SUBURBANIZATION OF POVERTY AND SPATIAL MISMATCH IN THE AUSTIN METRO AREA FROM 2000 TO 2017

by

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LIST OF ABBREVIATIONS

Abbreviations	Descriptions
US	United States
ACS	American Community Survey
NAICS	North American Industrial Classification System

ABSTRACT

The suburbanization of poverty is a process by which poverty is decentralizing from urban core areas and moving into the urban periphery. Much of the previous research on this topic explores the role that the 2008 financial crisis or housing displacement play in this process. This present study, however, seeks to expand upon this previous research by also applying the spatial mismatch theory to the question of the suburbanization of poverty. The spatial mismatch theory examines the spatial orientation of employment opportunities in urban areas and their proximity to low-income residents. This theory was originally used to examine inner-city poverty that primarily effected non-white neighborhoods in the urban core and its relation to white suburbanization or “White-flight”. This study seeks to examine the possible application of the spatial mismatch theory to the suburbanization of poverty. Austin, Texas and its surrounding areas have seen significant demographic changes in the past 20 years. The city itself has seen a massive increase in development and population in the urban core. However, it has also seen a decline in lower-income, non-white populations in its urban core. This present study incorporates data regarding work classification, race, and income at the census tract level in three counties, as well as commute time data to approximate distance from jobs. The results indicate that commute times increased of significantly for low-income, non-white, blue-collar workers, while white, higher-income, and white-collar workers in the Austin Metro Area did not see such a significant increase.

I. INTRODUCTION

In the United States, the suburb is often equated with higher socioeconomic status, as well as with racial and class homogeneity. Of course, this view certainly is not unfounded, considering the nature of suburbanization since its systematic and wide-spread acceleration after the Second World War. However, in recent years the reality of suburban life is changing throughout the country. Once suburbs were the destination of upper and middle-class whites in the city, fleeing what they perceived as incurable social ills that resided in the urban core. However, some suburbs are lately taking on a decidedly more working-class, and more racially diverse character (Kneebone & Berube, 2013). Poverty, once typically relegated to the inner-city, has begun to increase significantly in suburban areas. This trend is increasingly problematic as it separates the low-income residents in suburbs from services that are typically found in the urban core. Not only this, but the car-dependent and low-density nature of suburbs, creates a situation of isolation and atomization within these communities (Kneebone & Berube, 2013).

During the era of suburbanization, not only did white, upper-middle class residents leave the urban core, but with them went industrial, as well as commercial jobs (Kain, 1968). This created a spatial disconnect with the availability of employment opportunities, and poor and minority residents still living in the inner-city. “spatial mismatch theory” or the “spatial mismatch hypothesis” is the notion that this pattern of residential and economic segregation has contributed to increased poverty and created a systematic reproduction of poverty in the inner-city (Kain, 1992; Gobillon, Selod, & Zenou, 2007).

However, it does seem that the reality of increased suburban poverty, and the mechanisms of the spatial mismatch theory are at odds. Spatial mismatch as a theoretical framework, has not yet been applied to the suburbanization of poverty. However, because of new economic trends within neoliberal and post-industrial America, including the rise of the more professional technology and information-based economies, and the decline of retail and traditional manufacturing, a new understanding of the spatial mismatch theory could explain how urban and suburban poverty is reproduced in this new, decentralized manner.

The Austin Metro Area, a tri-county area of Travis, Hays, and Williamson counites, with be used as the location for this study. Employment types, racial and economic demographic shifts, and their relation to the suburbanization of poverty will be examined. First, is there evidence of the suburbanization of poverty in the Austin Metro Area. If so, what about the spatial distribution of employment? Are higher paying jobs in higher income neighborhoods and are lower paying jobs in lower income neighborhoods? In other words, is there a spatial mismatch between the kinds of jobs available in lower-income neighborhoods, as opposed to jobs available in higher-income neighborhoods in the Austin Metro Area? Also, has growth in specific industries fueled this potential spatial mismatch? The answers to these questions can provide insight into what the suburbanization of poverty means for employment opportunities in the Austin Metro Area.

To that end, this study will examine race, unemployment, & poverty rates as defined by US Census data, as well as commute times for different classifications of workers within or around specific neighborhoods. For the unit of analysis, this study will measure neighborhoods by Census tracts. Any spatial pattern of employment opportunities in terms of blue collar versus white collar jobs will be examined. For this study, blue-collar workers are defined as hourly-wage workers, as well as workers you typically work in construction, manufacturing, or other related services. White-collar workers are defined as salaried, professional workers, who typically work in more administrative or managerial positions. Are blue-collar workers found within the high poverty/low-income suburban neighborhoods? Are white-collar workers found centered mostly in high-income urban core neighborhoods?

Perhaps by examining the spatial locations of jobs we can begin to understand how spatial mismatch theory can be applied in the context of the suburbanization of poverty, despite historically, the theory examining inner-city poverty.

It is important to begin by reviewing the relevant literature highlighting the emerging study of suburban poverty, the spatial mismatch theory, to give further context on Austin as the setting for the study, as well as gaps in the previous literature. The data and methods section will lay out the parameters the present study uses to test the various hypotheses. Income level, race, commute times, and work status (blue-collar workers, white-collar workers, and “professional” workers) of Census tracts around the Austin metro and surround Travis County areas are examined in this study, in addition to their changes from 2000 to 2017. This data is then modeled with a spatial regression that controls for spatial autocorrelation. The results will include the findings and the statistical relationship of income, commute time, race, and type of work. The conclusion will examine the implications as well as the limitations of the present study.

II. LITERATURE REVIEW

The suburbanization of poverty is an emerging study within sociology and social geography. Previous literature has begun to discuss the process and potential causes of the suburbanization of poverty, including recent studies and statistics. Other researchers have studied the spatial distribution of poverty and unemployment since the 1950s in the United States. Additional context to the poverty and employment situations in Austin with be given, both historically and currently. Lastly, gaps within the literature are discussed.

The Growth of Suburban Poverty

To better frame the background of this study, we must first explore the history of suburban poverty, as well as the context in which the larger trend of suburbanization of poverty exists in. The suburbanization of poverty, as the trend exists currently, is a fairly recent phenomenon. As such, it is important to also examine the ways in which other sociological trends factor into this.

