ABSTRACT

Title of Dissertation: RECENT INTRA-METROPOLITAN PATTERNS OF JOBS AND WORKERS: IMPLICATIONS FOR THE SPATIAL MISMATCH HYPOTHESIS

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Since the seminal work of John Kain in the 1960s, scholars have explored the spatial mismatch between suburban job opportunities and the residential segregation of low-income Black populations in the inner city. Since then, the spatial structure of U.S. metropolitan areas has undergone dynamic changes and reshaped the demographic landscape and economic geography, which have important implications for the spatial patterns of mismatch in the 21st century. Particularly, the movement of Black populations to the suburbs has the potential to perpetuate spatial mismatch if those newly suburbanized Black populations continue to be spatially segregated in suburbs apart from where jobs have relocated. Although previous studies provide evidence for continued residential segregation, it is yet unclear how it affects spatial patterns of mismatch for suburban Black populations as well as the changing geography of opportunity.

In this dissertation, I examine the spatial patterns of mismatch with a particular focus on whether the spatial distributions in the 21st century continue to disadvantage the Black

population in accessing job opportunities. I also estimate the differing relationship between the neighborhood job accessibility and labor market outcomes by the residence in the city and the suburb, availability of auto, and the level of residential segregation. By incorporating the geographic scale of segregation and inequality, the measures used in this dissertation captures the spatial interactions with neighboring areas that take into account the spatial clustering as well as the concentration of opportunities and disadvantages.

The results reveal geographical evidence of a shift in the geography of spatial mismatch into the suburbs into which Black populations have predominantly moved since the 1980s, indicating that changes in urban structures contribute to the expansion of inequality of opportunities beyond the boundaries of the inner-city. Further, there is an increasing trend of within- neighborhood subarea inequality in both cities and the suburbs, which suggests a greater spatial heterogeneity at the local geographical level. The study concludes by arguing that the spatial mismatch is not disappearing from U.S. metropolitan areas. Rather, the geography of the spatial mismatch has merely shifted in such a way that the same pattern of neighborhood disadvantages now exists in the suburbs.

RECENT INTRA-METROPOLITAN PATTERNS OF JOBS AND WORKERS: IMPLICATIONS FOR THE SPATIAL MISMATCH HYPOTHESIS

by

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Chapter 1. Introduction

1.1 Problem Statement

The spatial mismatch hypothesis (SMH) of John Kain (1968, 1992) proposes that the spatial segregation of Black populations in the inner city and decentralization of jobs to the suburbs created spatial barriers to accessing jobs and affected employment outcomes for Black populations in the inner city. Kain's hypothesis emphasizes the role of geography in shaping labor market outcomes among Black populations, in which the spatial patterns of residential segregation and the lack of reliable transportation systems create a spatial structure of opportunity (Ihlanfeldt, 1994; Kain, 1968; Raphael, 1998). Kain's work inspired discussions among economists and sociologists during the 1980s and 1990s as segregation and social disadvantages deeply rooted in the inner city increasingly and disproportionately affected Black populations (Holzer, 1991; Ihlanfeldt, 1994; Stoll, 1999a; Wilson, 1987). The unemployment rate of the black male population (15.7 percent) was nearly triple the unemployment rate of white males (5.5 percent) (U.S. Bureau of Labor Statistics, 1984), and the higher black unemployment rate in the inner city than in the suburbs exacerbated the spatial disadvantage of inner city residents in finding employment (Farley, 1987). However, metropolitan areas across the U.S. have undergone dynamic structural changes and the resulting urban development patterns in the postmodern era have been characterized by a demographic shift to the suburbs and polycentric urban development patterns (Downs, 1999; B. Lee, 2007). A recent analysis of the urban landscape in the postmodern era found that only a fraction of cities are structured in a way that follows traditional spatial patterns. The majority of metropolitan areas are now characterized by a suburban and exurban landscape that poses a challenge to overcoming economic inequality issues in metropolitan areas (Wheeler, 2015).

Since Kain first proposed the SMH, U.S. metropolitan areas have undergone dynamic structural changes, such as the suburbanization of Black populations and poverty, polycentric development, the revitalization of inner cities through gentrification and transit-oriented developments (Delmelle, 2017; Ehrenhalt, 2012; Hu, 2015a; Hu & Giuliano, 2011a). The question, then, is whether the suburbanization of Black populations has resolved the spatial mismatch by bringing their residential locations closer to jobs in the suburbs. The movement of Black populations to the suburbs has the potential to perpetuate spatial mismatch if those newly suburbanized Black populations continue to be spatially segregated in suburbs apart from where jobs have relocated. This recreates spatial barriers to job access in the suburbs. This question has sparked discussions on the changing geography of the spatial mismatch beyond the boundaries of the inner city to the extent that the spatial structure of opportunity has been transformed (Delmelle, 2017; Farrell, 2014; Hu & Giuliano, 2011b).

A growing number of Black populations moved into the suburbs adjacent to the central city, and between 1970 and 1977, the share of the Black population in the suburbs increased by 34 percent compared to only 4.2 percent rise in the inner city of U.S. metropolitan areas (J. E. Farley, 1987). The suburbanization of black households during this period increased the racial diversity in the suburbs, but studies also suggest that Black populations remain segregated in the suburbs, isolated in predominantly Black neighborhoods that are socially, economically, and politically separated from the affluent, white-dominant areas that also feature rising employment (Andersen, 2019; Goetz et al., 2019; Massey & Tannen, 2018). These residential segregations of Black populations within the suburb is particularly evident in the Western and Southern metropolitan areas where many Black populations have migrated to in the early 2000s (M. J. Fischer, 2008; Sjoquist, 2000). At the same time, the geography of employment development –

the locational preferences of jobs – in more spatially localized clusters increased neighborhood differentiation in access to job opportunities (Leinberger 2010; Logan and Molotch 2007). These concurrent trends of population and employment redistribution in American metropolitan areas likely changed the spatial structure of opportunity and the landscape of neighborhood economic disparity – as such, spatial mismatch for Black populations continues as a result of resegregation in the suburbs. To investigate this trend, I examine the relative distribution of Black populations and economic opportunities and the spatial inequality of opportunities to identify the mechanisms of suburban sprawl, Black segregation, and the spatial concentration of economy that affect the structure of opportunity and disadvantage.

Although previous studies provide evidence for continued residential segregation that creates spatial inequality in neighborhood social and economic opportunities (Manduca 2019; Modai-Snir and van Ham 2018), it is yet unclear how it affects spatial patterns of mismatch for suburban Black populations as well as the changing geography of opportunity. In other words, is spatial mismatch persistent in American cities that merely shifted its geography into the suburbs? How do recent spatial structure changes contribute to the patterns of economic opportunities in the city and the suburbs? Further research is needed to identify intra-metropolitan spatial patterns of mismatch and whether suburbs are becoming the new inner city with concentrated disadvantage in accessing job opportunities. Further, the spatial variations at a local geographical level have increased as cities and suburbs become more diversified (Brown & Chung, 2006; M. J. Fischer, 2008; Reardon et al., 2008; Wong, 2005). Because systematic approaches in existing studies focused on metropolitan level spatial mismatch – that focuses on the aggregate trend of mismatch for the metropolitan area as a whole – these approaches have proven less effective in capturing the spatial pattern of mismatch at the local neighborhood level. A growing number of studies argue the importance of capturing local level spatial distributions that take into account the spatial distributions between neighboring areas (Brown & Chung, 2006; Reardon et al., 2008; Wong, 2005). Thus, to capture the local-level spatial variations that allow a more comprehensive understanding of the spatial structure of opportunity and the spatial patterns of inequality, I measure the spatial relationships of neighboring areas in the identification of local environments. By decomposing the spatial inequality into within- and between-neighborhood subarea components, this research demonstrates the spatial structure of inequality in U.S. metropolitan areas has changed. Lastly, by examining the association between job accessibility and neighborhood characteristics, differing relationships between job accessibility on labor market outcomes are explored.

An advanced understanding of the changing spatial structure of mismatch is crucial as this implies that spatial disadvantages continue for Black populations even when they migrate into the suburbs, as they continue to face spatial inequalities in the 21st century despite their residential relocation away from the inner city. By focusing on the changing spatial structure of Black residential segregation and the relative distribution of employment opportunities at the local geographical scales, this research presents the intra-metropolitan spatial pattern of mismatch as well as any shifts in neighborhood disadvantage. Moreover, I conduct an empirical analysis on the relationship between neighborhood access to job opportunities and labor market outcomes among Black individuals, focusing on differing effects of job accessibility by the level of neighborhood segregation. This improves the current understanding of how the neighborhood effects contribute to the role of job accessibility, and how these relationships vary by the metropolitan spatial patterns of mismatch. In this way, this research addresses one of the most pressing social problems of the nation: the geography of spatial inequality in the modern landscape of American cities.

1.2 Research Objectives and Contributions

The main objective of this research is to revisit the debate on the spatial patterns of mismatch regarding the recent structural changes in population and employment trends in U.S. metropolitan areas. Particularly, this research is aimed at examining whether the spatial patterns of mismatch in the inner city have extended to the suburbs as a result of Black suburbanization and continued residential segregation in the suburbs in the 21st century. Further, to what extent do these changes in spatial patterns affect the spatial structure of inequality of opportunity? Did spatial inequality within-neighborhood subareas increase? Or did inequality between-subareas increase? Lastly, the employment outcome of Black populations in the city and the suburbs are examined to test whether the spatial mismatch in the suburbs continues to affect employment outcomes. The differential effect of job accessibility in the inner city and suburbs can reveal the significance of the spatial mismatch on Black employment compared to the location of residence in the suburbs.

The findings of this research contribute to the scholarship by demonstrating the evidence of a shift of geographical disadvantage to the suburbs that argue the persistence of the spatial mismatch. By investigating one of the most important issues facing American cities – racial and spatial inequality, this research proposes the mechanism for how the segregation of Black populations in the suburbs continues to disadvantage these population groups in accessing economic opportunity. Further, the use of local environments that takes into account the spatial relationships between the neighboring areas advances the current understanding of spatial inequality at the local level. Therefore, by examining the spatial mismatch for Black populations in the suburbs and linking the job accessibility in the suburban residence to employment outcomes, this research provides a holistic understanding of the suburban spatial mismatch. Also, by emphasizing local-level spatial variation in economic opportunities, this research emphasizes the spatial structure of inequality in the twelve metropolitan areas observed in this research. This research proposes the importance of balanced economic growth and racial integration in the suburbs to address spatial inequality in U.S. cities. Future policies should not only focus on metropolitan-level segregation but segregation at the local level in both the inner city and in the suburbs and promote economic diversity rather than the concentration of economic growth to promote a more sustainable and equitable urban environment.

This dissertation is organized into five chapters. Chapter two presents a literature review of the spatial mismatch hypothesis and recent urban structural changes related to demographic and locational patterns of employment that provide the basis for examining the changed spatial pattern of mismatch. Chapter three examines the spatial distribution of the Black population and low-skilled jobs and characterizes the pattern of the spatial mismatch. The degree of spatial inequality by the neighborhood subareas is also presented in this chapter. Chapter four measures the effect of neighborhood job accessibility on the employment outcomes in metropolitan areas with different spatial mismatch patterns, and the differential effect of job accessibility in the city and suburb. In chapter five, a set of policy implications on ways to reduce spatial inequality of opportunities will be discussed with a focus on racial integration and inclusive neighborhoods.

Chapter 2. Literature Review

2.1 Spatial Mismatch hypothesis

The spatial mismatch hypothesis (SMH) argues the spatial separation of residential and employment locations created a spatial barrier for inner city Black populations to access jobs in the suburbs. The post-industrial economy in the late twentieth century shifted manufacturing-based economy to a knowledge-intensive economy, and as a result, labor-intensive manufacturing jobs in the inner city moved to the suburbs while more service-based jobs expanded within the inner city (Ihlanfeldt, 1994; P. O. Muller, 2004; Sassen, 1990). At the same time, because the housing market discrimination and the scarcity of affordable housing in the suburbs confined many low-skilled Black populations in the inner city, the job-worker mismatch in the inner city had a disproportionate effect on the unemployment rate among Black populations (Ihlanfeldt & Sjoquist, 1998; Immergluck, 1998; Kawabata, 2003; Parks, 2004; Sanchez, Shen, et al., 2004; Sugie & Lens, 2017).

Early empirical studies of the SMH examined the extent of the spatial mismatch between the residential locations of Black populations and jobs by comparing job-worker balances (J. Levine, 1998; Peng, 1997; Sultana, 2002), job accessibility, and proximity (Chung et al., 2001; Ellwood, 1983; Immergluck, 1998; Wang, 2001), and the effects of job accessibility on various labor market outcomes that include commuting times, earnings, and the employment rate (Ihlanfeldt & Sjoquist, 1989, 1991; Parks, 2004; Raphael, 1998; Stoll, 1999a). Overall, the findings of these studies were supportive of SMH in the existence of spatial disparities in job accessibility in the inner city and suburbs, differences in average earnings, and most importantly, its impact on employment outcomes (Holzer, 1991; Ihlanfeldt & Sjoquist, 1991; Immergluck, 1998; Kawabata, 2003; Parks, 2004; Sanchez, Shen, et al., 2004).

Regarding the conceptualization of SMH employed in these early studies, however, Ihlanfeldt (1994) argued that most studies only focus on a single mechanism of Kain's hypothesis – the effect of residential segregation and decentralization of jobs on Black employment. He distinguished the SMH into three parts:

1) Locations of Black residence affects the geographical distribution of Black employment – Black populations are more likely to work close to their home
2) Residential segregation of Black populations affects access to nearby employment opportunities –A smaller set of job opportunities nearby Black residences
3) Residential segregation and decentralization of jobs creates the spatial mismatch between where Black populations reside and where jobs locate to

Thus, SMH not only argues the impact of mismatch between jobs and workers in the inner city and the suburb but the effects of residential segregation on the geography of employment opportunity available to Black populations as well as the locations of their employment. Ihlanfeldt (1994) thus argues that SMH is not just an isolated case of inner city mismatch to suburban jobs, but an issue that may persist if residential segregation continues in the long run.

Over the years, discussions on the SMH have expanded to examine the effects of mismatch on other population groups – including immigrants (Hellerstein et al., 2009; C. Y. Liu & Painter, 2012; Painter et al., 2007), welfare recipients (Bania et al., 2008; M. Lens, 2014), low-income workers (Boschmann, 2011; Hu & Giuliano, 2011b; Sanchez, Shen, et al., 2004), and those that measure effects of aspatial factors – such as modal mismatch (Blumenberg, 2004; Grengs, 2010; Ong & Miller, 2005), skills mismatch (Fan et al., 2016; Houston, 2005; Stoll, 2005), and neighborhood social capital (Chapple, 2006; Chetty et al., 2014). These studies argue that although the geographical separation creates barriers in accessing jobs, the low-income households are more disadvantaged by the lack of access to automobiles (Grengs, 2010; Kawabata & Shen, 2007; Shen, 2001), and the mismatch to jobs in which the racial/ethnic job density affects employment outcomes (Hellerstein et al., 2008, 2009).

Despite the distinctions of the three hypotheses of SMH as explained by Ihlanfeldt (1994), the majority of empirical studies focus heavily on examining the extent of job accessibility among different population groups, and its effects on labor market outcomes (Bania et al., 2008; Howell-Moroney, 2005; Hu & Giuliano, 2014; Jin & Paulsen, 2018; Parks, 2004). Other studies that are related to Kain's first and second hypothesis examine the role of residential segregation in shaping the geography of opportunity and how it affects the geographic locations of Black employment. Black workers were more likely to find work in the vicinity to their residences for the limited access to job information in distant locations and high job search costs that confine their job search boundaries to their local neighborhood (Brueckner et al., 2002; Gobillon et al., 2007; Stoll, 2005). In a recent study by Marinescu & Rathelot (2018), they found that job seekers are about 35 percent more likely to apply to jobs within the same zip code, compared to jobs that are 10 miles away.

In an effort to examine how the number of job opportunities varies by the neighborhood racial/ethnic compositions, Stoll, Holzer & Ihlanfeldt (2000) compared the number of new jobs within each neighborhood type. They found that the White suburbs – a suburban neighborhood with White populations comprised 80 percent of the population – had the highest shares of new low-skill jobs compared to the Central Business District, Black central city, and White central city. Their finding showed the decentralization of low-skilled jobs locate in the vicinity to the affluent White suburbs, and Black populations in both central city and suburbs have lower access to these jobs than the White population. More recently, Kneebone & Holmes (2015) showed that the job proximity the suburban employment centers continue to increase, while the majority-minority neighborhood – census tract with non-Hispanic White population comprises less than 50 percent of the population – had the highest decline in job proximity between 2000 and 2012 in the 96 largest metropolitan areas. The findings show the Black suburbs (and majority-minority suburbs) indeed have different trajectories of economic growth compared to White suburbs, suggesting the residential segregation in the suburbs affects the job opportunities for suburban Black populations – the combined effects of residential segregation and spatial mismatch on Black employment outcomes (Howell-Moroney, 2005).

More recently, studies on the spatial mismatch discuss whether the theories underlying SMH have changed since when Kain first posited the hypothesis in the 1960s, and how persistent spatial mismatch is in U.S. metropolitan areas. The ever-increasing urbanization process over nearly half a century has drastically changed the urban spatial structure, which is characterized by suburban sprawl, polycentrism, gentrification, and urban revitalization (Covington, 2009; Freeman & Braconi, 2004; Lee & Leigh, 2007). Despite the changes in the geographical distributions of populations and employment, the spatial mismatch is likely to persist if the mechanisms which affect mismatch continue – racial discrimination, social polarization that led to residential segregation. In particular, these studies point out the growing trend of suburbanization of Black populations and minority groups contributed to increased spatial inequality within suburbs, suggesting a new spatial dimension of inequality within the regions across cities, suburbs, and rural areas (M. J. Fischer, 2008; Hardy et al., 2018; Hochstenbach & Musterd, 2018; Hu & Giuliano, 2011b; Moretti, 2012; Theys et al., 2019a). Studies indicate that segregation in one domain tends to spread to segregation of another, which concentrates racial minority groups and lower-income households that create the concentration of disadvantage

(Jargowsky, 2018; Kneebone & Holmes, 2016; Massey & Fischer, 2000). Moretti (2012) argued that the "economically thriving" areas are becoming more separated from the areas with declining industries with marginal workers who stay behind, which leads to increased spatial divergence in access to local resources and opportunities across space. This argument is getting more attention in recent years, as scholars recognize the "Racially Concentrated Areas of Affluence (RCAA)" as the driving factors that contribute to increased spatial inequality in the U.S. (Goetz et al., 2019, 2020; Howell, 2019). Over the years, the spatial mismatch has increased for the low-skilled workers, while it decreased for the high-skilled workers (Hu & Giuliano, 2011b; Theys et al., 2019a). These studies argue the continued segregation, shortages of affordable housing nearby suburban job centers, and the tendency of both low- and high- skilled jobs to move towards areas with high-skilled worker have played a major role that shape spatial polarization.

2.2 Suburbanization, Segregation, and Spatial inequality

Since the mid-20th century, the urbanization process in metropolitan areas has transformed the landscape of the population and economic dynamics across the cities and suburbs (B. Lee, 2007; Moretti, 2012; G. Orfield & Lee, 2006). Urban sprawl and the continued trend of decentralization into suburbs have unequally distributed people and economic activities; at the same time, urban renewal projects such as "smart growth" and transit-oriented developments drew jobs and affluent households back to the inner city, displacing poor inner city Black population to the suburbs (M. J. Fischer, 2008; Frey, 1993; Kneebone, 2016; B. Lee, 2007; Yang & Jargowsky, 2006a). These changing trends of urban development also transformed the residential patterns of Black populations in such a way that led to rapid migration of low- and moderate-income Black households to the suburbs during the 1970s and 1980s (Galster, 1991b; Logan & Schneider, 1984). However, Black households predominantly moved into old-, dilapidated-, and low-value housing which comprised mainly of Black populations whose experienced low-quality living conditions that resembled the city ghettos which has attributes of poverty, class, and that the physical separation to economic opportunities (Ellen, 1999; R. Farley, 1970). By the 1990s, Black populations comprised larger portions of the suburbs than the past years, but the locations of Black suburbs and affluent- and White suburbs were separated in different jurisdictions (Ellen, 1999). Scholars revealed the suburbanization of Black populations mirrored the residential segregation of the inner city, in a way that they continued to be spatially isolated from the other population groups with limited access to employment opportunities and other financial resources (O'Neill, 1985; Stoll et al., 2000; Yang & Jargowsky, 2006a).

Farley (1970) identified the different types of suburbs that Black populations predominantly moved into 1) central city spill-over suburbs – that are old, densely populated suburbs near employment centers, 2) newly developed suburbs which comprised mainly of Black populations, and 3) quasi-rural neighborhoods that lacked public provisions and largely characterized by low-value housing, which were also exclusively comprised of Black households. With the exception of central city spill-over suburbs, Black households who moved into the suburbs most often experienced residential segregation and low-quality living conditions. Between 1970 and 1976, 73 of 93 neighborhoods (78%) in which Black populations predominantly moved into had an above-average concentration of Black households, suggesting the resegregation in the suburbs (Lake, 2017). Consequently, Black suburbs had high levels of racial isolation with poor living conditions, which led to increased spatial differentials in local economic conditions within the suburbs (Logan & Schneider, 1984; Massey & Denton, 1988a; Yang & Jargowsky, 2006b). Galster (1991a) argued that even if Black households move into the suburbs, the spatial concentration of low-skilled Black populations has an adverse effect on the neighborhood economic conditions because social and economic opportunities follow households with higher socioeconomic status, as do job growth and educational and public services. Thus, a self-reinforcing system in which the concentration of affluent and wealthy populations attract capital investment with high tax base and infrastructures, and the segregation of "residuals" in filtered down neighborhoods have varying degree structures of opportunities that work as the basis for economic inequality (Glaeser & Hausman, 2019; Keil & Addie, 2015; Kneebone, 2016; C. Y. Liu & Painter, 2012; Logan & Molotch, 2007). This argument suggests that in addition to the unfavorable social and physical conditions of Black suburbs, the residents of these suburbs are also isolated from the economic growth areas, living far away from where jobs were locating to (Gobillon et al., 2007; Logan & Schneider, 1984). Gobillon and Selod (2019) argued that residential segregation "shuts off" the access to jobs by creating a physical distance between predominantly non-white neighborhoods with labor markets in efforts to avoid the unfavorable conditions of distressed neighborhoods, including high traffic congestions, poverty, high crime rates, and high unemployment rates. These findings suggest that despite Black migration to the suburbs, high levels of segregation in the suburbs increased the neighborhood differentials in local economic conditions and opportunities across local neighborhoods. This further leads to increased socio-spatial differentiation within suburbs including fiscal capacity, capital investment, public resources, political power, and economic opportunities that affect the labor market outcomes and economic inequality within the suburbs

(Gobillon & Selod, 2019; Hardy et al., 2018; Jargowsky, 2018; Marcińczak et al., 2015; Massey, 2004; Massey & Fischer, 2000).

Due to the growing evidence of continued segregation in the suburbs and the economic inequality of neighborhoods, discussions arose regarding the persistence of spatial mismatch for suburbanized Black populations, a changed spatial structure of opportunity, and rising spatial inequalities within suburbs. The majority of studies continue to focus on how job accessibility has changed as a result of job suburbanization and the effects of job accessibility on labor market outcomes of minority population groups (Brandtner et al., 2019; Fan et al., 2016; Ganning, 2018; Hu, 2019; Hu & Schneider, 2017; Miller, 2018; Shin, 2020). However, the changing urban spatial structure of mismatch deserves a new consideration as increasing shares of racial and ethnic minority groups now reside in the suburbs, and the understanding of the changed spatial pattern of inequality – the geography of economic and social opportunity – needs to be established in order to propose policy measures that address any remaining challenges for these population groups. Galster (1991a) argued the spatial mismatch as a combined issue of "urban economic structure" and "racial residential segregation" linked to the economic inequality of neighborhoods. Thus, by investigating whether the geographic disadvantage is a perpetuating trend that affects Black individuals and how the changes in urban structure affect the spatial pattern of mismatch, the mechanisms that lead to socio-spatial differentiation and geographic polarization can be revealed.

Other studies focus on how the spatial pattern of segregation and spatial inequality is changing, including the spatial mismatch among suburban poverty (Hu, 2015a; Hu & Giuliano, 2011b; Kneebone & Holmes, 2015; Theys et al., 2019b), immigrant population groups (Easley, 2018; C. Y. Liu & Painter, 2012), the impact of demographic and economic transformations on urban inequality (Bagchi-Sen et al., 2020; Bischoff, 2016; Dawkins, 2017; Delmelle, 2017), and changing spatial structure of inequality (M. J. Fischer, 2008; Hochstenbach & Musterd, 2018; D. Liu & Kwan, 2020; Marcińczak et al., 2015; Márquez et al., 2019; Panzera & Postiglione, 2020). These studies reveal strong patterns of segregation and low-skilled job employment distribution that continue to disadvantage minority population groups and geographical restructuring of urban opportunities and disadvantages. In particular, studies found the minority populations become increasingly concentrated into majority-minority areas, and the within-suburban sorting has increased – creating spatially concentrated disadvantage in the so-called ghettoized suburbs (Ehrenhalt, 2012; M. J. Fischer, 2008; Hu & Giuliano, 2011b; K. S. Johnson, 2014; C. Y. Liu & Painter, 2012; Schuetz et al., 2017). In the inner city, the level of segregation decreased and saw a rebound from economic challenges as gentrification and redevelopment projects has brought back service-oriented jobs and professional jobs to the inner cities, adding more layers to the shifts in job locations taking place across neighborhoods (Covington, 2009; Freedman, 2015; S. Lee & Leigh, 2007). Mallach (2018) further emphasized that despite efforts to revitalize neighborhoods, largely segregated and poverty-stricken ghettos are rarely benefitting. Also, the segregation by race and income in the suburbs and the concentration of disadvantage were found to affect the level of economic opportunities of the neighborhood (Massey & Brodmann, 2014; Reardon et al., 2008; Sharkey, 2013). These spatial trends of urban concentration and uneven economic growth in select subsections of the metropolis created enclaves of affluence that are advantageous in having better access to social and economic opportunities (Goetz et al., 2019; Howell, 2019). Based on these findings, it seems that despite the suburbanization of Black populations, they continue to live in segregated areas in the suburbs that affect the social and economic opportunities of the neighborhood. Also, the polarized development resulted in the concentration of affluent, majority-white populations into the wealthy suburb and increasingly back into the city, while lower-income and minority populations concentrate into other parts of the city and the suburb (Hu & Giuliano, 2011; Liu & Painter, 2012; Schuetz et al., 2017). However, although these evidence support the persistence of mismatch among Black suburbs, less is known about how these changes are reflected on the spatial patterns of mismatch and the geographic variation in economic opportunities.

2.3 Spatial Mismatch and Employment

In the following decades since the spatial mismatch hypothesis was proposed, empirical studies focused on examining the effect of job accessibility on labor market outcomes including employment, wages, and commuting times and distances (Ellwood, 1983; Ihlanfeldt, 1994; Ihlanfeldt & Sjoquist, 1989; Raphael, 1998; Stoll, 1999a, 2006; Weinberg, 2002). These studies focused on whether Black populations are disadvantaged from having lower access to job opportunities, and whether improvement in access to jobs can increase the likelihood of employment. Because of the potential endogeneity issue associated with residential location choices and labor market outcomes, early studies focused on the employment outcomes of youth, based on the assumption that the youth's residential location is likely to be exogenous if they are living with their parents (Ihlanfeldt & Sjoquist, 1991). The findings of these studies support the spatial mismatch hypothesis – Job accessibility is closely associated with Black youth employment (Ihlanfeldt & Sjoquist, 1990, 1991; Raphael, 1998; Stoll, 1999b). Empirical evidence in the early years was somewhat mixed due to differences in job accessibility measures and modeling approaches (Ihlanfeldt & Sjoquist, 1990), but studies since the 1990s show more consistent findings that support the significant role of job accessibility on labor market outcomes

(Gobillon et al., 2007; Jin & Paulsen, 2018; Kawabata, 2003; Sugie & Lens, 2017). Bunel & Tovar (2014) further supported that the study findings are likely to be unique depending on how the job accessibility is measured.

Over the years, the discussion on the role of space on labor market outcomes has expanded to other marginalized population groups – including welfare recipients (Bania et al., 2008; Blumenberg & Ong, 1998; M. Lens, 2014; Sanchez, Shen, et al., 2004), immigrant population groups (Easley, 2018; Hellerstein et al., 2009; Joassart-Marcelli, 2009; C. Y. Liu & Painter, 2012; Parks, 2004), and low-income households (Blumenberg, 2004; Boschmann, 2011; Hu et al., 2017) who are similarly restricted in residential choices and often without access to autos and therefore are more reliant on public transit services. In particular, the discussion on the modal mismatch has been of rising importance during the 2000s, arguing that one's access to auto can compensate for the physical separation of jobs and housing (Blumenberg & Manville, 2004; Deka, 2002; Fan et al., 2012; Ong & Miller, 2005). These studies recognize the physical separation of jobs and housing and that there exist geographical barriers but argue that low-income households are not disadvantaged by 'spatial' mismatch but rather disadvantaged by the 'modal' mismatch, the absence of automobile. Blumenberg and Pierce (2014) further found that access to auto greatly increases the employment outcomes of low-income households than other assistance impacts. While the advantage of auto access in accessing jobs is critical, the policy implication to provide subsidy on acquiring automobile is controversial for many reasons including the issues of increased traffic congestion, increased air pollution, and enormous costs associated with maintaining automobiles (Bhattacharya et al., 2013; Grengs, 2010). Thus, although the studies on the effectiveness of public transit accessibility on the labor market are rather mixed, transit undoubtedly provides access for low-income neighborhoods who are socially isolated by their residential location and those who are dependent on public transit (Alam, 2009; McKenzie, 2013; Sanchez, Shen, et al., 2004). Sugie and Lens (2017) also proposed that job opportunities in the daytime locations – a location where individuals spend their time during the day – can compensate for the deficits in their residential location, suggesting that policy implication of assisting traveling options via public transportation to job-rich areas can greatly improve the lack of job accessibility in the location of residence.

In addition to discussions on neighborhood attributes that contribute to the labor market outcomes, Johnson (2006) proposed the differing effects of job accessibility by race/ethnicity as a result of residential location constraints. His main argument was that because Black populations are more likely to be constrained in their residential location choices than White populations, the effects of job accessibility are likely to vary by race. His findings support the differential effect of job accessibility by race and the level of education. Less-educated Black individuals and Hispanics were sensitive to the changes in job accessibility, while the access to employment growth did not influence the reservation wages among White populations. His study supports the spatial mismatch hypothesis, and racial/ethnic minorities are more sensitive to the local job accessibility as a result of involuntary residential segregation.

Andersson et al. (2018) also found the job accessibility significantly decreases the duration of jobless especially for Black and other minority population groups, supporting the argument of Gobillon et al. (2007) that job accessibility influences the labor market outcomes of workers through increasing one's job search efficiency. Hu (2015b) hypothesized the effects of job accessibility may have declined over time, as a result of declined significance of physical separation via improved transportation systems and increased auto ownership. Further, she hypothesized how the changing spatial structure of employment towards polycentric development contributes to the effect of job accessibility on the employment and commute times at the census tract-level. She found that the share of Black populations is negatively associated with employment rate (worker-to-population ratio) while it decreases the commute travel time. Regarding the changes in job accessibility's effects on labor market outcomes, however, the study findings did not show any evidence that the effects have changed between 1990 and 2007-2011.

