that are influential and the type of workers that are affected by the presence of centers. Overall, we fill the gap in the literature by testing the relationship between employment centers and commuting with a focus on the heterogeneity among employment centers and workers using longitudinal data from 2002 to 2019.

2. Literature Review

2.1 Agglomeration economies and employment centers

Employment centers (e.g., CBD, subcenters) exist as a result of concentration, in which they support the idea of agglomeration economies. In particular, the employment center is one critical component for understanding the mechanisms of learning, matching, and sharing among firms, households, as well as retailers (Duranton & Puga, 2004). While these centers are generally located near transportation infrastructures, the employment centers further provide insights related to transportation and planning strategies. For instance, a polycentric urban form with multiple employment centers suggest that transport infrastructures should be designed to connect the centers and planning regulations should permit mixed land uses in those centers (Angel & Blei, 2016). If these employment centers no longer exist or include a relatively small portion of jobs within the region, transportation strategies become less relevant with the location of those centers. As such, understanding the employment center(s) is one important way to identify the spatial distribution of activities in cities, examine the connections between workplaces and workers, and devise transportation policies.

Employment centers may not exist if firms gain fewer benefits from clustering in certain locations. Some researchers have argued that the rapid growth in ICT technology and reduced transport costs have made clustering unnecessary, implying a pivot toward decentralized employment (Glaeser et al., 2001b; Mitchell, 1996). Relatedly, some studies suggest that decentralization is a common pattern in US cities (e.g., Gordon & Richardson, 1996; Lee, 2007) as there are increasing numbers of jobs in non-center areas. However, there is also research providing support for the persistence of the polycentric urban form in cities worldwide (Li & Derudder, 2022, Giuliano et al., 2019; 2022; Phelps & Ohashi, 2020).

Giuliano et al. (2022), for instance, find that the polycentric form is relatively persistent based on a comparison between 1990 and 2009 in Los Angeles. Through an investigation of the Los Angeles region, Kane et al. (2018) report that the number of centers increased from 46 to 53 between 1997 and 2014. Their study also shows that the percent of jobs within centers has slightly increased from 17.4% to 19.6%. Another study by Cortright (2015) find that the average employment growth rate in city centers was slightly larger than the peripheral areas based on an analysis of large metropolitan areas in the U.S.

One challenging task involved in understanding urban spatial structure when measuring employment centers is the methodological approach. At least three methods have been suggested for identifying areas with employment concentrations large enough to influence rent, distribution of employment or population, or employment density: (1) using cutoffs for size and employment density (Giuliano & Small, 1991), (2) using density gradients (McDonald, 1987), and (3) using nonparametric regression to identify centers based on the density surface (McMillen, 2001; Redfearn, 2007). Each methodological approach has its advantages and disadvantages, in that different methods can result in over- or underestimation of employment centers and are often sensitive to the extent of the study area. While some studies have suggested ways to quantify concentration and decentralization without identifying employment centers (Hipp et al., 2022), we do not address them here.

Furthermore, our understanding of employment centers and urban spatial structure could be different depending on the approach applied by researchers. The size and number of centers may differ depending on how we define and identify employment centers. By applying the Giuliano & Small (1991) method to the Los Angeles region, Giuliano et al. (2019) showed that the employment centers and the polycentric form have been quite persistent between 1980 and 2010. In contrast, Kane et al. (2018) found that employment centers in the Los Angeles region have exhibited a great variation in shape, size, location, and industrial composition over time. Given that there is no gold standard for identifying employment centers, most studies have selected an approach based on their research question. See Yu et al. (2021) for a detailed description of how employment centers can be identified differently using existing methodological approaches.

2.2 Employment centers and commuting distance

Employment centers attract trips and have a structuring influence on regions, further having an impact on commuting outcomes. One early study by Cervero & Wu (1997) found that workers in suburban employment centers experience shorter commutes in terms of trip times and are more likely to commute by driving. While there are numerous studies on the relationship between urban form and commuting, we only focus on commuting distance in this literature review. Commuting time is affected by factors such as mode choice, congestion, and transportation infrastructure (Wang, 2000), and thus provides limited insight regarding whether employees actually co-locate.

In theory, the spatial dispersion of employment opportunities can either increase or decrease commuting distance; compared to the monocentric form, the dispersion of jobs can create an environment where commuters can live closer to work, while it simultaneously allows random commuting (i.e., cross-commuting or inverse-commuting leading to longer commute distances) (Bertaud, 2002; Ma & Banister, 2007; Ha et al., 2021). Relatedly, empirical findings in the literature are also mixed.

Studies on how the dispersion of jobs impacts commuting could be categorized into those focusing on 1) the location of employment centers or 2) the polycentricity of urban form. A few studies have shown that the distance to employment centers (e.g., CBD, subcenters) is positively associated with commuting distance (Ding et al., 2017; Kim et al., 2012; Grunfelder & Nielsen, 2012). Similar results are also found in studies that focus on the relationship between polycentricity and commuting distance (Veneri, 2010; Zhao et al., 2011). The results are slightly mixed when employment density is controlled in the model; Ding et al. (2017) showed that the distance to CBD is positively associated with commuting distance, while employment density is not significantly related to commuting distance. Relatedly, Islam & Saphores (2022) showed that employment density and distance to CBD both have impacts on commuting distance, while the effect of distance to subcenters is insignificant.

The relationship between commuting distance and employment centers depends on several factors such as availability of faster transportation modes, increasing number of dual-worker households, availability of hybrid access to jobs, and preferences for housing locations as well as limited housing affordability (e.g., Islam & Saphores, 2022; Wolday et al., 2019; Schuetz, 2020). In addition, employment centers may have less effect on commuting in areas with an increasing number of jobs in non-center areas (Angel & Blei, 2016). For instance, for commuters in households with multiple workers, preferences for a certain neighborhood, and unaffordable housing prices near the workplace, may lead to longer commutes even if they live close to employment centers. Using the case of Paris, Aguilera (2005) shows that most people residing in a subcenter work outside of the employment cluster, while the majority of employees of a subcenter commute from distant locations. Other studies also suggest that the co-location hypothesis is insignificant, in which polycentric cities rather increase the length of commute trips (Guth, 2010; Grunfelder, 2015).

2.3 Heterogeneity in commuters and employment centers

Commuters are heterogeneous, having different socio-demographic characteristics (e.g., gender, income, job industry, occupation). Numerous studies have shown the differences in commuting among population groups with a focus on locations of residences and workplaces (Hanson & Pratt, 1988; Hu & Schneider, 2017; Sun et al., 2017; Kim et al., 2012; Maoh & Tang, 2012). Here, we particularly focus on existing research that addresses heterogeneity in workers by income given that income is associated with other factors such as age, job type, and preference for housing locations. In a study of the Chicago region, Wang et al. (2021) show that there is heterogeneity in residential location preferences across income groups; for example, low income households are less likely to decentralize due to limited financial capacity. The authors also suggest that high income households may value the urban amenities and job opportunities located in the regional center. Relatedly, Cervero & Wu (1997) show that high housing prices in and near employment centers may lead to longer commute distances. The authors also report that professional workers in suburban employment centers tend to live in nearby housing. Some low-income workers also have limited travel modes available, and studies report that they tend to have longer commute times even though their commuting distances are relatively short (Renne & Bennett, 2014). In contrast, another study shows that the average commuting time in the United States was shorter for workers below 200% poverty level (25 min.) compared to workers above 350% poverty level (28 min.) in 2020 (National Equity Atlas, 2023). Relatedly, Blumenberg & Ong (2001) explain that low-income workers experience difficulties in finding job opportunities far from their homes due to limited mobility.

Another important aspect of workers is the industry type of jobs. Employment centers can vary in their industry compositions. For instance, access to customers is more important in population-serving jobs, which are widely distributed across space, whereas professional services are more likely to benefit from spatial clustering (Giuliano et al., 2019). On one hand, Giuliano et al. (2019) show that industries such as information, professional and business services, health care and social assistance are more likely to be located in employment centers; on the other hand, the manufacturing and retail trade sectors are more likely to be located outside centers. The income level of workers can differ according to industry types, which implies that some workers benefit more from agglomeration economies. Similarly, studies have shown that the agglomeration effect and co-location patterns are heterogeneous across creative employment groups and occupation (e.g., Cruz & Teixeira, 2015; Kim et al., 2012).

Employment centers and commuters are heterogeneous, which may help explain the relationship between polycentricity and commuting outcomes. Some employment centers are more specialized, having a large share of one or two industry sectors, while others tend to have a mix of industries (Giuliano et al., 2019; Wang et al., 2021). High-income workers are more likely to have the skillsets and interests that benefit more from agglomeration economies, while low-income workers providing general services may find more job opportunities outside the centers (Hu & Schneider, 2017; Lee & Clarke, 2019). In these respects, the co-location theory may hold true for certain employment centers and commuters; for instance, employment centers mainly consisting of high-skilled and professional job opportunities may allow reduced commuting distance for only the qualified workers. In other words, there could be a set of employment centers and commuters that both benefit from agglomeration economies by spatially clustering and experiencing shorter commuting distance.

