MIGRATION AND THE MIGRANT IN MAJOR U.S. METROPOLITAN AREAS DURING AMERICA'S 'GREAT RECESSION'

by

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For my family: Cheryl, Henry, and Emmett.

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ABSTRACT

MIGRATION AND THE MIGRANT IN MAJOR U.S. METROPOLITAN AREAS DURING AMERICA'S 'GREAT RECESSION'

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This dissertation explores the nature of the migrant and migration within the context of the recent economic downturn in the U.S. Because most migration is rooted in economics—that is, the migrant expects a positive net economic return for the cost/investment of migrating—many questions of context appear in light of the 'Great Recession.' Research is performed in four complementary, though separate, areas of research: migration trends for 2006-2010, the spatial variation of migration distance decay, the employment niches of U.S. immigrants, and the impact of the U.S. foreign-born population on domestic labor and economic growth. Investigating migration trends, it is shown that the demographic variables linked to migration during the 2006-2010 period are in line with traditional migration theory, but that metropolitan out-migration may operate under a different set of norms than overall migration. Analysis also reveals spatial clusters throughout the United States of high and low out-migration rates. This research presents a novel method for identifying the elements of attraction for migrants in destination cities. Using a two-stage regression approach,

destination-specific distance-decay parameters (which are controlled for spatial structure) are regressed against socioeconomic variables describing each destination. Analysis demonstrates that unemployment, diversity, education, industry, and climate are significant pull factors, and are directly tied to the distance decay coefficients. This research also presents a novel method for measuring immigrant economic clustering using the Niche Index, a measure of the propensity of an immigrant group to form niches. The spatial distribution of niches is also investigated. It is shown that immigrant groups consistently form niches in the same industries across space, but the propensity to form niches is highly variable across space. Additionally, propensity to niche is shown to be driven by immigrant group population, metropolitan population, unemployment change, and English proficiency. Lastly, this research reveals cities with larger proportions of foreign-born residents had native-born workers who fared worse over the course of the recession: they experienced greater unemployment growth, less income growth, and an expansion of poverty. Higher education is also significantly correlated with improved outcomes for native-born workers during a recession, while metropolitan accessibility is correlated with poorer outcomes, likely due to inter-city competition for jobs. These four research components contribute to our understanding of the geography, demographics, economics, and sociology of migration, and how migration-related impacts varied from convention during the Great Recession.

1. INTRODUCTION

Human migration has been studied across a number of scientific disciplines, from demography to sociology, political science, economics, and geography (King, 2012). Understanding why, when, and where humans migrate allows us to answer critical questions about our economies, our populations, our migration policies, and their intersection in place and space. Migration is a complex phenomenon, evidenced by the diversity of social science disciplines involved in its research (Pellegrini & Fotheringham, 2002; Plane & Bitter, 1997). Complicating migration research is that each factor—economic, political, demographic, social, and environmental—can be weighed uniquely by each potential migrant, compounding the difficulty of identifying and modeling decision patterns (Black, Kniveton, & Schmidt-Verkerk, 2011).

The majority of migrants move in order to improve their social or economic condition, rejoin their family, or obtain an education (Greenwood, 1985). These pull factors draw international migrants not just to the U.S., but to U.S. cities. Cities are the economic engines of the U.S. economy, offer the most job and education opportunities, and support much of the nation's economic growth due to the innovation benefits of agglomeration and industrial/sectoral diversity (Glaeser, Kallal, Scheinkman, & Shleifer, 1992; Porter, 2000). As such, domestic migrants are drawn to cities for many of the same reasons as foreign-born: increased earnings potential and employment opportunities (Storper & Scott, 2009).

However, cities also offer the greatest competition for jobs and are relatively high-cost areas to move into. Thus, migration to cities requires investments (in skills development, housing, and transportation) that the migrant anticipates will be returned to him or her over time.

The U.S. Census reports that as of 2010, 12.9 percent of the national population was foreign-born, with more than 50 percent coming from Latin America and nearly 30 percent coming from Asia (these numbers include legal and illegal migrants, insofar as the illegal migrants participated in the U.S. Census's American Community Survey) (U.S. Census Bureau, 2012e). Urban and suburban areas house over 95 percent of the 40 million immigrants in the U.S. as of 2010 (J. H. Wilson & Singer, 2011). While this percentage has been fairly consistent since 1980, the raw number of immigrants since then has more than doubled. The urban destination is not a recent phenomenon for the migrant: the majority of U.S. immigration and internal migration since the beginning of the 20th century has been to U.S. cities (Massey, 1995; Bartel, 1989), though the international origins have shifted quite markedly over the course of the century.

Massey's (1995) review of 20th century U.S. immigration shows the mid-century shift from a European-dominated migrant community to one dominated by immigrants from the Americas and Asia. His conclusions that U.S. immigration flows should be expected to continue indefinitely as the origins and destinations become increasingly clustered has proven correct given recent Census statistics (J. H. Wilson & Singer, 2011). The importance of studying international migration is evidenced by the ample research on the topic across academic disciplines, but this may be at the expense of studying domestic migration (Ellis, 2012; King & Skeldon, 2010). Internal migration – that is, migration within a country's boundaries – actually composes the bulk of human migration and, as such, is a critical component to migration study. Greenwood's (1975, 1997) reviews of the determinants and consequences of U.S. internal migration highlight the important externalities, both positive and negative, of domestic migration: urban growth is both critically reliant on in-flows of migrants, but hamstrung by the need to service this growing populace (the majority of which are arriving at an age where they will soon be reproducing).

Migration to urban areas, whether from internal or international origins, represents the bulk of migration in most nations (Boyle, 2009; Fan, 2009; Plane, Henrie, & Perry, 2005). Likewise, urban areas, in most developed countries, are home to the majority of the nation's population (World Bank, 2011). Studying migration in the context of urban areas, then, allows us to investigate the largest flows and largest impacts, economically and socially. Recent research has shown that as cities have sprawled, international migrants have accompanied the domestic urbanites in their move to suburbia (J. H. Wilson & Singer, 2011). The data also show that smaller cities are attracting a greater proportion of new migrants than larger cities (J. H. Wilson & Singer, 2011).

Key to understanding any type of migrant or migration is contextualizing the behavior. These behaviors are not static over space and time, but vary by origin, destination, and time period. Accordingly, general theories provide a starting point for deciphering the nature of migrant behavior in a given context. The goal of this dissertation is to explore the nature of the migrant and migration within the context of the recent economic downturn in the U.S. America's 'Great Recession' officially began in December 2007 (NBER, 2008). Prior to the financial crisis of 2007-2008, national unemployment rates hovered around five percent (U.S. Bureau of Labor Statistics, 2012a). With the beginnings of the economic decline in December 2007 (NBER, 2008), overall unemployment began to increase in 2008, peaking at 10 percent in October 2009 (U.S. Bureau of Labor Statistics, 2012a). However, unemployment, like the effects of the recession itself, is not spatially homogeneous: while the average U.S. unemployment rate for 2009 was 9.3 percent, state unemployment ranged from 4.1 percent (North Dakota) to 13.4 percent (Michigan), and metropolitan areas ranged from 3.7 percent (Bismark, ND) to 27.9 percent (El Centro, CA) unemployment (U.S. Bureau of Labor Statistics, 2012c).

Just as the recession did not affect all places equally, immigrants and native residents were also not affected equally. From 2008 to 2009, the unemployment rate for natives increased from 5.8 percent to 9.2 percent, while foreign-born unemployment rose from 5.8 percent to 9.7 percent, marking the first time since 2003 that the foreign-born rate was higher than the native rate (U.S. Bureau of Labor Statistics, 2012a). In 2009, unemployment also varied spatially among and between immigrants and native residents, bearing exploration. On the surface, larger cities appear more insulated from financial upheaval than smaller cities, perhaps due to their greater economic diversity (cf. Quigley, 1998). But perhaps the larger foreign-born populations of these larger cities offer some employment insulation to natives, slowing native unemployment through their own higher unemployment rates and potentially raising wages in the process, as less competition remains in the job market and the remaining natives employed compensate for those that were laid off. Ottaviano and Peri (2006b) showed that increased cultural diversity in cities leads to increased gains in productivity and wages for natives in the long run. Given the recent economic turmoil, the question then arises of whether the inverse holds true: does increased diversity (as measured through a greater foreign-born population) lead to lower unemployment and larger wage gains?

Returning to the migrant as an age- and education-specific spatio-economic agent — that is, the migrant, as a member of a given age and education cohort, expects a positive net economic return for the cost/investment of migrating—many other questions of context are relevant in light of the Great Recession. Do migration rates shift during a recession? Do migrants select their destinations in the same way? How strongly is a destination's attraction tied its recession recovery? Do migrant economic niches shift in step with metropolitan employment? This dissertation will address these questions analytically through four areas of research. First, an updated contextual view of migration propensity will be presented using inter-county and metropolitan migration flows and the demographic characteristics of each county. This will be followed by an investigation of local distance-decay variation and migrant attraction to metropolitan areas during the Great Recession. Next, migrant economic clustering in metropolitan areas will be quantified, to include propensity to cluster, using recession-era data. Finally, the impact of migrant population on domestic wages and employment during the recession will be explored.

This research addresses migration-relation phenomena associated with both internal and international migrants. The analysis of internal migrants is generally concerned with their mobility, destinations, and pull factors. The analysis of international migration is concerned with their behaviors in and impacts on their local economies. Any study of migration must first contextualize the flows and, to the best extent possible, the demographics associated with these flows. This contextualization provides the necessary framework for assessing the patterns and trends identified in the follow-on analytical portions. Migration as a spatial interaction process is a quintessential research area in geography, and the ability to analyze the elements of attraction for migrant destinations allows us to see where they are going, and why they are going there. The migrant destinations of focus here are cities; in addition understanding where and why internal migrants are moving, this research also seeks to more fully understand the immigrant behaviors in these cities. Immigrant economic niches are a fundamental phenomenon supporting immigrant employment in cities, and immigrants' impact on local economies illuminates their role in determining the push-pull dynamics of the migration decision.

These four research areas are complementary and offer a well-rounded look at the dynamics of migration during the 2006-2010 time period. This dissertation presents key discoveries about internal and international migrants, and introduces new methods for the analysis of both. First, it is shown there is a qualitative difference in the migration flows at different scales of analysis. Metropolitan-level outflows are associated with significantly different demographics and pull factors than county-level outflows. A new method for assessing pull factors is introduced: a two-stage spatial interaction regression that utilizes local distance decay parameter estimates to identify elements of metropolitan attraction and repulsion. It is also shown that immigrant niches have both spatially homogeneous and heterogeneous tendencies, that much of the research on niches to date has been based on cities whose immigrants (as a whole) are less prone to clustering, and that many cities offer potentially unique takes on immigrant niche formation. Lastly, this research shows that a city's percentage foreign-born is significantly correlated with poorer performance of native-born labor force during the recession, as is the city's presence in an urban agglomeration.

A review of the relevant literature for these research areas is presented in the following section. This is followed by the presentation of the analytical methods, data, results, and discussion for each research topic. The dissertation concludes with a discussion of the significance of these research topics, the impact of the results to the fields of geography and migration research, and the implications of the results on future research.

2. BACKGROUND AND LITERATURE REVIEW

Human migration nearly always occurs to better one's personal or family well-being (Laber & Chase, 1971; Ravenstein, 1889). Whether fleeing a war-torn country for the safety of its neighbor, or moving to the city (or a new city) for a better paying job, migrants are undertaking risk and cost for the potential payoff of a better life. The causes and considerations of migration are multifaceted, yet it is at the confluence of the facets where someone chooses to migrate and selects a destination. Migration drivers (causes) and push and pull factors (considerations) populate the migrant's decision-making process with the necessary opportunity costs of moving from his current locale for some place "better."

Migration can be defined as the change in the center of gravity of one's mobility (Hägerstrand, 1957). This is an important definition, for it identifies migration as unique and different from commuting, which is regular movement between one's home and place(s) of employment. But this distinction does not leave us with a wholly clear understanding of migration; only what it is not. Empirical studies of migration have been less than consistent in defining the phenomenon, with most studies limiting migration strictly to inter-regional mobility but some equating it with residential mobility within a region (Rees, 2001). 'Long distance' is often a qualifier, as moves across boundaries may be shorter in distance than moves within a single zone (Boyle, 2009), but distance qualifiers are rarely captured in the migrant data. Migration can be viewed as a space-time phenomenon that spans the temporal spectrum from short-term to permanent just as it spans the spatial spectrum from local to international. The study of migration is therefore the study of movement and, given the variety of approaches to migration research and the variety of data with which to analyze it, migration is best defined by the scale of movement being analyzed.

Contextually, this places international migration across national borders and internal/domestic migration across some sub-national or regional boundary. While this distinction appears easily identifiable, both characterizations are highly subjective. The crossing of county boundaries may, for example, be a logical local scale for discriminating migration from residential mobility. However, this becomes confounded in most large metropolitan areas which are composed of multiple counties, or when the set of counties being studied are not relatively homogeneous in size (e.g., New Jersey counties average just over 350 square miles in area, while Arizona counties average over 7,500 square miles in area) (U.S. Census Bureau, 2010e). While international moves offer a more discernible qualification, the quality of international migration can meet dubious circumstances: should the 100 km move from Antwerpen, Belgium to Rotterdam, Netherlands be interpreted and studied differently than the 200 km move from Washington, DC to Philadelphia, PA (King & Skeldon, 2010)? Domestic and international migration is also subject to some temporal frame (at what point does the vacationer become a migrant?), but these are rarely studied in conjunction with spatial analysis (Roseman, 1971). Distinctions of this sort are typically defined by the data available and research goal (Boyle, 2009).

The study of migration is multifaceted. The essential questions of why to migrate, where to migrate, and how many will migrate compose the majority of early and current migration research, both within and outside the field of geography (Greenwood, 1975; Sjaastad, 1962; Tobler, 1995). In addition to the continual refinement of theories to the above questions, contemporary scholarship on international migration has also sought to understand the migrant assimilation process, their labor behaviors, and the impact on local economies. A regionalization trend has focused these questions heavily on Europe and the Americas, perhaps resulting in part from shifting migration policies in the face of terrorist extremism since the September 11, 2001 attacks (Mittelstadt, Speaker, Meissner, & Chishti, 2011). Recent research on internal migration has sought to understand the cultural impact of shifting ethnic populations internal to a country, while also seeking to harmonize the theories and results with those of international migration research.