2.4. Gap in the Literature

Continued discussions on residential segregation and uneven economic development have been a strong motivation for this research. Studies have shown that the spatial patterns of segregation and development potentially contribute to the persistence of the spatial mismatch and spatial inequality – despite dynamic spatial structure changes since in metropolitan areas of the U.S. although studies have investigated the continuing segregation and uneven economic development, empirical evidence on how these trends reshape the spatial patterns of mismatch remains elusive. Thus, by identifying the spatial structure of geography of opportunity and the disadvantage in metropolitan areas, I attempt to fill the research gap on whether or not spatial mismatch is a persistent trend in the U.S. provided that residential segregation of Black populations is persistent. Also, previous studies have focused on whether the spatial mismatch is associated with labor market outcomes, but the potential interactions with other neighborhood characteristics have not been examined widely.

Another missing link in the literature is that although the spatial mismatch is widely known as a spatial problem, spatial mismatch is understood as a conceptual framework. It is understood as the spatial separation between inner city workers and suburban jobs, but studies have yet been able to identify the spatial patterns of mismatch, even less how the spatial patterns have changed over time. This is largely due to how spatial mismatch is measured in studies that use aspatial measures such as dissimilarity index which does not take into account the spatial relationships among neighboring units. A few studies suggested a spatial measure of residential segregation that takes into account the spatial relationships (Brown & Chung, 2006; Reardon et al., 2008; Wong, 2005). Although the advantage of identifying spatial relationships is well recognized, no studies have yet explored the spatial patterns of mismatch.

Also, studies have found the geography of segregation are shifting to the suburbs and segregation are now occurring at a local level, within-city and within-suburbs (M. J. Fischer, 2008). At the same time, evidence suggests the growing urban inequality in metropolitan areas as a result of more localized economic development, which further disadvantaged segregated groups (Glaeser et al., 2009; Leinberger, 2010; Logan & Molotch, 2007). Although direct comparison of job availability by racial/ethnic population composition revealed that there are fewer jobs available within minority neighborhoods (Kneebone & Holmes, 2016; Stoll et al., 2000), little is known about the magnitude of inequality of opportunity for Black populations as well as spatial distributions of inequality by neighborhood subareas.

Furthermore, although the association between job accessibility and labor market outcomes has been widely discussed in the literature, the findings have shown mixed results. There are various explanations as to why the results are mixed – inconsistencies in job accessibility measurement and how the endogeneity is treated (Bunel & Tovar, 2014; Galster et al., 2010; Grengs, 2010). Others have found the effect of job accessibility are influenced by the neighborhood characteristics such as segregation levels (Cutler & Glaeser, 1997; Ihlanfeldt, 1999; Zenou, 2013) and is likely to be dependent on the race/ethnicity of individuals (R. C.

Johnson, 2006). To this day, little is known about the differing effects of job accessibility by neighborhood conditions (residence in the city and the suburb, and segregation levels), or household characteristics (availability of automobiles). Further, the associations between job accessibility and labor market outcomes may be stronger in metropolitan areas with traditional spatial patterns of mismatch, which suggests the effect of job accessibility may be different by metropolitan characteristics. I address these remaining challenges in examining the potential interactions between job accessibility and neighborhood conditions.

Based on the literature, I focus on how the changes in the residential patterns of segregation and localized economic development in metropolitan areas contribute to the changing geography of opportunity in the U.S. Specifically, I investigate the spatial patterns of mismatch using the spatial index of segregation, spatial inequality of opportunities, and examine differing effects of job accessibility on Black labor market outcomes to test whether spatial mismatch hypothesis continues to hold true in changed urban spatial structures.

Chapter 3. Spatial mismatch and geography of economic inequality

This chapter explores the spatial structure of economic opportunity is examined with respect to the residential location of the Black population and distribution of employment in goods producing and local service industries. In the 1950s, housing discrimination constrained the housing choices of Black households and the ability to follow jobs to the suburbs, contributing to the spatial mismatch between the inner city residential location and suburban jobs. However, growing evidence suggests that the residential patterns of Black households and the processes of uneven economic development have changed the spatial patterns of segregation and mismatch (M. J. Fischer, 2008; Hu & Giuliano, 2011b; Theys et al., 2019b). Although the increase in the suburbanization of Black population has been linked to rising suburban segregation and poverty in the suburbs, research on how it affects the geography of the spatial mismatch and inequalities in employment opportunities are scarce. This research fills these gaps by measuring the spatial distribution of the Black population and jobs that identify how the spatial pattern of mismatch has evolved, as well as how the geography of economic inequality is distributed across neighborhoods in a metropolitan area. In particular, the main questions addressed in this chapter are 1) How did the urban structural change affect the aggregate trends of spatial mismatch? 2) How do intra-metropolitan spatial patterns of mismatch vary across metropolitan areas? 3) Is there evidence of suburban spatial mismatch? And 4) How the spatial structure of inequality in employment opportunities has changed within- and between-neighborhood subareas. By measuring the spatial distribution of populations and jobs at the local geographical level, the findings of this research capture the spatial dimension of concentration and clustering of distributions.

3.1 Data, Variables, and Data Sources

The primary sources of population data for this analysis are the U.S. Census 2000 Summary File 1 (SF-1) and the 2015 American Community Survey five-year estimates at the census tract level. Employment data was derived from the 2002 and 2015 Longitudinal Employer-Household Dataset (LEHD) Origin-Destination Employment Statistics (LODES) datasets that tally total jobs by workplace area (U.S. Census Bureau, 2019). The LEHD employment data is aggregated at the census tract level. Although 2002 and 2015 LODES datasets are available for most states, data were not available in some states due to historical data unavailability and data sharing limitations and thus were not selected as the study area. These states include Arizona, Arkansas, District of Columbia, Massachusetts, Mississippi, New Hampshire, and Wyoming. Also, to take into account the geographical boundaries of census tracts that change over time, the census estimates from 2000 are interpolated to 2010 geographical boundaries using the 2000-2010 Census Tract Relationship File from the Longitudinal Tract Database (LTDB) from Brown University (Logan et al., 2014). The geographic boundaries data used in this study comes from the 2015 TIGER/Line shapefiles prepared by the U.S. Census Bureau. A Core-based Statistical Area (CBSA) which combines metropolitan statistical areas and micropolitan statistical areas is used to identify geographic boundaries of MSAs. The Place State-based geography boundary which includes incorporated places (legal entities) and census designated places (CDPs; statistical entities) is used in the identification of neighborhood subareas.

This study focuses on all Black individuals, and for intra-metropolitan level analysis in twelve metropolitan areas, all working-age Black individuals between 15 to 64 years old are used in the analysis. This does not limit populations to the employed or those who identify themselves as participating in the labor force, since labor force participation can be affected by the availability of jobs in the neighborhood (Hu & Giuliano, 2011b). The 2-digit NAICS code is used to examine how the spatial trend of mismatch has changed for the jobs that had been suburbanized during the post-war metropolitan development. Specifically, jobs in the goods-producing industry and local service and health care industry are used, because jobs in these industries make up around 77% of total U.S. jobs, and approximately 86.8% of Black workers were employed in the goods-producing and local service and health care jobs (U.S. Census Bureau, 2017).

First, to understand the overall trends of the spatial mismatch between 2000 and 2015, the aggregate trends at the 100 most populous metropolitan areas in the U.S.[1] are measured. The list of 100 MSAs can be found in Appendix A and is shown in Figure 1. Then, for a detailed examination of spatial patterns of mismatch – the distribution of Black populations and jobs – twelve metropolitan areas are selected for an intra-metropolitan level analysis. These twelve metropolitan areas represent differing cases of spatial mismatch in the four Census regions of the United States: Northeast, Midwest, West, and South. Also, data availability and the size of the metropolitan areas were taken into consideration. Although some of these metropolitan areas have been studied with great frequency throughout existing literature, including Atlanta, Chicago, Detroit, other metropolitan areas in the South and West were not studied as extensively despite high rates of Black migration and economic growth between 1980 and 1990 (Keating, 2010; Stoll et al., 2000). For example, Los Angeles and San Francisco metropolitan areas are representative of the Sun Belt states of the West that saw significant population growth and sprawling spatial patterns. Atlanta and Dallas are among the top regions that are sprawling with

[1] Based on total population counts from 2010 decennial census.

decentralized employment and racial segregation to the north and south (Ewing et al., 2002). The metropolitan areas in the Northeast and Midwest are legacy cities that have suffered a drastic decline in population and a corresponding decline in manufacturing between the 1950s and 1970s, as well as significant racial residential segregation.

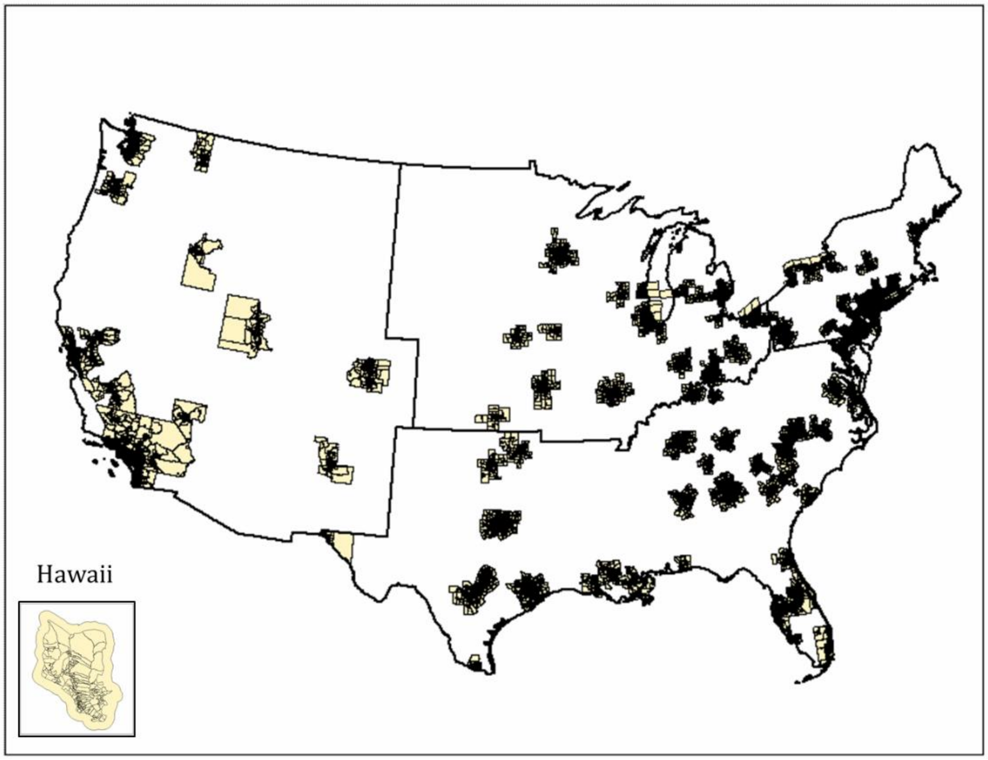


Figure 1. 100 Metropolitan areas selected for aggregate trend analysis

3.2 Research Methods

3.2.1. Identifying Neighborhood Subareas - Inner City, Inner Suburbs, and Outer Suburbs

Three neighborhood subareas are identified for intra-metropolitan analysis: the inner city, the inner suburb, and the outer suburb. The criteria for identifying neighborhood subareas are based on the census boundaries and urban development patterns including population densities and the housing densities by their built year (Airgood-Obrycki, 2019; Cooke & Marchant, 2006; Kneebone & Holmes, 2015; Lee & Leigh, 2007). The definition of suburbs varies by literature, but the distinction by the timing of the development as well as the geographical locations of "inner" and "outer" suburbs are the most widely used method (Cooke & Marchant, 2006; Downs, 1999; Hu & Giuliano, 2014; Lee & Leigh, 2005; Liu, 2009; Orfield, 2002). Place boundaries from the 2015 U.S. Census – a designated governmental unit incorporated under the state as the city – are used to identify the inner city (U.S. Department of Commerce, 1994). These place boundaries have a degree of legal entity as they have been established through the cooperation of local and state officials, and thus emphasizes the political entities that distinguish the central city of metropolitan areas (U.S. Department of Commerce, 1994). Other cities that are listed as metropolitan areas with populations of 100,000 or more are also identified as the inner city following Kneebone & Holmes (2015). Census tracts that are not classified as the inner city but have more than 400 pre-1969 housing units per square mile and any contiguous tracts that have more than 200 pre-1969 housing units per square mile with more than 1,000 residents per square mile are identified as the inner suburb (Airgood-Obrycki, 2019; Cooke & Marchant, 2006). Any tracts that are not identified as inner city or inner suburb in the above criteria are labelled as the outer suburb.

Table 1. shows the characteristics of neighborhood subareas that are identified in the 100 metropolitan areas. It shows the shares of census tracts in each subarea are fairly evenly distributed and features distinctive characteristics of population density and pre-and post- 1969 housing density. Since this identification method applies the same criteria for all metropolitan areas, areas with lower housing densities have a low share of inner suburbs identified relative to the outer suburb. Having different measures for different sizes of MSAs would make identification arbitrary, so I keep the above criteria for identifying neighborhood subareas for this research.

Table 1. Descriptive summary of neighborhood subareas of 100 MSAs

(density per square mile)

Neighborhood Subareas	Tract Count	(%)	Average Population Density	Average Housing Density Built Pre-1969	Average Housing Density Built Post-1969
Inner City	15,060	34.7%	14,494	4,479	1,628
Inner Suburb	13,020	30.0%	6,082	1,513	895
Outer Suburb	15,295	35.3%	1,596	61	517

3.2.2 Measuring Spatial Mismatch

The spatial mismatch is defined in this research as an uneven geographical distribution of Black populations and jobs within the local labor market boundary of metropolitan areas. The dissimilarity index is used to measure the extent of unevenness that analyses the disproportionality of the two groups (Black populations and jobs) in each areal unit of metropolitan areas. This index is most commonly used for measuring segregation and spatial mismatch, due to its simplicity of calculation, easy interpretation, and ability to measure mismatch uniformly across metropolitan areas (Li et al., 2013; Massey & Denton, 1988b; Stoll, 2006; Stoll & Covington, 2012). The dissimilarity (D) index takes the form (Massey & Denton, 1988a):

$$\mathrm{D} = \frac{1}{2}\sum_{i}\left|\frac{x_i}{X} - \frac{y_i}{Y}\right|$$

Where x_i and y_i are the two groups of interest in areal unit i, and X and Y are the total sums of each group in the whole area (metropolitan area) Thus, this index measures the mean absolute differences in two group’s proportions in an areal unit to represent the level of the unevenness of the larger geographical area. Despite the popularity of the dissimilarity index in measuring unevenness, the index poses some potential issues in reflecting spatial mismatch. Since the index measures the proportional shares of Black populations and jobs within each areal unit, it captures an internal homogeneity and fails to capture the spatial relationships with neighboring areas (Massey & Denton, 1988a; Stoll, 2006). Thus, by measuring the internal evenness of distributions within each areal unit, the dissimilarity index assumes census boundaries as actual boundaries of spatial interaction for measuring the residential unevenness (Reardon & O'Sullivan, 2004; Wong, 2005). However, since the geography of one's spatial interaction, for instance in searching for jobs, extends well beyond the boundary of a single geographical unit, disregarding the population and jobs in the neighboring areas fails to consider the spatial dimension of mismatch. For this reason, the dissimilarity index is considered as a global index that is "aspatial" compared to other spatial statistics that consider the spatial patterning at the local neighborhood level (Brown & Chung, 2006; Wong, 1998).

Past studies proposed other approaches to identify the spatial distribution of Black populations and jobs taking into account the distributions in neighboring areas. The most common measure uses Shen's (1998) gravity-based job accessibility measure that compares job accessibility for different income groups (Hu & Giuliano, 2011a), the location of residence (Howell-Moroney, 2005; Sugie & Lens, 2017). A common form of gravity model is as follows (Shen, 1998):

$$A_i = \sum_j \frac{O_j f\left(c_{ij}\right)}{D_j}, \qquad D_j = \sum_k P_k\, f(\,C_{kj})$$

Where A_i is the accessibility for people living in location i; O_j and P_k is the number of job opportunities and workers in location j and k; $f(C_{ij})$ and $f\left(C_{kj}\right)$ is the impedance function associated with the cost of travel between i and j, and k and j. Thus, the gravity-based job accessibility takes into account the spatial distribution of job opportunities and both the supply and demand side of employment that allow researchers to take into account the job availability and competitions from other areas. Although the gravity model is advantageous in measuring the aggregate level of job accessibility across different locations, it is less useful in identifying the spatial mismatch between workers and jobs within the local neighborhood environment. Because SMH links the residential segregation pattern of Black populations and the geographical distribution of jobs, employment opportunities within the segregated neighborhoods are of more concern than the access to jobs in the whole study area. Job accessibility is more useful in comparing the level of job accessibility across different areas, or disparity in accessibility using different travel modes than the geographical distributions of jobs and workers within the neighborhood boundary.

In addition to directly comparing job accessibility measures, other studies incorporated the spatial interactions of population groups of neighboring areas into dissimilarity index. Wong (2005) formulated a general dissimilarity index (GD) that uses the composite population counts by defining the neighborhood boundary of each areal unit to measure the spatial segregation of a region:

$$GD = \frac{1}{2}\sum_{i}\left|\frac{cw_i}{\sum_i cw_i} - \frac{cb_i}{\sum_i cb_i}\right|$$

Where cw_i and cb_i represents the total composite count of White populations and Black populations within the neighborhood i; $\sum_i cw_i$ and $\sum_i cb_i$ represents the total composite count of populations in the whole study area. In this way, the general dissimilarity index measure accounts for the spatial interactions with neighboring areas in measuring unevenness in two population proportions. Similarly, Fan et al. (2014) and Qi et al. (Qi et al., 2018) proposed the dissimilarity index based on transit travel time (D-Transit) that uses the composite count of populations and jobs:

$$DTransit = \frac{1}{2} * \sum_{i=1}^{n} \left| \frac{w_i}{\sum_{i=1}^{n} w_i} - \frac{ca_i}{\sum_{i=1}^{n} ca_i} \right|$$

$$ca_i = \sum_{j=1}^{n} e_j f(t_{ij})$$

$$f(t_{ij}) = \begin{cases} 1; if\ t_{ij} \leq 60mins \\ 0; if\ t_{ij} > 60mins \end{cases}$$

Where, ca_i represents the composite count of jobs accessible within 60 min of transit travel from areal unit i. t_{ij} represents the travel time by transit between the centroid of the areal unit I and the centroid of areal unit j. All indices range between 0 (perfect balance) and 1 (perfect imbalance).

A more recent study developed the distance-weighted spatial mismatch index (DSMI) that measures the minimum distance the population have to move to achieve total evenness in the distribution of population and jobs in each areal unit, that is (Theys et al., 2019b):

$$DSMI = \min_{s_{ij}} \sum_{i,j} s_{ij} d_{ij}$$

And

$$\sum_{j} s_{ij} = s_i \forall i;$$

$$\sum_{i} s_{ij} = -s_j \forall j\,; s_{ij} \geq 0 \forall i, j$$

Where s_{ij} is the share of movers from areal unit i to j; and d_{ij} is the standardized distance between two areal units. Then, DSMI yields the total minimum distance that people (or jobs) need to move to eliminate the spatial mismatch. However, these distance-based measures require intensive computational analysis for larger geographical areas, and the interpretation is difficult compared to measuring dissimilarity index (Massey & Denton, 1988a; Stoll, 2006; Wong, 2004).

In this research, I am using Wong's (2004, 2005) general spatial segregation measure that takes into account the spatial relationships with neighboring areas without much computational burden, while also effectively capturing the spatial interactions of a region. By using the composite count of Black populations and jobs of each areal unit, the general dissimilarity (GD) index incorporates the spatial interaction of Black individuals and jobs in the surrounding areas of each areal unit as if they are in the same unit, depending on how one defines the neighborhood. Using the composite count of Black populations in areal unit i, $cblack_i$ can be defined as Wong (2005):

$$cblack_i = \sum_r d(black_r)$$

Where $black_r$ refers to the count of Black populations in census tract r, $d(.)$ is a function defining the neighborhood of i, r refers to census tracts within the metropolitan area. In this research, I define the surrounding units of areal unit i as the local labor market boundary – the function defining the neighboring areas $d(\cdot)$. Figure 2 shows an illustration of how neighborhood areas are defined using the distance from the centroid of each census tract. A large gray circle represents the local labor market boundary – a buffer of a tract centroid. Thus, by drawing a buffer boundary from the centroid of the census tract, the total number of Black populations within the boundary are captured. In this way, the spatial distributions of Black populations in neighboring areas are considered.

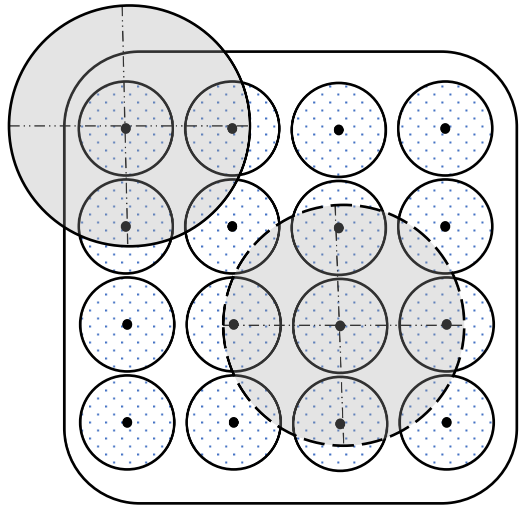


Figure 2 The Local Labor Market Boundary for Composite Population Counts

Five-mile is used to define the local labor market area of each census tract, which incorporates jobs located up to 10 miles from end-to-end in diameter from the boundary of the neighborhood[2]. Since the census boundaries are insensitive to the geographic scale of residential patterns or what individuals consider as a neighborhood, consideration of geographic scales other than the census boundaries has been proposed in measuring segregation patterns (B. A. Lee et al., 2008; Reardon et al., 2008). In Reardon et al. (2008), they distinguished the micro-and macro-scale segregation patterns in which the macro scale corresponds to local environment area of the 4,000-meter radius that is smaller than the commuting distance, but an area that people consider as a neighborhood or an activity space. The five-mile radius is around an 8,000-meter radius that is about twice the size of the local environment than the geographic scale used in Reardon et al. (2008) which they identified this area as a job catchment area that people would consider jobs to be within their Using the above composite count of Black populations and jobs.

[2] Average commute distances of 7 to 10 miles from the place of residence to work in major metropolitan areas (Kneebone and Holmes 2016).

Using this local market boundary, a generalized dissimilarity index for each metropolitan area can be calculated using:

$$GD = \frac{1}{2}\sum_{i}\left|\frac{cblack_i}{\sum_i cblack_i} - \frac{cjob_i}{\sum_i cjob_i}\right|$$

where $cblack_i$ and $cjob_i$ are the composite count of Black populations and jobs in the neighborhood environment of census tract i. $\sum_i cblack_i$ and $\sum_i cjob_i$ are the sum of the composite count of Black populations and jobs within the metropolitan area. The index value represents the disproportionality of the two groups considering the distributions in the five-mile buffer areas. This index ranges from 0 (complete evenness) to 1 (complete unevenness) that indicates the total dissimilarity in the distribution of Black populations and jobs within the local neighborhood environment of metropolitan areas. Therefore, this index measures the differences in the relative shares of Black populations and jobs within the local labor market environment to the representative to the metropolitan area as a whole. The disproportionality in the two, then, represents whether Black populations are overrepresented in the local environment relative to the jobs or jobs are overrepresented relative to the Black populations. Multiplying the index by 100 allows the index to be interpreted as a percentage of Black populations or jobs that are mismatched within their local environments. Since the general dissimilarity index is bounded between 0 and 1, this index is useful in showing an overall level of mismatch for metropolitan areas.

Nevertheless, another concern with the dissimilarity index is that – since it computes an aggregate trend for the whole metropolitan area – it does not effectively identify the spatial patterns of where the mismatch is occurring. Since the main objective of the present study is to understand how Black suburbanization has reshaped the spatial mismatch in the suburbs, the aggregate trend is insufficient for this research purpose. Because there are differences in the observed spatial patterns between those analyzed at a larger scale – such as at the state or county levels – and those observed on a more localized level suggests that it is important to consider spatial patterns at the neighborhood level (Massey, 2001). In Massey (2001), he found the spatial patterns of Black households at the state and county level showed racial integration, but at the neighborhood level, the segregation was rising, emphasizing that the aggregate measure of spatial patterns may mask the trends that are occurring at the neighborhood level. Thus, although the aggregate trends are useful in comparing the spatial mismatch across metropolitan areas, they may not convey the spatial patterns of mismatch within the metropolitan areas at the neighborhood level.

The values of the general dissimilarity of each census tract (GD scores) are used to represent the intra-metropolitan spatial distributions of a relative surplus of Black populations and jobs. The general dissimilarity score from the above equation can be rewritten for each local neighborhood environment:

$$GD_i = \frac{cblack_i}{\sum_i cblack_i} - \frac{cjob_i}{\sum_i cjob_i}$$

Thus, the negative values of the GD_i indicates that there is a surplus of jobs within the local environment relative to the shares of Black populations, and the positive values represent the surplus of Black populations relative to the share of jobs. By measuring the spatial mismatch using local labor market boundaries, the generalized dissimilarity index overcomes the issues of taking into spatial relationships to neighboring areas without introducing a computational burden, all while taking into account the contiguity of neighborhoods within the boundary of one’s job search area. The index can be interpreted in the same manner as the dissimilarity index, but the GD represents the unevenness between the local environment rather than between census tracts as if census boundaries are discrete entities. This interpretation is more sensible for real-world applications wherein employment opportunities are not exclusive to the populations within the same census tract, and jobs in the neighboring census tracts affect the job search activities.

3.2.3 Measuring spatial inequality

The spatial inequality is defined in this research as disparities in the spatial distribution of economic opportunities relative to the proportional share of the Black populations within each local environment. Using the ratio of Black populations and jobs of each local environment as an indicator of distributional balance, the extent of inequality is identified by measuring how diverse local environments are, compared to the metropolitan average Black-job balance. Thus, the spatial inequality that is being measured here is an *intercommunity* distribution that reveals disparities in the geographical distribution of opportunities.

Economic inequality has been studied widely to understand the distribution of income and expenditure consumption among individuals or households within a nation or region (Jenkins & Kerm, 2011). Deviations from perfect equality or the regional averages are used to represent the unevenness in distribution. Common inequality measures include comparing the ratios of populations by the income groups. The Gini index, which measures the mean absolute differences from total equality, and the Generalized entropy (GE) index, which calculates the irregularities or dispersions in the distribution of information to the total entropy of the region (Czyż & Hauke, 2015; Massey & Denton, 1988b). These inequality measures have different properties (or assumptions) that make some measures more appropriate than others for evaluating different circumstances. These include the properties of the *Principle of Transfers* and *Scale Independence* (Cowell, 2011; Jenkins & Kerm, 2011). The *Decomposability* property of inequality measures allows one to break down the total inequality of a region into subgroup components, such as neighborhood subareas. Although the Gini index offers many advantages in measuring inequality – especially due to its simplicity in interpretation and the ability to make comparisons across regions or countries – this index does not satisfy the decomposability property (Cowell, 2011). Since this research aims to examine the spatial structure of inequality – how inequality is distributed across neighborhood subareas and the contributions of inequality within each subarea to the overall inequality of the region (Jenkins & Kerm, 2011) – the decomposability property is useful for the current study.

Among inequality measures, Theil's index satisfies the decomposition property and thus, is used in this research to measure the inequality in the distribution of Black populations and jobs. Focusing on Black suburbanization and location trends of employment, this research assesses the overall inequality as well as the spatial distribution of inequality by neighborhood subarea. As briefly introduced, Theil's index is a special case of the generalized entropy index that measures the "degree of disorder" or the "distance" from the uniform distribution (Cowell, 2011; Massey & Denton, 1988a). In the past, this index was commonly used to measure income inequality (Akita, 2003; Márquez et al., 2019), but more recently, it has been used to measure residential segregation (M. J. Fischer, 2008; Reardon & Bischoff, 2011) and the distribution pattern of regional development (Kudrycka, 2015; Werner et al., 2014). Similar to how studies have applied the concept of entropy in measuring the regional distribution of populations, land uses, and regional development, I use Theil's index to analyze the overall level of inequality in economic opportunities among Black populations for the twelve metropolitan areas.

Like many other inequality measures that do not consider the spatiality of regional inequality – the spatial locations of distributions and spatial interactions among neighboring areas –Theil's index also fails to take into account the spatial dimension of inequality. Whereas measures of economic inequality focus on the distribution of income among populations without spatial reference, inequality of opportunities is spatial – meaning that the locations of different demographic populations and their proximity to jobs affect the geography of opportunity. Because conventional inequality measures treat areal units as separate entities with the assumption that these geographical areas – such as census tracts – are discrete units without spatial interactions among neighboring areas (Brown & Chung, 2006; Márquez et al., 2019). A growing number of studies argue the spatial patterns greatly influence the extent of inequality and that it is critical to capture the spatial relationships (or, the spatial spillovers) through which economic activities and the demographic makeup of neighborhood populations affect each other. For instance, the overall degree of inequality of metropolitan areas will vary depending on the spatial configurations of populations and jobs within metropolitan areas – either a checkerboard pattern where jobs and populations are uniformly distributed across the metropolitan area or clustering of jobs and populations into different locations.

To illustrate how different spatial configurations may yield different levels of spatial inequality, two hypothetical employment distribution scenarios are presented in Figure 3. A total of 520 jobs are assigned to areal units in two metropolitan areas, and only the spatial distribution patterns are different. In Scenario A, 400 jobs (76.9 percent of total jobs) are located in subarea A while all other subareas have 40 jobs. In Scenario B, each subarea has 130 jobs (25 percent of total jobs) that are equally distributed across subareas, but the distribution within the subarea is rather uneven. Intuitively, Scenario A features greater inequality than Scenario B, due to the high concentration of employment in a single subarea while other subareas have less than 10 percent of total jobs. However, because the traditional Theil's index does not account for the spatial patterns between neighboring areas but considers each areal unit as independent, Theil's index is the same for two scenario cases. Thus, despite the differences in spatial distribution patterns in the two scenarios that affect the magnitude of segregation (and inequality), traditional Theil's index fails to capture the spatial patterns. On the other hand, by using the composite population count in local labor market boundary as illustrated in Figure 2, it can capture the spatial interaction between neighboring areas as well as identify the clustering patterns in the distribution.