Historically, large metropolitan areas, which make up the largest portion of the United States' population, also housed the largest percentage of the nation's poor. During the Post-War era of rapid industrialization and urbanization, these numbers grew. According to Kneebone & Berube (2013), poverty remained a largely rural affair before this era, but by 1970 just over half of the nation's poor were urban residents, by 2000, it was over 60 percent (Kneebone & Berube, 2013). Exploring the same time frame and demographic changes within the suburbs, we see another interesting picture. In 1970 less than 20 percent of the nation's poor lived in the suburbs, however by 1980s and 1990s, these numbers began to grow (Kneebone & Berube, 2013; Lacy, 2016). In the 1990s, the suburban poor population grew twice as fast than urban poor populations, 19 percent and 8 percent respectively (Kneebone & Berube, 2013). By 2000, the population of individuals in poverty was larger in the suburbs than in the urban areas. Kneebone & Berube also point out that the federal measure of poverty does not include other, "near poor" populations, which had a significant increase in suburban areas during the 1990s and 2000s (2013).

The racial and ethnic makeup of suburban poverty is note-worthy as well. Exclusionary practices of suburbs have left an imprint on the demographic makeup as poverty increases in suburbs (Kneebone & Berube, 2013). Overall, it has been observed that white populations are still the highest percentage of poor suburbanites (Howell & Timberlake, 2014). However, suburbs are becoming more diverse, both as they are typically the new destination for new migrants, as well as populations that have been traditionally excluded from those spaces (Kneebone & Berube, 2013; Lacy, 2016). Affordability of the aging housing stock also provided a means in which groups traditionally excluded from the suburbs access to them (Howell & Timberlake, 2014). Yet, as mentioned before, the housing situation would become a source and not a solution to suburban poverty, due to the housing crisis of late 2000s (Kneebone & Berube, 2013).

The large-scale suburbanization of poverty in the United States, is a fairly new process. Recently, researchers have tried to point out what makes this process concerning to social scientists and policy makers alike. Suburban poverty creates a unique set of obstacles for individuals and families. Not only this, public policy, from the local to the federal levels has been either unable or unwilling to properly address this growing concern.

On the topic of federal policy, there have been many various policy trends that have historically both entrenched poverty and segregation, as well as modest poverty alleviation. Urban poverty was centralized and exacerbated by the policy of “redlining”, systematically denying loans and financial services to poor and/or non-white majority neighborhoods, during the early-to-mid 20th century. The concentration of poverty to inner-city areas lead to many of the poverty reduction programs in the United States, notably such as the “War on Poverty” campaign initiated by the Johnson Administration in the 1960s. These programs have not kept up with the suburbanization of poverty, however (Kneebone & Berube, 2013; Lacy, 2016). Many government services and agencies that people in poverty rely on, are typically located in downtown, or more centralized areas of cities (Kneebone & Berube, 2013). Not only this, but suburbs have historically been car-centric developments, with very few options for public transportation. This of course creates a situation that further compounds poor people into areas with little access to jobs (Kneebone & Berube, 2013).

Potential Causes of Suburban Poverty

A compounding list of factors is often the understood source of this trend. The Housing Crisis of 2007-08 is often cited as a major cause (Kneebone & Berube, 2013), as well as the outdated and underdeveloped programs by local and federal agencies to alleviate that poverty (Kneebone & Berube, 2013). According to Kneebone and Berube (2013), the bulk of suburban poverty growth occurred directly following the housing bust in 2008 and the Great Recession that set in. The large service economies present in suburbia in this period saw a significant decline, creating a situation of joblessness and unemployment among suburban residents (Kneebone & Berube, 2013; Lacy, 2016). Not only did service industry jobs decline, in the north-eastern portion of the United States, manufacturing continued to decline. Also, construction jobs, largely spurred by the housing bubble, would decline dramatically during the housing crisis (Soursourian, 2012; Kneebone & Berube, 2013).

However, as discussed, the role that the racial and economic diversification of suburbs play in the increase of suburban poverty should not be discounted. However, largely the diversification process has been the result of a myriad of other social and economic factors. Returning to the point mentioned before about affordability, which is arguably one of the largest factors in how racial and ethnic minorities were able to move into once exclusive suburbs, is a key factor increasing suburban poverty (Soursourian, 2012; Kneebone & Berube, 2013; Howell & Timberlake, 2014; Lacy, 2016).

Theories of Spatial Mismatch

Spatial patterns of social-economic status and social inequality have been explored by sociologists and social geographers alike. Urban areas are largely defined by their spatial-social distributions, and thus they are important to examine. Considering that this thesis will examine the nature of suburban poverty in Austin, understanding spatial distributions of poverty are key.

Spatial mismatch theory was first proposed by John Kain and asserts that employment opportunities for Black populations in major cities due to the process of White Flight and suburbanization (1968). Kain found that the process of suburbanization had sent many of the high paying, low skill jobs away from the urban core. These jobs, along with public services and public investment were increasingly being relocated into suburbs during the 1950s and 1960s (Kain, 1968). This spatial reorganization was largely the result of housing segregation, and Kain had observed that the higher the level of housing and spatial segregation. (i.e., centralization of Black ghettos, distance of central city to suburbs) increased unemployment levels for Black populations in the central city (Kain, 1968). Even in places where there were no legal statues of racial segregation, employers would often discriminate against hiring Black workers.

Spatial mismatch theory also examines how the physical distance between inner-city Black population and higher-paying jobs in the suburbs and the effect it has on real wages for inner-city workers (Kain, 1968; 1992). The flight of employment opportunities from the urban core drove down wages for the few jobs that were left, with low-skill urban core workers earning less than their suburban counterparts (Kain, 1992; Gobillon, Et Al, 2007). Transportation also became an important aspect of spatial mismatch. The inner-city poor were less likely to have a car in some urban areas, with a few variances by region (Kain, 1992), This would prove to be a key factor as suburban development and growth has been historically automobile-centric, and few suburbs have well connected and reliable public transit routes (Kain, 1992; Gobillon, et al., 2007).

