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Revisiting the Relationship between Urban Form and Excess Commuting in US Metropolitan Areas

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Abstract

This article revisits the relationship between urban form and excess commuting by analyzing 206 metropolitan statistical areas in the United States. Using the most recent Census Transportation Planning Products, we revalidated the importance of using multidimensional indices when examining excess commuting across metropolitan areas. We found that higher levels of polycentricity aggravate cross-commuting, while higher central city dominance improves excess commuting. In addition, our results indicate the significant impact of sprawl or jobs–housing dispersal on excess commuting. These findings shed light on the multidimensional relationship between urban form and excess commuting.

Keywords

excess commuting, urban form, US metropolitan areas, Brotchie's triangle model

Introduction

The relationship between urban form and commuting efficiency has been extensively researched by urban and geography scholars during recent decades (Ma and Banister 2007; Ewing and Cervero 2010; Chowdhury, Scott, and Kanaroglou 2013; Lin, Allan, and Cui 2015). A reason for this attention was to reduce commuting costs for individuals by understanding the role of urban forms in commuting. Although the remarkable study of Cervero and Kockelman (1997) showed that local-scale urban form factors (including density, diversity, and design) affect commuting, the impact of urban form on commuting efficiency is still unclear on a regional scale. This issue is further complicated by the variety of study areas, approach methods, and discrepancies in sociodemographic attributes (Crane 2000; Ma and Banister 2007; Horner, Schleith, and Widener 2015).

Previous studies have dealt with urban form in terms of sprawl, polycentricity, and dispersion of urban areas (Green 2007; Chowdhury, Scott, and Kanaroglou 2013; Lopez 2014; Hamidi et al. 2015). Previous research results showed that urban sprawl may lead to both increases and decreases in commuting costs (Sultana and Weber 2007; García-Palomares 2010; Zhao, Lü, and Gert de Roo 2010; Gainza and Livert 2013). In addition, Ma and Banister (2007) argued that there could be a huge gap in commuting distance between cities with an equal degree of polycentricity, further emphasizing that commuting patterns cannot be determined by urban form alone. In this regard, O'Kelly and Lee (2005) noted that sociodemographic factors can play significant roles in commuting patterns, while O'Kelly and Mikelbank (2002) reported that housing price influences housing location choice, leading to commuting changes. However, it is still clear that we should gain a better understanding of the relationship between urban form and commuting.

One of the most common measurement for commuting efficiency, that is, excess commuting ratio, was introduced by Hamilton (1982) and has been applied in numerous studies (White 1988; Small and Song 1992; Horner 2002; Yang 2005). Several studies have focused on commuting efficiency based on this index, and researchers have provided extensions of the index (Kanaroglou, Higgins, and Chowdhury 2015). For example, Horner (2002) proposed an index that considers both the maximum and minimum commute, while Yang and Ferreira (2008) suggested a proportionally matched commute index. The reason for the development of such extensions to the original index is that the single one has limitations when examining commuting efficiency according to time and space (Kanaroglou, Higgins, and Chowdhury 2015).

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Despite the development of various indicators and indices for understanding excess commuting, there has been a lack of studies that apply those indicators and indices for examining the relationship between urban form and excess commuting. In addition, as excess commuting indices vary with respect to the modifiable areal unit problem (MAUP) or computation approach, it is necessary to analyze the impact of urban form on excess commuting while keeping important methodological issues in mind. Moreover, from a planning perspective, a systematic analysis of the association between urban form and commuting efficiency will lead to more confident decisions by policy makers.

Thus, we examined the following research questions in this study by applying multidimensional commuting and excess commuting indicators. First, how is urban form related to commuting indicators? A previous study reported that the minimum commute decreases as the urban form decentralizes (Ma and Banister 2007); however, it is unclear which aspects of urban form are significantly associated with commuting. Besides, it is unclear which aspects of urban form are associated with the actual commute. Theoretically, urban form changes toward compactness, polycentricity, and dispersal will all lead to a decrease in actual commute.

Second, how is urban form associated with various excess commuting indices? As reported in previous studies, the use of the original excess commuting index alone may lead to poor analysis of commuting efficiency (Yang 2008; Chowdhury, Scott, and Kanaroglou 2013). Thus, we also considered the absolute excess commuting distance and the commuting potential utilized ratio along with the original excess commuting ratio index.

Lastly, how does urban form relate to commuting indicators and result in discrepancies in excess commuting indices? We address this question by applying Brotchie's (1984) triangle model, which provides a framework for analyzing urban spatial structure and commuting and has been implemented in several studies (Ma and Banister 2007; Chowdhury, Scott, and Kanaroglou 2013). Using this question, we addressed how urban form affects excess commuting levels, focusing on the relationship between urban form and commuting indicators.

To answer the questions formulated above, we analyzed the relationship between urban form and excess commuting based on 206 metropolitan statistical areas (MSA) of the United States. Particularly, our objectives in this paper are to (1) understand how urban form is associated with commuting indicators and excess commuting indices and (2) describe how urban form affects the degree of excess commuting regarding its influence on commuting indicators. We used the 2006–2010 Census Transportation Planning Products (CTPP) to compute commuting and excess commuting indicators while applying a linear programming method to examine the relationship between urban form and commuting.

The remainder of the article is as follows. First, we review previous studies on extensions to excess commuting measures and the relationship between urban form and excess commuting. Second, we introduce our data source and analytical framework for this study. Third, we discuss the relationship between urban form and commuting indicators and excess commuting indices in the fourth section by applying regression models and Brotchie's triangle model. Finally, we highlight our main findings for policy implications and suggest further work in the fifth section.

Literature Review

Concepts and Measures for Excess Commuting

The concept of excess commuting was proposed by Hamilton (1982) as the difference between the actual commute and the theoretical minimum commute under the monocentric model assumption. To achieve a more realistic measure, White (1988) adopted the linear programming method for calculating the theoretical minimum commute. Using this linear programming approach, the minimum commute is calculated while the number of jobs and workers in each spatial unit are constrained. The excess commuting concept developed by Hamilton (1982) and White (1988) has been widely adopted for understanding commuting efficiency, the transport–land use connection, and its association with urban form (Horner 2002; Ma and Banister 2007; Hu and Wang 2015; Jun et al. 2016).

Previous works provided extensions of the original index to overcome its limitations. Horner (2002) suggested a new approach based on the theoretical maximum commute, which determined the upper bound of the commute possible according to the urban form. Horner focused on the percentage of commuting potential utilized, where the difference between the theoretical minimum and the observed commute is the potential used, and the commuting potential is the gap between the theoretical minimum and maximum commute. Using this index, Horner intended to understand the degree to which commuting flow approaches its upper limits. The practicality of this concept was examined in several studies (Ma and Banister 2006; Horner and Schleith 2012). However, Chowdhury, Scott, and Kanaroglou (2013) argued that using the commuting potential utilized ratio alone could result in an incomplete understanding of commuting efficiency. They argued that the commuting potential utilized ratio could be over- or underestimated because of the city size and urban form.

Charron (2007) asserted that both the theoretical minimum and maximum commutes are outliers and suggested a new commuting indicator, which is the random commute. When measuring random commute, it is assumed that commuters do not consider commuting cost when traveling (Charron 2007). Murphy and Killen (2011) also argued that the random commute could be a more appropriate commuting indicator. In addition, Charron (2007) and Yang and Ferreira (2008) suggested an indicator of proportionally matched commute calculated by considering each zone share of the entire labor market. However, the random commute and the proportionally matched commute produce similar outcomes (Layman and Horner 2010; Kanaroglou, Higgins, and Chowdhury 2015).

Although various indicators were developed to explore commuting efficiency, Layman and Horner (2010) argued that each indicator explains a portion of commuting. They also reported that the indicators of minimum, maximum, random average, and proportionally matched commute are highly correlated, implying that all indicators are relevant. In addition, Layman and Horner (2010) reported the importance of the observed commute when applying the random average or proportionally matched commute to understand commuting efficiency.

Previous works attempted to improve and better understand the index motivated by the following three main issues (Niedzielski, Horner, and Xiao 2013; Hu and Wang 2015; Horner 2010).

First, the scale effect is a well-known issue. As Hamilton (1989) suggested, the size of the spatial unit when calculating excess commuting can lead to underestimation. This issue has been verified by Small and Song (1992), who reported that the excess commuting ratio can differ due to the scale of the zones. In addition, Niedzielski, Horner, and Xiao (2013) showed that the minimum commute and excess commuting ratio are systematically scale-dependent values. Recently, Hu and Wang (2015) applied a Monte Carlo simulation approach to overcome this effect, simulating the zonal data to disaggregated data, which consequently improved the estimation of intra- and inter-zonal commuting costs.