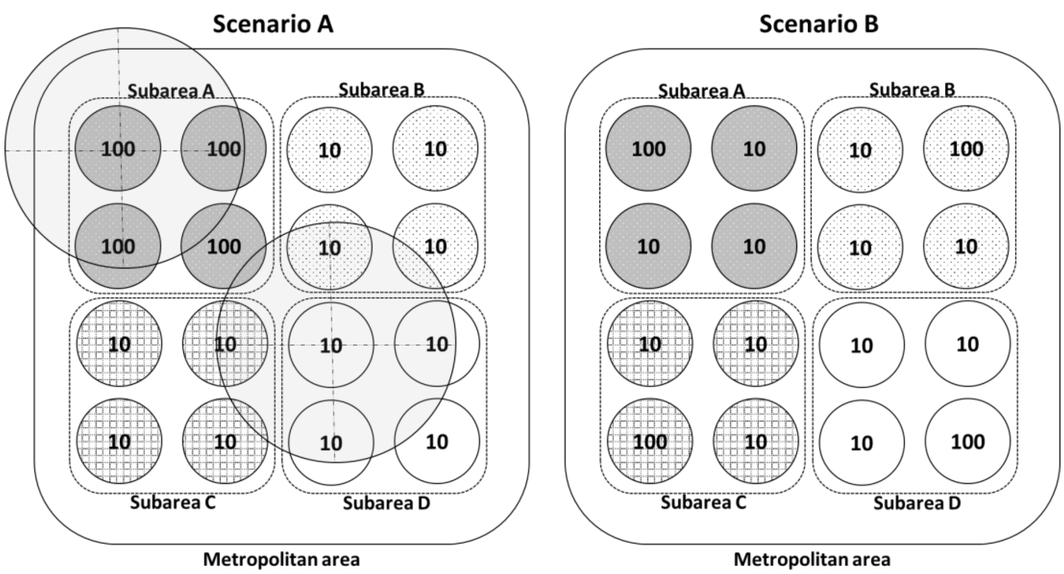


Figure 3. Scenarios of metropolitan areas with two different spatial distributions

Table 2 further describes differences in the magnitude of inequality using the traditional Theil's index and the spatial Theil's index. Spatial relationships are identified using Rook's contiguity – areal units that share a boundary (areal units that are in a diagonal direction that only share a corner are not considered). The values of Theil's index are the same for two scenarios, a value of 0.5926. However, the values of spatial Theil's index that uses the local boundary composite count are 0.3489 for Scenario A, and 0.0566 in Scenario B. Spatial inequality is greater in Scenario A because areal units in subarea D do not share a boundary with a job-rich area (with 100 jobs) in subarea A. In Scenario B, almost all areal units share a boundary with job-rich areas within their subarea. The spatial Theil's index is further broken down to within- and between- subarea inequality. It shows that the majority of inequality in Scenario A is derived from the differences between-subarea while all inequality in Scenario B is from within-subarea (internal heterogeneity). The contributions of each subarea to the total within- inequality shows that 48.9 percent of within-inequalities are driven from subarea B and C because the areal units these two subareas share a boundary with job-rich areas in subarea A. In Scenario B, subareas equally contribute to the overall within-subarea inequality. The two hypothetical scenarios illustrate the differences in two inequality indexes – the traditional Theil's index that focuses on the concentrations of jobs in each areal unit, and the spatial Theil's index that takes into account the spatial patterns of interaction with neighboring areas. In the following section, I will further explain how I use the spatial Theil's index to measure the spatial inequality of opportunity for Black populations – spatial variations in the distribution of Black populations and jobs – and further describe the details of the decompositions of spatial inequality measure.

Table 2. Theil's index and spatial Theil's index derived from the case scenarios in Figure 2

	Scenario A	Scenario B
Theil's index	0.5926	0.5926
Spatial Theil's	0.3489	0.0566
% Between	82%	0%
% Within	18%	100%
Subarea A	0.3%	25%
Subarea B	48.9%	25%
Subarea C	48.9%	25%
Subarea D	1.9%	25%

In the same manner, the local labor market boundary is drawn using five-mile buffer areas from the centroid of census tracts for measuring general dissimilarity index, the same five-mile boundary is used to measure spatial inequality. This takes into account the spatial distributions of Black populations and jobs within a five-mile buffer boundary as the local environment of each tract. Let y_i be the proportional shares of Black populations and jobs in each local environment i, where $cblack_i$ is the composite count of Black populations in the local neighborhood environment of census tract i, and c$jobs_i$ is the composite count of jobs in the local environment of census tract i. $\sum_i black_{ij}$ and $\sum_i jobs_{ij}$ are the total sum of Black populations and jobs in the labor environment of the metropolitan area. y_i can be written in the form of:

$$y_i = \frac{black\ share_i}{job\ share_i} = \left(\frac{cblack_i}{\sum_i cblack_i}\right) \Big/ \left(\frac{cjobs_i}{\sum_i cjobs_i}\right)$$

This is the ratio of ratios that measures the relative proportion of Black populations in each local environment to the proportion of jobs and captures whether there is a surplus of Black populations in each local environment. y_i then, is used in this research to represent the Black-to-Job proportion. If there is total equality in the distribution of Black populations and jobs, the ratio would equal to 1; if there is an overrepresentation of Black populations than the share of jobs, it will result in $y_i > 1$, and indicate lower shares of economic opportunities within the local environment. Thus, using the Black-to-Job proportion of each areal unit across the metropolitan area, this represents the equality and/or inequality in the distribution of two groups. Alternatives such as the use of proportional differences (e.g., dissimilarity scores) are also considered to represent the relative distributions, but by the nature of Theil's index, the natural logarithm is defined only for $y_i > 0$, and thus the proportional ratio y_i is used to measure spatial inequality across relative distributions. Theil's index (T) takes the form (Cowell, 2011):

$$T = \frac{1}{N}\sum_{i=1}^{N}\frac{y_i}{\bar{y}} ln\left(\frac{y_i}{\bar{y}}\right)$$

Where y_i is the ratio of a proportional share of Black populations and job opportunities within the local environment of census tract i, $\bar{y}$ is the metropolitan average. N is the number of census tracts within the metropolitan area. By comparing the relative distribution of Black populations and jobs, this index measures how diverse each local environment are from the metropolitan average $\bar{y}$. The index would become 0 if the distribution of Black populations and jobs are uniform across the metropolitan area, representing total equality (or integration). When there is total inequality – that is, when the spatial distribution of Black populations and jobs opportunities are concentrated in a single local environment – the index takes the maximum value, which is $\ln(\mathrm{N})$, since $\mathrm{E}(1) = \frac{1}{\mathrm{n}}\left[0 + 0 + \cdots + \frac{y_n}{\bar{y}}\ln\left(\frac{y_n}{\bar{y}}\right)\right] \approx \frac{1}{\mathrm{n}}[n \ln n] \approx \ln(n)$ (Reardon et al., 2008).

3.2.4 Additive Decomposability of Theil's Index

One of the key advantages of using Theil's index is that the property of additive decomposition allows one to break down spatial inequality into between and within-group components (Reardon et al., 2008; Reardon & Firebaugh, 2002). It is additive, which means that the inequality values of within-group and between groups can be added together to produce the overall inequality value (Shorrocks, 1980). Using the hierarchical structure of metropolitan areas – whereby local environments nest inside the neighborhood subarea (as illustrated in Figure 1) – Theil's index can distinguish whether inequality is derived from within-group components (such as within-neighborhood subareas) and between-group components (Akita, 2003). Thus, in addition to measuring the degree of spatial disparity in the distribution of Black populations and jobs for a metropolitan area, this analysis extends the scope of the research question by disaggregating the spatial disparity at the subarea level.

The decomposition model then can be written as (Akita, 2003):

$$T = T_{Between} + T_{Within}$$

Where a between-subarea inequality TB can be expressed as

$$T_B = \sum_{s \in m} \frac{N_s}{N} \frac{\bar{y}_j}{\bar{Y}} ln\left(\frac{\bar{y}_s}{\bar{Y}}\right)$$

Where ys is the average of yi in neighborhood subarea "s" within the metropolitan area "m", and Ns is the number of census tracts in neighborhood subarea s.

And within-subarea inequality TW as

$$T_W = \sum_{s \in m} \frac{N_s}{N} \frac{\bar{y}_s}{\bar{Y}} T_s$$

Where

$$\mathrm{T_s} = \frac{N_{is}}{N_s} \sum_{i \in s} \frac{y_{is}}{\bar{y}_s} \ln \frac{y_{is}}{\bar{y}_s}$$

T_s represents the inequality within each subarea s, y_{is} is the average of y_i within the neighborhood subarea s. N_{is} is the total number of census tracts within the neighborhood subarea s. Then, the above equations can be written as:

$$T = T_B + T_W = \sum_{s \in m} \frac{N_s}{N} \frac{\bar{y}_s}{\bar{Y}} ln\left(\frac{\bar{y}_s}{\bar{Y}}\right) + \sum_{s \in m} \frac{N_s}{N} \frac{\bar{y}_s}{\bar{Y}} \left(\frac{N_{is}}{N_s} \sum\nolimits_{i \in s} \frac{y_{is}}{\bar{y}_s} ln \frac{y_{is}}{\bar{y}_s}\right)$$

The within-group inequality is the weighted average of Theil's index for each subarea (T_s), and the between-group inequality uses the subgroup averages ($\bar{y}_s$) to calculate variability between subareas. Lastly, the contribution rates of within- and between- groups is calculated using:

$$T_W = \frac{T_W}{T} \times 100\%, T_B = \frac{T_B}{T} \times 100\%$$

3.2.5 Socio-Spatial differentiation

In addition to measuring spatial inequality, the degree of spatial differentiation – the uneven distribution of resources across space – in the socioeconomic, housing, and job characteristics in the Black and White neighborhoods are examined. This analysis measures the associations between racial segregation and neighborhood characteristics that provide a potential explanation for persistent spatial mismatch for Black populations. Using Moran's I spatial autocorrelation analysis, spatial clustering of segregated neighborhoods is identified[3]. Black neighborhoods represent neighborhoods where there is a high concentration of Black populations relative to White populations, and the White neighborhoods represent where there is a high concentration of White populations relative to Black populations within each census tract. Also, the neighborhoods with a population density of 1,000 per square mile are selected to limit the inclusion of low-density suburbs. For the comparison of economic activities and socioeconomic characteristics in the two neighborhood groups, the t-test is used to examine statistically significant differences in the social, economic, and housing characteristics.

Similar to Stoll et al. (2000) whose study examined the spatial distribution of employment opportunities based on the racial/ethnic compositions of the neighborhood, this

[3] The black-white segregation is used to identify racial residential segregation. Population counts is based on 2015 ACS at census tract level. For this measure, the census tracts, rather than the catchment areas are used. Also, the Moran's I using inverse distance is used.

analysis measures whether the economic characteristics are associated with residential segregation; specifically whether White neighborhoods have a higher concentration of economic opportunities. Previous studies have shown uneven suburban development patterns that create spatial differentiation between the “favored quarter” and “unfavored” neighborhoods where the infrastructure investment and development concentrate in the affluent-white neighborhoods, while Black populations become segregated on the other side of the metropolitan area. Thus, in addition to measuring associations between residential segregation and socioeconomic characteristics of residents, spatial differentiation in economic opportunities are compared that reveal a potential mechanism of the spatial mismatch for Black populations.

Table 3 further describes neighborhood characteristics that are used to measure spatial differentiation – socioeconomic characteristics of populations, housing characteristics, and job characteristics.

Table 3. Description of variables to be measured for neighborhood differentials

Variables	**Description**
Socioeconomic Characteristics	
Percent of college graduates	Percent of population over 25 years with a college degree
Percent unemployed	Percent of unemployed population over 16, in labor force
Percent households below poverty	Percentage of households under poverty
Percent households with public assistance	Percent of households with public assistance income
Housing Characteristics	
Median household income	Median Household income
Median housing built year	Median year structure built
Percent housing constructions after 2000	Percentage of housing built after 2000
Median housing value	Median housing value
Percent housing vacant	Percentage of housing currently vacant
Percent owner-occupied	Percentage of housing occupied by the owner
Job Characteristics	
Total Jobs, 2015	Total number of jobs
Jobs by industry (Manufacturing), 2015	Total number of manufacturing jobs
Jobs by industry (Local service), 2015	Total number of local service jobs
Jobs by industry (Professional service), 2015	Total number of professional service jobs

Jobs by industry (Education and public), 2015	Total number of education and public jobs
Jobs by industry (Health care), 2015	Total number of health care jobs
Change of total jobs, 2002-2015	Change of total jobs between 2002 and 2015
Change of jobs (Manufacturing), 2002-2015	Change of jobs between 2002 and 2015
Change of jobs (Local service), 2002-2015	Change of jobs between 2002 and 2015
Change of jobs (Professional service), 2002-2015	Change of jobs between 2002 and 2015
Change of jobs (Education and public), 2002-2015	Change of jobs between 2002 and 2015
Change of jobs (Health care), 2002-2015	Change of jobs between 2002 and 2015

3.3 Analysis and Findings

3.3.1 Spatial Distribution of Population and Employment

The patterns of population movement and jobs movement in the 100 metropolitan areas by the regions – Northeast, Midwest, West, and South – are shown in Tables 4 and 5. The population change between 2000 and 2015 in Table 4 shows the overall population living in 100 Metropolitan statistical area increased about 24.36 million, with the greatest increase in the outer suburb by 18.6 million. By race and ethnicity, non-Hispanic whites declined greatly in the inner suburb by 4.5 million, followed by a decline of .9 million in the inner city. The non-Hispanic Black population has decreased slightly in the inner city, while the share of the Black population in the inner suburb and outer suburb has increased. For Hispanic or Latino, the populations have increased throughout all neighborhood categories, but greatest in outer suburbs. The overall population trends indicate suburbanization of the population in all races/ethnicity. Despite these trends in population changes, a significant share of Black was found within the inner city. By the regions, around 60 percent of the Black population resided within the inner city in the Northeast, 57 percent in the Midwest, 47 percent in the West, and 38 percent in the South. In the South, around 41 percent of Black resided in the outer suburb, with only 21 percent of Black within the inner suburb. The largest share of whites was found in the inner suburbs of the Northeast, while in the other three regions, the largest share of whites occupied in the outer suburb.

The population trend confirms a general trend in which the “white flight” is occurring in the inner city as well as inner suburbs based on the definition presented by Harshbarger and Perry (2019), in which the white population has declined in these neighborhoods while the share of black and Hispanics has increased. It also indicates both Black and Hispanic population has expanded to suburbs, a pattern of shrinking urban core and sprawl of population into the outer suburbs. By the regions, metropolitan areas in the South had the highest population growth across all race and ethnicity groups, especially in the outer suburbs. The pattern of white flight in the inner city and inner suburbs is shown throughout regions, with the greatest population loss in the inner suburb. The decline of the Black population in the inner city was also examined across regions except in the South. This trend is the greatest in the Midwest by nearly 0.4 million in the 100 largest metropolitan areas. The Hispanic population grew in all neighborhood subareas across regions, especially in the inner city of Northeast and Midwest, and outer suburbs of West and South metropolitan areas.

The distribution trend of jobs by industry categories for each neighborhood subareas are shown in Table 5. The trends for total jobs and industries in goods-producing and local service are used following Andersson et al. (2018). Overall, the largest share of total jobs is within the inner city by 38.9 percent followed by outer suburbs. All jobs, including low-skilled jobs in goods-producing and local service sectors, had the least share of jobs in the inner suburb in 100 metropolitan areas. By the regions, the inner city had the largest share of total jobs, while the goods producing jobs were found within the outer suburbs in all regions. The greatest share of local service jobs was found within the inner suburbs of Northeast and Midwest regions, while a large share of service jobs was located within the inner city in the West and outer suburbs of the South region. The overall trend showed a large share of goods producing jobs has suburbanized in the outer suburb, especially in the Midwest and South regions.

The trends of job changes between 2000 and 2015 showed an increase of 11.27 million jobs in 100 metropolitan areas, among which 63 percent of total job increase were within the outer suburb. Overall, jobs in the goods producing industry fell by nearly one million, while jobs in the local service industry increased by 4.3 million. The goods producing jobs fell the most in the inner suburb, especially in the Northeast and Midwest, while the number increased in the outer suburb. Local service jobs on the other hand increased the most in the inner city in the Northeast and Midwest and the least in the inner suburb. In the West and South, both goods producing jobs and low skilled jobs increased the most in the outer suburb, indicating growing suburban expansion in these regions.

Table 4. The trend of population change in 100 MSAs by race and ethnicity by neighborhood subareas, 2000 to 2015

(In millions, % share)

		2000				2015				% change			
		Total	**White**	**Black**	**Hispanic**	**Total**	**White**	**Black**	**Hispanic**	**Total**	**White**	**Black**	**Hispanic**
	Total	169.2	107.1	22.8	26.57	193.5	108.4	26.22	40.03	24.36 (14.3%)	1.23 (1.1%)	3.41 (14.9%)	13.45 (50.6%)
100 MSAs	Inner City	55.2	24.9	12.7	12.1	59.3	24	12.4	15.8	4.11 (7.4%)	-0.9 (-3%)	-0.3 (-2%)	3.71 (30.7%)
	Inner Suburb	54.9	35.3	6.02	9.28	56.5	30.7	6.91	13.1	1.57 (2.8%)	-4.5 (-12%)	0.88 (14.7%)	3.83 (41.2%)
	Outer Suburb	59	46.8	4.01	5.17	77.7	53.6	6.84	11	18.6 (31.6%)	6.74 (14.3%)	2.82 (70.4%)	5.9 (114.1%)
Northeast	Inner City	11.97	4.58	3.34	2.69	12.43	4.24	3.24	3.19	0.45 (3.8%)	-0.33 (-7%)	-0.09 (-2%)	0.49 (18.3%)
	Inner Suburb	15.26	11.36	1.54	1.50	15.54	10.05	1.75	2.47	0.28 (1.8%)	-1.3 (-11%)	0.20 (13.5%)	0.96 (64.3%)
	Outer Suburb	9.11	8.27	0.28	0.24	10.10	8.62	0.40	0.51	1.05 (11.5%)	0.35 (4.2%)	0.11 (40.7%)	0.27 (112.4%)
Midwest	Inner City	10.77	5.39	3.55	1.22	10.44	4.92	3.18	1.55	-0.32 (-2%)	-0.46 (-8%)	-0.37 (-10%)	0.33 (27%)
	Inner Suburb	12.54	9.74	1.38	0.83	12.37	8.46	1.73	1.38	-0.16 (-1%)	-1.27 (-13%)	0.34 (24.8%)	0.54 (65.3%)
	Outer Suburb	12.32	11.24	0.37	0.30	15.06	12.83	0.68	0.69	2.73 (22.2%)	1.59 (14.1%)	0.30 (80.6%)	0.39 (129.6%)
West	Inner City	15.92	7.32	1.35	4.66	17.70	7.21	1.29	6.00	1.83 (11.5%)	-0.10 (-1%)	-0.05 (-4%)	1.34 (28.7%)
	Inner Suburb	16.23	7.94	0.83	5.03	17.20	6.92	0.82	6.44	1.03 (6.3%)	-1.01 (-12%)	-0.009 (-1%)	1.40 (27.7%)
	Outer Suburb	11.38	7.82	0.38	1.93	16.00	9.26	0.63	3.77	4.63 (40.7%)	1.44 (18.4%)	0.25 (68.1%)	1.84 (95.2%)
South	Inner City	16.53	7.69	4.51	3.52	18.67	7.66	4.74	5.07	2.13 (12.9%)	-0.03 (0.3%)	0.22 (4.9%)	1.54 (43.9%)
	Inner Suburb	10.91	6.28	2.25	1.90	11.34	5.30	2.60	2.82	0.42 (3.9%)	-0.97 (-15%)	0.34 (15.2%)	0.91 (48.1%)
	Outer Suburb	26.24	19.53	2.97	2.69	36.49	22.89	5.11	6.09	10.2 (39%)	3.35 (17.1%)	2.14 (72.2%)	3.40 (126.1%)

Table 5. The trend of employment change in 100 MSAs by industry categories by neighborhood subareas, 2002 to 2015

(In millions, %share)

	Category	2002 Total	2002 Inner city	2002 Inner suburb	2002 Outer suburb	2015 Total	2015 Inner city	2015 Inner suburb	2015 Outer suburb	% Change Total	% Change Inner city	% Change Inner suburb	% Change Outer suburb
100 MSAs	Total Jobs	77.6	30.64 (39.5%)	23.51 (30.3%)	23.49 (30.3%)	88.9	34.59 (38.9%)	23.69 (26.6%)	30.62 (34.4%)	11.3	3.95 (12.9%)	0.18 (0.8%)	7.13 (30.4%)
	Goods - producing	20.7	6.8 (32.6%)	5.5 (26.7%)	8.4 (40.6%)	19.9	6.2 (31.2%)	4.5 (22.6%)	9.2 (46.2%)	-0.8	-0.55 (-8.1%)	-1.04 (-18.8%)	0.78 (9.3%)
	Local services	24.3	9.1 (37.4%)	8 (-32.9%)	7.2 (29.7%)	28.6	10.5 (36.7%)	8.2 (28.5%)	9.9 (34.8%)	4.31	1.42 (15.6%)	0.18 (2.3%)	2.71 (37.5%)
Northeast	Total Jobs	15.9	5.46	6.62	3.85	17.6	6.46	6.61	4.55	1.69	1 (18.4%)	-0.01 (-0.1%)	0.69 (18.1%)
	Goods-producing	3.79	0.95	1.57	1.26	3.38	0.86	1.23	1.27	-0.4	-0.08 (-9%)	-0.33 (-21%)	0.01 (1.4%)
	Local service	4.53	1.34	2.09	1.08	5.25	1.72	2.17	1.35	0.71	0.37 (28.2%)	0.07 (3.4%)	0.26 (24.5%)
Midwest	Total Jobs	17.4	5.87	6.19	5.35	18.5	6.16	5.72	6.64	1.1	0.28 (4.8%)	-0.46 (-7%)	1.28 (24%)
	Goods-producing	4.95	1.37	1.58	1.99	4.45	1.14	1.17	2.13	-0.4	-0.22 (-16%)	-0.41 (-26%)	0.13 (6.9%)
	Local service	5.26	1.64	2.05	1.55	5.77	1.75	1.96	2.05	0.51	0.1 (6.6%)	-0.08 (-4%)	0.49 (31.8%)
West	Total Jobs	18.9	8.4	5.87	4.7	22.5	9.83	6.47	6.18	3.51	1.43 (17%)	0.6 (10.3%)	1.47 (31.3%)
	Goods-producing	5.17	1.92	1.37	1.87	5.14	1.81	1.26	2.05	-0.03	-0.11 (-5%)	-0.1 (-7%)	0.18 (9.8%)
	Local service	6.23	2.77	2.08	1.37	7.29	3.18	2.24	1.86	1.05	0.4 (14.6%)	0.15 (7.6%)	0.49 (35.7%)
South	Total Jobs	25.2	10.8	4.82	9.56	30.2	12.1	4.87	13.2	4.95	1.23 (11.3%)	0.04 (0.9%)	3.67 (38.3%)
	Goods-producing	6.78	2.5	1	3.27	6.91	2.37	0.82	3.71	0.12	-0.12 (-4%)	-0.18 (-18%)	0.43 (13.3%)
	Local service	8.24	3.3	1.73	3.2	10.2	3.82	1.77	4.65	2.01	0.51 (15.7%)	0.43 (13.3%)	1.45 (45.5%)

3.3.2 Aggregate trends of spatial mismatch

The dissimilarity index at the census tract and the five-mile catchment areas are computed to show an aggregate trend of the spatial mismatch in 2000 and 2015. The index for 100 MSAs is provided in Appendix B, and Table 6 shows the regional average and total average value of the spatial mismatch. The values of the dissimilarity index range from 0 to 1, in which the value of 1 represents perfect dissimilarity in the share of the Black population and jobs in the metropolitan area. The catchment area dissimilarity index measures the proportional share of the Black population and jobs of the local labor market boundary which is a five-mile buffer area of census tracts.

Table 6. Spatial mismatch using dissimilarity index for goods-producing and service jobs for the Black population

	Census Tract Spatial Mismatch				Catchment Area Spatial Mismatch			
	00		15		00		15	
	Goods Producing	Local Service	Goods Producing	Local Service	Goods Producing	Local Service	Goods Producing	Local Service
Northeast	0.69	0.66	0.69	0.65	0.26	0.23	0.26	0.22
Midwest	0.73	0.69	0.72	0.65	0.28	0.27	0.27	0.26
South	0.62	0.61	0.62	0.58	0.23	0.24	0.24	0.23
West	0.69	0.58	0.70	0.58	0.26	0.23	0.25	0.21
Total	0.67	0.62	0.67	0.60	0.25	0.24	0.25	0.23

The average spatial mismatch for the Black population in 100 MSAs is 0.67 for goods-producing jobs and 0.62 for local service jobs in 2015. This indicates that 67 percent or 60 percent of either Black households or these jobs should relocate to achieve perfect equality in the distributions within metropolitan areas. It shows the spatial mismatch for Black households is highest in the Midwest for both goods-producing and local-service jobs, while the spatial mismatch in metropolitan areas in the South declined for both industries. The catchment area dissimilarity index shows a much lower degree of mismatch compared to census tract mismatch since this compares the distribution of Black households and jobs between the local labor markets, which are considered as overlapping environments rather than exclusive geographic areas as census tracts. The spatial mismatch index using catchment area thus can be interpreted as, on average, what percentages of the Black population or jobs within the local labor market are dissimilar to other local labor markets. The catchment area spatial mismatch also shows MSAs in the Midwest have the highest spatial mismatch for the Black population for both industry categories, while South and West have the lowest spatial mismatch. This indicates that as much as the Black population and jobs are distributed unevenly between census tracts, the distributions within the local labor markets measured by catchment areas share similar patterns.

The changes in the spatial mismatch between 2000 and 2015 in the 100 largest metropolitan areas in the U.S. using both census tract and catchment areas are shown in Table 7. The spatial mismatch measured at the census tract level indicates changes in the distribution of the Black population and jobs between census tracts, and the spatial mismatch measured at the catchment area indicates changes in the distributions between the 5-mile radius local labor market. On average, the spatial mismatch to local service jobs decreased by two percent at the census tract level, and one percent at the catchment area. Although the changes in the spatial mismatch for goods producing jobs are non-significant, the decline in the spatial mismatch for local service jobs is statistically significant. This suggests the spatial mismatch to goods producing jobs remained relatively consistent, while the mismatch to service jobs decreased throughout metropolitan areas between 2000 and 2015. The changes in the spatial mismatch at the catchment area also show a similar trend for both goods producing jobs and local service jobs, while the degree of changes is smaller than at the census tract level. This indicates the spatial mismatch between census tracts shows a greater decline than between catchment areas, suggesting the spatial distribution of the Black population and jobs at the local labor market areas did not change as much in 2015.

The changes in spatial mismatch show some variations by the regions. The catchment area spatial mismatch shows a significant decline in the Midwest, especially for local service jobs. In the South, the spatial mismatch to goods producing jobs increased while the mismatch to local service jobs slightly decreased. This implies the locational dispersion of the Black population and goods producing jobs are growing, whereas overall patterns of mismatch to local services jobs are declining. In other regions, although the overall levels of spatial mismatch have declined in 2015 compared to 2000, the differences in the two time periods are statistically non-significant.

Table 7. Changes in the spatial mismatch for the Black population between 2000 and 2015 in 100 MSAs (in percentages)

	Census Tract Spatial Mismatch				Catchment Area Spatial Mismatch			
	Goods Producing	p	Local Service	p	Goods Producing	p	Local Service	p
Northeast	0.2%		**-1.7%**		0.8%		**-0.6%**	
Midwest	**-1.3%**		**-3.8%**	***	**-0.9%**		**-1.6%**	**
West	1.6%	+	0.4%		**-0.5%**		**-1.6%**	
South	0.0%		**-2.6%**	***	0.9%	+	**-0.2%**	+
Total	0.2%		**-2.0%**	*******	0.2%		**-0.9%**	******

+ p<0.1;*p<0.05; **p<0.01; ***p<0.001

It is interesting to note that although the changes in spatial mismatch measured at census tracts in the West show an increasing trend, the mismatch measured at the catchment area declined in 2015. What this entails is that unevenness in the distribution of Black populations and jobs increased between census tracts, but the changes occurred within the labor market boundary and these changes led to more even distribution of Black population and jobs between catchment areas. This also implies that not taking into account the labor market boundaries in measuring spatial mismatch, whether the mismatch is calculated at a reasonable scale, may overestimate actual changes in spatial distribution within urban geography. For this reason, I will use the catchment area as the main analysis unit for examining the spatial pattern of mismatch and measuring spatial inequality.

Also, although the majority of studies utilize dissimilarity index to represent the extent of the spatial mismatch in metropolitan areas, such aggregate trends of mismatch overlook intra-metropolitan spatial mismatch, the locational distribution of spatial mismatch. Since metropolitan areas vary in their development patterns, a single index for the spatial mismatch is insufficient to analyze dynamic trends of spatial mismatch. Thus, in the following sections, the geospatial distribution of spatial mismatch within metropolitan areas is shown as well as the extent of spatial inequality within and between neighborhoods for each metropolitan area.

3.3.3 Metropolitan-level Spatial Distribution of Population and Employment

To describe the geographical trends of Black suburbanization, the total number of working-age Black populations, the shares, and the percentage changes between 2000 and 2015 are shown for each neighborhood subarea in Table 8. Overall, working-age Black populations increased the most in the outer suburb (81.3 percent increase) followed by the inner suburb (32.9 percent increase). In nearly all the observed metropolitan areas, around half of Black populations continue to live in the inner city by 46.2 percent, but the population changes over 15 years show that the shares of the Black population have increased in the suburbs while their numbers fell in the inner city. By the percentages, more working-age Black populations now live in the suburbs (53.8 percent) than in the inner city, suggesting the demographic inversion in U.S. metropolitan areas as well as the trend of Black migration into the suburbs. Black population increase in the outer suburb is especially notable in the two the South: Dallas and Atlanta (108.8 percent and 142.5 percent increase, respectively) where the Black suburbanization was already in process before 2000. The other two metropolitan areas are in the Midwest: Detroit and Minneapolis, in which Black populations increased the most in the outer suburb by approximately 111.9% and 193.2%, respectively. Although more than half of Black populations (65.9 and 59.6 percent, respectively) continue to reside in the inner city in New York and Detroit, these metropolitan areas also show Black population growth in the suburbs is greater than in the inner city. In Atlanta, around 87.3 percent of working-age Black populations reside in the suburbs, suggesting a clear sign of demographic inversion into the suburbs. Overall, Table 8 supports the Black suburbanization trend is indeed occurring as their shares are increasing in the suburbs, but a large share of Black populations continues to live in the inner city in 2015 in these metropolitan areas.

Table 8. Distribution of working-age Black populations for metropolitan areas by regions

	2015 Black population (in thousands)			2015 Black share			Percentage change 2000-2015		
	Inner city	Inner suburb	Outer suburb	Inner city	Inner suburb	Outer suburb	Inner city	Inner suburb	Outer suburb
Northeast									
New York	1567.2	699.7	100.5	66.2%	29.6%	4.2%	1.2%	11.6%	41.2%
Philadelphia	444.2	292.3	116.4	52.1%	34.3%	13.6%	9.1%	23.5%	44.3%
Pittsburgh	49.9	68.4	11.1	38.6%	52.9%	8.5%	-10.2%	26.1%	44.7%
Midwest									
Chicago	558.2	403.4	128.4	51.2%	37.0%	11.8%	-15.4%	14.7%	80%
Detroit	383.6	208.8	59.1	58.9%	32.1%	9.1%	-21.3%	59.7%	112%
Minneapolis	77.7	59.4	37.2	44.5%	34.1%	21.4%	20.1%	143.4%	191.8%
West									
Los Angeles	297.8	268.1	51.7	48.2%	43.4%	8.4%	-7.5%	-6.1%	44.5%
San Francisco	118.5	91.4	38.5	47.7%	36.8%	15.5%	-17.6%	-1.8%	35.4%
Seattle	49.5	65.4	28.3	34.6%	45.7%	19.8%	1.7%	63.8%	76.5%
South									
Dallas	371	79.9	268.3	51.6%	11.1%	37.3%	22.7%	12.5%	142.5%
Atlanta	162.6	264.4	857.2	12.7%	20.6%	66.7%	-2.6%	2.1%	108.8%
Baltimore	266.8	173.5	109.6	48.5%	31.6%	19.9%	-1.6%	44.8%	53.1%
Total	4347	2674.7	1806.2	46.2%	34.1%	19.7%	-1.8%	32.9%	81.3%

The spatial mismatch in the twelve metropolitan areas using the GD index is presented in Table 9. The metropolitan-level spatial mismatch in 2000 and 2015 and the changes over the two periods are shown. Consistent with the literature, the spatial mismatch is the highest in Detroit, Los Angeles, and Chicago for goods producing jobs in 2015. It indicates that as much as Black populations are separated from the goods producing jobs within their residence census tract areas, Black populations in these metropolitan areas have the highest level of mismatch to jobs even when the distributions of the surrounding areas are considered for. As for the local service and health care jobs, New York, Chicago, San Francisco, and Detroit (in the order of highest to lowest value) have the highest level of spatial mismatch. This indicates that in San Francisco, although the Black populations are not as spatially mismatched to the goods producing jobs, the spatial mismatch is particularly significant to the local service jobs.