Choosing Austin

As previously stated, this study will primarily focus on the Austin Texas metro area. Austin has a very unique urban history, and the processes of its growth and development have often been an asymmetrical process.

Researchers have often noted that Austin is one of the few major American cities that have a declining Black population. Census Data from 2000 to 2010 showed a 5 percent decrease in this population (Tang & Ren, 2014). This point is further underscored by the rapid increase in the general population growth in Austin, that of about 20 percent between 2000 and 2010. Tang and Ren report that other Texas cities with comparable increases in general population such as San Antonio and El Paso, also saw equivalent growth in African American populations (2014). Though other major Texas cities, such as Dallas and Houston also saw a decrease in Black population. However, these decreases were significantly smaller, and their general population increases much smaller as well (Tang & Ren, 2014). Poverty has also declined statistically within the city limits of Austin. However, poverty has seen an increase in the suburban outlying areas to the north and northeast (Vock, 2015). Often towns such as Manor or Elgin, which, until recently were small, rural towns, are structurally ill-equipped to provide the necessary services for the formally urban poor (Vock, 2015).

The historical development of Austin is also important to acknowledge. Austin was early to adopt racial and class-based zoning regulations. In the 1920s, it proposed it's first modern "Master Plan" which was largely based on the forced displacement and segregation of non-white populations, particularly African Americans, to the eastern edge of the city (Tretter, Cowen, Heynen, & Wright, 2016). The plan would also favor industrial development in these eastern and northeastern sections (Tretter et al., 2016). This development pattern continues to this day as western Austin is still largely white, wealthy, and very politically powerful (Tretter et al., 2016). Thus, lower-class and minority populations in the city have been the first to be displaced by economic growth in

Austin. As the economic growth and development continue, more are displaced, only now primarily due to price increases and land value changes than by legal force (Tretter et al., 2016).

Gaps in the Literature

Above are two processes that have helped define the spatial organization of poverty, discrimination in urban spaces since the end of World War II, as well as a brief bit of context behind why the Austin metro areas was chosen. It is important to note, however the connections between spatial mismatch theory and the suburbanization of poverty have not been directly made in the past.

The issue of land use, as well as the theories of urban "growth machines" are important to consider here. In other words, it has been theorized that cities are social, economic, and political entities that first and foremost focus on economic growth, and increasing investment and production/consumption (Molotch, 1976). Historically, we have seen through the work of Kain and others that urban investment and development had begun to leave the urban core during the 1950s and 1960s. However, in recent years there has been a political and economic focus on "urban revitalization" that has led to increased investment and development in the urban core (Birch, 2009). Central business districts have seen the vast majority of economic growth in the past 20 years (Birch, 2008; Hyra, 2014). Austin itself has experienced this tremendously due to various political, environmental, and educational factors, not least of which being the location of the University of Texas as well as a strong high-tech sector (Tretter, et al., 2016). This increasing redevelopment has led to gentrification – or the housing and spatial displacement of vulnerable populations from their neighborhoods in favor of high-cost housing and more affluent populations – in the Austin area.

The Role of Gentrification and Displacement

Gentrification is no doubt a very prominent issue that grips nearly every large urban area in the United States and the much of the developed world (Smith, 1996). Austin is of course very noteworthy in its ongoing and intense gentrification and displacement (Tang & Ren, 2014; Way & Wegmann, 2018).

The relation that gentrification has to the overall increase in suburban poverty is difficult to pin down. Some researchers have been seemingly reluctant to say with absolute certainty that this is a strong driver of the increase in suburban poverty (Kneebone & Berube, 2013; Lacy, 2016). Many of these researchers, such as Kneebone, as well as Scott Allard state that while gentrification has created greater inequality in urban areas, it is not a strong driving factor in the overall increase in suburban poverty (Kneebone & Berube, 2013; Allard, 2017). They argue a process of "poverty in place", a combination of factors such as the decline of suburban job opportunities and the personal economic affects that the Great Recession had on many families in suburbs, all this coupled with the lack of proximity to social services, or a general social safety net (Kneebone & Berube, 2013; Allard, 2017).

However, much research has noted the massive displacement that is caused either directly or indirectly by gentrification (Tang & Ren, 2014; Zuk, Bierbaum, Chapple, Gorska, & Loukaitou-Sideris, 2018; Way & Wegmann, 2018). This is coupled with local research in Austin, in which we know that there has been increases of low-income populations in periphery small towns such as Manor and Elgin (Vock, 2015).

Suburban poverty studies may have not made much attempt to plug in the ideas of displacement from the urban cores in a significant way, due to the difficult nature of defining and gathering the relevant data as well as the increasingly decentralized and multi-faceted nature of poverty.

The trend of growth and development in the central business districts and urban cores of cities also deviates from the trends of growth and employment that Kain bases his spatial mismatch theory on, as they are returning to the urban core.

What previous literature has not quite done yet is synthesize a framework that examines the aspects of urban growth machine theories, and spatial mismatch theories to explain the processes of the increasing trends of suburban poverty in American cities. This study will examine the viability of connecting these concepts. In particular, this study will attempt to examine in within the context of changing spatial organizations of poverty in urban areas, is there a new variation of Kain's spatial mismatch theory. This study is interested in the increasing redevelopment of urban cores and if the spatial disconnect between suburbs and urban cores have any connection to increasing rates of suburban poverty.

Hypotheses

In considering the well-documented demographic changes in the Austin metro-area, as well as the theoretical frameworks discussed prior, this study will test that following hypotheses:

1. Census tracts on the outer rings of eastern and northern Austin will likely see a decrease in average income from 2000 to 2017. This area will likely also see increased blue-collar workers.

2. Census tracts in the center of Austin, primarily in the neighborhoods just east of downtown and I-35 will see an increase in both average income and white-collar workers from 2000 to 2017.

3. These census tracts will also see a changing racial and ethnic make ups. It will be likely that the outer rings of eastern and northern Austin and its suburbs see an increase in none-white minority populations whereas the areas around downtown see an increase in white populations.

4. It is likely there will be a relationship between the increase of white-collar, high income earners in the urban core, and the suburbanization of poverty and blue-collar work.