Second, the unit for measuring commuting cost is a source of the variance in excess commuting. Travel time and distance are highly related, resulting in less discrepancy in the excess commuting index. However, based on their empirical results, Hu and Wang (2015) asserted that using commuting time reported by survey respondents as commuting costs could lead to an overestimate of the excess commuting value.

Third, Horner (2010) reported that assuming worker interchangeability when applying the linear programming method could be a critical source for under- or overestimating the minimum (maximum) commute. Horner (2010) highlighted the importance of disaggregating worker data when conducting the linear programming method to fine-tune commuting indicators. In addition, he suggested stratifying the commuting data by worker class, gender, household characteristics, and transportation modes.

Urban Form and Excess Commuting

Over the past decades, researchers have identified the relationship between urban form and excess commuting. Studies have focused on sprawl, polycentricity, decentralization and jobs–housing balance to explain the changes in commuting (Yang 2005; Ma and Banister 2007; Chowdhury, Scott, and Kanaroglou 2013). However, the relationship is still controversial. For instance, Wachs et al. (1993) reported that congestion results in a longer commute rather than in a jobs–housing imbalance. Yang (2005) showed that spatial decentralization with different formats could improve commuting efficiency, whereas sprawl has often been associated with increased commuting length (Sultana and Weber 2007; Zhao, Lü, and de Roo 2010). Sociodemographics, characteristics of residences and job markets, and wage level were given as reasons why urban form and commuting are irrelevant in some cases (Buliung and Kanaroglou 2002; Cropper and Gordon 1991; Ma and Banister 2006; Chowdhury, Scott, and Kanaroglou 2013).

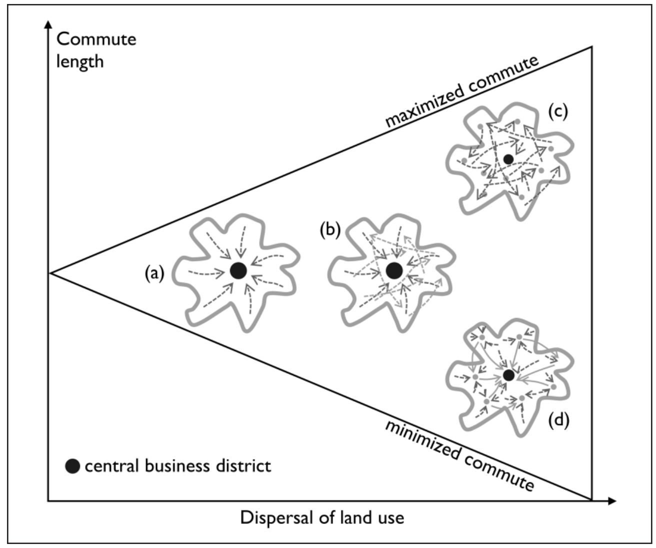


Figure 1. Conceptual framework for the relationship between urban form and commuting: (a) classical monocentric model, (b) composite model, (c) polycentric model with random movement, (d) polycentric model of urban-village form.
Source: Extracted from Ma and Banister (2007, 633).

The relationship between urban form and excess commuting has been further developed by Ma and Banister (2007), who argued that the actual commute can either increase or decrease as a city becomes more dispersed. They applied the triangle model of Brotchie (1984), which helps to understand the relationship between commuting and urban form (see Figure 1). Figure 1 shows a conceptual relationship between urban form and commuting behavior (Ma and Banister 2007) using Brotchie's triangle model and the urban spatial structure theory of Bertaud (2002). Based on this conceptual framework, they explained the changes in excess commuting through 11 possible scenarios. In addition, they accounted for the importance of commuting indicators when examining the relationship between urban form and excess commuting.

Brotchie's (1984) triangle model was first developed to understand the impact of technological changes on urban interactions. It showed that the trip length could be different for equal degrees of land use dispersal depending on the

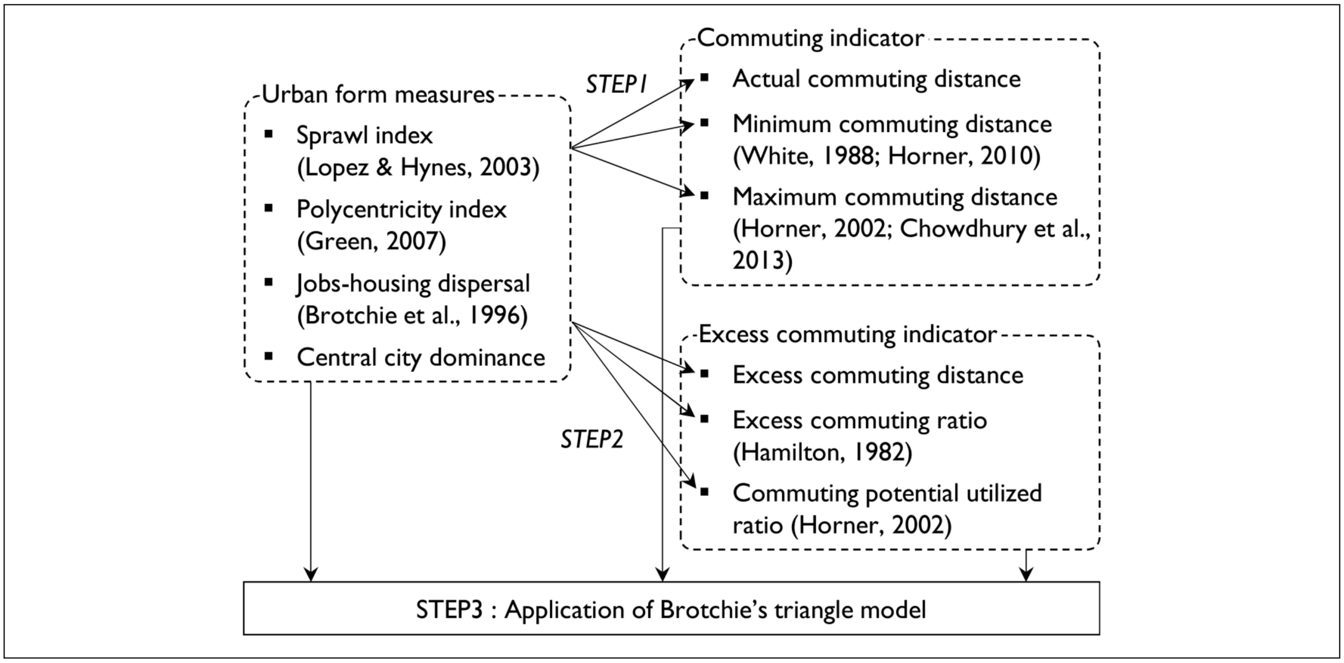


Figure 2. Research process.

transportation technology. For instance, cheap personalized transportation modes could lead to complete dispersal of interactions (thereby increasing trip length), while energy shortfall or high travel cost could lead to only localized interactions of very short trips. Brotchie's triangle model considers the theoretical maximum and minimum commute under an equal land use dispersal, and it can be extended for analyzing the relationship between urban form and commuting.

Additionally, Chowdhury, Scott, and Kanaroglou (2013) analyzed the relationship between urban form and commuting efficiency by applying Brotchie's triangle to three Canadian urban areas. There were three important findings in their research. First, they demonstrated that both the original excess commuting index and the commuting potential utilized ratio can be misunderstood when comparing commuting efficiency across space. Second, they concluded that there is no stable relationship between urban form and commuting behavior. However, the outcomes were drawn from only three areas and therefore cannot be generalized. In addition, they addressed the need to controlling for city size when comparing excess commuting across cities.

It is evident from previous studies that the original excess commuting index alone is insufficient for analyzing commuting efficiency across cities. Yang (2008) also pointed out that the excess commuting ratio can appear to increase just because of the changes in spatial structure, regardless of an individual's commuting behavior. As an alternative, both the original excess commuting index and the commuting potential utilized ratio should be considered together. However, Chowdhury, Scott, and Kanaroglou (2013) reported that both the excess commuting ratio and commuting potential utilized ratio could lead to a misunderstanding of commuting efficiency when comparing cities, suggesting the importance of examining commuting indicators. This conclusion also agrees with Ma and Banister (2007) and Layman and Horner (2010) and indicates the necessity for analyzing commuting efficiency using multi-dimensional commuting indicators and excess commuting indices.

Methodology

The following steps outline the methodology for answering our research questions (see Figure 2). In Step 1, we employ the ordinary least squares (OLS) regression model to estimate the relationship between the multidimensional aspects of urban form and commuting indicators. In this process, the independent variables are composed of urban form measures and exogenous variables used to control the size of the MSAs. In Step 2, we also analyze the impact of urban form on excess commuting indices by applying the procedure described above. In the final step, we use Brotchie's (1984) triangle model to analyze the overall relationships between commuting indicators, excess commuting indices, and urban form measures. To obtain a better understanding, we recalculated the commuting indicators using the regression equation derived from the second step.

