Article

Urban Studies

Urban Studies
1–25

Reprints and permissions:
sagepub.co.uk/journalsPermissions.nav
DOI: 10.1177/0042098016684099
journals.sagepub.com/home/usj
SAGE

Does accessibility matter? Understanding the effect of job accessibility on labour market outcomes

Jangik Jin
University of Wisconsin-Madison, USA

Kurt Paulsen
University of Wisconsin-Madison, USA

Abstract
In this study, we examine the effect of access to employment opportunities on labour market outcomes, especially focusing on unemployment rates and household income in the Chicago metropolitan area during 2000–2010. Using accessibility measures derived from detailed employment data, we calculate job accessibility by race and income. In order to deal with the endogeneity problem, we employ instrumental variables with a generalised spatial two-stage least square (GS2SLS) model with fixed-effects. Our findings suggest that job accessibility plays a significant role in explaining unemployment rates and household income. Consistent with Kain's spatial mismatch hypothesis, increases in job accessibility for African Americans lead to decreases in unemployment. Results also show that increased job accessibility for low-income households not only reduce unemployment but also improve household income.

Keywords
employment accessibility, household income, spatial effects, spatial mismatch, unemployment rates

Received October 2015; accepted November 2016

Introduction

For nearly 50 years since the publication of Kain's (1968) 'spatial mismatch' research, scholars have debated the relationship between urban spatial structure (patterns of residential and firm location) and the labour market outcomes of lower-income households and disadvantaged minorities. Kain (1968) argued that lower rates of employment for African Americans were partially due to the combined forces of

Corresponding author:
Jangik Jin, Department of Urban and Regional Planning, University of Wisconsin-Madison, Urban and Regional Planning, 925 Bascom Mall, Madison WI 53706, USA.
Email: jjin8@wisc.edu

employment–suburbanisation while housing segregation limited black households to central-city locations. Labour market outcomes are influenced not only by individual factors such as years of education, but by the spatial accessibility of employment. African American families moved to northern and Midwestern industrial cities (such as Chicago) in search of manufacturing employment from 1916 through the 1960s. As these higher-wage low-skilled manufacturing jobs began to leave industrial cities, black households who wished to move to the suburbs for education or employment faced significant barriers of segregation and discrimination. Employment decentralisation, the decline in manufacturing employment and residential segregation combined to reduce the employment prospects for African American households, particularly those with lower levels of education. Moreover, as Kain argued, educational improvements alone would not necessarily reduce the employment gap between blacks and whites because of these spatial factors.

The spatial mismatch hypothesis has generated much literature and research, but there is still ongoing debate about the presence – and magnitude – of the effect on labour market outcomes. Some scholars have argued that better accessibility to employment opportunities reduce the probability of unemployment/underemployment (Kawabata, 2003; Ong and Houston, 2002; Sanchez, 1999), while others have argued spatial accessibility is a less significant factor than employment discrimination or group differences in educational levels (Boustan and Margo, 2009; Cervero et al., 2002; Hellerstein et al., 2008; Holzer, 1991; Ihlandfeldt and Sjoquist, 1998; Wachs and Taylor, 1998). Because poorer white households in central cities also experience similar labour market effects (Arnott, 1998; Ihlanfeldt, 2006) residential segregation by race may not play as strong a role as reduced transportation opportunities (Grengs, 2010; Ong and Miller, 2005; Taylor and Ong, 1995).

Recently, scholars have argued that these contradictory results are mostly due to measurement and methodological differences (Bania et al., 2008; Houston, 2005; Ihlanfeldt, 2006; Mouw, 2000; Ong and Miller, 2005). Many studies rely on cross-sectional data, where correlations may not distinguish between cause and consequence. We know that in US metropolitan regions, the spatial patterns of race, class, educational outcomes and housing are heavily correlated. Labour market outcomes and residential location patterns are also endogenous (people move to be near good jobs and employment accessibility is capitalised into housing prices) and are likely influenced by unobserved correlates (unobserved factors that influence labour market outcomes may be correlated with unobserved household characteristics that also influence housing search.)

In addition to the endogeneity problem, there are further methodological challenges in testing the effect of job accessibility on labour market outcomes (Houston, 2005): (1) measuring job accessibility, (2) categorising labour market segmentation, and (3) capturing spatial spillover effects. The goal of this study is to test the effect of spatial patterns of employment opportunities on labour market outcomes, particularly for African American and low-income households while addressing these four methodological challenges. We employ a fixed-effects model with two-period panel data and job accessibility measures with spatially detailed employment information in the Chicago metropolitan area. We use instrumental variable techniques to deal with the endogeneity between employment opportunities and labour market outcomes. Moreover, to account for unobserved spatial spillover effects, spatial econometric models are employed.

Literature review

The spatial mismatch hypothesis was initially developed in Kain's (1968) influential article, 'Housing segregation, negro unemployment and metropolitan segregation'. Kain argued that employment outcomes of African Americans were limited because of (1) employment decentralisation, (2) residential segregation, and (3) the significant effects of distance on job search and commuting costs. Using data from 98 workplace areas in Chicago and Detroit, he found that African American employment decreased as the distance from the centre of the inner-city increased.

Since Kain's initial publication, a number of studies have examined the spatial mismatch hypothesis in US metropolitan regions. Offner and Saks (1971) criticised Kain's empirical results. They retested the hypothesis using Kain's data, and found that the results were sensitive to specification error. Ellwood (1986) found that accessibility only slightly affects labour market outcomes, and suggested that there is no evidence that job proximity affects the differential in black–white employment rates at least in the Chicago metropolitan area. He argued that 'race, not space' is the key factor in explaining labour market outcomes.

In the 1990s, several authors reviewed the literature on the spatial mismatch, but they presented different conclusions with different perspectives (Holzer, 1991; Ihlanfeldt, 1992; Jencks and Mayer, 1990; Kain, 1992). Kain (1992) and Ihlanfeldt (1992) argued that empirical findings strongly support the hypothesis, while Holzer (1991) argued that the evidence was only moderately significant, but not substantial. On the other hand, Jencks and Mayer (1990) concluded that increasing employment accessibility has unclear effects on labour market outcomes and policy makers should be cautious.

Different results across the research literature may be the result of different measurement and methodological choices (Bania et al., 2008; Houston, 2005; Ihlanfeldt, 2006; Mouw, 2000). In order to address endogeneity linking neighbourhood locations and labour market outcomes, some studies have attempted alternative approaches, such as focusing on teenagers who recently finished school and found a job. Because teenagers live with their parents, their residential location could be considered to be exogenous. Ellwood (1986) showed that job proximity had a small effect on youth unemployment rates in Chicago. However, his result was criticised because his calculation of the geographic distribution of employment was based on a small sample of workers. O'Regan and Quigley (1998) pointed out that this approach also suffers from the endogeneity problem because children's labour force outcomes are highly correlated with that of their parents.

Raphael (1998) noted the shortcomings of cross-sectional data-based analysis, and used employment growth (not employment levels) to measure job accessibility. He concluded that black male youth in the San Francisco-Oakland-San Jose metropolitan area are disadvantaged because they live in neighbourhoods with weak or negative employment growth. However, the general applicability of the results to broader labour market conditions remains difficult (Bania et al., 2008).

More recently, scholars have attempted to deal with the endogeneity problem using data from multiple time periods (Bania et al., 2008; Matas et al., 2010; Mouw, 2000). Mouw (2000) used two time periods of data for census tracts in Chicago and Detroit, and found that a decline in the spatial proximity of jobs was associated with an increase in the unemployment rates for African Americans. Bania et al. (2008) used a longitudinal data set for welfare recipients in Cleveland, Ohio. They also used a number of different job accessibility measures, but found no significant evidence that job accessibility affects labour market outcomes. Matas et al. (2010) controlled for endogeneity by using a reduced form of an employment probability equation, and they found that low job accessibility via public transport was negatively associated with female employment probability in Barcelona and Madrid.

Stoll and Covington (2012) argued that racial segregation between blacks and whites was the primary determinant in spatial mismatch. Barton and Gibbons (2017) found that the concentration of different forms of transit was associated with changes in neighbourhood median household income. However, Hu (2015) argued that inner-city poor job seekers did not face a spatial mismatch because their job accessibility was higher than that of job seekers in suburban areas. Many of these studies did not directly address the endogeneity between accessibility and labour market outcomes.

Overall, since Kain's (1968) analysis, a number of studies have indicated the importance of job accessibility on employment outcomes, especially for disadvantaged populations. Nevertheless, there is still no consensus in the literature as to the existence or magnitude of the effect. This present research attempts to contribute to this literature with a longitudinal approach that appropriately addresses endogeneity.

Methods

Measuring the access to employment opportunities

One of the key issues in spatial mismatch research is how to measure job accessibility for individual residential locations. For a long time, Hansen's (1959) gravity-based models have been the most widely used to measure accessibility to employment opportunities. The basic equation is as follows:

$$A_i = \sum_j E_j e^{-\gamma d_{ij}} \qquad (1)$$

where, A_i is the accessibility index for location i, E_j is the number of jobs in location j, d_{ij} is the Euclidean distance between location i and j, γ is an empirically derived impedance coefficient, $i = 1, 2, \ldots, N$, and $j = 1, 2, \ldots, N$.