III. DATA AND METHODS

In order to test these hypotheses, the analysis will utilize Census and American Community Survey data at the census tract levels for the area of analysis. This area of analysis is what will be referred to as the Austin Metro Area, a tri-county area including Travis, Williamson, and Hays counties. This area of analysis encompasses the entire City of Austin proper as well as its most immediate suburbs and satellite towns such as Pflugerville, Round Rock, Buda, Manor, Del Valle, and Georgetown. Census tract level analysis will be used to provide a clear, neighborhood-level picture of the potential changes in the Austin Metro Area.

These data were then examined longitudinally starting from census data taken directly from the Census Bureau in 2000, 2010, then finally data from the American Community Survey in 2017. The American Community Survey, or ACS, is a Census Bureau-led yearly study that is primarily used in more densely populated areas to examine demographic trends and create demographic predictions. It still uses the same Census classifications and thus provides us with data even outside the time frame of Census years. To measure these changes over time, each of these data are measured as the difference in percentage of each variable between 2000 and 2017. For example, for the independent "blue-collar" variable, is the change in percentage of blue-collar workers from 2000 to 2017 in a given census tract. This is done to measure any potential decrease or increase in the percentages of a variable over time, and in addition to examine the spatial organization of these potential changes.

Dependent Variables

Three different dependent variables are used here to analyze the spatial orientation of work in the Austin Metro area: blue collar, white collar, and Professional, Scientific, and Technical services. According to metadata from the Census, the primary difference in definition between "white-collar" and "blue-collar" is salaried pay, with white-collar jobs being those that are salaried and blue collar being those that are either hourly or contract work. The "Professional" variable stands for the NAICS classification for "Professional, Scientific, and Technical Services" which includes a wide array of jobs in industries from software development to legal services. NAICS or North American Industrial Classification System is a standard metric that creates categories for various business and industrial sectors that the census and other federal agencies use for statistical analysis. (US Census Bureau, 2021) This is the only NAICS classification that was chosen, as it saw the largest growth of any other classification from 2000 to 2010 in the Austin Metro Area. (US Census Bureau, 2021) However, this variable proved to be somewhat problematic when calculating it's change longitudinally as it has been measured differently over the years, thus creating potential inconsistencies in the data. The variables for white collar and blue collar are both measured as the percentage of white-collar and blue-collar workers in, for the case of this study, a given census tract.

Independent Variables

This study uses several different dependent variables to measure the changes of income, work, and demographics in the Austin area. Commute times, race, income, unemployment, and education are tested against the dependent variables that measure type of employment.

First, in order to examine the changes in the spatial organization of race and ethnicity in the Austin area, the change in percentage of white households is used. As the percentage of white household increases in a census tract, for example, then likewise there could be a decrease of non-white households over time.

Education is measured but it is limited to those with a college degree. This variable was measured differently between the 2000 and 2010 census, so in order to properly use this variable, it had to be aggregated. Before 2010, the census did not place bachelors, masters, and doctorate degree holders in different categories, as is done with higher-education data collected after the 2010 census. This aggregation of this data however is not useful as a change variable still, as the data would likely still be inaccurate. Due to this, the variable that measures college education specifically measures the percentage of the population with bachelor’s degrees in the year 2017.

In order to create a variable that measures percentage of low-income households, the change in percentage of households making $25,000 or less is used. This is significantly lower than the average income in Austin. (Census Bureau, 2021) In addition to the change in low-income households, this study also measures the change in percentage of unemployment per census tracts from 2000-2017.

Commute times are also measured, as this is used primarily to examine the distance that people must travel to get to work. Commute times are broken up into 4 categories: commute that’s less than 15 minutes, commutes from 15 to 29 minutes, commutes from 30 to 59 minutes, and commutes greater than 1 hour. Like the other variables, all the commute time variables are aggregated to measure the change in percentage over time. Commute times, as a variable, is by and large a proxy variable for the distance between a worker and job.

Table 1. Variables and Data Sources

Dependent Variables	**Mean**	**Std. Dev.**	**Max**	**Min**	**Source**	**Description**
Change in Percent White-Collar Workers from 2000 to 2017	-1.61%	10.58%	45.29%	-47.45%	US Census & American Community Survey	The change in percentage of salaried or "white collar" workers in the Austin Metro Area.
Change in Percent Blue-Collar Workers from 2000 to 2017	-3.59%	8.61%	66.67%	-50.00%	US Census & American Community Survey	The change in percentage of hourly or "blue collar" workers in the Austin Metro Area.
Change in Percent Professional Workers from 2000 to 2017	9.96%	6.30%	33.27%	0%	US Census & American Community Survey	The change in Census designated Professional, Scientific, and Technical Services, as defined by the NAICS in the Austin Metro Area.
Independent Variables	**Mean**	**Std. Dev.**	**Max**	**Min**	**Source**	**Description**
Change in Percent White Households	0%	10.53%	43.00%	-100.00%	US Census & American Community Survey	The change in percentage of white/non-Hispanic households in the Austin Metro Area.
Change in Precent Unemployment	-4.50%	6.17%	3.25%	-54.37%	US Census & American Community Survey	The change in percentage of the population that is Unemployed.
Change in Percent Commute time <15 mins.	0.92%	8.64%	87.50%	-31.25%	US Census & American Community Survey	The change in percentage of workers whose travel time to work is less than 15 minutes.
Change in Percent Commute time 15 mins. to 29 mins.	-0.54%	8.01%	23.93%	-37.50%	US Census & American Community Survey	The change in percentage of worker's travel time between 15 to 29 minutes.