Study Area

The spatial unit of analysis is MSAs in the United States. In 2010, a total of 378 MSAs were designated on contiguous counties that show a high degree of economic and social

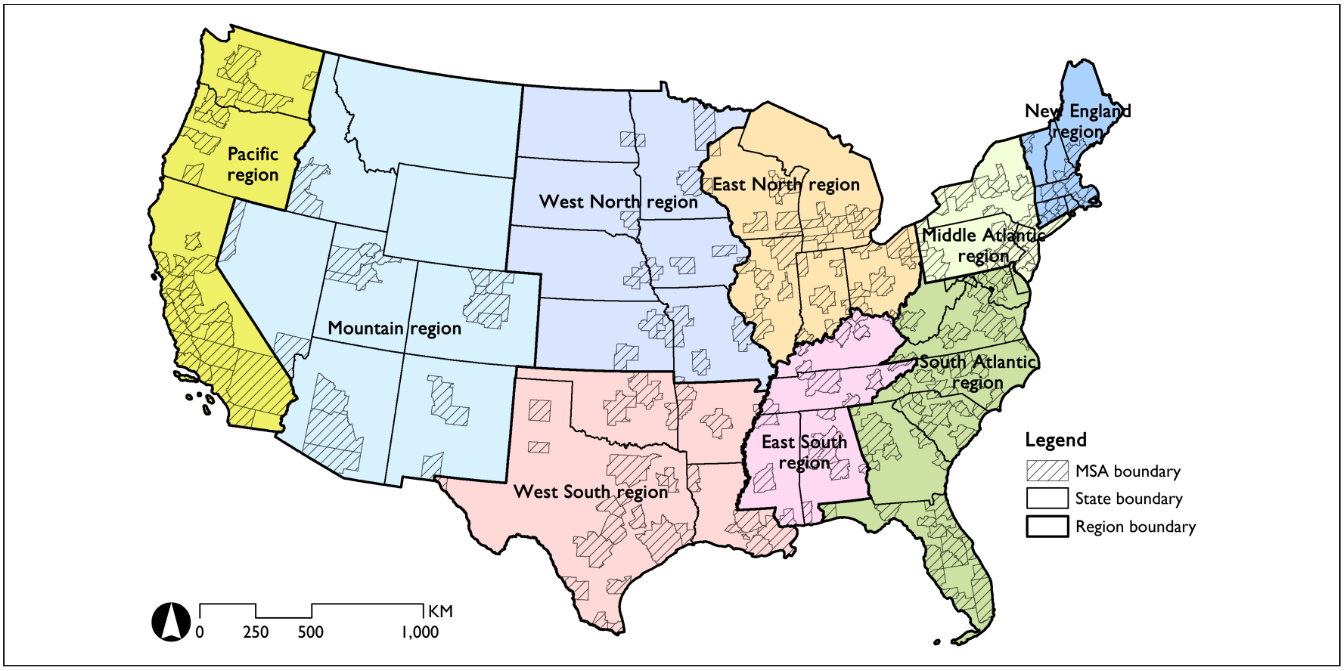


Figure 3. Study area.

integration based on commuting flows. We first selected 207 MSAs where the total population exceeds 200,000. MSAs where populations are low may not have crucial problems in commuting efficiency and may result in error in estimating the relationship between urban form and excess commuting. Two hundred six MSAs were selected as our final samples after excluding the Honolulu, Hawaii, MSA, which is not located on the US mainland. To control the scale between MSAs and regional differences, we applied total area, total population, population density, and regional dummy as independent variables. We applied the regional dummy variable to control the spatial heterogeneity among regional areas. We expected that the regional dummy variable would control regional characteristics such as modal split, income levels, housing price, and culture. Figure 3 shows the MSAs and the boundaries of nine regions: East North Central, East South Central, Middle Atlantic, Mountain, New England, Pacific, South Atlantic, West North Central, and West South Central.

Commuting Indicators and Excess Commuting Indices

We computed the commuting indicators by using matrix data of commuting flow and cost. We used the recent Census Transportation Planning Products (CTPP) for commuting flows, which is based on the 5-year (2006–2010) American Community Survey. The CTPP data also includes information related to intrazonal commuting. We used the census tract (CT) as the spatial unit of calculating commuting flows and costs. We used the network distance for the commuting cost. The commuting cost matrix was created using the OD cost matrix analysis of ArcGIS 10.0 using the road network data set provided from Topologically Integrated Geographic Encoding and Referencing (TIGER). Intrazonal distances were calculated by the radius of a circle with the same area for each CT unit, in which several studies were applied to measure excess commuting (Horner 2002; Yang 2008). Several methods were proposed to control city population, shape of spatial unit, economic potential, etc., for approximating intrazonal distance (Frost and Spence 1995; Kotavaara, Antikainen, and Rusanen 2011). According to these studies, calculating intrazonal distance based on the radius of a circle with the same area for each unit may result in an overestimation problem. However, these studies have applied municipal-level spatial units, which are usually larger than that of the CT unit applied in this study.

Commuting indicators include actual commute (C_{obs}), minimum commute (C_{min}), maximum commute (C_{max}), and adjusted maximum commute (C_{adj_max}). First, C_{obs} was calculated using the actual commuting flow. The formulation for C_{obs} is as follows:

$$C_{obs} = \sum_i \sum_j \frac{n_{ij} \times c_{ij}}{N}, \quad (1)$$

where n_{ij} is the number of commuters from i to j, c_{ij} is the network distance between i and j, and N is the total number of commuters.

Second, C_{min} is computed using the linear programming method (White 1988). When using the linear programming method, we disaggregated the commuting data to 7 groups by workers' industry type. This was proposed by Horner (2010), who suggested separating the origin-destination data by worker class to achieve a better result for C_{min}. The formulation solved through the linear programming method is as follows (Horner 2010). Solve

$$C_{min} = min(\sum_i \sum_j \sum_k \frac{n_{ijk} \times c_{ij}}{N}), \tag{2}$$

subject to the constraints $\sum_j n_{ijk} = O_{ik}$, $\sum_i n_{ijk} = D_{jk}$, and $n_{ijk} \geq 0$, where n_{ijk} is the number of commuters from i to j of workers' industry type k, O_{ik} is the number of commuters in zone i of workers' industry type k, and D_{jk} is the number of workplaces in zone j for workers' industry type k. In short, O_{ik} and D_{jk} are the aggregated number of commuters and workplaces for industry type k for zones i and j, respectively.

Third, C_{max} was also calculated by applying the linear programming method. C_{max} was computed by disaggregating the origin-destination data. In this case, the problem for the formulation is to maximize the average commute while constraining the total number of workers and workplaces for each zone. The formulation can be expressed as in equation (3), while the constraints are the same as those in equation (2) (Horner 2002, 2010).

$$\begin{aligned} C_{max} &= \max\left(\sum_i \sum_j \sum_k \frac{n_{ijk} \times c_{ij}}{N}\right) \\ &= \min\left(\sum_i \sum_j \sum_k -\frac{n_{ijk} \times c_{ij}}{N}\right). \end{aligned} \tag{3}$$

Lastly, C_{adj_max} was applied in our study to address the MAUP issue. As Kanaroglou, Higgins, and Chowdhury (2015) argued, C_{max} is biased by discrepancies in city size. Thus, we adjusted C_{max} by applying the size factor (Chowdhury, Scott, and Kanaroglou 2013). First, we computed the *size factor* for each MSA. The *size factor* was calculated by dividing the C_{cbd} (total commuting cost if all jobs were in the CBD) of each MSA by the lowest value of C_{cbd} among the 206 MSAs. Second, C_{max} was adjusted by dividing each MSAs' C_{max} by their size factor (Chowdhury, Scott, and Kanaroglou 2013).

$$C_{adj\_max} = \frac{C_{max}}{\text{size factor}} \tag{4}$$

Three excess commuting indices were applied in our study. The first is the excess commuting distance, which is the absolute length of excess commuting. The excess commuting distance can be easily calculated by the gap between the actual and minimum commute. The formulation for excess commuting distance (excess commute) is as follows.

$$\begin{aligned} &\text{Excess commute} = \text{actual commute} - \\ &\qquad \text{minimum commute} = C_{obs} - C_{min} \end{aligned} \tag{5}$$

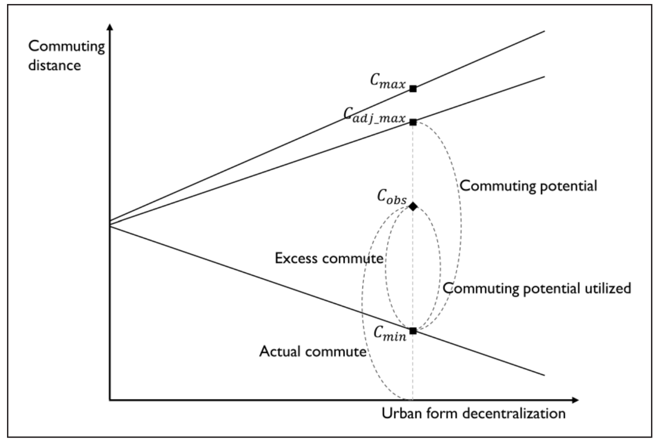


Figure 4. Schematic diagram of excess commuting indices.

