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Authors

Hipp, John R
Lee, Sugie
Kim, Jae Hong
et al.

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John R. Hipp*

Sugie Lee

Jae Hong Kim

Benjamin Forthun

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* Department of Criminology, Law and Society, Department of Sociology, and Department of Urban Planning and Public Policy at the University of California, Irvine. Address correspondence to John R. Hipp, Department of Criminology, Law and Society, University of California, Irvine, 3311 Social Ecology II, Irvine, CA 92697; email: john.hipp@UCI.edu. This research is supported in part by the Metropolitan Futures Initiative (MFI) at the University of California, Irvine and the Korea Research Foundation (NRF-2021R1A2C2006539).

Employment Deconcentration and Spatial Dispersion in Metropolitan Areas: Consequences for commuting patterns

Abstract

There is interest in understanding which characteristics of metropolitan areas impact the length of time or distance residents spend commuting. We utilize two measures recently introduced to the urban environment literature capturing distinct dimensions of employment decentralization –the level of employment deconcentration and employment spatial dispersion in metropolitan areas – to assess how they are related to commuting patterns across metropolitan areas. These two measures of urban/metropolitan spatial structure avoid challenges in identifying "job centers" and allow for a more systematic investigation of how employment decentralization affects commuting patterns. Furthermore, we detect key differences for the implications of these measures for commuting across 329 US metropolitan regions based on their population size. We find that greater employment deconcentration in very small MSAs is associated with longer commute times and distance, whereas greater employment deconcentration in large or very large MSAs is associated with *shorter* commutes. And whereas spatial dispersion is not related to commute times in very small MSAs, greater spatial dispersion is associated with longer commutes in very large MSAs. This study thus demonstrates the efficacy of these new measures for capturing the spatial pattern of employment in regions and how this is related to commuting patterns.

Keywords: metropolitan regions; employment deconcentration; urban scale; commuting time

Bios

John R. Hipp is a Professor in the department of Criminology, Law and Society, Department of Sociology, and the Department of Urban Planning and Public Policy at the University of California Irvine. He is the director of the Metropolitan Futures Initiative (MFI). His research interests focus on how neighborhoods change over time, how that change both affects and is affected by neighborhood crime, and the role networks and institutions play in that change. He approaches these questions using quantitative methods as well as social network analysis. He has published substantive work in such journals as *American Sociological Review, Criminology, Social Forces*, *Social Problems, Mobilization, City & Community, Urban Studies* and *Journal of Urban Affairs*. He has published methodological work in such journals as *Sociological Methodology, Psychological Methods*, and *Structural Equation Modeling*.

Sugie Lee is a Professor in the Department of Urban Planning & Engineering and a director of Urban Design & Spatial Analysis Lab.(UDSAL) in Seoul, Korea. He is interested in urban mobility, walkability, and urban safety as well as the application of urban bigdata and machine learning to address urban problems. He has published in such journals as *Journal of Planning Education & Research, Urban Studies, Land Use Policy, Transport Policy, Environment and Planning B, Cities*.

Jae Hong Kim is an Associate Professor in the Department of Urban Planning and Public Policy at the University of California Irvine. His research focuses on land use, economic development, and urban system modeling. His work has been published in journals such as *Environment and Planning A, Journal of Planning Education and Research, Journal of Planning Literature*, and *Urban Studies*.

Benjamin Forthun is a Ph.D. candidate in the department of Criminology, Law and Society at the University of California Irvine.

Employment Deconcentration and Spatial Dispersion in Metropolitan Areas: Consequences for commuting patterns

Introduction

The decentralization of employment is an important feature of contemporary metropolitan areas that has attracted a great deal of attention in both academic and policy circles. The conventional characterization of urban/metropolitan spatial structure as a monocentric system started to lose ground in the last century with less than a quarter of jobs on average located within three miles of the core in the 100 largest US metropolitan areas (Glaeser, Kahn, and Chu 2001). This trend of employment decentralization, often labelled as 'job sprawl,' has continued in the twenty-first century, while the distribution of employment varies substantially across industries (Glaeser, Kahn, and Chu 2001; Kneebone 2009).

Although much attention has been paid to the spatial restructuring of metropolises, conflicting views have been expressed in the literature as to the widespread trend of employment decentralization and the consequences for commuting patterns. There has been, in particular, long-standing disagreement on whether employment decentralization in a metropolitan area is beneficial or harmful from the region's commuting perspective (see e.g., Cervero and Landis 1992). A group of researchers have contended that employment decentralization is a process that can contribute to making a metropolis more efficient in terms of commuting, but not all agree with this claim (Gordon, Kumar, and Richardson 1989; Levinson and Kumar 1994; Sultana 2000; Sun, He, Zhang, and Wang 2016). There are numerous studies reporting evidence contrary to this optimistic view on the consequence of decentralization (see, e.g., Aguilera 2005;

Cervero and Wu 1998; McGuckin and Srinivasan 2003; Schwanen, Dieleman, and Dijst 2001; Vandersmissen, Villeneuve, and Thériault 2003; Wolday, Naess, and Tønnesen 2019).

In this study, we attempt to reconcile the conflicting views and provide a more nuanced understanding of the implications of urban spatial structure for commuting patterns with special attention to which characteristics of urban/metropolitan spatial structure matter and how. To accomplish this, we use two new measures of urban/metropolitan spatial structure that represent two different dimensions of employment decentralization – (1) employment deconcentration and (2) spatial dispersion – and thus enable us to discern the ways in which employment decentralization takes place in different regions. Our analysis of 329 US metropolitan statistical areas (MSAs) shows that these two measures have distinct impacts on commuting patterns—measured as commute time and commute distance—suggesting that mixed views in the literature can be reconciled to some extent when attention is paid to the detailed characteristics of employment decentralization. The results also indicate that the consequences of employment decentralization for commuting depend on the stage of growth for the MSA and the size of the metropolitan region.

The remainder of this paper is divided into five sections. Section 2 first provides background on the theoretical rationale for why the urban form might impact commute patterns, and then reviews the literature studying the relationship between urban form and commute times and distance. Section 3 describes our data, and the analytic methods, which use a parallel set of analyses for the models with the outcomes related to commute time and those related to commute distance. Section 4 describes the results for how our measures of business decentralization are related to commuting patterns, and we also stratify our models by size of MSAs. Section 5 discusses the implication of our findings, and concludes.

Measuring employment decentralization and understanding metropolitan spatial structure

Previous research

Since Von Thunen (1826), Alonso (1964), Mills (1967) and Muth (1969) posited that cities are characterized by a monocentric form—in which businesses are clustered in the center—researchers have conducted studies of the spatial location of businesses in metropolitan areas to assess if this is the case. In Alonso's view, the typical development of a city has a downtown area that develops initially with a large business concentration, and the region then grows out from this center. In the earlier stages of these cities, there is a single center, and therefore most residents commute in to their jobs in the central business district from the surrounding area. In part, this central location maintains its economic dominance because there are beneficial externalities for businesses located in this center area, as they have easy access to suppliers who are also located in this central location. For businesses directly serving the public, there are advantages to the consumer when several different businesses are located close to one another, increasing shopping convenience, and therefore make such locations more desirable to these businesses. There can also be knowledge transfer between businesses in a location as workers move between firms and interact with each other more actively (Angel 1991; Saxenian 1994; Schoonhoven and Eisenhardt 1992), as well as the transfer of information between workers in the knowledge economy (Giuliano, Kang, and Yuan 2019). For all of these reasons, location in this central district is economically beneficial for businesses.

At some point as a region grows, despite the aforementioned advantages, the monocentric urban form is less likely to be efficient particularly from a commuting perspective. The congestion on the roads heading in to the central location becomes too constraining, and greatly increases commute times. Thus, despite the benefits to businesses of the central location, the increased commuting time for workers become too much of a negative externality. There is then increasing interest on the part of businesses to locate further from the center. These businesses do not just move randomly, but rather tend to move to peripheral locations that are districts that again allow for the clustering of businesses—what we can consider business subcenters. These subcenters allow for a modified level of the beneficial externalities that central business districts experience. If there is a relatively high concentration of businesses in these new subcenters, then these business subcenters further from the downtown area give rise to what is generally referred to as a polycentric form (Krehl and Siedentop 2019; Riguelle, Thomas, and Verhetsel 2007; Taubenböck, I.Standfuß, M.Wurm, A.Krehl, and S.Siedentop 2017; Vasanen 2012). These multiple subcenters form over time to allow workers more reasonable commutes to their workplace, but still provide beneficial externalities for the businesses.

Whereas one possibility is for a monocentric region to morph into a polycentric one if these subcenters have a relatively high concentration of businesses, the development as a region grows could instead result in forms other than polycentricity. In short, if businesses also relocate to locations throughout the region that are separate from these new subcenters, then polycentricity does not capture the complexity of this employment decentralization. One perspective is that rather than a small number of discrete subcenters as seen in the polycentric form, there can be many subcenters of various sizes in a more scattered form (Hajrasouliha and Hamidi 2017; Salvati, Venanzoni, Serra, and Carlucci 2016). One study referred to this as scatteration (Garcia-López and Muñiz 2019).