Change in Percent Commute time 30 mins. to 59 mins.	-3.24%	7.85%	25.00%	-26.91%	US Census & American Community Survey	The change in percentage of workers whose travel time is between 30 to 59 minutes.
Change in Percent Commute time 60+ mins.	-1.91%	4.85%	50.00%	-18.04%	US Census & American Community Survey	The change in percentage of workers whose travel time is greater than an hour.
Percentage of Population with College Education 2017.	26.55%	11.88%	49.39%	0%	US Census & American Community Survey	The percentage of the population that is college educated. (Bachelor's degree) for 2017.
Sample Size	332					

These data were primarily accessed from Census Bureau data aggregated and mapped in SimplyAnalytics, then exported into tables. From there each data set, for example, percentage of blue-collar workers, was created as a change variable by subtracting the most recent years, in this case 2017, to data from the 2000 census. From there they were imported into ArcGIS, compiled into a single master-list dataset, and were created into maps showing the changes at a census tract level. There were, in total, 332 census tracts that were examined in the tri-county area of analysis. These data were then imported into GeoDa where they were tested with a linear regression model. Moran's I was then used to examine spatial autocorrelation

Table 2: Bivariate Correlations

		0	1	2	3	4	5	6	7	8	9	10
0	Change in Blue Collar Workers 2000 - 2017	1.000										
1	Change in White Collar Workers 2000 - 2017	-0.383	1.000									
2	Change in Professional Workers 2000 - 2017	-0.161	0.399	1.000								
3	Change in White Households 2000 - 2017	-0.320	0.084	-0.038	1.000							
4	Change in Unemployment 2000 - 2017	0.101	0.058	0.176	-0.397	1.000						
5	Percent with College Education (Bachelors) 2017	0.412	-0.523	-0.268	-0.389	0.060	1.000					
6	Change in Commute Time: 15mins or Less, 2000 - 2017	0.161	0.309	0.055	-0.185	-0.003	-0.052	1.000				
7	Change In Commute time: 15min to 29mins, 2000 - 2017	0.071	0.051	0.089	-0.088	0.099	0.009	-0.182	1.000			
8	Change in Commute Time: 29mins to 59mins, 2000 - 2017	0.199	-0.057	-0.106	0.027	-0.080	0.028	-0.259	-0.458	1.000		
9	Change in Commute Time: 60 mins or Greater, 2000 - 2017	0.414	-0.131	-0.144	0.007	0.037	0.068	-0.107	-0.163	0.136	1.000	
10	Change in Percent of Households earning less than $25,000 per year.	0.079	-0.292	-0.028	0.022	0.187	0.345	-0.282	0.076	-0.063	0.072	1.000

Both spatial error and spatial lag models were used in the regression analysis for each independent variable; The change in percentage of blue-collar workers from 2000 to 2017, the change in percentage of white-collar workers from 2000 to 2017, and the change in percentage of “Professional” workers from 2000 to 2017. Each independent variable was tested against the change in percentage of white households from 2000 to 2017, the change in percentage of unemployment from 2000 to 2017, Percent of college education in 2017, and change in commute times from 2000 to 2017, ranging from less than 15 minutes, 15 minutes to 29 minutes, 30 minutes to 59 minutes, and 1 hour or greater.

IV. RESULTS AND ANALYSIS

This analysis of the hypothesis regarding the relationship between types of employment and changes in neighborhood demographics used spatial lag and spatial error models. Included in this analysis is a regression model, as well as various map figures showing the spatial changes of the dependent variables over time. As indicated by these maps, there is a notable decrease in percentage of blue-collar workers in the urban core, especially in the areas just east of Downtown. Meanwhile, in the in urban periphery, again primarily eastward, the percentage of blue-collar workers increase. White-collar workers, however, increase in the urban core. Additionally, the Moran's I statistic was used to examine spatial autocorrelation, in other words, if the results were spatially clustered or randomly dispersed.

The results show that the change in percentage of blue-collar workers is inversely or negatively correlated with the percentage of white (non-Hispanic) households in a census tract. As shown below in Table 3, it can be interpreted that with every 1% increase in the change in white (non-Hispanic) households in each census tract, there is a .19% decrease the change in blue collar workers within that census tract. Changes in income show us the opposite, as the change in blue-collar workers is positively correlated with the change in households with an annual income less than $25,000. As the change in households earning less than $25,000 increases by 1% in a census tract, there is a .17% increase in the change in blue-collar workers. Conversely, the change in percentage of white-collar workers in a census tract is positively correlated with the change in percentage of white (non-Hispanic) households in a census tract. As the change in white (non-Hispanic) households in a census tract increased by 1%, the change in white-collar workers increased by .22%. Meanwhile, the change in white-collar workers is inversely correlated with the change in percent of households making less than $25,000 per year. An increase of 1% in the change in low-income households shows a decrease of .27% in the change in white-collar workers.

The change in unemployment was also tested against the change in blue-collar workers. As unemployment increased by 1% there was a decrease of -0065% in blue-collar workers, however it should be noted that this change is non-significant. When tested with white-collar workers, the change in unemployment was significant, and showed a positive relationship.

Commute times show various results as well. Commute time variables are split up into 4 groups, all of which depict a change in percent from 2000 to 2017; commutes of less than 15 mins, commutes of 15 to 29 minutes, commutes of 30 to 59 minutes, and commutes greater than 60 mins (or 1 hour). The change in percent of blue-collar workers show some correlations with the change in commute times, and generally there was a significant increase for all four commute time change variables.

A 1% increase in commute times less than 15 minutes in a census tract is associated with a 0.4 percent increase in blue-collar workers, this increased to roughly 0.8 percent when there is a 1% increase in commute times of over an hour. In contrast, a 1% in commute times less than 15 minutes shows an increase of 0.4 in white-collar workers, whereas a 1% increase in commute times of over an hour showed no significant association. The strongest association for white-collar workers was the shortest commute time variable. What this means that when comparing the models for percentage of blue and white-collar workers is that longer commute times were more strongly associated with blue-collar workers, not white-collar workers. While the data only measure commute times by categories, this provides evidence that blue-collar workers have experienced a greater increase in commute times overall.

The “Professional” variable, or the change in percentage of workers in the NAICS-classified Professional, Technical, and Scientific services classification did not show any significant changes when tested with the other variables, except when tested against education, and unemployment. An increase of college educated populations by 0.14%, and 0.19% in unemployment both resulted in a 1% increase in professional employees a census tract.