3. Data and methods

3.1 Los Angeles region

The Los Angeles region is well known for its high level of polycentricity, with the presence of multiple employment centers. Here, we refer to the Los Angeles-Long Beach, CA Combined Statistical Area (CSA) as the Los Angeles region, which includes five counties: Los Angeles, Orange, Riverside, San Bernardino, and Ventura. The CSAs are identified for adjacent metro- and micropolitan areas with significant commuting flows indicating their interdependence. The five-county region in Los Angeles has been examined by multiple studies, such as Giuliano et al. (2019) and Kane et al. (2018). The region accommodated a population of approximately 18 million and 7 million jobs, which is the second largest US CSA unit following New York-Newark, NY-NJ-CT-PA CSA. The Los Angeles region has been widely studied in previous research to examine hypotheses regarding agglomeration economies and co-location (e.g., Kane et al., 2018; Giuliano et al., 2019). Empirical findings from the literature based on the Los Angeles region show consensus and some conflicts regarding the changes in urban spatial structure and employment centers. For instance, Gordon & Richardson (1996) showed that the percentage of jobs in centers dropped over time, further suggesting that agglomeration economies are declining.

Previous studies suggest that there are more than 30 employment centers in the Los Angeles region. Giuliano & Small (1991) first suggested that there were 35 centers based on the two-cutoffs approach (i.e., more than 10 jobs per acre and more than ten-thousand jobs total) using data from 1980. Another finding from Forestall & Greene (1997) found 120 centers based on a more generous approach. Most recently, Giuliano et al. (2019) identified 48 centers (95%/10K cutoffs) and 13 centers (99%/20K cutoffs) in 2009 by applying the Giuliano & Small method, which shows that the results are sensitive to cutoff values. Kane et al. (2018) applied a non-parametric identification approach and found 53 centers in 2014. The differences in the results can mainly be attributed to the data source for employment, the spatial unit of analysis, and the identification approach. By using different approaches, interpretation of the persistence of urban form may differ: Giuliano et al. (2019) found a persistent polycentric structure, while Kane et al. (2018) suggested that the boundaries and industrial compositions of centers vary greatly across time.

Our study area includes the five counties that are within the Los Angeles region. There are 3924 census tracts located within our study area, which is our spatial unit of analysis in the statistical models. We selected our study area to contribute to the long history of research on urban spatial structure and commuting in this area. Additionally, the Los Angeles region is unique since it exhibits one of the most polycentric structures, and it is a place that has experienced dynamic changes in terms of urban spatial structure and employment decentralization. According to the Longitudinal Employer-Household Dynamics (LEHD), the number of workers in the region increased from 13.7 million to 17.3 million between 2002 and 2019. Figures A1 to A4 illustrate the distribution of residential and workplace locations for low and high income workers. For instance, we see low-income workers' residential locations more concentrated in areas proximate to the downtown areas.

3.2 Data

We used the annual Origin Destination (OD) Employment Statistics data (2002 to 2019) from the LEHD. This data provides the aggregated number of workers based on their residence and workplace at the census block level. Based on the OD data from this source, we estimated the average commuting distance for each census tract by calculating the network distance between the centroids of census tracts. In doing so, we excluded data that have their origin or destination located outside of our study area. By using the Workplace Area Characteristics (WAC), we identified the location and characteristics of employment centers.

3.3 Identification of employment centers

While there is no perfect approach that ensures objectivity (Yu et al., 2021), we apply the Giuliano & Small (1991) approach which allows us to identify employment centers in a more consistent way over time (e.g., see Kane et al. (2018) which identifies employment centers in the Los Angeles region using Redfearn's (2007) approach). In this approach, we identify areas that are adjacent based on the cutoff settings for employment density and employment size. While we have several options for identifying employment centers, we use the 95th percentile value for the density cutoff and 10,000 for the size cutoff. Using stricter cutoff values generally results in a smaller number of centers. Since we are interested in a larger study area, we use a more generous approach. The spatial unit of analysis is also a factor that may lead to different results. A recent study by Giuliano et al. (2019) suggests that administrative units are inappropriate as they vary in shape and size across time and space. To address this issue, we follow the method suggested by Giuliano et al. (2019) that uses a one-square-mile regular hexagon as the spatial unit.

We first created one-square-mile regular hexagons across our study area. We next merged census blocks to the hexagon that contained the block centroid and estimated the number of jobs for each hexagon. The LEHD data provides the number of jobs at a fine-grained scale, which provides more precision when aggregating to hexagons as our spatial unit. We used hexagons that exceeded the employment density criterion, and then used two cutoffs to identify the employment centers. We then used the inverse distance function to identify the employment centers, as suggested by McDonald & Prather (1994). Here, we apply stepwise regression models to test each of the identified centers from the cutoffs, excluding centers that did not show a significant effect on the density gradient. We iterated this process for 18 different time periods (2002-2019) using the LEHD data.

3.4 Variables

Our dependent variable is the average commuting distance based on the LEHD OD data. Based on the OD data at the census tract level, we estimated the network distance between the origin and destination. We then estimated the average commuting distance for each census tract by using the number of workers as weights, and then log transforming this measure. We calculated this value annually for 18 years from 2002 to 2019.

Our main explanatory variable is the logged distance to the nearest employment center. After identifying employment centers as described above, we estimated the network distance to the edge of the nearest center from the centroid of each census tract. Furthermore, we have a set of variables that address the characteristics of the nearest employment center. We identified the location of the nearest employment center and created dummy variables for whether each center is located within Los Angeles City, Los Angeles County, and Orange County. These variables allow us to test if employment centers located in more dense and centralized areas might affect commuting outcomes differently given their unique position and development history (Giuliano et al., 2007; Giuliano et al., 2019). Since the employment centers are identified by using a hexagonal spatial unit, there are some cases where a center is included in more than one administrative boundary. In this case, we only created a dummy variable for the county that includes the largest share. For instance, if 40% of the center is located within Los Angeles County and the remainder is located across Orange County, we designated this center as being in Orange County.

Next, we created dummy variables indicating whether the center 1) is persistent across the 18 years of our analysis, 2) has high density, 3) has a high level of industrial diversity, 4) has a high employment to population ratio, and 5) has a large size. Since the size and shape change slightly across time, we designated centers as persistent if more than half of the center area was consistently identified as an employment center. For the other four variables, we created dummy variables by focusing on the top quartile. For the level of industrial diversity, we estimated the entropy index based on seven industry types according to the NAICS code[i]. We here note that employment center(s) located in downtown area(s) may have different effects on commuting distance. However, we do not treat them distinctively in our models since there are limited number of employment center(s) in the downtown areas. Furthermore, the main features of CBD's are arguably captured in several of our measures, including large size, persistence, and high density.

For socio-demographics, we used the ratio of younger adults and the ratio of low-income workers living in each census tract using the LEHD dataset. These two variables control for age and income which are known to have effects on commuting outcomes (Ding & Bagchi-Sen, 2019; Ha et al., 2020). Middle-aged and workers from high income households show longer commute distances (Axisa et al., 2012; Mercado & Páez, 2009). However, we do not directly test this relationship but rather the association between the socio-demographic composition and commute distances of the census tracts due to the aggregated nature of our data. In addition, we included residential neighborhood factors, mainly addressing the job density within 3 km and the level of industry diversity for each census tract measured by using the entropy index. One of the main reasons for this approach was to control for the effect of neighborhood attributes related to employment before testing the relationship between the distance to the nearest employment center and commuting distance.

3.5 Methods

We used a series of tract fixed effects (FE) models to estimate the relationship between commuting distance and distance to nearest employment center. Our outcome variable is the log-transformed commuting distance measured at the census tract level; we applied log-transformation to adjust the right-skewed distribution and improve the linear relationship with our measures. We have three types of explanatory variables: (1) socio-economic factors (SF), (2) residential neighborhood factors (NF), and (3) the distance to nearest employment center (DNC). Additionally, we have two types of variables to assess the interaction effects: (1) location (LC) and (2) attributes (AC) of employment centers. We have three population groups (all workers, low-income workers (i.e., jobs with earnings $1250 per month or less), and high-income workers (i.e., jobs with earnings greater than $3333 per month)). For each population group, we tested four models: (1) without interaction variables, (2) with interaction effects of center locations, (3) with interaction effects of center attributes, and (4) with interaction effects of both center locations and attributes. The full model can be written as:

$$\ln(commuting\ distance)_t = \beta_1 SF_t + \beta_2 NF_t + \beta_3 DNC_t + LC_t + \beta_4 DNC_t \times LC_t + AC_t + \beta_5 DNC_t \times AC_t + \beta_6 N + \varepsilon_t$$

where t indicates the time of the data and N is a vector of indicator variables for all tracts in the study area (the fixed effects).