The changes in the metropolitan-level spatial mismatch in 2000 and 2015 show the spatial mismatch declined in most metropolitan areas. By the industry, spatial mismatch to goods producing jobs declined in more metropolitan areas than to local service and health care jobs. Spatial mismatch to goods producing jobs declined in almost all metropolitan areas except for two: San Francisco and Baltimore - metropolitan areas with polycentric employment sub-centers in the suburbs. For the goods producing jobs, the level of mismatch declined the most in Detroit, Minneapolis, followed by Dallas and Atlanta. These areas had the highest Black population growth in the suburbs between 2000 and 2015 in Table 8. This implies that the decline in the spatial mismatch in these metropolitan areas is attributable to the Black suburbanization that brings people closer to suburban jobs. Despite these declines, Detroit and Chicago continue to remain as areas with the highest degree of spatial mismatch in 2015.

Table 9. Black Spatial Mismatch Indices in the twelve Metropolitan Areas

	2000		2015		2000-2015 Change	
	Goods producing	Local service	Goods producing	Local service	Goods producing	Local service
Northeast						
New York	0.369	0.418	0.356	0.426	-0.014	0.007
Philadelphia	0.361	0.282	0.355	0.269	-0.006	-0.012
Pittsburgh	0.294	0.245	0.288	0.221	-0.006	-0.024
Midwest						
Chicago	0.385	0.415	0.381	0.430	-0.004	0.014
Detroit	0.455	0.469	0.400	0.408	-0.055	-0.061
Minneapolis	0.274	0.195	0.213	0.169	-0.062	-0.026
West						
Los Angeles	0.395	0.410	0.385	0.386	-0.010	-0.025
San Francisco	0.334	0.404	0.356	0.414	0.022	0.010
Seattle	0.244	0.247	0.241	0.291	-0.003	0.044
South						
Baltimore	0.264	0.204	0.289	0.196	0.025	-0.007
Dallas	0.360	0.356	0.323	0.325	-0.037	-0.031
Atlanta	0.359	0.373	0.327	0.356	-0.032	-0.018

3.3.4 Intra-Metropolitan Spatial Patterns of Mismatch

In addition to the aggregated GD index, the local variations in the locations of mismatch are demonstrated using the GD scores – the disproportionality of Black populations and jobs for each local environment before they are aggregated to metropolitan areas. The GD scores can reveal whether there is a disproportionate representation of Black populations relative to jobs or vice versa. Thus, both types of spatial mismatch are identified: 1) a surplus of Black populations with a low proportion of jobs in surrounding areas, and 2) high concentrations of jobs with a small proportion of Black populations. For the latter case, it identifies a pattern where Black job-seekers are underrepresented in an opportunity surplus area. Further, the spatial dimension of mismatch is useful in demonstrating the variations in the spatial pattern of mismatch between the two metropolitan areas that has the same level of mismatch. It may be that the spatial mismatch is spread evenly throughout the metropolitan area similar to a checkerboard pattern, or local concentration of Black populations and jobs in different clusters. As such, the spatial dimension of mismatch can demonstrate variations in the intra-metropolitan spatial pattern as well as test whether the geography of mismatch is indeed shifting to the suburbs of metropolitan areas.

Figures 4 and 5 present the general dissimilarity scores of twelve metropolitan areas in 2015 for goods producing jobs local service and health care jobs. In the subsequent section, the changes in the GD scores between 2000 and 2015 are presented to demonstrate the locations of an increase in the disproportionality. The neighborhood subareas are shown using three boundaries, whereby the innermost region is the inner city, the second most centralized region is the inner suburb, and the outermost region is the outer suburb. The degree of spatial mismatch is presented using the standard deviations that show how much the dissimilarity scores of each catchment area deviate from the metropolitan average. The negative scores indicate that the share of jobs is higher than the share of Black households, and the positive scores indicate that the share of Black populations is higher than the share of jobs.

Spatial patterns of mismatch to goods producing jobs in Figure 4 shows that many of the metropolitan areas in the Northeast and Midwest display a traditional pattern of mismatch whereby the Black surplus neighborhoods in the inner city are surrounded by job opportunities in the suburbs. These are indicated by clusters of Black surplus areas in the inner city and surrounding job-rich areas in the suburbs of metropolitan areas as shown in Figure-4 (b) Philadelphia, (c) Pittsburgh, (e) Detroit, and (f) Minneapolis. In other metropolitan areas, the spatial patterns of mismatch are more diverse. In Figure-4 (d) Chicago, job surplus neighborhoods are clustered around the northwestern part of the suburb, while Black surplus neighborhoods are concentrated in the southern part of the inner city and to the inner suburb. This indicates the spatial pattern of mismatch in Chicago is even more geographically separated than the other metropolitan areas where job-rich neighborhoods are located just outside the inner city boundary. The spatial pattern in Figure-4 (a) New York demonstrates a reverse pattern of mismatch where job-rich neighborhoods are concentrated in the center of the inner city while Black surplus neighborhoods surround these job centers. In metropolitan areas in the South, there is an obvious pattern of suburban spatial mismatch, whereby Black surplus neighborhoods extend beyond the boundaries of the inner city into the inner- and outer-suburbs. This pattern is most evident in Figure-4 (j) Dallas and (k) Atlanta where a large number of Black populations have migrated into the southern suburbs and the spatial pattern of mismatch is divided into north and south. As hypothesized earlier, the spatial pattern of mismatch closely follows segregated Black suburbs, creating a suburb-to-suburb spatial mismatch that increases the spatial disparity of the suburbs.

Figure 5 shows the spatial pattern of mismatch to local service and health care jobs. In Figure-5 (b) Philadelphia and (e) Detroit, the patterns of spatial mismatch are similar to the traditional spatial mismatch pattern – that is, a Black surplus in the inner city and a surplus of suburban job opportunities surrounding the inner city. It is also shown in Figure-5 (l) Baltimore, where local service jobs are located around the suburbs while the Black surplus neighborhood is concentrated in the northern part of the inner city. Also, it is noticeable the spatial patterns of mismatch to local service jobs demonstrate more localized clusters of jobs. As shown in Figure-5 (d) Chicago, (i) Seattle and (h) San Francisco, a high concentration of service jobs are clustered in the inner city. This implies that for local service and health care jobs, the spatial pattern of mismatch is concentrated within the inner city where the inner city Black populations are spatially separated from the inner city jobs – demonstrating inner city spatial disparity.

Based on these differing patterns of mismatch in the twelve observed metropolitan areas, I classify spatial mismatch patterns into four major types: 1) traditional spatial mismatch pattern of inner-city Black and suburban jobs, 2) geographical polarization to the north-south or east-west – a division of Black surplus neighborhoods and job surplus neighborhoods in different parts of the metropolitan areas, 3) spatial mismatch within the inner city – polarized urban core, and 4) suburb-to-suburb spatial mismatch – suburbanized Black surplus neighborhood and job surplus neighborhood. Many of the metropolitan areas in the Northeast and Midwest regions including the Rust Belt regions continue to reflect traditional patterns similar to Kain's hypothesis that represent instances in which inner-city Black populations are spatially mismatched from suburban jobs. In the west, especially in San Francisco and Seattle, clusters of employment surplus neighborhoods were found in both the inner city and in the inner suburb, demonstrating a polycentric development trend. In the "New South" regions – Atlanta and Dallas – where a large portion of the Black populations had already relocated to the suburbs before the 2000s – the majority of Black populations are located in the suburbs to the south and east, while job surplus neighborhoods are concentrated in the northern part of the inner city and suburbs. This implies the spatial pattern of economic disparity dividing the region to the north and south.

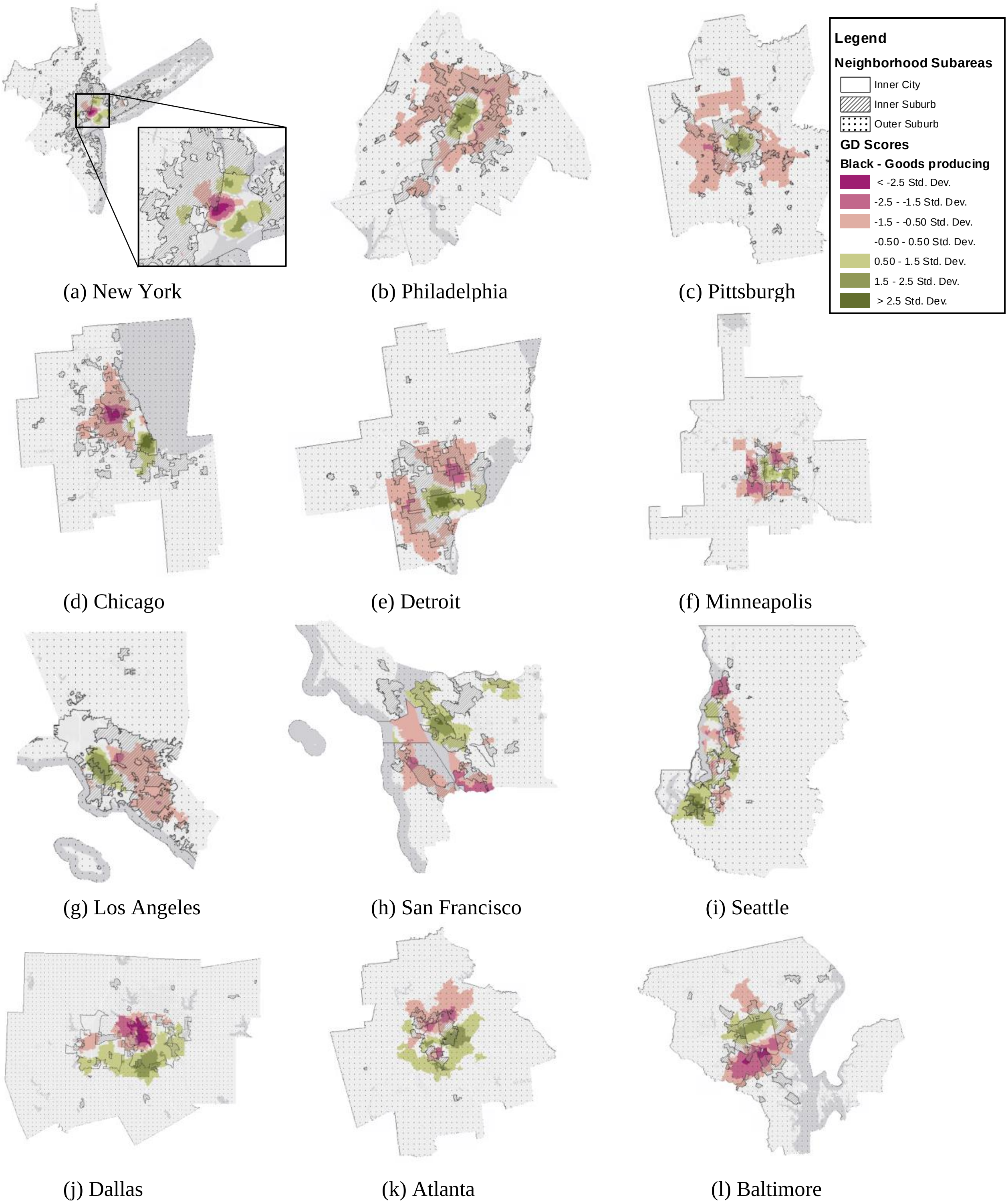


Figure 4. Spatial mismatch between Black populations and goods producing jobs, 2015

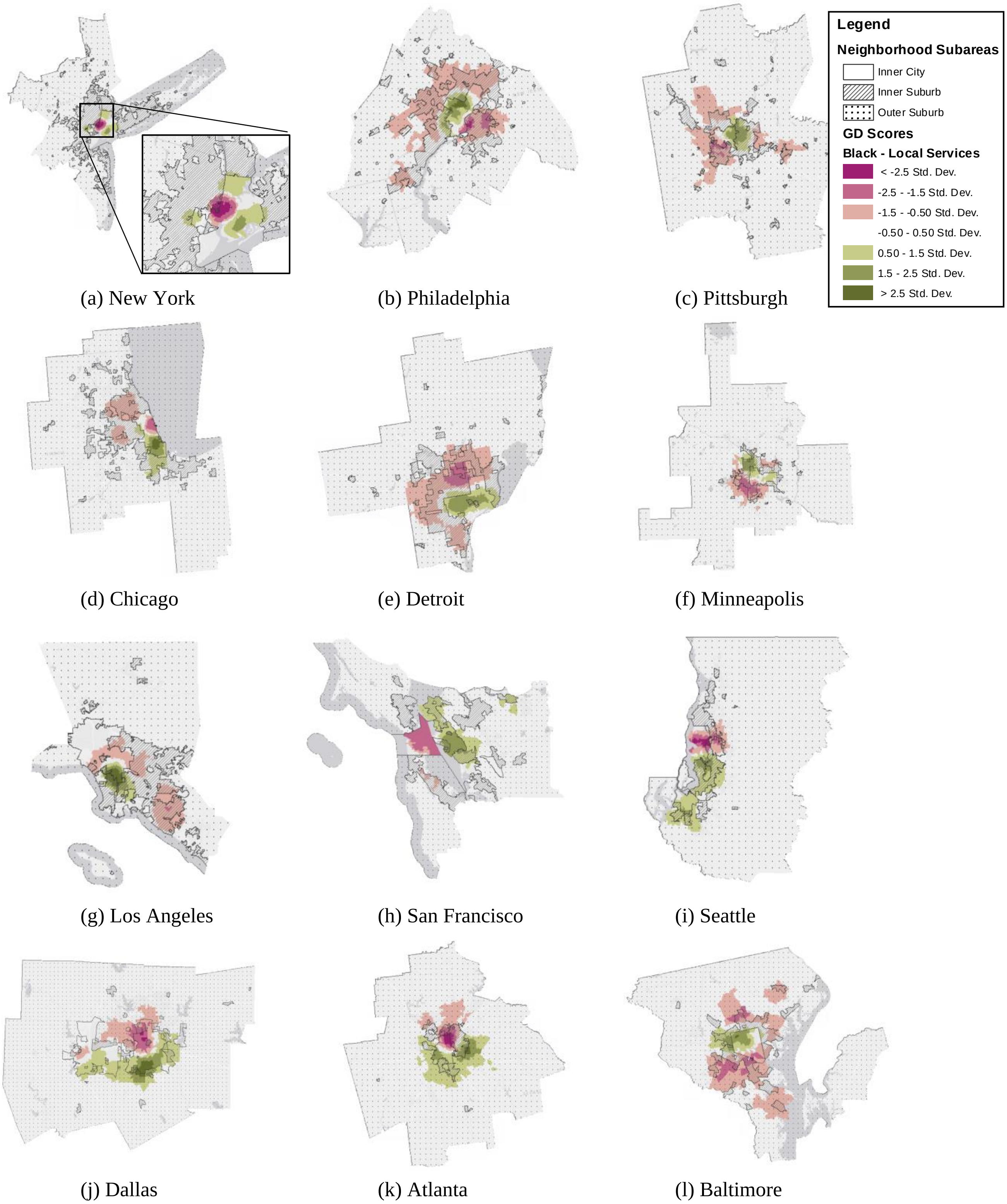


Figure 5. Spatial mismatch Black populations and local service and health care jobs, 2015

3.3.5 Changes in Spatial Pattern of Mismatch, 2000-2015

To demonstrate the changes in the disproportionality of Black populations and jobs within each local neighborhood environment, the absolute changes in the magnitude of GD scores are displayed in Figures 6 and 7. This reveals the magnitude of changes in the dissimilarity rather than the directions of change, in which the positive and negative value indicates the spatial mismatch in the local environment increased or decreased in 2015 compared with 2000, respectively. Once again, the changes in the spatial patterns using the standard deviations demonstrate the degree of changes from the metropolitan average.

Overall, spatial trends show the disproportionality in the inner city declined while the suburb shows an increasing trend, implying the suburbs have become more mismatched in 2015 than in 2000. These decline in the inner city are shown in Figure-6 (d) Chicago, (e) Detroit, (g) Los Angeles, (j) Dallas, and (k) Atlanta, where both Black suburbanization and decreased share of jobs in the inner city due to continued expansion of goods producing jobs into the suburbs has resulted in decreased relative shares of Black populations and jobs in the inner city. The exception is in Figure-6 (a) New York and (h) San Francisco – metropolitan areas with a concentration of employment center in the urban core – demonstrating the trend where the disproportionality had increased in the inner city. In the two metropolitan areas, the increase in the inner city is driven in part by the growing share of jobs in the inner city. This suggests that although the suburbanization of goods producing jobs has decreased the relative shares of jobs in the inner city in most metropolitan areas, other metropolitan areas with a strong urban core that continue to attract jobs resulted in an increased mismatch in the inner city.

In the suburbs, these patterns of change are more complex. In Figure-6 (c) Pittsburgh, (d) Chicago, (e) Detroit, (g) Los Angeles, and (i) Seattle, spatial mismatch decreased in the inner suburb where Black populations largely moved into, but the mismatch has increased throughout the outer suburb. This implies the suburbanization of Black populations was able to offset the disproportionality in the inner suburb where there were relatively more jobs than the share of the Black population. However, the increase in the disproportionality in the outer suburb suggests that jobs are growing in these outlying suburbs away from where Black populations are moving in to and Black suburbanization was only able to offset the existing level of mismatch in the inner suburbs. These patterns are most evident in the South, in Figure-6 (j) Dallas and (k) Atlanta, in which the spatial mismatch increased primarily in the southern suburbs where a large share of Black populations has suburbanized.

The changes in spatial patterns of mismatch to local service and health care jobs in Figure 7 shows spatial mismatch increased in more localized clusters compared to the goods producing jobs. This is especially noticeable in Figure-7 (d) Chicago and (i) Seattle, which shows the spatial mismatch increased in the northern section of the inner city. In these metropolitan areas, the spatial mismatch has also increased in the southern suburbs where a large share of Black populations has moved into. This pattern demonstrates an increasing spatial disparity within the inner city among metropolitan areas with localized clusters of service jobs in the inner city, while Black populations are increasingly segregated away from where jobs are growing. Overall, the disproportionality of Black populations and local service jobs tend to increase in a more concentrated manner that is localized over a compact area.

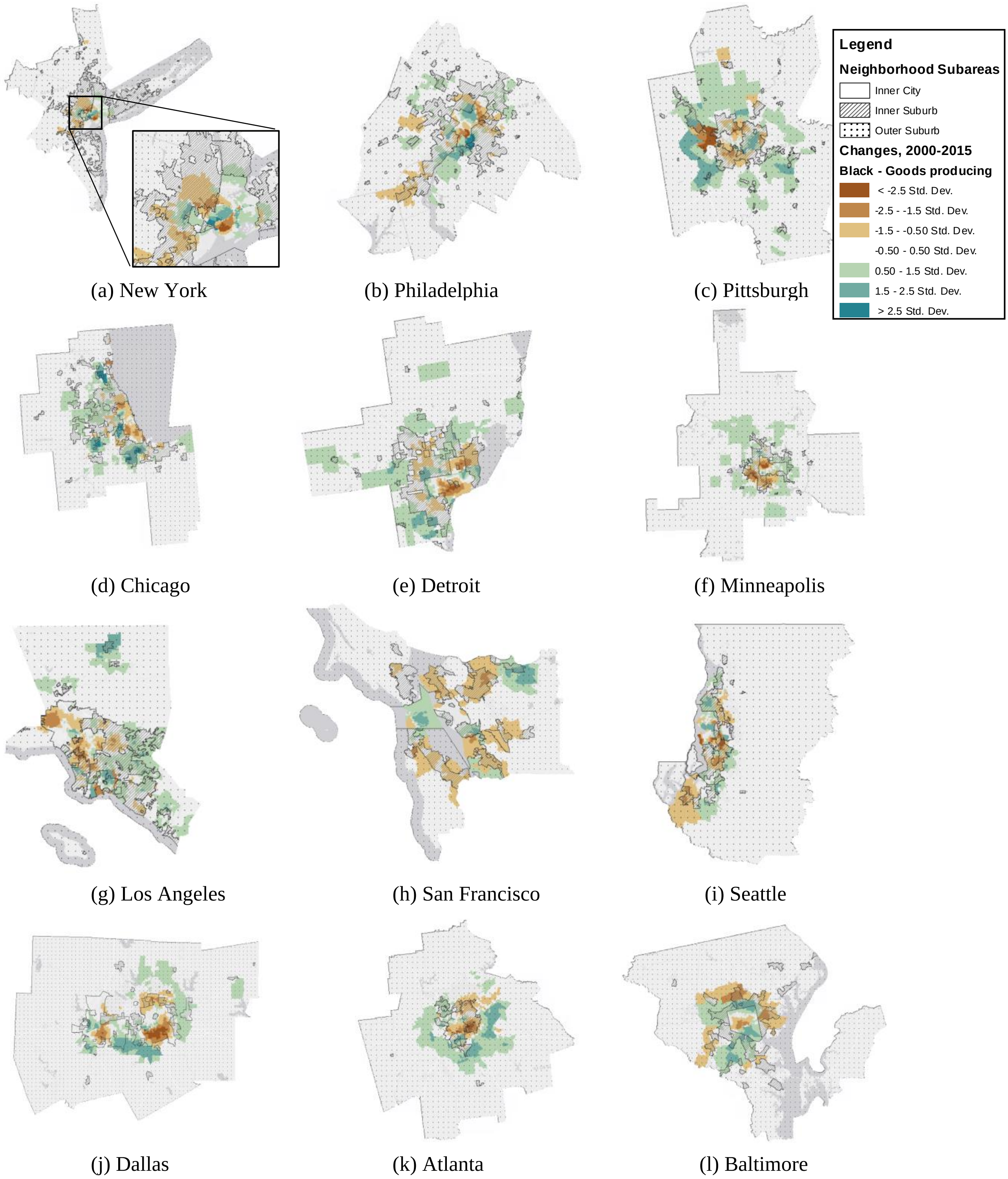
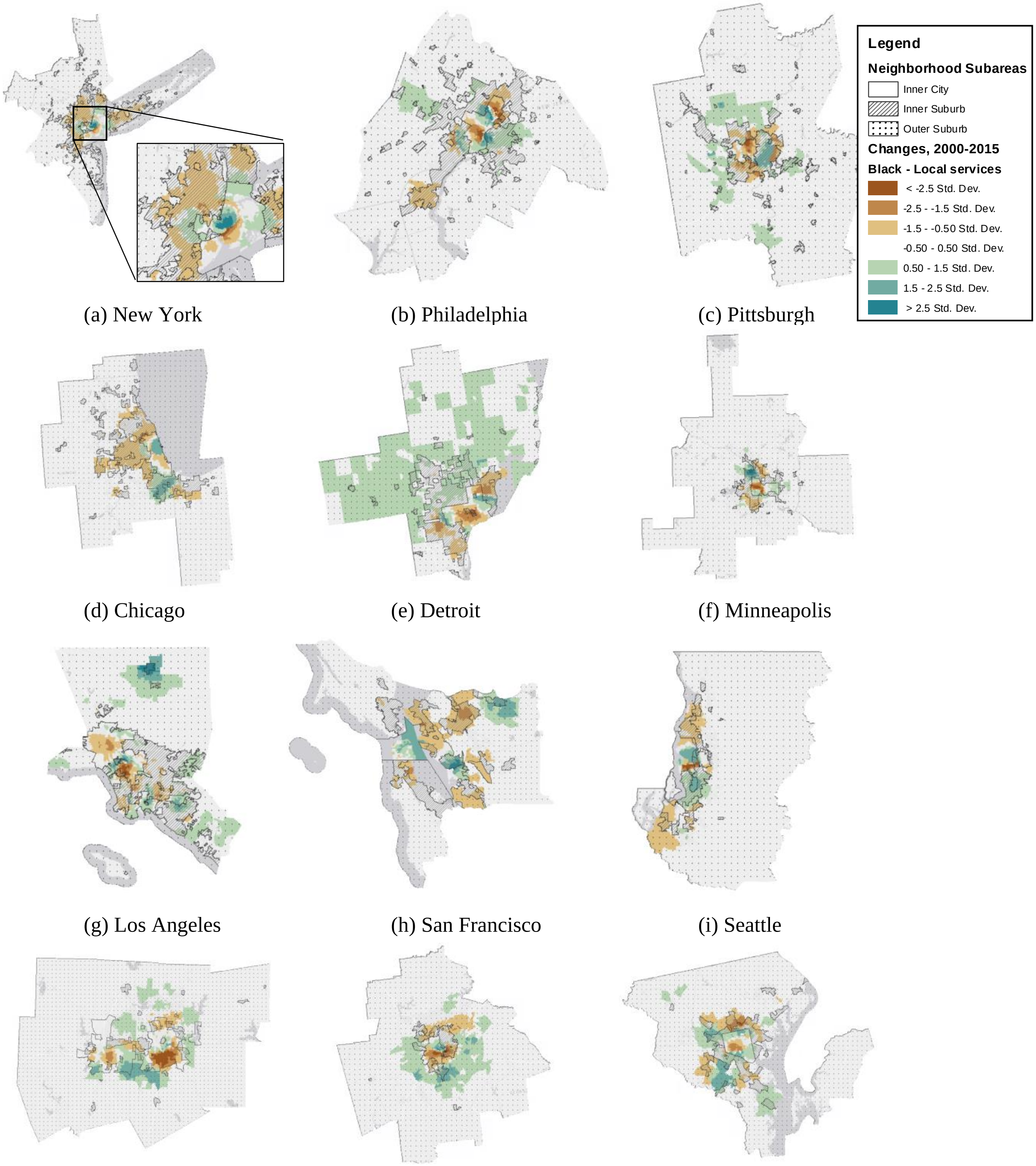


Figure 6. Changes in dissimilarity scores of Black populations and goods producing jobs, 2000-2015



(a) New York (b) Philadelphia (c) Pittsburgh

(d) Chicago (e) Detroit (f) Minneapolis

(g) Los Angeles (h) San Francisco (i) Seattle

(j) Dallas (k) Atlanta (l) Baltimore

Figure 7. Changes in dissimilarity scores of Black populations and local service and health care jobs, 2000-2015

3.3.6 Spatial Inequality in Economic Opportunity

In addition to examining the shifting pattern of mismatch into the suburbs where Black populations have predominantly moved into, spatial disparities in the distribution of job opportunities relative to the Black populations across local environments are measured using the spatial Theil's index. The overall level of inequality, the proportion of within- and between-neighborhood subarea inequality, and the shares of inequality within each neighborhood subarea are presented in this section. By measuring the spatial Theil's index across the three industry categories – total jobs, goods producing jobs, and local service and health care jobs in 2000 and 2015 – the overall level of spatial inequality and the proportion of within- and between-subarea inequality by their percentages are shown in Table 10. The results demonstrate an uneven distribution of Black populations and jobs in each local environment relative to the representative metropolitan average distribution.

In nearly all the observed regions, overall spatial inequality values decreased in 2015 compared with 2000, indicating that the ratio of Black populations to jobs within the local environments is now more evenly distributed than in 2000. Minneapolis and Detroit achieved the largest decrease in the overall level of inequality (from 0.29 in 2000 to 0.21 in 2015, and from 0.73 to 0.55, respectively). Based on industry, spatial inequality of local service jobs decreased at a higher rate than of manufacturing jobs, suggesting that Black populations typically live closer to local service job opportunities than to manufacturing jobs. Still, spatial inequality of manufacturing jobs decreased in metropolitan areas in the Midwest, including in Chicago and Detroit. This is interesting given that these cities were among the regions with the highest levels of spatial mismatch during the 1960s as a result of economic restructuring that caused the decentralization of manufacturing jobs into the suburbs. The changes in the overall level of inequality suggest that Black migration to the suburbs indeed offset the spatial mismatch to decentralized jobs. On the other hand, metropolitan areas in the West and South showed an increasing trend of inequality in goods producing jobs, despite the fact that the inequality of total jobs and local service jobs had decreased. This finding indicates a worsened spatial disparity in the distribution of Black populations and manufacturing job opportunities, particularly in metropolitan areas in the "New South" and the Western regions that saw the largest growth of Black populations. Such increased inequality in goods-producing jobs in these regions implies that when Black populations relocated into the suburbs, they did not move into suburbs close to the areas of manufacturing job growth. Considering that manufacturing industries tend to cluster into employment subcenters, the increase in inequality of manufacturing industries is not surprising. However, because the level of inequality across manufacturing jobs in the 2000s was so high in the Midwest, the demographic structural changes resulted in decreased spatial inequality.

Table 10 also presents the spatial structure of inequality – that is, the contribution of within- and between-neighborhood subarea inequality to the overall inequality of the metropolitan area. Across all metropolitan areas, within-subarea inequality exceeds the between-subarea inequality value, although the extent to which this is true varies across regions. In metropolitan areas in the Northeast and Midwest, approximately 72.6 percent of the total inequality value stems from within-subareas in 2015. This means that the spatial variations within the inner city, within the inner suburb, and within the outer suburb determine the overall inequality in the metropolitan area. In the West and South, the within-subarea inequalities make up around 93.4 percent of the total inequalities in 2015. This suggests that the spatial pattern of inequalities in the 21st-century metropolitan areas result from inequalities at the local level within each neighborhood subarea, rather than as the result of inequalities spanning city boundaries. This also demonstrates that there is a little spatial variability, if any, between neighborhood subareas; that is, the local environments of the inner-city, inner suburb, and outer suburb have similar ratios of Black populations and jobs. Although the traditional understanding of the spatial mismatch hypothesis posited significant variations in the distribution of Black populations and jobs by neighborhood subareas, the current finding suggests that many of the spatial variations arise from within-subareas. Detroit represents the metropolitan area with the highest between-subarea inequalities. In this case, between-neighborhood subarea inequalities contribute to about 53 percent of Detroit's total inequality value in 2015. This indicates that, in Detroit, approximately half of the overall inequality rate stems from the between-subarea, and the relative distribution of Black populations and jobs varies across the inner city, inner suburb, and outer suburb. Further, because within-inequality increased in nearly all metropolitan areas between 2000 and 2015, this suggests that there is an increasing local divergence in the local-level distributions of populations and jobs.