King's (2012) review of the geographer's role in shaping migration research, while providing a concise overview of major theoretical camps and championing the role of historical and future role of geographers in migration studies, largely ignores the contributions of quantitative geographers and those studying post-migration phenomena. Geographers such as Fotheringham, Sheppard, Plane, Tobler, and Wilson, who contributed much to our understanding of migration as a spatial interaction process, are omitted, as are any mention of scholars investigating the integration, assimilation, segregation, and labor patterns of migrants (cf. Fotheringham, 1984; Plane, 1993; Sheppard, 1978; Tobler, 1981; A. G. Wilson, 1971). While it is easy to conceptualize migration as massive transnational movements of volumes of people, today's migration researchers are doing much to illuminate the subtleties of migrants and their decision-making process. In fact, Tobler

(1995) argues that this micro-focus may be detrimental to understanding whether Ravenstein's laws are still relevant today.

The remainder of this chapter is devoted to reviewing the relevant scholarship and concepts supporting the analytical work of this dissertation. This dissertation will research four areas: migration propensity, the spatial variation of migration distance decay, the employment niches of U.S. immigrants, and the impact of the U.S. foreign-born population on domestic labor. These four topics address four critical nodes in migration analysis, which are highly interdependent. To frame this research, an overview of the major theoretical foundations for why people migrate is presented first, to include a review of the specific factors that drive migration, characterize the migrant, and influence his propensity to migrate. This is followed by a survey of the current discussion of the relationship between migration and distance, as well as the analysis of migration using the gravity spatial interaction process and the role of distance in this analysis. Next, an overview of the phenomenon of niche formation among immigrant communities is presented. Finally, research on the role of the community of migrants on metropolitan labor and economic growth is discussed, in context of the importance and benefits of urban economic and cultural diversity. These sections, taken together, should illuminate the foundational principles of who migrants are and why they migrate, how their mobility can be modeled, why and how these migrants form economic niches, and their impact on local economies.

2.1. Migration and the Migrant

This dissertation will analyze both internal and international migrants. While these two types of migration, in many respects, are considerably different spatially and socially, many of the underlying principles of both are similar. As such, neo-classical migration theory will be discussed first, which underlays this research's assumptions about the migrant and his behavior – that individual migration decisions are rooted in an economic cost-benefit analysis, which impacts a migrant's decision if to go and where to go. Following this, the concept of push and pull factors, and intervening opportunities, will be reviewed, along with their role in the mobility of the migrant. The factors that moderate one's propensity to migrate will also be highlighted.

2.1.1. Neo-classical migration theory

The vast majority of internal and international migration is rooted in the economics of a cost-benefit analysis (Borjas, 2001). As such, the foundational theory of migration evolved out of neo-classical economics (Castles & Miller, 2009). Neo-classical theory puts migration as a response to geographic differences in labor and human capital supply and demand in an effort to maximize individual utility (Borjas, 1989a). An individual, driven by pull factors, selects a destination and labor market that maximizes his utility, that is, returns the greatest income for his skills. Labor markets with an overabundance of labor relative to capital experience a decreased relative wage, while labor markets with larger capital to labor ratio experience higher relative wages (Arango, 2000). As such, migration is as much a human capital investment by the migrant as a response to income differentials (Borjas, 2001; Sjaastad, 1962). Migration is the equilibrating mechanism for these markets: as workers immigrate to markets with higher wages, the relative wages in those markets decrease as the labor pool swells while the opposite occurs in the losing markets. If the theoretical equilibrium is reached, migration ceases; however, the market reaction to migration and the migrants' reaction to the market are lagged significantly, and therefore that an equilibrium state is unlikely.

Not all migrants possess the same skills, and not all locations (labor markets) need each skill equally. Each migrant has a unique probability of gaining employment in their new labor market that is significantly more complex than a simple wage differential between the origin and destination (Greenwood, 2001; Ritchey, 1976). Traditional theory states that areas with positive relative wage differentials experience positive net migration, and this has been shown to be true by many scholars (Berger & Blomquist, 1992; Graves & Linneman, 1979; Kennan & Walker, 2011). Ritchey (1976), however, points to several empirical studies that have shown little to no relationship between the two variables. He argues that despite average wage differentials that may be in the favor of a particular place, a place's in-migration and out-migration are positively correlated. This is supposedly due to counter-streams induced by sectoral wage differentials that are directionally reversed. Rogers (1990) suggests the problem is the use of the net migration metric (migration inflow minus outflow) that obfuscates patterns of migrant stream directionality within internal migration research.

Conceptualizing migration as a phenomenon within the neo-classical context allows for a clear and empirically testable view of migration and the migrant (Borjas, 1989a; Castles

& Miller, 2009). While the interdisciplinary migration literature documents six other alternative theories of migration, these other theories do less to refute the neo-classical principles than to caveat them in various historical circumstances or world regions.[1] Of these six, the role of migration networks is perhaps the most important to highlight in the context of this research.

Migration networks constitute the family and social (ethnic, racial, residential, etc.) networks that connect migrants in a destination and connect them to their countrymen, family, and friends in their origin (Arango, 2000). Migration networks serve to attract new migrants to destinations through success stories and increases in socioeconomic status (Fawcett, 1989). Migration networks also support the international migrant in his new destination by sharing resources, such as housing, food, and money (Choldin, 1973), and are crucial in the formation of migrant niches, which is detailed in a later section (Schrover, van der Leun, & Quispel, 2007). For internal migrants, networks serve a similar purpose in providing information on job, housing, and recreational opportunities; reducing the fear of the unknown; and providing psychological support as the migrant leaves his familiar, comfortable place (T. Wilson, 1998).

2.1.2. The decision to migrate

The decision to migrate occurs after careful consideration of a number of factors, not the least of which is economic. The root motivation may be income maximization and net return on migration costs, but many factors caveat this decision. Push factors are origin-

[1] Comprehensive reviews and critiques of the 'competing' theories can be found in Massey et al. (1993), Arango (2000), and chapter two of Castles & Miller (2009).

based attributes that make the potential migrant dissatisfied with his current situation and more likely to consider a move to correct his situation. Pull factors are destination-based attributes that attract a potential migrant (Burnley, 2009; Lee, 1966). Push and pull factors occupy a variety of categories, including economic, demographic, political, social, and environmental (Black et al., 2011). The circumstances of each migrant are unique, leading to a personalized assessment of the push and pull of origins and destinations. While one potential migrant eschews cold-climate destinations, the same destinations may exhibit substantial pull on another migrant.

It is the assessment of the push-pull factors that the migrant uses to determine if and where to move, but the process is not simply a mathematical tallying of the positives and negatives associated with the origin and potential destinations. The decision is also governed by the intervening obstacles[2] each migrant will encounter between the origin and any destination (Lee, 1966). Intervening obstacles are the hurdles presented in migrating to a specific destination, and thus each destination and migrant present a unique set of obstacles. Cost is an obvious obstacle, but others include physical barriers, information, and, in the case of international migrants, immigration laws.

Beyond wage differentials, the migrant's age, gender, level of education, and race all contribute to his probability of moving. Young adults have the highest probability of being a migrant, with migration probability peaking among a person's mid- to late-twenties (Plane & Heins, 2003). As residents age, they are less likely to migrate because they have children, foster stronger and closer ties to their community, and as their children age they reinforce

[2] Intervening obstacles are not to be confused with intervening opportunities, which will be addressed later.

their parents' ties with their own to schools, other children, and the community. Migration probability declines until retirement age where it increases slightly (Rees, 2001).

Increased education is strongly correlated with increased probabilities to migrate, and increased likelihood to migrate longer distances. Higher levels of education expand a person's ability to obtain and make use of information on employment opportunities and cultural differences in distant places. Greater education also increases one's employable market as specializations are gained and the labor supply for a specialty is relatively small (Schwartz, 1973). The notable exception to this rule is the significant portion of migrants that are students leaving for campus life at a university.

The migration propensity of the sexes is less cut and dry. Men compose the larger percentage of migrants, but this claim is demographically sensitive. As female education increases, female probability to migrate increases (Enchautegui, 1997; Mincer, 1977). It is unclear from existing literature and data, however, how this directly compares to male propensity increases with increased education. In many of the empirical analyses aimed at deciphering the precipitants of migration, gender is included as a variable of consideration. Unfortunately, the results are mixed to the point that most migration theory papers include gender as a determinant, noting its significance is subject to vary by context.

Race is in a similar situation to gender regarding migration propensity. There is no overwhelming evidence that a particular ethnic group migrates more than another, internally or internationally. Empirically, however, it is a variable that should be considered given that local social conditions, to include racism and discrimination, likely play a large part in determining who migrates. Demographically, different races respond to migration stimuli in different ways: Cebula (1974), for example, shows that a climate variable had a negative relationship with white migration volume and a positive relationship with African-American migration volume.

In addition to the demographic characteristics that influence propensity to migrate, space and the arrangement of places plays an important role as well. The attraction of places is not fixed in time, and substantive patterns of movement in the U.S. have been documented during the latter half of the 20th century. Prior to the 1970s, domestic migration reinforced the long-standing trend of urbanization, with dispersion within the cities gradually accelerating as transportation networks expanded (Fuguitt & Beale, 1996). The 1970s saw the 'nonmetropolitan turnaround' where rural areas experienced net in-migration for the first time during the century (Rayer & Brown, 2001). Urbanization resumed in the 1980s with reaccelerating metropolitan growth, but the 1990s again saw another surge in nonmetropolitan net increases (Mitchell, 2004).

While there have been no studies that describe whether the 'counterurbanization' trend is continuing, Rayer and Brown (2001) show that even the above-mentioned patterns are not uniform across space and place. There has been significant regional variation in the acceleration or deceleration of growth during each of these trends. For example, all types of Mid-Atlantic counties experienced negative mean net migration rates for the period of 1980-1985; for the 1985-1990 period, large metro core counties experienced even larger negative net migration rates while metro fringe counties, medium and small metro core counties, and non-metro adjacent counties all experienced positive mean net migration (Rayer & Brown, 2001). This spatial and place variation is manifested throughout their analysis, which covers

1980-1995, but is undoubtedly present in any discussion of the propensity to migrate. Outside the urbanization/counterurbanization dynamic, the U.S. population mean center shift over the past 50 years (U.S. Census Bureau, 2010d) highlights a broad pattern of population convergence in western and southern states and away from traditional population centers in the northeast and Mid-Atlantic U.S.

Migration is a highly complex human phenomenon, as evidenced by the often contradictory empirical analyses, the shifting spatial trends throughout the U.S. (and global landscape), and the profusion of migration theories and their continual modifications. While this dissertation focuses on the migrant in the context of neo-classical motivations, there are many assumptions that underlay the neo-classical theory that may not hold for a given cohort of migrants. All migrants may not be utility maximizers: some migrants move for retirement, some for educational opportunities, some to care for loved ones, and some because their employment made the decision for them. Some migrants may not be 'rational actors' and rather select destinations on whims with the goal of starting anew (Boyle, 2009). These moves complicate the ability to model migration, and while the 'non-utility-maximizer' streams of migration might be individually small, they may aggregate large enough to bias any model (Boyle, 2009). As such, while quantitative analysis of migration is critical to understanding the impacts and interplay of a range of variables on migration propensity, mobility, pull factors, and economic impacts, any results are highly contextually dependent not wholly representative of the diversity of the migrant (whether internal or international) community.

2.2. Migration and Distance Decay

Principal among the geographic research on migration is the impact of distance on migrant activity. Distance is typically factored into migration models to not only describe the space of movement, but also to represent the cost of movement and understand the relationship between migrant origins and destinations (Dorigo & Tobler, 1983). Treating migration as another form of spatial interaction, conventional knowledge among migration researchers is the greater the distance between two areas, the fewer migrants will move (flow) between them (O'Kelly, 2009). This phenomenon is known as distance decay or friction of distance: as the distance between any two places increases, the amount of migration between them is expected to decay as a function of that distance.

Distance decay was perhaps first put forth in E. G. Ravenstein's seminal work "The Laws of Migration" (1885). Ravenstein's very first "law" states that the majority of migrants move only a short distance, with his second law stating that the number of migrants from any place to a destination declines proportionately as the distance between the origin and destination increase (Ravenstein, 1885). Ravenstein, in a second "Laws of Migration" paper, concludes that "…distance from the centre of attraction, modified by facilities of access, and the existence of rival centres of attraction, would appear to be in all cases the principal factor to be taken into account" (Ravenstein, 1889, pp. 262–263). His suggestions regarding accessibility and competing destinations would lay the groundwork for modern day spatial interaction models.

Several attempts to explain distance decay have resulted in two predominant theories: the psychic cost theory and the information theory. The information theory states that potential migrants have less information about farther away places than nearer places, and thus tend to migrate to the nearer places about which they know more. This information or knowledge can range from knowledge of potential job opportunities to knowledge of friends, family, or social groups upon which they can rely after the move (Winters, de Janvry, & Sadoulet, 2001). The psychic cost theory states that potential migrants will have more difficulty maintaining contact with their friends, family, and accustomed social institutions in farther away places than in nearer places, and thus tend to migrate to nearer locations to more easily maintain these contacts (i.e., have lower psychic cost) (Greenwood, 1975; Ritchey, 1976; Schwartz, 1973). Tobler's (1970) "first law of geography" ties in nicely with the psychic cost and information theories in that a migrant might expect people, norms, and institutions severely different from those of his current locale at farther locations than at nearer locations. A lack of information about the more distant locations may compound psychic cost by not consoling fear through an understanding of the true nature of differences and similarities between two areas.

Another predominant explanation of distance decay, which has been formulated as an alternative method of modeling the phenomenon, is the concept of intervening opportunities. The theory and model of intervening opportunities were proposed by Stouffer (1940) and were subsequently revised and expanded by him in the context of migration (Stouffer, 1960), and it is a central tenet of Ullman's principles of spatial interaction (Ullman, 1980). Stouffer's theory of intervening opportunities attempts to explain the distance decay of migration flow as a function of the number of alternative destinations available to a migrant from any given origin. The relationship between migration flows and distance has been understood and, for the most part, accepted since Ravenstein wrote his laws of migration in 1885. Although it can be phrased multiple ways, in essence fewer migrants should be expected between an origin and a far off destination than between an origin and a near destination. Stouffer sought to explain this 'distance effect' through opportunities rather than proximity. He succinctly stated "…the number of persons going a given distance is directly proportional to the number of opportunities at that distance and inversely proportional to the number of intervening opportunities (Stouffer, 1940, p. 846)."

Thus, the intervening opportunities model estimates flow between an origin and destination as an inverse function of the number of opportunities between any origin/destination pair (Mckercher & Lew, 2003). The intervening opportunities model does utilize a measure of distance in its formulating in order to establish some range of movement, but this is only utilized to estimate/calculate the number of intervening opportunities in that distance range. Quantitatively, an explicit measure of distance is ignored.

One of the implicit assumptions of the spatial interaction model, particularly those of mobility, is competition among destinations within the interaction system (Ullman, 1980). There is competition among the various shopping centers in local retail-based spatial interaction models, and there is competition among nations in international trade-based models. Among the mobility and migration spatial interaction models, the competition is among the destinations to which people travel. Each destination offers a unique set of attributes relative the origin and relative to each other which the migrant must digest in his decision of where to go (Haynes & Fotheringham, 1984). These attributes form the destination's place utility, which is the attractiveness of a destination, relative to alternative destinations, as perceived by a migrant. Introduced by Wolpert (1965), place utility essentially revisits the concept of migration push/pull factors, where the satisfaction of the migrant with his origin is pitted against his perceived satisfaction with potential destinations.