Measuring decentralization across many metropolitan areas

The different dimensions of urban spatial structure are critical issues when examining the relationship between urban spatial structure and commuting patterns. Although there are no clear definitions in measuring urban spatial structure, most studies have tried to identify spatial clustering of employment centers and the decentralization of employment into suburbs (Giuliano, Redfearn, Agarwal, Li, and Zhuang 2007; Giuliano and Small 1991). Particularly challenging for this literature, as pointed out by scholars, are the numerous methodological challenges in defining and measuring employment centers. One particularly thorny challenge is choosing appropriate cutoff values as the criteria for (gross) employment density and total employment for identifying subcenters, and these choices are typically somewhat arbitrary with little external justification (Hajrasouliha and Hamidi 2017; Hipp, Kim, and Forthun 2021). It is particularly difficult to determine cutoff values when comparing across a large number of metropolitan areas that vary greatly based on population size and density. Another challenge is the choice of spatial unit of analysis when measuring urban spatial structure. While some studies use census tracts or block groups (Hajrasouliha and Hamidi 2017; Yao and Kim 2019) or traffic analysis zones (Vandersmissen, Villeneuve, and Thériault 2003), other studies use smaller units of analysis such as 1 sq. km grid cells (Hipp, Kim, and Forthun 2021; Kane, Hipp, and Kim 2018; Krehl and Siedentop 2019). The results can differ based on these choices. Hipp et al. (Hipp, Kim, and Forthun 2021) indicated that smaller units are advantageous as they increase the plausibility of the assumption of homogeneity of employment patterns within the units despite the resulting computational challenges. Relatedly, there is uncertainty of the proper choice for defining contiguity of smaller units to be combined into a subcenter (e.g., rook, queen, etc.), and again the results can differ based on this choice as well.

Other researchers have responded to these challenges by instead employing relative comparisons for determining subcenters. Such strategies include using nonparametric regression to identify subcenters (McMillen 2001; Redfearn 2007), or use of various geographic Local Indicators of Spatial Association (LISA) statistics (Krehl and Siedentop 2019; Riguelle, Thomas, and Verhetsel 2007; Salvati, Venanzoni, Serra, and Carlucci 2016). Although useful for detecting relative peaks in the environment, such strategies encounter challenges when attempting to compare subcenters across a large number of MSAs. Indeed, a body of recent studies have elaborated on the various difficulties and indeterminacies of measuring subcenters (see e.g., Gardner and Marlay 2013; Hajrasouliha and Hamidi 2017; Lee 2007; McMillen 2001; Redfearn 2007). Recognizing these challenges, there is a need to instead better capture and analyze variations in employment concentration in alternative ways.

Equilibrium of subcenters and commuting patterns

As a region grows there are at least two broad processes at work. One is the desire of businesses to co-locate, and the economic advantages that provides. A second is the desire of workers (and thus businesses) for shorter commutes. Typically, in younger cities there will be a central business district where nearly all jobs are located, resulting in low deconcentration and low spatial dispersion. However, as the city grows, at some point there is not space for more businesses in the downtown area, and therefore newer businesses will locate further away, resulting in greater deconcentration. To the extent that these more distant businesses co-locate, this will result in business subcenters. This implies that these newer businesses will be clustered to at least some degree. But if any subcenter becomes too large, the congestion for commuters becomes particularly undesirable, and triggers the need for additional subcenters (Giuliano, Kang, and Yuan 2019).

This implies that there are two broad processes at work: the degree of concentration (subcenters) and the degree of spatial dispersion (the spread of businesses throughout the metropolitan area). Theoretically, Anas et al. (Anas, Arnott, and Small 1998) therefore proposed two spatial dimensions of employment distribution in a metropolitan area—spatial clustering and spatial decentralization. In an empirical study, Meijers and Burger (2010) suggested two dimensions of regional urban form—the centralization-dispersion dimension and the monocentricity-polycentricity dimension. To capture the impact of these two general processes on commuting patterns in regions, researchers have often taken as a starting point the need to measure business subcenters. However, this is difficult to do as defining subcenters can be arbitrary as we just described, and yet this is crucial for the strategy.

Because of the difficulties of measuring subcenters, a recent study proposed an alternative strategy that does not attempt to identify subcenters using a single definition, but instead attempts to more directly measure the degree of deconcentration of jobs, as well as the spatial dispersion of jobs (Hipp, Kim, and Forthun 2021). Given that deconcentration and spatial dispersion are the constructs of interest as they comprise the two subdimensions of decentralization, this study argued that directly measuring them rather than getting stuck in the thorny issue of defining subcenters may be an effective alternative strategy. This strategy simply measures the degree of spatial deconcentration of jobs in a metropolitan region, as well as the spatial dispersion of these jobs. By "deconcentration", we mean the extent to which businesses are not simply located within a central job center, or in a small number of large subcenters. By "spatial dispersion" we mean the extent to which there are larger distances between the businesses in a region. By directly measuring the locations of jobs—rather than attempting to measure the presence of job subcenters as an intervening step—this strategy provides a more direct measure of the constructs of interest. We will describe the strategy in more depth in the data and methods section.

Employment decentralization and commuting patterns

The question for us here is how the level of deconcentration of jobs in a region impacts commuting patterns, and how the level of spatial dispersion of jobs impacts commuting. In short, is there an optimal combination of deconcentration and spatial dispersion that results in shorter commute times? Considering these two dimensions explicitly can allow one to better comprehend the longstanding, conflicting views on the relationship between commuting and employment decentralization.

Furthermore, the earlier discussion of how a small city may begin with a downtown location, and then grow from there, highlights that it may be important to account for where the region is in the development process when assessing how deconcentration and spatial dispersion impact commuting patterns. In a smaller region, low levels of deconcentration and spatial dispersion that occur when there is a monocentric form may result in shorter commutes. This is because these smaller metros have not reached the level of job density that results in traffic congestion and inflated commute times. However, as the metropolitan region grows, spatial dispersion of jobs may be needed to avoid the sorts of congestion that otherwise have negative consequences for commute times. Thus, in larger areas, greater spatial dispersion, along with a level of business concentration, may result in shorter commute times. As metropolitan areas grow, increasing road capacity likely has little impact on the speed of traffic, which will not reduce congestion; as a result, there can be economies of scale from public transportation for larger regions (Mogridge 1997).

These measures of employment decentralization can to some degree map on to the traditional ideas of urban form. Specifically, a metropolitan area with low employment deconcentration and low spatial dispersion exemplifies the monocentric form, as we described earlier. A hypothetical example is shown in Figure 1a. An area with low employment deconcentration but high spatial dispersion characterizes a polycentric urban form (Figure 1b). An area with high employment deconcentration and high spatial dispersion embodies scatteration (Figure 1d). Finally, an area with high employment deconcentration but low spatial dispersion would capture a form that has not been articulated in the literature (Figure 1c). How might the urban form relate to commuting patterns? We turn to this question next.

<<<Figure 1 about here>>>

Urban form and commuting patterns

During the past several decades, many researchers have explored the relationship between urban spatial structure and commuting patterns because of its potential policy implications regarding commuting distance and time. Some scholars have argued that a polycentric or dispersed urban form is more likely to reduce or stabilize commuting time and distance due to the co-location hypothesis of jobs and housing: that is, the dispersal of jobs in the region implies that it is at least theoretically possible for residents to live relatively close to jobs they work at (Crane and Chatman 2004; Gordon, Kumar, and Richardson 1989; Gordon, Richardson, and Jun 1991; Levinson 1998; Levinson and Kumar 1994; Sultana 2000; Sun, He, Zhang, and Wang 2016). Gordon et al. (Gordon, Richardson, and Jun 1991) examined the change of commute times between 1980 and 1985 in the 20 largest U.S. metropolitan areas and concluded that average commute times either fell or remained the same during the study period. Their explanation was that enough commuters were making location adjustments that involve a change in residence or a change in the workplace.

Levinson and Kumar (1994) also questioned why travel times have remained stable despite an increase in average commuting distance in the Washington metropolitan region during a 20-year period from 1968 and 1988. They posited the rational locator hypothesis that jobs and housing mutually co-locate to minimize travel costs. A subsequent study by Levinson (1998) argued that the decentralization of jobs maintains stability in commuting durations despite rising congestion and increasing travel distances in a case study of the Washington D.C. metropolitan region. Sultana (2000) also found that spatially dispersed employment centers led to a shorter commute time than a more centralized concentration of jobs in a case study of the Atlanta metropolitan area. Similarly, using data for 164 Chinese cities, Sun et al. (Sun, He, Zhang, and Wang 2016) found that average commute time was associated with city size and jobs-housing separation but negatively with density and polycentricity. They argued that compact, mixed-use, and polycentric spatial development may reduce commute time in Chinses cities.