The main advantage of this model is that it provides a simple and accurate single parameter measurement of actual commuting patterns (Cervero et al., 1999). However, Shen (1998) refined the basic gravity model for measuring accessibility. He argued that demand potential should be considered when measuring accessibility since employment opportunities exist in locations with various levels of demand potential. He suggested the formulation of a refined gravity-based model as follows:

$$A_i = \sum_j \frac{E_j e^{-\gamma d_{ij}}}{D_j}, \; D_j = \sum_j P_k e^{-\gamma d_{ij}} \qquad (2)$$

where A_i is the accessibility of people living in a location i, D_j is the demand potential in a location j, and P_k is the number of people in a location k seeking the job opportunities, $k = 1, 2, \ldots, N$. Based on this equation, we estimate the demand for jobs that are located in block group j from job seekers in block group k. Potential job seekers are defined as persons 18–64 years old in this study.

Shen's refined model is more effective than Hansen's original accessibility measure because it overcomes and improves the limitations of Hansen-type accessibility by accounting for employment competitors. Several current studies adopted this formula to measure job accessibility, and showed its applicability (Hu, 2013, 2015). Using this equation, we calculate separate job-accessibility measures for African American households, white households and low- and high- income[1] households. In a neighbourhood, we calculate five accessibility measures such as total job accessibility, African American job accessibility, white job accessibility, low-income job accessibility and high-income job accessibility to examine their effects on labour market outcomes. In order to match job seekers and job opportunities, we use different industrial segments in calculating job accessibility for low-income and African American households, as discussed in section 'Data'.

Model specification

Endogeneity issues. Residential location is likely to be endogenous to other individual factors that influence labour market outcomes. There are at least three reasons for endogeneity (Ihlanfeldt, 2006). First, residential locations are self-selected. Residential locations are not randomly assigned, instead people choose their location to achieve their utility maximisation. If workers with high-paying jobs choose neighbourhoods with higher employment opportunities, estimation results may be biased. The second reason is that reverse causality may exist (i.e. labour market outcomes also can affect job accessibility). Empirical studies on residential location and travel behaviour have shown that individual commuting distance increases when income increases. If household income increases, people trade off their commuting costs (i.e. job accessibility) for housing values or neighbourhood attributes. Third, higher levels of employment accessibility are capitalised into land rents and housing prices, thus making household sorting by employment accessibility a function of income.

To test the spatial mismatch hypothesis, the basic model can be illustrated by the following linear equation (Ihlanfeldt, 2006; Mouw, 2000):

$$LMO_{it} = \beta_1 A_{it} + \beta_2 X_{it} + \beta_3 P_{it} + H_j + \varepsilon_{it} \tag{3}$$

where i is an individual worker, j is a neighbourhood where the worker i lives at time t, LMO is labour market outcomes, A is the accessibility index, X is observed individual characteristics, P is unobserved individual characteristics, H is fixed-unobserved neighbourhood characteristics, and ε is an error term. It is expected that if β_1 is positive, an increase in job accessibility leads to an improvement in labour market outcomes (i.e. higher income and/or lower unemployment rates).

Scholars have demonstrated that longitudinal data on individual workers could have an advantage in solving endogeneity issues. If we use longitudinal individual data, for example, we obtain the first-difference equation as shown in equation (4). And if it is assumed that individual unobserved characteristics do not change over time ($P_{it+1} - P_{it} = 0$), the unobserved effect of P is differenced out of the model.

$$\begin{aligned} LMO_{it+1} - LMO_{it} &= \beta_1 (A_{it+1} - A_{it}) \\ &+ \beta_2 (X_{it+1} - X_{it}) + \beta_3 (P_{it+1} - P_{it}) \\ &+ \beta_4 (H_{it+1} - H_{it}) + (\varepsilon_{it+1} - \varepsilon_{it}) \end{aligned} \tag{4}$$

However, Mouw (2000) pointed out that the assumption that the workers' unobserved characteristics do not change over time is implausible (i.e. $P_{it+1} - P_{it} \neq 0$). This is because individual preferences can change over time because of changes in age, education, income, marital status or other factors.

Alternatively, we can use neighbourhood-level data to attempt to deal with the endogeneity problem. Using the neighbourhood-level data also has a disadvantage in terms that the demographic attributes of neighbourhoods may change because of migration. But, Mouw (2000) argued that if it is assumed that neighbourhood characteristics do not change over time, a 'fixed-effects' model can be used to estimate the effect of employment accessibility on the change in labour market outcomes over time. Based on his argument, this assumption is more feasible because the characteristics of neighbourhoods do not change much over time. In contrast, individual workers may migrate in and out of a neighbourhood over time based on their own preferences or situations in the labour market. If we use neighbourhood-level data, we can use a mean value of individual socioeconomic characteristics as shown in equation (5). P can be divided into φ_j and ω_{jt}.

$$\overline{P_{it}} = \frac{\sum^{P_{it}}}{N_j} = \varphi_j + \omega_{jt} \tag{5}$$

where N_j is the number of workers in a neighbourhood j, φ_j is neighbourhood-specific characteristics that do not change over time, and ω_{jt} is neighbourhood characteristics that change over time. By assuming that the neighbourhood unobserved characteristics do not change over time ($\omega_{jt} = 0$), we can finally obtain a simple first-difference equation described as follows:

$$\Delta LMO_i = \beta_1 \Delta A_i + \beta_2 \Delta \bar{X}_i + \Delta \varepsilon_i \tag{6}$$

In this case, $\bar{X}$ is average individual characteristics of each neighbourhood. Therefore, instead of individual data, in this study, we use changes in neighbourhood-level data (i.e. 2000 and 2010 census block group data) to investigate how changes in job accessibility influence changes in labour market outcomes. Whereas many previous studies use census tracts as the spatial unit, our block-group data provide for more fine-grained neighbourhood details. Neighbourhood data include detailed information on the spatial location of jobs, which enables us to construct spatial measures of changes in job accessibility over time.

Instrumental variables. Although we use neighbourhood-level data following Mouw's (2000) approach, it cannot fully deal with the endogeneity because changes in accessibility change the composition of neighbourhoods, the neighbourhood composition simultaneously influences accessibility. Hence, we use instrumental variables that are correlated with changes in job accessibility, but not with the labour market outcomes. We sought out instrumental variables focusing on factors affecting firms' location decisions because a spatial distribution of the firms largely influences changes in job accessibility (De Bok and Sanders, 2005; Shen, 1998; Shukla and Waddell, 1991). One component of the spatial mismatch hypothesis is that changes in job accessibility are caused by the relocation of firms (especially from a city centre to suburban areas).

Specifically, we use two instrumental variables: distance to major roadways (including every interstate highway, state highways and arterial roadways) and distance to employment subcentre. These two variables are exogenous but are correlated with changes in job accessibility as they potentially influence firms' location decisions. Firms tend to locate near important transportation infrastructure such as highways or major roads. Subcentres also have substantial effects on the distribution of jobs, as shown in many empirical studies (Giuliano and Small, 1999; Rosenthal and Strange, 2003).

Generally, valid instrumental variables must: (1) be correlated with the endogenous regressor (in this case, changes in job accessibility); and (2) be exogenous to the dependent variable (in this case, labour market outcomes). In terms of the instrument for distance to roadways, the basic framework of the major roadway system in the Chicago metropolitan area has not changed much between 2000 and 2010. We use 2005 roadway network data obtained from the FHA (Federal Highway Administration), and then calculate the distance from each centroid of the block group to the nearest roadway. The road network in the Chicago area is shown in Figure 1. Access to roadways is spatially distributed, as the average distance from each neighbourhood to nearest major roadway is 0.5 miles (see Table 2).