It has been argued, however, that all destinations are not competing with each other; rather destination competition is limited to some spatial zone identified through the migrant's hierarchical decision-making process (Pellegrini & Fotheringham, 2002). Whether conceptualized relative to the origin (e.g., destinations near the origin are competing with each other, whereas destinations far from the origin are only competing with other far-away destinations) or relative to the destination (e.g., the migrant selects a geographic region within which a specific destination is chosen), the presence of competition within the system affects the probability of interaction with any given destination. This is conceptualized through the competing destinations spatial interaction (gravity) model (Fotheringham, 1983).

The competition among the destinations can be modeled through a measure of spatial structure of any destination: destinations with higher accessibility have more competition and thus have a lower probability of receiving migrants. Empirically, failing to account for the accessibility/spatial structure of destinations results in over-estimation of migration between an accessible origin and destinations, while interaction will be under-estimated for inaccessible origins and destinations (Tiefelsdorf, 2003). Thus, the competing destinations model is simply a modified version of traditional gravity models that includes an accessibility variable.

This research focuses on the role of distance, and how the spatial variation of distance decay can be utilized to assess the attraction of a destination. As such, the gravity model of spatial interaction is utilized, rather than the intervening opportunities model, to assess this variation of distance-decay parameters. However, intervening opportunities for migrants are not ignored, as the gravity model used will control for the spatial structure of origins and destinations. The following section discusses the history of the gravity model and its place in spatial interaction literature. This will be followed by a discussion of relevant research on the spatial heterogeneity of distance-decay.

2.2.1. The gravity model and spatial interaction

One of the earliest attempts to model movement between a set of origins and destinations was presented by Zipf (1946) who showed highway, railway, and airline traffic could be modeled extremely well through a basic equation where the product of two locations' masses is divided by the shortest distance between them. This model, historically called the gravity model due to its similarity to Newton's law of gravitational attraction, has evolved and manifested in a multitude of forms (see Haynes and Fotheringham (1984) for a detailed review) that have formed the foundation of spatial interaction research over the second half of the 20th century.

Central to all spatial interaction frameworks is distance decay. People and places are less likely to interact with farther locations than nearer ones, and this rate of decreasing interaction varies by the interaction phenomenon. Grocery stores, for example, may experience steep distance decay curves, as people generally shop at the grocery nearest their residence. Shopping malls might carry a less steep distance decay curve as people are more inclined to travel to locations with their favorite clothing stores rather than simply the closest (Haynes & Fotheringham, 1984). This variation in the friction of distance is controlled by a decay parameter that transforms the actual distance into what could be termed a perceived distance. This parameter describes the interaction patterns over space when all other variables are held constant (Fotheringham, 1981). Figure 1 shows this graphically: phenomenon with larger distance decay parameters experience sharper drops in interaction over a distance.

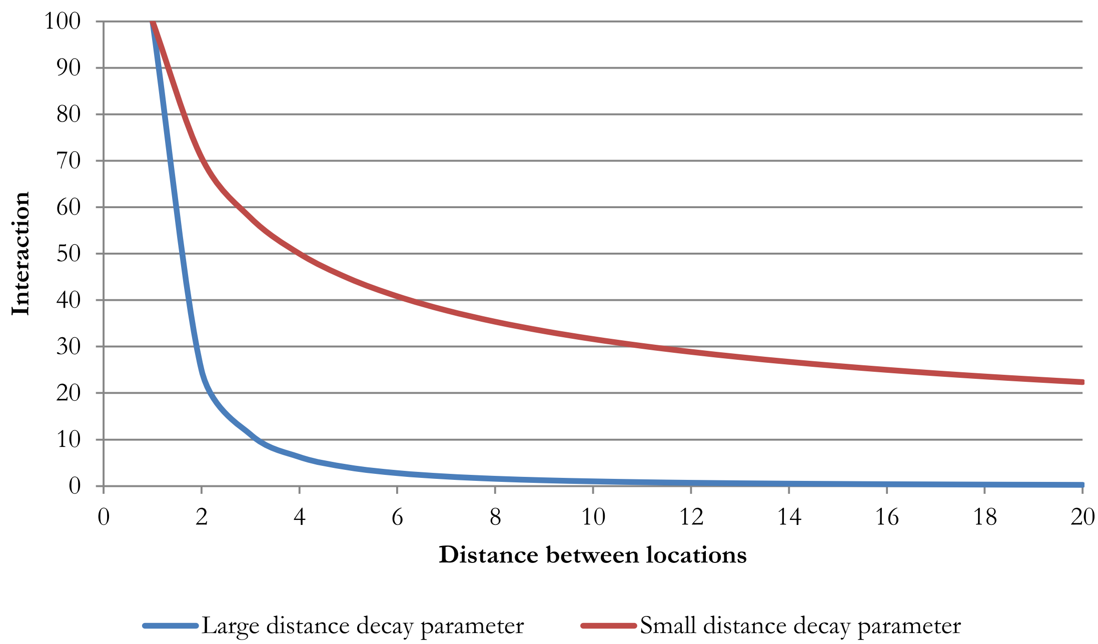

Figure 1: Example spatial interaction curves with large and small distance decay parameters.

Distance decay is represented as three functions throughout the spatial interaction literature: inverse function, negative exponential function, and negative power function. The inverse function is a form of the negative power function where the exponent is negative unity (d_{ij}^{-1}). This function simply multiplies the spatial interaction model by the inverse of distance to quantitatively state that, for example, at a distance of ten, one-tenth of the interaction will take place as at a distance of one. The negative power function ($d_{ij}^{-\beta}$) varies this exponent between zero and some larger negative number (Fotheringham (1981) reports seeing empirical studies with decay parameters as strong as –5.2) to describe the interaction. The negative exponential function ($e^{-\beta d_{ij}}$) raises Euler's constant to the product of distance and the parameter. Although the negative power and exponential functions are often used interchangeably, empirical evidence suggests the exponential function best models short-distance mobility (e.g., journey-to-work) while the power function best models longer-distance mobility (e.g., migration) (Boyle & Flowerdew, 1997; Fotheringham & O'Kelly, 1989).

While the gravity model can be formulated for an entire interaction system to estimate flows, and properties of those flows, it can also be formulated as origin-specific and destination-specific. These formulations allow analysis of all flow out of an origin (the former) and all flow into a destination (the latter). Utilizing these specifications allows the researcher to assess the impact of the gravity model components on each location rather than globally. This is related to the concept of a local regression model, wherein the parameters are estimated uniquely for each location. These models allow us to operate under the assumption that the gravity model elements of attraction, repulsion, and friction of distance vary at each location.

2.2.2. Spatial variation of distance decay

While generally a fixed descriptor, distance decay has been shown to vary across space. This variation is intuitive if distance decay represents a perception of distance between any two places and its effect on interaction, and perceptions vary from place to place. Fotheringham showed that distance decay varied for airline travel between major U.S. cities (Fotheringham, 1981). Plane (1984) used variations in distance-decay parameters to map 'inferred distance' between U.S. states. Gordon (1985) attempts to explain variations in distance decay through an economic lens, suggesting that variations in information friction, unit interaction costs, substitutability, and utility of money lead to spatially varying distance decay. Eldridge and Jones (1991) map the variation in distance-decay parameters from migration data to reshape the U.S. as cartograms. Soininen et al. (2007) study the variation in distance decay from an ecological perspective. Their study of the effect of distance decay on community similarity showed that distance decay is spatially varying by community location, but also contextually varying by community type.

Distance decay variations have also been studied in the context of spatial structure: distance-decay parameters in accessible locations tend to be less negative while inaccessible locations have more negative decay parameters (Tiefelsdorf, 2003). The interpretation of this pattern would indicate that people in accessible locations perceive distance with less friction; however, it is has been shown that this interpretation is incorrect and is a result of a missing component in the gravity model that controls for spatial structure (Haynes & Fotheringham, 1984).

The origin-specific spatial interaction models of Fotheringham and many others studying spatial interaction (cf. Fotheringham, Nakaya, Yano, Openshaw, & Ishikawa, 2001; Fotheringham, 1981; Tiefelsdorf, 2003) aim to illuminate the perceptions of a place, contextualizing the spatial cognition of those in the origin. They argue it is more intuitive to state that people from a location perceive distance in a certain way than it is to say people who move to a place perceive distance in a certain way (as would be interpreted using a destination-specific model) (Haynes & Fotheringham, 1984). Destination-specific models, however, serve a much more utilitarian purpose, particularly in the context of competing destinations. Instead of generalizing a view about the people who move to a destination, the distance-decay parameter for the destination can instead be interpreted as a function of that destination.

Formulating the interaction model as destination-specific facilitates the explanation of distance decay at each location and why it varies across space. From a destination's perspective, distance decay represents the average difficulty of getting to that location from any origin. Thus, if a destination receives the majority of its migrants from nearby origins, a more negative (or larger absolute) parameter is expected. Conversely, if a destination gets a greater proportion of its migrants from far-off locations, it's distance decay parameter should be less negative (or smaller in absolute terms) (Tiefelsdorf, 2003). Distance decay, then, is directly related to the attractiveness of the destination: the wider the attraction of the destination, evidenced by a larger distance distribution of its migrant volume, the less friction-of-distance the destination imposes.

2.3. Migrant Clustering and Economic Niches

Beyond the mobility and decision-making research related to migration, scholars have long been interested in why immigrants, once settled, concentrate in specific industries/sectors. Rather than dispersing across all industries available to them in their new home economy, immigrants frequently form economic niches based largely upon nationality or ethnicity. Some scholars attribute niching to residentially based ethnic solidarity and its resulting enclave economies that, in many ways, mirror regions' primary economies (Sanders & Nee, 1987; K. L. Wilson & Portes, 1980). Other research suggests that migration networks and entrenched employment in particular industries offer conduits for new immigrants into the U.S. labor market (Hudson, 2002; Waldinger, 1994). Among the debate has been the question of whether these economic niches are self-reinforcing and grow over time, or whether niches vary temporally as the economic representations of the U.S. lead immigrant groups to shift niches as their numbers grow and mature in the country (Waldinger, 1996).

Recent scholarship has shown that economic niching occurs for specific immigrant groups, nationalities, or ethnicities within a single urban or regional area (Ellis, Wright, & Parks, 2007; Hudson, 2002; Waldinger, 1994; Wright, Ellis, & Parks, 2010; Wright & Ellis, 1996, 2000) as well as the nation as a whole (Ceccagno, 2007; Eckstein & Nguyen, 2011; Gratton, 2007). Scholars have attempted to generalize the similarities of niche formation across space (Logan, Alba, & Stults, 2003; Wang, 2004), but few studies have illuminated how the niching for a group varies among different regions. Gratton (2007) showed that Ecuadorian immigrants in New York City, as a group, have their own economic niches, but male and female Ecuadorians occupy different occupation niches due to both human capital and prejudicial factors. The prevailing research suggests immigrant niches are composed of one or a limited number of industries (Waldinger, 1994), with groups tending to concentrate in similar industries in multiple metropolitan areas.

Immigrant groups are highly prone to niche formation because of limited information about and connections to the primary labor market of their new home economy. They utilize their ethno-national, familial, and residential networks to seek and find employment, and typically in jobs occupied by those of a similar predicament (Waldinger, 1994). The body of literature on niching appears to show that nearly any social categorization of workers will lead to the identification of sectoral clustering. Whether assessing employment patterns of a single immigrant nationality (K. L. Wilson & Portes, 1980), across multiple immigrant nationalities (Ellis et al., 2007; Min & Bozorgmehr, 2000), by gender (Light, 2007), across Asian nationalities (Wang, 2004), of South Asian franchise owners (Rangaswamy, 2007), by race (Hudson, 2002; Waldinger, 1994; Wright & Ellis, 1996), or a combination of the above (Moya, 2007; Waldinger, 1996), niches are prevalent in both local/regional and national economies.

While niches are pervasive in most economies and labor markets, there are related phenomena that evolve from or are complementary to niches. The first phenomenon is the ethnic division of labor. Often imprecisely used synonymously with niche formation in the research literature, the division of labor can best be characterized as occupational/job specialization (Wright & Ellis, 2000). The difficulties encountered in any study of niching is segmenting theories of the ethnic (or gender) division of labor with those of niche formation, as a significant portion of the analytical work to substantiate the former focuses on industries/sectors which characterize the latter.

The second phenomenon related to niche formation is the ethnic enclave economy. Ethnic enclave economies (also referred to as enclave economies or entrepreneurial niches) occur when an immigrant or ethnic group dominates not only the labor of an industry (as with niches), but also the ownership (Logan, Alba, Dill, & Zhou, 2000). Immigrant entrepreneurs, preferring to hire co-ethnics, develop an ethnic labor market separate from the dual markets described in segmentation theory. Immigrant workers in an enclave achieve many of the benefits of the primary segment (e.g., upward mobility, investment in human capital) as the firms reap advantages through isolation from the open competitive market (K. L. Wilson & Portes, 1980). While general employment data provide useful benchmarks for the identification of niches, ethnic enclaves may be the driving factors behind niche formation. Ethnic enclaves present a potential problem of data bias. Attributing niche presence to a secondary labor market or an enclave economy can be difficult absent firm-specific data.

It is evident that immigrant niches are simultaneously a social, demographic, and economic phenomenon, and the underlying forces that drive an immigrant to niche have likewise been explained using theoretical constructs associated with each of these disciplines. The next section describes the predominant theories of niche formation, which, rather than contradict each other, form a relatively holistic view of niching when taken together. We then move from theoretical to quantitative, discussing the metrics used to identify niches within an economy, and the spatial variation of niches across the U.S.

2.3.1. Theories of niche formation

The current body of research suggests there are three basic theoretical approaches to explain the phenomenon of niche formation: neo-classical economic theory, segmentation/social capital theory, and succession theory. Each of these individually explains only part of the dynamics of immigrant (and non-immigrant) niche formation. A brief review will show, however, that taken as a whole each serves to explain a component of the job selection process and segmentation within a labor market.

As previously described, neo-classical economic theory (often referred to as human capital theory in the niche literature), roots all actions in utility maximization (Borjas, 1989b). Immigrants are considered within a Darwinian survival-of-the-fittest scenario whereby their job selection and wages are solely a function of their fitness for employment in a labor market (Hudson, 2002; Wang, 2004). Within this context, immigrants attempt to maximize their pay while their counterpart, the employer, seeks to maximize production (defined as perfectly aligned skills for the job). On the surface, neo-classical theory calls for the job decision to be formed based on the needs of employers and the overall labor market at a given point in time, regardless of the ethnic background of the job applicant, suggesting that niches form based on the inherent skills and abilities of an immigrant group (as preference for job selection is only applied to the immigrant's fitness). While the human capital theory offers an attractively simple view of immigrant labor, it cannot explain situations where groups with vastly different biological or cultural characteristics (e.g., African Americans and Mexican immigrants) both rely on niches in the same industry (Logan et al., 2000).