In contrast, other scholars have suggested that a polycentric or dispersed metropolis might not reduce commute times or distances due to difficulties in matching jobs and housing and other determining factors of commuting patterns (Aguilera 2005; Cervero and Wu 1998; Ewing 1997; Giuliano and Small 1993; Kain 1968; Kain 1992; Schwanen, Dieleman, and Dijst 2001; Vandersmissen, Villeneuve, and Thériault 2003; Veneri 2010). Cervero and Wu (1998), for instance, examined the relationship between employment decentralization and commuting patterns in the San Francisco Bay Area from 1980 to 1990. They concluded that contrary to the co-location hypothesis, employment decentralization has not brought about a shorter commute time or distance. Furthermore, Vandersmissen et al. (Vandersmissen, Villeneuve, and Thériault 2003) found that the shift from a monocentric to a dispersed city form was responsible for increasing commuting time in a case study of the Quebec metropolitan area from 1977 and 1996. McGuckin and Srinivasan (2003) also reported that commute times and distance increased in most of the large metropolitan areas when analyzing journey-to-work trends in the major U.S.

metropolitan areas from 1960 and 2000. Regarding the relationship between urban spatial structure and commuting patterns, Giuliano and Small (1993) pointed out that urban spatial structure had only a minor effect on commuting and emphasized the importance of other determinant factors in location decisions beyond just commuting costs.

A few studies on European cities have presented similar conclusions on the relationships between urban spatial structure and commuting patterns (Aguilera 2005; Schwanen, Dieleman, and Dijst 2001; Wolday, Naess, and Tønnesen 2019). Based on their study of Netherlands metropolitan regions, Schwanen et al. (Schwanen, Dieleman, and Dijst 2001) argued that commute distances and times for auto drivers were longer in most polycentric regions. They concluded that metropolitan spatial structure would explain only a small portion of the variation in individuals' commuting patterns. Similarly, Aguilera and Mignot (2004) examined the change of commute distance in suburban subcenters (major suburban employment centers close to the city center) and outlying subcenters (smaller employment centers farther away) in French metropolitan areas. Their analysis results indicated that the outlying subcenters could not overcome the growing distance between home and work locations leading to lower jobs-housing proximity in a context of growing suburbanization. A subsequent study by Aguilera (2005) examined the co-location hypothesis using the three biggest French metropolitan areas from 1990 to 1999. She found that commuting distance increased in sub-centers due to the jobs-housing mismatch. In another recent case study of the Oslo metropolitan area in Norway, Wolday et al. (Wolday, Naess, and Tønnesen 2019) also pointed out that polycentric urban forms would have limited advantages as a strategy for sustainable mobility because workers in suburban workplaces were more likely to use automobiles and experience longer commute distances.

Employment decentralization and commuting patterns

Thus, the relationships between urban spatial structure and commuting patterns are controversial with mixed results across various studies in different case study areas using various measures of urban form (Li, Xiong, and Wang 2019; Ma and Banister 2007; Modarres 2011; Stead and Marshall 2001). While a few studies (Engelfriet and Koomen 2018; Ha, Lee, and Kwon 2021; Yao and Kim 2019) use multiple metropolitan areas to examine the relationship between urban form and commuting patterns, most previous studies focus on one metropolitan area. On the one hand, these case studies have the ability to generate analytical and theoretical insight (Flyvbjerg 2006; Yin 2009). Furthermore, if a number of case studies provide similar results, they have the ability to provide empirical generalization. On the other hand, to the extent that they provide more unique results, they will have limited ability to generalize their results, although meta-analysis or an alternative method could be used for generalization. In addition, the results can be different depending on the size of case study areas such as city, urbanized area, metropolitan area, or various sized metropolitan areas. Transportation mode choice and commuting patterns, in general, are more likely to be associated with metropolitan size. Schwanen et al. (Schwanen, Dieleman, and Dijst 2001) indicated that the commute time of an auto driver could rise with metropolitan size, whereas commute distance would depend on employment density and the growth of jobs in metropolitan regions. Similarly, Engelfriet and Koomen (2018) argued that city size would be one of the most important determinants of commuting patterns. We will explicitly explore this question in this study by comparing across different sized metropolitan areas.

Summary

To overcome the limitations of previous studies and avoid controversial issues of subjective measures of urban form, this study proposes using two measures capturing two subdimensions of employment decentralization—deconcentration and spatial dispersion—in assessing their relationship with commuting patterns. This approach allows us to avoid constructing business subcenters, involving a range of methodological challenges as discussed above. Furthermore, we compare across all metropolitan areas in the U.S. in 2000 and 2010 to assess how these measures of employment decentralization are related to average commute times and distances. We also assess how these decentralization measures are related to various commuting times and distances to assess whether they impact very short or very long commutes differently. We stratify our sample by size of metropolitan areas to assess whether our measures operate differently depending on the size of the metropolis, and its stage in the development process.

Data and Methods

Data

We combined data from several sources. First, our outcome measures come from the Census Transportation and Planning Packages (CTPP) data for 2000 and the 2006-10 5-year estimates (hereafter we refer to these as 2010). Many of our independent variables are constructed from the U.S. Census in 2000 and the American Community Survey (ACS) 2006-10 5-year estimates. Our key measures of employment decentralization in these 329 metropolitan statistical (MSA) areas, as defined by the U.S. Census, are constructed from the Reference USA Historical Business Data, providing data on the location of every business in the U.S. and the number of employees for each business establishment in 2000 and 2010 (Infogroup 2015).

Employment decentralization and commuting patterns

Dependent variables

Our dependent variables are constructed from the CTPP data for 2000 and 2010.[1] For the measures of commute time, we used data on those who commute by automobile, given that there are systematic differences in the time duration of commute (per distance) by commuting modes. The urban form measures such as employment deconcentration and spatial dispersion likely have significant impacts on those who commute by automobile. In addition, it should be noted that the primary transportation mode of U.S. commuters is automobile. The National Household Travel Survey 2017 indicated that transportation mode shares for private vehicle were 90.8% in 2001 and 89.4% in 2009 (U.S. Department of Transportation (DOT) 2017). Therefore, we focused on the number of workers within various time bins who commute by automobile. The data provide information on the number of workers commuting within various time bins: 0-4 minutes, 5-14 minutes, 15-19 minutes, 20-29 minutes, 30-44 minutes,45-59 minutes, 60-74 minutes, 75-89 minutes, 90 or more minutes. We computed the proportion of commuters that are within each of these bins. We compute *average commute time* by multiplying the proportion of commuters in each bin by the midpoint time (the top bin we multiplied by 120 minutes), and summing them. In other models, we used the proportion in each of these bins as the outcome measures.

We also estimated ancillary models predicting commute distances that parallel our models for commute times, but in these models we focus on commute distance for all commuters. For these models, we computed the distance of commutes based on the distance between centroids of census tracts for the CTPP data for all commuter flows.[2] We computed the

[1] The CTPP is a sample-based dataset, and therefore has some limitations in capturing the travel behavior of the entire population. For smaller units of analysis, this sample will introduce additional uncertainty. However, since we are aggregating our measures to MSAs, the sampling variability introduced is extremely small. Furthermore, alternative data sources such as the Longitudinal Employer-Household Dynamics (LEHD) do not provide information on commuting time, and therefore the CTPP is the optimal data source available to us.

[2] We calculated the geodesic distance between the centroid of the residential block and the employment block based on all commuters in the tract (regardless of commute mode).

average distance of commutes for residents in each census tract, and then computed the average across all tracts in the MSA. To capture various distances of commutes, we also computed the proportion of commuters in various distance bins: 0-3 kilometers (km.); 3-5 km., 5-10 km., 10-15 km., 15-20 km., 20-30 km., 30-40 km., 40-50 km., and 50 or more km.

Employment decentralization measures

As briefly noted above, we attempt to capture distinct aspects of employment decentralization by employing two measures recently introduced to the literature. More specifically, we follow the strategy of Hipp and colleagues (Hipp, Kim, and Forthun 2021). We created a grid of 1 sq. km. cells covering the entire conterminous U.S., based on a projection system for the large geographic extent, and excluded grid cells outside of any Urbanized Areas (UAs) based on the 1999 UA boundary definition. All businesses were geocoded to latitude/longitude points, aggregated to the appropriate grid cell, and we computed the total number of jobs in each grid cell in each MSA.[3] All variables were constructed based on the extent of the urbanized area in each MSA; nonetheless, for brevity we use the term MSA in the remainder of the manuscript. We then sorted the grid cells within each MSA by descending order of jobs, and determined the minimum percentage of grid cells within an MSA that contain 50% of the jobs for our measure of *employment deconcentration*. Likewise, we computed the minimum percentage of grid cells containing 60%, 70%, and 80% of the total jobs in each region. These employment deconcentration measures were created in 2000 and 2010, and log transformed to account for more extreme values. Higher values reflect greater deconcentration.