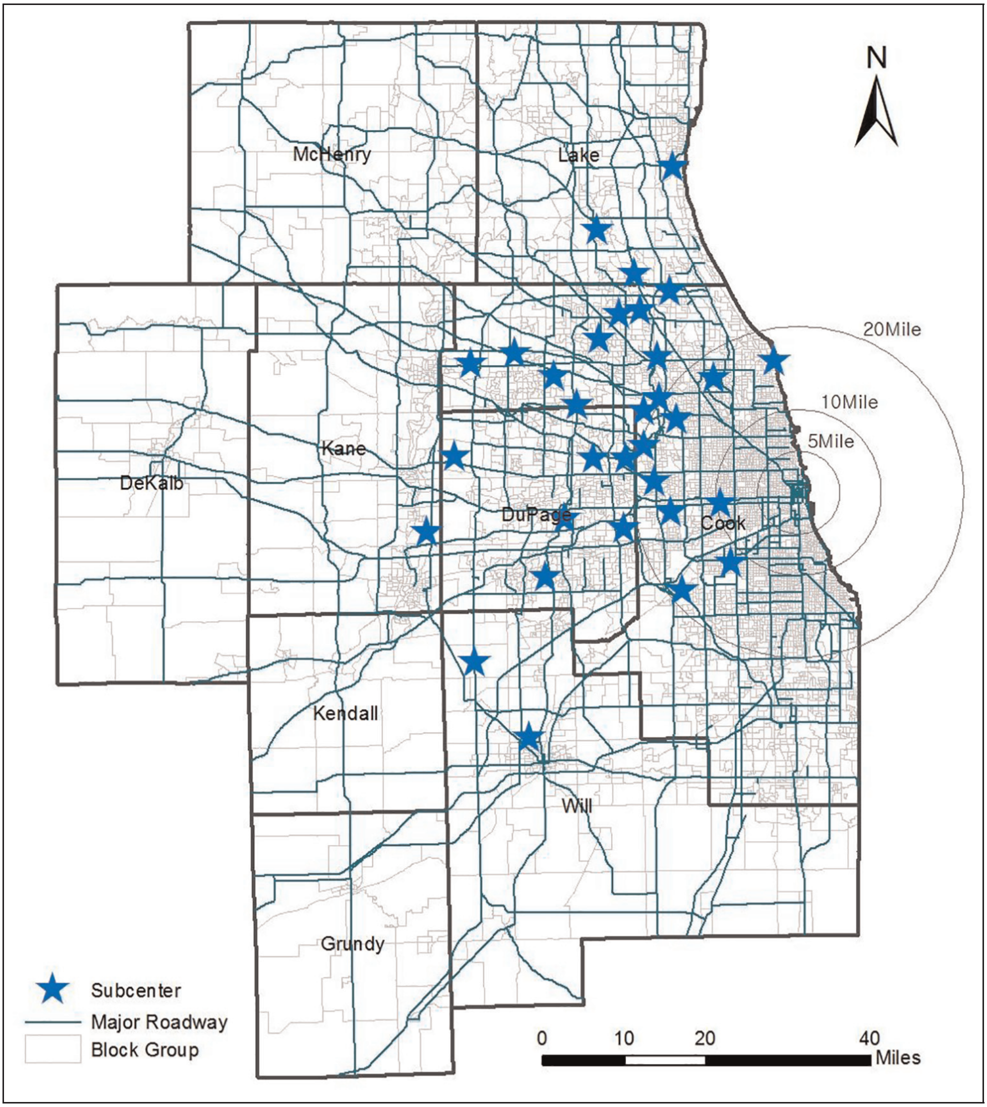

Figure 1. Distribution of subcentres and major roadways in the Chicago metropolitan area.

Subcentre identification has been conducted by several previous studies (Giuliano and Small, 1991; McMillen, 2001, 2003; McMillen and McDonald, 1998). In this study, we adopt the 32 employment subcentres in the Chicago metropolitan region identified by McMillen (2003), and calculate the distance from each centroid of the block group to the nearest subcentre.

Although these instruments have strong theoretical support, one continued concern is that the distribution of distance to subcentres and roads across neighbourhoods may be correlated with unobserved neighbourhood characteristics which affect labour market outcomes. In other words, neighbourhoods close to highways and subcentres may be fundamentally different than nonproximate neighbourhoods. While there is no way to test a priori whether IVs are valid, the concern that unobserved neighbourhood characteristics might influence the dependent variable is adequately addressed by our fixed-effects framework.

We implement instrumental variables techniques by using a two-stage least squares (2SLS) estimator. However, because of the spatial effects described in the next section, we utilise a generalised spatial two-stage least square (GS2SLS) estimator (Drukker et al., 2013a, 2013b).

Spatial autocorrelation issues. Generally, it is understood that neighbouring areas have a stronger interaction than geographically distant areas, and that households tend to cluster in neighbourhoods by socio-demographic characteristics. Although spatially correlated errors do not result in biased estimates, these errors can produce inefficient estimates and biased standard errors (Anselin, 1988). Spatial econometric techniques allow for an examination of the role of geographic spillovers by accounting for the spatial characteristics of neighbourhood data.

In this study, we model spatial dependence based on a contiguity-based binary weight matrix. To diagnose the existence of spatial dependence in model residuals, we use Moran's I statistics for residuals, Lagrange multiplier (LM) tests for the lag dependence and error dependence, and robust LM tests for the lag dependence and error dependence with the fixed-effects model. According to Anselin and Rey (1991), Moran's I is commonly used for detecting spatial dependence, but it cannot determine what type of spatial dependences (e.g. spatial lag dependence or spatial error dependence) exists in regression residuals. Therefore, it cannot provide information on which model is appropriate in explaining the spatial dependence.

On the other hand, LM tests for lag and error dependence can detect the characteristics of spatial dependence (Anselin, 1988). However, because the presence of the alternative form of spatial dependence can affect the tests, robust forms of both tests have been used to identify which spatial regression model is more appropriate. In this study two types of spatial econometric models, spatial lag and spatial error, are employed. The spatial lag model (SLM) is depicted as:

$$Y = \rho WY + X\beta + u \tag{7}$$

and the spatial error model (SEM) is described as:

$$\begin{aligned} Y &= X\beta + u \\ u &= \rho Wu + \varepsilon \end{aligned} \tag{8}$$

where Y is the vector of dependent variables, X is the matrix of explanatory variables, W is the spatial weight matrix, u is the vector of residuals, and ε is the vector of error terms that are independent but not necessarily identically distributed. Before using the spatial models, OLS (ordinary least square) models (equation 6) are estimated and LM tests for which spatial model is more appropriate are presented (see section 'Diagnostic test for spatial autocorrelation').

Two-stage least squares model. In the first stage, we estimate the expected value of job accessibility using instrumental variables and controls, as follows:

$$\widehat{\Delta A} = f\left(D_{majorroad}, D_{subcentre}, \Delta\bar{X}\right) \tag{9}$$

where $D_{majorroad}$ is distance to the nearest major roadways and $D_{subcentre}$ is distance to nearest employment subcentre. The second phase is to regress labour market outcomes on estimated job accessibility and neighbourhood variables, as follows:

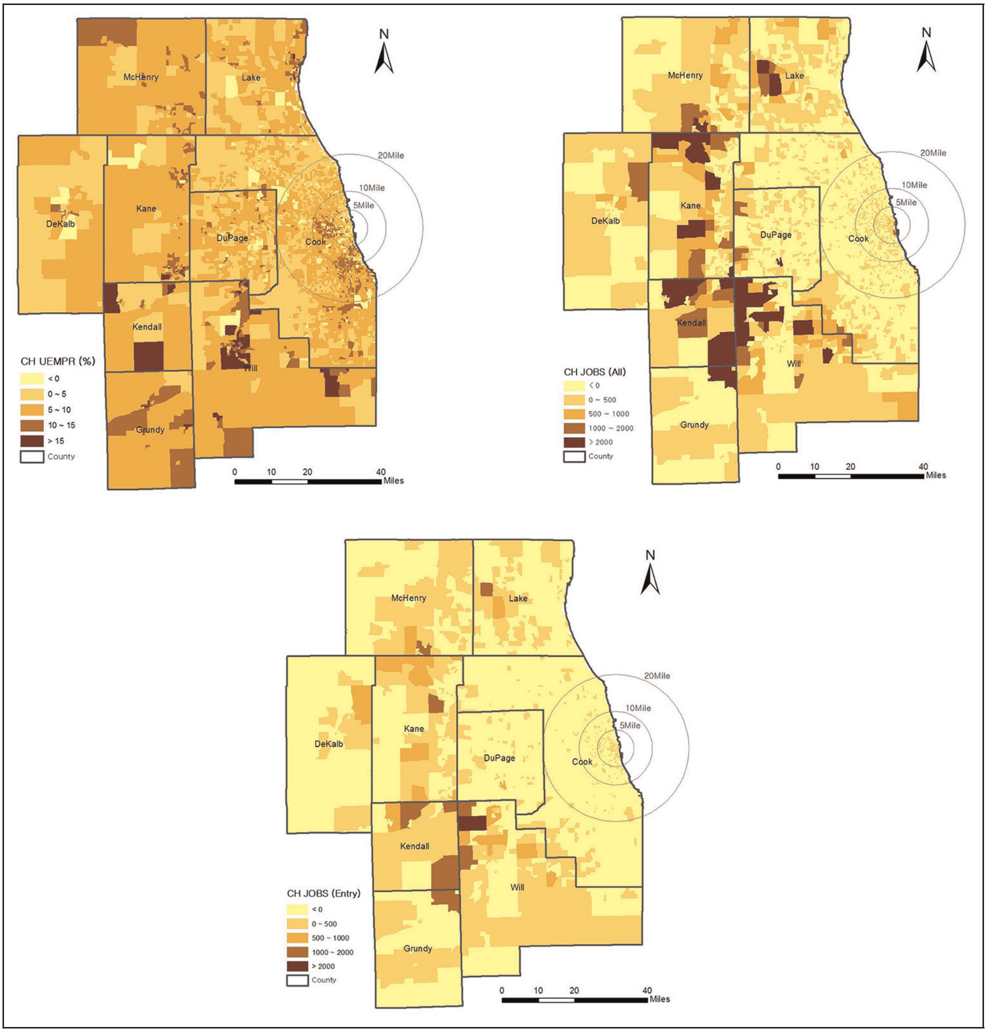

Figure 2. Change in unemployment rates and change in the number of jobs (2000–2010).

$$\Delta LMO = \rho W(\Delta LMO) + \beta_1 \widehat{\Delta A} + \beta_2 \Delta \bar{X} + \varepsilon \quad (10)$$

Study area and data

Study area

Our study area is the Chicago metropolitan region, which includes nine counties: Cook, Dekalb, DuPage, Grundy, Kane, Kendall, Lake, McHenry and Will. Census block group is used as a geographical unit of analysis. The Chicago metropolitan area has one of the highest levels of employment decentralisation among US metropolitan areas (Stoll, 2005), and the unemployment rate is relatively high and concentrated in the inner-city, especially on the south side. As shown in Figure 2, unemployment rates in