Moran’s I was also utilized to examine spatial autocorrelation in the residuals. In this case, Moran’s I examines the relationship the residuals have to one another in a given geographical space. Spatial autocorrelation is the spatial organization of the regression model. A Moran’s I close to +/-1 would, for example, indicate higher positive or negative spatial autocorrelation, or more clustering or non-random dispersal of the residuals. We see that the highest spatial autocorrelation is the spatial lag of the change in white-collar workers. It could be determined, then, that the residuals form the white-collar models exhibit the greatest autocorrelation and as such the estimates are the least likely to be unbiased due to spatial dependence after testing against all other independent variables. Alternatively, the professional workers variable had the lowest spatial autocorrelation, indicating the residuals were more randomly dispersed and the slope estimates more likely to be unbiased due to spatial dependence. All the same, the magnitude of the Moran’s I for all models is relatively low, giving us confidence that the slope estimates in the six models are unbiased.

Table 3. Regression Models

	Spatial Error Blue Collar		Spatial Lag Blue Collar		Spatial Error White Collar		Spatial Lag White Collar		Spatial Error Professional		Spatial Lag Professional	
Independent Variables/ Covariates	b	Std. Error	b	Std. Error	b	Std. Error	b	Std. Error	b	Std. Error	b	Std. Error
Percent Change White Households	-0.1885***	0.0393	-0.1774***	0.0383	0.2207***	0.0539	0.2079***	0.0503	0.0228 (ns)	0.0249	0.0220 (ns)	0.0246
Percent Change Unemployment	-0.0655 (ns)	0.0673	-0.0592 (ns)	0.0643	0.1960*	0.0922	0.1881*	0.0868	0.0870*	0.0433	0.0867*	0.0428
Change in Commute Time: 15mins or Less, 2000 - 2017	0.4076***	0.0470	0.4065***	0.0485	0.4550***	0.0639	0.4495***	0.0652	0.0343 (ns)	0.0321	0.0337 (ns)	0.0322
Change In Commute time: 15min to 29mins, 2000 - 2017	0.4008***	0.0519	0.4149***	0.0537	0.3109***	0.0704	0.3065***	0.0723	0.0537 (ns)	0.0356	0.0519 (ns)	0.0357
Change in Commute Time: 29mins to 59mins, 2000 - 2017	0.4761***	0.0545	0.4763***	0.0550	0.2539***	0.0743	0.2199**	0.0742	-0.0119 (ns)	0.0367	-0.0147 (ns)	0.0366
Change in Commute Time: 60 mins or Greater, 2000 - 2017	0.8162***	0.0735	0.8005***	0.0736	-0.0760 (ns)	0.1001	-0.0438 (ns)	0.0997	-0.0832 (ns)	0.0491	-0.0883 (ns)	0.0490
Percent Education Attainment - College Degree 2017	-0.0396 (ns)	0.0361	-0.0245 (ns)	0.0306	0.2919***	0.0502	0.2443***	0.0436	0.1402***	0.0209	0.1371***	0.0216
Change in Percent of Households making Less than $25,000 annually	0.1737***	0.0406	0.149***	0.0388	-0.2745***	0.0558	-0.2507***	0.0527	-0.0425 (ns)	0.0259	-0.0423 (ns)	0.0256
Lamda	0.3093	0.0811			0.3455	0.0790			0.0509	0.0930		

Moran's I (residuals)	-0.005		0.05		-0.012		0.017		0.000		0.009	
R-Squared	0.4822		0.4660		0.3645		0.3560		0.1810		0.1802	
Rho			0.1908				0.2878				0.0172	
n			332				332				332	