Second is the excess commuting ratio (EC_r) introduced by Hamilton (1982). This index is mostly used in the excess commuting literature for examining commuting efficiency considering time and space. EC_r is calculated by the difference between the actual and minimum commute expressed as the ratio of the actual commute. As seen in Figure 4, EC_r indicates the percentage of excess commuting among the actual commuting distances. The mathematical formulation for EC_r is:

$$EC_r = \frac{\text{excess commute}}{\text{actual commute}} = \frac{C_{obs} - C_{min}}{C_{obs}} \times 100. \tag{6}$$

Lastly, the commuting potential utilized ratio (CPU_r) was used to assess commuting efficiency from a different aspect. This index indicates the ratio of the potential commute utilized, where the potential is measured by the gap between C_{max} and C_{min} (see Figure 4). Applying this concept makes it possible to identify the degree to which commuting is approaching its upper limits (Horner 2002). However, it is reported that the CPU_r index may be biased by city size, as the maximum commute exponentially increases per city size (Chowdhury, Scott, and Kanaroglou 2013). Thus, we adjusted C_{max} using the size factor. The mathematical formulation for CPU_r is equation 7 (Horner 2002):

$$\begin{aligned} CPU_r &= \frac{\text{commuting potential utilized}}{\text{commuting potential}} \\ &= \frac{C_{obs} - C_{min}}{C_{adj\_max} - C_{min}} \times 100. \end{aligned} \tag{7}$$

Urban Form Indices

To explore the relationship between urban form and excess commuting, we applied four measures of urban form: sprawl index, polycentricity index, jobs–housing dispersal index, and central city dominance. We used the population and commuting data provided from the CTPP data based on the 5-year (2006–2010) American Community Survey. Although we used the commuting data to compute urban form variables, we focused on the spatial allocation of workers' residences and workplaces when measuring urban form. For example, commuting and excess commuting indicators may show a gap between two cities with an equal urban form due to different commuting flows. In short, commuting and excess commuting indicators are computed based on people's commuting behavior, while urban form variables focus more on the static information of jobs and housing distributions. Several indicators have been suggested for urban form from previous studies. However, we selected indicators that can be technically computed for 206 MSAs while focusing on the spatial distribution of residences and/or workplaces.

First, we applied the sprawl index developed by Lopez and Hynes (2003). This density-balanced sprawl index is based on the discrepancy between the proportion of the population residing in higher- and lower-density CTs and can be expressed as the following formulation (Lopez and Hynes 2003, 333).

$$SI = \left(\left(\frac{S\%_i - D\%_i}{100} + 1 \right) \right) \times 50 \tag{8}$$

Here, $D\%_i$ is the percentage of total population in high-density CTs i, and $S\%_i$ is the percentage of total population in low-density CTs i. There are a few reasons for employing this unidimensional index, although several studies have reported the importance of a multidimensional index when measuring sprawl (Hamidi et al. 2015). From a technical perspective, composite indices for sprawl are difficult to calculate for metropolitan areas with different population sizes (Lopez 2014). Lopez and Hynes (2003) also reported that unidimensional measures for urban sprawl show a high correlation with other multidimensional measures. We wanted our sprawl measure to have a straightforward meaning. Finally, the sprawl index of Lopez and Hynes (2003) is beneficial because we can generate the sprawl index for all 206 metropolitan regions using population density at the census tract level.

Second, we used the polycentricity index (PI). The concepts of sprawl and polycentricity are similar in terms of the urban form being decentralized. However, while a city can be polycentric with consistent compactness, it can also be the opposite. In our study, we borrowed the functional polycentricity measure from Green (2007), which can be calculated by applying the commuting data and social network analysis. Although there can be various measures for polycentricity, we employed the measure developed by Green (2007), which focuses on the functional term of polycentricity. The polycentricity index determined by Green (2007) considers the level of in-commuting and out-commuting of each analysis unit regardless of geographical location. The following formulation is applied. See Green (2007, 2084–88) for the detailed calculation method.

$$PI = \frac{\left(P(\text{in-commuting}) + P(\text{out-commuting}) \right)}{2} \times \varnothing \tag{9}$$

Here, *P(in-commuting)* and *P(out-commuting)* are the polycentric levels computed for in-commute and out-commute, respectively, and $\varnothing$ is the complementarity modifier value applied to weigh the polycentricity degree of each functional network.

Third, we applied the jobs–housing dispersal (JH_D) index to measure the spatial distribution of workplaces and residences. It may seem that the PI and JH_D indices are highly related; however, the PI index focuses more on job locations, whereas the JH_D index considers the spatial balance of both jobs and housing. The JH_D index was borrowed from Brotchie et al. (1996) and expresses the ratio of the job dispersal from the CBD to the housing dispersal. The following formulation is applied (Chowdhury, Scott, and Kanaroglou 2013, 196):

$$JH_D = \left(\frac{1}{E} \sum_j d_j e_j \right) / \left(\frac{1}{H} \sum_j d_j h_j \right). \tag{10}$$

Here, E and H are the number of workplaces and commuters, respectively, e_j and h_j are the number of workplaces and commuters in zone j, respectively, and d_j is the distance from the city center to zone j. This index seems to indicate the jobs–housing balance level; however, there is a subtle difference between the two. The jobs–housing balance level, which can be understood through the minimum commute, examines whether the jobs and housing are close to each other. On the other hand, the JH_D index only focuses on whether the dispersal of jobs and housing from the city center is similar, and a value of 1.0 indicates that the dispersal of jobs and housing are equal.

Lastly, we considered the percentage of jobs in the central city compared to the total number of workplaces in the MSA. Applying this index controls for MSAs with equal polycentricity with different degrees of central city dominance. For instance, a city with high polycentricity of high central city dominance indicates a polycentric city that maintains the central city concentration. In contrast, a city with high polycentricity and low central city dominance expresses a city moving toward polycentricity while losing central city dominance. We defined the central city as the *place* spatial unit that represents each MSA.

Analysis

Descriptive Statistics and Correlation Matrix

Table 1 shows the descriptive statistics of the variables used. The average actual commuting distance (C_{obs}) of the 206

Table 1. Descriptive Statistics.

Variables	Unit	Mean	SD.	Min.	Max.	VIF (Model 1-4)	VIF (Model 5-6)
Commuting indicators							
Actual commuting distance (C_{obs})	km	15.101	2.960	8.740	26.052	–	–
Minimum commuting distance (C_{min})	km	7.136	1.708	3.750	14.996	–	–
Maximum commuting distance (C_{max})	km	35.577	12.896	15.135	91.787	–	–
Adjusted maximum commuting distance (C_{adj_max})	km	33.073	3.603	20.407	40.087	–	–
Excess commuting index							
Excess commuting distance ($C_{obs} - C_{min}$)	km	7.966	1.938	4.207	15.092	–	–
Excess commuting ratio (EC_r)	%	52.674	6.856	34.860	74.172	–	–
Commuting potential utilized ratio (CPU_r)	%	31.540	9.395	14.514	70.264	–	–
Urban form measures							
Sprawl index (Lopez 2014)	Index	66.807	20.526	11.040	100.000	2.62	2.61
Polycentricity index (Green 2007)	Index	0.548	0.068	0.417	0.763	2.35	2.08
Jobs–housing dispersal index (Chowdhury, Scott, and Kanaroglou 2013)	Index	0.814	0.095	0.539	1.078	1.63	1.62
Central city dominance	Index	42.581	19.468	2.989	97.821	1.95	1.90
Control variables							
Total population of MSA	Millions	1.123	1.973	0.201	18.701	4.76	3.04
Total area of MSA	km^2	7716.261	6871.463	523.121	63427.892	2.75	–
Population density	pop/ km^2	143.285	132.853	11.128	963.158	4.84	3.22

Note: MSA = metropolitan statistical areas.

MSAs was approximately 15.1 km, and the minimum commuting distance ($C_{\min}$) and maximum commuting distance (C_{max}) were 7.1 km and 35.6 km, respectively. Referring to Figure 5, C_{obs} was relatively high in MSAs located in the west and south regions, including Riverside–San Bernardino–Ontario, CA; Houston–Sugar Land–Baytown, TX; and Atlanta–Sandy Springs–Marietta, GA. The average excess commuting distance ($C_{obs} - C_{min}$) was 8.0 km. The excess commuting ratio (EC_r) varied from 34.9% to 74.2%, and the mean value was 52.7%. Additionally, the average of commuting potential utilized ratio (CPU_r) was 31.5%, ranging from 14.5% to 70.3%.