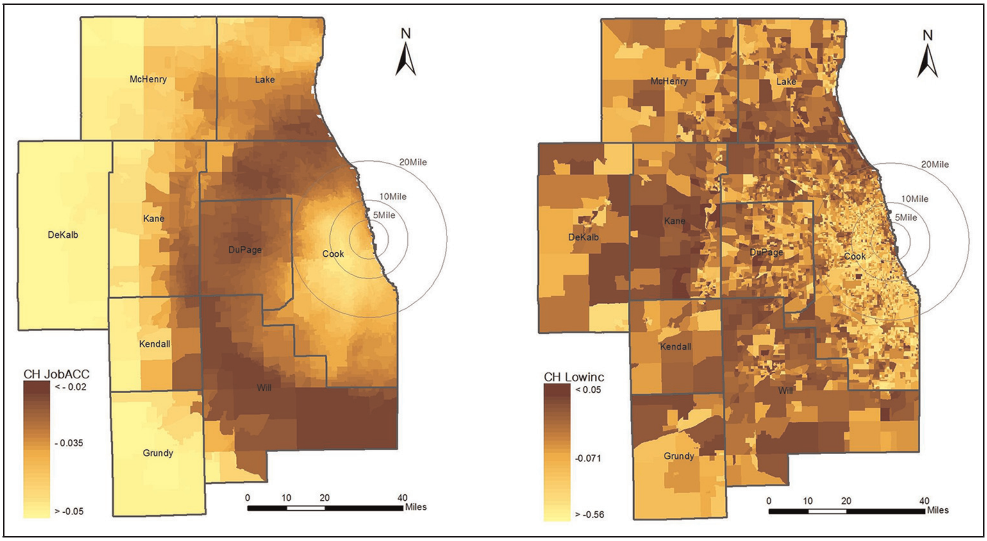

Figure 3. Change in job accessibility and change in fraction of low-income households (2000–2010).

the central Chicago area have increased, whereas jobs have increased in suburban areas between 2000 and 2010, affecting job accessibility during the time period (see Figure 3).

Data

Household data at the neighbourhood level (household size, education, income, race, etc.) come from the 2000 and 2010 census block groups (in consistent boundaries) and are described in Table 2. These data are measured in changes from 2000 to 2010 for each block group. We include 5937 block groups in the nine-county Chicago metropolitan area.

In order to measure employment accessibility at the block-group level, we obtain employment data for 2000 and 2010 at the firm level. Data was acquired through ESRI's Business Analyst and the source data comes from Infogroup.[2] Data is at the firm level, and shows for each firm or business its location, the number of employees, and its industrial classification (two-digit NAICS[3] code). We aggregate the firm level data to the block-group level for both 2000 and 2010 data to count the number of employees (number of 'jobs') in each NAICS sector for each block group. Appendix 3 provides basic statistics on block-group employment data by sector.

It is important here to draw a distinction between our employment data and unemployment data. Employment data used to measure 'job accessibility' is actual counts of the number of jobs, by sector, which are located in any particular census block group. The unemployment rate, based on the census, represents the share of the civilian labour force in a particular block group who are classified as 'unemployed' by the census. Recalling equation (2) above to calculate our accessibility indices, the number of jobs in a block group comes from our employment data and the number of potential job-demanders comes from the census demographic data (by race and income).

Because our employment data is available at the industrial sector level, we can calculate separate accessibility indexes for clusters of

Table 1. Business classification, Chicago metropolitan area (2000–2010).

NAICS code	NAICS sectors	% Employment 2000	% Employment 2010
11	Agriculture, Forestry, Fishing & Hunting	0.21%	0.21%
21	Mining	0.04%	0.04%
23	Construction	5.63%	5.01%
22	Utilities	0.67%	0.61%
48–49	Transportation & Warehousing	5.54%	5.28%
31–33	**Manufacturing**	**15.46%**	**11.09%**
42	**Wholesale Trade**	**4.19%**	**4.10%**
44–45	**Retail Trade**	**10.69%**	**10.27%**
72	**Accommodation & Food Services**	**5.29%**	**5.95%**
51	Information	3.36%	2.54%
52	Finance & Insurance	6.84%	7.60%
53	Real Estate & Rental & Leasing	2.03%	2.38%
54	Professional, Scientific & Technical Services	8.06%	7.70%
56	Administrative & Support & Waste Management & Remediation Services	4.05%	4.66%
61	Education Services	8.01%	9.88%
62	Health Care & Social Assistance	10.11%	12.75%
71	Arts, Entertainment & Recreation	1.74%	1.88%
81	Other Services	4.66%	4.87%
92	Public Administration	3.43%	3.18%
	Total	100.00%	100.00%

Source: Business Analyst, ESRI.

different industrial sectors. Our overall job accessibility index ('ACC' in Table 2) counts all jobs in all industries and uses all working age populations. For reasons described below, we also use all jobs in our accessibility indexes for whites and for high-income households. For developing the accessibility index for low-income and black households, we focus on those industrial sectors more likely to have entry-level or lower-skilled positions available, following Hu (2013). These are shown in bold in Table 1, and include manufacturing, wholesale trade, retail trade, and accommodation/food service. The jobs represent 35% of jobs in the metropolitan area. The five accessibility indexes are used as independent variables in our analysis. Each 'change in job accessibility' measure is the difference between the year-2000 accessibility index and the year-2010 accessibility index.

Empirical results

Descriptive statistics

Table 2 presents descriptive statistics and definitions of the variables used in this study, measured in changes from 2000 to 2010. Labour market outcomes are measured by a block group's unemployment rate and household income. The positive sign on unemployment means that the overall unemployment rate increased during the 2000s. Real median household income shows a decline during this period.

Out of our five accessibility indices (all persons, white and black households, high-income and low-income households), only the index for low-income households increased from 2000 to 2010, likely reflecting the large economic downtown in the later years of the decade. Growth in low-income households in suburban areas (e.g. outside

Table 2. Summary statistics and definition of variables.

Variable	Mean	S.D.	Definition
△UEMR	6.527	3.356	Change of unemployment rates, 2000–2010
△MEDINC	−2658.320	6953.232	Change of median income, 2000–2010
△ACC	−0.035	0.005	Accessibility to all employment opportunities
△ACC_BLACK	−0.246	0.318	Accessibility to African American employment opportunities
△ACC_WHITE	−0.024	0.010	Accessibility to Whites' employment opportunities
△ACC_LOWINC	0.345	0.095	Accessibility to low-income households' employment opportunities
△ACC_HIGHINC	−2.216	0.425	Accessibility to high-income households' employment opportunities
△EDU	0.164	1.723	Change of fraction of above bachelor degree
△BLACK	−0.004	0.026	Change of fraction of African American population
△LOWINC	−0.083	0.061	Change of fraction of low-income household
△HIGHINC	0.056	0.054	Change of fraction of high-income household
△POPDEN	66.891	1783.527	Change of population density
△HHSIZE	−0.035	0.532	Change of household size
△FEMALE	0.003	0.072	Change of fraction of female labour force (age 18~64)
DIST_MAJORROAD	0.464	0.406	Distance to the major roadway (mile)
DIST_SUBCENTER	6.042	9.628	Distance to the employment subcentre (mile)

of the 20-mile radius from the CBD) may also be another possible explanation (see Figure 3). Specifically, persons in poverty have grown in northwest and southwest sides of the city during the 2000s (Paral, 2011: 18). As shown in Figure 3, decreased job accessibility in suburban areas (e.g. outside of the 20-mile radius) is much lower than that of in the inner-city (e.g. within 10 miles from the CBD). This indicates that inner-city jobs have declined much more than suburban jobs, while all the jobs have decreased during the 2000s. The overall job accessibility decline represent continued dispersal of job opportunities to the suburbs, consistent with the results in Figure 3.

In this study, seven neighbourhood control variables are used.[4] The means and standard deviations shown in Table 2 represent the average change in block groups during the period, not the overall change across the region. The average percent of a block-group population which was black and low-income declines during the 2000s, indicating some minimal amount of population dispersion and integration.

Diagnostic test for spatial autocorrelation

The Moran's I diagnostic test reveals that spatial autocorrelation exists in the basic OLS models (equation 6). Moreover, the results of the Local Indicators of Spatial Autocorrelation (LISA) analysis (see Figure 4) suggest that residuals exhibit spatial dependence. The robust LM tests (described in section 'Spatial autocorrelation issues' above) in Tables 3–4 show that spatial lag models are better for all regressions of both unemployment rates and household income.