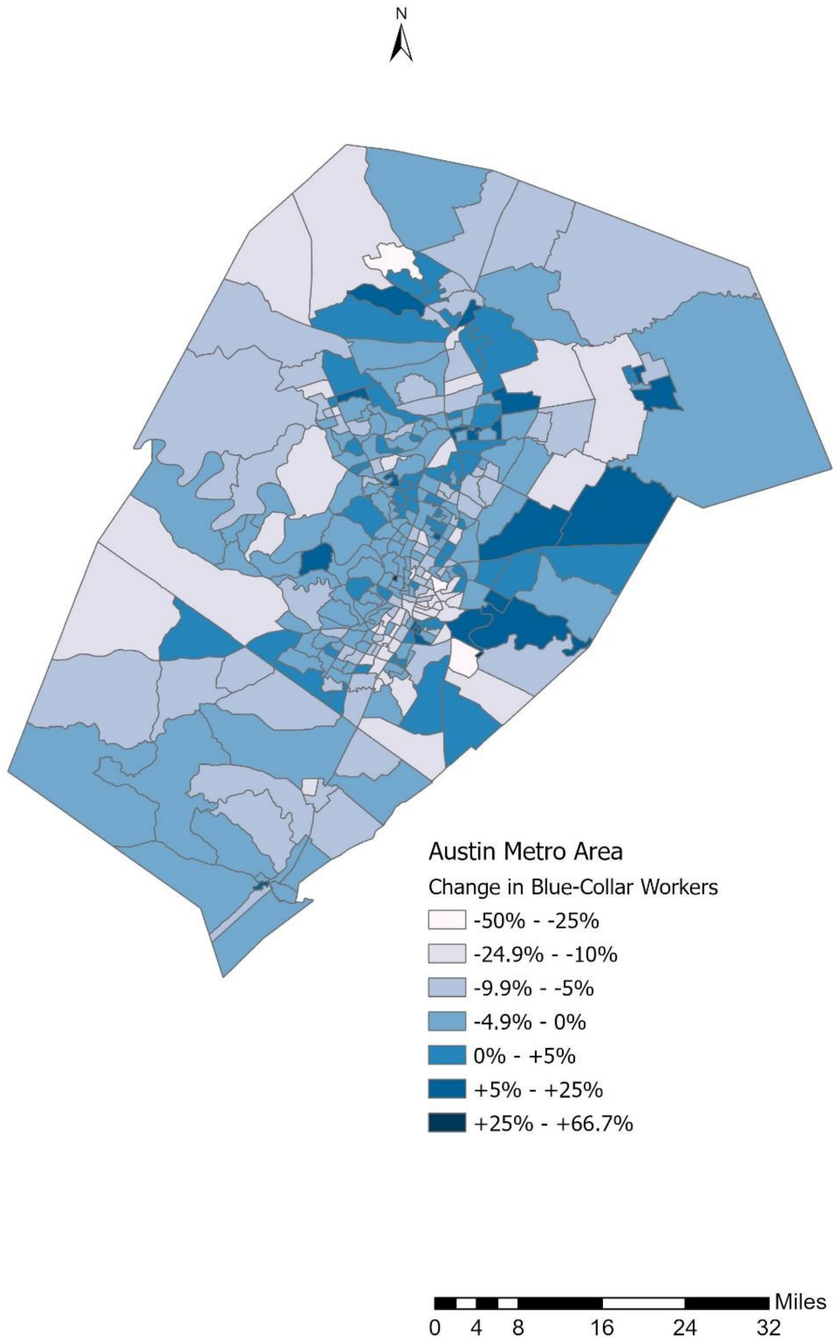

Figure 1: Change in Percentage of Blue-Collar Workers from 2000 to 2017

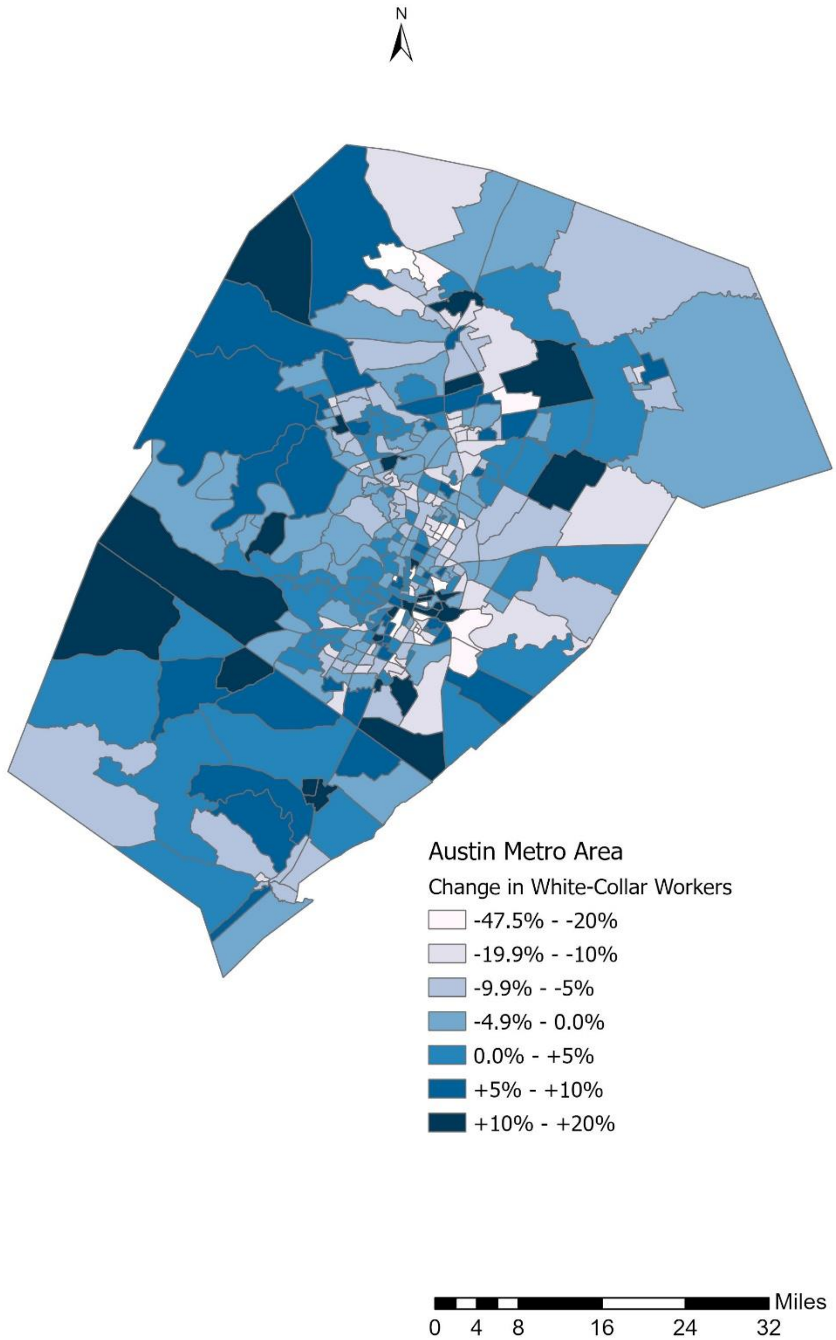

Figure 2: Change in Percentage of White-Collar Workers from 2000 to 2017

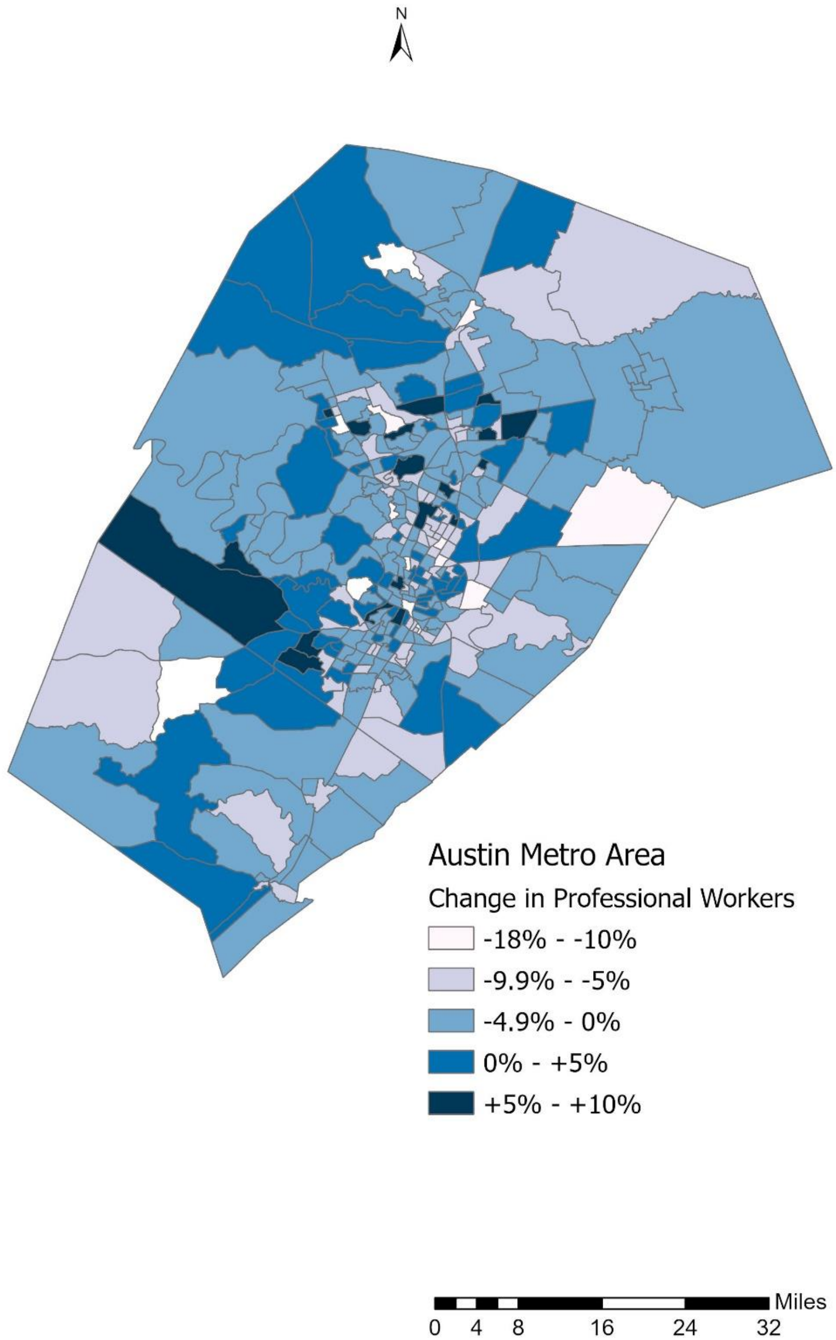

Figure 3: Change in Percentage of Professional Workers from 2000 to 2017

The results of the regression model as well as the results of the Moran's I test indicate that there are significant relations between white or blue-collar workers and income, demographics, and commute times in a census tract. The spatial patterns indicate from these data that white-collar workers live in census tracts that contain more white households, higher income households, and they are typically bordered by other high-white-collar census tracts. These predominantly white-collar census tracts also tend to have shorter commute time, despite overall commute times increasing. Inversely, census tracts that are high in blue-collar workers tend to be less white, less wealthy, and are more spatially dispersed throughout the Austin Metro Area. These census tracts also have higher commute times. This confirms spatial mismatch theory to the extent that lower-income and less skilled workers have longer commute times, and thus are further from their jobs than higher skilled, higher-income workers.

V. CONCLUSION

This study examined the association between blue-collar workers, white-collar workers, racial and income demographics, and commute times in the Austin Metro Area. The results from the analysis show that an area of east Austin, just east of downtown, saw a significant increase in higher-income, white-collar, white households. Lower-income, non-white, blue-collar households decreased in the urban core, and increased in the suburban areas of the city. In addition to this, low-income, non-white, and blue-collar households also saw a substantial increase in commutes when compared to in higher-income, white-collar, white households. These results are in line with both the suburbanization of poverty as well as the spatial mismatch theory.

Implications

When spatial mismatch was first originated, it focused on the de-industrialization of the urban core and the effects that had in inner-city neighbors, non-white populations, and low-income, unskilled workers (Kain, 1968). This study, however, examines how this theory – the spatial mismatch of lower-income workers and nearby job opportunities – could be applied to the changing urban environment. Suburban poverty is increasing due to a myriad of factors (Kneebone & Berube, 2013) but this study offers a space to explore the interconnection between these two phenomena. This study is very board and uses general census-based data. Moving forward, more specific data, such as the actual number of employers, places of business, and job centers in an area could be utilized in order examine potential changes of these factors spatially in an urban area. Austin has a very specific historic development pattern that has favored greater development and land use intensification in its urban core, especially in east Austin. (Tretter et al., 2016)