The fixed effects model allows us to estimate within effects when units – in our case, census tracts – are measured repeatedly (Firebaugh et al., 2013). The tract fixed effects demean commuting distances for each census tract, and therefore the only variation we are estimating is whether the dependent variable is either below or above the mean value of each tract. This allows us to examine the relationship between the changes in independent variables and changes in the dependent variable within each tract, rather than the assessing the relationship between independent and dependent variables *across units*. We used frequency weights for the model based on the number of workers in each census tract; for the models of low- or high-income workers, we created weights based on the number of either low- or high-income workers living within each census tract. The number of workers living in each census tract varies greatly, which makes it appealing for weighting samples. Robust standard errors were used with the jackknife function, and the analyses were performed using STATA 17. It should be noted that we did not consider using the random effects model, as it is limited in its ability to provide reliable estimates of causal interest (Gunasekara et al., 2014). We also report the results using a pooled linear regression model to provide information on how the results differ from the fixed-effects models.

4. Results

4.1 Descriptive statistics

4.1.1 Average commuting distance

The average commuting distance in the Los Angeles region was relatively stable, although it showed some increase between 2002 and 2008; the average commuting distance of all workers increased from 28.9 km to 31.5 km over the study period. As shown in Figure 1, high-income workers tended to commute longer distances compared to the low-income workers. Between 2002 and 2019, the average commuting distance slightly increased for high-income workers from 30.7 km to 32.1 km, whereas it increased from 28.1 km to 30.9 km for low-income workers. In 2019, for example, the difference in average commuting distance between the two commuter groups was 1.2 km.

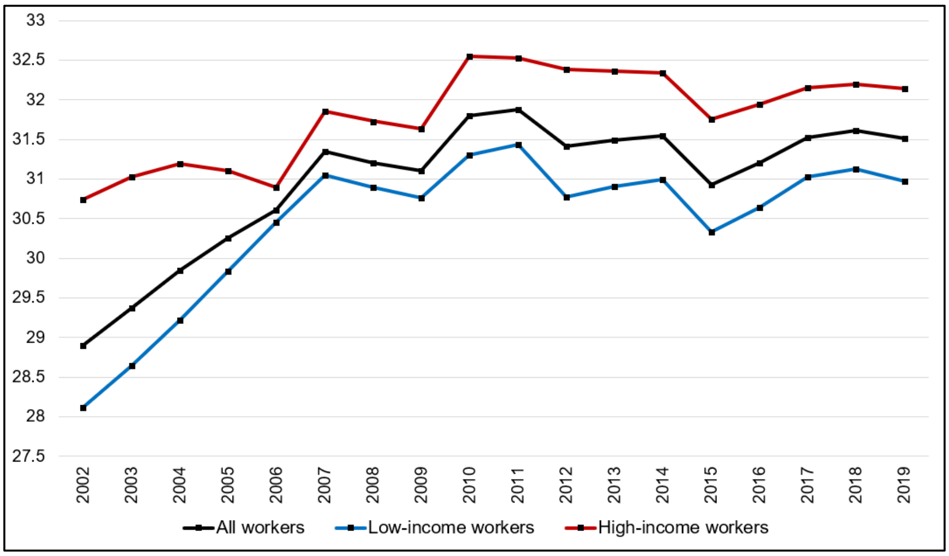

Figure 1. Trends of average commuting distance (km) in Los Angeles region, 2002-2019.

4.1.2 Employment centers in Los Angeles region

Table 1 shows the descriptive characteristics of employment centers in the Los Angeles region from 2002 to 2019 and Figure 2 compares the spatial distribution of employment centers between 2002 and 2019. The number of employment centers was quite consistent, ranging from 73 to 78. Comparing 2002 and 2019, the percentage of employment within centers increased from 36.7% to 37.4%, which suggests that agglomeration economies are persistent. Job density increased by 23.6% in areas defined as employment centers, while it increased by 24.5% in areas not defined as employment centers. We note that the employment centers in the region contain a significant number of jobs; in 2019, for example, the total area of employment centers within the urbanized area in the region accounts for only 4.7%, while they contain 37.4% of the employment. The median density of employment centers also increased from 6901.6 to 7562.0 jobs per square-km between 2002 and 2019, which also suggests that jobs tend to cluster more over time. The median entropy index of industry composition and the employment to population ratio did not show significant changes over time. The distribution of the attributes of employment centers are also shown in Figure 3.

One thing to note is that the number of employment centers identified in this paper is slightly larger than those from other recent studies. For instance, Giuliano et al. (2021) found 48 employment centers within the Los Angeles region in 2009. Another study by Kane et al. (2018) identified 53 centers using the non-parametric estimation approach. The difference in the results may come from several factors. First, different data sources were applied to identify the spatial distribution of jobs. Specifically, Giuliano et al. (2021) use the National Establishment Time-Series (NETS) data, whereas Kane et al. (2018) use the point-level establishment data provided from Reference USA. The coverage of the data may affect the results; for instance, using the 95th percentile cutoff based on employment density is sensitive to the number of spatial units for analysis. Second, the employment center identification approach also matters. As we have seen in the literature, the location, size, and shape of employment centers vary across studies, which may be the reason for the differences in our results. Finally, all these studies use arbitrary spatial units (e.g., hexagon or grid). Unlike administrative spatial units, the arbitrary units may differ slightly according to how the researchers have created them, which in turn may influence the outcomes. Nonetheless, the number of employment centers does not change radically across the different strategies.

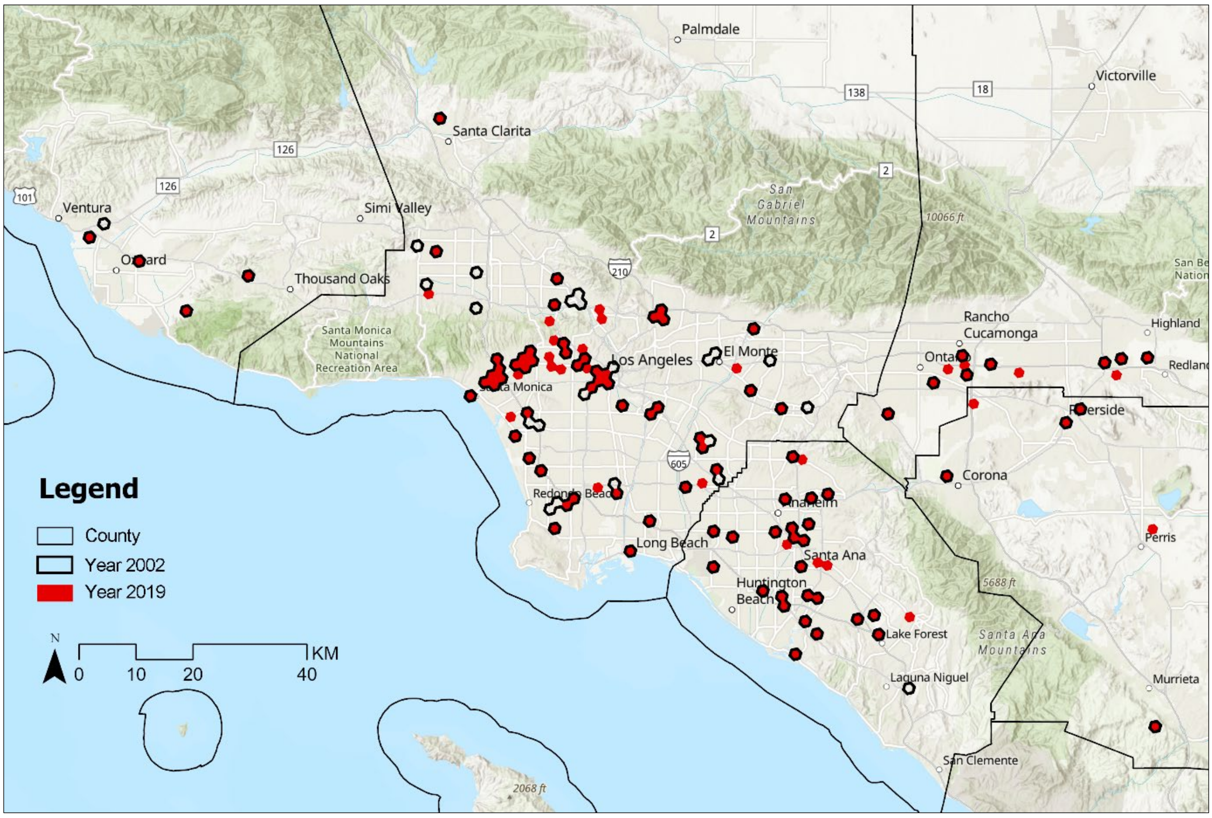

Figure 2. Los Angeles region employment centers, 2002 and 2019.

Table 1. Descriptive characteristics of job density and employment centers in Los Angeles region, 2002-2019.