Appendix Table A1 presents the variables measured for the ten largest and smallest populated MSAs. For instance, the C_{obs} for New York–White Plains–Wayne, NY–NJ was 15.9 km, and C_{min} was 6.7 km. These values result in an EC_r index of 57.8%. In contrast, C_{obs} in Los Angeles–Long Beach–Glendale, CA, was 18.2 km, and C_{min} was 4.7 km, resulting in a high EC_r index of 74.2%. Appendices B and C show the spatial variance of the EC_r and CPU_r indices. As expected, the two excess commuting indices did not show consistency, implying the importance of considering both indices. In particular, MSAs such as Philadelphia–Camden–Wilmington, PA–NJ–DE–MD, Boston–Cambridge–Quincy, MA–NH, and Saginaw–Saginaw Township North, MI, showed large discrepancies in their EC_r and CPU_r indices. Meanwhile, four urban form measures also showed differences, implying that each variable characterizes a different aspect of urban form. For example, although Philadelphia–Camden–Wilmington, PA–NJ–DE–MD, and Atlanta–Sandy Springs–Marietta, GA, showed similar polycentricity levels, they showed a large gap in sprawl levels.

Table 2 shows the correlation between commuting indicators, excess commuting indices, and urban form variables. First, C_{obs} showed a strong positive relationship with C_{min}, implying that areas with higher C_{min} result in longer C_{obs}. Overall, the results show that C_{obs} values are shorter in areas with a higher jobs–housing balance, where C_{min} indicates jobs–housing balance level (Horner 2002, 2007). Meanwhile, C_{obs} and C_{max} also showed a strong correlation, indicating that the increase in the upper limit of commutes results in longer C_{obs}. Second, EC_r and CPU_r showed a weak positive correlation. This indicates that the two excess commuting indices are related to a certain degree, but not in a totally complementary manner. Third, C_{obs} showed the strongest relationship with the polycentricity index among the urban form indices. This result suggests that commutes are longer in areas with higher polycentricity. Lastly, there were few significant correlations between urban form indices. For instance, the sprawl index showed a negative correlation with polycentricity, indicating that areas with higher sprawl are more likely to be less polycentric. However, as reported in Table 1, the maximum VIF value of urban form indices did not exceed 3.0, indicating no multicollinearity.

Urban Form and Commuting Indicators

We first examined the relationship between urban form and commuting as the first step. Table 3 shows the relationship

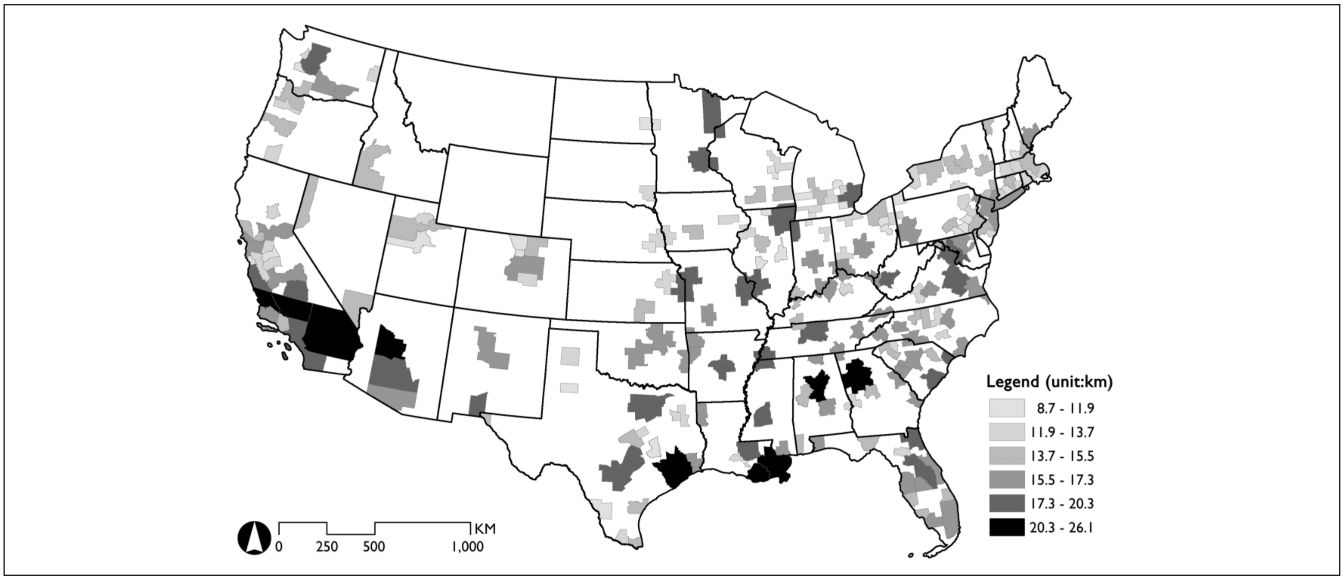


Figure 5. Spatial variation of actual commuting distance (C_{obs}).

between urban form and commuting indicators based on the regression model. For model 1 in Table 3, the results show how urban form indices are associated with minimum commute ($C_{\min}$). C_{min} refers to the spatial distribution of jobs and housing, so a low C_{min} implies that the locations of jobs and housing are balanced across the MSA. The sprawl index showed a positive relationship with C_{min} , while other urban form variables showed negative coefficients. This implies that MSAs with higher sprawl are associated with an unbalanced distribution of jobs and housing. Moreover, assuming all people commute in a way that collectively minimizes their average commute, the result indicates that people should commute longer distances where the sprawl level is high. Yet polycentricity did not show significant relationship with C_{min} , although it showed a negative coefficient.

The jobs–housing dispersal index showed a negative and significant coefficient, implying that C_{min} is lower in areas with a balanced spatial distribution of jobs and housing. Last, central city dominance showed a negative relationship with C_{min} . According to the literature, a high central city dominance is related to a monocentric city, resulting in an increase of C_{min} because most individuals will commute to the central city. However, the results indicate that higher central city dominance is associated with lower C_{min} when other aspects of the MSA are controlled. The positive correlation between C_{min} and the central city dominance supports this result (see Table 2).

The total population and total area showed positive relationships with C_{min} . This result indicates that the spatial distribution of jobs and housing is more unbalanced in larger MSAs. In addition, population density showed a negative association with C_{min} , implying that a denser city is likely to require shorter commuting distances. For regional dummy variables, most of the regions showed a higher C_{min} than the East North Central dummy. This indicates that the metropolitan areas in the East North Central region have a higher jobs–housing balance.

For model 2, the dependent variable is actual commuting distance (C_{obs}) . As seen in Table 3, higher sprawl relates to longer commuting distance, indicating that sprawl is likely to increase C_{obs} . The coefficient of polycentricity shows that MSAs with higher polycentricity are associated with longer commutes. Moreover, this result indicates that people show a tendency for cross-commuting in polycentric cities even though it has been reported that higher polycentricity leads to shorter commutes by increasing the jobs–housing balance. The dispersal of jobs and housing showed insignificant association with actual commuting distance, even though the association was negative. Urban areas with higher central city dominance showed shorter commutes. This result indicates the significance of maintaining central city dominance for reducing commuting distance (Schwanen, Dieleman, and Dijst 2004; Vandersmissen, Villeneuve, and Thériault 2003).

The results show that actual commuting distances are high in metropolitan areas of higher total population and larger areas. Regarding the regional dummy variables, the south and west regions of the United States mainland, including East South Central, South Atlantic, West South Central, and Pacific, showed higher commuting distances than did East South Central. This result can be attributed to the discrepancy in income levels, sociodemographics, and automobile usage.

In model 3, the dependent variable is the maximum commute (C_{max}) , which indicates the possible commuting distance when people commute in a way that maximizes the average commuting distance. The coefficients indicate that C_{max} is higher when both the levels of sprawl and

Table 2. Correlation Matrix Between Variables.

	C_{obs}	C_{min}	C_{max}	C_{adj_max}	$C_{obs} - C_{min}$	EC_r	CPU_r	Sprawl index	Poly-centricity Index	JH Dispersal Index	Central City Dominance
C_{obs}	1.000***										
C_{min}	0.783***	1.000***									
C_{max}	0.739***	0.353***	1.000***								
C_{adj_max}	0.069	−0.165**	0.246***	1.000***							
$C_{obs} - C_{min}$	0.837***	0.315***	0.817***	0.251***	1.000***						
EC_r	0.055	−0.566***	0.399***	0.388***	0.583***	1.000***					
CPU_r	0.820***	0.551***	0.621***	−0.377***	0.766***	0.181***	1.000***				
Sprawl index	0.054	0.354***	−0.200***	−0.176**	−0.229***	−0.459***	−0.009	1.000***			
Poly-centricity index	0.336***	−0.039	0.432***	0.194***	0.548***	0.467***	0.308***	−0.453***	1.000***		
JH dispersal index	0.002	−0.391***	0.368***	0.140**	0.347***	0.657***	0.186***	−0.276***	0.066	1.000***	
Central city dominance	−0.125*	0.151**	−0.450***	−0.245***	−0.323***	−0.440***	−0.122*	−0.015	−0.088	−0.474***	1.000***

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

Table 3. OLS Regression Model (Commuting Indicators).