Table 10. Spatial inequality in the distribution of Black populations and opportunities, 2000 and 2015

		00						15					
		Total Jobs	(%)	Goods Producing	(%)	Local Services	(%)	Total Jobs	(%)	Goods Producing	(%)	Local Services	(%)
Northeast	**New York**												
	Theil	0.46		0.49		0.48		0.39		0.45		0.43	
	Within	0.29	62.1%	0.31	63.0%	0.29	59.3%	0.28	72.7%	0.33	73.3%	0.29	68.7%
	Between	0.18	37.9%	0.18	37.0%	0.20	40.7%	0.11	27.3%	0.12	26.7%	0.13	31.3%
	Philadelphia												
	Theil	0.42		0.56		0.45		0.40		0.63		0.42	
	Within	0.31	73.5%	0.35	63.3%	0.31	69.0%	0.31	76.1%	0.45	71.8%	0.29	69.6%
	Between	0.11	26.5%	0.20	36.7%	0.14	31.0%	0.10	23.9%	0.18	28.2%	0.13	30.4%
	Pittsburgh												
	Theil	0.38		0.50		0.37		0.34		0.49		0.34	
	Within	0.28	73.7%	0.31	60.9%	0.26	68.4%	0.27	80.0%	0.30	61.1%	0.25	75.1%
	Between	0.10	26.3%	0.20	39.1%	0.12	31.6%	0.07	20.0%	0.19	38.9%	0.08	24.9%
Midwest	**Chicago**												
	Theil	0.86		0.98		0.90		0.80		0.80		0.83	
	Within	0.62	72.7%	0.69	70.2%	0.66	73.0%	0.64	79.7%	0.60	75.1%	0.69	82.6%
	Between	0.23	27.3%	0.29	29.8%	0.24	27.0%	0.16	20.3%	0.20	24.9%	0.15	17.4%
	Detroit												
	Theil	0.73		0.78		0.75		0.55		0.62		0.58	
	Within	0.31	42.8%	0.35	45.3%	0.30	39.7%	0.26	47.0%	0.33	53.0%	0.24	41.5%
	Between	0.42	57.2%	0.43	54.7%	0.46	60.3%	0.29	53.0%	0.29	47.0%	0.34	58.5%
	Minneapolis												
	Theil	0.29		0.42		0.32		0.21		0.30		0.27	
	Within	0.17	56.5%	0.19	44.6%	0.18	56.7%	0.16	79.8%	0.18	60.3%	0.22	79.1%
	Between	0.13	43.5%	0.23	55.4%	0.14	43.3%	0.04	20.2%	0.12	39.7%	0.06	20.9%
West	**Los Angeles**												
	Theil	0.65		0.60		0.68		0.54		0.65		0.64	
	Within	0.63	97.7%	0.57	94.2%	0.67	98.1%	0.53	98.2%	0.59	91.3%	0.62	97.4%

	Between	0.02	2.3%	0.04	5.8%	0.01	1.9%	0.01	1.8%	0.06	8.7%	0.02	2.6%
	San Francisco												
	Theil	0.45		0.44		0.46		0.48		0.46		0.47	
	Within	0.45	99.4%	0.43	99.0%	0.46	98.5%	0.48	99.0%	0.45	97.2%	0.47	99.4%
	Between	0.00	0.6%	0.00	1.0%	0.01	1.5%	0.00	1.0%	0.01	2.8%	0.00	0.6%
	Seattle												
	Theil	0.40		0.54		0.45		0.32		0.47		0.29	
	Within	0.39	98.6%	0.54	99.4%	0.45	99.8%	0.30	94.1%	0.47	99.6%	0.27	94.1%
	Between	0.01	1.4%	0.00	0.6%	0.00	0.2%	0.02	5.9%	0.00	0.4%	0.02	5.9%
South	**Atlanta**												
	Theil	0.63		0.52		0.64		0.52		0.58		0.48	
	Within	0.59	94.1%	0.48	91.7%	0.61	95.3%	0.51	99.1%	0.57	98.4%	0.47	98.7%
	Between	0.04	5.9%	0.04	8.3%	0.03	4.7%	0.00	0.9%	0.01	1.6%	0.01	1.3%
	Dallas												
	Theil	0.57		0.58		1.36		0.54		0.66		0.54	
	Within	0.56	99.0%	0.54	93.7%	1.36	99.7%	0.52	96.9%	0.65	98.5%	0.53	98.1%
	Between	0.01	1.0%	0.04	6.3%	0.00	0.3%	0.02	3.1%	0.01	1.5%	0.01	1.9%
	Baltimore												
	Theil	0.27		0.38		0.31		0.22		0.42		0.27	
	Within	0.18	67.3%	0.23	61.5%	0.16	52.6%	0.16	73.3%	0.32	75.6%	0.16	61.2%
	Between	0.09	32.7%	0.15	38.5%	0.15	47.4%	0.06	26.7%	0.10	24.4%	0.10	38.8%

To further demonstrate the spatial structure of inequality and from which subarea the within-inequalities are derived from the most, the contributions of each neighborhood subarea to the total within-inequalities are shown in the bar graph in Figures 8 and 9. These figures show the different spatial structures of inequality across metropolitan areas for both goods-producing jobs and local service and health care jobs in 2015. The topmost metropolitan area with the highest inner city inequality is shown on the top – New York and Chicago. The Metropolitan area with the highest outer suburb inequality that makes up approximately 86.2 percent of total within-inequality is Dallas, on the bottom of the graph. As such, using contributions of each subarea to the within-inequality, I classify the spatial structure of inequality into four categories – 1) Polarized inner city – a high concentration of inequality within the inner city, 2) Industrial suburb – inequality within the industrial inner suburb, 3) Polycentric regions – dispersion of inequality across subareas, and 4) Suburban expansion – concentration of inequality within the outer suburb. Each type represents how spatial inequality is distributed differently throughout each metropolitan area. Following New York and Chicago that exhibit the highest concentration of inequalities within the inner city, metropolitan areas including Philadelphia, Pittsburgh, Detroit, and Baltimore demonstrate an industrial suburb pattern in which approximately half or more (up to 70 percent) of the inequalities in the region are derived within the industrial inner suburb. These areas also represent historically manufacturing inner suburbs following a period of economic restructuring where much of the jobs had decentralized into the inner suburb. The spatial structure of inequality continues to show that many within-inequalities can be traced to the inner suburbs. In the metropolitan regions of the West – namely, Los Angeles and San Francisco – inequality is distributed uniformly across neighborhood subareas, which suggests a polycentric development pattern. In metropolitan areas that exhibited suburban expansion patterns of both populations and jobs – such as Seattle, Minneapolis, Atlanta, and Dallas – many of the inequalities can be attributed to the outer suburb. In Atlanta and Dallas, as much as 67.6 percent and 86.2 percent of the region's inequality stems from the outer suburb, respectively. The decomposition of inequality by neighborhood subarea also highlights the fact that the long-held image of American suburbs as affluent, job-rich, and predominantly White is no longer accurate. This is particularly evidenced by how much the Atlanta and Dallas metropolitan areas have changed in recent years. U.S. suburbs are divided into two – the neighborhood of disadvantage where Black populations are largely segregated into, and the other, concentration of affluence and job growth. Even more, these trends did not vary much across different industries. Furthermore, across nearly all metropolitan areas, the degree of outer suburb inequality increased in 2015 compared with 2000, which suggests that recent suburban expansion has only further contributed to increased spatial disparities within the suburbs across all the metropolitan areas observed in this study.

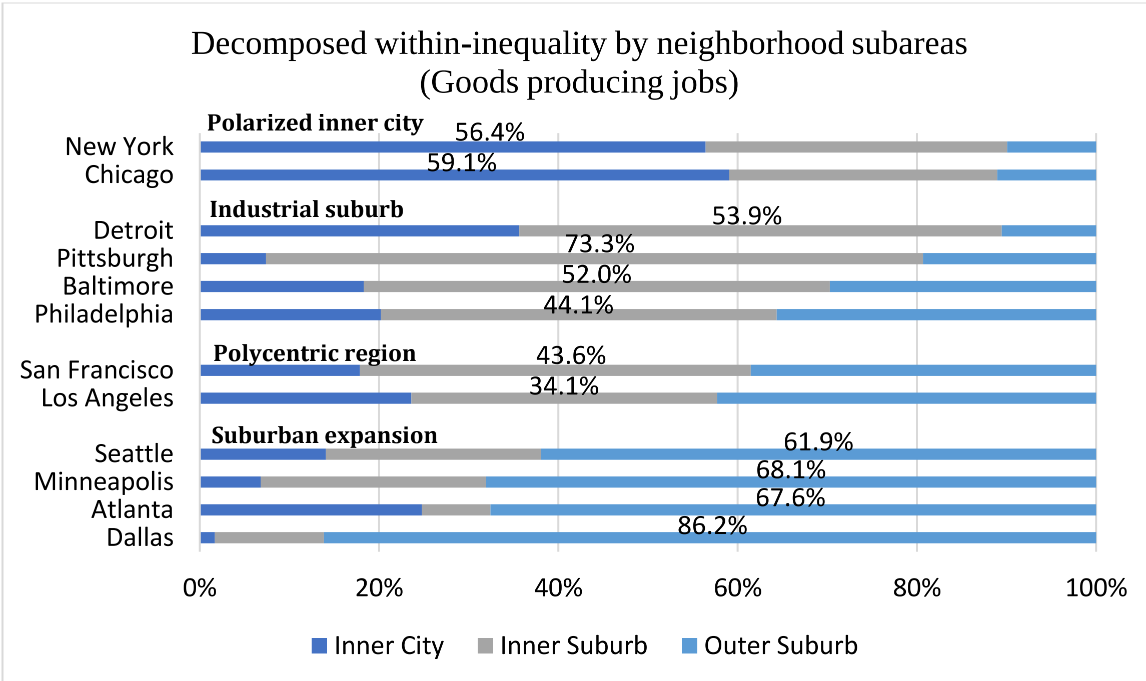


Figure 8. Spatial inequality by neighborhood subareas in 2015, goods-producing jobs

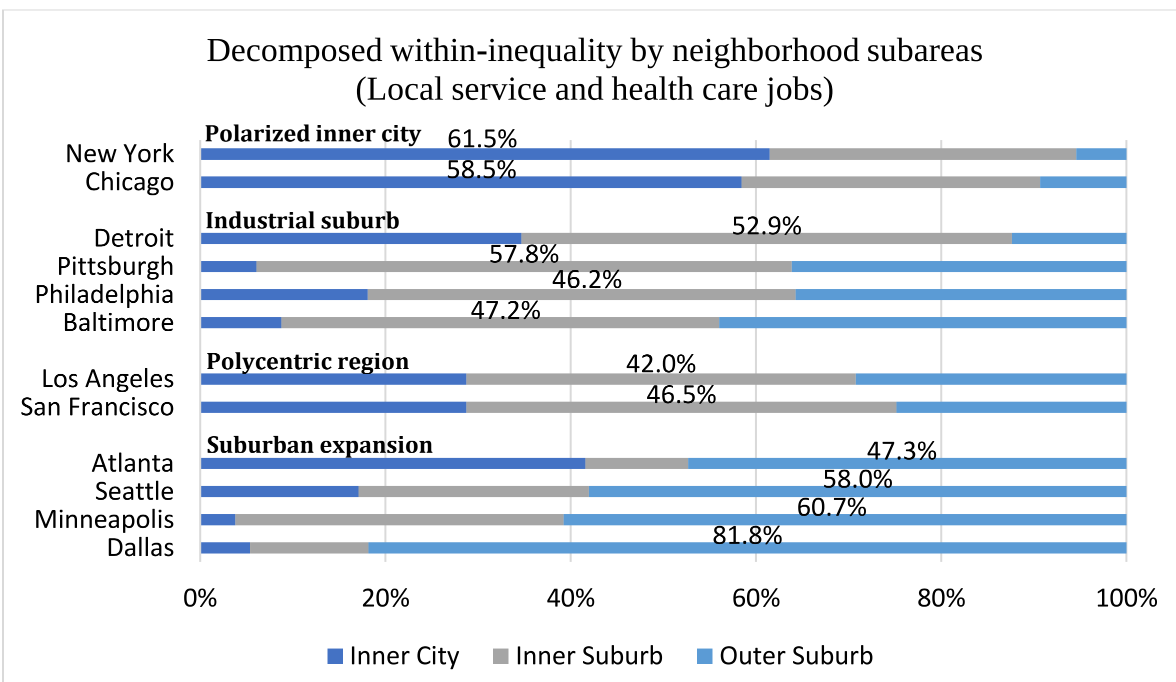


Figure 9. Spatial inequality by neighborhood subareas in 2015, local service jobs

3.3.7 Socio-Spatial Differentiation

The differences in the neighborhood characteristics in the Black and White neighborhoods are compared to examine the magnitude of spatial differentiation. Using Moran's I analysis, the spatial clustering of White populations and Black populations in the twelve metropolitan areas is identified. Table 11 shows a summary of census tracts that are identified as Black neighborhoods and White neighborhoods, and the metropolitan Black-White segregation index. Overall, census tracts identified as Black neighborhoods that closely cluster together are approximately 26.67 percent of total tracts, and White neighborhoods are approximately 21.87 percent. Except for Seattle, smaller metropolitan areas including Pittsburgh, Minneapolis, and Baltimore have the lowest clustering of White neighborhoods (9.7 %, 6.6%, and 12.6%, respectively) which suggests White populations are more dispersed in a low-density neighborhood.

Table 11. Descriptive summary of Black and White neighborhoods identified using Moran's I

	Northeast			**Midwest**		
	New York	Philadelphia	Pittsburgh	Chicago	Detroit	Minneapolis
Tracts identified as Black neighborhoods	1,372	361	159	579	359	249
	29.2%	24.4%	22.4%	26.1%	27.6%	31.6%
Tracts identified as White neighborhoods	906	339	69	706	412	52
	19.3%	23.0%	9.7%	31.9%	31.7%	6.6%
Total Tracts in MSA	4,700	1,477	711	2,215	1,301	789
Black-White Segregation	0.77	0.67	0.67	0.76	0.74	0.56
	West			**South**		
	Los Angeles	San Francisco	Seattle	Dallas	Atlanta	Baltimore
Tracts identified as Black neighborhoods	751	251	193	317	249	209
	25.6%	25.6%	26.8%	23.9%	26.2%	30.6%
Tracts identified as White neighborhoods	1,006	209	193	310	207	86
	34.3%	21.3%	26.8%	23.4%	21.8%	12.6%
Total Tracts in MSA	2,929	980	721	1,324	951	683
Black-White Segregation	0.68	0.62	0.52	0.57	0.59	0.65

The mean differences in the neighborhood socioeconomic, housing, and employment characteristics between the Black and White neighborhoods are shown in Table 12. A positive value implies White neighborhood has a higher mean value than the Black neighborhood, and a negative value implies Black neighborhoods have a higher mean value than White neighborhoods. A statistically significant mean difference reveals spatial differentiation in neighborhood characteristics associated with residential segregation. Almost all socioeconomic and housing characteristics are significantly different in the Black neighborhoods and the White neighborhoods. On average, White neighborhoods have 20 percent higher college graduates, a 4.1 percent lower unemployment rate, 17.5 percent lower poverty rate, and 4.3 percent lower households receiving public assistance. As for housing characteristics, the median household income in White neighborhoods is $44,414 higher than in Black neighborhoods, which is around twice the median household income of residents in a Black neighborhood. The difference in median housing built year showed housing in the White neighborhood were built around 15 years later than Black neighborhoods (the median housing built year in Black neighborhoods was 1959). The difference in the median housing value in Black and White neighborhoods is $163,215, and the owner-occupancy rate is 25.2 percent higher in the White neighborhoods.

The job characteristics also show significant differences between Black and White neighborhoods, including the number of total jobs by job sector as well as changes between 2002 and 2015. The differences in the total number of jobs were particularly significant in New York, Philadelphia, Chicago, Atlanta, and Dallas. On average, there are 1,244 more jobs in White neighborhoods compared to Black neighborhoods. These metropolitan areas demonstrate wealthy- economic growth areas that are distinguishable from disadvantaged areas – Suburbs surrounding the inner city in New York and Philadelphia, Northwest suburbs of Chicago, and

Northern suburbs of Atlanta and Dallas. These metropolitan areas also demonstrate the highest concentration of inequality within the inner city and outer suburb, suggesting spatial disparity in economic opportunities increases with concentrated residential segregation. On the other hand, in Minneapolis, there are 1,089 more jobs in Black neighborhoods than in White neighborhoods, showing an opposite trend that more jobs are available within Black neighborhoods. This pattern is also shown in Pittsburgh and Seattle, although it is not statistically significant. A potential explanation for such a trend is that these metropolitan areas had the lowest shares of tracts identified as White neighborhoods (except for Seattle), suggesting suburban sprawl of White populations in low-density areas that are less likely to have a high concentration of jobs. Minneapolis also demonstrated the lowest level of a spatial mismatch for Black populations, partially supporting the idea that less concentration of jobs in White neighborhoods contributes to lower spatial mismatch.

By the industry sectors, the manufacturing, local service, and professional jobs featured statistically significant mean differences in the number of jobs between the Black and White neighborhoods. It indicates that not only do the local service and professional jobs tend to locate close to White neighborhoods, but also there are more manufacturing jobs within White neighborhoods than the Black neighborhoods. Lastly, the changes in the number of jobs between 2002 and 2015 show that differences are less significant than the differences in the total number of jobs. However, in Atlanta and Dallas, job growth in the White neighborhoods is statistically higher than in the Black neighborhoods, especially the local service and professional jobs. This is followed by Baltimore, Los Angeles, San Francisco, Chicago, Philadelphia, although the differences in the job growth are smaller than in Atlanta and Dallas. The findings of this analysis show evidence for spatial differentiation in economic characteristics that demonstrate an economic advantage in the White neighborhood, especially in metropolitan areas with a higher concentration of White populations. This is consistent with recent studies that increasingly find the concentration of whites create the place of advantage, the 'Racially Concentrated Areas of Affluence" by Goetz et al. (2019) and 'Truly Advantaged Places' of Howell (2019) – that argue the concentration of White populations in advantaged neighborhoods excludes other races and results in uneven distribution of opportunities. The current analysis of spatial differentiation also shows that in all aspects, White neighborhoods are advantageous in job opportunities that are especially profound among metropolitan areas with a high concentration of White populations and where the geographical division of race is more distinct.

Table 12. Mean differences in neighborhood characteristics

	Northeast						Midwest					
	New York		Philadelphia		Pittsburgh		Chicago		Detroit		Minneapolis	
Variables	Mean Diff.	p	Mean Diff.	p	Mean Diff.	p	Mean Diff.	p	Mean Diff.	p	Mean Diff.	p
Socioeconomic Characteristics												
Percent college graduates	0.18	***	0.21	***	0.08	***	0.21	***	0.17	***	0.13	***
Percent unemployed	-3.59	***	-4.48	***	-3.32	***	-6.68	***	-7.62	***	-3.21	***
Percent HH below poverty	-17.21	***	-23.03	***	-15.75	***	-22.42	***	-27.36	***	-14.26	***
Percent HH with public assistance	-0.04	***	-0.06	***	-0.04	***	-0.05	***	-0.05	***	-0.07	***
Housing Characteristics												
Median household income	$47,042	***	$46,488	***	$62,779	***	$45,724	***	$38,066	***	$35,949	***
Median housing built year	15	***	22	***	15	***	22	***	24	***	25	***
Percent constructions after 2000	0		0.04	***	0.04	***	0.05	***	0.08	***	0.15	***
Median housing value (in $1,000s)	1.28		158.4	***	72.1	***	134.9	***	109.4	***	81.6	***
Percent housing vacant	-0.03	***	-0.1	***	-0.08	***	-0.12	***	-0.21	***	-0.03	***
Percent owner-occupied	0.47	***	0.25	***	0.22	***	0.31	***	0.25	***	0.28	***
Job Characteristics												
Total Jobs, 2015	1087	***	864	***	-85		1648	***	511	*	-1089	*
Jobs by Manufacturing, 2015	219	***	242	***	140	*	432	***	185	***	-165	
Jobs by Local service, 2015	419	***	393	***	168		568	***	321	***	-132	
Jobs by Professional service, 2015	291	***	214	**	-285		383	***	-47		-416	
Jobs by Education and public, 2015	97	***	5		-37		179	***	36		-31	
Jobs by Health care, 2015	62		11		-70		95	*	16		-345	***
Change of total jobs, 2002-2015	-87		165	*	-33		201	**	168		280	
Change of Manufacturing jobs	-16		36		-31		-40		28		88	
Change of Local service jobs	5		86	**	69		114	***	71		151	*
Change of Professional service jobs	6		68	**	32		20		-68		158	
Change of Education and public jobs	-89	***	-7		-31		66	*	52		-35	
Change of Health care jobs	19		-17		-71		51		84	**	-82	

***p<0.05; **p<0.01; ***p<0.001**

	West						South					
	Los Angeles		San Fran		Seattle		Atlanta		Dallas		Baltimore	
Variables	Mean Diff.	p	Mean Diff.	p	Mean Diff.	p	Mean Diff.	p	Mean Diff.	p	Mean Diff.	p
Socioeconomic Characteristics												
Percent college graduates	0.25	***	0.24	***	0.19	***	0.23	***	0.31	***	0.19	***
Percent unemployed	-2.22	***	-3.41	***	-1.28	***	-5.75	***	-2.56	***	-5	***
Percent HH below poverty	-15.26	***	-10.8	***	-8.54	***	-19.74	***	-17.73	***	-18.19	***
Percent HH with public assistance	-0.05	***	-0.04	***	-0.03	***	-0.02	***	-0.02	***	-0.05	***
Housing Characteristics												
Median household income	$36,714	***	$49,325	***	$30,528	***	$48,497	***	$46,053	***	$45,803	***
Median housing built year	11	***	-5.32	***	1.4		11	***	12	***	26	***
Percent constructions after 2000	0.01	*	-0.04	***	0.01		0.02		0.1	***	0.08	***
Median housing value (in $1,000s)	202.4	***	581.4	***	149.2	***	173.2	***	117.8	***	176.9	***
Percent housing vacant	-0.02	***	-0.01	**	-0.02	***	-0.11	***	-0.05	***	-0.12	***
Percent owner-occupied	0.26	***	0.1	***	0.15	***	0.24	***	0.2	***	0.29	***
Job Characteristics												
Total Jobs, 2015	607	*	335		-786		2052	***	571	***	852	*
Jobs by Manufacturing, 2015	60		51		100		256	**	-20		32	
Jobs by Local service, 2015	265	***	145	*	-267		771	***	263	**	487	***
Jobs by Professional service, 2015	329	***	232	*	-175		924	***	302	**	191	**
Jobs by Education and public, 2015	-79		18		-6		-115		18		38	
Jobs by Health care, 2015	31		-9		-238	*	215		7		103	
Change of total jobs, 2002-2015	10		181		177		931	***	612	***	233	
Change of Manufacturing jobs	-1		22		-36		54		121		6	
Change of Local service jobs	0		83		14		285	***	218	***	135	*
Change of Professional service jobs	70		100		-16		320	***	236	***	3	
Change of Education and public jobs	-65		-10		7		97		-15		-3	
Change of Health care jobs	7		-14		-118		175	**	54		103	

p<0.05; **p<0.01; ***p<0.001

3.4 Discussions

The main objective of the research was to investigate how the changes in the spatial distribution of the Black population and jobs in the 21st century contribute to the spatial mismatch hypothesis. The findings from the twelve major metropolitan areas in the U.S. suggest that the spatial patterns of mismatch have become more nuanced in 2015 than it was first proposed by Kain in 1968. The mapping of the spatial dissimilarity index showed that although many metropolitan areas in the Midwest and Northeast have traditional spatial patterns of mismatch in which Black populations remain segregated in the inner city while jobs are concentrated in the suburbs. However, in the South region including Atlanta and Dallas where large shares of Black populations have shifted to the suburbs, the spatial mismatch now features suburb-to-suburb mismatch. For local services and health care industries, metropolitan areas demonstrated a spatial mismatch within the inner city, suggesting a more localized spatial pattern of a mismatch as a result of increase socio-spatial polarization in the city. The shift in the geography of spatial mismatch implies the spatial mismatch is a persistent urban challenge in the U.S. that is closely associated with the spatial patterns of residential segregation.

Also, the spatial inequality in opportunity revealed that the overall level of inequality has decreased in almost all metropolitan areas. However, the decomposition of inequality by the neighborhood subarea implies that within-subarea inequality has increased through metropolitan areas, further supporting the argument that spatial disparities are increasing at local levels. The findings also suggest that in metropolitan areas with increased shares of Black populations in the suburbs, the spatial inequality in the suburbs has also increased – that is, increased racial diversity in the suburbs did not result in racial integration but led to increased spatial differentiation.

A comparison of the spatial distribution of jobs by the neighborhood racial compositions – Black-majority and White-majority neighborhoods – further supported that there were significantly more job opportunities available in White neighborhoods. In these neighborhoods, overall socio-economic status was also higher, suggesting the economic preferences are closely associated with the socio-economic status of the population. This implies that residential segregation not only constrains minority populations in job accessibility but also influences where jobs locate to, which leads to the continuing cycle of spatial mismatch. I also found that such patterns are more evident in metropolitan areas where the White populations are concentrated in clusters rather than spread throughout the region. In other words, the findings of this research suggest that the spatial inequality in job opportunity is stronger in areas where there are “Racially Concentrated Areas of Affluence” (Goetz et al., 2019). This is to say that studies of residential segregation and spatial mismatch have primarily focused on the Black residential patterns, but it may be that the concentration of wealthy population is the driving force of spatial inequality in the U.S. However, because current research only derived these results based on a comparison of the job opportunities by the neighborhood racial compositions, the associations between the concentration of affluence and the spatial mismatch cannot be defined in the current scope.

Chapter 4. Empirical Evidence on the Effect of Spatial Mismatch on Employment

This chapter examines the relationship between neighborhood job accessibility and the labor market outcomes, focusing on Black individuals. Although the effect of job accessibility on employment outcomes has been widely discussed in the literature, research on the magnitude of the differing effect of job accessibility by the neighborhood level of segregation has not been examined closely. Based on the findings of previous research that argue the effects of neighborhood job accessibility on labor market outcomes may differ by the neighborhood segregation levels (Cutler & Glaeser, 1997; Ihlanfeldt, 1999; Zenou, 2013), I examine the differing effects of job accessibility by the share of Black populations in the neighborhood. Further, since the spatial patterns of mismatch have changed in the U.S. metropolitan areas that are now more nuanced, the contribution of neighborhood job accessibility on labor market outcomes may differ by the metropolitan spatial patterns. However, the majority of the studies either focus on individual metropolitan areas for their analysis or, assume the effect of job accessibility would be similar across the regions that fail to consider the spatial distributions of populations and jobs of the metropolitan areas (Bania et al., 2008; Ihlanfeldt, 2006). I hypothesize that living in highly segregated neighborhoods negatively influences the effects of job accessibility on labor market outcomes among Black individuals, due to the neighborhood characteristics associated with segregation – constrained social network and lack of socio-economic infrastructures. Also, the spatial distribution of Black populations suggest that Black populations continue to live in highly segregated neighborhoods in the suburbs. Then, what are the effects of job accessibility in the suburbs? To investigate these relationships, I focus on examining 1) the association between neighborhood job accessibility and labor market outcomes,

2) effect of job accessibility by the location of residence in the city and the suburbs, and 3) those with and without access to automobile, and 4) differential effects of job accessibility on labor market outcomes by the shares of Black populations in the neighborhood. Based on the findings from differing spatial patterns of mismatch in previous chapters, three metropolitan areas are selected – Atlanta, Dallas, and Chicago – to examine whether the contribution of job accessibility on labor market outcomes varies among three metropolitan areas. Thus, by exploring how neighborhood job accessibility is associated with labor market outcomes of Black individuals in three different spatial patterns of mismatch, this research aims to address differential effects of job accessibility.

4.1 Study Background, Study Area and Data

Kain (1968) hypothesized that the residential segregation of Black populations and the decentralization of jobs results in the spatial separation of housing and jobs, which negatively influences the labor market outcomes among Black populations. The Spatial Mismatch Hypothesis emphasizes the effect of 1) residential segregation and 2) suburbanization of jobs, on employment outcomes among inner-city Black populations (Ihlanfeldt, 1994). Although the impact of decentralization of jobs has been well investigated by measuring job accessibility, the effect of residential segregation on the labor market outcomes among Black populations has not been studied much, even less on how the changing spatial patterns of segregation are associated with labor market outcomes. In Gobillon and Selod (2007), they examined how residential segregation of immigrant populations and the neighborhood job accessibility contribute to finding employment in the Paris region. They found neighborhood segregation as the main factor that decreases the employment rate, due to the low quality of social network in the segregated neighborhood. Their study did not find any significant relationship between job accessibility and the unemployment rate. Similarly, in Sweden, Wixe and Pettersson (2020) examined whether neighborhood immigrant segregation – the shares of foreign-born individuals in the neighborhood – affects the probability of being employed, and found a negative relationship between segregation and unemployment rate. Zenou (2013) further proposed that living in a segregated neighborhood with low job accessibility influences unemployment outcomes and wages Black populations, because the segregation localizes the job information exchange and poor social network with individuals who can provide information on job openings. His study suggests that neighborhood segregation intensifies the negative effects of having low job accessibility through limited social interaction and closed information transmission. Based on research findings that support the neighborhood segregation negatively affects the influence of job accessibility on labor market outcomes, measuring differing effects by the neighborhood share of Black populations – in areas with low shares of Black populations, moderate shares, and high shares of Black populations – can reveal whether there exist interaction effects between the neighborhood segregation and job accessibility on labor market outcomes.

Three metropolitan areas – Chicago, Atlanta, and Dallas – are selected for measuring the effect of local economic opportunities on employment outcomes. Studies on the spatial mismatch and Black employment have been widely studied in the Midwest metropolitan areas, but the effect on Southern metropolitan areas with growing spatial mismatch within suburbs has not been explored widely. Chicago represents a traditional pattern of the spatial mismatch wherein the inner city Black populations are mismatched from suburban job opportunities, while Atlanta and Dallas represent metropolitan areas with suburbanized Black populations and job opportunities. The primary dataset for the analysis is the 2015 ACS Public Use Microdata Samples (PUMS) that provide individual-level data on labor force participants that include the socioeconomic, household, and geographic characteristics. PUMS data are commonly used to analyze the impact of spatial mismatch on employment status since it provides individual-level data (Joassart-Marcelli, 2009; C. Y. Liu, 2009; Painter et al., 2007; Tyndall, 2017; Weinberg, 2002). The 5-year estimates represent samples that are collected over 60 months from 2011 to 2015, which has the advantage of the increased statistical reliability of samples and thus improved precision of data (U.S. Census Bureau, 2018). The use of 5-year estimates requires some considerations in measuring the employment status of individuals since the years 2011 and 2012 may be influenced by the aftermath of the Great recession during 2007 and 2009. During these periods, the U.S. labor market saw great loss of jobs as well as employment contractions, which may influence the employment status of individuals in 2011. However, since 1-year estimates data have larger margins of error and considerable drop in the sample sizes makes it less reliable for statistical analysis, and given that those impacted by the recession may still be influenced by the neighborhood opportunities in finding employment, the 5-year estimates are used in earlier literature[4] (Essletzbichler, 2015).

The PUMS data are then merged with 2015 LEHD LODES workplace area characteristics and ACS data for job counts that are aggregated to Public Use Microdata Areas (PUMAs), which is the smallest geographic unit identified in PUMS –geographic areas with over 100,000 population using census tracts and counties as building blocks (U.S. Census Bureau, 2018). Because the size of PUMAs is dependent on the population size, PUMAs in large MSAs tend to be smaller in size, which enables PUMAs to be in a reasonable size to capture the differences in the neighborhood job opportunities (Essletzbichler, 2015). The count of jobs comes from 2015 LEHD Origin-Destination Employment Statistics (LODES) data that is

[4] 3-year estimates of ACS are discontinued since 2013

aggregated to the PUMA level. Although the job information from LEHD are the number of actual workers employed rather than the number of vacancies or job openings, previous literature which established that the number of jobs (employed workers) are highly correlated with the job creation and job openings (Shen, 1998), and Anderson et al., (2018) found a correlation of 0.986 with the number of jobs at the beginning quarter and the number of new hires. Thus, I use the number of employed workers interchangeably with the number of job opportunities.