Year	Number of emp. centers	Total emp. within centers	% of emp. within centers	Mean job density in center areas	Mean job density in non-center areas	Density (Employment per square-km)			Average entropy index of industry composition			Average employment to population ratio		
						25%	50%	75%	25%	50%	75%	25%	50%	75%
2002	74	2,428,504	36.7	8,497.6	693.1	5,362.6	6,901.6	9,921.6	0.69	0.76	0.83	4.65	7.76	14.92
2003	76	2,373,249	35.7	8,458.0	706.7	5,343.3	6,915.1	9,407.4	0.71	0.77	0.83	4.59	7.53	14.48
2004	77	2,448,917	36.1	8,727.7	716.7	5,160.2	7,146.3	10,190.1	0.70	0.76	0.84	4.75	7.72	13.43
2005	78	2,491,027	35.8	8,960.7	738.3	5,380.3	7,252.5	10,247.8	0.70	0.77	0.85	4.36	7.19	13.59
2006	77	2,537,495	35.9	9,043.4	749.1	5,370.1	7,350.1	9,999.9	0.69	0.78	0.84	4.80	8.39	14.38
2007	78	2,589,488	36.3	9,144.0	751.6	5,540.6	7,732.3	10,093.8	0.66	0.77	0.83	4.67	7.34	14.36
2008	75	2,564,495	35.8	9,139.6	760.4	5,594.2	7,960.6	10,134.8	0.68	0.78	0.85	4.19	7.12	14.55
2009	75	2,529,593	36.6	9,015.2	724.5	5,420.2	7,268.8	9,746.7	0.66	0.77	0.85	4.69	7.49	15.77
2010	78	2,595,133	36.9	8,762.0	735.6	4,906.5	7,074.0	9,444.2	0.67	0.76	0.84	4.76	7.45	14.67
2011	77	2,657,576	37.4	8,818.1	738.0	5,216.4	6,950.1	9,600.7	0.69	0.76	0.85	4.72	7.43	14.25
2012	77	2,659,009	37.4	8,822.9	738.4	5,288.5	6,652.2	9,911.8	0.69	0.77	0.85	4.61	8.07	13.71
2013	77	2,663,214	36.5	9,152.4	767.4	5,472.5	6,839.9	9,944.8	0.67	0.76	0.85	4.66	7.98	14.05
2014	76	2,793,134	37.3	9,188.7	779.3	5,626.9	6,812.1	9,698.5	0.71	0.77	0.85	4.56	7.28	13.15
2015	74	2,842,030	37.1	9,512.2	799.1	6,091.2	7,349.4	10,151.2	0.68	0.77	0.84	4.56	7.26	13.77
2016	73	2,953,457	37.3	9,885.1	823.3	6,339.8	7,435.4	10,425.3	0.69	0.77	0.85	4.72	7.34	14.74
2017	77	2,987,113	37.2	9,911.6	836.6	6,320.7	7,522.4	9,814.8	0.69	0.75	0.84	4.65	7.06	12.62
2018	76	3,059,272	37.4	10,064.2	849.9	6,380.1	7,616.7	10,301.9	0.70	0.76	0.84	4.29	7.11	13.20
2019	77	3,111,324	37.4	10,504.8	863.2	6,391.2	7,562.0	10,550.1	0.70	0.77	0.83	4.37	7.54	12.68

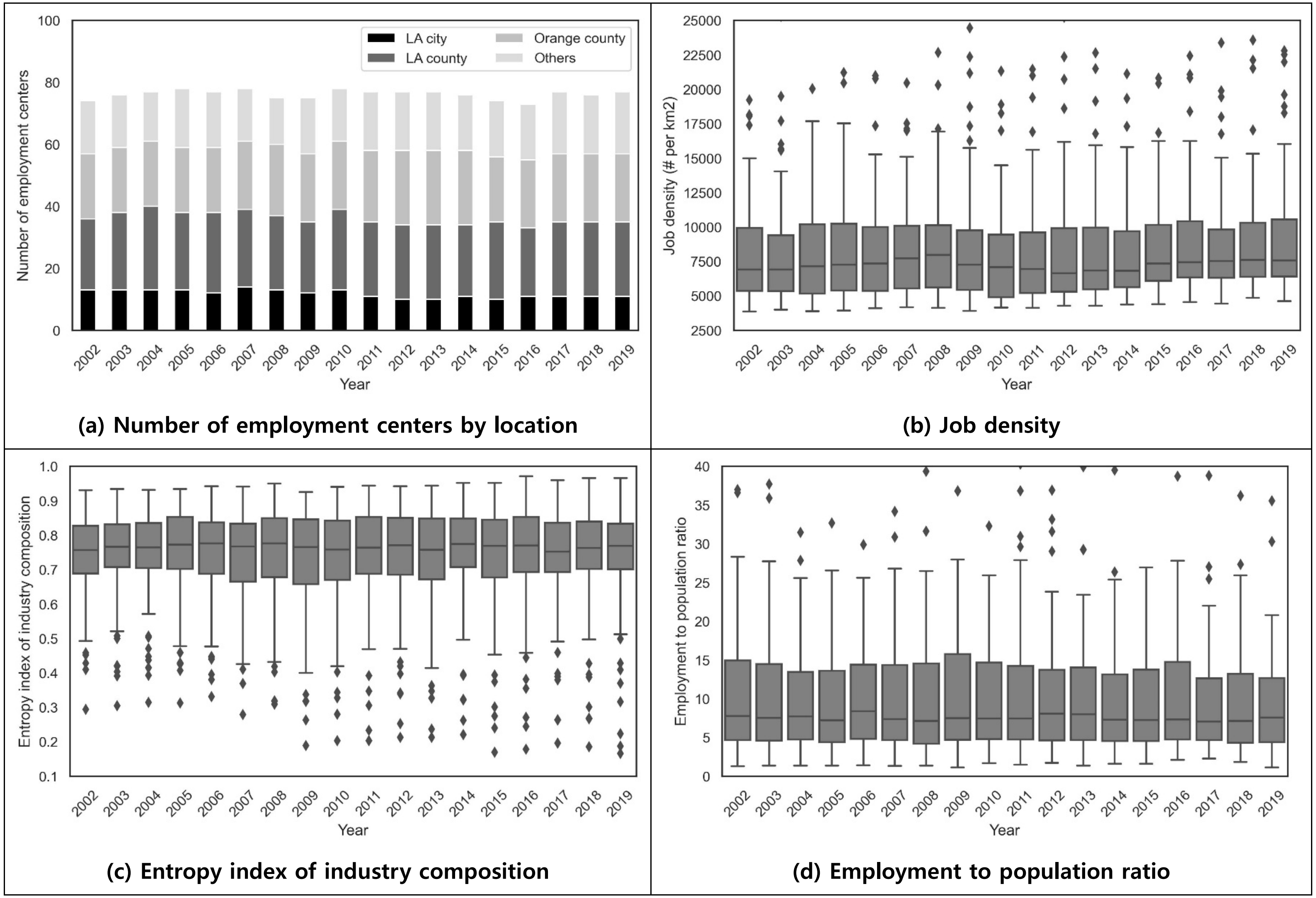

Figure 3. Distribution of employment center attributes, 2002-2019.

4.1.3 Correlation analysis

Table A1 and A2 show the correlation among our main variables (see Appendix). Table A1 shows that the job density and the industry mix of jobs measured at the neighborhood level are negatively associated with the distance to the nearest employment center. This is an expected result not only because generally there are a smaller number of jobs as the distance increases from employment centers but because those jobs tend to be less diverse often dominated by retail or basic service providers in non-center locations. The correlation coefficient for job density and industry mix of jobs within 3 km was 0.206, statistically significant at the confidence level of 95%. Table A2 shows the correlation among the attributes of employment centers. Persistency is positively correlated with job density and the employment to population ratio. Employment centers with high industry diversity showed negative correlations with job density and the employment to population ratio. Lastly, the size of employment centers did not show significant correlation with other attributes. The results generally show that the attributes of employment centers have low levels of correlation.

4.2 Average commuting distance models

4.2.1 All workers

We next examine the estimates of the fixed effects models. Table 2 shows the model results; the outcome variable is logged commuting distance, and all workers are considered. Starting with Model 1-1, census tracts with an increasing percentage of younger adult workers (i.e., aged 20-34) experience larger increases in commuting distance. And tracts with an increasing percentage of low-income workers experience a larger decrease in commuting distance. These results were all statistically significant and consistent across the four models presented in Table 2. Considering residential neighborhood factors, census tracts with increasing job density within 3 km and decreasing industry diversity experienced decreasing commuting distances. Nonetheless, even after controlling for socio-economic and residential neighborhood factors, the distance to nearest employment center showed a significant and positive sign. This result indicates that workers that experienced decreasing distance to an employment center (either because the center is new, or the center expanded closer to them) tend to experience decreasing commuting distances, which supports the co-location theory.

Moving to the second and third models in Table 2, model 1-2 includes the interaction terms related to the location of employment centers. Here, the coefficient of the distance to nearest employment center (b=0.001) can be interpreted as the base value for employment centers located within counties other than Los Angeles or Orange County. Employment centers located in Los Angeles County have greater influence on commuting distance. For example, the coefficient of distance to nearest employment center for census tracts that have their nearest center located in Los Angeles County is 0.004 (= 0.001 + 0.003). In contrast, the interaction term for Orange County centers showed a negative sign which diminishes the relationship between distance to the nearest employment center and commuting distances. This result suggests that the proximity to the nearest center does not contribute to shorter commuting distances in Orange County. Model 1-3 estimates the effect of interaction terms relevant to center attributes. The results show that employment centers that are persistent, have high job density and industry mix, have higher employment to population ratio, and have larger size tend to have a greater impact on reducing commuting distance. These findings imply that employment centers are heterogeneous in terms of their impact on commuting distances of workers living close to them.