	Model 1		Model 2		Model 3	
	Minimum Commute (C_{min})		Actual Commute (C_{obs})		Maximum Commute (C_{max})	
Variables	Coefficient	t	Coefficient	t	Coefficient	t
Urban form						
Sprawl index	0.029***	4.74	0.039***	3.79	0.042	1.04
Polycentricity index	−2.188	−1.24	5.707*	1.93	6.547	0.56
JH dispersal index	−5.401***	−5.22	−0.430	−0.25	27.754***	4.07
Central city dominance	−0.011**	−2.00	−0.031***	−3.35	−0.224***	−6.11
MSA scale and density						
Total population	0.197**	2.30	0.311**	2.16	2.273***	4.02
Total area	0.000***	5.32	0.000***	7.35	0.001***	7.30
Population density	−0.003**	−2.33	−0.003	−1.43	−0.012	−1.39
Regional dummy						
East south central	1.950***	5.27	3.006***	4.83	7.403***	3.04
Mountain	0.948**	2.35	0.609	0.90	−5.540**	−2.08
Middle Atlantic	0.150	0.45	−0.356	−0.63	−0.994	−0.45
New England	0.587	1.41	0.567	0.81	4.187	1.53
South Atlantic	1.241***	4.60	2.180***	4.80	4.914***	2.76
West north central	0.923**	2.31	0.536	0.80	3.784	1.43
West south central	1.418***	4.55	2.370***	4.52	3.377	1.64
Pacific	1.256***	3.97	1.908***	3.58	3.213	1.54
Intercept	9.759***	6.18	8.008***	3.01	5.868	0.56
N	206		206		206	
F	$F(15, 190) = 19.67$		$F(15, 190) = 21.60$		$F(15, 190) = 29.76$	
Statistics						
Probability >F	0.000		0.000		0.000	
R^2	0.608		0.630		0.701	

Note: Reference category for regional dummy is "East north central" region. MSA = metropolitan statistical areas.
***p < 0.01; **p < 0.05; *p < 0.1.

Table 4. OLS Regression Model (Excess Commuting Indices).

	Model 4		Model 5		Model 6	
	Excess Commute (EC)		Excess Commuting Ratio (EC_r)		Potential Utilized Ratio (CPU_r)	
Variables	Coefficient	t	Coefficient	t	Coefficient	t
Urban form						
Sprawl index	0.010	1.61	−0.057***	−2.62	0.109***	2.75
Polycentricity index	7.896***	4.44	33.356***	5.65	28.110***	2.61
JH dispersal index	4.971***	4.75	35.085***	9.54	22.469***	3.35
Central city dominance	−0.020***	−3.61	−0.035*	−1.80	−0.076**	−2.13
MSA scale and density						
Total population	0.115	1.32	−0.430*	−1.76	2.674***	6.01
Total area	0.000***	6.98				
Population density	0.000	−0.08	0.011***	2.82	−0.024***	−3.50
Regional dummy						
East South Central	1.055***	2.83	−2.687**	−2.04	9.456***	3.95
Mountain	−0.339	−0.83	−2.949**	−2.15	7.630***	3.06
Middle Atlantic	−0.507	−1.49	−1.643	−1.37	−0.918	−0.42
New England	−0.019	−0.05	−1.616	−1.10	1.236	0.46
South Atlantic	0.939***	3.45	−1.520	−1.58	6.622***	3.78

(Continued)

Table 4. Continued

	Model 4		Model 5		Model 6	
	Excess Commute (*EC*)		Excess Commuting Ratio (EC_r)		Potential Utilized Ratio (CPU_r)	
Variables	Coefficient	*t*	Coefficient	*t*	Coefficient	*t*
West North Central	−0.387	−0.96	−4.175***	−2.94	2.378	0.92
West South Central	0.953***	3.03	−1.601	−1.45	10.520***	5.23
Pacific	0.652**	2.04	−2.108*	−1.89	6.119***	3.01
Intercept	−1.751	−1.10	11.835**	2.11	−10.878	−1.07
N	206		206		206	
F	$F(15, 190) = 28.19$		$F(14, 191) = 30.31$		$F(14, 190) = 11.23$	
Statistics						
Probability >*F*	0.000		0.000		0.000	
R^2	0.690		0.690		0.452	

Note: Reference category for the regional dummy is the "East North Central" region. MSA = metropolitan statistical areas.
***p < .01; **p < .05; *p < .1.

polycentricity are high. This result agrees with Ma and Banister (2006); however, the two variables were not significant at p <0.1. Meanwhile, the results indicate that C_{max} is higher in MSAs where the spatial distribution of jobs and housing are equal. Assuming all people change their commuting behavior toward cross-commuting, this result implies that commuting distances are higher in areas with higher jobs–housing dispersity. Central city dominance showed a negative coefficient, indicating that commuting distance is less maximized in MSAs where the central city has a higher dominance of jobs.

Urban Form and Excess Commuting Indices

Regarding the second step of the analysis, Table 4 presents the relationship between urban form and excess commuting indices. In model 4, the dependent variable is the absolute value of excess commuting (*EC*), which is the gap between C_{obs} and C_{min}. First, higher sprawl was positively associated with *EC* but is not significant at p <0.1. Regarding the relationship between sprawl and commuting indicators, sprawl increases both C_{min} and C_{obs}, resulting in no significant association with *EC*. Polycentricity decreases the minimum commute (C_{min}) while increasing actual commute (C_{obs}), resulting in a positive association with *EC*. The results for jobs–housing dispersal index were similar to those of polycentricity. However, it should be noted that polycentricity affects C_{obs} more, whereas the jobs–housing dispersal index significantly influences C_{min} (see Tables 3 and 4). Central city dominance was negatively associated with both C_{min} and C_{obs}. Yet the impact of central city dominance on *EC* was negative because its impact on C_{obs} was more intense.

In model 5, the dependent variable is the excess commuting ratio (EC_r). As shown in Table 4, higher sprawl is associated with a lower EC_r. This result can be explained by the sprawl positively affecting C_{obs} while not significantly affecting *EC*. A positive relationship between sprawl and C_{obs} may be the reason for the negative association between EC_r and sprawl based on the mathematical formulation of EC_r. High levels of polycentricity and jobs–housing dispersal were positively associated with EC_r. Specifically, polycentricity increases C_{obs}, and the jobs–housing dispersal index decreases C_{min}, while both result in an increase in EC_r. This issue can be dealt with by applying Brotchie's triangle in the next part of this study. Central city dominance negatively affects EC_r, indicating the importance of retaining the central city dominance.

Last, the dependent variable for model 6 is the potential utilized ratio (CPU_r). CPU_r was first proposed by Horner (2002) to overcome the limitations of EC_r. However, we should still be cautious when interpreting CPU_r because it is calculated using the commuting indicators as a ratio. The sprawl index showed positive association with CPU_r, which is different from the results of model 5. This result provides evidence for the argument that EC_r and CPU_r should be considered simultaneously. Meanwhile, the other three variables related to urban form showed results consistent with model 5.

Application of Brotchie's Triangle Model

We here apply Brotchie's triangle to examine the relationship between urban form and commuting as the third step. There are two main reasons for applying the Brotchie's triangle model. First, it helps us understand whether the changes in urban form lead to more random commuting or rational commuting. Second, it helps us better understand the multidimensional relationship between urban form, commuting indicators, and excess commuting indices. Figure 6 shows