Segmentation theory suggests that a labor market is divided into primary and secondary labor market segments. The primary segment is characterized by better work conditions, higher wages, long-term employment, and opportunities for upward mobility. The secondary segment is comprised of the opposite: poor work conditions, low wages, short-term employment, and minimal opportunities for advancement (Hudson, 2002; Sanders & Nee, 1987; Schrover et al., 2007; Wang, 2004; K. L. Wilson & Portes, 1980).. Domestic minorities (because of discrimination and fewer opportunities to develop important skillsets) and immigrants (because of cultural, language, and information barriers) tend to represent the majority of employees in the secondary labor market. Barriers to mobility from the secondary to primary segment may trap many immigrants in these less-than-desirable occupations (Sanders & Nee, 1987), and worker succession through family relationships and place-of-birth ties reinforces the niching process as new migrants seek employment through their limited connections (Wright & Ellis, 2000). Social capital applied to the immigrant niching phenomenon consists of the benefits (but also constraints) levied to migrants as a result of their connection to various familial, ethno-national, racial, and residential networks. Tightly associated with the concepts of bounded solidarity, enforceable trust, and embeddedness (Portes & Sensenbrenner, 1993), social capital develops within groups based upon some set of commonalities and forms the foundation by which members support each other through information and opportunities. Niches form as immigrants currently employed in a sector of the economy feed knowledge of the (secondary) job market and employment opportunities to new immigrants within their social network (Waldinger, 1996).

Succession theory, referred to by Wang (2004) as "macroeconomic structural transformation" and by Kloosterman and Rath (2001) as the "vacancy chain", suggests that immigrant and minority niches are achieved as white workers (or more assimilated, entrepreneurial immigrants) decentralize and suburbanize, leaving vacant lower-wage and less-desirable jobs available for non-white ethnic groups and newcomers. This, however, implies cross-fertilization of the primary and secondary labor markets, with the primary segment recruiting into the secondary for labor needs (Waldinger, 1989). Waldinger (1996) describes the occurrence of this process in New York City, while Wright and Ellis (Wright & Ellis, 1996) reinforce his conclusions but question whether the succession of whites should be considered the dominant variable going forward. Thus, succession theory operates through two potential processes: the movement of whites (or, again, some other dominant ethnic group) out of less-desirable primary segment industries and jobs, and the movement of successful immigrants from the secondary to the primary segment. In each process, a chain reaction of invasion and succession occurs whereby vacancies are filled by some subset of the foreign-born populace. If this invasion group is homogeneous enough (which is likely through the use of the social capital inputs), a niche will materialize.

These three theories do not form mutually exclusive stances on niche formation but rather complement each other by describing different facets of the phenomenon. There is no doubt that succession has taken place in cities over the past 100 years as suburbanization has, in many ways, re-characterized urban America. But succession need not just be a product of out-migration; the assimilation of immigrant groups into the broader urban culture and economy facilitates their movement from the secondary labor market to the primary, opening perhaps more desirable niche space to other immigrant groups (Model, 1993). The interwoven ethnic and residential networks provide conduits for the flow of information and access to job opportunities. But the selection process, regardless of the ethnicity of the candidate, remains grounded in both human and social capital assessments.

2.3.2. Quantifying niche formation and propensity

Immigrant niching has largely been defined as some metric of overrepresentation of the immigrant group within an industry when compared to the overall labor force (Model, 1993; Schrover et al., 2007; Waldinger, 1996; Wright et al., 2010). Model (1993) clarifies overrepresentation as when a group's concentration is one and half times the general labor force's concentration (that is, an overrepresentation of 50 percent or greater). In most studies quantifying immigrant niche formation, this cutoff is used with location quotients, though the threshold has been lowered to 20 percent overrepresentation in some cases (Hudson, 2002; Wright & Ellis, 2000). Stipulations of minimum industry employment by ethnicity, or overall, are often used to alleviate sampling biases. Ranges from 1000 employees (Waldinger, 1996) to 10,000 employees (Ellis et al., 2007) have been used in previous research. Quantitatively identifying niches hinges upon the comparative (or base) labor force, as the industry representation in this labor force is considered the normal. The base labor force must be of the same scale and location as the immigrant labor force to avoid bias.

Thus, it is unwise to confirm an immigrant group's overrepresentation in an industry in Minneapolis using Wisconsin or the United States as the base labor force.

An aspect of niching that has received increasing attention in the literature is a group's propensity to form niches. Understanding how likely an immigrant, ethnic, or gender group is to form niches in a city provides insight into the overall ability of the group to assimilate, how they participate in the metropolitan economy, and how their employment behaviors differ from other immigrant groups or their peers in another city. Wright et al. (2010) show that niching probability varies greatly by ethnic heritage and gender. For example, they show Mexican men are twice as likely to form niches in Los Angeles as Chinese men, whereas Mexican and Chinese women have roughly the same niching probability. Ellis et al. (2007) also attempt to model propensity to niche, but as a function of competition and accessibility from immigrant residences. Their results show that both variables affect the probability of niching, and the effect can vary given the size/strength of a niche. Ethnicity and foreign-born status have also been shown to significantly positively or negatively affect the probability of niche formation (Hudson, 2002). These documented variations in niching propensity illuminate the non-uniformity of the impact of social factors in job selection within a single city. This research will test if this idea extends across multiple cities.

2.3.3. Spatial variation in niche formation

The majority of niche research to date has focused on a limited number of cities, primarily the gateway cities of New York and Los Angeles, with little assessment of the variation of niches over space. Looking strictly at the research on these two cities, we can immediately see that niche industries are not homogeneous across space. Zhou (1998) shows that Chinese immigrants to New York and Los Angeles are significantly overrepresented in different industries and occupations, concluding that history, geography, and differences in labor market attract different groups of immigrants of the same nationality. However, Hudson's (2002) analysis of Atlanta shows that the ethnic niches present there generally represent those found in other major metropolitan areas. Ultimately, the distribution of niches is heavily dependent on the state and structure of the local economy and demography.

2.4. Foreign-Born Impacts on the Local Labor Force

While economic, social, and demographic forces lead immigrant workers to niche-based jobs, niches are not what draw immigrants to U.S. cities. It is the vast economic and educational opportunities available in cities, and the potential for many to work toward the 'American Dream,' that serve as the ultimate attraction for foreign-born workers (Fan, 2009). Cities offer economic opportunities because of the sectoral, or industrial, diversity within their economies. Industrial diversity has been shown to be an important contributor to urban economic growth. Glaeser et al. (1992) show that increased diversity of industries leads to faster growth of the industries themselves and the city economy (employment) as a whole. Additionally, a diversity of firms within an industry leads to faster growth within that industry, and the increased competition and knowledge spillovers ripple through the urban economy. Quigley (1998) addresses the impact of heterogeneity on consumption, production, and agglomeration in general, stating that larger cities, by virtue of being more diverse, are more productive and have a higher standard of living for its residents.

The impact of urban diversity has not only been studied from the perspective of sectoral competition and its impact on the production function, but also from the perspective of ethnic pluralism and its impact on urban primary and secondary labor markets (Florida, 2002b). Urban areas are the destination for nearly all U.S. immigrants and thus their impact on the metropolitan economy represents the majority of their impact to the U.S. economy. Economic theory leads us to believe immigration benefits the destination as a whole by allowing domestic labor to specialize according to its efficiencies, but native-born substitutes will suffer lowering wages due to an increased labor supply (Borjas, 2003; Smith, 2001). Card (2001) shows that large migrant inflows lead to short-run decreases in relative employment rates and wages for low-skilled labor, especially in gateway cities. Card (2005), however, shows that there is little relationship between increased immigrant labor and low-skill domestic wages. The weak relationship between increased immigrant labor and native employment and wages can be explained by local demand shocks or local shifts in economic structure as a result of the increased labor supply (Card, 2005).

Immigrants need not be assumed to be solely a low-skilled lot, competing just with native low-skilled labor and reducing wages in the process. Dustmann et al.'s (2005) study of the impact of immigration on the British labor market shows that, at the national level, the education level of immigrants is on par with that of British natives. In the U.S., the existing stock of migrants is overly represented by high-school dropouts (U.S. Census Bureau, 2012d), but new immigration presents an inverted parabola of increasing low-skilled labor (high-school dropouts) and bachelor's and master's degree-holders (U.S. Census Bureau, 2010f). Nor must immigrants replace native labor by accepting lesser pay. Card's (2001) data reveal that in 66 of 175 study cities, the mean log hourly wage of immigrant men is higher than that of native men.

Other researchers conclude immigrant labor has no effect on native employment and minimal effect on overall native wages (Friedberg & Hunt, 1995). Longhi et al.'s (2005) meta-analysis shows the wage effect clusters around zero, with some studies showing a positive and others a negative effect. In the short run, wages are depressed due to an influx of (foreign-born) labor, but this is mitigated in the long run as capital accumulates and resets the capital-labor ratio to its equilibrium level (Ottaviano & Peri, 2006b). These conclusions, however, treat migration as a fixed event that distorts an economy in equilibrium rather than the reality of constant in- and out-streams of domestic and international labor.

Ottaviano & Peri (Ottaviano & Peri, 2005, 2006a, 2006b) contradict the majority of research on the topic by demonstrating that natives' wages are positively affected by increases in immigrant labor. They conclude that gains for natives exhibited by their models are a function of the imperfect substitutability of immigrant workers for natives, leading to the conclusion that increased diversity has positive impacts on the overall economic welfare of natives. Card (2007) somewhat confirms this, showing that urban areas with larger in-flows of migrants tend to have larger pools of low-skilled labor, leading to diverging (lower lows and higher highs) and higher average wages.

Several research studies have addressed the role of immigrant labor on the unemployment rate of natives. Simon and Moore's (1993) analysis of unemployment and immigration from 1960 to 1977 reveals no statistically significant effect of immigration volume and native unemployment rate. Their analysis only addresses annual migration flows and not the impact of aggregated migration flows (i.e., the entire foreign-born population). Winegarden & Khor (1991) analyze the impact of illegal immigration on native unemployment at the state level and find similar results. The large and relatively immediate influx of Cuban immigrants to Miami following Castro's 1980 lifting of U.S. emigration from the Mariel port also yielded no direct increases to native (white and black) unemployment rates (Card, 1990). Jean & Jimenez (2011), when looking at OECD immigration and unemployment, find that increasing shares of immigrants in the labor force rather than immigrant in-flow volumes, has a delayed, weakly negative, but only temporary impact on native unemployment levels.

2.5. Research Opportunity

There is clear opportunity to fill several research gaps in the migration literature. Migration has been addressed across a number of disciplines, many of which ignore the various roles geography and space play in the migration. While space and geography are inherent and understood in the context of modeling migration as spatial interaction, it is often missing from the discussion of migration propensity, migration niches, and migrant economic impacts. The central theme of research for this dissertation is to address the spatial variation of these migration-related phenomena.

First, there is a general need to modernize our understanding of migration propensity. Little has been published recently regarding changes in the propensity to migrate in the 21st century, and there appears to be a dearth of research on the spatial variation in this propensity. Second, there is an opportunity to revisit spatial interaction research in the context of migration. Destination-specific spatial interaction models have not been used to assess the migration distance-decay parameter variation across space. Third, the phenomenon of niche formation has been addressed thoroughly, but no research has looked at the spatial variation of this behavior and what may cause it. Lastly, much has also been published regarding the impact of foreign-born populations on local labor markets, but no studies have assessed whether these impacts are uniform across space.

In addition to these general research gaps in our understanding of the geography of migration, the recent economic events present an unprecedented opportunity to assess how these migration-related phenomena react to economic upheaval. America's 'Great Recession' recalibrated economics at the national, state, and local level, but not uniformly across the nation (U.S. Bureau of Labor Statistics, 2012b). These economic fluctuations undoubtedly led to changes in migration propensity, changes in place-specific distance decay, changes in the formation and distribution of niches, and changes in impact of migrants on local economies and domestic labor.

Thus, this research takes aim at the two principle segments of migration research – internal and international – through two critical components within each. With regard to internal migration, this research contextualizes the mobility of the 2006-2010 period, and identifies discrepancies between the flows at different scales. This 2006-2010 period will be the focus of this research because it includes the Great Recession, but also includes the pre-recession bubble and post-recession recovery. This research also uses spatial interaction modeling of internal migration flows to determine which metropolitan characteristics draw (or pull) these migrants to their destinations, allowing both the research and policy community to better understand what attracts and repels migrants. With regard to international migration, this research investigates immigrant economic clustering (as opposed to spatial clustering) and determines whether these behaviors are consistent across space. Immigrant impacts on the native-born labor force are also examined for the 2006-2010 period, again providing researchers and policy-makers alike insight into the dynamic relationship between immigrants and local economies.

The next chapter presents the methodologies, data, and results that will fill these research gaps. Each section will first provide an overview of the research question(s) to be investigated. This will be followed by a methodological overview and justification, and a discussion of the data used in each analysis. Results will be presented, and the sections will close with a discussion of the significance of each piece of research.

3. METHODS, DATA, AND RESULTS

This dissertation will address four sets of research questions in the context of the 2006-2010 migration period, and the economic conditions that persisted during that time. These are: (1) What are the current trends in migration at the metropolitan and county level, and how do these vary across space? (2) Is the distance-decay parameter a viable estimator of destination attractiveness, and what local attributes can explain destination attractiveness in this context? (3) Does migrant propensity to form niches and niche composition vary over space, and what factors contribute to these variations? (4) How does the foreign-born population impact the local domestic labor market, and how do these impacts vary over space? This research will leverage the opportunities presented in Section 2.5 and provide critical insight into the geography of migration.

These four research questions, while they could stand alone in their analytics, are significantly interdependent contextually, and each informs the results of the other. To fully understand the distance-decay estimates, one must have an awareness of the rates of migration throughout the U.S., and demographically who those migrants are. Identifying which niches are present among immigrant groups and how consistent they are over space provides clarity as to where economically motivated movers of a given industry may go, and who they will be competing with in their new destinations. And understanding the economic impact of immigrants during a recession period not only feed context to the employment competition picture, but illuminates areas for policy considerations to ensure all demographics, immigrant and native, economically flourish during any period. The following sections address the methodologies for the above research topics.

A central theme of this dissertation is the economic decision-making, behavior, and impacts of the migration. As such, the migrant is interpreted through a neo-classical lens. From a model perspective, all migrants, both internal and international, are assumed to be rational actors operating under the principle of utility maximization. The maximization leads them to select a destination that provides the greatest net-return on migration, and their economic decisions in this destination are aimed at maximizing the return on their skills.