Model 1-4 estimates the results when simultaneously including the interaction terms related to both center location and attributes. The coefficient of the distance to nearest employment center reduced to smaller than 0.001 and statistically insignificant. Since we include multiple interaction terms, the coefficients should be interpreted with caution. For instance, if the nearest employment center is located in Los Angeles County with high job intensity, the overall effect of the distance to nearest employment center is not near 0. Also, we control for job density within 3 km (logged) based on the workers' residential area so the results here can be viewed as evidence of the net contribution of employment centers that have diverse effects on nearby residents. The results from Model 1-4 are similar to those estimated from Models 1-2 and 1-3. Finally, model 1-5 is based on the pooled OLS model which shows similar results to the fixed effects models along with a much higher R-square value, which is common in models comparing across units, rather than within units.

4.2.2 Low-income workers

We next explore the model results for low-income workers (see Table 3). In general, the estimates are mostly consistent with the results for all workers, while there are a few differences to highlight. For low-income workers, the coefficient of distance to nearest employment centers also showed a positive sign even after controlling for socio-economic and residential neighborhood factors (see Model 2-1). This result clearly suggests that low-income workers commute shorter distances if they live near an employment center.

One notable finding is that the distance to nearest employment center did not show a significant association with commuting distance in Model 2-4. However, as described earlier, we should not interpret this coefficient solely, but with consideration of the interaction terms. For instance, if the nearest center is in Los Angeles County and if it has a high employment to population ratio, the coefficient of distance to nearest center should be interpreted as 0.009 (= -0.000 + 0.006 + 0.003) and significant. Similar to the models for all workers, low-income workers tend to commute shorter distances if they live close to an employment center located in Los Angeles County, exhibiting higher job density, industry mix, and employment to population ratio. The coefficient for persistency did not show statistical significance.

4.2.3 High-income workers

Lastly, Table 4 shows the model estimates for high-income workers. While most of the results are again consistent with the model estimates for all workers, high-income workers living in census tracts with more low-income workers tend to commute longer distances. For our variable of interest, high-income workers living in census tracts with an increasing distance to the nearest employment center experience increases in commuting distance. The results were slightly different when it comes to the location dummy variables; the dummy variables all showed a negative sign which suggests that the effect of the distance to nearest employment center is the greatest for those located in areas other than Los Angeles and Orange County. The interaction terms with the attributes of nearest employment center all showed a positive and significant coefficient; employment centers that are persistent, have high job density, diversity, and employment to population ratio with larger size exert more influence on commuting distances for high-income workers.

Table 2. Fixed-effect models (1-1 to 1-4) and pooled OLS model (1-5) (DV: logged average commuting distance, All workers)

Variables	Model 1-1		Model 1-2		Model 1-3		Model 1-4		Model 1-5	
	Coef.	(sig.)	Coef.	(sig.)	Coef.	(sig.)	Coef.	(sig.)	Coef.	(sig.)
Socio-economic factors										
Ratio of age 20-34	1.141	***	1.138	***	1.142	***	1.140	***	0.777	***
Ratio of low income ($1,250/month or less)	-0.123	***	-0.128	***	-0.117	***	-0.121	***	-0.612	***
Neighborhood factors										
ln (job density within 3 km)	-0.036	***	-0.036	***	-0.034	***	-0.034	***	-0.082	***
Industry mix level of jobs within 3 km	0.068	***	0.067	***	0.066	***	0.066	***	-0.186	***
Distance to nearest employment center (DNC)	0.002	***	0.001	***	<0.001		<0.001		0.066	***
Location of nearest employment center										
Los Angeles City			-0.048	***			-0.028	***	-0.271	***
Los Angeles County			-0.055	***			-0.051	***	-0.368	***
Orange County			0.012	***			0.019	***	-0.165	***
DNC * Los Angeles City			0.003	***			0.002	***	-0.037	***
DNC * Los Angeles County			0.003	***			0.002	***	0.021	***
DNC * Orange County			-0.001	***			-0.001	***	-0.035	***
Attributes of nearest employment center										
Persistent from 2002 to 2019					0.005	***	0.001	***	-0.003	***
High job density					-0.030	***	-0.028	***	0.123	***
High industry diversity					-0.013	***	-0.016	***	0.032	***
High emp. to pop. ratio					-0.033	***	-0.035	***	-0.067	***
Large size					-0.033	***	-0.029	***	-0.461	***
DNC * Persistent from 2002 to 2019					<0.001	***	<0.001	***	-0.003	***
DNC * High job density					0.001	***	0.001	***	-0.022	***
DNC * High industry diversity					0.001	***	0.001	***	0.001	***
DNC * High emp. to pop. ratio					0.002	***	0.002	***	0.085	***
DNC * Large size					0.002	***	0.001	***	0.047	***
Constant	10.097	***	10.138	***	10.109	***	10.138	***	1.053	***
Model statistics										
R-squared									0.702	
Within	0.062		0.063		0.064		0.065			
Between	0.466		0.469		0.472		0.470			
Overall	0.409		0.413		0.412		0.412			

* p < 0.1; ** p < 0.05; *** p < 0.01

Table 3. Fixed-effect models (2-1 to 2-4) and pooled OLS model (2-5) (DV: logged average commuting distance, Low income workers)

Variables	Model 2-1		Model 2-2		Model 2-3		Model 2-4		Model 2-5	
	Coef.	(sig.)	Coef.	(sig.)	Coef.	(sig.)	Coef.	(sig.)	Coef.	(sig.)
Socio-economic factors										
Ratio of age 20-34	1.514	***	1.509	***	1.516	***	1.510	***	1.258	***
Ratio of low income ($1,250/month or less)	-0.864	***	-0.870	***	-0.848	***	-0.851	***	-1856	***
Neighborhood factors										
ln (job density within 3 km)	-0.036	***	-0.036	***	-0.034	***	-0.034	***	-0.100	***
Industry mix level of jobs within 3 km	0.107	***	0.105	***	0.105	***	0.103	***	-0.223	***
Distance to nearest employment center (DNC)	0.003	***	-0.001<		<0.001		-0.001<		0.030	***
Location of nearest employment center										
Los Angeles City			-0.086	***			-0.057	***	-0.204	***
Los Angeles County			-0.134	***			-0.126	***	-0.352	***
Orange County			0.027	***			0.039	***	-0.125	***
DNC * Los Angeles City			0.005	***			0.003	***	-0.014	***
DNC * Los Angeles County			0.006	***			0.006	***	0.001	***
DNC * Orange County			-0.002	***			-0.003	***	-0.019	***
Attributes of nearest employment center										
Persistent from 2002 to 2019					0.019	***	0.014	***	0.030	***
High job density					-0.030	***	-0.027	***	0.054	***
High industry diversity					-0.039	***	-0.041	***	0.024	***
High emp. to pop. ratio					-0.055	***	-0.058	***	-0.167	***
Large size					-0.045	***	-0.044	***	-0.115	***
DNC * Persistent from 2002 to 2019					-0.001	***	-0.001<		-0.006	***
DNC * High job density					0.001	***	0.001	***	-0.015	***
DNC * High industry diversity					0.003	***	0.003	***	0.001	***
DNC * High emp. to pop. ratio					0.003	***	0.003	***	0.020	***
DNC * Large size					0.003	***	0.002	***	0.011	***
Constant	10.172	***	10.259	***	10.200	***	10.268	***	1.131	***
Model statistics										
R-squared									0.701	
Within	0.086		0.088		0.089		0.091			
Between	0.453		0.458		0.459		0.480			
Overall	0.382		0.391		0.386		0.409			

* p < 0.1; ** p < 0.05; *** p < 0.01

Table 4. Fixed-effect models (3-1 to 3-4) and pooled OLS model (3-5) (DV: logged average commuting distance, High income workers)