Effects of employment accessibility on unemployment

The effect of employment accessibility on unemployment rates is modelled using GS2SLS, and presented in Table 5

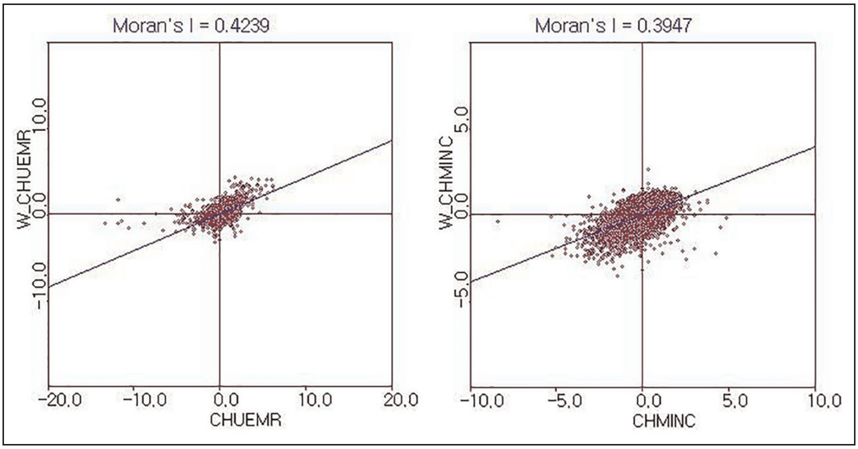

Figure 4. Moran's *I* statistics.

(Appendix 1 presents results of the first stage). Model 1 uses changes in overall job accessibility, Models 2 and 3 are for black and white households, respectively. Models 4 and 5 are for low- and high-income households. In order to verify the validity of instrumental variables, we conduct Hansen's over-identification test with the null hypothesis that the instrumental variables are orthogonal to the regression error. These tests indicate that our instruments are valid except for Model 5 (for high-income households). For high-income households, it could be that the process linking location to unemployment is a fundamentally different process not captured by our instruments.

All of our change in job accessibility indices are statistically significant in predicting changes in unemployment rates. Negative coefficients on changes overall, black and low-income accessibility indicate that, all else being equal, increased job accessibility was associated with reduced unemployment rates. Measured at the mean, a one standard deviation increase in the change in job accessibility for overall jobs would reduce the unemployment rate 0.43 percentage points. Similarly for job accessibility for black and low-income household a one standard deviation increase (0.318 and 0.095) in the change in the accessibility index would likely reduce the unemployment rate 0.57 and 0.47 percentage points, respectively. Particularly, as compared with the magnitude, improvement of accessibility for African American households is the most effective policies in reducing unemployment rates in the Chicago metropolitan area.

These results provide strong evidence consistent with the 'spatial mismatch' hypothesis and suggest that improving job accessibility to those industries more likely to have entry-level employment can reduce unemployment rates for lower-income and African American households. From a regional perspective overall, improving overall job accessibility is associated with reductions in overall unemployment as well. In contrast, changes in accessibility for white is positively associated with unemployment rates. Specifically, a one standard deviation increase in accessibility index would lead to an increase in the unemployment rate of 0.42 percentage points. One possible explanation is that middle-skill jobs have dramatically decreased during the economic recession, which may result in the different patterns of labour market outcomes between

Table 3. Ordinary least square (OLS) models of unemployment rates.

	OLS(1)	OLS (2)	OLS (3)	OLS (4)	OLS (5)
△EDU	−0.0591*	−0.0598*	−0.0627**	−0.0534*	−0.0591*
	(0.0242)	(0.0241)	(0.0239)	(0.0241)	(0.0242)
△BLACK	1.5977	2.0305	7.1130**	−0.8451	1.2944
	(2.3763)	(2.3320)	(2.3675)	(2.3387)	(2.3538)
△LOWINC	−9.9613**	−9.5785**	−8.8644**	−11.4037**	−10.1880**
	(0.8735)	(0.8183)	(0.8168)	(0.8247)	(0.8314)
△HIGHINC	−2.1961**	−2.6952**	−2.1839**	−3.8561**	−2.2764**
	(0.8455)	(0.8361)	(0.8287)	(0.8520)	(0.8393)
△POPDEN	−0.0003**	−0.0002**	−0.0002**	−0.0002**	−0.0003**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
△HHSIZE	−0.4043**	−0.3754**	−0.3635**	−0.3871**	−0.4053**
	(0.0949)	(0.0945)	(0.0939)	(0.0943)	(0.0949)
△FEMALE	0.4536	0.4629	0.3254	0.3187	0.4535
	(0.6020)	(0.5992)	(0.5953)	(0.5984)	(0.6021)
△ACC	−6.7839				
	(9.2913)				
△ACC_BLACK		−1.0129**			
		(0.1352)			
△ACC_WHITE			51.3252**		
			(4.3980)		
△ACC_LOWINC				−4.1927**	
				(0.4777)	
△ACC_HIGHINC					−0.0022
					(0.1037)
CONST	5.6981**	5.7428**	7.2502**	7.3680**	5.9171**
	(0.3193)	(0.0905)	(0.1431)	(0.1863)	(0.2590)
Fixed-effects	Yes	Yes	Yes	Yes	Yes
N	5937	5937	5937	5937	5937
R^2	0.392	0.382	0.308	0.315	0.391
Moran's I	51.0**	51.8**	50.9**	51.3**	52.6**
LM (lag)	2775.6**	2814.5**	2735.5**	2803.4**	2902.4**
Robust LM (Lag)	201.6**	156.9**	182.0**	203.5**	160.1**
LM (error)	2579.9**	2660.8**	2568.7**	2610.7**	2747.6**
Robust LM (error)	5.9*	3.2	15.2**	10.7**	5.3*

Notes: *Significant at 95%; **significant at 99%; std. errors are in parentheses.
Coefficients of all variables are consistent with the results for the GS2SLS models, but less variables of changes in job accessibility are statistically significant in OLS models than in GS2SLS models; When both LM tests reject the null hypothesis, the best way to figure out a better model is to select a model with the largest value for the robust test statistics between SLM and SEM (Anselin, 2005).

African Americans and Whites (Autor, 2011). Hence, even if job accessibility has increased, unemployment rates for white households could increase during the recession. Although further investigations should be followed, this indicates that efforts to provide better accessibility for white households would not be helpful to reduce unemployment rates.

The coefficients of the control variables behave roughly the same in all models and have expected signs. The negative coefficient on education indicates that increases in the proportion of a census block-group

Table 4. Ordinary least square (OLS) models of median household income.

	OLS(6)	OLS (7)	OLS (8)	OLS (9)	OLS (10)
△EDU	116.64**	117.61**	113.68**	110.55**	116.57**
	(38.89)	(39.34)	(39.17)	(39.29)	(39.28)
△BLACK	−9526.17*	−17,287.10**	−10,416.18**	−15,221.04**	−15,260.77**
	(3817.93)	(3808.22)	(3874.58)	(3819.58)	(3819.55)
△LOWINC	−78,067.05**	−83,808.57**	−82,852.72**	−82,896.79**	−82,808.30**
	(1403.52)	(1336.30)	(1336.69)	(1346.81)	(1349.16)
△HIGHINC	46,922.15**	43,960.19**	44,660.74**	46,793.99**	43,999.82**
	(1358.45)	(1365.33)	(1356.25)	(1391.43)	(1361.95)
△POPDEN	0.17*	0.15	0.14	0.12	0.17*
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
△HHSIZE	−48.47	−36.79	−21.11	−103.78	−38.14
	(152.47)	(154.36)	(153.65)	(154.01)	(154.07)
△FEMALE	790.04	795.39	608.94	975.09	736.91
	(967.27)	(978.51)	(974.29)	(977.23)	(976.99)
△ACC	−199,506.50**				
	(14,928.22)				
△ACC_BLACK		−1391.15			
		(1220.72)			
△ACC_WHITE			69,524.69**		
			(7197.67)		
△ACC_LOWINC				6001.06	
				(5780.10)	
△ACC_HIGHINC					1286.47**
					(168.33)
CONST	−17,878.65**	−11,532.72**	−9487.37**	−13,355.40**	−8263.13**
	(513.02)	(147.83)	(234.13)	(304.32)	(420.37)
Fixed-effects	Yes	Yes	Yes	Yes	Yes
N	5937	5937	5937	5937	5937
R^2	0.484	0.472	0.476	0.473	0.473
Moran's I	33.6**	33.2**	32.1**	33.0**	32.5**
LM (lag)	1358.4**	1357.8**	1232.4**	1332.6**	1236.3**
Robust LM (Lag)	304.6**	324.3**	273.8**	315.6**	259.4**
LM (error)	1120.4**	1091.0**	1018.8**	1074.3**	1043.4**
Robust LM (error)	66.6**	57.5**	60.2**	57.3**	66.4**

Notes: *Significant at 95%; **significant at 99%; std. errors are in parentheses.
Coefficients of all variables are consistent with the results for the GS2SLS models, but less variables of changes in job accessibility are statistically significant in OLS models than in GS2SLS models; When both LM tests reject the null hypothesis, the best way to figure out a better model is to select a model with the largest value for the robust test statistics between SLM and SEM (Anselin, 2005).

population with a college degree are associated with decreases in the unemployment rate in that block group. Increases in block-group population density was associated with reduced unemployment, although the magnitude is small. Even though the average percent of a block group that was low income declined over this period for the whole region, Table 5 indicates that an increase in the percent of low-income households in a block group was associated with reductions in unemployment.

Table 5. Spatial two-stage least square models of unemployment rates.