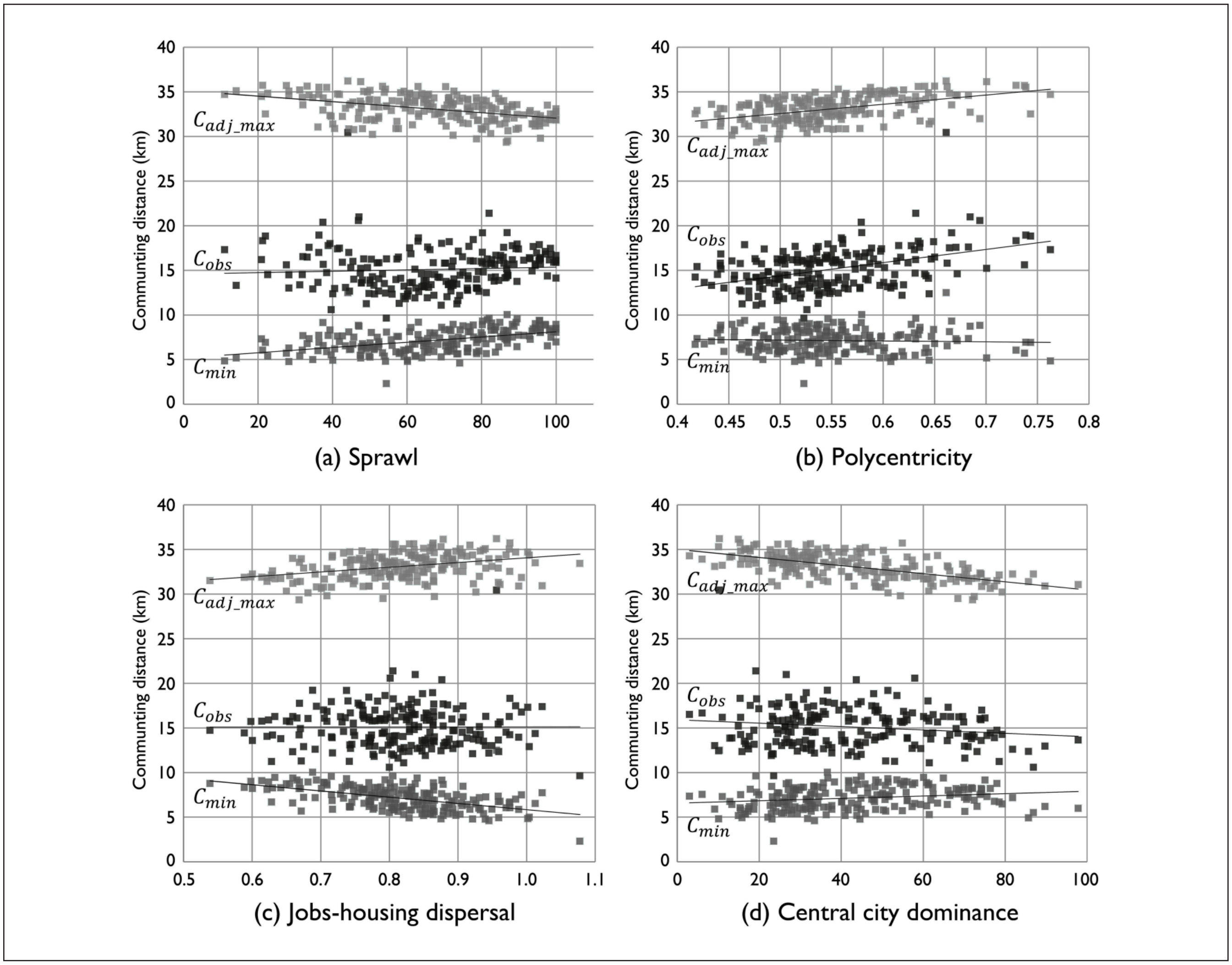


Figure 6. Relationship between urban form and commuting indicators based on Brotchie's triangle model.

the scatterplots and the corresponding trend lines between urban form measures and commuting indicators. We use Brotchie's approach for understanding excess commuting indices based on Figure 6.

First, sprawl showed positive associations with both C_{min} and C_{obs} while having a negative relationship with EC_r. However, it is counterintuitive to argue that higher sprawl enhances commuting efficiency. As stated previously, sprawl does not affect EC while related with longer C_{act}. This indicates that the negative relationship between sprawl and EC_r is more likely attributed to the positive relationship between sprawl and C_{act}. Meanwhile, sprawl showed no significant association with C_{max}, while it showed a positive relationship with CPU_r. Yet, as seen in Figure 6A, the scatterplot for sprawl and C_{obs} showed a slightly U-shaped curve. This implies that a certain degree of sprawl can minimize commutes. This should be examined further in detail.

Second, polycentricity showed negative and positive relationships with C_{min} and C_{max}, respectively, but these were not significant. Polycentricity showed a positive relationship with C_{obs}, implying that commuting distances are longer in polycentric cities. As seen in Figure 6B, polycentricity does not significantly affect C_{min}, yet it intensely increases C_{obs}, resulting in a positive impact on EC_r. This result indicates that polycentricity does not have a large impact on urban form balance, while it does affect commuting behavior toward cross-commuting. Thus, we can conclude that higher polycentricity increases commuting cost.

Third, the jobs–housing dispersal index did not show significant association with C_{obs}, while it did significantly affect both C_{min} and C_{max}. The jobs–housing dispersal index was negatively related with C_{min} and positively related with C_{max}, both resulting in an increase in EC_r and CPU_r. Although it is obvious that a higher jobs–housing dispersal index is associated with higher excess commuting, we should be cautious in concluding that higher jobs–housing dispersal decreases commuting efficiency. The discrepancies in EC_r and CPU_r between MSAs with different degrees of the jobs–housing dispersal index are caused by the gaps in C_{min} and C_{max}, not C_{obs}.

Last, central city dominance was negatively associated with all three commuting indicators. As seen in Tables 3 and 4, central city dominance showed a negative relationship with both C_{obs} and C_{min} and resulted in a slight decrease in EC_r. Meanwhile, central city dominance was negatively associated with commuting potential, which is the gap between C_{max} and C_{obs}. However, it also showed a negative relationship with C_{obs}, resulting in a decrease in CPU_r. As shown in Figure 6D, higher central city dominance is clearly associated with shorter C_{obs} even though the commuting potential decreases, indicating that higher central city dominance is related to better commuting efficiency.

Conclusion

We revisited the controversial relationships between urban form and excess commuting by analyzing 206 MSAs in the United States, which should lead us to a more generalized finding. We used multidimensional indicators of urban form and excess commuting and applied Brotchie's triangle model to overcome the limitations of previous studies and contribute to the literature on the association between urban form and excess commuting. The results offer new insights on the influence of urban form on commuting attributes and the excess commuting concept.

First, we validated the significance of using both excess commuting indices when examining commuting efficiency. Although the excess commuting ratio (EC_r) and the potential utilized ratio (CPU_r) showed a positive correlation, a single measure can lead to a misunderstanding because the correlation was weak. In addition, the relationships between urban form measures and the two excess commuting indices were slightly dissimilar, indicating that one measure should not be used alone.

Second, higher polycentricity and central city dominance are clearly associated with excess commuting. MSAs with higher polycentricity were associated with longer commuting distance, further increasing both the excess commuting ratio (EC_r) and the potential utilized ratio (CPU_r). This result implies that urban forms with higher polycentricity are not likely to enhance the jobs–housing balance because they greatly increase the tendency for cross-commuting. Meanwhile, higher central city dominance showed a relationship with better commuting efficiency. MSAs with higher central city dominance were more likely to show shorter commutes despite the longer minimum commuting distance and lower commuting potential. To sum up, the results imply that planners should be aware of the methods that can maintain the centrality of central city areas.

Last, our findings imply that sprawl and jobs–housing dispersal are associated with excess commuting; however, researchers should be aware of misinterpreting this result. Higher sprawl was related with longer commutes. However, it showed negative relationships with excess commuting ratio (EC_r), indicating that the results are not robust enough. The jobs–housing dispersal index clearly increased both the excess commuting ratio (EC_r) and commuting potential utilized ratio (CPU_r), indicating its negative impact on excess commuting. Despite this result, we believe that the influence of jobs–housing dispersal should be carefully studied because it does not have a significant impact on peoples' actual commutes. These results can be interpreted as circumstantial evidence for using both commuting and excess commuting indicators when examining commuting efficiency.