Variables	Model 3-1		Model 3-2		Model 3-3		Model 3-4		Model 3-5	
	Coef.	(sig.)	Coef.	(sig.)	Coef.	(sig.)	Coef.	(sig.)	Coef.	(sig.)
Socio-economic factors										
Ratio of age 20-34	0.903	***	0.901	***	0.905	***	0.904	***	1.646	***
Ratio of low income ($1,250/month or less)	0.457	***	0.452	***	0.464	***	0.461	***	0.458	***
Neighborhood factors										
ln (job density within 3 km)	-0.023	***	-0.023	***	-0.021	***	-0.021	***	-0.093	***
Industry mix level of jobs within 3 km	0.034	***	0.033	***	0.032	***	0.032	***	-0.051	***
Distance to nearest employment center (DNC)	0.002	***	0.002	***	0.001	***	0.002	***	0.021	***
Location of nearest employment center										
Los Angeles City			0.020	***			0.012	***	-0.380	***
Los Angeles County			0.011	***			0.008	***	-0.397	***
Orange County			0.017	***			0.021	***	-0.184	***
DNC * Los Angeles City			-0.002	***			-0.001	***	0.002	***
DNC * Los Angeles County			-0.002	***			-0.001	***	0.017	***
DNC * Orange County			-0.003	***			-0.002	***	-0.007	***
Attributes of nearest employment center										
Persistent from 2002 to 2019					0.007	***	0.005	***	0.027	***
High job density					-0.032	***	-0.030	***	0.010	***
High industry diversity					-0.010	***	-0.011	***	-0.016	***
High emp. to pop. ratio					-0.039	***	-0.040	***	-0.168	***
Large size					-0.035	***	-0.033	***	-0.126	***
DNC * Persistent from 2002 to 2019					<0.001	***	<0.001	***	0.001	***
DNC * High job density					0.001	***	0.001	***	-0.013	***
DNC * High industry diversity					0.001	***	0.001	***	0.002	***
DNC * High emp. to pop. ratio					0.002	***	0.003	***	0.022	***
DNC * Large size					0.002	***	0.002	***	0.010	***
Constant	9.980	***	9.998	***	9.995	***	9.993	***	1.041	***
Model statistics										
R-squared									0.645	
Within	0.052		0.053		0.054		0.055			
Between	0.377		0.357		0.376		0.338			
Overall	0.323		0.305		0.319		0.286			

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

4.2.4 Summary

Our findings suggest that the distance to the nearest employment center is significantly associated with longer commuting distances. The results are meaningful since we attempt to identify the relationship after controlling for socio-economic and residential neighborhood factors. Furthermore, our fixed effects models focus exclusively on change within tracts, and do not compare across tracts which allows us to infer causal relationships. The within R-squared values of all models ranged from 0.05 to 0.09 in our models while it was greater for the models based on low-income workers. Our independent variables explain around 5-9% of the variation in the changes in commuting distances over time. While the within R-squared for our fixed effects models were somewhat low, this is a common feature of fixed effects models. The low explanatory power of our fixed effects models suggest that only a limited portion of the variance in commuting distance is explained by the changes in our explanatory variables over time; however, the model results still indicate the significant relationships. Furthermore, the R-squared values for the OLS versions of our models comparing *across* units were nearly .70, which shows a quite high explained variance, highlighting the limited amount of variability that there is to explain within units.

Figures 4 and 5 summarize the results of the fixed-effects models and present the estimated effects of the distance to nearest employment center on commuting distance; Figure 4 assumes the location of the employment center as Los Angeles County and Figure 5 assumes it as other counties than Los Angeles and Orange County. The figures show that the effect of the nearest employment center on commuting distance differs by the characteristics of employment centers as well as by different income groups. As we will discuss in more depth shortly, these figures show that: 1) employment centers have stronger effects on commuting distance in Los Angeles County; 2) Los Angeles employment centers impact low income workers more strongly than high income workers; and 3) in more distant counties, employment centers tend to more strongly impact commute distances of high income workers compared to low income workers.

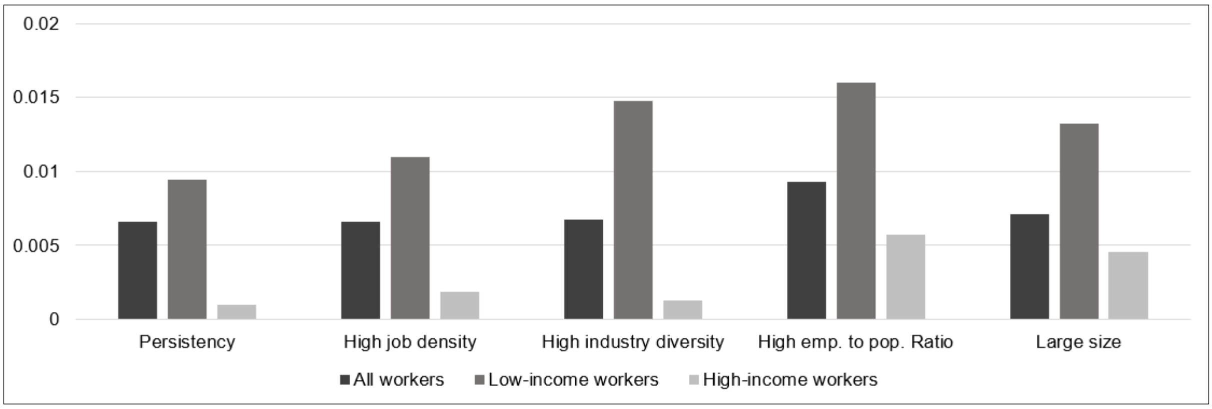

Figure 4. Estimated effects of distance to nearest employment center on commuting distance. Location of employment center assumed as Los Angeles County.

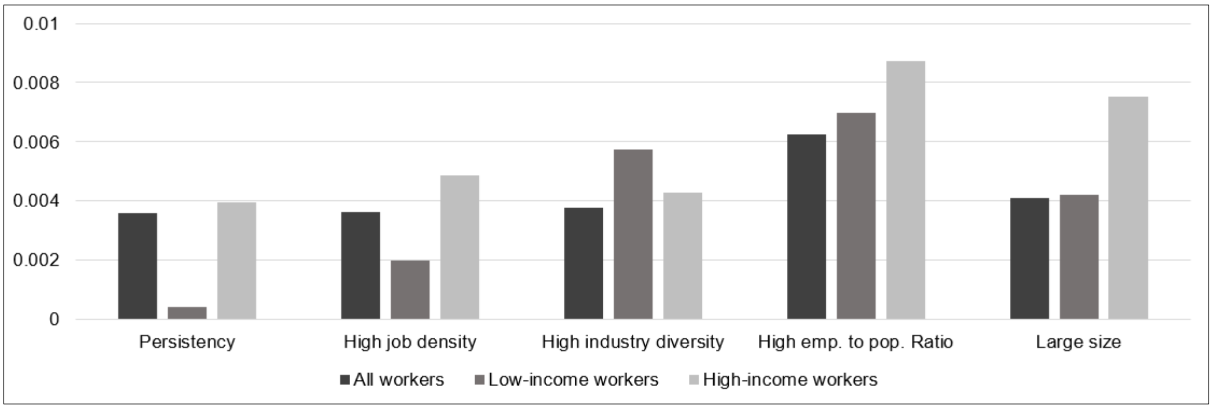

Figure 5. Estimated effects of distance to nearest employment center on commuting distance. Location of employment center assumed as counties other than Los Angeles and Orange County.

We note that the relationship tested in this paper is subject to the self-selection issue. In particular, residential self-selection implies that individuals may choose to live in certain areas due to constraints, preferences, and modal availability (Cao, 2009). Low income workers who could not afford high housing prices near employment centers may instead reside in distant areas (Cao, 2009). It is also possible that some low income workers live close to the employment centers because they either cannot afford cars for long-distance commutes or have more job availabilities in employment centers (Bohte et al., 2009). For high income workers, they may choose where they live according to their lifestyle preferences, which may lead to a weak relationship between commute distance and the distance to the nearest employment center. This component may partly explain the relatively lower explanatory power of the models for high-income workers.

5. Discussion and conclusions

This paper investigated how distance to the nearest employment center is related to commuting distance in the Los Angeles region. By using longitudinal data on commuting and employment locations, we were able to determine that commuters experiencing an increasingly near employment center tend to have decreasing commuting distances. The relationship was statistically significant even after controlling for socio-economic and neighborhood factors. In particular, we applied a fixed effects model, which captures variation within tracts as a more rigorous test of this relationship. We have further examined the heterogeneity across employment centers and workers by applying interaction terms and testing multiple fixed effects models. Between 2002 and 2019, we find that the polycentric urban form in the Los Angeles region has been consistent, where more than 35% of the jobs within the region are located in employment centers. Among large US metropolitan areas, the Los Angeles region has the largest share of jobs in employment centers (Angel & Blei, 2016), which makes a unique case to explore the effect of employment centers on commuting.

One notable finding is that not all employment centers are equal. Based on the interaction terms related to location and attributes of employment centers, the results suggest that some centers exert more influence on commuting distance. Compared to other places in the region, for instance, the proximity to employment centers was found to have a greater effect on reducing commute lengths in Los Angeles County. Related to the attributes of centers, the centers that were persistent throughout the period from 2002 to 2019 showed greater influence on commuting distance than non-persistent ones. In addition, centers with a higher density, higher employment to population ratio, and larger size showed greater effects on reducing commuting distance of nearby residents. The results imply that employment centers are heterogeneous in terms of their location and attributes, with different impacts on commuting distance of workers living near them.

Employment centers that have high job density and a high employment to population ratio imply that there are a greater number of jobs located within the center. These employment centers may have characteristics that lead to further employment growth, which in turn can exert more influence on commuting behavior. For instance, Giuliano et al. (2011) show that accessibility is a critical component for employment centers to grow; employment centers with greater labor force accessibility may attract more workers from locations in proximity.

In addition, employment centers with greater industry mix may provide potential to reduce commuting distances especially for households with multiple workers. Moreover, persistent employment centers are likely to have attracted more jobs and provide better accessibility to workers with accumulated infrastructure levels which may contribute to shorter commuting distances.