	GS2SLS(1)	GS2SLS(2)	GS2SLS(3)	GS2SLS(4)	GS2SLS(5)
△EDU	−0.0605*	−0.0610**	−0.0627**	−0.0585*	−0.0614**
	(0.0237)	(0.0235)	(0.0232)	(0.0234)	(0.0238)
△BLACK	5.1080*	2.6062	6.1422*	0.8281	3.8835
	(2.4142)	(2.2810)	(2.4268)	(2.3446)	(2.4086)
△LOWINC	−6.6230**	−8.3501**	−8.2282**	−9.4469**	−7.8401**
	(0.9615)	(0.8204)	(0.8236)	(0.8881)	(0.9029)
△HIGHINC	−1.3615	−3.1312**	−2.3126**	−2.7266**	−2.8249**
	(0.8422)	(0.8164)	(0.8010)	(0.9330)	(0.8289)
△POPDEN	−0.0001**	−0.0001**	−0.0001**	−0.0001**	−0.0001**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
△HHSIZE	−0.3765**	−0.3336	−0.3485**	−0.3727**	−0.3512**
	(0.0933)	(0.0926)	(0.0915)	(0.0918)	(0.0937)
△FEMALE	0.3720	0.3788	0.2427	0.3001	0.3205
	(0.5911)	(0.5857)	(0.5786)	(0.5813)	(0.5914)
△ACC	−86.6337**				
	(16.9928)				
△ACC_BLACK		−1.8022**			
		(0.2222)			
△ACC_WHITE			42.6760**		
			(8.0984)		
△ACC_LOWINC				−4.9486**	
				(1.2677)	
△ACC_HIGHINC					1.0942**
					(0.3073)
CONST	2.6208**	5.1322**	6.4908**	5.6148**	8.0034**
	(0.5417)	(0.1418)	(0.2674)	(0.4609)	(0.7764)
Spatial lag term	0.0120**	0.0128**	0.0146**	0.0172**	0.0133**
	(0.0031)	(0.0030)	(0.0029)	(0.0029)	(0.0032)
Fixed-effects	Yes	Yes	Yes	Yes	Yes
N	5937	5937	5937	5937	5937
R^2	0.402	0.401	0.402	0.402	0.400
Over-identification	0.024	0.463	0.090	2.644	5.249**

Notes: *Significant at 95%; **significant at 99%; std. errors are in parentheses.

Effects of employment accessibility on household income

Our analysis of the effects of changes in job accessibility on household income is presented in Table 6. Over-identification tests indicate that the instrumental variables used in these models are valid for models 7–9, but not for the overall accessibility and accessibility for high-income households.

Although improved job accessibility reduces unemployment for African American households, the results in Table 6 do not show a statistically significant change in real median household income at the block-group level. Recall that the time period in question did see an overall reduction in median household income, so it is possible that households improved their employment status but were no better (nor worse) off in terms of income. However, the coefficient on changes in job accessibility for low-income households are statistically significant and positive. A one unit increase in the change in job accessibility for index for

Table 6. Spatial two-stage least square models of median household income.

	GS2SLS(6)	GS2SLS(7)	GS2SLS(8)	GS2SLS(9)	GS2SLS(10)
△EDU	108.31**	107.50**	105.93**	91.60*	106.61**
	(36.17)	(35.99)	(35.96)	(36.61)	(36.26)
△BLACK	−5224.89	−10,073.71**	−7239.52	−4674.45	−7651.21*
	(3669.76)	(3507.44)	(3747.67)	(3675.16)	(3670.34)
△LOWINC	−66,037.84**	−67,896.48**	−67,658.55**	−66,067.81**	−67,552.64**
	(1548.80)	(1503.03)	(1499.99)	(1548.40)	(1514.28)
△HIGHINC	43,163.40**	40,458.65**	40,793.61**	45,855.49**	40,465.97**
	(1368.27)	(1259.07)	(1259.12)	(1545.55)	(1267.15)
△POPDEN	0.08*	0.08*	0.08*	0.06	0.09**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
△HHSIZE	72.26	90.18	94.99	1.15	108.55
	(141.94)	(141.46)	(141.31)	(143.82)	(142.81)
△FEMALE	757.64	752.29	673.14	1159.85	696.75
	(899.82)	(895.32)	(894.88)	(910.89)	(902.18)
△ACC	−149,347.00**				
	(30,382.84)				
△ACC_BLACK		−498.22			
		(351.92)			
△ACC_WHITE			29,514.46*		
			(12,994.66)		
△ACC_LOWINC				12,824.79**	
				(2122.84)	
△ACC_HIGHINC					1499.70**
					(571.72)
CONST	−14,157.70**	−8916.94**	−8071.69**	−13,463.03**	−5507.51**
	(1118.78)	(214.49)	(346.48)	(804.95)	(1244.88)
Spatial lag term	0.05**	0.06**	0.06**	0.06**	0.06**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Fixed-effects	Yes	Yes	Yes	Yes	Yes
N	5937	5937	5937	5937	5937
R^2	0.550	0.566	0.566	0.503	0.536
Over-identification	11.118**	2.471	2.091	1.087	12.265**

Notes: *Significant at 95%; **significant at 99%; std. errors are in parentheses.

low-income households was associated with a US$12,825 increase in median household income at the block-group level.

In other words, standard deviation (0.095) of job accessibility for low-income households suggests that a one standard deviation increase in job accessibility for low-income households leads to an increase in median household income of US$1218. Similarly, increased job accessibility for white leads to US$637 increase in median household income, respectively. This result indicates that the increased job accessibility provides economic benefits regarding median household income for specific groups including white and low-income households. As compared with the magnitude of the standardised coefficients, job accessibility is more important for low-income households. With respect to the spatial mismatch hypothesis, an increase in job accessibility by providing entry-level jobs for low-income households enables poor households to have better earnings, after controlling for the endogeneity.

The differences in effects of changes in job accessibility on household income between white and black may represent ongoing occupational segregation and/or continued discrimination in employment. But the large effects of accessibility on low-income households' income suggests that improving job accessibility can potentially produce large gains in household welfare.

The control variables function as expected. Increases in education level and population density were associated with increased income. The percent of block-group residents who are black is only significant in the regression utilising the 'black accessibility' index measure, which may explain the statistical insignificance of the accessibility index on income and indicating the continued effects of residential segregation.

Discussion and conclusions

This study contributes to the 'spatial mismatch' literature and finds evidence consistent with Kain's hypothesis. Our contribution to the literature includes addressing this issue with measuring changes in accessibility, using sector-specific employment data, employing fixed-effects and instrumental variable techniques, and correcting for spatial effects. Turning specifically to Kain's hypothesis, we find that improving employment accessibility for black households is statistically significant in reducing unemployment, even in a decade when overall unemployment increased. While black households with improved employment accessibility had lower unemployment, this did not translate into increased household income in a period of declining household income. The effects of accessibility on labour market outcomes, while significant, are limited and mixed.

As compared with job accessibility between 2000 and 2010, overall job access has decreased during the 2000s in Chicago because of the economic recession. Obviously, an economic downturn during the period has significantly affected a decrease in jobs and thus an increase in unemployment rates, which consequently results in the decreased job accessibility for groups of blacks, whites and high-income households. Nevertheless, one of the important findings is that increases in employment proximity to those four industrial sectors thought to provide more entry-level job opportunities for African Americans and low-income households lead to decreases in unemployment rates and increases in household income at the neighbourhood level. In order to compare the effects of job accessibility measured by entry-level jobs with the job accessibility measured by all jobs, we calculated additional job accessibility for black and low-income households and estimate their effects on labour market outcomes. As shown in Appendix 2, increased job accessibility for low-income households measured by all jobs would not improve labour market outcomes, rather can lead to an increase in unemployment rates and a decrease in household income. In addition, the effect of increased job accessibility for African American households influences a reduction of unemployment rates, but its effect ($0.58*0.67 = 0.39$) is smaller, as compared with the effect of job accessibility measured by entry-level jobs ($1.80*0.31 = 0.56$).

These results suggest important policy implications that improvement of access to entry-level jobs for job seekers those who are in groups of African Americans and low-income households contributes to better labour market outcomes. Providing better matched-jobs would be even better for them. Therefore, policy makers should carefully consider how to improve access to employment opportunities for them. One caution is that while increasing job accessibility for African Americans reduces unemployment rates, it does not improve their incomes. Two possible explanations are suggested. First, household income used in this study is not wage income, thus cannot be used as a direct measure of labour market outcomes. Income includes other 'money' received, thus it is much broader than wages. Second, workers who live in places of higher accessibility for African Americans are more likely to be employed, but they tend to have lower wage incomes potentially because of entry-level job opportunities.

One necessary simplification in this study is the use of 'distance' to measure accessibility rather than true measures of travel time. What this means is that improvements in accessibility would only measure either moving people closer to jobs or moving jobs closer to people. Many metropolitan regions across the country are also experimenting with improving the travel time and costs in transporting underemployed persons to available jobs, something our model would not necessarily capture. Further study would be needed to test whether improvements in travel time have similar effects on labour market outcomes. Moreover, our model cannot estimate the cost–benefit ratio of investments in facilitating job growth in the central city as opposed to expanding affordable housing opportunities in suburban job centres.