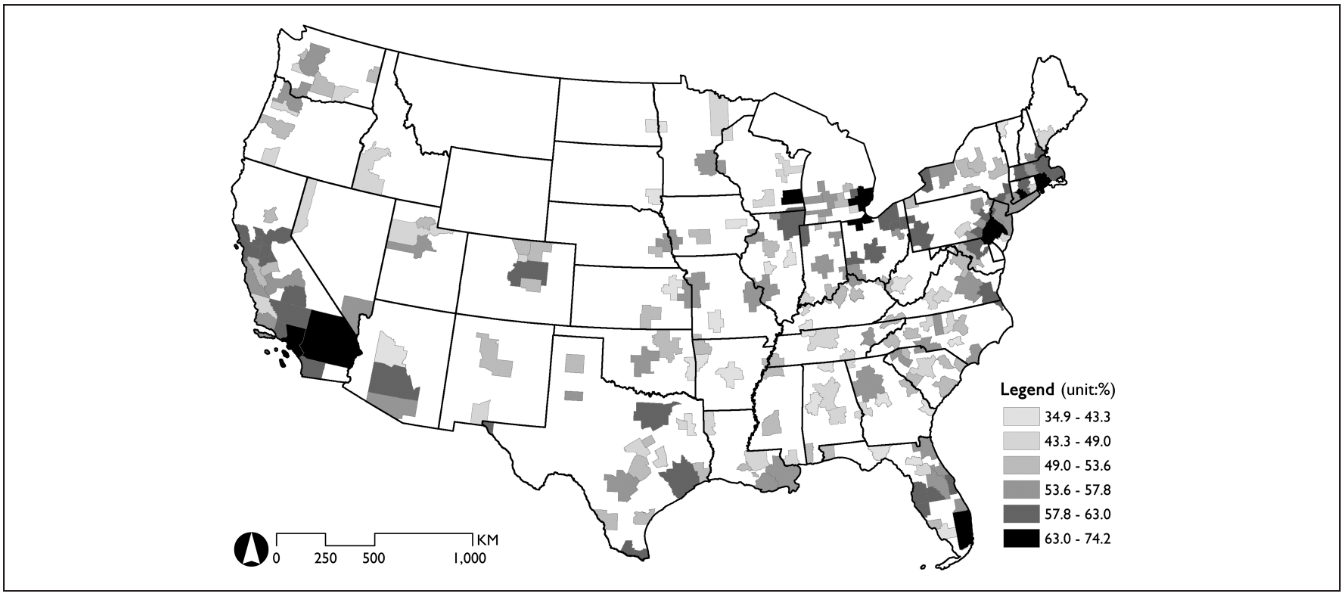
Two primary lessons were learned in this research. First, planners should be aware that higher polycentricity is associated with both longer commutes and higher excess commuting. Because higher polycentricity has been generally perceived to be associated with higher jobs–housing balance, policy makers may think that higher polycentricity can reduce cross-commuting. However, this study shows the opposite results regarding the relationship between polycentricity and commuting. Second, planners should note the importance of central city dominance. Based on our results, MSAs with higher central city dominance reported shorter commutes and lower excess commuting. Hence, planners should not underestimate the importance of the central city when planning urban forms for enhancing commuting efficiency.

While this study contributes to the literature on urban form and commuting, there is still much potential for extending the research scope. First, future work could focus on the impacts of urban form changes in excess commuting levels by examining multiyear data sets. By doing so, we may learn how urban form changes are related to commuting behavior transitions. Second, it would be possible to examine the sensitivity problem on various urban form measures. Future work could analyze the relationship between excess commuting and urban form while applying diversified urban form measures characterized by land use, diversity, and design aspects. For instance, we could only focus on sprawl, while testing various sprawl measures proposed in previous studies. Then, it would be possible to derive a categorical conclusion to resolve the dispute about the relationship between urban form and commuting.

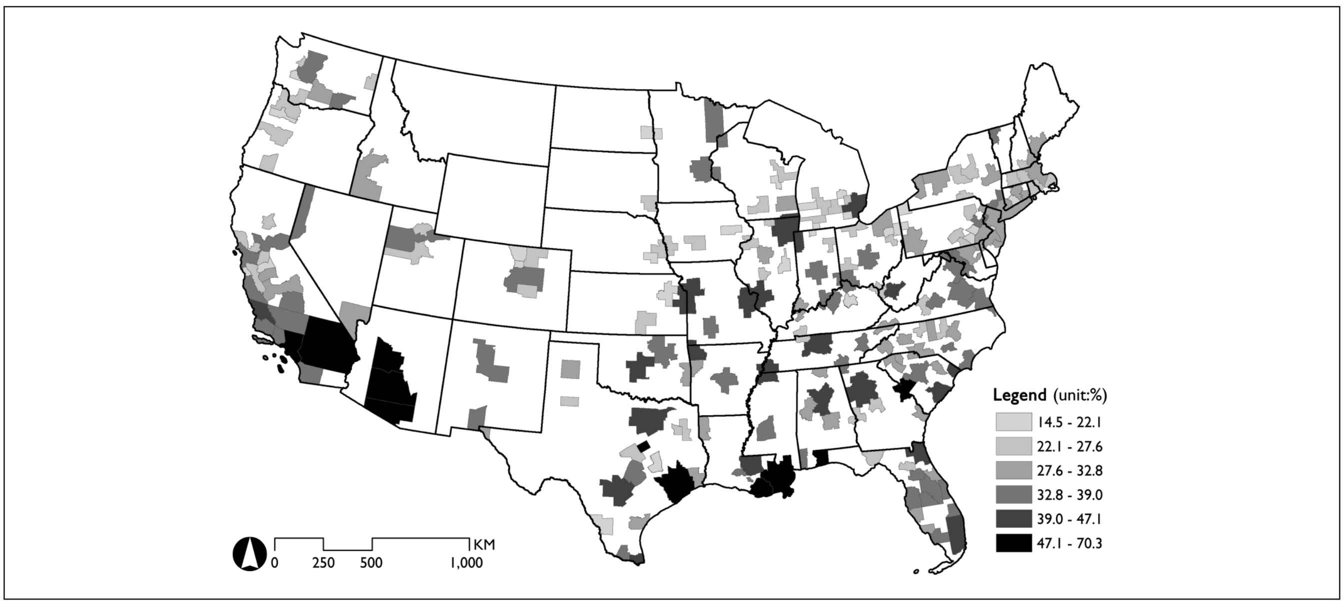
Appendix A

Table A1. Measured Variables for the 10 Largest and Smallest Populated MSAs.

Rank	Metropolitan Statistical Area (MSA)	C_{obs}	CPU_r	C_{max}	C_{adj_max}	$C_{obs} - C_{min}$	EC_r	CPU_r	Sprawl Index	Polycentricity index	JH Dispersal Index	Central City Dominance
1	New York–Northern New Jersey–Long Island, NY–NJ–PA	15.883	6.710	62.302	36.422	9.172	57.750	30.871	21.990	0.743	0.848	47.920
2	Los Angeles–Long Beach–Santa Ana, CA	18.199	4.700	62.680	23.911	13.498	74.172	70.264	11.040	0.763	1.002	31.810
3	Chicago–Joliet–Naperville, IL–IN–WI	18.311	6.999	65.052	34.618	11.312	61.778	40.958	36.360	0.739	0.863	31.492
4	Dallas–Fort Worth–Arlington, TX	20.133	7.951	64.909	36.213	12.182	60.509	43.105	47.080	0.685	0.838	26.613
5	Philadelphia–Camden–Wilmington, PA–NJ–DE–MD	14.874	5.040	54.856	38.059	9.834	66.118	29.782	47.450	0.631	0.893	26.005
6	Houston–Sugar Land–Baytown, TX	23.012	9.058	58.161	36.237	13.953	60.636	51.340	46.940	0.694	0.801	57.950
7	Miami–Fort Lauderdale–Pompano Beach, FL	16.874	6.036	74.624	31.117	10.838	64.229	43.213	21.240	0.729	0.976	15.339
8	Washington–Arlington–Alexandria, DC–VA–MD–WV	18.971	9.281	53.418	34.832	9.690	51.079	37.923	38.860	0.615	0.754	24.817
9	Atlanta–Sandy Springs–Marietta, GA	21.466	9.531	63.661	35.166	11.935	55.600	46.558	82.040	0.632	0.805	19.188
10	Boston–Cambridge–Quincy, MA–NH	15.301	6.314	52.669	36.365	8.988	58.738	29.908	49.370	0.601	0.836	22.702
⋮	–	–	–	–	–	–	–	–	–	–	–	–
197	Burlington–South Burlington, VT	15.033	9.048	34.188	25.479	5.984	39.810	36.421	72.370	0.433	0.801	28.251
198	Prescott, AZ	26.052	14.996	72.846	33.250	11.057	42.440	60.569	95.490	0.465	0.840	36.771
199	Springfield, IL	11.822	7.041	18.604	27.447	4.780	40.438	23.427	73.360	0.463	0.628	78.542
200	Houma–Bayou Cane–Thibodaux, LA	22.635	10.132	46.248	33.036	12.502	55.235	54.585	89.930	0.485	1.023	24.405
201	Florence, SC	15.512	7.882	33.068	33.572	7.630	49.186	29.699	100.000	0.477	0.788	34.269
202	Tyler, TX	13.086	6.871	20.550	31.426	6.215	47.491	25.310	86.640	0.477	0.669	72.091
203	Saginaw–Saginaw Township North, MI	11.177	5.459	21.568	31.967	5.717	51.155	21.569	76.280	0.517	0.845	30.731
204	Las Cruces, NM	19.161	9.822	32.422	34.919	9.339	48.740	37.211	70.490	0.470	0.923	61.888
205	Fargo, ND–MN	10.911	6.184	18.052	32.623	4.728	43.328	17.881	55.790	0.566	0.675	70.967
206	Medford, OR	13.593	7.610	24.557	30.298	5.983	44.015	26.370	67.460	0.439	0.748	52.420



Appendix B. Spatial variation of excess commuting ratio (***EC**$_r$*).



Appendix C. Spatial variation of commuting potential utilized ratio (***CPU**$_r$*).

Declaration of Conflicting Interests

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