We also observed differences between low- and high-income workers. The commuting distances of low-income workers were not necessarily associated with the distance to the nearest employment center; the effect was the greatest when the employment center was located in Los Angeles County. For high-income workers, their commuting distance was positively associated with the distance to the nearest employment center while the effect size increased when the employment center is located in counties other than Los Angeles and Orange county. This result suggests that many high-income workers living within Los Angeles and Orange county might not commute to an employment center in proximity. Overall, when considering the location of employment centers, those located nearer the region center more strongly impact commuting distance of low-income workers, while the ones located in the peripheral areas have greater impact on high-income workers.

Employment centers are an outcome of both economies and diseconomies of agglomeration. While there have been efforts to encourage employment center growth at the local level, existing studies show mixed results of their success. For instance, Agarwal (2015) shows that policy measures such as expenditure on development, growth control, and business fees do not show a significant effect on employment center growth. Instead, the author suggests that facilitating access to the labor force may provide potential to indirectly encourage employment center growth. While our results show that some characteristics of employment centers are associated with greater effects on commuting distance, it would not be appropriate to assume that an employment center can be easily reshaped in a certain way by a single policy measure or initiative. That said, by highlighting the heterogeneous nature of the benefits of employment centers, this study encourages policymakers to refine their understanding of the workings of their employment centers and carefully monitor how the centers evolve over time. It is also important to pay attention to who gains and who loses since not all workers will equally benefit from employment centers as shown in this study through a comparison of high-income and low-income workers. In some circumstances, it would be desirable to provide more affordable housing units near employment centers for more sustainable and inclusive place making.

Empirical evidence highlights the benefits of short commutes. Short-distance commuters exhibit better job performance and contribute to greater economic growth of employers (Ma & Ye, 2019). Commuters with longer commute lengths experience reduced satisfaction and subjective well-being (Manaugh & El-Geneidy, 2013; Nie & Sousa-Poza, 2018). Moreover, shorter commuting length is a desirable goal for cities as it is conducive to reducing the negative externalities of transport. Unfortunately, it is not an easy task to accomplish. Low-income workers may have limited ability to choose their home and workplace, while high-income workers have other factors to consider when selecting their residential area. Moreover, we have seen growth in commuting distance in the past, which have led to ideas such as encouraging the overall connectivity within regions rather than encouraging transportation strategies that focus on improving access to employment centers (e.g., Angel & Blei, 2016). However, our results imply that employment centers have the potential to reduce commute lengths depending on their characteristics and the income level of workers. For cities, we further suggest that improving access to employment centers that have a greater possibility to affect commuting outcomes could be beneficial.

We note limitations and methodological issues of this study. First, we acknowledge that our results do not address the self-selection issue. The residential location of workers is not randomly assigned but is a self-selected result which may affect the relationship between commuting and distance to the nearest employment center. Second, earning categories defined in the LEHD data are not adjusted for inflation over time. This could result in workers being classified in a different income bin; in other words, the percentage of low-wage category decreases, and the percentage of high-wage category increases year by year as a result of inflation. While we acknowledge this data limitation, we use the LEHD data because of its primary advantages. The LEHD data is updated annually making it possible to examine changes over time, particularly for understanding residential and workplace location and the commute outcomes. With this data issue, our results on the change in commute distances for low-wage workers would represent a poorer population over time due to inflation. Similarly, the results for high-wage workers would include more “mid-income” workers over time because of inflation. Nonetheless, we suggest that our results contribute to the literature since we find differences between the low and high-wage workers. Lastly, we agree that there are several ways to identify employment centers within a region and the results may differ when using other methodological approaches. In our case, we applied the approach suggested by Giuliano & Small (1991) not only because it is the most widely used in the literature, but also because it relies on a fixed threshold which allows us to explore the changes over time in a more robust way.

Nevertheless, this study contributes to the literature on urban spatial structure, polycentricity, and commuting, particularly by deciphering the location and attributes of employment centers that may exert a greater impact on commuting distances. Furthermore, the results have implications for understanding the agglomeration effect and co-location theory in a polycentric metropolitan area. Future studies may explore other attributes of employment centers that might impact commuting outcomes. In addition, other dimensions such as socio-economic characteristics of commuters and other commuting outcomes such as mode choice and travel time could be further investigated. Since the Los Angeles region has an exceptional urban spatial structure with a high degree of polycentricity, the results may not be generalizable to other regions that have a smaller number of employment centers with more concentration. Lastly, we also note that the COVID-19 pandemic may result in different relationships between commuting and employment centers as the number of workers working from home has dramatically increased. While the time scope of our results is limited to 2002 – 2019, future work may further investigate how the pandemic has reshaped the employment centers and their association with commuting.

Appendix

Table A1. Correlation between distance to nearest employment center and job related measures at the neighborhood level

Variables	(a)	(b)	(c)
(a) Dist. to nearest emp. center	-	-	-
(b) Job density within 3km	-0.412 *	-	-
(c) Industry mix of jobs within 3 km	-0.197 *	0.206 *	-

* $p < 0.05$

Table A2. Correlation among attributes of employment centers

Variables	(a)	(b)	(c)	(d)	(e)
(a) Persistent from 2002 to 2019	-	-	-	-	-
(b) High job density	0.271 *	-	-	-	-
(c) High industry diversity	0.017	-0.175 *	-	-	-
(d) High emp. to pop. ratio	0.315 *	0.379 *	-0.124 *	-	-
(e) Large size	-0.040	-0.048	0.035	-0.172	-

* $p < 0.05$

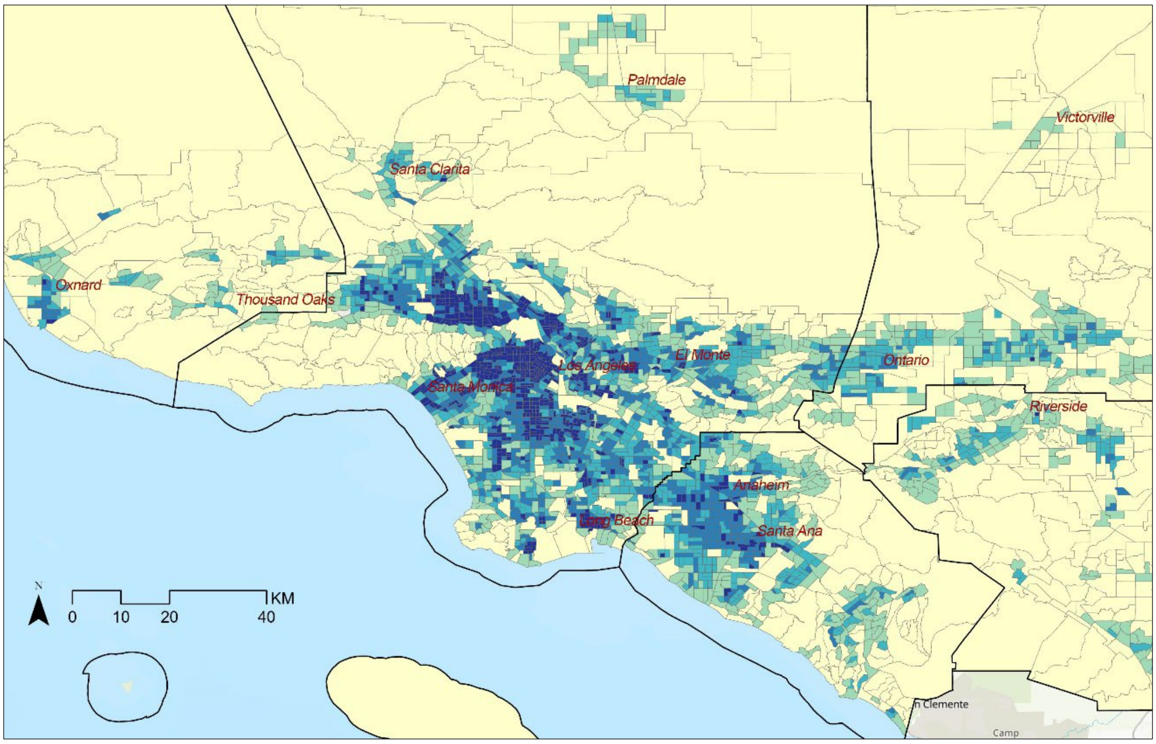

Figure A1. Distribution of low income workers' residential density. Colors are generated by quintiles, darker colors indicating higher density.