3.1. Current Trends in Migration

3.1.1. Methods

To frame the mobility within the U.S. during the latter half of 21st century's first decade, the migration rates and associated demographics for all contiguous U.S. counties and major metropolitan areas are explored. This time period buffers the Great Recession and will both contextualize modern propensity to migrate and illuminate the changes in migration rates over time and in conjunction with the economic downturn. As migration rates have been empirically shown to vary by age, education, and gender (McKenzie & Rapoport, 2010; Mincer, 1977; Stillwell, Hussain, & Norman, 2008), these variables are critical to understanding the mobility among the U.S. Counties and metropolitan areas. High proportions of residents in their early 20s (e.g., a county containing a large four-year university) will likely experience significantly more outflow than a comparably populated county with a normal population distribution. Thus, contextualizing migration with these variables paints a more realistic picture of mobility.

Using out-flows for each county from 2006-2010, and corresponding demographic data, county and metropolitan area migration trends are described, to include overall rates and their relationship to local demographic elements: education, age, and gender. While focusing on descriptive statistics and correlations, Moran's I and Getis-Ord G global spatial autocorrelation tests are employed. The Moran's test illuminates the presence and direction of spatial autocorrelation among the county-level out-migration rates by measuring the joint deviation from the mean of an observation and its neighbors. Moran's I will be positive, up to one, when neighboring observations tend to deviate in the same direction from the mean, indicating a clustering of like values; Moran's I will be negative, to negative one, when neighboring values tend to deviate in opposite directions, indicating a dispersion of like values (Burt, Barber, & Rigby, 2009). The global G test shows whether the autocorrelation is a function of high or low migration rates clustering together, or whether there is a mix of both, by taking a proportion of neighbor values to all values. High $G(d)$, where d is the search distance or conceptualization of neighbor relationships for autocorrelation, indicate high values cluster together, while low $G(d)$ values indicate low values cluster together (Getis & Ord, 1992). There is no 'correct' scale of spatial influence or association when assessing the phenomenon of migration rates. Because the size and definition of a 'neighborhood' and 'neighbors' is spatially different in different regions of the U.S., several conceptualizations of spatial relationships will be employed in an attempt to identify the appropriate neighbor/weighting scheme for migration rates. These weighting schemes and neighbor relationships are inverse distance weighting, inverse distance squared weighting, 5 nearest neighbors equally weighted, 10 nearest neighbors equally weighted, and fixed distance bands for inclusion of neighbors up to distances of 500km, 1000km, and 1500km from each observation location (county centroids or metropolitan centroids). These multiple distance bands were chosen because they normalize for the spatial disparities in county size and neighbor distances between the eastern and western U.S.; a starting distance band any smaller would have left many western U.S. counties without a neighbor. Additionally, it is convention within the research to explore multiple distances when there is no *a priori* justification to use a given distance band (Getis & Aldstadt, 2004; Getis & Ord, 1992).

3.1.2. Data

Migration trends for the 2006-2010 period are assessed using U.S. Census Bureau American Community Survey (ACS) data. The ACS provides detailed demographic data on multiple geographies, ranging from the block group level to the state level. The ACS is a sampled dataset similar to, and replacing following the 2000 decennial census, the Census Bureau's decennial census long form. The ACS is published annually as 1-year, 3-year, and 5-year datasets, where the 3-year and 5-year version aggregate 1-year datasets over a specified period. This research utilizes the 2006-2010 5-year ACS tables to obtain population, education, age, and gender data for each county and study city (U.S. Census Bureau, 2010a).

The research throughout this dissertation will focus on the U.S. metropolitan areas with populations greater than one million. There are 51 cities that meet this criterion, shown in Table 1 with their populations and the number of counties composing each. Figure 2 depicts them on a map. The U.S. Census Bureau provides demographic data for numerous political units and among them are counties and metropolitan areas. The Census Bureau also defines the spatial bounds of each metropolitan area in their Core-Based Statistical Area (CBSA) definitions (U.S. Census Bureau, 2013a). CBSA definitions are used to determine which counties to include in each metropolitan area for aggregating migration flows for each city.

Table 1. The 51 U.S. metropolitan areas with populations greater than one million. These cities are the analytical focus of this dissertation.

Metro Area	Pop.*	Counties	Metro Area	Pop.*	Counties
New York, NY	18,700,715	25	Orlando, FL	2,083,626	4
Los Angeles, CA	12,723,781	2	San Antonio, TX	2,057,782	8
Chicago, IL	9,384,661	14	Kansas City, MO	1,999,718	14
Dallas, TX	6,154,265	13	Las Vegas, NV	1,895,521	1
Philadelphia, PA	5,911,638	11	Columbus, OH	1,798,377	10
Houston, TX	5,709,313	9	San Jose, CA	1,793,888	2
Miami, FL	5,478,869	3	Indianapolis, IN	1,717,259	11
Washington, DC	5,416,691	24	Charlotte, NC	1,687,440	10
Atlanta, GA	5,125,113	29	Virginia Beach, VA	1,663,070	16
Boston, MA	4,489,250	7	Austin, TX	1,627,571	5
Detroit, MI	4,345,978	6	Providence, RI	1,602,822	6
San Francisco, CA	4,244,889	5	Nashville, TN	1,541,541	14
Riverside, CA	4,114,751	2	Milwaukee, WI	1,539,897	4
Phoenix, AZ	4,080,707	2	Jacksonville, FL	1,319,195	5
Seattle, WA	3,356,089	3	Memphis, TN	1,301,248	9
Minneapolis, MN	3,229,181	16	Louisville, KY	1,261,825	12
San Diego, CA	3,022,468	1	Richmond, VA	1,235,365	17
Saint Louis, MO	2,792,309	15	Oklahoma City, OK	1,218,920	7
Tampa, FL	2,745,350	4	Hartford, CT	1,203,823	3
Baltimore, MD	2,683,160	7	Buffalo, NY	1,137,266	2
Denver, CO	2,464,415	10	Birmingham, AL	1,115,485	7
Pittsburgh, PA	2,358,313	7	New Orleans, LA	1,105,020	8
Portland, OR	2,170,801	7	Salt Lake City, UT	1,090,848	2
Cincinnati, OH	2,110,398	15	Raleigh, NC	1,069,694	3
Sacramento, CA	2,107,092	4	Rochester, NY	1,049,836	6
Cleveland, OH	2,086,589	5			

* Population estimate from 2006-2010 ACS 5-year dataset (U.S. Census Bureau, 2010a).

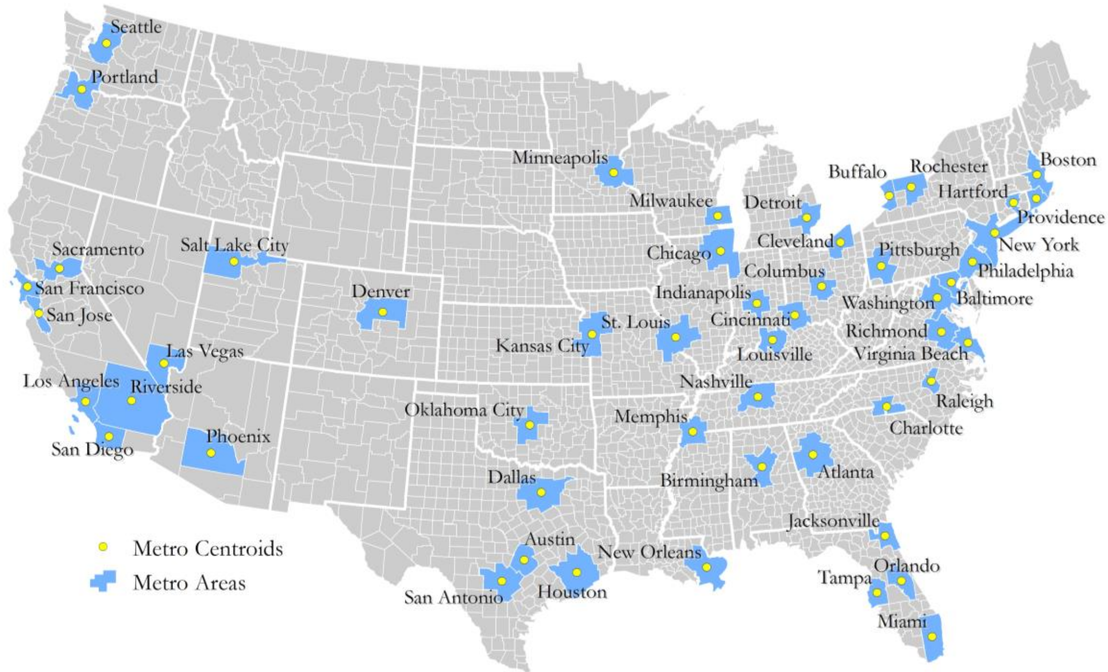

Figure 2. The 51 U.S. metropolitan areas with populations greater than one million. These cities are the analytical focus of this dissertation, and they are shown as areas and centroids.

Migration flows were obtained from the Census Bureau's county-to-county flow files, which are also derived from ACS data (U.S. Census Bureau, 2012b). These flow files provide migration estimates between all pairs of counties in the U.S. The Census publishes county-to-county flow files for 5-year periods: due to the ACS sampling scheme, only every five years is the entire coverage of U.S. guaranteed (U.S. Census Bureau, 2010c). These datasets present, in tabular form, the matrix of migration flows between all U.S. counties and Puerto Rico. Omitting Puerto Rico, Alaska, and Hawaii, the remaining dataset consists of the county-to-county flows for the 3,109 counties (or county equivalents) in the contiguous U.S.

Because the flows are published at the county level, metropolitan area migration flows are obtained by aggregating the county-level flows using the CBSA definitions.

This migration dataset is both the best available migration data for this time period, but is also limiting due to how it is tabulated. Because the dataset covers the five-year period, a migrant could move to a new destination only to return to their origin two years later, and (if they are captured in the sample) be twice counted as a migrant. While this is not necessarily problematic (they did in fact migrate twice), it does illuminate the potential concerns for migration calculations, as using this methodology for tabulating flows could yield total flows greater than total population (i.e., a single person can be counted in multiple flows if he migrates multiple times). This could yield migration rates that make little sense in the context of demographic variables. Additionally, while flows between large metropolitan counties are generally large enough to have relatively small margins-of-error, because the county-to-county flows are a product of the ACS sampling scheme, small counties can have migration margins-of-error greater than the flows themselves. For example, of the 12,858 origin-destination pairs representing in-migration to counties in the state of Florida, 10,252 of them have margins-of-error greater than the estimated flow value. This corresponds to 80 percent of observations. This is fairly representative of the entire dataset, as the overall percentage of margins-of-error greater than their corresponding flows is 82 percent.

Despite these accuracy concerns, the migration data provided by the U.S. Census is the most comprehensive dataset of its kind, and it has the added benefit of corresponding demographic variables that, for better or worse, have the same accuracy. All in all, any conclusions drawn from analytical results using these data should be done so with full understanding of the inherent limitations of the data.

3.1.3. Results

The Census ACS estimates 45,121,865 U.S. residents moved out of their county of residence during the 2006-2010 to become migrants. For the 3,109 U.S. counties and equivalents, the median total outflow was 3,407, with out-flows ranging from 5 in Loup County, NE, to 1,349,014 in Los Angeles, CA. The average out-migration rate across all counties was 0.140, or 140 out-migrants per 1000 county residents. Loup County, NE, also had the lowest out-migration rate with 0.008 (8 out-migrants per 1000 residents), while the highest out-migration rate was found in Treasure County, MT with 0.450 (450 out-migrants per 1000 residents). One county, McPherson County, NE, was estimated to have no out-migrants during the study period. Figure 3 maps the out-migration rates for all U.S. counties and county equivalents using Jenks Natural Breaks.

In-migration rates across the U.S. are considerably lower on average, indicating fewer 'big gain' counties (relatively speaking, as the rates are based on individual county populations). The average in-migration rate across the U.S. was 0.060 (60 in-migrants per 1000 residents), with the lowest rate at 0.001 (1 in-migrant per 1000 residents) in Liberty County, MT, and the highest rate at 0.460 (460 in-migrants per 1000 residents) in Chattahoochee County, GA. Figure 4 presents the in-migration rates for all counties and county equivalents using Jenks Natural Breaks. Out-migration and in-migration rates are positively correlated ($r = 0.46$), indicating that in- and out- rates are generally alike.

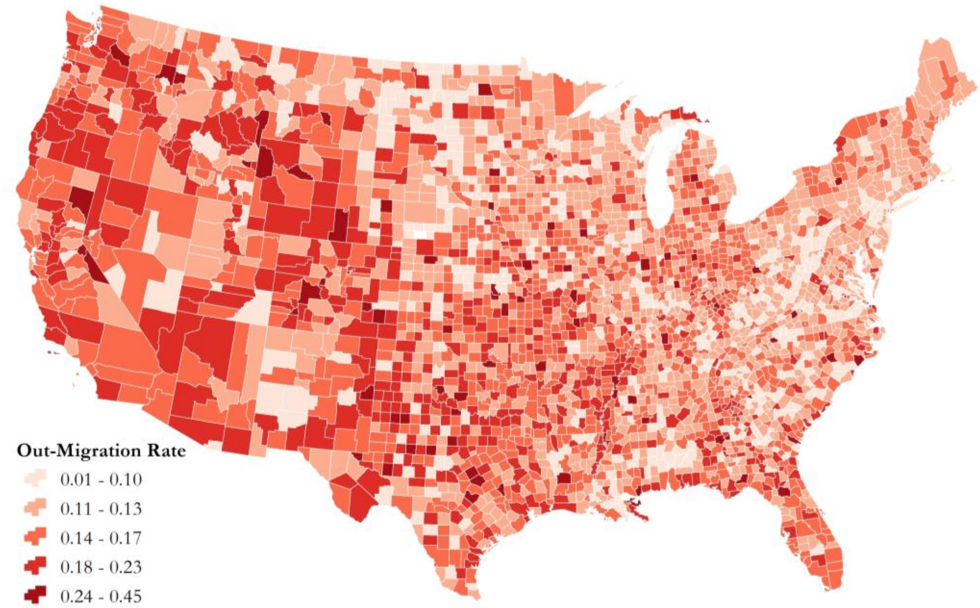

Figure 3. Out-migration rate for all U.S. counties, presented in five classes using Jenks Natural Breaks.