4.2 Research methodology

4.2.1 Measuring local job accessibility

The concept of job accessibility measure is the potential for reaching job opportunities within a certain distance or travel time. The cumulative opportunity measure is the simplest approach to measuring the geographical accessibility that counts the total numbers of opportunities that are reachable within a specific time or distance thresholds (Vickerman, 1974). The gravity-based accessibility measure proposed by Hansen (1959) is the most commonly used approach that measures the number of opportunities using a distance decay function that assigns lower weights to jobs that are located further away. Because Hansen's gravity model only considers the supply side of jobs when measuring job accessibility, Shen (1998) further modified the gravity model that takes into account the demand side of the jobs – the competition among job seekers for available jobs. Shen's accessibility measure considers the supply and the demand potential that is most commonly used in literature (Grengs, 2010; Hu, 2017; Jin & Paulsen, 2018). The model follows:

$$A_i = \sum_j \frac{O_j e^{-\gamma d_{ij}}}{D_j}, \qquad D_j = \sum_j P_k e^{-\gamma d_{ij}}$$

Where A_i is the accessibility for people living in location i; O_j is the number of job opportunities in location j; γ is an empirically derived impedance function associated with the travel cost. 2015 National Household Travel Survey (NHTS) is used to obtain the γ separately for the three metropolitan areas ($\gamma_{atlanta} = -0.04, \gamma_{chicago} = -0.084$; $\gamma_{dallas} = -0.024$)[5]; d_{ij} is the distance between location i and j; D_j is the demand potential (competition) in location j; P_k is the number of job seekers living in location k; For metropolitan with N locations, $i, j, k = 1,2, \dots N$.

Based on this model, I measured the job accessibility of each PUMA, using total working age (15-64) populations as potential job seekers.

Figure 11 shows the estimated job accessibility of three metropolitan areas by PUMAs. Areas with the highest accessibility scores are shown in dark brown, and the lowest accessibility scores are shown in light yellow. Similar to the spatial patterns of mismatch, areas with the highest job accessibility are in the northern suburbs of Atlanta and Dallas, and the northwest part of Chicago. In the inner city, job accessibility is lowest – especially to the south side of Chicago and Dallas. An exception is in Atlanta, which shows job accessibility in the inner city is higher than in the suburbs on the southeast side. This suggests that at least in the case of Atlanta, moving into the suburbs does not lead to increased job accessibility and Black suburbs on the east side of Atlanta have lower access to jobs than in the city.

[5] The estimated weighted jobs in Atlanta using $\gamma = -0.04$ discounts jobs in 1 mile=0.96, 5 mile=0.8187, 10mile=0.67, 15mile=0.5488.

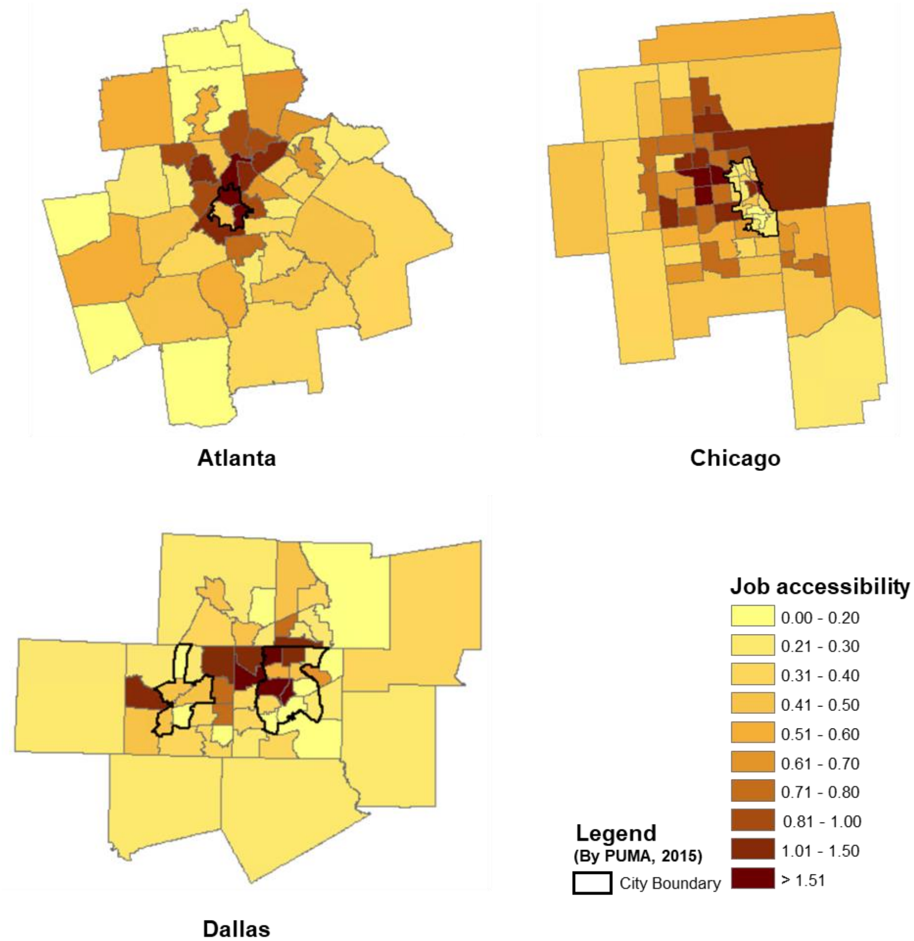


Figure 10. Job accessibility index in three metropolitan areas – Atlanta, Chicago, Dallas, 2015

4.2.2 Empirical Model and Description of Variables

Employment effects

A probit model is used to measure employment outcomes of Black populations in relation to the local job accessibility, and individual, household, and neighborhood characteristics. The main objective of this analysis is to examine whether metropolitan spatial patterns of job accessibility affect labor market outcomes of Black populations and if there exists differential effect of job accessibility in the city and in the suburb, household auto availability, and the shares of Black populations in the neighborhood. I hypothesize that job accessibility is positively associated with labor market outcomes among Black populations. However, the effect of job accessibility will be lower among Black populations who live in highly segregated suburbs as a result of higher isolation in the suburbs and fewer economic resources (Gobillon & Selod, 2007; Massey, 2001). The probit model for estimating the effect of spatial mismatch on employment outcomes can be specified as follows. Let E^* be the latent variable related to the employment status E of individual i such that

$$E_i = \begin{cases} 1 & if\ E_i^* > 0 \\ 0 & otherwise \end{cases}$$

By assuming the Cumulative Distribution Function (CDF) of the standard normal distribution, the model takes the form:

$$Pr(E_i = 1|x_i) = \Phi(\beta_0 + \boldsymbol{x\beta})$$

$$Pr(E_i = 0|x_i) = 1 - \Phi(\beta_0 + \boldsymbol{x\beta})$$

Where E_i represents employment outcome of individuals i, x is the vector of explanatory variables, which includes individual and neighborhood characteristics. Dependent variable E_i is whether an individual is employed or not. Explanatory variables include age, ethnicity, gender, educational attainment, auto availability, marriage status, having own children, and neighborhood characteristics that include job accessibility, residence in the city and the suburb, and Black share in the neighborhood. Thus, this model estimates the effects of the local labor market job accessibility on the probability of employment outcome.

<u>Income effects</u>

Then, to examine the relationship between earnings and neighborhood job accessibility, I use a Log-linear model that takes the form:

$$\ln(y_i) = \beta_0 + \beta_1 I_i + \beta_2 H_i + \beta_3 N_i + \varepsilon$$

Where $\ln(y_i)$ is the natural logarithm of earned income of individual i, I_i is a vector of individual characteristics, H_i is a vector of household characteristics, N_i is a vector of neighborhood characteristics. Detailed explanatory variables are discussed in the following section, in Table 13. For both models, I use the interaction terms to examine whether differing effects of job accessibility on labor market outcomes (employment status and income) exist as a function of residence in the city and in the suburb, auto ownership (that examine whether the effect of job accessibility varies for individuals with and without access to auto), and with neighborhood share of the Black population.

The problem of endogeneity is an important consideration when examining the causal relationship between job accessibility and labor market outcomes since residential locations are endogenous to an individual's labor market outcomes (Ihlanfeldt, 2006; Ihlanfeldt & Sjoquist, 1998). Individuals self-select into their preferred residential locations, which may lead to over-estimation or under-estimation of the effects of job accessibility. Thus, the effect of the local labor market on employment cannot be easily separated from the effect of labor market outcomes. As briefly discussed in the literature, early studies addressed the endogeneity problem by focusing on the youth employment outcomes to control for potential endogeneity problem of residential location choices, assuming that the youth's residential location is likely to be exogenous if they are living with their parents (Ihlanfeldt & Sjoquist, 1991; Raphael, 1998; Stoll, 1999b). Others used the quasi-randomized experiment surveys such as the Moving to Opportunity (MTO) program participants or the Temporary Assistance for Needy Families (TANF) and other welfare recipients, measuring the effect of neighborhood change on finding jobs, and leaving welfare (Aliprantis & Richter, 2020; Bania et al., 2008; Blumenberg et al., 2019; M. C. Lens & Gabbe, 2017). More recently, studies use advanced econometric models by using an instrumental variable to account for unobserved confounders that are correlated with changes in job accessibility (Baum-Snow, 2007; Jin & Paulsen, 2018; Miller, 2018). Instruments employed in these studies include the highway constructions, the distance to roadways and highways, and the distance to employment subcenters – assuming that these factors are exogenous to the labor market outcomes but influence firm's location choices that affect job accessibility. However, because the highway systems and the distance to employment subcenters can affect employment outcomes, these are regarded as weak instruments, which may lead to a poor prediction of job accessibility effects. For this reason, these studies further use a fixed-effects model with panel data, which controls for the changes in unobserved neighborhood characteristics other than the relocation of firms (Jin & Paulsen, 2018; Miller, 2018; Weinberg, 2002). Although the use of instruments and fixed-effects model can control for endogeneity issues, the use of neighborhood-level and establishment-level data fails to control for personal characteristics that influence the labor market outcomes of individual workers. Other studies confine their analysis to non-movers, arguing that housing location decision among these population groups is exogeneous to their present employment status (Galster et al., 2010; Matas et al., 2010), but decision to move may also be associated with other unobserved variables such as tenure and housing affordability. As such, there is no consensus regarding measures to control for endogeneity issues, which may have led to inconsistent findings on the effect of job accessibility on labor market outcomes (Galster et al., 2010).

Due to the difficulty associated with addressing the endogeneity problem, only the relationship between the local job accessibility and labor market outcomes are inferred in this research, rather than determining the causal effect of neighborhood job accessibility. Nonetheless, this research takes advantage of the rich set of individual-level microdata from

PUMS that allows control for personal and household characteristics which are unobserved in neighborhood-level data. Further, following Hellerstein et al. (2009) and Joassart-Marcelli (2009), I attempt to approximate the effect of job accessibility on labor market outcomes by examining variations among different population groups. These studies argue that comparing the effect of job accessibility among groups who are likely to have self-selected into their neighborhood (wealthy whites, households with access to cars), and those who are likely to be more constrained in their residential location choice (ethnic and racial minorities, households without access to cars, living in highly segregated neighborhoods), one can distinguish the effect of job accessibility for observed groups. A similar approach is taken in Johnson (2006), who assumed the residential location decisions of Black and Hispanic workers are more constrained than White workers and estimated the differential effect of job accessibility among different race/ethnicity groups. In this research, I compare the effect of job accessibility among Black individuals, by the 1) residence in the city and the suburbs, 2) having auto ownership, and 3) neighborhood share of Black populations. By comparing these groups of individuals, I can distinguish the effect of job accessibility among those who live in the suburbs, that are likely to be more dependent on neighborhood characteristics due to absence of automobile, and those who live in a highly segregated neighborhood. The results will be able to reveal how the relationship between job accessibility and labor market outcomes vary among individuals, depending on their residential location characteristics.

The individual samples for this analysis are persons who are in their working age (17 - 65), in the labor force, currently not enrolled in school or the military, and not having a disability. The dependent variables are the employment status and the personal earned income. Independent variables include individual and household characteristics (such as age, Hispanic or

Latino origin, education attainment, auto availability in the household, marital status, and presence of own children under age 5) and neighborhood characteristics (such as residence in the city/suburb, percent of Black populations in PUMA, and job accessibility). For measuring interaction effects of job accessibility and percent Black, PUMAs are grouped into three –Black share is low (less than 30 percent of the total population in PUMA), the Black share is moderate (between 30 and 60 percent), and Black share is high (over 60 percent of Black population in PUMA), which allows measuring the moderation effect of Black shares in the neighborhood on the relationship between job accessibility and labor market outcomes. Other neighborhood effects, such as percent of households under poverty, the distance to CBD, and the distance to the nearest employment subcenters were considered but these variables were highly correlated with the percent of Black populations in PUMA and job accessibility. Thus, only the location of residence in the city and suburb, the Black percentage in PUMA, and job accessibility are included in the study.

Table 13. Description of variables for employment analysis

Variable	Description
Dependent variables	
Employment status	= 1 if employed; 0 otherwise
Income	= Total personal earned income from wages or own business
Individual characteristics	
Age	= Age in years
Male	=1 if male; 0 if female
Hispanic and Latino	=1 if Hispanic origin; 0 otherwise
Less than high school	=1 if less than high school degree
High school degree	=1 if high school degree (or equivalent)
College	=1 if college degree and above
Household characteristics	
Auto ownership	=1 if more than 1 vehicle available
Married with spouse	=1 if married with a spouse; 0 otherwise
Own children under 5 years old	=1 if the number of own children under age 5 in household

Neighborhood Characteristics	
Suburb	=1 if residence in suburb (inner and outer); 0 if city
Black population percentage	= Percent of Black population in PUMA
Black Percentage – Low	= 1 if the Black population in PUMA less than 30 percent
Black Percentage – Moderate	= 1 if the Black population in PUMA between 30 and 60 percent
Black Percentage – High	= 1 if the Black population in PUMA over 60 percent
Job accessibility	= Job accessibility of PUMA

4.3 Analysis and findings

4.3.1 Descriptive Statistics

Descriptive statistics of the samples from 2015 PUMS in Table 12 shows the means and the standard deviations of the dependent variables, individual, household, and neighborhood characteristics for each metropolitan area: Atlanta, Dallas, and Chicago. The employment rate of Black individuals is shown separately for the city and the suburb. On average, the employment rate is around 5.6 percent higher, and earned income is $5,199 higher in the suburbs. The difference in employment and earning is quite large in Atlanta and Chicago, and there is only a slight gap in Dallas. The average age of respondents is approximately 41 years, and only 1 percent of the samples are of Hispanic or Latino origin. 43 percent of the population are male. 63 percent of the sample have some kind of college education, 29 percent have either a high school diploma or GED, and 7 percent have less than a high school degree. Household auto ownership is around 90 percent in Atlanta and Dallas, but only 72 percent of samples have access to auto in Chicago. 35 percent of samples are married with a spouse, and around 12 percent of samples have own children under age 5 in the household.

Regarding neighborhood characteristics, as expected, 86 percent of the sampled population in Atlanta lives in the suburbs, followed by 71 percent in Dallas, and 49 percent in Chicago. An average share of Black populations was calculated from the 2015 Census to determine the percentage share of Black populations in each PUMA. In Atlanta, sampled population resides in a neighborhood in which approximately 50 percent of the overall population is Black, followed by 46 percent in Chicago, and 24 percent in Dallas. The distribution of samples are further grouped by the shares of Black populations in the PUMA are low (less than 30 percent of the overall population in PUMA is Black), moderate (between 30 – 60 percent of the population in PUMA is Black), and high (over 60 percent of the population in PUMA is Black). In Chicago, around 59 percent of samples lived in areas with low shares of the Black population, while in the city, only 16 percent of samples live in low Black share areas, and 56 percent of samples live in areas with high shares of Black populations. In Dallas, there is no PUMA in the city with more than 60 percent of the populations are Black, and thus 57 percent of samples in the city live in low Black share areas, and 43 percent live in moderate Black share areas. In the suburbs, 74 percent of samples live in a low Black percentage area, suggesting that Black residents are more likely to live in areas with a lower share of Black populations. In Atlanta, around half of the samples who live in the suburbs live in areas with high shares of Black populations where over 60 percent of populations are Black –highly segregated neighborhoods. Job accessibility by the Black shares PUMA groups show that job accessibility is highest in areas with low Black shares in all three metropolitan areas. In Atlanta and Dallas, the average job accessibility is higher in the city than in the suburbs, which suggests that the level of job accessibility is lower in the suburbs where the samples reside in. An exception is in Chicago, which shows that job accessibility is higher in the suburbs in which there are moderate- and high- share of Black populations (0.27 and 0.22 in the city, and 0.44 and 0.48 in the suburb). In Atlanta, job accessibility in the city is the highest in the city with low- and moderate- Black shares, but in areas with a high percentage of Black populations, job accessibility is similar in the city and the suburbs. This suggests that in Atlanta, samples live in areas with a similar level of job accessibility if the share of Black populations in the neighborhood is high. The descriptive statistic shows disparities in job accessibility in areas with a lower share of Black populations and areas with a higher share of Black populations. Job accessibility lowest in highly segregated neighborhoods where over 60 percent of populations are Black. In Chicago, however, the average job accessibility is higher in the suburbs.

Table 14. Descriptive statistics of variables used in the probit and linear regression model

	Atlanta		Chicago		Dallas	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Dependent variables						
Employment status (=1)						
City	0.82	(0.38)	0.78	(0.42)	0.89	(0.31)
Suburb	0.89	(0.31)	0.85	(0.35)	0.92	(0.28)
ln(earned income)						
City	9.99	(1.25)	10.06	(1.24)	10.12	(1.14)
Suburb	10.19	(1.16)	10.24	(1.22)	10.3	(1.07)
Total personal earned income						
City	$28,673	($45,205)	$28,284	($48,398)	$31,502	($39,592)
Suburb	$32,086	($42,208)	$35,100	($51,981)	$36,870	($46,451)
Individual characteristics						
Age	41.21	(11.88)	41.50	(12.38)	41.69	(11.79)
Hispanic	0.01	(0.12)	0.02	(0.13)	0.02	(0.13)
Gender (male=1)	0.46	(0.50)	0.45	(0.50)	0.47	(0.50)
Education Attainment						
Less than Highschool	0.07	(0.26)	0.08	(0.27)	0.06	(0.23)
Highschool equivalent	0.28	(0.45)	0.29	(0.45)	0.29	(0.45)
College	0.65	(0.48)	0.63	(0.48)	0.65	(0.47)
Household Characteristics						
Auto ownership (=1)	0.90	(0.30)	0.74	(0.44)	0.91	(0.29)
Married with spouse	0.48	(0.50)	0.37	(0.48)	0.51	(0.50)
Own child under age 5	0.14	(0.34)	0.11	(0.32)	0.13	(0.34)
Neighborhood Characteristics						
Residence in suburb	0.86	(0.35)	0.49	(0.50)	0.71	(0.45)
Black share	0.50	(0.28)	0.46	(0.24)	0.24	(0.17)
Black share groups						
City						
Low (<30%)	0.10		0.16		0.57	
Moderate (30 - 60%)	0.28		0.28		0.43	
High (>60%)	0.62		0.56		-	
Suburb						
Low (<30%)	0.22		0.59		0.74	
Moderate (30 - 60%)	0.30		0.23		0.17	
High (>60%)	0.49		0.18		0.09	
Job accessibility	0.64	(0.41)	0.47	(0.52)	0.45	(0.42)
(by Black share group)						
City						
Low (<30%)	1.70	(0)	0.97	(1.43)	0.74	(0.63)
Moderate (30 - 60%)	1.69	(0)	0.27	(0.04)	0.16	(0.01)
High (>60%)	0.49	(0)	0.22	(0.08)	-	
Suburb						
Low (<30%)	0.62	(0.43)	0.69	(0.27)	0.48	(0.35)
Moderate (30 - 60%)	0.58	(0.26)	0.44	(0.04)	0.19	(0.04)
High (>60%)	0.50	(0.36)	0.48	(0)	0.30	(0)

4.3.2 Probit regression results

I begin by exploring the relationship between job accessibility and employment outcomes. As discussed in the previous section, I only examine the relationship between variables due to potential endogeneity issues that may bias the effects of job accessibility on labor market outcomes. Table 15 presents the results of the employment model. The first column shows model (1) which examines the relationship between neighborhood characteristics and employment outcome, but without any interactions. The second column, model (2) shows the relationship between each neighborhood characteristics (specifically, shares of Black populations in the neighborhood, and job accessibility) and employment by the place of residence in the city and the suburb. Model (3) in the third column shows the relationship between neighborhood characteristics and employment by auto ownership, which allows distinguishing the relationship for those with and without auto ownership. The fourth column shows model (4) which shows the relationship between job accessibility and employment outcomes by the shares of Black populations in the neighborhood – Black share is low (less than 30 percent is Black), moderate (30 to 60 percent is Black), and high (over 60 percent is Black).

Results of model 1 show that the shares of Black populations in the neighborhood are negatively associated with Black employment in Atlanta and Chicago. Also, in Chicago, job accessibility is positively associated with Black employment, suggesting that Black individuals who have high job accessibility are more likely to be employed. Most coefficients of individual and household characteristics are as expected. Higher education attainment is positively and significantly associated with the likelihood of being employed, as well as the auto ownership in the household. Marital status with a spouse has a strong positive relationship with employment. However, the coefficient for being male is negatively associated with employment outcomes, suggesting that Black females are more likely to be employed than Black males. A potential explanation for this finding is that male workers are more keen to identify themselves as in the labor force and their employment status, while female workers may not identify themselves as in the labor force if they return to housewife status. A lower probability of employment among Black males also reflects employer discrimination against Black males for the lack of "soft skills", compared to Black female workers. Moss and Tilly (1996) argue the employer's perception of Black males as having lower "soft" skills poses a barrier when finding employment. Holzer (2021) also suggests employer discrimination, lower educational attainment, and a high incarceration rate among Black males as contributing factors for lower employment rates compared to White male and Black female workers.

Results of model 2 and model 3 show that the shares of Black populations in the neighborhood are negatively associated with Black employment – especially in the city, and those without access to the auto. I also find that in all three metropolitan areas, job accessibility is positively associated with Black employment for individuals who do not have access to the auto. For individuals with auto, job accessibility was negatively associated with employment, suggesting that employed individuals with auto access tend to live in areas with low job accessibility. The relationship between job accessibility and employment, however, show different associations in the city of Atlanta and Chicago. In Atlanta, job accessibility is negatively associated with Black employment, while job accessibility in Chicago shows a positive relationship with Black employment. This suggests that in the city of Atlanta, Black individuals are more likely to be employed in neighborhoods with lower job accessibility, while in Chicago, Black individuals have higher chances of being employed in neighborhoods with higher job accessibility. This may reflect that the relationship between Black employment and job accessibility may be associated with other neighborhood characteristics. Thus, to explore the interactions in neighborhood variables, model 4 examines the relationship between job accessibility and employment by the shares of Black populations in the neighborhood – low-, moderate-, and high- Black population shares in the neighborhood. Results show that in Atlanta, job accessibility is significantly and positively associated with Black employment in PUMAs with low shares of Black populations (less than 30 percent of the populations are Black), but the relationship is negative in moderate- and high- Black share neighborhoods. This implies that although an increase in job accessibility is positively associated with the probability of being employed, the relationship becomes negative if the neighborhood composition is predominantly Black (more than 60 percent of the populations are Black). In Chicago, such interactions do exist – the association between job accessibility and employment depends on the share of Black populations – but having higher Black shares does not negate the effect of job accessibility on employment. Instead, an increase in job accessibility in the predominantly Black neighborhood is associated with a higher probability of being employed, suggesting higher marginal effects of job accessibility on Black employment.

To better show differences in relationships between job accessibility and employment by the share of Black populations in the neighborhood, I present predictive margins of employment based on model 4. Figure 11 shows the predicted employment over levels of job accessibility (0 to 1), by the share of Black populations that are low-, moderate-, and high. Results show that in Atlanta, individuals who live in predominantly Black neighborhoods have a lower probability of being employed as job accessibility increases. On the other hand, in neighborhoods with lower shares of Black populations, an increase in job accessibility is positively associated with Black employment. In Chicago, the changes in job accessibility do not affect employment in neighborhoods with lower shares of Black populations. However, in predominantly Black neighborhoods, the marginal increase in job accessibility is positively associated with Black employment. This suggests that unlike in Atlanta where the neighborhood share of Black populations counteracts the effect of job accessibility on the probability of being employed, an increase in job accessibility in highly segregated areas leads to higher chances of being employed in Chicago. In Dallas, the results are similar to Atlanta in which the predicted margins decrease as job accessibility increases in neighborhoods with moderate- and high- shares of Black populations. However, the confidence interval becomes wider at a job accessibility score over 0.5, suggesting that the associations between job accessibility and employment are difficult to predict. This is likely due to low job accessibility scores in neighborhoods with moderate- and high- shares of Black populations in Dallas, which implies that job accessibility is lower in predominantly Black neighborhoods.

Table 15.Probit model results of employment outcomes

	Model 1			Model 2 (Job accessibility * Puma suburb)			Model 3 (Job accessibility * Auto)		
Emp	Atlanta	Chicago	Dallas	Atlanta	Chicago	Dallas	Atlanta	Chicago	Dallas
Individual characteristics									
Age	0.0395***	0.0444***	0.0593***	0.0395***	0.0447***	0.0592***	0.0395***	0.0445***	0.0585***
	(0.0101)	(0.0107)	(0.0120)	(0.0101)	(0.0106)	(0.0122)	(0.0101)	(0.0106)	(0.0122)
Age^2	-0.0004***	-0.0003**	-0.0006***	-0.0004***	-0.0003**	-0.0006***	-0.0004***	-0.0003**	-0.0006***
	(0.00012)	(0.0001)	(0.0001)	(0.00012)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)
Hispanic	0.0904	0.518***	0.436**	0.0929	0.524***	0.435**	0.0884	0.520***	0.436**
	(0.171)	(0.201)	(0.202)	(0.172)	(0.198)	(0.203)	(0.171)	(0.199)	(0.202)
Male	-0.0299	-0.196***	-0.0498	-0.0305	-0.197***	-0.0502	-0.0304	-0.196***	-0.0506
	(0.0458)	(0.0461)	(0.0470)	(0.0460)	(0.0465)	(0.0470)	(0.0459)	(0.0459)	(0.0469)
Highschool graduate	0.332***	0.300***	0.143**	0.331***	0.301***	0.142**	0.333***	0.299***	0.141**
	(0.0564)	(0.0362)	(0.0641)	(0.0566)	(0.0352)	(0.0646)	(0.0567)	(0.0367)	(0.0646)
College graduate	0.568***	0.583***	0.414***	0.566***	0.584***	0.411***	0.569***	0.582***	0.412***
	(0.0617)	(0.0398)	(0.0709)	(0.0619)	(0.0384)	(0.0716)	(0.0622)	(0.0397)	(0.0713)
Household characteristics									
Auto availability	0.424***	0.547***	0.536***	0.421***	0.551***	0.535***	0.524***	0.497***	0.789***
	(0.0411)	(0.0389)	(0.0604)	(0.0423)	(0.0393)	(0.0602)	(0.136)	(0.132)	(0.130)
Married with spouse	0.272***	0.295***	0.242***	0.271***	0.295***	0.241***	0.271***	0.295***	0.241***
	(0.0379)	(0.0511)	(0.0613)	(0.0378)	(0.0507)	(0.0607)	(0.0379)	(0.0510)	(0.0609)
Own child under age 5	-0.0385	0.149***	0.0448	-0.0378	0.151***	0.0446	-0.0372	0.148***	0.0480
	(0.0552)	(0.0509)	(0.0610)	(0.0552)	(0.0508)	(0.0609)	(0.0550)	(0.0509)	(0.0613)
Neighborhood characteristics									
Suburb	0.0418	-0.177**	0.0352	-0.331***	-0.330*	0.0821	0.0367	-0.177**	0.0344
	(0.0348)	(0.0696)	(0.0487)	(0.0709)	(0.179)	(0.184)	(0.0341)	(0.0703)	(0.0488)
Black percentage *Interaction: (City; Auto =0)*	-0.279***	-0.458***	-0.0939	-0.680***	-0.571***	-0.101	-0.309**	-0.500***	0.385
	(0.0782)	(0.132)	(0.135)	(0.0356)	(0.196)	(0.384)	(0.149)	(0.193)	(0.352)
Job accessibility *Interaction: (City; Auto =0)*	0.00495	0.122***	0.0118	-0.106***	0.108**	0.0609	0.131*	0.112***	0.232**
	(0.0527)	(0.0389)	(0.0660)	(0.0136)	(0.0445)	(0.0833)	(0.0707)	(0.0400)	(0.109)

Interaction:									
Black percentage * Suburb				0.413***	0.276	0.0126			
				-0.0849	-0.24	-0.407			
Job accessibility * Suburb				0.0935	0.0504	-0.118			
				-0.0701	-0.125	-0.156			
Black percentage * Auto							0.0337	0.0718	-0.543
							-0.143	-0.191	-0.351
Job accessibility * Auto							-0.161*	0.0305	-0.267***
							-0.084	-0.0986	-0.101
Constant	-0.499**	-0.884***	-0.879***	-0.117	-0.819***	-0.892***	-0.576**	-0.858***	-1.079***
	(0.238)	(0.251)	(0.268)	(0.214)	(0.282)	(0.294)	(0.266)	(0.275)	(0.262)
Observations	22,695	19,204	13,070	22,695	19,204	13,070	22,695	19,204	13,070
Pseudo R-squared	0.0781	0.1352	0.0874	0.0782	0.1356	0.0876	0.0784	0.1352	0.0882

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 15. (Continued)

Emp	Model 4 (Job accessibility * Black percentage) Atlanta	Chicago	Dallas
Individual characteristics			
Age	0.0396***	0.0447***	0.0591***
	(0.0101)	(0.0108)	(0.0121)
Age^2	-0.0004***	-0.0003**	-0.0006***
	(0.00012)	(0.0001)	(0.00015)
Hispanic	0.0874	0.517***	0.432**
	(0.173)	(0.199)	(0.201)
Male	-0.0317	-0.197***	-0.0493
	(0.0462)	(0.0460)	(0.0471)
Highschool graduate	0.327***	0.293***	0.144**
	(0.0573)	(0.0373)	(0.0650)
College graduate	0.559***	0.570***	0.416***
	(0.0623)	(0.0412)	(0.0719)
Household characteristics			
Auto availability	0.418***	0.557***	0.540***
	(0.0431)	(0.0380)	(0.0605)
Married with spouse	0.272***	0.296***	0.243***
	(0.0378)	(0.0506)	(0.0604)
Own child under age 5	-0.0346	0.147***	0.0449
	(0.0551)	(0.0517)	(0.0613)
Neighborhood characteristics			
Suburb	0.0694**	-0.316***	0.0472
	(0.0346)	(0.0837)	(0.0598)
Black percentage group	-0.0207	-0.367***	0.135
Interaction: (job accessibility =0)	(0.0372)	(0.0829)	(0.197)
Job accessibility (Black share group = 1, Low)	0.194**	0.0761	0.0100
	(0.0803)	(0.0493)	(0.0734)
Job accessibility * Black percentage =2 (Moderate)	-0.194**	0.450***	-0.979
	(0.0763)	(0.147)	(0.909)
Job accessibility * Black percentage =3 (High)	-0.283***	1.264***	-1.237
	(0.101)	(0.292)	(1.303)
Constant	-0.621**	-0.441	-1.032***
	(0.253)	(0.329)	(0.316)
Observations	22,695	19,204	13,070
Pseudo R-squared	0.0793	0.1377	0.0877

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

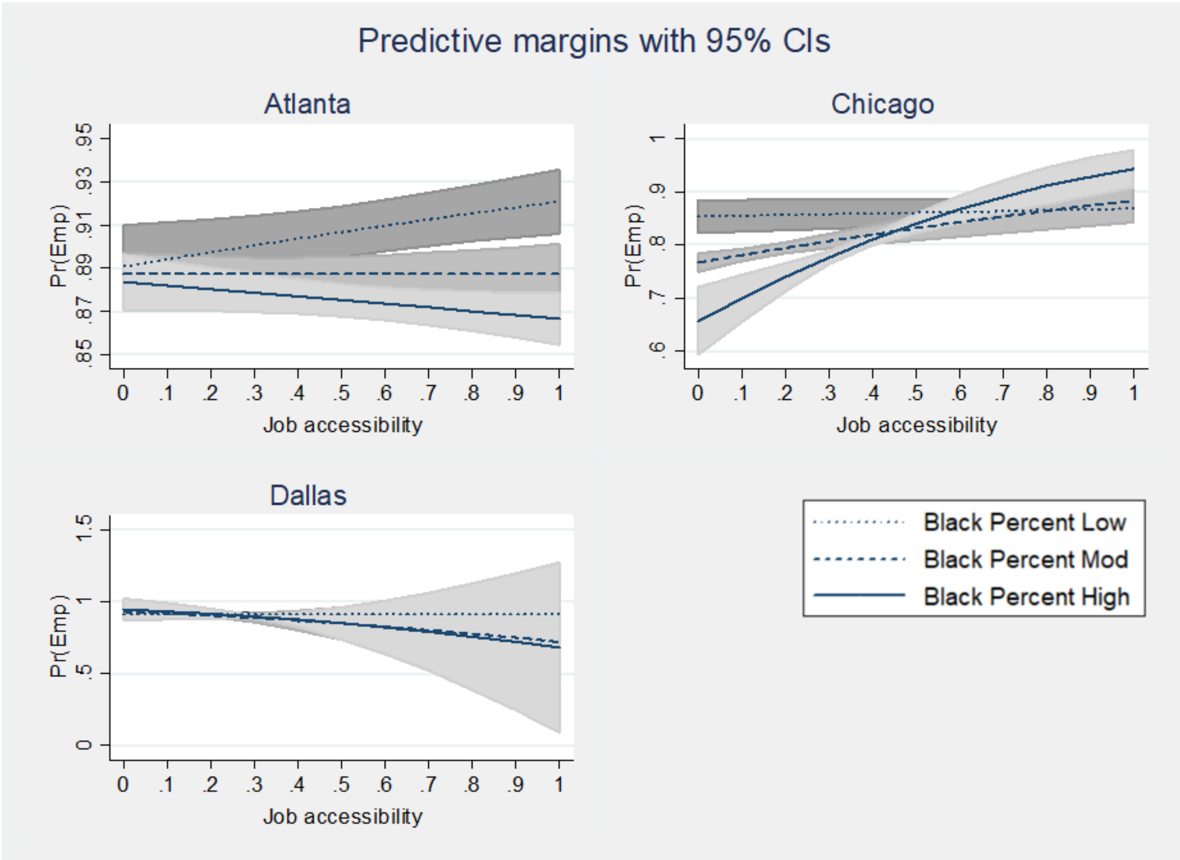


Figure 11. Predictive margins of employment outcome over neighborhood Black share with 95% confidence intervals

4.3.3 Regression results

Table 19 reports the relationship between job accessibility and log of earned income. In the same manner as the employment model, model (1) examines the relationship between neighborhood characteristics (shares of Black populations in the neighborhood and job accessibility) and log earned income, but without any interactions. Model (2) and (3) report interactions between neighborhood characteristics and log earned income, by the place of residence in the city and the suburb, and for those with- and without auto ownership. Lastly, model (4) shows the relationship between job accessibility and employment outcomes by the shares of Black populations in the neighborhood. As reported in the first column of Table 19, the shares of Black populations in the neighborhood are negatively associated with earned income, which is consistent with the observations of the employment model. I also find that job accessibility is positively associated with earned income in all three metropolitan areas, suggesting that individuals living in neighborhoods with high job accessibility have higher earnings. In Dallas, the residence in the suburb is positively associated with earned income, implying that Black individuals who live in suburbs tend to have higher earnings. Coefficients of individual and household variables are as expected, in which individuals with higher education level, having access to auto, and married with a spouse are significantly and positively associated with earned income. Also, although the result of the employment model in the previous section showed that males have a lower probability of being employed than female counterparts, the results in table 16 show that male workers have higher earned income. A potential explanation is that although female workers have a higher probability of being employed but they are more likely to work at a lower-paying job. In other words, Black male workers are more likely to look for a higher paying job than female workers, and female workers are willing to accept a job for less pay than to be unemployed and the vicinity to the job opportunities may be a more important consideration for their decision to work. The differences in earned income between male workers and female workers may also represent gender wage gaps.