To create the *spatial dispersion* measure for each MSA, we computed the average distance between the grid cells containing the top 50% of jobs (what we term the "high

[3] The firm creating the Reference USA data (InfoUSA) goes to considerable effort to determine that workers are counted at the appropriate branch of the company, rather than aggregating them to the headquarters.

employment cells"), weighted by the number of jobs in each cell. Thus, we compute the pairwise distance between these high employment cells and then calculate the average of these pairwise distances weighted by the number of jobs in each of the cells (DHE). We define job counts y_i in a cell i = 1, … τ, in which τ is the number of high employment cells in a metropolitan area, and job counts y_i in another high employment cell j = 1, … τ, with $dist_{ij}$ capturing the distance between the two high employment cells:

(1) $$DHE = \sum_{i=1}^{\tau} \sum_{j=1}^{\tau} dist_{ij} \times (y_i \times y_j) \,/\, \sum_{i=1}^{\tau} \sum_{j=1}^{\tau} (y_i \times y_j)$$

Note that multiplying y_i and y_j together yields pairwise distance between every set of jobs in the high employment cells in the region. To account for the size of the MSA, we standardize this measure by computing the average distance (AD) between *every* grid cell in a region:

(2) $$AD = \sum_{i=1}^{I} \sum_{j=1}^{J} dist_{ij} \times \left(y_i \times y_j\right) / \sum_{i=1}^{I} \sum_{j=1}^{J} \left(y_i \times y_j\right)$$

here we are using all grid cells in a metropolitan area, and therefore i = 1, … I in a metropolitan area and j = 1, … J in a metropolitan area (I and J each represent the total grid cells in an MSA). The ratio of the average distance between the high employment cells and the average distance of all grid cells in a metropolitan area is our measure of spatial dispersion (SD):

(3) $$SD = DHE/AD$$

where DHE and DA come from equations 2 and 3, respectively. Larger values indicate greater spatial dispersion, whereas values smaller than 1 indicate more clustering compared to that expected by chance. Similar spatial dispersion measures were created based on 60%, 70%, and 80% of the total employment.

Independent variables

Employment decentralization and commuting patterns

Urban economic theories, pioneered by Alonso (1964), Mills (1967) and Muth (1969), suggest that population and income play an important role in determining urban size and thus commuting time (or distance). In reality, however, commuting patterns can also be influenced by many other factors. In this study, we constructed several measures for the MSAs that prior literature shows are important for explaining the length of commutes in a region, as done by Lee et al. (2009) and other studies. The goal of these measures is to account for the composition of households in a region when assessing the impact of the spatial pattern of jobs through our two measures of employment deconcentration. Given the likely importance of the general size of the MSA, we constructed a measure of *population*. Evidence suggests that greater density can reduce commute times in some circumstances, so we constructed a measure of *population density*, which divides the population by the land area. Socio-economic status (SES) has important consequences for commute patterns, as there is some evidence that such households have longer commutes—though a recent study found contradictory evidence (Kane, Hipp, and Kim 2017)–so we constructed a measure of *average household income* (Sun, He, Zhang, and Wang 2016; Wolday, Naess, and Tønnesen 2019). There is some evidence that businesses exit areas with more racial minorities (Wilson 1987), and therefore we construct measures of *percent Black* and *percent Latino* (McLafferty and Preston 2019; Sultana 2005). Prior research has suggested that the presence of multiple workers in a household can impact commute patterns as it may impact the optimal housing location to minimize commutes given more than one job location for the household, so we constructed a measure of the percent one-worker households, in which the denominator is all households with workers. Likewise, the presence of children can impact decisions on how far one is willing to commute, so we constructed a measure of the *percent children* in the MSA. We expect that in a tighter employment market (higher unemployment) workers will be more willing to commute longer distances (to avoid unemployment). We therefore constructed a measure of the *unemployment rate*. Finally, we accounted for the industrial composition of workers in the region by including measures of the *percent employees* in: 1) *manufacturing*; 2) *retail*; 3) *FIRE* (finance; insurance; real estate); 4) *health and education*; 5) *food* industries.[4]

Methods

We estimated a series of pooled regression models, following the approach of Lee et al. (Lee, Gordon, Richardson, and Moore 2009). Thus, we estimated models on the 2000 and 2010 data simultaneously. The models can be written as:

(1) $y_t = \beta_1 ED_t + \beta_2 SD_t + BX_t + \beta_3 YR + \varepsilon_t$

where y is the outcome measure (either average commute time, or the proportion in a particular commute time bin) at time point *t*, ED is our employment deconcentration measure at the same time point with effect β_1 on the outcome variable, SD is our spatial dispersion measure at the same time point with effect β_2 on the outcome variable (each log transformed), X is our set of remaining independent variables at time point *t* with their coefficients in vector B, YR is a dummy variable indicating 2010 with effect β_3 on the outcome variable, and ε_t is a random error with an assumed normal distribution.

We also tested whether these coefficients differed over the two time points by estimating a model that included interactions between the measures and the YR variable. This model showed a worse fit, based on the BIC values, indicating that there are few differences in these coefficients over the two time points. We tested quadratic versions of our two key variables, and

[4] A concern we had is that industrial composition may be, to some extent, endogenous with the spatial patterns of employment. Therefore we estimated models both with and without these measures of the industrial composition of employees, and the results were essentially the same.

they did not exhibit significant effects. We also tested for a possible interaction effect of these two key measures by creating a multiplicative interaction variable.

We estimated three sets of models. The first set of models are estimated on the entire sample of 329 MSAs for the outcome measure of average commute time, and we included separate models for each of our four employment deconcentration and spatial dispersion measures (based on the top 50, 60, 70, or 80% of jobs). The second set of models is similar to the first set, except that the sample is split into four population sizes of MSAs: 1) very small (less than 100,000 population); 2) small (between 100,000-500,000 population); 3) large (between 500,000-1 million population); 4) very large (greater than 1 million population).[5] The third set of analyses estimates models in which the outcome variables are the measures capturing the proportion of commuters in each of the nine time bins; these models are estimated separately on each of the four MSA size groups.[6] We also estimated parallel ancillary models using the commute distance measures as outcome variables. For each set of models, we also tested possible interaction effects between employment deconcentration and spatial dispersion, but these multiplicative variables were not statistically significant in the models predicting commute times, although they did show effects in the ancillary models predicting commute distance, as we describe later.

Results

Descriptive statistics

[5] We classified an MSA in the largest possible population bin. Therefore if a MSA was in the small bin in 2000 but grew to be placed in the large bin by 2010, we re-classified it to the large bin for the models.
[6] For these latter models there is no need to estimate them as seemingly unrelated regression (SUR) models, as the results in SUR would be the same as these results given that the variables are the same in each model.

Employment decentralization and commuting patterns

We begin by describing the summary statistics, presented in Table 1. We present the overall summary statistics for all MSAs in the first column (averaged across both time points), and then split by the four different population categories in the columns to the right. We see that average commute time increases with population size, from 20.3 minutes in very small MSAs, on average, to 23 minutes in small MSAs, 25 minutes in large MSAs, and to 28.1 minutes in very large MSAs. In the ancillary analyses we use average commute distance as the outcome measure, and we see that whereas commute distances are shorter in very small MSAs (about 21 km. on average), they are relatively similar across the other three sized MSA groupings (about 23-24 km. on average). The employment deconcentration measures generally increase with larger MSAs: in very small MSAs, 50% of jobs are concentrated in just 4.1% of grid cells, on average. This is also the case in small MSAs, whereas 4.7% of grid cells contain 50% of jobs in large MSAs and it requires 5.3% of grid cells in very large MSAs. For the measures based on larger proportions of jobs (60, 70, or 80%) we see a similar pattern of more deconcentration in larger MSAs.

The pattern is a little different for the spatial dispersion measures. In very small MSAs, the spatial distance between the grid cells with the top 50% of jobs are just 48.9% as far from each other as are the average grid cells in these MSAs, on average. There is more spatial dispersion in the small MSAs, as their grid cells are 55.5% as far from each other as average cells in the MSAs, and even more dispersed in large MSAs, which are 60.4% as far from each other as average cells. The twist is that there is actually somewhat less spatial dispersion in very large MSAs compared to large ones as their high job cells are 57.2% as far from each other as average cells in the MSA, on average. The pattern is similar when considering the measures capturing the spatial dispersion of larger proportions of jobs.

For the other independent variables, there are also some differences across various sized MSAs. The larger MSAs not only have larger population, but also greater population density, on average. There is a larger percentage of Black residents in very large MSAs, and a larger percentage of Latinos in large and very large MSAs. There tend to be more manufacturing, retail, and health/education employees in very small MSAs, but more FIRE employees in larger MSAs. Average household income rises with larger MSAs, whereas the other measures are generally similar across MSA size groups.

<<<Table 1 about here>>>

Average commute time models

We next turn to our first set of models, shown in Table 2. The first model just includes our control variables, and explains 63% of the variance in the average commute time. The results for the control variables are presented in Table A1 in the Appendix. Commute time tends to be longer in MSAs with more population, higher average income, more retail employees and higher unemployment rates. In contrast, average commute times are shorter in MSAs with more one-worker households, more FIRE employees, and more children. However, the racial composition and the population density of MSAs is not significantly related to commute times in the overall sample.

<<<Table 2 about here>>>

In model 2 we include our two measures of employment deconcentration and spatial dispersion among the top 50% of jobs, and we see that the model fit is improved. Although the amount of deconcentration of jobs among these top 50% is unrelated to average commute time, greater spatial dispersion of these job concentrations is associated with longer commute times. A one standard deviation increase in spatial dispersion is associated with 0.44 minutes longer commutes (a .12 standard deviation increase in commute time). As we look at the level of deconcentration of the top 60, 70, or 80% of jobs we see that the effects of spatial dispersion are even stronger. A one standard deviation increase in spatial dispersion among the top 80% of jobs is associated with a .15 standard deviation increase in commute time. We also see that employment deconcentration for a larger percentage of jobs (80%) is associated with shorter commutes: a one standard deviation increase in deconcentration is associated with .11 standard deviations shorter commutes.