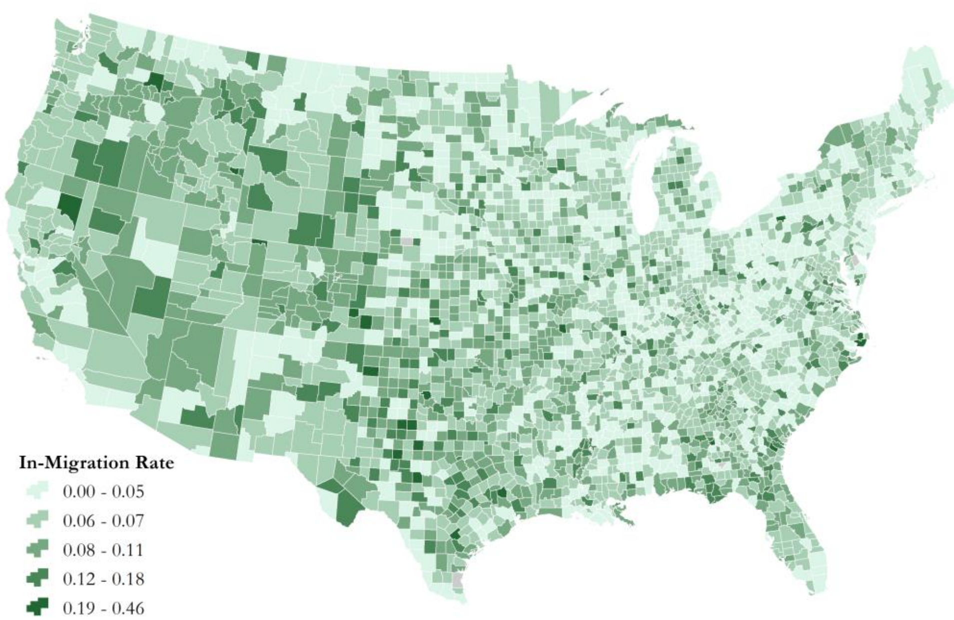

Figure 4: In-migration rate for all U.S. counties, presented in five classes using Jenks Natural Breaks.

There are a number of counties with statistically higher in- and out-migration rates, and a handful that are statistically higher in both categories. Defining high rates as those two standard deviations above the mean for in- and out-migration, 109 counties are high out-migration rate counties, and 123 are high in-migration rate counties. Thirty-eight of these high in- and out-migration counties are high in both categories, or 'high turnover' counties. Figure 5 show the high in-migration, high out-migration, and high turnover counties.

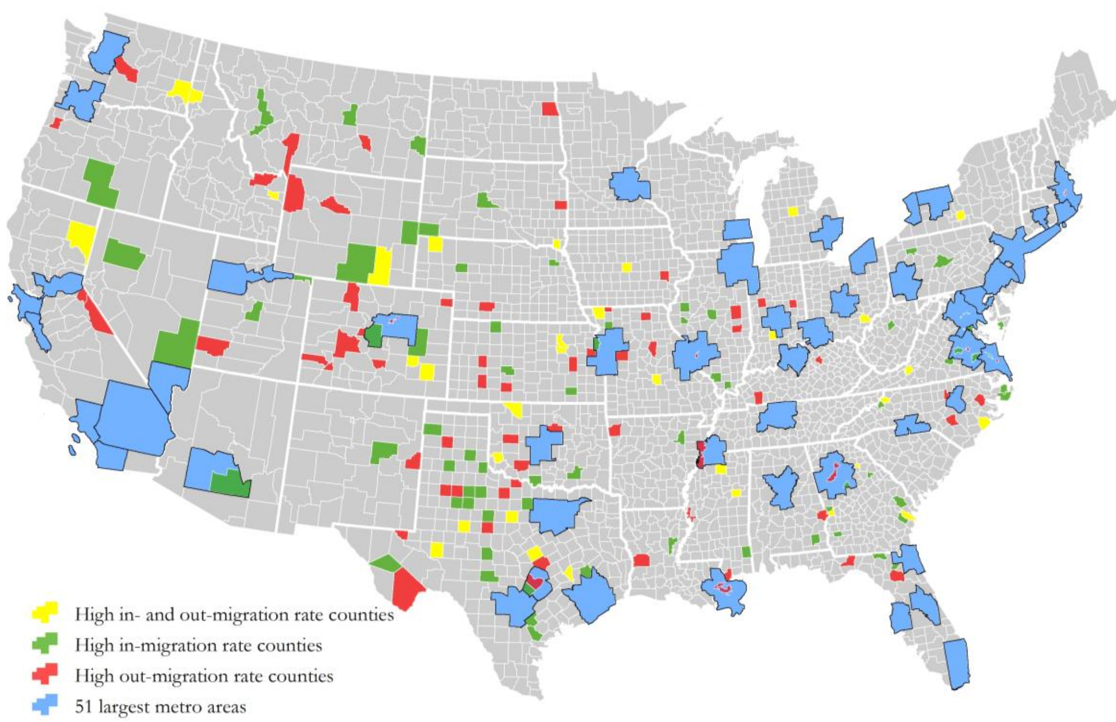

Figure 5. Counties with high in- and high out-migration rates with the 51 study cities.

Of these 232 high-rate counties, only 28 fall within the metropolitan bounds of the 51 study cities. Memphis, TN, New Orleans, LA, St. Louis, MO, and Boston, MA had high out-migration rate counties. Phoenix, AZ and Kansas City, KS had high in-migration rate counties. Denver, CO, Austin, TX, Atlanta, GA, Washington, DC, Richmond, VA, and Virginia Beach, VA all had at least one high in-migration rate county and one high out-migration rate county, indicating potential intra-city population shifts. None of the 51 metro areas include high-turnover counties. Thirty-four of the 109 high out-migration counties contain a metropolitan area (that is, any metropolitan area, including but not limited to the 51 metros associated with this research), indicating that a majority of high out-migration is associated with small cities, towns, and rural areas. Only nine of the 123 high in-migration rate counties contain a metropolitan area, again indicating that small cities and, potentially, rural areas, are associated with high in-migration.

While this does paint a partial picture of where the flows are leaving from and coming to, the high-rate areas are very much a function of their base population. Small counties in the Midwest and Western U.S. need only gain or lose a relatively small number of residents to get classified as a high-rate county. For example, Fallon, MT had an in-migration rate of 0.14, a significant outlier from the mean in-migration rate of 0.06. However, they received 361 migrants with a population of 2,612. Cumberland County, ME, on the other hand, received 17,776 migrants with a population of 276,946, yielding an in-migration rate nearly equal to the mean.

Moran's I tests for spatial autocorrelation show significant clustering of similar in- and out-migration rates for both counties and cities. Regardless of the conceptualization of spatial relationship (inverse distance weighting, inverse distance squared weighting, 5 or 10 nearest neighbors, or fixed distance bands at a range of distances up to 1500km), the spatial autocorrelation results are positive and significant. For county-level rates, the largest Moran's

I statistics are observed using the five nearest neighbor weighting. The Moran's I index value for county in-migration using five nearest neighbors is 0.156 (p-value = 0.000), while the index value for out-migration using five nearest neighbor weighting is 0.186 (p-value = 0.000). Assessing the Getis-Ord G statistic for county migration rates using five nearest neighbor weighting shows that the autocorrelation observed is associated predominantly with higher rates. The calculated G statistic for in-migration is small at 0.000335, but with a z-score of 12.268 it is highly significant (p-value = 0.000). Likewise, the G statistic for out-migration is 0.000327 with a z-score of 10.108, again indicating high-rate clusters predominate.

For metro-level migration rates, the largest Moran's I statistic for in-migration autocorrelation was observed with inverse distance squared weighting, followed very closely by five nearest neighbor weighting (I = 0.370 and 0.368, respectively, both p-value = 0.000). The five nearest neighbor weighting also produced the largest Moran's I for metro out-migration rates as well (I = 0.513, p-value = 0.000). Running the Getis-Ord G test on metro in-migration using the inverse distance square weighting provides some statistical evidence that high-rates cluster together (G(d) = 0.0209, p-value = 0.018). However when the G tests are performed on in-migration and out-migration rates using five nearest neighbor weighting, there is no significant evidence that clusters are high-rate (in-migration G(d) = 0.0205, p-value = 0.216; out-migration G(d) = 0.0201, p-value = 0.557). Overall, there is rather clear evidence that in-migration and out-migration rates are spatially autocorrelated – that is, the rates for a given location are likely similar to, and potentially influenced by, the rates at that location's neighbors. At both the county and metro levels, this is best captured by assessing values of the five nearest neighbors, however this is deduced from basic exploratory analysis and lacks a theoretical grounding. The full results of the Moran's I tests for all conceptualizations of spatial relationships are presented in the Appendix.

Analysis of the migration rates shows the findings of previous research regarding education and migration hold true during the 2006-2010 time period, although the variables are only moderately correlated. Table 2 shows the correlations and significance levels between county-level out-migration and education level for two age groups: 18-24 year olds and age 25 and over. Generally speaking, the greater educated a county's population, the higher that county's out-migration rate is likely to be. Among those aged 18-24, the dichotomy occurs between high school graduates with no college education (where there is a negative correlation to migration rate) and residents with some college or an Associate's degree (where there is a positive correlation). An interesting observation is there appears to be no correlation among the percent of 18-24 year olds with a Bachelor's degree and the migration rate, when the prevalent theory would suggest these new graduates would have many more employment opportunities available to them. This may be a symptom of the recession, during which employment opportunities for the young, including college graduates, greatly diminished (U.S. Bureau of Labor Statistics, 2010). These young college graduates may have been forced to return to their parents' home, or remain in their college town working a student job, while they searched for employment.

Among those aged 25 and over, the major dichotomy also appears to be between having only a high school diploma (negative correlation) and having college education (positive correlation). In this age group, Bachelor's and Graduate degrees have stronger (though still moderate) positive correlations with migration rate, which contrasts with the younger college-educated cohort.

Turning to age, previous research is shown to be supported over the 2006-2010 period. Assessing over five age groups, the propensity to migrate decreases with increasing age. The 18-24 year old age group is most strongly associated with high migration rates, while the 45-64 year old age group is least associated with high migration rate. This is as expected, as the conventional theory of age-related migration suggests high migration rate among young adults, steadily decreasing to retirement age, and with a slight up-tick as portions of the 65+ demographic relocate for retirement (Plane & Heins, 2003). The correlation coefficients for age are shown in Table 2.

As far as can be discerned from this data, there appears to be no relationship between the sexes and migration rate. Assessing by percent male and males per 100 females, the correlations are near zero. This is unsurprising, as only in outlier situations are there counties where sexes are not roughly evenly distributed. Given the relative small changes in gender ratio across space and the relative large changes in migration rate, the minimal correlation between the two variables is expected. This also falls in-line with previous research, which has failed to show any definitive link between gender and migration propensity.

Table 2. Correlations between migration rate for the U.S. Counties, and education levels, age levels, and gender.

Variable	Correlation
Education Level	
Age 18-24	

Variable	Correlation
No High School	–0.09 ***
High School	–0.20 ***
Some College/Associates Degree	0.22 ***
Bachelor's Degree	0.07 ***
Graduate Degree	N/A†
Age 25+	
No High School	–0.08 ***
High School	–0.34 ***
Some College/Associates Degree	0.11 ***
Bachelor's Degree	0.24 ***
Graduate Degree	0.29 ***
Age Group	
18-24	0.49 ***
25-34	0.30 ***
35-44	–0.11 ***
45-64	–0.36 ***
65+	–0.34 ***
Gender	
Male (percent)	0.02
Males per 100 Females	0.03

*** indicates significance at the 99.9 percent significance level with df=3,106. † indicates data not available.

Out-migration rates for the 51 metropolitan study areas ranged from 0.11 in New York, NY, to 0.22, in Las Vegas, NV. The average out-migration rate across the cities is 0.16. New York saw the largest number of residents move out of the metro area, with 1,980,258 leaving over the five year period. Buffalo had the lowest number of out-migrants, with 143,441. In-migration rates for the cities were much lower than out-migration, indicating significant net migration losses. New York had the lowest in-migration rate for the period with 0.012 and 230,838 in-migrants. Austin, TX, had the highest in-migration rate at 0.070 and 108,872 in-migrants. Figure 6 depicts the out-migration and in-migration rates, along with raw net-migration losses.

All 51 study cities experienced significant net domestic migration losses over the five-year period. The greatest losses were in New York, with estimated net losses of 1,749,420. Raleigh, NC, had the lowest net-migration losses with 92,777. The correlation between in- and out-migration rates is strongly positive ($r = 0.74$), indicating that, rather than a systematic realignment among migrants the 51 cities, these cities consistently received less migrants than they lost. Looking at the 51 cities in aggregate, 5,216,262 migrants arrived while 24,382,793 migrants departed, indicating a total net loss of 19,166,530 migrants among the 51 cities.

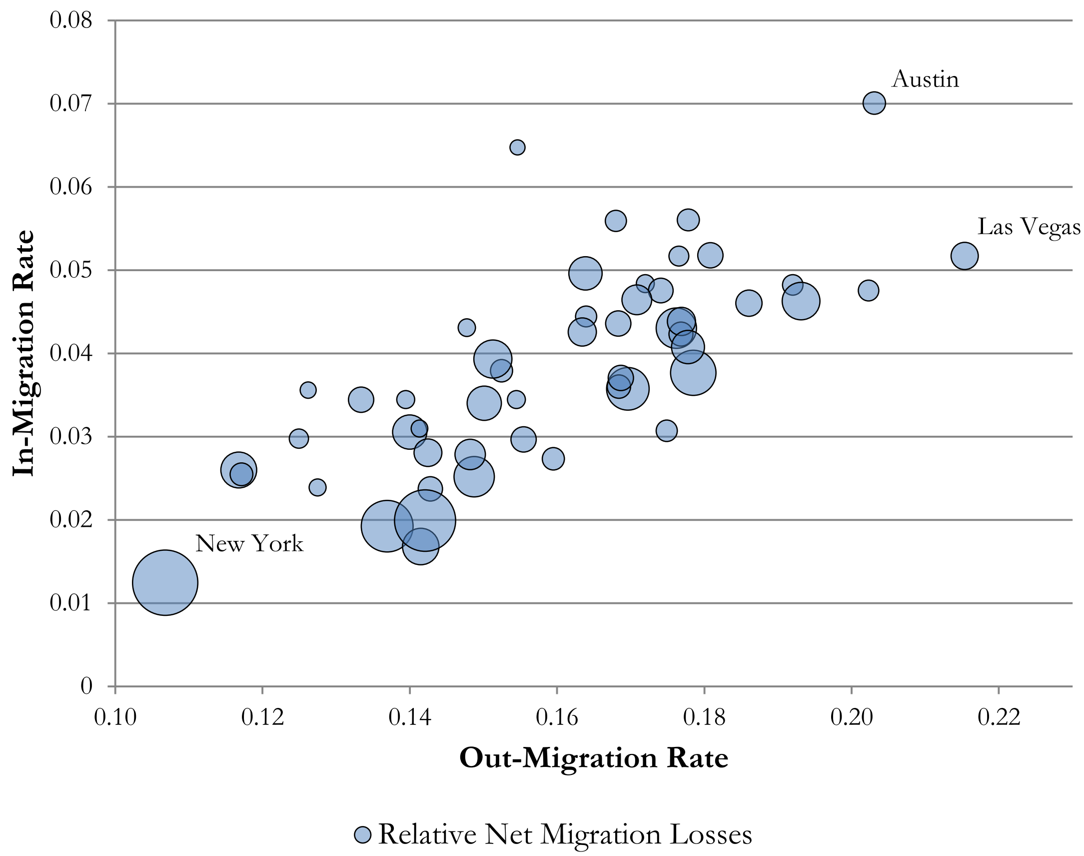

Figure 6. Chart of out-migration and in-migration rates, and raw net migration losses for the 51 study cities.