Stoll (2005) ranked all the metropolitan regions in the USA in terms of 'job sprawl' and the spatial mismatch between black residents and jobs. In terms of the largest 95 US metropolitan regions (population over 500,000), Chicago has the 22nd highest level of 'job sprawl', consistent with our own analysis in Figures 2 and 3. With a high degree of job dispersal, it is possible that improving housing opportunities in suburban areas with high employment opportunities is more likely to improve 'job accessibility' (particularly for African American and lower-income households) than are policies designed to try to reinvigorate employment in the central areas of the city. In the suburban areas of Cook County and the surrounding eight counties, the majority of the housing is single-family housing (CMAP, 2015). Paulsen (2012) shows that increasing the diversity of the suburban housing stock can significantly improve outcomes for lower-income and minority households. The results presented here also suggest that expanding housing opportunities in closer proximity to jobs in the four sectors identified in our analysis would likely reduce unemployment in African American and low-income households.

Our results, however, are not without limits. Our analysis only examines black and white households, but further research should include Hispanic and Asian households to test whether job accessibility plays the same role across communities because their proportion has substantially grown, and currently they have also experienced high unemployment rates (Weigensberg et al., 2011). Our research (like Kain's and others) focuses on Chicago, a more traditional (post)-industrial city. Our methodology can be replicated in other regions of the country, and comparative analysis would show whether accessibility matters more or less in more centre-dominated or dispersed regions.

Acknowledgement

We would like to thank the three anonymous reviewers who provided helpful comments on this paper.

Funding

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Notes

1. Low-income households are defined to have annual income below US$25,000 (approximately the bottom 20%), while high-income households have annual income above US$100,000 (approximately the top 20%).
2. ESRI (http://www.esri.com/software/business analyst/data-and-reports) collects national unique business data from Infogroup (http://www.infogroup.com).
3. The North American Industry Classification System.
4. Correlations among explanatory variables are available upon request and diagnostics for multicollinearity indicate no concerns.

References

Anselin L (1988) Lagrange multiplier test diagnostics for spatial dependence and spatial heterogeneity. *Geographical Analysis* 20(1): 1–17.

Anselin L (2005) *Exploring Spatial Data with GeoDa: A Workbook*. Urbana, IL, Spatial Analysis Laboratory, Department of Geography, University of Illinois, Center for Spatially Integrated Social Science (CSISS).

Anselin L and Rey S (1991) Properties of tests for spatial dependence in linear regression models. *Geographical Analysis* 23(2): 112–131.

Arnott R (1998) Economic theory and the spatial mismatch hypothesis. *Urban Studies* 35(7): 1171–1185.

Autor D (2011) The polarization of job opportunities in the U.S. labor market: Implications for employment and earnings. *Community Investments* 23(2): 11–16.

Bania N, Leete L and Coulton C (2008) Job access, employment and earnings: Outcomes for welfare leavers in a US urban labor market. *Urban Studies* 45(11): 2179–2202.

Barton M and Gibbons J (2017) A stop too far: How does public transportation concentration influence neighborhood median household income? *Urban Studies* 54(2): 538–554.

Boustan L and Margo R (2009) Race, segregation, and postal employment: New evidence on spatial mismatch. *Journal of Urban Economics* 65(1): 1–10.

Cervero R, Rood T and Appleyard B (1999) Tracking accessibility: Employment and housing opportunities in the San Francisco Bay Area. *Environment and Planning A* 31(7): 1259–1278.

Cervero R, Sandoval O and Landis J (2002) Transportation as a stimulus of welfare-to-work: Private versus public mobility. *Journal of Planning Education and Research* 22(1): 50–63.

Chicago Metropolitan Agency for Planning (CMAP) (2015) Housing stock diversity in metropolitan Chicago. Agency report. Available at: http://www.cmap.illinois.gov/about/updates/policy/-/asset_publisher/U9jFxa68cnNA/content/housing-stock-diversity-in-metropolitan-chicago.

De Bok M and Sanders F (2005) Firm relocation and accessibility of locations: Empirical results from the Netherlands. *Transport Research Record* 1902: 35–43.

Drukker D, Egger P and Prucha I (2013a) On two-step estimation of a spatial autoregressive model with autoregressive disturbances and endogenous regressors. *Econometric Reviews* 32(5–6): 686–733.

Drukker D, Prucha I and Raciborski R (2013b) Maximum likelihood and generalized spatial two-stage least-squares estimators for a spatial-autoregressive model with spatial-autoregressive disturbances. *The Stata Journal* 13(2): 221–241.

Ellwood D (1986) The spatial mismatch hypothesis: Are there teenage jobs missing in the ghetto? In: Freeman RB and Holzer HJ (eds) *The Black Youth Employment Crisis*. Chicago, IL: University of Chicago Press, pp. 147–185.

Giuliano G and Small K (1991) Subcenters in the Los Angeles region. *Regional Science and Urban Economics* 21: 163–182.

Giuliano G and Small K (1999) The determinants of growth of employment subcenters. *Journal of Transport Geography* 7: 189–201.

Grengs J (2010) Job accessibility and the modal mismatch in Detroit. *Journal of Transport Geography* 18(1): 42–54.

Hansen W (1959) How accessibility shapes land use. *Journal of the American Institute of Planners* 25(2): 73–76.

Hellerstein J, Neumark D and Mclnerney M (2008) Spatial mismatch or racial mismatch? *Journal of Urban Economics* 64(2): 464–479.

Holzer H (1991) The spatial mismatch hypothesis: What has the evidence shown? *Urban Studies* 28(1): 105–122.

Houston D (2005) Methods to test the spatial mismatch hypothesis. *Economic Geography* 81(4): 407–434.

Hu L (2013) Changing job access of the poor: Effects of spatial and socioeconomic transformations in Chicago, 1990–2010. *Urban Studies* 51(4): 675–692.

Hu L (2015) Job accessibility of the poor in Los Angeles: Has suburbanization affected spatial mismatch? *Journal of the American Planning Association* 81(1): 30–45.

Ihlanfeldt K (1992) *Job Accessibility and the Employment and School Enrollment of Teenagers*. Kalamazoo, MI: W. E. Upjohn Institute for Employment Research.

Ihlanfeldt K (2006) A primer on spatial mismatch within urban labor markets. In: Arnott R and McMillen D (eds) *A Companion to Urban Economics*. Boston, MA: Blackwell Publishing, chapter 24.

Ihlandfeldt K and Sjoquist D (1998) The spatial mismatch hypothesis: A review of recent studies and their implications for welfare reform. *Housing Policy Debate* 9(4): 849–892.

Jencks C and Mayer S (1990) Residential segregation, job proximity, and black job opportunities. In: Lynn LE and McGeary M (eds) *Inner-City Poverty in the United States*. Washington, DC: National Academy Press, pp. 187–222.

Kain J (1968) Housing segregation, negro employment, and metropolitan decentralization. *Quarterly Journal of Economics* 82(2): 175–197.

Kain J (1992) The spatial mismatch hypothesis: Three decades later. *Housing Policy Debate* 3(2): 371–392.

Kawabata M (2003) Job access and employment among low-skilled autoless workers in U.S. Metropolitan Areas. *Environment and Planning A* 35(9): 1651–1668.

McMillen D (2001) Nonparametric employment subcenter identification. *Journal of Urban Economics* 50: 448–473.

McMillen D (2003) Employment subcenters in Chicago: Past, present, and future. *Economic Perspectives* 2Q: 2–14.

McMillen D and McDonald J (1998) Suburban subcenters and employment density in metropolitan Chicago. *Journal of Urban Economics* 43: 157–180.

Matas A, Raymond J and Roig J (2010) Job accessibility and female employment probability: The cases of Barcelona and Madrid. *Urban Studies* 47(4): 769–787.

Mouw T (2000) Job relocation and the racial gap in unemployment in Detroit and Chicago, 1980 to 1990. *American Sociological Review* 65(5): 730–753.

Offner P and Saks D (1971) A note on John Kain's 'Housing segregation, negro employment and metropolitan decentralization'. *The Quarterly Journal of Economics* 85(1): 147–160.

Ong P and Houston D (2002) Transit, employment, and women on welfare. *Urban Geography* 23(4): 344–364.

Ong P and Miller D (2005) Spatial and transportation mismatch in Los Angeles. *Journal of Planning Education and Research* 25(1): 43–56.

O'Regan K and Quigley J (1998) Where youth live: Economic effects of urban space on employment prospects. *Urban Studies* 35(7): 1187–1205.

Paral R (2011) What does the 2010 Census tell us about metropolitan Chicago. The Chicago Community Trust and Affiliates, Midwest and Illinois Publications. Available at: http://www.robparal.com/downloads/CCT_2010CensusFindings_0511.pdf.

Paulsen K (2012) The evolution of suburban relative housing-unit diversity. *Housing Policy Debate* 22(3): 407–433.

Raphael S (1998) The spatial mismatch hypothesis and black youth joblessness: Evidence from the San Francisco Bay Area. *Journal of Urban Economics* 43(1): 79–111.

Rosenthal S and Strange W (2003) Geography, industrial organization, and agglomeration. *The Review of Economics and Statistics* 85(2): 377–393.

Sanchez T (1999) The connection between public transit and employment: The cases of Portland and Atlanta. *Journal of the American Planning Association* 65(3): 284–296.

Shen Q (1998) Location characteristics of inner-city neighborhoods and employment accessibility of low-wage workers. *Environment and Planning B* 25(3): 345–365.

Shukla V and Waddell P (1991) Firm location and land use in discrete urban space: A study of the spatial structure of Dallas-Fort Worth. *Regional Science and Urban Economics* 21: 225–253.