Although these initial results are informative, in our next set of models we assess whether these measures operate differently in big versus small MSAs by splitting the sample based on population size. The results are shown in Table 3, and we only present the coefficients for our two key measures of interest (the full regression results are presented in Table A1 in the Appendix for the variables based on the top 50% of jobs). The first panel of the table shows the four models when viewing the employment deconcentration of the top 50% of jobs. What is particularly notable is how our measures operate differently for small versus large MSAs. In model 1 for very small MSAs, higher employment deconcentration is associated with *longer* commutes (b=58.7), which is opposite of large and very large MSAs, in which deconcentration is associated with shorter commutes (models 3 and 4 for large and very large MSAs, respectively) (b= -108.4 and b= -27.9). The pattern remains similar when measuring concentration of larger numbers of jobs, although the positive deconcentration effect in very small MSAs weakens and the negative effect in larger MSAs also weakens. Thus, it appears that it is the deconcentration of the top 50% of jobs that is particularly important for explaining commute times in small and large MSAs.

<<<Table 3 about here>>>

Employment decentralization and commuting patterns

We also see in Table 3 that the amount of spatial dispersion has particularly strong effects on commute times in very large MSAs. A one standard deviation increase in spatial dispersion among the top 50% of jobs is associated with a .31 standard deviation increase in commute times in very large MSAs, which is a large effect. The effect is only somewhat weaker when considering the spatial dispersion of larger percentages of jobs. We also see that the spatial dispersion of jobs in small MSAs is also associated with longer commutes. This effect is strongest when considering the spatial dispersion of the top 80% of jobs, as a one standard deviation increase is associated with .16 standard deviations longer commute times.

Putting these together, in the cases of large and very large MSAs, the two distinct dimensions of employment decentralization show countervailing effects. While employment deconcentration appears to contribute to reducing the average commute time, a higher degree of spatial dispersion is associated with commute time increase. In other words, the commuting implications of decentralization may highly depend on how decentralization takes place in the region, and the two measures used in this study highlight this important point.

Predicting various commute durations

While average commute times are informative, they can obscure differences among particularly short or long commutes. Therefore, in our next set of models our outcome measures are the proportion of workers within various duration bins. We present the results visually by showing the t-values for the coefficients for our two measures of interest in Figures 1-4 to easily see statistical significance. Figure 2 shows the results based on the top 50% of jobs. The first panel of this figure (Figure 2a) shows the results using our measures for the very small MSAs, and each pair of bars show the t-values of the coefficients for a particular model. The first two bars are for the model in which the outcome variable is the percent of workers with commutes of less than five minutes, the next two are for the model with the percent of workers with commutes of 5-14 minutes, etc. The left-most red bar shows that very small MSAs with greater employment deconcentration have more workers with very short commutes (less than 5 minutes), and given that this is greater than 1.96, this is a statistically significant result. The other red bars in this panel show that these very small MSAs with more deconcentration have fewer commuters in the 15-19 minute range, but more commuters in the 30-44, 45-59, 60-74, and 75-89 minute ranges (as these bars are all greater than |1.96|). Thus, it is interesting to note that higher deconcentration leads to longer duration commutes in these very small MSAs, but also more very short duration commutes. In this panel, there are fewer very long commutes in very small MSAs with more spatial dispersion (the blue bars), as there are fewer commutes in the 45-59, 60-74, and 75-89 minute ranges. The pattern was the same when viewing the employment deconcentration of the top 60, 70 or 80% of jobs.

<<<Figure 2 about here>>>

In Figure 2b we show the model results for small MSAs. Notably, the results are quite different from the very small MSAs. In these MSAs, spatial dispersion has a much stronger impact on commuting than does employment deconcentration. Small MSAs with more spatial dispersion experience fewer mid-range commutes (15-29 minutes), but more very short duration commutes (0-4 minutes). And this pattern holds no matter what percentage of jobs is considered (50-80%). The effects are much weaker for employment deconcentration, and we only found that more deconcentration results in more short-duration commutes (less than 5 minutes).

Figure 2c shows the results for large MSAs, and these results are different yet. Large MSAs with more deconcentration have more short- and moderate-duration commutes (less than 30 minutes). However, large MSAs with more deconcentration have fewer of the longer duration commutes (30 or more minutes). The pattern is quite different for these longer commutes for large MSAs with more spatial dispersion, as they have *fewer* 20-29 minute commutes.

Finally, Figure 2d shows the results for very large MSAs, and the pattern is similar to that for the large MSAs, though with stronger effects. We see that very large MSAs with more deconcentration have more mid-range duration commutes (20-44 minutes), but fewer very long commutes (greater than 60 minutes). In contrast, very large MSAs with more spatial dispersion have more of the very long duration commutes (greater than 60 minutes), but fewer mid-range commutes (20-44 minutes).

Ancillary models predicting commute distances

While our primary interest is in explaining commute times given the potential for congestion as metropolitan regions grow, we also assessed the robustness of our measures for explaining commute distances in parallel ancillary models. The general pattern of the results was similar to those predicting commute times.[7] As shown in Table 4, MSAs with more employment deconcentration experience longer commute distances, on average, in very small MSAs but shorter commute distances in very large MSAs. The pattern was similar whether we measured the top 50%, 60%, 70% or 80% of employees, with the only difference being somewhat stronger effects in small MSAs when measuring deconcentration based on the top

[7] One interesting difference is that there was a strong interaction effect between our measures of deconcentration and spatial dispersion when predicting average commute distance; this effect was nonsignificant in the models predicting commute times. Plotting these interactions showed that in very small MSAs deconcentration has a strong positive effect in MSAs with low spatial dispersion. Thus, the longest commute distances in very small MSAs occur in those with high deconcentration and low spatial dispersion, and the shortest commute distances occur in those with low deconcentration and low spatial dispersion. For small MSAs, deconcentration has a negative relationship with commute distances when there is high spatial dispersion, but a positive relationship when there is low spatial dispersion. The pattern is reversed in large and very large MSAs, as the combination of higher deconcentration and high spatial dispersion results in longer commutes, whereas higher deconcentration combined with low spatial dispersion actually results in shorter distance commutes.

80% of employees. There was some evidence of longer commute distances, on average, in very large MSAs with more employment deconcentration among the top 80% of employees.

<<<Table 4 about here>>>

When we split commutes by distance bins, we found results generally similar to those for commute times. As seen in Figure 3a, very small MSAs with more deconcentration (based on the top 50% of jobs) have more long-distance commutes (the red bars on the right side of this figure) and fewer very short commutes (less than 3km.). In small MSAs (Figure 6b), those with more spatial dispersion have fewer short distance commutes (the blue bars on the left side) and more long distance commutes (right side). Spatial dispersion operates similarly for commute distances in the larger MSAs, especially very large MSAs (Figures 3c and 3d). Furthermore, large and very large MSAs with more deconcentration have more short distance commutes and fewer long distance commutes. The main difference in these plots in Figure 3 for commute distances compared to the earlier ones for commute times occurs for very short commutes: whereas we earlier saw that very small MSAs with more deconcentration have more very short duration commutes (0-4 minutes), here we see that these MSAs do not have more very short *distance* commutes, but in fact have *fewer* short distance commutes. For small MSAs, whereas those with more spatial dispersion had more very short duration commutes, we see here that the generally do not have more short *distance* commutes.

<<<Figure 3 about here>>>

Conclusion

This study explored how two dimensions of employment decentralization—business deconcentration and business spatial dispersion—are related to commute times across all 329 metropolitan areas in the U.S. Our results not only showed that these two measures of the urban form are related to commute times and distances, but the relationships vary depending on how large the metropolitan region is. Therefore, presuming that a particular form is optimal—such as monocentric, polycentric, etc.—does not appear reasonable. Instead, it appears that the relationship between the urban form and commute times and distances differs based on the size of a metropolitan region. We have followed others in suggesting that this likely occurs because of two competing processes—the desire of businesses to cluster together for agglomeration purposes, and the fact that too much business clustering will lead to congestion and therefore longer commutes, which is undesirable for workers. One consequence is that we found countervailing effects of deconcentration and spatial dispersion on commuting patterns in large metropolitan areas. We next discuss our key findings.

A particularly important finding is that the effect of the form of decentralization on commuting patterns differs greatly over metropolitan areas of different sizes (and stage of development). As a consequence, our models estimated on the complete set of MSAs provide an incomplete picture. In these models, greater amounts of spatial dispersion were associated with longer commute times, on average. And this pattern was even stronger when we computed the amount of spatial dispersion based on the top 80% concentration of jobs, rather than just the top 50% concentration. Thus, it is not just the most concentrated businesses that matter for this pattern, but in fact it appears to be a much broader effect given that it is even stronger when measuring the spatial dispersion of such a high proportion of jobs. Similarly, the longest commutes based on distance occurred in MSAs with *simultaneously* high deconcentration and high spatial dispersion, which may reflect the inability of a large number of workers to follow jobs in a highly dispersed setting, particularly if they have specific skills. Nonetheless, there were important differences across smaller and larger metropolitan areas.