Because most migration occurs over short distances, any assessment of migration to cities should consider how much of the total migrant stock arrived from nearby locales. Given the infinite characterizations of 'nearby,' one useful distinction is a metropolitan area's exurban region. Davis et al. (1994) describe exurban areas as extending 60-70 miles outward from a city's circumferential highways; however, there is no official distinction of the exurban political units associated with each city by the U.S. Census. As rough approximation of Davis et al.'s (1994) definition, this research uses the non-metro counties contiguous to each metropolitan area as the exurban region. Migration from these counties into each metropolitan area could be accomplished by a short move over one county boundary into the city's suburbs, or a longer move into the central city.

Contiguous exurban counties account for 11.7 percent, on average, of the migrants coming into these 51 study cities, however there is a great amount of variation. At 1.3 percent, San Diego, CA, received the lowest percentage of its migrants from its exurbs, indicating more than 98 percent of the city's in-migrants were attracted from other cities or far-off rural areas. This is likely a function of the prominence of military residents in this metropolitan area, which would arrive from distant posts and bases throughout the world, and the fact that San Diego is surrounded by other cities (Riverside, CA; Los Angeles, CA) and only one county that is considered its exurbs. Hartford, CT, on the other hand, received a much larger share of migrants from its exurbs, with 36.2 percent. A potential influencing factor on flows from exurbs, and any migration flows for that matter, is the availability of affordable housing options in these metro areas. Housing costs are generally much greater in metropolitan than exurban areas and have been increasing in recent years. Incomes, on the other hand, while greater on average in metropolitan areas than in exurban areas, have not kept pace with housing increases (Quigley & Raphael, 2004).

When looking at metropolitan-level out-migration rates, the relationships with education, age, and gender offer an interesting contrast to the county-level relationships. Table 3 provides these correlations. Young high school dropouts have a relatively strong positive correlation with out-migration rates, as opposed to the minimal negative correlation between the two at the county level. While high school graduates in the 18-24 age range have a similar negative relationship between the two spatial units, the some college/Associate's degree variable has the opposite relationship. This is perhaps due to the high accessibility of educational opportunities in metropolitan areas, which most counties do not have. The percentage of Bachelor's degree holders is only slightly positively correlated with out-migration rates, which is in-line with the county-level correlations.

An interesting deviation occurs from the county-level correlations among the 25 and over age group in metropolitan areas. While high school dropouts and graduates maintain similar correlations, the some college/Associates degree cohort has a relatively strong positive correlation with high migration, while Bachelor's degree has no correlation and Graduate degree has a negative correlation. These values are contrary to the expected relationships, which are that more education increases the probability of migration. It is possible these unexpected relationships, opposite their normal direction, are a function of the recession. Employees with graduate degrees were less likely to be laid off during the recession than their lesser-educated counterparts (Farber, 2011), and given this modicum of stability in uncertain times they may also be less inclined to take new, higher risk employment opportunities. Employees with lesser education, such as those with high school diplomas or only some college, were more at risk for job loss (Farber, 2011). This group may have sought employment in other cities, and they may have pursued retraining/education opportunities (e.g., obtaining an Associate's or Bachelor's degree) to improve their chances of finding employment elsewhere.

Age has a similar relationship to migration rates in metropolitan areas as in counties. Rather than the correlations decreasing consistently across the age cohorts, however, the second 25-44 age group is more strongly associated with high migration rates than the 18-24 year olds. This may be an indication that the young, both higher and lesser educated, find their first jobs in the city where they were last educated, and once they have obtained experience and resources to enable a move away from the city (i.e., age 25-44), their chance of mobility increases.

The relationship between gender and migration rate is also significantly different at the metropolitan level than at the county level. The metropolitan percent male has a strong positive correlation with out-migration rate, suggesting that men may be more prone to migrating out of metropolitan areas than women.

Table 3. Correlations between out-migration rate for the 51 study cities, and education levels, age levels, and gender.

Variable	Correlation
Education Level	
Age 18-24	
No High School	0.49 ***
High School	–0.23
Some College/Associates Degree	–0.23
Bachelor's Degree	0.16
Graduate Degree	N/A †
Age 25+	
No High School	0.08
High School	–0.23
Some College/Associates Degree	0.58 ***
Bachelor's Degree	0.00
Graduate Degree	–0.38 **
Age Group	
18-24	0.26
25-44	0.45 ***
45-54	–0.59 ***
55-64	–0.45 ***
65+	–0.54 ***
Gender	
Male (percent)	0.61 ***

Variable	Correlation
Males per 100 Females	N/A †

*** and ** indicate significance at the 99.9 percent and 99 percent significance levels with df=49. † indicates data not available.

3.1.4. Discussion

Migration flows varied significantly across U.S. counties. While there is significant positive correlation between in- and out-migration rates among U.S. counties, few counties had excessively high rates. Of those that did, no broad spatial patterns were apparent, indicating the out-migration and in-migration rates are generally a localized phenomenon. Spatial autocorrelation tests indicate positive spatial autocorrelation of in- and out-migration rates, with higher rates predominating the county-level clustering. However, examination of high in- and out-migration rate counties (defined by rates greater than two standard deviations from the mean) indicates a relatively uniform dispersal of these counties across the U.S. A majority of high in- and out-migration migration counties were not a part of any metropolitan areas, indicating small cities are rural areas are both losing and gaining larger proportions of their populations to migration their large city counterparts.

The current trends observed in migration do not contradict traditional migration theory when viewed at the county level. The analytical results, however, suggest that metropolitan migration may operate under a different set of norms than migration overall. Metropolitan migration differs in its relationship to education levels and gender ratio, while age-specific correlations are roughly similar. This is an important discovery for it signifies the potential ecological fallacy of inferring a particular set of migration dynamics observed at the county level are present and apply among inter-city movements. Additionally, these results imply the migration push and pull factors that impact the decision to migrate and destination selection may vary by the scale at which the analysis takes place. Migration scholars should be careful to not assume, or posit, ubiquitous relationships between migration-related variables based on a particular scale of analysis.

These results, while important and illuminating, must be caveated by the limitations of the data used to derive them, particularly in light of the previous discussion of the margins-of-error associated with the migration estimates. Given both the benefits and drawback of this data, research of this kind should be continually undertaken using annually updated migration datasets (the U.S. Census Bureau only recently began publishing these 5-year county-to-county migration flows) to confirm and refine the findings of this research regarding the qualitative differences in migration at the county and metro scales.

3.2. Spatial Interaction Regression

The migration rates discussed in the previous section are indications of the proportions of people are leaving origin counties or cities, and the proportions of people arriving in counties or cites. Rates, however, speak nothing to where the people who arrive in a particular destination originated from, or what characteristics about that destination may have pulled them to it. For a given destination, people will arrive from both near and far origins, and generally speaking the smaller the volume of migrants from far-off origins, the larger the destination's distance decay parameter will be. The distance-decay parameter represents the friction associated with moving to or away from a place or set of places. In the case of estimating distance-decay parameters for destinations, it represents the ease of migrating from any origin to the destination. As such, distance-decay is a function of the attractiveness of a place: a place with wider attraction has a smaller distance-decay parameter, and vice versa. Identifying the characteristics that drive distance-decay variation, then, is akin to explaining the elements of attraction for a given flow of migrants.

This process is grounded in the assumption that distance-decay is non-stationary across space. Global spatial interaction models assume a fixed relationship between all variables, including distance decay, between all places. The concept that relationships vary over space is not a new one and there are many statistical methods that attempt to address this, such as geographically weighted regression (GWR) and the spatial expansion method, through locally weighting points and curve-fitting methods (Fotheringham, Brunsdon, & Charlton, 2002). While these methods are robust at their intended purpose, their assumptions about spatial relationships and methodologies do not fit the goals of this research. GWR estimates local variable coefficients: a unique coefficient is estimated for each independent variable at each sample point, by utilizing and weighting some set of nearby points (Brunsdon, Fotheringham, & Charlton, 1996). The spatial expansion method assumes variation over space, but simply as a function of space itself and not the distance between places or interaction between them (Foster, 1991). Additionally, the set of measured variables associated with each local estimation, while they may vary due to inclusion or exclusion, do not vary in value. With spatial interactions, however, each estimation point possesses a different set of distances which influence the amount of interaction, which is the dependent variable. Thus, GWR methods are not wholly applicable in this situation.

Geographic distance is a fixed property between all cities, but it is the impact of distance that is variable. As the attractiveness of a city increases so too do the migrant flows to it, indicating a reduced cost of distance. It is this relationship between attraction and space that will be modeled. Attractiveness of a destination has previously been modeled using regression forms of the gravity model. Tobler (1979) estimated destination attractiveness utilizing net migration at each place (rather than actual flows), but assumed a constant distance decay over space. Baxter and Ewing (1981), Tobler (1983), and Fotheringham (2000) relate the log-linear regression constant to destination attractiveness, and they derive the attractiveness by interpreting the coefficients of dummy variables. While their models provide a novel estimation of relative attractiveness, their origin-specific models ignore the relationship between distance, spatial structure, and attractiveness, and they consequently disregard the distance friction parameter derived via the regression.

A two-stage process is employed in which (1) a spatial interaction model is used to derive the distance decay parameters for each city using Poisson regression (Fotheringham & O'Kelly, 1989), and (2) regression is used to estimate the contribution of a set of variables to these friction factors. Each of these steps will be addressed in the next two subsections. The distance coefficients estimated from the first model serves as the dependent variables of the second model.

3.2.1. Methods

3.2.1.1. Deriving the distance decay parameter

The base regression form of the gravity spatial interaction model is used to derive a distance decay parameter for each of the 51 U.S. metropolitan areas with populations over 1 million. The model is formulated such that the destinations are these 51 cities. The model is run over three sets of origins: (1) the 51 largest cities (i.e., the destinations are the same as the set of origins), (2) all U.S. counties (excluding Alaska and Hawaii, because their distances travelled to the 51 cities will bias the decay estimates), and (3) all U.S. counties, excluding those contiguous to the destination metropolitan areas. Multiple origins are used for two purposes. First, there is a desire to determine if the second model is equally appropriate for modeling distance decay for the two separate types of origins (cities and counties). Results from the analysis of migration propensities indicate there may be significant differences in the demographics of migrants when viewed at difference scales – county versus metropolitan area. If this is true, it is important to test whether the destination-based pull factors apply equally to migrant pooled based on metropolitan area origins, and migrants leaving from individual counties. Second, it is important to test if there is a local-move bias from the inclusion of flows from counties contiguous to the metro areas. There may be residents in these contiguous counties that are making short-distance residential moves into the metropolitan area, while keeping the same employment, and thus whose status as a migrant may bias the distance decay calculation. Because moves from a contiguous county across one border into the metro area outskirts and a move to the city center are both considered migration, an additional analysis is performed of the flows into a metropolitan area, omitting those from contiguous counties.

The in-migration for a metropolitan area is calculated as the sum of the flows from all U.S. counties $i = 1, 2, \ldots, n$ into each county j that composes the metro area. Distances are calculated as the Euclidean measure between the destination metro area centroid, and the origin unit centroid (that is, metro area centroid for metro origins, and county centroids for county origins). While this is a somewhat crude measurement of the distance between two areas, it is conventional within the migration literature and should prove satisfactory given the national scale of this analysis.

The traditional migration gravity model is formulated such that the amount of migrant flow between two areas is a function of the product of the relative attraction of each place moderated by their distance from one another. This research employs a variant of the traditional model, the destination-specific attraction-constrained (DSAC) gravity model (A. G. Wilson, 1971). Destination-specific gravity models are formulated to model the flow into a single destination from all origins, rather than all destinations; it is used here because the concern of this analysis is the distance-decay parameter associated with each destination. Attraction-constrained models have been shown to provide more accurate estimates of spatial interaction and the role of distance than production-constrained or unconstrained models (Fotheringham & O'Kelly, 1989; Tobler, 1983). AC models conserve in-flow to the destination through a balancing factor that satisfies the constraint $\sum_{j=1}^{n} \widehat{T_{ij}} = \sum_{j=1}^{n} T_{ij}$. The balancing factor, B_j, is generally formulated as:

$$B_j = \frac{1}{\sum O_i / d_{ij}}$$

where B_j is the total migration in-flow to destination j, O_i is the total out-migration from origin i, and d_{ij} is the distance between the origin and destination. The denominator is summed across all origins.

Following Fotheringham's (1983) competing destinations model, an accessibility measure will be included to address the effects of spatial structure on migration. Controlling for the accessibility of the origins reduces the chance of misspecification of the distance parameter estimates (Fotheringham, 1981). Contrary to Fotheringham's concern with the arrangement of destinations for an origin-based model, the concern here is with the arrangement and accessibility of the origins. Origins arranged in an agglomeration are more accessible to destinations than more isolated origins (i.e., there are many more nearby intervening opportunities). This accessibility influences the interaction in the system and biases the distance-decay parameters. The accessibility measure for an origin relative to a destination is defined as (Fotheringham, 1983):

$$A_{ij} = \left(\sum_{\substack{k=1 \\ k \neq i}}^{n} m_k / d_{ik} \right) - m_j d_{ij}$$

where m_j and m_k are the mass (population) of destinations j and k, respectively, and d_{ik} and d_{ij} are the distances between the origin and those destinations. It is important to note that the summation is across all possible destinations from the origin, rather than a smaller number of flows that may actually exist. Thus, m_k is summed across the 50 potential destination cities, even if a particular origin city or county did not send flows to that destination.

Combining these elements, the destination-specific attraction-constrained competing destinations (DSACCD) model is formulated as:

$$T_{ij} = D_j B_j A_i^{\delta} m_i^{\lambda} d_{ij}^{\beta}$$

where the terms are defined as:

D_j – mass (total inflow) of the destination j

B_j – balancing factor for destination j

A_i – accessibility measure for origin i

m_i – mass (total outflow) of the origin i

d_{ij} – distance between origin i and destination j

δ – parameter indicating the effect an origin's accessibility on the migration out-flow (expected negative sign; more accessible origins will interact proportionately less with any destination)

λ – parameter indicating the effect of the origin's population on the migration out-flow (expected positive sign; larger populations have a larger migrant stock)

β – parameter indicating the strength of distance-decay on the flow between i and j (expected negative sign; greater distances impose more friction, restricting interaction)

The gravity model can be estimated using standard linear regression and other regression methods, however studies have shown that modeling migration spatial interaction as a Poisson process yields superior model results and eliminates some biases inherent in ordinary least squares (OLS) model calibration (Flowerdew, 2010; Fotheringham & O'Kelly, 1989). Therefore, the spatial interaction models in this research are calibrated using Poisson regression and MLE with a log-link, following Flowerdew and Lovett (1988).