The results of Model 2 shows interactions between neighborhood characteristics and the residence in the city and the suburb on earnings. I find metropolitan differences in the relationship between job accessibility and earned income. In Atlanta, job accessibility in the city is negatively associated with earnings, where the relationship is positive in the suburb. In other words, Black individuals who live in the city tend to have lower earnings if the neighborhood job accessibility is high, while those who live in the suburb have higher earnings if the job accessibility is high. This suggests that suburbs have better access to higher-paying jobs, which increases the amount of earned income as accessibility increases. In Chicago and Dallas, the relationship is opposite – job accessibility in the city is positively associated with earnings, and the relationship is negative in the suburb. These results suggest that Black individuals tend to have higher earnings if they live in a city with high job accessibility. In the suburb, individuals who earn higher income tend to live in neighborhoods with lower job accessibility, a pattern expected for those who self-select into neighborhoods based on their preference other than access to jobs. Results of model 3 report the association between neighborhood characteristics and earnings are only significant for individuals without auto ownership. This is consistent with the employment model since those without automobiles are more likely to be lower-income and thus are more influenced by the neighborhood characteristics.

Model 4 shows the associations between job accessibility and earned income and the interactions with the shares of Black populations in the neighborhood. Importantly, job accessibility is positively associated with earnings in all three metropolitan areas, while the magnitude of the associations varies. I also find that the marginal effects of job accessibility on earnings are highest in neighborhoods with less than 30 percent of Black in Atlanta. However, the marginal effect in Chicago and Dallas is highest in predominantly Black neighborhoods (over 60 percent of populations are Black), suggesting that increases in job accessibility have the largest effect in segregated neighborhoods. These differing relationships are further shown in Figure 12, which shows predictive margins over job accessibility scores. Overall, job accessibility is positively associated with earnings, suggesting individuals who live in neighborhoods with better job accessibility earn a higher income. However, in Atlanta, the marginal increase is greater in neighborhoods with low shares of Black populations as opposed to Chicago and Dallas where a marginal increase is greater in predominantly Black neighborhoods. This is consistent with the findings of the employment model that show the marginal increase in job accessibility has a larger effect in neighborhoods with a higher share of Black populations.

Table 16. Linear model results of log income

	Model 1			Model 2 (Job accessibility * Puma suburb)			Model 3 (Job accessibility * Auto)		
ln (income)	Atlanta	Chicago	Dallas	Atlanta	Chicago	Dallas	Atlanta	Chicago	Dallas
Individual characteristics									
Age	0.0883***	0.0869***	0.104***	0.0883***	0.0871***	0.104***	0.0882***	0.0871***	0.104***
	(0.00763)	(0.00613)	(0.00812)	(0.00762)	(0.00620)	(0.00814)	(0.00762)	(0.00615)	(0.00816)
Age^2	-0.0009***	-0.0009***	-0.0011***	-0.0009***	-0.0009***	-0.0011***	-0.0009***	-0.0009***	-0.0011***
	(9.21e-05)	(6.89e-05)	(8.93e-05)	(9.20e-05)	(6.97e-05)	(8.94e-05)	(9.20e-05)	(6.92e-05)	(8.97e-05)
Hispanic	-0.0350	-0.109	-0.00364	-0.0329	-0.107	-0.00232	-0.0354	-0.106	-0.00349
	(0.0628)	(0.0829)	(0.0805)	(0.0626)	(0.0816)	(0.0802)	(0.0634)	(0.0831)	(0.0805)
Male	0.126***	0.116***	0.127***	0.126***	0.116***	0.127***	0.126***	0.116***	0.127***
	(0.0185)	(0.0232)	(0.0180)	(0.0185)	(0.0232)	(0.0182)	(0.0185)	(0.0232)	(0.0181)
Highschool graduate	0.173***	0.150**	0.275***	0.172***	0.152**	0.271***	0.172***	0.150**	0.276***
	(0.0400)	(0.0574)	(0.0426)	(0.0398)	(0.0579)	(0.0426)	(0.0402)	(0.0575)	(0.0429)
College graduate	0.503***	0.417***	0.598***	0.501***	0.418***	0.594***	0.502***	0.416***	0.600***
	(0.0422)	(0.0642)	(0.0505)	(0.0421)	(0.0646)	(0.0503)	(0.0424)	(0.0642)	(0.0507)
Household characteristics									
Auto availability	0.341***	0.336***	0.339***	0.338***	0.339***	0.338***	0.309***	0.242***	0.412***
	(0.0333)	(0.0321)	(0.0447)	(0.0331)	(0.0314)	(0.0450)	(0.102)	(0.0729)	(0.117)
Married with spouse	0.157***	0.128***	0.166***	0.156***	0.127***	0.165***	0.157***	0.127***	0.166***
	(0.0208)	(0.0168)	(0.0230)	(0.0209)	(0.0167)	(0.0232)	(0.0208)	(0.0170)	(0.0230)
Own child under age 5	0.0362	0.0470	0.0468	0.0369	0.0495	0.0462	0.0371	0.0469	0.0468
	(0.0225)	(0.0368)	(0.0368)	(0.0225)	(0.0364)	(0.0367)	(0.0225)	(0.0366)	(0.0366)
Neighborhood characteristics									
Suburb	0.00609	-0.0530	0.0852***	-0.286***	-0.0179	0.0796	0.00195	-0.0516	0.0863***
	(0.0294)	(0.0370)	(0.0253)	(0.0409)	(0.0799)	(0.0648)	(0.0285)	(0.0365)	(0.0256)
Black percentage *Interaction: (City; Auto =0)*	-0.102**	-0.0953	-0.0178	-0.429***	-0.152**	-0.170	-0.197*	-0.196**	0.276
	(0.0450)	(0.0610)	(0.0791)	(0.0186)	(0.0595)	(0.137)	(0.116)	(0.0932)	(0.299)
Job accessibility *Interaction: (City; Auto =0)*	0.0646**	0.0839***	0.0693*	-0.0193***	0.0959***	0.0994**	0.0919	0.0580***	0.0659
	(0.0305)	(0.0260)	(0.0368)	(0.00599)	(0.0146)	(0.0440)	(0.0589)	(0.0186)	(0.0912)
Interaction:									
Black percentage * Suburb				0.337***	0.0847	0.184			

				(0.0442)	(0.108)	(0.154)			
Job accessibility * Suburb				0.0688*	-0.137*	-0.101*			
				(0.0374)	(0.0746)	(0.0600)			
Black percentage * Auto							0.103	0.142	-0.311
							(0.100)	(0.111)	(0.303)
Job accessibility * Auto							-0.0337	0.0498	0.00764
							(0.0506)	(0.0426)	(0.102)
Constant	7.411***	7.544***	6.910***	7.713***	7.567***	6.947***	7.450***	7.606***	6.839***
	(0.132)	(0.161)	(0.202)	(0.156)	(0.162)	(0.193)	(0.171)	(0.167)	(0.214)
Observations	16,664	13,480	10,544	16,664	13,480	10,544	16,664	13,480	10,544
R-squared	0.095	0.090	0.127	0.096	0.091	0.127	0.096	0.090	0.127

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 16. (continued)

ln (income)	Model 4 (Job accessibility * Black percentage) Atlanta	Chicago	Dallas
Individual characteristics			
Age	0.0884***	0.0870***	0.105***
	(0.00766)	(0.00617)	(0.00814)
Age^2	-0.0009***	-0.0009***	-0.0011***
	(9.24e-05)	(6.95e-05)	(8.94e-05)
Hispanic	-0.0345	-0.108	-0.00131
	(0.0624)	(0.0810)	(0.0802)
Male	0.126***	0.116***	0.127***
	(0.0185)	(0.0231)	(0.0181)
Highschool graduate	0.173***	0.150**	0.272***
	(0.0397)	(0.0584)	(0.0427)
College graduate	0.503***	0.414***	0.596***
	(0.0420)	(0.0656)	(0.0502)
***Household characteristic**s*			
Auto availability	0.340***	0.340***	0.337***
	(0.0331)	(0.0337)	(0.0451)
Married with spouse	0.157***	0.127***	0.165***
	(0.0210)	(0.0168)	(0.0236)
Own child under age 5	0.0366	0.0472	0.0469
	(0.0224)	(0.0363)	(0.0368)
Neighborhood characteristics			
Suburb	0.00822	-0.0902**	0.0716**
	(0.0262)	(0.0390)	(0.0298)
Black percentage group	-0.0330	-0.0935***	-0.123**
Interaction: (job accessibility =0)	(0.0238)	(0.0323)	(0.0608)
Job accessibility	0.0851**	0.0767***	0.0688*
Interaction: (Black percentage low)	(0.0363)	(0.0284)	(0.0370)
Job accessibility * Black percentage Moderate	-0.0283	0.147	0.646**
	(0.0325)	(0.133)	(0.278)
Job accessibility * Black percentage High	-0.0253	0.385***	1.011**
	(0.0735)	(0.141)	(0.410)
Constant	7.427***	7.655***	7.038***
	(0.170)	(0.170)	(0.193)
Observations	16,664	13,480	10,544
R-squared	0.096	0.090	0.127

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

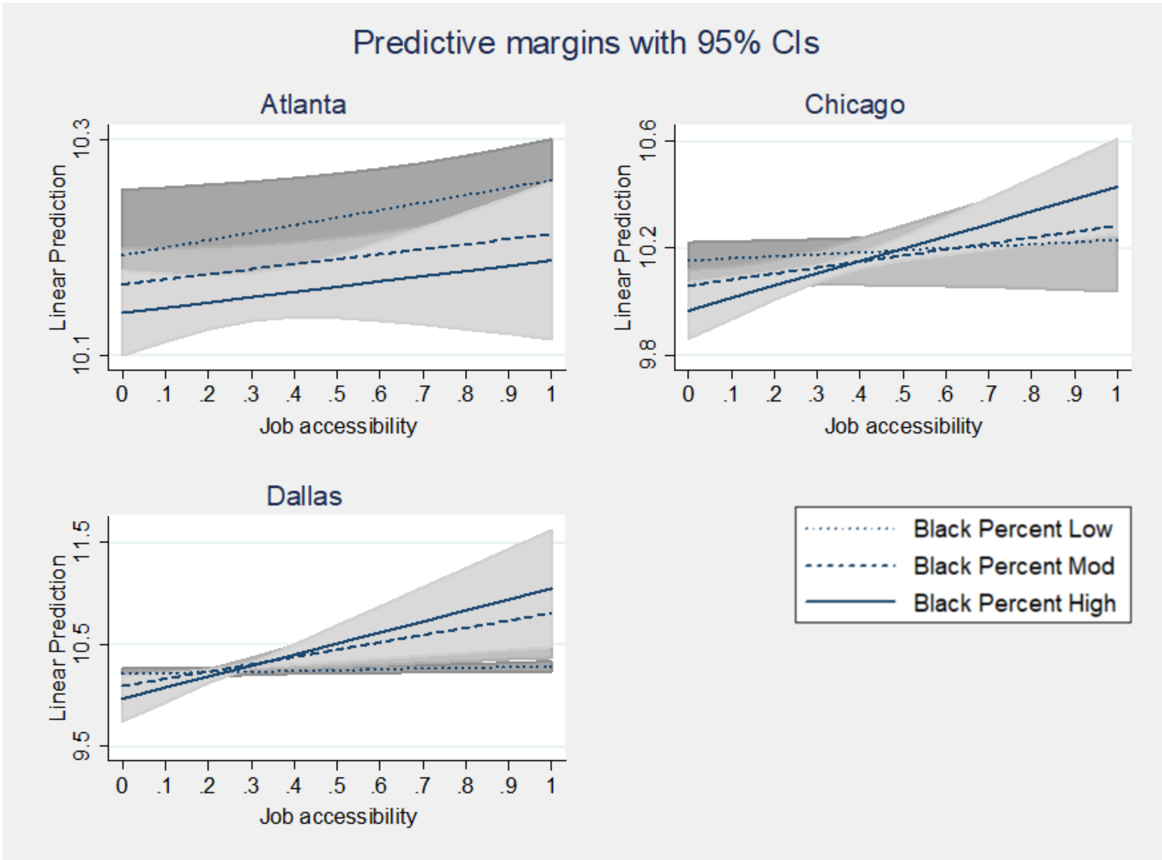


Figure 12. Predictive margins of log income over neighborhood Black share with 95% confidence intervals

4.3.4 Decomposition of employment and income gaps

In addition to the differing effects of job accessibility, the contributions of individual, household, and neighborhood characteristics to the differential in labor market outcomes by the residence in the city and suburb are examined using the Oaxaca-Blinder (OB) decomposition method. I use the two-fold decomposition that uses the coefficients from a pooled model over two groups as the reference (Jann, 2008; Yun, 2004). The two-fold model decomposes the mean difference in the dependent value between the two groups into the “explained” and “unexplained” component, in which the explained portion represents the differences in estimated outcome is attributable to the group differences in explanatory variables. The unexplained portion represents the group differences in unobserved predictors, which is often referred to as the discrimination effect that cannot be explained by the differences in observed characteristics (Jann, 2008). In the case of this research, the unexplained component may refer to unobserved factors that affect individuals to live in the city and in the suburb that is not observed from the independent variables in the model.

Table 17 shows the decomposition of the differences in the labor market outcomes, based on the estimation of probit regression to explain the likelihood of being employed and linear regression to explain log income. It shows how much the variables in the analysis can explain the differences in labor market outcomes in the *(explained component)*, and how much of each individual, household, and neighborhood characteristics contribute to the explained component. The difference in the employment rate in the city and the suburbs among Black individuals were 7.7 percent in Atlanta, 7.8 percent in Chicago, and 2.7 percent in Dallas. Overall, the employment rate in Dallas is relatively high when compared to Atlanta and Chicago, and it seems the differences in employment outcome in the city and the suburb is not as substantial. However, in Atlanta and Chicago, employment rate differences for the city residents and suburban residents are quite large, considering the employment rate gap between Black and White populations in 2015 was around 4.97 percent (Kang & Williamson, 2016). The decomposition analysis results indicate that the differences in characteristics can explain around 88.5 percent, 139.9 percent, and 83.2 percent of the employment gap in the city and the suburb in Atlanta, Chicago, and Dallas, respectively. The explained component is quite large in Chicago, accounting for 139.9 percent of the total gap of 7.8. This implies that if the city residents have the same characteristics as the suburban residents, but kept their coefficient, the employment gap would become even larger (10.9 percent). This suggests that the difference in the characteristics in the city and suburb is large, especially auto ownership (explains 38.3 percent of the total gap, calculated by $-0.0418 \div -0.109$) and percent Black in the neighborhood (27.2 percent of the total gap, calculated by $-0.0297 \div -0.109$). In Atlanta, around 59.3 percent of employment gaps come from household characteristics (especially auto ownership and marital status), and the neighborhood characteristics explain around 16.9 percent. 12.5 percent of the employment gap in the city and the suburb are unobserved in the analysis, which may be contributed to housing location choices or other neighborhood effects that are not captured by the share of Black populations and job accessibility. In Dallas, 62.7 percent of the employment gap is attributable to the difference in household characteristics, and individual characteristics explain around 35.1 percent. However, the unexplained component is the largest among the three metropolitan areas, suggesting that although the gap is smaller, around 16.8 percent of the differences are unobserved characteristics that affect the employment gap in the city and the suburb.

The decomposition of the log income model shows that the difference in earnings in the city and the suburb are greatest in Atlanta, followed by Dallas, and Chicago. The portions explained by the differences in characteristics account for 97 percent in Atlanta and 130.7 percent in Chicago, suggesting that the differences in earnings in the two metropolitan areas can be explained by the model. The detailed decomposition shows that in both Atlanta and Chicago, auto ownership explains around 42.6 percent (-0.0829÷-0.1948) and 45.4 percent (-0.1024÷-0.2257) of the differences in income, respectively. This implies that around half of the mean differences in income (that is, raw income gap of $3,413) among the city residents and suburban residents are attributable to the differences in auto ownership, in which individuals without access to auto in the household have lower income. In Chicago, consistent with the employment model, the characteristic differences explain the income gap beyond the actual income gap, suggesting that the income gap would increase if the city residents had the characteristics of the suburban residents. Further, the neighborhood characteristics explained around 20.8 percent of the income gap – the differences in the share of Black populations and job accessibility in the city and the suburb explains 20.8 percent of the income difference in Chicago. In Dallas, the differences in characteristics only explain about half of the income gap (raw income gap of $6,859) in the city and the suburb, and around half of the income differences are unobserved in the model. This suggests that in Dallas, compared to the employment model, the individual, household, and neighborhood characteristics in the log income regression model only explain half of the income gap.

Table 17. Decomposition of the differences in employment and log income by the residence in the city and the suburb

	Employment Model						Log Income Model					
	Atlanta		**Chicago**		**Dallas**		**Atlanta**		**Chicago**		**Dallas**	
		(%)		(%)		(%)		(%)		(%)		(%)
City	81.80%		77.50%		89.00%		9.99		10.06		10.12	
Suburb	89.50%		85.30%		91.70%		10.19		10.24		10.30	
Raw Difference	-7.70%		-7.80%		-2.70%		-0.20		-0.17		-0.18	
Explained Component	-0.068	**88.5%**	-0.109	**139.9%**	-0.023	**83.2%**	-0.19	**97.0%**	-0.23	**130.7%**	-0.09	**52.7%**
Individual characteristics	-0.0163	23.8%	-0.017	15.6%	-0.008	35.1%	-0.0809	41.5%	-0.0508	22.5%	-0.0518	54.5%
Age	-0.0184		-0.0179		-0.0036		-0.1783		-0.1302		-0.0144	
	(0.0041)		(0.0032)		(0.0026)		(0.0307)		(0.0208)		(0.0268)	
Age^2	0.0134		0.0108		0.0015		0.1450		0.1122		-0.0020	
	(0.0036)		(0.0029)		(0.0020)		(0.0266)		(0.0183)		(0.0233)	
Hispanic	-0.0001		-0.0012		-0.0003		0.0002		0.0009		0.0000	
	(0.0003)		(0.0006)		(0.0002)		(0.0003)		(0.0007)		(0.0000)	
Male	0.00019		0.0018		3.92E-05		-0.0035		-0.0044		-0.0012	
	(0.0001)		(0.0003)		(0.0000)		(0.0017)		(0.0012)		(0.0013)	
Highschool graduate	0.0046		0.0032		0.00152		0.0096		0.0061		0.0142	
	(0.0010)		(0.0006)		(0.0006)		(0.0031)		(0.0022)		(0.0037)	
College graduate	-0.0160		-0.0137		-0.0072		-0.0539		-0.0352		-0.0485	
	(0.0019)		(0.0012)		(0.0012)		(0.0078)		(0.0052)		(0.0073)	
Household characteristics	-0.0405	59.3%	-0.05529	50.7%	-0.01429	62.7%	-0.1207	62.0%	-0.1279	56.7%	-0.0488	51.4%
Auto availability	-0.0255		-0.0418		-0.0078		-0.0829		-0.1024		-0.0259	
	(0.0026)		(0.0022)		(0.0010)		(0.0097)		(0.0089)		(0.0039)	
Married with spouse	-0.0152		-0.0132		-0.0064		-0.0368		-0.0249		-0.0221	
	(0.0017)		(0.0013)		(0.0010)		(0.0049)		(0.0047)		(0.0034)	
Own child under age 5	0.00021		-0.0003		-0.0002		-0.0010		-0.0006		-0.0008	
	(0.0002)		(0.0001)		(0.0001)		(0.0007)		(0.0004)		(0.0006)	
Neighborhood characteristics	-0.0116	16.9%	-0.0368	33.7%	-0.00049	2.1%	0.0068	-3.5%	-0.0471	20.8%	0.0056	-5.9%
Black percentage	-0.01198		-0.0297		-0.0007		-0.0186		-0.0264		-0.0006	
	(0.0018)		(0.0028)		(0.0007)		(0.0061)		(0.0117)		(0.0022)	
Job accessibility	0.0004		-0.0071		0.0002		0.0253		-0.0207		0.0062	
	(0.0030)		(0.0017)		(0.0007)		(0.0099)		(0.0059)		(0.0025)	

Note: Robust standard errors are in parenthesis. employment model uses the probit decomposition.

4.4 Discussion

The relationship between the neighborhood job accessibility and labor market outcomes of Black individuals is tested in this chapter. Using job accessibility as an indicator for the spatial mismatch, the different associations between job accessibility and labor market outcomes (specifically, employment and earned income) are examined by the residence in the city and the suburb, auto ownership, and neighborhood share of Black populations. This approach allows for identifying the effects of job accessibility for different groups of individuals, as well as whether there is an interaction effect between the neighborhood share of Black populations and job accessibility. The findings of the research support the spatial mismatch hypothesis, in which the neighborhood job opportunity affects the probability of being employed and the earnings of Black individuals, although the variation in its significance and magnitude vary by the metropolitan areas. Findings also show evidence that job accessibility has strong associations with Black labor market outcomes particularly in the city, which may reflect residential location preferences in the suburbs. Labor market outcomes among Black individuals without access to auto were closely associated with job accessibility, suggesting that these individuals are more likely to be influenced by neighborhood characteristics. As for individuals with access to auto, the neighborhood job accessibility was negatively associated with the probability of being employed, which may represent a reverse causality that these individuals self-select into neighborhoods with lower job accessibility but that offer other preferable neighborhood attributes.

Another interesting finding from this research is that in metropolitan areas with a traditional spatial pattern of mismatch, job accessibility is the lowest in the inner city where Black populations are segregated into. In Chicago, for example, an increase in access increases the probability of being employed, especially in highly segregated neighborhoods (with more than 60 percent of the populations are Black). On the other hand, in metropolitan areas where large shares of Black populations have moved into the suburbs, job accessibility in the inner city is greater than in the suburbs, but the Black suburbs also have a moderate level of job accessibility. In Atlanta, job accessibility in neighborhoods with low shares of Black populations is positively associated with Black employment, but accessibility in highly segregated neighborhoods has negative associations with employment outcomes. This suggests that the neighborhood shares of Black populations have greater associations with Black employment than job accessibility in Atlanta.

The results of the income model are consistent with the employment model, but the magnitude of associations is stronger, suggesting that neighborhood job accessibility is more associated with earnings than employment. In all three metropolitan areas, job accessibility is positively associated with income among Black workers, suggesting that living in neighborhoods with better access to jobs increases their earned income. However, in the suburbs of Chicago and Dallas, job accessibility is negatively associated with earnings, suggesting that in the suburbs, individuals who live in neighborhoods with low job accessibility have a higher income. This may be the result of residential location preferences, in which individuals choose to live in areas with neighborhood attributes other than job accessibility. This also implies that in Atlanta, those with higher earnings are more likely to live in neighborhoods with higher job accessibility in the suburb, as opposed to Chicago and Dallas where individuals with higher earnings tend to live in neighborhoods with low job accessibility in the suburb.

The Blinder-Oaxaca decomposition shows that much of the differences in the labor market outcomes among Black individuals living in the city and the suburbs can be attributable to the differences in individual, household, and neighborhood characteristics. Particularly, having access to auto and the neighborhood share of Black populations are major characteristics that contribute to the differences in labor market outcome. To summarize, the findings of this research support a significant relationship between neighborhood job accessibility and labor market outcomes of Black individuals. Much of the variation in the significance and the magnitude arises from the different spatial distribution of populations. In Chicago where the majority of Black populations are concentrated in the city, an increase in job accessibility in the city is positively associated with the probability of being employed and earnings. However, the effect of job accessibility on being employed is less clear in the suburbs, and reverse causality is implied, in which individuals with higher earnings live in lower job accessibility. This pattern is similarly found in Dallas. In Atlanta where much of the Black populations have suburbanized, living in the neighborhood with higher job accessibility is positively associated with earnings. However, the residence in neighborhoods with high shares of Black populations offsets the effect of job accessibility, and in Atlanta, living in low Black share neighborhood has higher returns on the labor market outcomes of Black individuals than the neighborhood job accessibility.

Chapter 5. Conclusions and Policy Discussion

5.1 Conclusion and Discussions

Overall, this research presents geographical evidence of changes in spatial mismatch patterns from the inner cities to the suburbs, particularly in metropolitan areas where large shares of Black populations have moved into during the 1980s. This research identified different spatial patterns of mismatch and categorized them into four major types: 1) traditional spatial mismatch pattern of inner-city Black and suburban jobs, 2) geographical polarization to the north-south or east-west, 3) spatial mismatch within the inner city – polarized urban core, and 4) suburb-to-suburb spatial mismatch – suburbanized Black surplus neighborhood and job surplus neighborhood. Also, the spatial inequality of opportunity and its decompositions using the spatial Theil's index revealed that overall trends of inequality of major metropolitan areas in the U.S. decreased between 2000 and 2015, which mainly derived from the decrease in between-subarea inequality. In almost all metropolitan areas, the contribution of within-subarea inequality increased, indicating the spatial distribution of Black populations and jobs are more unequal within subareas than between inner city and suburban boundary. Further, the findings of spatial inequality support the increasing importance of local inequality regarding the population and opportunity distribution. This research contributes to the literature in several ways: 1) it presents an analysis of the spatial structure of opportunity that takes into consideration the spatial relationships between neighboring areas, 2) it puts forth the growing patterns of Black suburban segregation in connection with the spatial mismatch to provide evidence for the mechanisms of the spatial mismatch, and 3) it identifies the rising inequalities in distributions that are derived from within-neighborhood subareas, further indicating increased local inequality in the U.S. This research calls for a renewed focus on measuring spatial patterns at the local geographical scales that are often overlooked in studies at the regional or national level that focuses on the aggregate trends. For instance, racial diversification in the suburbs may be seen as evidence of increased racial integration, supporting the theory that suburban migration of Black populations contributes to increased racial integration in U.S. cities. Instead, as this research demonstrates, the analysis of spatial patterns at the local level may reveal continued residential segregation that has shifted to the suburbs. At the same time, increased local inequality in the distribution of population and jobs suggests a greater role of local policies aimed at more inclusive and integrated distributions towards more equitable and sustainable urban areas.

For long, studies have questioned the link between the exclusionary land-use regulations and residential segregation, spatial mismatch, and urban inequality (Berry, 2001; Ihlanfeldt, 2004; M. C. Lens & Monkkonen, 2016; Pendall, 2000). These studies found the density restrictions and urban growth boundaries that set a limit on housing supplies are used to exclude certain groups of populations that result in structural segregation (M. C. Lens & Monkkonen, 2016). The findings of this research demonstrate continued spatial mismatch among suburban Black populations and that the spatial patterns of inequality vary by the metropolitan area. To further investigate potential links to the local land use regulations, I use the Wharton Residential Land Use Regulations Index (WRLURI) of Gyourko et al. (2008), to analyze the regulatory environment of municipalities within each metropolitan area. The Wharton index uses different subindexes including the general land use regulations of each municipality, the local and state political involvement in planning processes, and the regulatory processes that represent the restrictive land-use policies. I summarized the aggregate WRLURI value that represents an overall regulatory environment, and four subindexes – Local and State Political Involvement Index (LPII and SPII) and Density and Supply Restriction Index (DRI and SRI), in Table 18.

Aggregate WRLURI values have been standardized to mean zero with a standard deviation of one. So, the low value indicates that the land regulations are less restrictive compared to the national average, while high values indicate the regulatory environment is more strict.