In smaller metropolitan areas, it appeared that a more advantageous urban form for shorter commutes was something closer to a monocentric form. In very small MSAs, commute times were shortest when there was high concentration of jobs. In small MSAs it was the small spatial distance between jobs that was more advantageous for shorter commute times. These very small and small MSAs had shorter commute durations because they reduced the proportion of very long commutes, and increased the proportion of moderate commutes. Likewise, the shortest distance commutes in very small MSAs occurred in those with low deconcentration and low spatial dispersion—again, a classic monocentric form. However, interestingly, these more advantageous MSAs had fewer very short duration commutes. One possibility is that there are a higher percentage of commuters who walk or use a bicycle in these smaller MSAs, and therefore these shorter distance commutes do not translate into shorter duration. This is speculative, as we did not have the ability to disentangle this in our data, but should be a focus of future research. For very small MSAs, this may occur if these business concentrations are large enough that they do not allow for nearby housing, thus reducing the proportion of these very short commutes (less than 5 minutes). For small MSAs, the lack of spatial dispersion may also limit the ability of residents to live very close to work, which would otherwise allow for these very short duration commutes. Nonetheless, these more concentrated forms are most beneficial for commuting in very small MSAs, on average.

The pattern was opposite for larger metropolitan areas, as the most advantageous urban form for shorter duration commutes occurred with more business *deconcentration*. And the shortest *distance* commutes in these larger MSAs occurred when deconcentration was paired with low spatial dispersion: a form of scatteration, but closer in towards the center of the MSA. In large MSAs, this deconcentration resulted in many shorter commutes and fewer mid-range commutes, whereas in very large MSAs it resulted in many mid-range commutes and fewer very long commutes. Thus, the geographic scale of very large MSAs may make it impractical to optimize commutes by enhancing the number of very short commutes. This may be because the large number of specialized jobs makes it difficult for people with the "right skills" to live nearest to particular jobs. Instead, it appears that lowering the number of very long commutes is a better route to reducing average commute times in very large metro areas. This pattern was reinforced by the fact that the most advantageous urban form for very large MSAs not only contained business deconcentration, but simultaneously contained *low* spatial dispersion. This form led to many mid-range commutes and few very long commutes,. It may be that whereas in a very large metro area greater spatial dispersion is needed to achieve a higher proportion of very short duration commutes (less than 5 minutes) by automobile commuters—nonetheless, a better overall result appears to occur when very long commutes are minimized.

We acknowledge some limitations of this study. First, we aggregated all jobs, and did not distinguish by specific sector or industry. We adopted this strategy as an initial exploration of the impact of business decentralization, but future research will want to make these distinctions. Second, while we focused on the consequences of business concentration for commuting patterns, we did not also consider population or housing distribution patterns. Again, this will need to be a focus of future research. Third, we limited our analyses of commute times to one mode of transportation (those who drove alone). Although this was necessary to compare commute times in a consistent manner, future research will want to also assess the extent to which the urban form impacts durations of non-auto commuters. To partially address this limitation, we estimated ancillary models focused on the distance of commutes, and found similar results for our measures of deconcentration and spatial dispersion. Fourth, we had data from 10 and 20 years ago, so we cannot say that these patterns still hold currently. Given that the coefficients were effectively the same in both 2000 and 2006-10, we think it unlikely that the coefficients would be sharply different in more recent years, but this will need to be assessed in future work.

This study has demonstrated the utility of measuring the urban form by using measures of two dimensions of business decentralization: business deconcentration and spatial dispersion. Using these two measures sidesteps the thorny challenge of defining subcenters across metropolitan areas of widely varying sizes. We have shown that these two measures have strong relationships with commuting times and distances across these MSAs, and that the patterns differ sharply based on the size of the MSA and its stage of development. The results demonstrated that whereas business deconcentration is associated with longer commute times and distances in very small MSAs, the pattern is opposite in large and very large MSAs. Furthermore, a lack of spatial dispersion of jobs is beneficial in some environments for reducing commute times and distances. These results are enlightening, and highlight the importance of considering the spatial scale of urban areas when assessing the most advantageous urban form for reducing commuting.

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Tables and Figures

Table 1. Summary statistics for variables used in analyses. Total sample, and by population size

	Total		Very small		Small		Large		Very large	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Average commute time (minutes)	23.72	3.80	20.33	2.69	23.02	3.30	24.98	2.55	28.15	2.83
Average commute distance (km.)	23.57	7.77	20.95	4.01	24.05	9.03	23.01	6.82	24.39	4.75
Job deconcentration top 50%	4.4%	1.6%	4.1%	1.3%	4.1%	1.3%	4.7%	1.8%	5.3%	2.1%
Job deconcentration top 60%	6.7%	2.1%	6.4%	1.7%	6.4%	1.8%	7.2%	2.3%	8.1%	2.7%
Job deconcentration top 70%	10.1%	2.8%	9.7%	2.2%	9.6%	2.3%	10.8%	3.1%	12.0%	3.5%
Job deconcentration top 80%	15.2%	3.6%	14.6%	2.9%	14.5%	3.1%	16.0%	4.1%	17.7%	4.4%
Spatial dispersion top 50%	55.5%	19.1%	48.9%	22.9%	55.5%	19.9%	60.4%	15.0%	57.2%	12.7%
Spatial dispersion top 60%	58.8%	17.4%	52.1%	20.8%	59.0%	18.1%	63.3%	14.0%	60.4%	11.7%
Spatial dispersion top 70%	61.9%	16.0%	54.8%	18.2%	62.4%	16.7%	65.5%	13.2%	63.5%	10.9%
Spatial dispersion top 80%	65.1%	14.9%	57.5%	15.1%	65.6%	15.8%	68.6%	12.6%	66.5%	9.8%
Population (logged)	12.68	1.07	11.33	0.17	12.31	0.48	13.48	0.24	14.56	0.55
Population density	3.12	3.89	1.73	0.63	2.39	1.21	3.82	4.78	6.43	7.62
Percent Black	11.50	11.50	11.14	14.17	10.66	11.58	11.96	9.08	14.59	9.92
Percent Latino	11.88	15.27	5.65	8.89	11.13	14.71	16.18	20.98	16.56	14.18
Average household income	59.89	14.32	52.17	7.96	58.36	13.92	60.44	10.74	71.54	15.59
Percent 1-worker households	44.89	10.33	44.84	10.64	44.98	10.47	45.41	9.86	44.22	9.96
Percent with children	46.90	4.73	45.97	4.02	46.64	5.18	47.53	4.42	48.13	3.27
Unemployment rate	7.87	2.81	7.61	2.69	7.88	2.88	8.07	2.78	7.86	2.68
Percent manufacturing employees	10.10	5.79	11.45	6.93	9.90	6.11	10.26	4.42	9.61	4.11
Percent retail employees	13.46	2.04	14.30	2.39	13.55	2.15	12.75	1.33	12.96	1.37
Percent FIRE employees	13.97	4.06	11.85	2.90	13.17	3.88	14.83	3.03	18.04	3.34
Percent Health/education employees	24.72	5.53	26.55	4.93	25.11	6.03	24.84	4.54	21.66	3.20
Percent food industry employees	10.28	3.31	9.72	1.80	10.53	3.77	9.50	1.48	10.40	3.37

Subsamples by population size: very small: < 100,000. Small: 100,000 - 500,000. Large: 500,000 - 1 million. Very large: > 1 million

Table 2. Predicting average commute times in minutes of those traveling alone by automobile, using job deconcentration and spatial dispersion measures based different job thresholds

	(1)		(2)		(3)		(4)		(5)	
Job deconcentration top 50%			-3.737							
			-(0.52)							
Job deconcentration top 60%					-8.201					
					-(1.49)					
Job deconcentration top 70%							-10.202	*		
							-(2.35)			
Job deconcentration top 80%									-11.939	**
									-(3.46)	
Spatial dispersion top 50%			2.311	**						
			(2.72)							
Spatial dispersion top 60%					2.470	*				
					(2.56)					
Spatial dispersion top 70%							2.474	*		
							(2.36)			
Spatial dispersion top 80%									3.704	**
									(3.23)	
R square	0.635		0.639		0.639		0.640		0.646	

*Note: ** p < .01; * p < .05; † p < .10. Unstandardized coefficients. T-values in parentheses. N = 658 SMSA time points. All models include all control variables.*

Table 3. Predicting average commute times in minutes of those traveling alone by automobile, using job deconcentration and spatial dispersion measures based on various job thresholds for different MSA population sizes