Stoll M (2005) *Job Sprawl and the Spatial Mismatch Between Blacks and Jobs*. Washington, DC: The Brookings Institution.

Stoll M and Covington K (2012) Explaining racial/ethnic gaps in spatial mismatch in the US: The primary of racial segregation. *Urban Studies* 49(11): 2501–2521.

Taylor B and Ong P (1995) Spatial mismatch or automobile mismatch? An examination of race, residence and commuting in US metropolitan areas. *Urban Studies* 32(9): 1453–1473.

Wachs M and Taylor B (1998) Can transportation strategies help meet the welfare challenge? *Journal of the American Planning Association* 64(1): 15–19.

Weigensberg E, Kreisman D, Park K, et al. (2011) Chicago's labor force in context. Chicago. Chapin Hall at the University of Chicago. Available at: https://www.chapinhall.org/sites/default/files/Chicago_Context_Report_1.pdf.

Appendix 1

First-stage regression of changes in job accessibility.

	△ACC	△ACC_BLACK	△ACC_ WHITE	△ACC_ LOWINC	△ACC_ HIGHINC
DIST_MAJORROAD	0.0005**	0.0131*	−0.0009**	−0.0189**	−0.0952**
	(0.0001)	(0.0076)	(0.0003)	(0.0030)	(0.0136)
DIST_SUBCENTER	−0.0003**	−0.0351**	0.0009**	0.0022**	0.0154**
	(0.0000)	(0.0007)	(0.0000)	(0.0002)	(0.0010)
△EDU	0.0000	−0.0005	0.0001	0.0012	0.0010
	(0.0000)	(0.0019)	(0.0001)	(0.0006)	(0.0030)
△BLACK	0.0428**	0.6350**	−0.1105**	−0.4878**	−2.2275**
	(0.0031)	(0.1835)	(0.0061)	(0.0629)	(0.2888)
△LOWINC	0.0324*	0.5719**	−0.0245**	−0.2739**	−1.3405**
	(0.0011)	(0.0644)	(0.0021)	(0.0221)	(0.1014)
△HIGHINC	0.0152**	−0.0108	−0.0112**	−0.3866**	0.2653*
	(0.0011)	(0.0658)	(0.0022)	(0.0225)	(0.1035)
△POPDEN	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
△HHSIZE	0.0000	0.0074	−0.0003	0.0056*	−0.0241*
	(0.0001)	(0.0074)	(0.0002)	(0.0025)	(0.0117)
△FEMALE	0.0003	0.0359	0.0018	−0.0354*	0.0145
	(0.0008)	(0.0471)	(0.0016)	(0.0162)	(0.0742)
CONST	−0.0318**	0.0027	−0.0301**	0.3423**	−2.3829**
	(0.0001)	(0.0084)	(0.0003)	(0.0029)	(0.0132)
N	5937	5937	5937	5937	5937
R^2	0.298	0.346	0.287	0.133	0.100

Notes: *Significant at 95%; **significant at 99%; std errors are in parentheses.

Although the first-stage regression results reported here are subject to endogeneity, interpretation can provide some theoretical justification for our use of distance to roadways and subcentres as instruments. As can be seen, the 'effect' of distance to roads and subcentres changes between the overall accessibility and accessibility for black households, and those for white households and the two income categories. It is important to remember in interpreting these results that the dependent variable is measured in the change in accessibility, and that average accessibility by block group declined during this period for all except the low-income group (Table 2).

For overall accessibility (all jobs, all households), block groups which were further away from major roads saw more increases in accessibility than did block groups which were closer to major roads. Given the relatively dispersed nature of major roadways (Figure 1), this result would mean that either more jobs were created in places further away from roads, or that people moved away from block groups closer to roads and into block groups further away from roads. Our analysis of the jobs-change maps suggests that the first explanation is more significant: jobs were moving away from census block groups closer to major roadways. This is consistent with a general story of the dispersal of employment opportunities throughout the metropolitan areas. The negative coefficient on job subcentre distance means that block groups which were located closer to job subcentres saw increases in accessibility. This could reflect either additional job growth in existing subcentres or additional housing being constructed in block groups close to subcentres. While we do not have the data to discriminate amongst these two explanations, the data suggest that both phenomena occurred during this period.

For black households, recall that the index measures how accessible jobs in the four sectors identified in Table 1 are for black households. All else being equal, a block group which was further away from a major roadway saw black job accessibility increase. The results for distance to subcentres for black accessibility is the same as the overall measure.

So why are the results exactly the opposite for white households and for both low- and high-income households? We think that the reason lies in the intersection between different household preferences for living close to work, household income, and the availability of frequent-service public transportation. Recall that the way this accessibility index is constructed, an increase in accessibility can either result from additional jobs being created in an area, or households being able to move closer to jobs (or both). Without additional data and research, we cannot determine a priori which is the case. And we recognise that interpretation of coefficients which clearly suffer from endogeneity is tenuous at best. Because jobs were moving away from proximity to major roadways (reflecting a continuing change from manufacturing industries to service industries which are less roadway-access dependent), overall accessibility increased. But the complicated dynamics of household movement and housing construction as a response to changes in job accessibility are more difficult to determine. Because white households face fewer constraints on housing search, these results could be consistent with white households continuing to move to suburban locations which are nonetheless closer to major roadways because of their need for vehicle-based commuting. Our results, while tentative, are consistent with emerging patterns of job and housing change in the Chicago region, and provide some theoretical reasoning behind using distance to roads and subcentres as instrumental variables.

Appendix 2

Spatial two-stage least square models of unemployment rates and median household income with changes in job accessibility measured by all jobs.

	Unemployment rates		Median household income	
	GS2SLS(10)	GS2SLS(11)	GS2SLS(12)	GS2SLS(13)
△EDU	−0.0588*	−0.0595*	107.45**	103.27**
	(0.0234)	(0.0233)	(35.96)	(36.07)
△BLACK	0.0084	0.9606	−10,120.95**	−3748.02
	(2.2660)	(2.3909)	(3516.97)	(3698.01)
△LOWINC	−10.1780**	−9.3949**	−67,624.90**	−65,082.75**
	(0.8199)	(0.9544)	(1526.77)	(1577.21)
△HIGHINC	−4.7335**	−2.6612**	40,808.29**	47,403.40**
	(0.8667)	(1.0348)	(1341.74)	(1746.02)
△POPDEN	−0.0001**	−0.0001**	0.08*	0.08*
	(0.0000)	(0.0000)	(0.03)	(0.03)
△HHSIZE	−0.3456**	−0.3764**	73.23	52.19
	(0.0919)	(0.0917)	(141.26)	(141.57)
△FEMALE	0.3092	0.3287	748.96	768.40
	(0.5814)	(0.5805)	(894.64)	(897.12)
△ACC_BLACK	−0.5767**		58.39	
	(0.0783)		(120.98)	
△ACC_LOWINC		0.0622		−1343.46**
		(0.1398)		(238.10)
CONST	5.2103**	5.1872**	−8716.59**	−7018.92**
	(0.1399)	(0.2622)	(190.18)	(356.88)
Spatial lag term	0.0159**	0.0173**	0.07**	0.06**
	(0.0029)	(0.0029)	(0.00)	(0.00)
Fixed-effects	Yes	Yes	Yes	Yes
N	5937	5937	5937	5937
R^2	0.401	0.403	0.566	0.554
Over-identification	2.522	1.132	1.687	2.196

Notes: *Significant at 95%; **significant at 99%; std errors are in parentheses.

Appendix 3

Basic statistics of employment data at the block-group level (unit: number).

NAICS code	NAICS sectors	2000				2010			
		Mean	S.D.	Min	Max	Mean	S.D.	Min	Max
11	Agriculture, Forestry, Fishing & Hunting	1.6	5.9	0	76	1.5	6.0	0	82
21	Mining	0.3	1.7	0	32	0.3	1.7	0	36
23	Construction	37.2	40.3	0	496	32.9	45.6	0	870
31-33	Manufacturing	103.1	101.2	0	1351	73.6	85.1	0	1558
42	Wholesale Trade	26.5	31.9	0	503	25.9	35.5	0	639
44-45	Retail Trade	69.8	68.2	0	938	66.7	78.8	0	1445
48-49	Transportation & Warehousing	35.5	35.9	0	596	33.8	39.0	0	707
22	Utilities	4.6	9.6	0	159	4.2	10.1	0	174
51	Information	20.9	28.2	0	378	15.8	22.8	0	413
52	Finance & Insurance	42.4	52.3	0	750	46.5	65.1	0	1220
53	Real Estate & Rental & Leasing	12.8	16.8	0	252	14.9	20.7	0	286
54	Professional, Scientific & Technical Services	49.9	78.4	0	1483	47.9	76.6	0	1402
56	Administrative & Support & Waste Management & Remediation Services	24.9	26.8	0	323	27.7	32.5	0	488
61	Education Services	52.1	58.3	0	1006	64.2	79.0	0	1299
62	Health Care & Social Assistance	65.9	60.0	0	733	82.9	89.4	0	1583
71	Arts, Entertainment & Recreation	11.6	15.8	0	356	12.5	18.9	0	343
72	Accommodation & Food Services	34.7	41.4	0	727	38.7	48.1	0	684
81	Other Services	30.2	29.1	0	378	31.1	33.4	0	525
92	Public Administration	22.2	24.8	0	391	20.9	25.5	0	463