WRLURI value in Table 18 shows that the metropolitan areas in the Midwest and South are less regulated than the metropolitan areas in the Northeast and West. Among the twelve metropolitan areas, Dallas is the least regulated with an average WRLURI value of -0.33 which indicates the housing market regulations in Dallas is below the national average (0.3 standard deviations below the mean), followed by Atlanta with a WRLURI value of 0.04. Chicago, Pittsburgh, and Detroit have WRLURI values less than 0.1, which indicates that the land regulations in these metropolitan areas are around the national average. Except for Pittsburgh, these metropolitan areas are also the areas that exhibit high levels of spatial mismatch and inequality. Especially, in Dallas and Atlanta, the spatial pattern of mismatch extends to the outer-most suburb, demonstrating suburban-to-suburban mismatch. Weak state regulations to constrain local politics to provide affordable housing ad fragmented community organization resulted in dependence on local politics for housing planning and economic development efforts (E. J. Muller & Ferguson, 2009). In Chicago and Detroit, the level of spatial mismatch is the highest among the twelve metropolitan areas. This suggests that below average to average restrictive land-use regulations do help explain the overall levels of spatial mismatch and the spatial structure of inequality. Metropolitan areas in the West – Seattle, San Francisco, and Los Angeles, and in the Northeast – Philadelphia and New York are more moderately regulated with WRLURI values are approximately 0.5-1 standard deviation above the national average. Stricter land use regulations in Western metropolitan areas partially explain the polycentric pattern of inequality in these metropolitan areas although the overall level of spatial mismatch in Los Angeles and

San Francisco are comparable to Chicago. In general, the low regulatory environment is associated with the suburban expansion of populations and economic development that contribute to the spatial patterns of suburban inequality as shown in Dallas and Atlanta. Also, metropolitan areas with the regulatory environment around the national average exhibit high levels of spatial mismatch, although the spatial patterns are not as dispersed as in Southern metropolitan areas. On the other hand, associations between moderate- to the higher-regulatory environment and spatial mismatch and inequality are less clear, especially in Philadelphia and New York. Other factors besides the land use regulations captured in the Wharton index may contribute to the spatial distributions of populations and jobs, but at least in the current analysis, it seems less restrictive regulations allow dispersed development patterns that increase the geographical distance between populations and jobs.

Table 18. Wharton index in the twelve observed metropolitan areas

		Observations	WRLURI	LPPI	SPII	DRI	SRI
Northeast	New York	19	0.65	0.1	-1	0.37	0
	Philadelphia	56	1.03	0.49	0.66	0.53	0.13
	Pittsburgh	44	0.07	-0.21	0.66	0.23	0.07
Midwest	Chicago	100	0.07	0.37	-0.93	0.16	0.27
	Detroit	45	0.09	-0.06	0.59	0.18	0.16
	Minneapolis	97	0.33	0.05	0.54	0.11	0.3
West	Los Angeles	34	0.52	0.11	1.02	0.18	0
	San Francisco	13	0.87	0.49	1.02	0.08	0
	Seattle	22	0.98	0.12	2.42	0.14	0.23
South	Dallas	31	-0.33	0.25	-0.47	0.13	0.13
	Atlanta	28	0.04	0.35	0.11	0.25	0.57
	Baltimore	5	1.08	0.45	0.32	0.2	1.4

In addition to the overall regulatory environment of municipalities, studies found the stronger local political pressure in the housing market regulations is closely associated with segregation by income through increased local fragmentations (M. C. Lens & Monkkonen, 2016; Logan & Molotch, 2007). To examine whether this relationship holds true for the twelve observed metropolitan areas, the Local Political Pressure Index (LPPI) and State Political Pressure Index (SPII) that represent the involvement of local actors and state legislature in the land development processes are examined. These two subindexes have a negative correlation of -0.14, suggesting an inverse relationship (although minimal) between the local involvement and the state involvement. In other words, metropolitan areas with strong local involvement than the national average are likely to have weaker state involvement and vice versa. The state legislature involvement (SPII) in New York and Chicago are the lowest among the twelve metropolitan areas (-1 and -0.93, respectively), followed by Dallas and Atlanta (-0.47 and 0.11, respectively). These metropolitan areas are among the top metropolitan areas with the highest concentration of inequality within the inner city and the outer suburb. Because these metropolitan areas have stronger local political pressure than state political involvement, the concentration of inequality at a local level seems reasonable. Metropolitan areas in the West have the highest state legislature involvement among the twelve metropolitan areas. Considering the polycentric pattern of inequality across neighborhood subareas, it seems plausible the higher state political pressure contributes to lower local-level inequality. Lens & Monkkonen (2016) also argue that statewide regulations that have power over the local political interests can curb exclusionary practices and unequal development trends, resulting in lower levels of segregation in the region.

Density restrictions have been linked to low-density development and segregation of high-income households by excluding minority and low-income households from their neighborhoods (Ihlanfeldt, 2004; M. C. Lens & Monkkonen, 2016). How are Density Restrictions Index (DRI) and Supply Restrictions Index (SRI) associated with spatial mismatch and inequality? The DRI and SRI indicate whether municipalities require minimum lot size requirements or constraints on supplying new housing units to the market. These are more direct measures that restrict the new housing developments through requiring the minimum lot sizes and limiting the number of new housing supply units than other regulatory policies. However, these values have not been standardized in the Wharton index, and thus the value only indicates the average number of ‘yes’ answers in the survey questionnaire. Therefore, it is difficult to assume the values represent the restrictive environment of metropolitan areas, or whether the values come from a single municipality. For this reason, the summary of DRI and SRI is only briefly discussed here, and more emphasis is given to the discussions from the literature. Philadelphia and New York have the highest density restrictions (0.53 and 0.37 respectively), while the supply restriction is the highest in Atlanta (0.57), followed by Minneapolis and Chicago (0.3 and 0.27, respectively)[6]. In general, it seems larger metropolitan areas have more restrictive regulations than the smaller areas, possibly due to the high population density that is already in place. Also, it is surprising to find Atlanta has the highest supply restriction among the twelve metropolitan areas in this study, considering their expansion to the suburbs. However, it should be noted that these density and supply restrictions vary greatly by where these restrictions are being imposed. The supply caps on the northern suburbs of Atlanta may explain exclusionary housing policies that result in the segregation of Black populations in the southern suburb. On a similar note, Levine (1998; 1999) found the growth controls in Minneapolis that put a cap on the number of multi-family rental

[6] The unusually high SRI value in Baltimore comes from the Town of Hampstead in Baltimore that scored 6 (meaning this municipality has constraints or caps on supplying new building permits and caps on both single family and multi-family units for construction, multifamily dwellings, and the number of units in multifamily housing).

housing intensifies residential segregation and jobs-housing balance by excluding low-income and minority households near suburban employment centers.

Transportation systems have a major impact on urban areas by shaping the demographic landscape and economic growth. The passage of the Federal-Aid Highway Act of 1956 allowed residential and economic development in the suburbs farther away from the inner city, which caused increased residential segregation and spatial inequality (Leinberger, 2010; Sanchez, Stolz, et al., 2004; Sjoquist, 2000). In Chicago, the initial limited-access highways that opened in 1958 – Tri-State, East-West, and Northwest Tollways in the Western suburb (map shown in Appendix C) which paved the way for the north and southwest suburban growth (McClendon, 2005). This transport-led suburban development can be found in almost all major metropolitan areas in the U.S., including but not limited to northern suburbs of Atlanta and Dallas, northwest of Philadelphia where the largest regional mall the King of Prussia Mall opened in 1963 at the intersection of major highways, and the Eastside of Seattle (Leinberger, 2010). In addition to the pro-growth impact of transportation projects, other studies have found the highway constructions resulted in the displacement of minority and low-income households by forcing them out from economic growth areas in the inner city. These projects include the proposal of the Century Freeway (I-105) in Los Angeles, an east-west interstate highway located at the southern edge of the inner city, and Edsel Ford Expressway (I-94) of Detroit that disproportionately affected inner city Black neighborhoods (Sanchez, Stolz, et al., 2004).

Based on these contextual aspects of local land use regulations and transportation infrastructures, the findings of this research support the view that Black populations in the suburbs continue to face spatial mismatch to job opportunities through suburban segregation and unequal local economic growth. The sorting of neighborhoods – otherwise known as the spatial stratification – likely affects the competitive power of neighborhoods, benefiting affluent neighborhoods by attracting capital investment that drives local economic growth and spatial disparity (Logan & Molotch, 2007; Massey, 2004; Sampson, 2009; Small & McDermott, 2006). Similarly, Glaeser (2013) and Diamond (2016) suggest that local amenities are endogenous with areas of highly skilled populations and that inequalities in wages understate the inequality of available amenities across neighborhoods. These findings further support the close association between residential segregation by race and income as a strong driver for spatial inequality in access to economic opportunities in the U.S.

Planning approaches to reduce spatial mismatch have been proposed in the past, including strategies to promote economic growth in disadvantaged neighborhoods by bringing jobs closer to people, housing assistance programs that promote the relocation of people in closer proximity to jobs, and improving transportation options for people to access job opportunities (Fan et al., 2012; Gobillon & Selod, 2007). Although current research does not examine the link between such planning practices and the spatial patterns of mismatch directly, findings suggest that persistent residential segregation and the city's land-use policies that often promote concentrated economic development that contributes to increased spatial disparity – the spatial differentiation between where Black populations reside in the suburbs and where job growth is occurring – resulting in persistence of the spatial mismatch in the U.S. The spatial mismatch in the suburbs into which Black populations have migrated reveals that continued segregation of Black populations in the 21st century contributes to continued spatial disadvantage but in different geography. To address the problem of persistent mismatch, residential segregation and spatial sorting by race and income needs to be mediated through more inclusionary housing policies and promoting economic integration in economically growing neighborhoods. Further, the findings of this research identified that the spatial pattern of mismatch is particularly evident in metropolitan areas with a strong economy, such as the northwestern suburbs of Chicago and the northeastern suburbs of Atlanta and Dallas. Although a concentration of economy in such sub-centers can increase the overall productivity and economic growth in the metropolitan area, it is at the cost of spatial disparities in economic opportunities. This is consistent with recent studies that argue the between-inequality are declining across metropolitan areas, while within-inequality is growing. Because spatial mismatch in the 21st century is a byproduct of residential segregation and spatial inequality, 1) housing integration and 2) polycentric development in the suburbs that strengthen local neighborhoods and ensure the economic development of a wider region within metropolitan areas.

Further, local variations in spatial patterns of mismatch found in this research demonstrate how critical it is to consider spatial heterogeneity across the urban landscape when assessing the extent of spatial mismatch. Further, both the shifting geography of mismatch to the predominantly Black suburbs and the increased spatial inequality between suburban neighborhoods are highlighted in this research. This research proposes a methodological approach to assess the spatial dimension of mismatch that incorporates the spatial interaction among populations and jobs within neighboring areas. The five-mile buffer area used in this research to represent the local neighborhood environment is based on average commute distances, but different geographical scales can be used to assess spatial interactions. Advanced measures such as gravity-based accessibility measures may also be used to examine populations and job access from each areal unit. Nevertheless, spatial patterns of mismatch using the five-mile buffer area in this study capture the spatial distribution of Black populations and jobs within the immediate neighborhood boundary and enable one to identify spatial disparity within the nearby inner city. Based on this, this research confirms that the spatial mismatch is not disappearing at the local neighborhood level. Also, heterogeneity in spatial patterns of mismatch exists. To promote equality of economic opportunities across all neighborhoods, future land-use regulations and housing policies should address ways to achieve stable racial and economic integration for balanced growth and equality of opportunity. With regards to promoting equitable economic growth across neighborhoods, which Enrico Moretti (2012) describes as "the new geography of jobs", future policies must consider strategies towards inclusive economic growth across industry sectors to increase diversity and foster sustainable economic growth in the U.S. cites.

Appendices

Appendix A. List of 100 MSAs included in the aggregate trend analysis

Rank	Name	2010 Census
1	New York-Newark-Jersey City, NY-NJ-PA MSA	19,567,410
2	Los Angeles-Long Beach-Anaheim, CA MSA	12,828,837
3	Chicago-Naperville-Elgin, IL-IN-WI MSA	9,461,105
4	Dallas-Fort Worth-Arlington, TX MSA	6,426,214
5	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD MSA	5,965,343
6	Houston-The Woodlands-Sugar Land, TX MSA	5,920,416
7	Miami-Fort Lauderdale-West Palm Beach, FL MSA	5,564,635
8	Atlanta-Sandy Springs-Roswell, GA MSA	5,286,728
9	San Francisco-Oakland-Hayward, CA MSA	4,335,391
10	Detroit-Warren-Dearborn, MI MSA	4,296,250
11	Riverside-San Bernardino-Ontario, CA MSA	4,224,851
12	Seattle-Tacoma-Bellevue, WA MSA	3,439,809
13	Minneapolis-St. Paul-Bloomington, MN-WI MSA	3,348,859
14	San Diego-Carlsbad, CA MSA	3,095,313
15	St. Louis, MO-IL MSA	2,787,701
16	Tampa-St. Petersburg-Clearwater, FL MSA	2,783,243
17	Baltimore-Columbia-Towson, MD MSA	2,710,489
18	Denver-Aurora-Lakewood, CO MSA	2,543,482
19	Pittsburgh, PA MSA	2,356,285
20	Portland-Vancouver-Hillsboro, OR-WA MSA	2,226,009
21	Charlotte-Concord-Gastonia, NC-SC MSA	2,217,012
22	Sacramento–Roseville–Arden-Arcade, CA MSA	2,149,127
23	San Antonio-New Braunfels, TX MSA	2,142,508
24	Orlando-Kissimmee-Sanford, FL MSA	2,134,411
25	Cincinnati, OH-KY-IN MSA	2,114,580
26	Cleveland-Elyria, OH MSA	2,077,240
27	Kansas City, MO-KS MSA	2,009,342
28	Las Vegas-Henderson-Paradise, NV MSA	1,951,269
29	Columbus, OH MSA	1,901,974
30	Indianapolis-Carmel-Anderson, IN MSA	1,887,877
31	San Jose-Sunnyvale-Santa Clara, CA MSA	1,836,911
32	Austin-Round Rock, TX MSA	1,716,289
33	Virginia Beach-Norfolk-Newport News, VA-NC MSA	1,676,822
34	Nashville-Davidson–Murfreesboro–Franklin, TN MSA	1,670,890
35	Milwaukee-Waukesha-West Allis, WI MSA	1,555,908
36	Jacksonville, FL MSA	1,345,596
37	Oklahoma City, OK MSA	1,252,987

38	Louisville–Jefferson County, KY-IN MSA	1,235,708
39	Hartford-West Hartford-East Hartford, CT MSA	1,212,381
40	Richmond, VA MSA	1,208,101
41	New Orleans-Metairie, LA MSA	1,189,866
42	Buffalo-Cheektowaga-Niagara Falls, NY MSA	1,135,509
43	Raleigh-Cary, NC MSA	1,130,490
44	Birmingham-Hoover, AL MSA	1,128,047
45	Salt Lake City, UT MSA	1,087,873
46	Rochester, NY MSA	1,079,671
47	Grand Rapids-Wyoming, MI MSA	988,938
48	Urban Honolulu, HI MSA	980,080
49	Tulsa, OK MSA	937,478
50	Fresno, CA MSA	930,450
51	Bridgeport-Stamford-Norwalk, CT MSA	916,829
52	Albuquerque, NM MSA	887,077
53	Albany-Schenectady-Troy, NY MSA	870,716
54	Omaha-Council Bluffs, NE-IA MSA	865,350
55	New Haven-Milford, CT MSA	862,477
56	Bakersfield, CA MSA	839,631
57	Knoxville, TN MSA	837,571
58	Greenville-Anderson-Mauldin, SC MSA	824,112
59	Oxnard-Thousand Oaks-Ventura, CA MSA	823,318
60	Allentown-Bethlehem-Easton, PA-NJ MSA	821,173
61	El Paso, TX MSA	804,123
62	Baton Rouge, LA MSA	802,484
63	Dayton, OH MSA	799,232
64	McAllen-Edinburg-Mission, TX MSA	774,769
65	Columbia, SC MSA	767,598
66	Greensboro-High Point, NC MSA	723,801
67	Akron, OH MSA	703,200
68	North Port-Sarasota-Bradenton, FL MSA	702,281
69	Stockton-Lodi, CA MSA	685,306
70	Charleston-North Charleston, SC MSA	664,607
71	Syracuse, NY MSA	662,577
72	Colorado Springs, CO MSA	645,613
73	Winston-Salem, NC MSA	640,595
74	Wichita, KS MSA	630,919
75	Cape Coral-Fort Myers, FL MSA	618,754
76	Boise City, ID MSA	616,561
77	Toledo, OH MSA	610,001
78	Madison, WI MSA	605,435

79	Lakeland-Winter Haven, FL MSA	602,095
80	Ogden-Clearfield, UT MSA	597,159
81	Deltona-Daytona Beach-Ormond Beach, FL MSA	590,289
82	Des Moines-West Des Moines, IA MSA	569,633
83	Youngstown-Warren-Boardman, OH-PA MSA	565,773
84	Augusta-Richmond County, GA-SC MSA	564,873
85	Scranton–Wilkes-Barre–Hazleton, PA MSA	563,631
86	Harrisburg-Carlisle, PA MSA	549,475
87	Palm Bay-Melbourne-Titusville, FL MSA	543,376
88	Chattanooga, TN-GA MSA	528,143
89	Spokane-Spokane Valley, WA MSA	527,753
90	Provo-Orem, UT MSA	526,810
91	Lancaster, PA MSA	519,445
92	Modesto, CA MSA	514,453
93	Portland-South Portland, ME MSA	514,098
94	Durham-Chapel Hill, NC MSA	504,357
95	Santa Rosa, CA MSA	483,878
96	Lexington-Fayette, KY MSA	472,099
97	Lafayette, LA MSA	466,750
98	Lansing-East Lansing, MI MSA	464,036
99	Pensacola-Ferry Pass-Brent, FL MSA	448,991
100	Visalia-Porterville, CA MSA	442,179

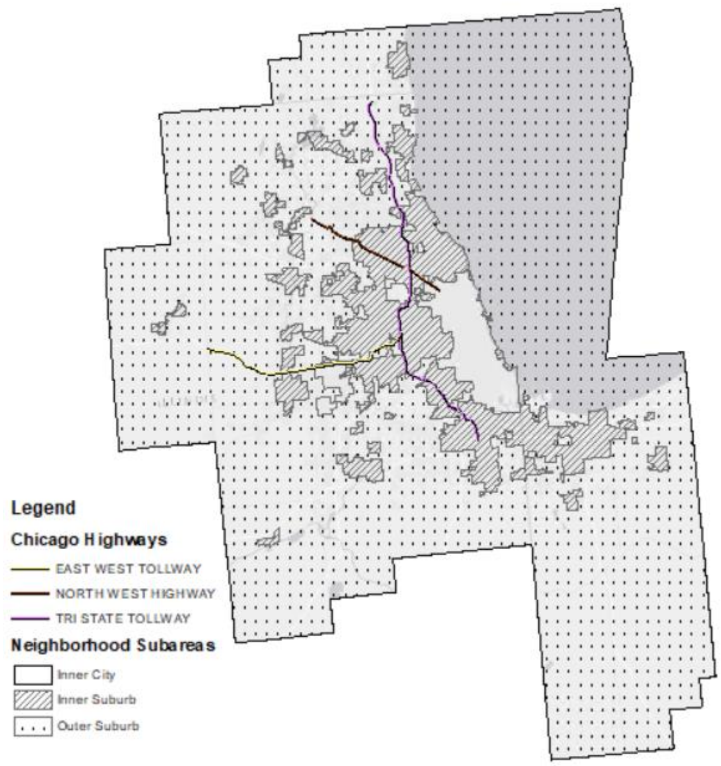
Appendix B. Aggregate trends of spatial mismatch in 100 MSAs by regions

	Dissimilarity Index				Catchment Area Dissimilarity Index			
	00		15		00		15	
	Goods Producing	Local Service	Goods Producing	Local Service	Goods Producing	Local Service	Goods Producing	Local Service
Northeast								
New York-Newark-Jersey City, NY-NJ-PA	0.81	0.78	0.79	0.75	0.37	0.42	0.36	0.44
Syracuse, NY	0.77	0.70	0.77	0.67	0.24	0.19	0.25	0.17
Buffalo-Cheektowaga-Niagara Falls, NY	0.77	0.78	0.76	0.72	0.25	0.25	0.25	0.24
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	0.75	0.73	0.75	0.70	0.37	0.29	0.36	0.27
Pittsburgh, PA	0.73	0.71	0.73	0.70	0.29	0.25	0.29	0.23
Scranton--Wilkes-Barre--Hazleton, PA	0.68	0.61	0.71	0.66	0.23	0.15	0.27	0.14
Hartford-West Hartford-East Hartford, CT	0.72	0.66	0.70	0.64	0.33	0.28	0.31	0.26
New Haven-Milford, CT	0.69	0.66	0.68	0.61	0.36	0.27	0.33	0.22
Lancaster, PA	0.71	0.65	0.67	0.60	0.27	0.20	0.30	0.17
Rochester, NY	0.69	0.70	0.67	0.65	0.09	0.14	0.12	0.15
Albany-Schenectady-Troy, NY	0.65	0.62	0.65	0.61	0.23	0.20	0.18	0.18
Harrisburg-Carlisle, PA	0.67	0.68	0.65	0.61	0.27	0.23	0.28	0.23
Bridgeport-Stamford-Norwalk, CT	0.60	0.65	0.63	0.64	0.23	0.31	0.26	0.35
Allentown-Bethlehem-Easton, PA-NJ	0.63	0.58	0.62	0.55	0.16	0.12	0.21	0.12
Portland-South Portland, ME	0.49	0.45	0.59	0.57	0.13	0.08	0.19	0.12
Midwest								
Chicago-Naperville-Elgin, IL-IN-WI	0.82	0.79	0.80	0.75	0.40	0.43	0.39	0.44
Detroit-Warren-Dearborn, MI	0.84	0.80	0.79	0.71	0.46	0.47	0.41	0.41
Milwaukee-Waukesha-West Allis, WI	0.82	0.82	0.79	0.77	0.33	0.31	0.33	0.29
Cleveland-Elyria, OH	0.79	0.76	0.76	0.73	0.44	0.40	0.39	0.36
Omaha-Council Bluffs, NE-IA	0.79	0.72	0.76	0.67	0.41	0.37	0.38	0.34
Toledo, OH	0.75	0.72	0.74	0.65	0.11	0.18	0.18	0.17
Wichita, KS	0.73	0.60	0.74	0.60	0.22	0.14	0.26	0.14
Dayton, OH	0.77	0.72	0.73	0.67	0.35	0.41	0.32	0.40
Kansas City, MO-KS	0.75	0.72	0.73	0.66	0.34	0.37	0.33	0.31
Columbus, OH	0.71	0.64	0.71	0.64	0.25	0.27	0.23	0.24
Grand Rapids-Wyoming, MI	0.71	0.66	0.71	0.60	0.19	0.17	0.20	0.15
St. Louis, MO-IL	0.71	0.70	0.71	0.68	0.34	0.36	0.31	0.35
Louisville/Jefferson County, KY-IN	0.65	0.64	0.71	0.63	0.21	0.27	0.23	0.28
Des Moines-West Des Moines, IA	0.70	0.60	0.70	0.60	0.15	0.21	0.17	0.21
Indianapolis-Carmel-Anderson, IN	0.74	0.70	0.70	0.64	0.30	0.27	0.25	0.27
Minneapolis-St. Paul-Bloomington, MN-WI	0.75	0.67	0.69	0.58	0.28	0.20	0.21	0.17

Youngstown-Warren-Boardman, OH-PA	0.69	0.71	0.69	0.69	0.29	0.23	0.21	0.21
Akron, OH	0.70	0.69	0.67	0.62	0.25	0.22	0.27	0.23
Lansing-East Lansing, MI	0.65	0.56	0.65	0.55	0.08	0.14	0.10	0.14
Madison, WI	0.56	0.50	0.62	0.51	0.11	0.07	0.17	0.07
South								
Baltimore-Columbia-Towson, MD	0.77	0.70	0.77	0.67	0.27	0.21	0.29	0.20
Cincinnati, OH-KY-IN	0.75	0.71	0.73	0.67	0.30	0.25	0.32	0.26
El Paso, TX	0.74	0.66	0.73	0.66	0.30	0.27	0.31	0.27
Dallas-Fort Worth-Arlington, TX	0.73	0.65	0.72	0.63	0.37	0.37	0.34	0.34
Palm Bay-Melbourne-Titusville, FL	0.67	0.70	0.70	0.63	0.33	0.35	0.37	0.31
Miami-Fort Lauderdale-West Palm Beach, FL	0.72	0.69	0.70	0.65	0.36	0.31	0.39	0.31
Oklahoma City, OK	0.67	0.60	0.69	0.57	0.22	0.18	0.24	0.17
Houston-The Woodlands-Sugar Land, TX	0.72	0.67	0.69	0.60	0.29	0.33	0.29	0.31
New Orleans-Metairie, LA	0.70	0.68	0.68	0.65	0.24	0.17	0.25	0.16
Tulsa, OK	0.71	0.62	0.68	0.58	0.21	0.32	0.18	0.25
Nashville-Davidson--Murfreesboro--Franklin, TN	0.66	0.62	0.68	0.60	0.18	0.19	0.22	0.21
Knoxville, TN	0.63	0.59	0.66	0.63	0.28	0.30	0.28	0.34
Tampa-St. Petersburg-Clearwater, FL	0.68	0.69	0.65	0.61	0.34	0.32	0.32	0.29
McAllen-Edinburg-Mission, TX	0.62	0.63	0.65	0.66	0.21	0.24	0.19	0.19
San Antonio-New Braunfels, TX	0.64	0.64	0.64	0.58	0.23	0.29	0.27	0.28
Atlanta-Sandy Springs-Roswell, GA	0.65	0.63	0.64	0.59	0.37	0.41	0.34	0.37
Jacksonville, FL	0.59	0.58	0.64	0.60	0.21	0.31	0.21	0.32
Virginia Beach-Norfolk-Newport News, VA-NC	0.59	0.56	0.64	0.54	0.12	0.19	0.13	0.18
Lexington-Fayette, KY	0.64	0.51	0.63	0.52	0.13	0.10	0.15	0.08
North Port-Sarasota-Bradenton, FL	0.65	0.69	0.63	0.64	0.16	0.23	0.18	0.32
Cape Coral-Fort Myers, FL	0.65	0.68	0.62	0.68	0.34	0.38	0.28	0.41
Durham-Chapel Hill, NC	0.60	0.55	0.61	0.53	0.16	0.17	0.28	0.19
Orlando-Kissimmee-Sanford, FL	0.62	0.66	0.61	0.59	0.22	0.27	0.24	0.28
Birmingham-Hoover, AL	0.61	0.63	0.60	0.61	0.22	0.29	0.23	0.32
Greensboro-High Point, NC	0.59	0.56	0.60	0.51	0.22	0.19	0.24	0.16
Deltona-Daytona Beach-Ormond Beach, FL	0.60	0.58	0.59	0.55	0.20	0.11	0.20	0.13
Richmond, VA	0.60	0.64	0.59	0.62	0.15	0.27	0.14	0.26
Winston-Salem, NC	0.62	0.57	0.59	0.55	0.22	0.22	0.23	0.19
Columbia, SC	0.55	0.57	0.57	0.55	0.25	0.14	0.32	0.16
Austin-Round Rock, TX	0.62	0.57	0.57	0.56	0.19	0.16	0.13	0.19
Charlotte-Concord-Gastonia, NC-SC	0.57	0.54	0.57	0.53	0.23	0.22	0.26	0.24
Lakeland-Winter Haven, FL	0.54	0.55	0.57	0.50	0.17	0.15	0.21	0.13
Chattanooga, TN-GA	0.54	0.58	0.56	0.57	0.14	0.13	0.14	0.12
Baton Rouge, LA	0.57	0.59	0.55	0.53	0.22	0.25	0.23	0.24
Raleigh, NC	0.52	0.56	0.55	0.55	0.23	0.25	0.24	0.23

Lafayette, LA	0.50	0.52	0.53	0.47	0.24	0.24	0.23	0.21
Charleston-North Charleston, SC	0.50	0.53	0.52	0.51	0.12	0.12	0.17	0.18
Greenville-Anderson-Mauldin, SC	0.51	0.55	0.52	0.55	0.21	0.18	0.22	0.19
Augusta-Richmond County, GA-SC	0.52	0.52	0.51	0.51	0.23	0.23	0.22	0.25
Pensacola-Ferry Pass-Brent, FL	0.50	0.52	0.47	0.49	0.19	0.17	0.15	0.13
West								
Los Angeles-Long Beach-Anaheim, CA	0.79	0.72	0.79	0.70	0.41	0.43	0.40	0.41
Urban Honolulu, HI	0.80	0.75	0.77	0.73	0.34	0.45	0.31	0.40
Denver-Aurora-Lakewood, CO	0.75	0.69	0.77	0.68	0.37	0.38	0.42	0.39
San Jose-Sunnyvale-Santa Clara, CA	0.74	0.51	0.76	0.57	0.34	0.21	0.31	0.13
San Francisco-Oakland-Hayward, CA	0.77	0.71	0.76	0.68	0.35	0.42	0.36	0.42
San Diego-Carlsbad, CA	0.77	0.68	0.75	0.64	0.43	0.33	0.40	0.31
Las Vegas-Henderson-Paradise, NV	0.72	0.68	0.74	0.66	0.33	0.34	0.33	0.35
Sacramento--Roseville--Arden-Arcade, CA	0.74	0.67	0.74	0.63	0.27	0.28	0.24	0.25
Modesto, CA	0.66	0.48	0.73	0.52	0.13	0.09	0.13	0.08
Fresno, CA	0.65	0.54	0.73	0.50	0.14	0.18	0.19	0.16
Portland-Vancouver-Hillsboro, OR-WA	0.72	0.58	0.72	0.60	0.32	0.28	0.23	0.20
Riverside-San Bernardino-Ontario, CA	0.72	0.61	0.72	0.59	0.36	0.30	0.33	0.30
Seattle-Tacoma-Bellevue, WA	0.73	0.61	0.72	0.62	0.25	0.26	0.24	0.29
Ogden-Clearfield, UT	0.70	0.53	0.71	0.50	0.21	0.13	0.16	0.12
Bakersfield, CA	0.69	0.56	0.70	0.51	0.22	0.14	0.24	0.13
Albuquerque, NM	0.66	0.51	0.68	0.55	0.21	0.12	0.25	0.14
Oxnard-Thousand Oaks-Ventura, CA	0.62	0.58	0.68	0.54	0.20	0.32	0.14	0.24
Stockton-Lodi, CA	0.70	0.57	0.68	0.50	0.23	0.12	0.30	0.10
Spokane-Spokane Valley, WA	0.65	0.49	0.67	0.54	0.16	0.07	0.17	0.09
Boise City, ID	0.54	0.46	0.66	0.58	0.14	0.07	0.18	0.07
Provo-Orem, UT	0.65	0.47	0.65	0.57	0.25	0.07	0.15	0.07
Colorado Springs, CO	0.62	0.57	0.64	0.54	0.20	0.20	0.17	0.18
Salt Lake City, UT	0.63	0.48	0.62	0.58	0.14	0.07	0.18	0.11
Visalia-Porterville, CA	0.63	0.54	0.62	0.51	0.32	0.29	0.33	0.18
Santa Rosa, CA	0.55	0.47	0.58	0.51	0.15	0.07	0.19	0.11

Appendix C. Three initially constructed limited-access highways in Chicago



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