	Very small		Small		Large		Very large	
	(1)		(2)		(3)		(4)	
Job deconcentration top 50%	58.731	**	11.753		-108.417	**	-27.907	**
	(3.24)		(0.93)		-(4.32)		-(2.70)	
Spatial dispersion top 50%	-2.533	†	1.672		-0.777		6.972	*
	-(1.83)		(1.38)		-(0.30)		(2.52)	
	(5)		(6)		(7)		(8)	
Job deconcentration top 60%	41.219	**	-1.645		-78.357	**	-19.775	*
	(2.96)		-(0.17)		-(4.28)		-(2.50)	
Spatial dispersion top 60%	-3.327	*	2.361	†	-1.811		5.765	†
	-(2.11)		(1.73)		-(0.59)		(1.95)	
	(9)		(10)		(11)		(12)	
Job deconcentration top 70%	34.237	**	-9.119		-59.690	**	-15.382	*
	(3.03)		-(1.22)		-(4.29)		-(2.45)	
Spatial dispersion top 70%	-4.189	*	2.482	†	-2.057		5.453	†
	-(2.20)		(1.69)		-(0.62)		(1.73)	
	(13)		(14)		(15)		(16)	
Job deconcentration top 80%	22.940	*	-14.728	*	-44.417	**	-12.473	*
	(2.45)		-(2.55)		-(4.06)		-(2.44)	
Spatial dispersion top 80%	-1.568		3.300	*	-1.498		5.476	
	-(0.63)		(2.08)		-(0.42)		(1.60)	
N	86		388		80		104	

*Note: ** p < .01; * p < .05; † p < .10. Unstandardized coefficients. T-values in parentheses.*

Table 4. Predicting average commute distance for all commuters, using employment deconcentration and spatial dispersion measures based on 50% employment thresholds for different MSA population sizes

	Very small		Small		Large		Very large	
	(1)		(2)		(3)		(4)	
Employment deconcentration top 50%	0.959	*	-0.014		-0.592		-0.619	**
	(2.47)		-(0.04)		-(1.00)		-(2.72)	
Spatial dispersion top 50%	0.011		0.033		0.117	†	0.073	
	(0.37)		(1.08)		(1.91)		(1.37)	
	(5)		(6)		(7)		(8)	
Employment deconcentration top 60%	0.857	**	-0.223		-0.575		-0.569	**
	(2.88)		-(0.87)		-(1.32)		-(3.35)	
Spatial dispersion top 60%	-0.011		-0.001		0.134	*	0.111	*
	-(0.34)		-(0.03)		(1.98)		(2.00)	
	(9)		(10)		(11)		(12)	
Employment deconcentration top 70%	0.606	*	-0.353	†	-0.519		-0.498	**
	(2.50)		-(1.78)		-(1.58)		-(3.75)	
Spatial dispersion top 70%	0.013		-0.005		0.134	†	0.134	*
	(0.33)		-(0.14)		(1.84)		(2.31)	
	(13)		(14)		(15)		(16)	
Employment deconcentration top 80%	0.498	**	-0.408	**	-0.431	†	-0.425	**
	(2.64)		-(2.64)		-(1.69)		-(4.01)	
Spatial dispersion top 80%	0.032		-0.002		0.109		0.157	*
	(0.65)		-(0.05)		(1.37)		(2.48)	
N	86		388		80		104	

*Note: ** p < .01; * p < .05; † p < .10. Unstandardized coefficients. T-values in parentheses.*

Figures

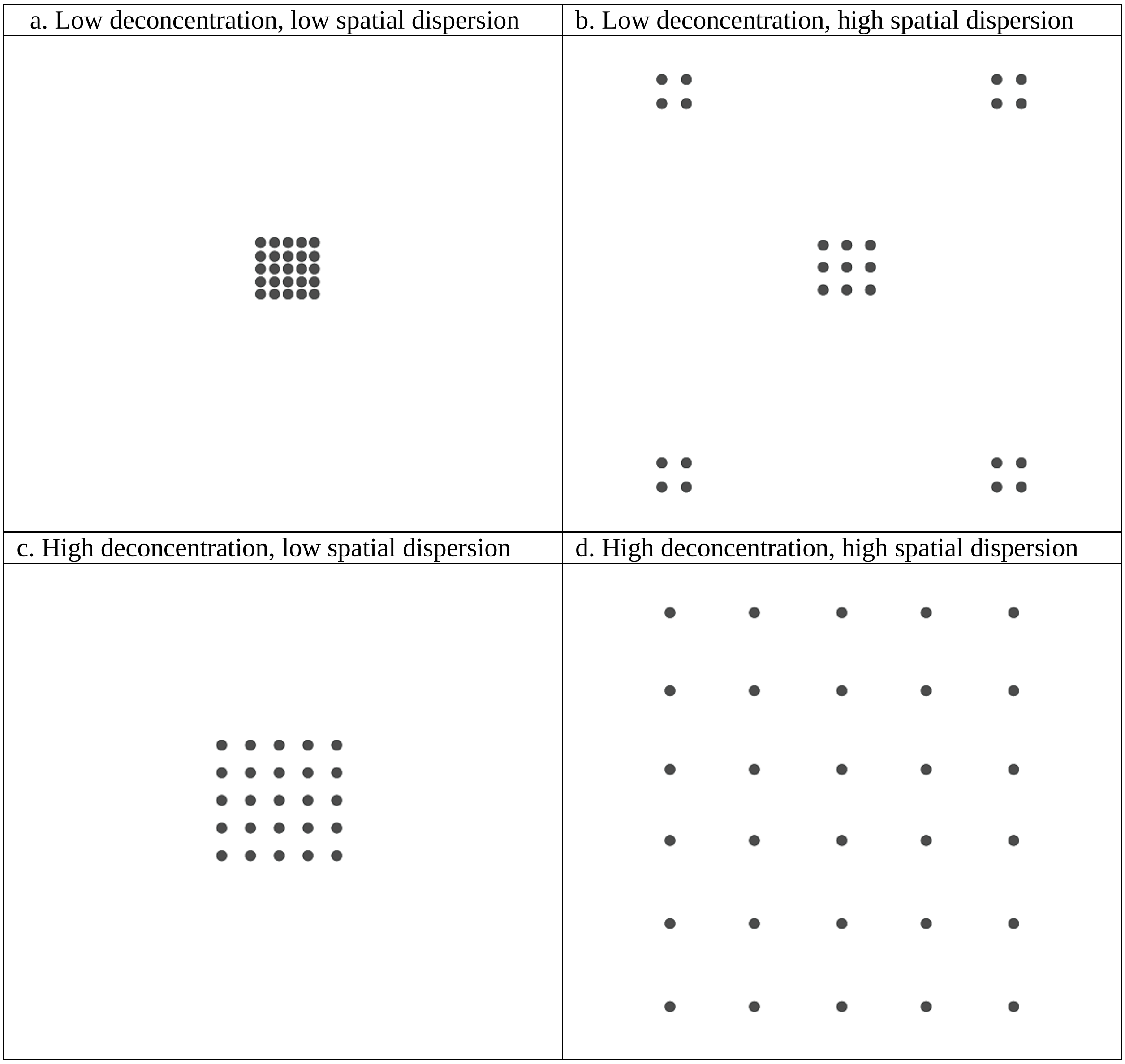

Figure 1. Four hypothetical regions demonstrating high/low deconcentration and spatial dispersion