This study provides the framework to examine spatial mismatch and suburban poverty in other urban areas throughout the United States. Additionally, a qualitative approach could be used to further this study. For example, one could explore the lives of those effected by suburban poverty and spatial mismatch. Further research in these areas could lead to a deeper understanding of urban growth machines, and broaden the public discourse of displacement, urban development, and even gentrification.

Limitations

This study did have limitations, most importantly in regards to the nature of the data in the variables. The definitions of blue-collar and white-collar are very broad, and this study only examined the percentage of workers in these respective categories. As previously mentioned, one improvement to this study would be to examine the actual spatial organization and locations of jobs and places of employment themselves. One way this could be done is to examine zoning categorizations - such as commercial or industrial - as well as land use intensity or density.

As mentioned in earlier sections of this study, some variables were ill-suited to be studied longitudinally over the time span of the study. Specifically, the "professional" variable and the education variable. The professional variable was an aggregated variable based in the NAICS "Professional, Technical, and Scientific" industry classification. This variable was measured differently over time. For example, the "Technical" classification, or jobs primarily focused on computer technology and software development, was not present in the 2000 census. The education variable was also measured inconsistently over the time frame of this study. From the 2010 census onward, education data separated higher education by degree classifications, whereas before then, higher education was simply measured as college degree or graduate degree.

Lastly, the data was collected from the 2000 census, the 2010 census, and a 2017 American Community Survey study. The ACS is largely used for projections and because it is not as widespread or in-depth, it potentially could produce inconsistencies within the data.

Closing

To conclude, this study shows that the Austin Metro Area has seen a shift in populations. Areas of the urban core, in particular east Austin saw an increase in white, higher-income, white-collar workers, whereas suburban areas saw an increase in non-white, lower-income, blue-collar workers. These blue-collar workers also saw an increase in commute times greater in significance to the white-collar workers in the urban core. This study, however, did not support the hypothesis that the category of "Professional, Scientific, and Technical Services" would be positively correlated to changes in annual income and white households in these census tracts from 2000 to 2017.

These changes in the urban demographics of the Austin Metro Area could show the effects of the development and land-use intensification of the urban core on low-income, non-white populations, as more and more people are pushed into the urban periphery, and being replaced by more affluent, white households. This study could add further knowledge of inter-urban population changes and the relationship these have to income, race, and place.

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