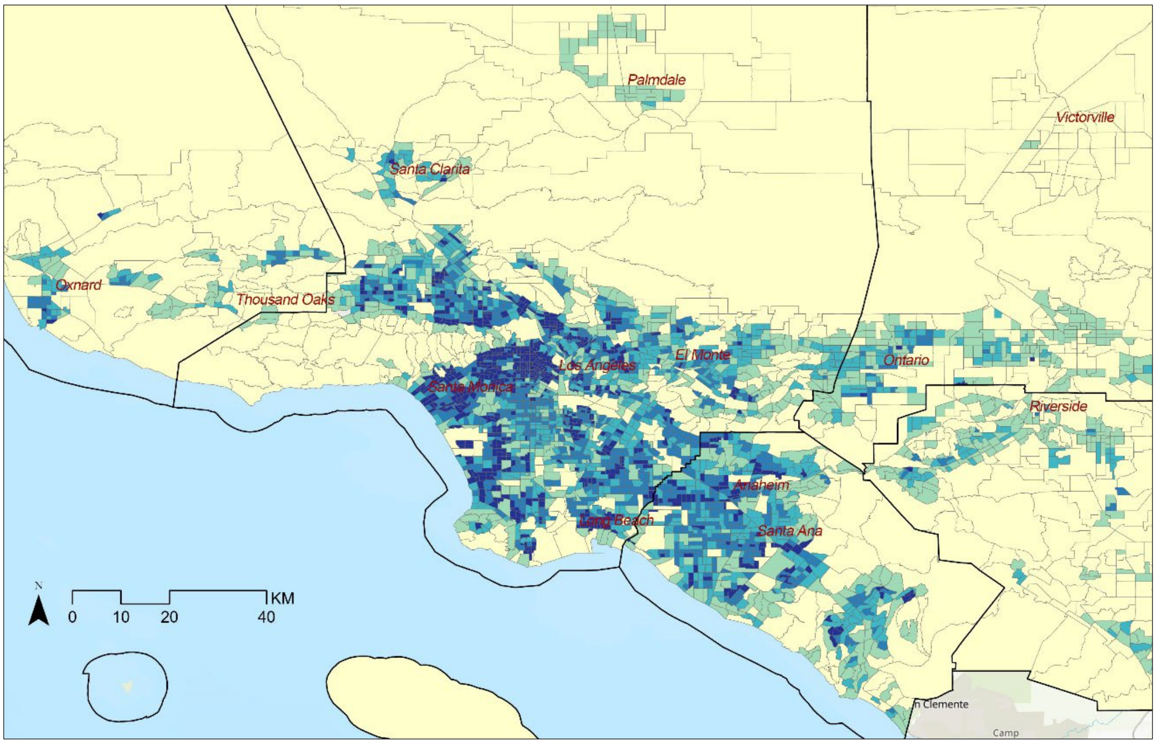

Figure A2. Distribution of high income workers' residential density. Colors are generated by quintiles, darker colors indicating higher density.

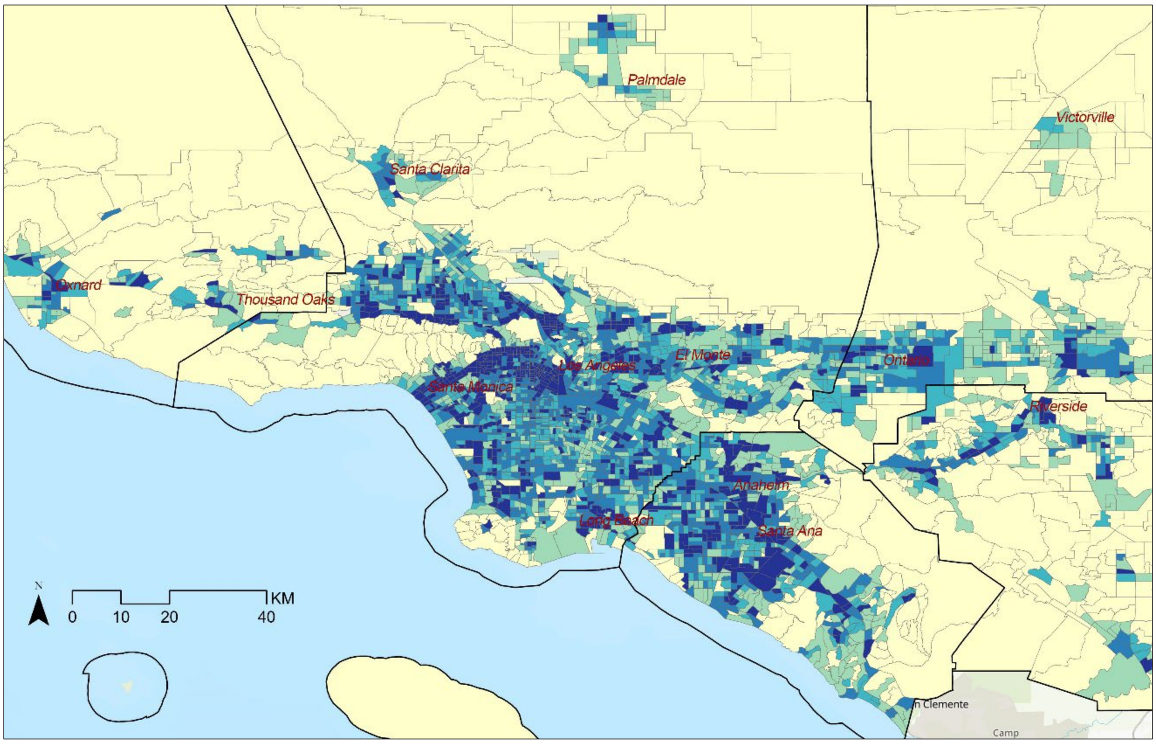

Figure A3. Distribution of low income workers' workplace density. Colors are generated by quintiles, darker colors indicating higher density.

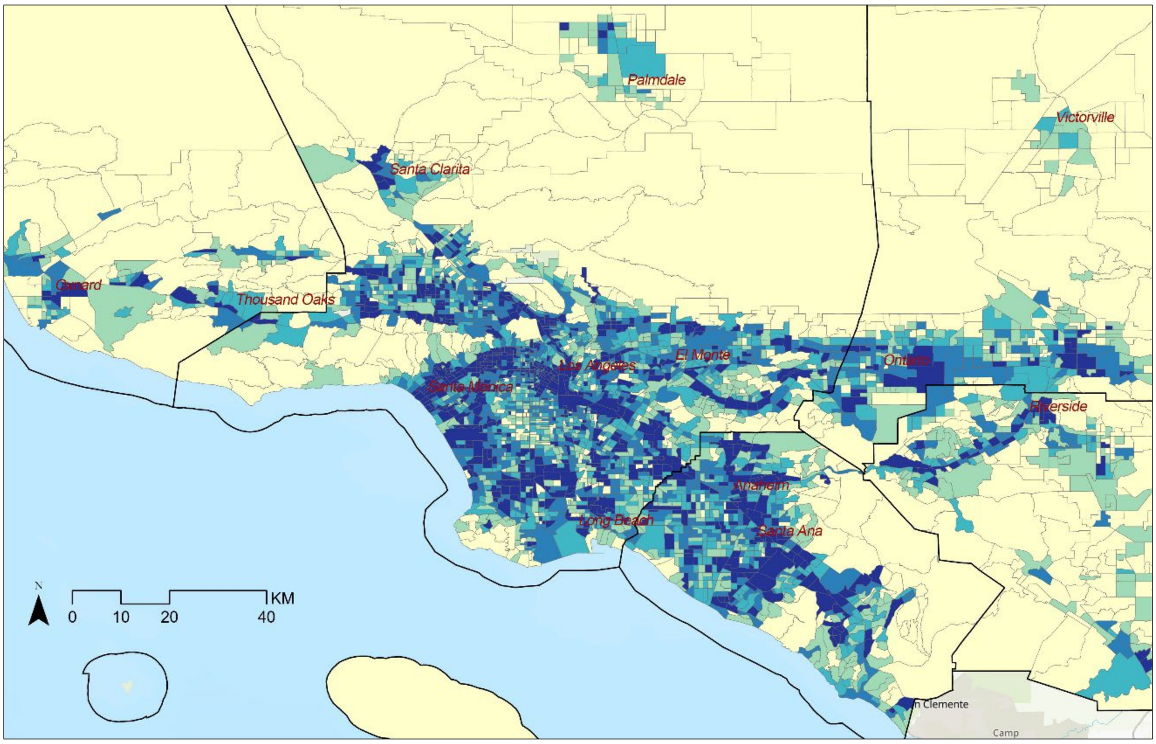

Figure A4. Distribution of high income workers' workplace density. Colors are generated by quintiles, darker colors indicating higher density.

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[i] The seven types of industry are identified based on the NAICS codes identified in the LODES data:

(1) 11 (Agriculture, Forestry, Fishing and Hunting), 21 (Mining, Quarrying, and Oil and Gas Extraction), 22 (Utilities), 23 (Construction),

(2) 31-33 (Manufacturing),

(3) 42 (Wholesale Trade), 44-45 (Retail Trade), 48-49 (Transportation and Warehousing),

(4) 51 (Information), 52 (Finance and Insurance), 53 (Real Estate and Rental and Leasing), 54 (Professional, Scientific, and Technical Services), 55 (Management of Companies and Enterprises), 56 (Administrative and Support and Waste Management and Remediation Services),

(5) 61 (Educational Services), 62 (Health Care and Social Assistance),

(6) 71 (Arts, Entertainment, and Recreation), 72 (Accommodation and Food Services),

(7) 81 (Other Services [except Public Administration]), 92 (Public Administration).