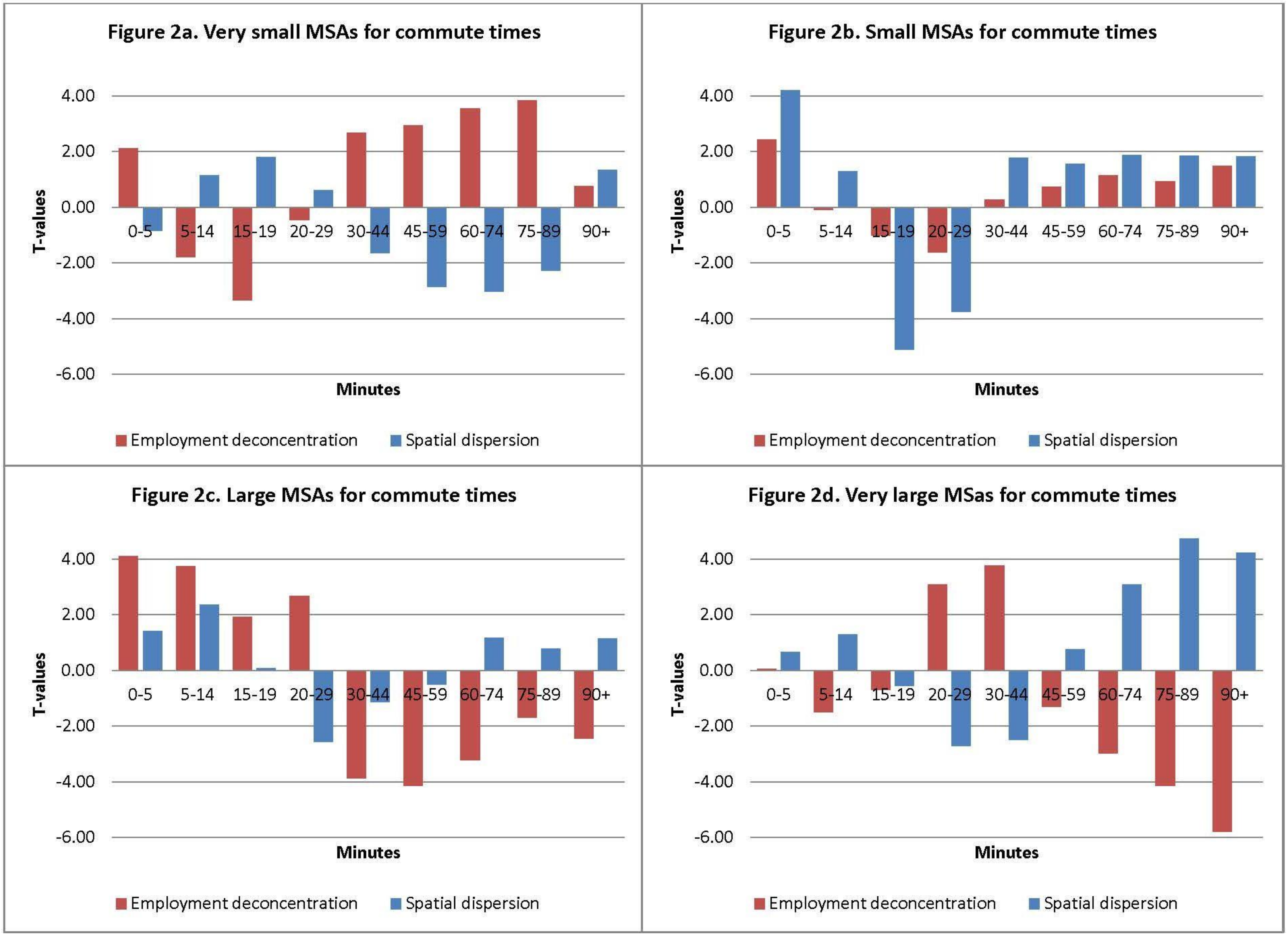

Figure 2. Results based on top 50% of employees

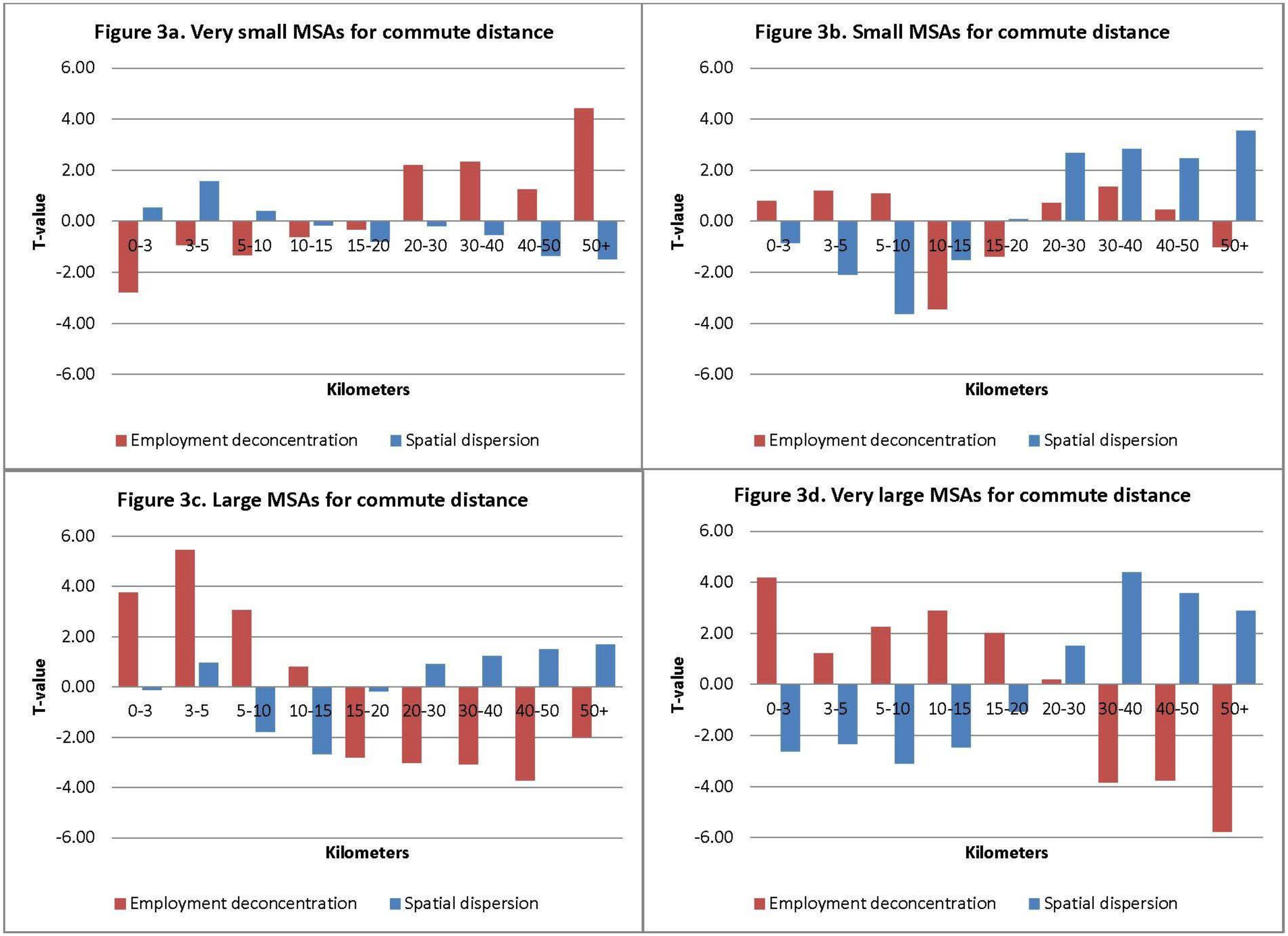

Figure 3. Predicting commute distance bins based on deconcentration and spatial dispersion of top 50% of jobs

Table A1. Predicting average commute times of those traveling alone by automobile, using job deconcentration and spatial dispersion measures based on 50% job thresholds for different MSA population sizes

	Very small		Small		Large		Very large		Total sample	
Job deconcentration top 50%	60.601	**	11.355		-102.402	**	-27.731	**	-3.737	
	(3.14)		(0.90)		-(3.97)		-(2.70)		-(0.52)	
Spatial dispersion top 50%	-2.703	†	1.604		-1.267		6.835	*	2.311	**
	-(1.84)		(1.32)		-(0.47)		(2.49)		(2.72)	
Population	1.261		2.083	**	-1.678	†	2.432	**	1.761	**
	(0.98)		(6.66)		-(1.88)		(7.80)		(14.97)	
Population density	-1.149	*	-0.292	†	0.524	**	0.031		0.092	**
	-(2.45)		-(1.87)		(5.82)		(1.05)		(3.20)	
Percent Black	0.016		0.012		0.071	**	0.075	**	0.037	**
	(0.70)		(0.77)		(2.59)		(3.86)		(3.40)	
Percent Latino	0.038		-0.007		0.010		0.069	**	0.011	
	(1.53)		-(0.58)		(0.59)		(4.57)		(1.30)	
Average household income	0.177	**	0.140	**	0.203	**	0.143	**	0.135	**
	(3.27)		(10.77)		(6.24)		(8.37)		(13.66)	
Percent 1-worker families	0.157	*	-0.059		0.170		0.107		0.005	
	(2.24)		-(1.19)		(1.45)		(1.42)		(0.14)	
Percent with children	-0.287	**	-0.055		-0.010		-0.112	†	-0.106	**
	-(4.10)		-(1.54)		-(0.12)		-(1.65)		-(3.81)	
Unemployment rate	0.466	**	0.389	**	0.152		0.205		0.326	**
	(2.90)		(5.43)		(1.01)		(1.63)		(5.91)	
Year=2010	-7.525	**	-1.691	†	-5.590	**	-5.726	**	-2.841	**
	-(4.42)		-(1.89)		-(2.79)		-(3.93)		-(4.18)	
Percent manufacturing employees	0.097	*	-0.071	*	0.049		-0.139	†	-0.040	
	(2.03)		-(2.13)		(0.62)		-(1.92)		-(1.64)	
Percent retail employees	0.135		0.116	†	0.167		0.508	**	0.199	**
	(1.42)		(1.66)		(0.84)		(3.05)		(3.90)	
Percent FIRE employees	0.118		-0.231	**	-0.029		-0.063		-0.178	**
	(1.28)		-(4.94)		-(0.25)		-(0.61)		-(4.91)	
Percent Health/education employees	0.095	†	-0.036		0.028		0.055		-0.019	
	(1.91)		-(1.24)		(0.40)		(0.65)		-(0.81)	
Percent food industry employees	-0.134		-0.046		0.885	**	-0.027		-0.041	
	-(0.97)		-(1.07)		(4.26)		-(0.29)		-(1.20)	
Intercept	-2.278		-4.674		20.594		-24.657	**	-3.689	
	-(0.15)		-(0.92)		(1.42)		-(2.58)		-(1.20)	
R square	0.685		0.455		0.690		0.800		0.639	
N	86		388		80		104		658	

*Note: ** p < .01; * p < .05; † p < .10. Unstandardized coefficients. T-values in parentheses.*