The DSACCD gravity model above is still in a relatively general form. Other examples in the literature incorporate specific variables of attraction or repulsion to account for age, education, and economic conditions within an origin (given this is a destination-specific model, all variables describing the destination are constant). Because the concern of this research is the distance-decay parameter and not an accurate estimation/prediction of migrant flow (which has regardless been controlled for by utilizing an AC model), the model is employed in its above form, using total outflow of the origin as the mass variable. Table 4 presents the model's independent variables, with the expected sign and significance of each.

Table 4. Spatial interaction variables and their expected sign and significance.

Variable	**Description**	**Expected sign and significance**
Balancing Factor	Balancing factor ensuring flow constraint is met	N/A
Accessibility	Measure of the accessibility of each origin	(–), significant
Mass	Population of each origin	(+), significant
Distance	Distance between origin county or metro area and destination metro area	(–), significant

Because the model is executed over three sets of origins, the result will be three sets of distance decay parameters. The first set will represent the friction of distance to the destination from any of the other 51 cities in the study set. This set of values will represent the relative attractiveness of each city for inter-urban migration. The second and third sets of distance-decay parameters will represent the friction of distance to the destination from any county in the U.S.

As mentioned above, the majority of spatial interaction literature assumes spatial non-stationarity for distance decay. Testing for non-stationarity of the distance-decay parameter is done with the non-stationarity test from the GWR literature (Brunsdon, Fotheringham, & Charlton, 1998). This method compares the standard error of the estimated global distance decay parameter with the standard deviation of the estimated local distance decay parameters. A ratio is taken of the two variance measures ($\sigma_{\beta_i}/SE_\beta$) such that values close to unity indicate a stationary distance decay, while large values indicate a non-stationary process.

3.2.1.2. Explaining distance-decay parameter variation

A tenet central to this research is that the variation in distance decay parameters among a set of destinations highlights the variation of their success as centers of attraction for migrants. Each city brings a unique combination of social and economic characteristics that define its place utility uniquely for each migrant. By controlling for origin push and accessibility within a destination-specific model, the distance decay coefficient inherits the endogenous elements of attraction evaluated by the pool of migrants flowing to the city.

Assessing these distance decay parameter estimates together, common threads among these elements of attraction can be identified: this is done by assessing the socio-economic aspects of cities.

A multivariate OLS regression is used to quantify the role and significance of metropolitan characteristics influencing distance decay. Tests for spatial dependence in the residuals are performed using Moran's I (Anselin, 1988). Multiple representations of relationships will be used to test to ensure any spatial pattern present is identified and explored. These neighbor relationships include: inverse distance weighting, inverse distance squared weighting, five nearest neighbors equally weighted, ten nearest neighbors equally weighted, and fixed distance bands for all neighbor cities within 500km, 1000km and 1500km. If the Moran's I results indicate significant spatial dependence, the model should be executed as a spatial lag or error regression. The absolute value of the distance decay coefficients derived from the DSACCD model is the dependent variable in the regression. The independent variables are a set of economic and social characteristics for each city. These are discussed below.

(1) The population of the metropolitan area is included to control for endogenous and exogenous characteristics of the city. City population or size is regularly interpreted as a surrogate for other attraction measures in gravity modeling and is generally highly correlated with migrant flow volume. Rather than the total city population, the age 16 and over population is used, as these are the major contributors to metro economy and culture. Because the goal is to explain the distance-decay variation, the below variables should remove the endogeneity of this relationship. Thus, while it is expected the coefficient on this

variable will be negative (i.e., larger populations lead to lower distance decay), the relationship is expected to be insignificant and captured by other variables. A significant negative relationship would indicate that the size of the city is a driving factor in the attractiveness of a city, as interpreted through distance-decay.

Several economic measures of the city are included. These variables allow me to quantify the impact of each on the overall attraction of the city to migrant, and taken together the role of economic characteristics as a whole. (2) Median gross rent for the metropolitan area is included to assess the cost of housing on attractiveness. Housing costs have been shown to have a varying relationship with migration: some studies suggest there is no relationship (Berger & Blomquist, 1992; Nord, 1998), while others show a positive (Cameron & Muellbauer, 1998) or negative relationship (Hailu & Rosenberger, 2004). This variable should have a positive coefficient and be significant, as higher housing costs should lower the attractiveness of the destination. This variable is logged to reduce heteroskedasticity. (3) Variance of the gross rent within the metropolitan area is also included. This is calculated as the coefficient of variation (CV) for the county-level gross rents within the metropolitan area. As discussed in Section 3.1, metropolitan housing costs have continued to rise while income growth has not kept pace. This variable tests whether metropolitan areas with a greater range of housing options (i.e., a larger variance indicates regions in the metro area with more affordable housing, while also have areas with more extravagant housing) have higher attraction than areas with more uniform rent levels. This variable should have a significant negative relationship, as more rent variance should make a destination attractive to a broader range of migrants.

Three unemployment rates for the metropolitan area are included: (4) white unemployment, (5) Hispanic unemployment, and (6) African-American unemployment. Unemployment rates have generally been shown to have little effect on the aggregate migration to a city (Greenwood, 2001), but this may be masked within and a function of urban accessibility: an accessible city with high unemployment rates for a given demographic may not deter migrants because of the perceived ability to have a larger search area for employment in the new city. Given that accessibility has been controlled for when determining the distance-decay parameters, unemployment may yield a positive relationship to distance decay, particularly in light of the large employment losses that occurred during the Great Recession.

(7) Per capita income (PCI) is included, as well, to test whether higher-income metropolitan areas, all other things being equal, are more attractive than lower-income metropolitan areas. Overall earnings differentials between origins and destinations have been shown to effect migrant flows (Berger & Blomquist, 1992), so it is expected that earnings has a positive relationship on the overall attractiveness of the city, and thus a negative relationship with distance decay.

The culture of an area is also an important attraction for some migrants (Manson & Groop, 2000). While the primary decision for migration is typically economically rooted, the cultural aspects of the destination may be significant pull or push factors. Three variables are included to capture this cultural effect: (8) Florida's Bohemian Index (Florida, 2002a) (9) the percent foreign-born of the metropolitan area, and (10) the diversity of the city's foreign-born population. These three variables represent a multicultural attraction of a city. The

Bohemian Index for each city is an aggregated location quotient for the 'bohemian' occupations. These occupations are authors; designers; musicians and composers; actors and directors; craft-artists, painters, sculptors, and artist printmakers; photographers; dancers; and artists, performers, and related workers (Florida, 2002a). Following Ottaviano and Peri (2006b), foreign-born diversity of the city is calculated using an index akin to the Gini-Simpson diversity index (Jost, 2006), which represents the probability that any two individuals selected from the foreign-born population have different countries of birth. Diversity is calculated as

$$D = 1 - \sum_{i=1}^{n} p_i^2$$

where p_i is the proportion of the metro area's foreign-born population that is born in country i, and $i = 1, 2, \dots, n$ is a list of 133 potential countries of origin and 'other' categories provided by the data. The diversity index has a range of 0 to 1, where an index value of 0 indicates all of the foreign-born were born in the same country and a value of 1 indicates perfect dispersion across all countries. The Bohemian Index has been linked to high economic growth, employment, and population growth (Florida, 2003), but it has also been shown that more ethnically diverse cities have experienced negative net migration (Ellis & Wright, 1998; Frey, 1996). While it is unlikely that any potential migrant would make his selection decision based upon these qualities, they together represent an overall level of cultural opportunity that should increase a city's attractiveness. It is expected that each of these will have a negative relationship with distance decay.

Education levels in an area are a driving force behind economic growth (Acs & Armington, 2004), but also an indicator of the potential criminal activity (Thornberry, Moore, & Christenson, 1985). Three education measures for each city: (11) the percent of population 25 and over with no high school diploma, (12) the percent of the population 25 and over with only a high school diploma (i.e., no college degrees), and (13) the percent of the population with graduate degrees. It is hypothesized that more educated cities will be more attractive to migrants, and thus distance decay is expected to have a negative relationship with the percent of high school dropouts, and a positive relationship with the percent of high school graduates and graduate degrees.

An analysis of migration determinants and elements of attraction would be incomplete without an assessment of the employment structure of the cities, especially given the period of analysis spans America's Great Recession. Unemployment due to the recession of 2007 to 2009 was not equally dispersed across the economy: the construction and manufacturing industries were much more severely affected than other industries (U.S. Bureau of Labor Statistics, 2010) and also slower to recover than other sectors (Levine, 2012). Additionally, a select group of the service sectors experienced significantly higher job loss than the rest (U.S. Bureau of Labor Statistics, 2011). To ensure the employment structure and the impact of the recession on sector employment are accounted for, the percent employment in three sector categories is used: (14) major employment losses: construction and manufacturing sectors; (15) moderate employment losses: wholesale trade, retail trade, transportation and warehousing, information, financial, and professional services sectors; and (16) employment gains: health care and education sectors. Table 5 shows the sectors that comprise each of these variables and their employment outcomes during the recession. Positive relationships are expected for construction/manufacturing employment and service employment: cities with greater employment in these areas likely deterred in-migration due to the recession's impacts on these industries. Conversely, a significant negative relationship between education/health employment and distance decay should manifest. It is hypothesized the growth experienced by these sectors during the recession attracted extra migrants to these cities, driving down distance decay.

Table 5. The employment structure categories and employment growth of economic sectors during the recession with their NAICS codes (U.S. Bureau of Labor Statistics, 2011).

Major Emp. Loss		**Moderate Emp. Losses**		**Employment Gains**	
Sector	**Emp Change**	**Sector**	**Emp Change**	**Sector**	**Emp Change**
Construction (23)	–19.8%	Wholesale Trade (42)	–7.6%	Education and Health Care (61-62)	+3.3%
Manufacturing (31-33)	–14.6%	Retail Trade (44-45)	–6.7%		
		Transportation and Warehousing (48-49)	–7.3%		
		Information (51)	–7.6%		
		Financial (52)	–5.8%		
		Professional Services (53)	–8.9%		

Lastly, Census migration data have shown that U.S. migration trends over the past several decades have been to areas with warmer climates (Greenwood, 1985). To control for this phenomenon, and to quantify the effect of climate on attraction, (17) the variance of monthly mean daily temperatures and (18) the average annual precipitation for each metropolitan area are included. It is hypothesized that both variables will have a positive effect on distance decay; that is, greater temperature variance and higher precipitation levels will lead to greater distance decay values.

The independent variables are presented in Table 6 with an expected sign and significance.

Table 6. Independent variables for distance-decay parameter regression.

Variable	**Description**	**Expected sign and significance**
Population	Population 16 and over for the metropolitan area	(–), insignificant
Rent	Log of the median gross rent dollar value	(+), significant
Rent Variance	Coefficient of variation of the county-level median rent dollar values within each metro area	(–), significant
Unemployment – White	White unemployment rate	(–), insignificant
Unemployment – Hispanic	Hispanic unemployment rate	(–), insignificant
Unemployment – African American	African-American unemployment rate	(–), insignificant
*Income –PCI **	Log of per capita income for the metro area	(–), significant
Diversity – Percent Foreign-born	Percentage of population that is foreign-born	(–), significant
Diversity – Bohemian Index	Measure of the quantity of artistic occupations in the city	(–), significant
Diversity – Origins	Origin diversity index value of the foreign-born population	(–), significant
Education – No HS	Percent of the population age 25+ with no high school diploma	(+), significant

Variable	Description	Expected sign and significance
Education – HS	Percent of the population age 25+ with only a high school diploma	(–), insignificant
Education – GD	Percent of the population age 25+ with a graduate degree	(–), significant
Employment – CM	Percent of population employed in construction and manufacturing sectors	(+), insignificant
Employment – SS	Percent of population employed in select service sectors.	(+), insignificant
Employment - EH	Percent of population employed in education and health care sectors.	(–), insignificant
Climate – Temp. Variability	Variance of the monthly average temperatures	(+), significant
Climate – Precip.	Total annual precipitation	(+), significant

* Multicollinearity tests indicated ethnically disaggregated per capita income variables should be adjusted to a single variable.

3.2.2. Data

This portion of the dissertation utilizes multiple data sources to assemble the needed data for analysis. Census county-to-county migration flow files for 2006-2010 (U.S. Census Bureau, 2012b) as the migration data source, as in the previous section. This data is used to estimate the distance-decay parameter for each city. The Census migration data are aggregated from the Census ACS surveys and are published as a 5-year dataset to provide seamless geographic coverage of the U.S. The migration flows represent an estimate of the number of movers between any two counties over the 5-year period. As mentioned above in Section 3.1, this dataset is both limiting and the best available migration data for this time period. If they are captured by the ACS sample, a migrant can be counted more than once in the dataset – if they make more than one migration (e.g., chain migration) or if they return to their original origin (e.g., return migration). While this is not necessarily problematic if the person is in fact migrating multiple times, using this methodology for tabulating flows could yield total flows greater than the total population.

Of more concern with this dataset are the margins-of-error associated with the inter-county flows. Also described above in Section 3.1, over 80 percent of the origin-destination pairs in this dataset have margins-of-error greater than their associated flows. These large (relatively speaking) margins-of-error are predominantly associated with smaller-sampled origin-destination relationships, and thus the flows between large metropolitan areas generally have margins-of-error smaller than the flows. Despite this, a portion of this section of the dissertation research uses inflows from non-metro origin counties which, in many cases, have margins-of-error greater than the flows themselves. This is an inherent limitation of this dataset that must caveat any conclusions drawn upon these analyses.

Because the Census migration flows are at the county level and this research's interest is a distance-decay parameter for the metropolitan area, the flows of the counties that compose each of the largest U.S. metropolitan areas are aggregated to determine a flow estimate for the city. These metro areas are identified, as in the previous section, as those with a population of one million or greater, as estimated by the 2006-2010 Census ACS 5-year estimate. This dataset was chosen for the population estimate because it provides a more reliable estimate for the migration period (2006-2010). For the full list of 51 cities, their populations, and the number of counties composing each, refer to Table 1 in section 3.1.2.

An added benefit of utilizing the ACS 5-year migration data is it corresponds to the 2006-2010 ACS 5-year demographic dataset. This dataset is utilized to obtain the demographic and economic variables for the OLS regression: rent, unemployment levels, income levels, diversity levels, education levels, and employment levels (U.S. Census Bureau, 2010a). The National Oceanic and Atmospheric Administration's (NOAA) National Climatic Data Center (NCDC) is the source of the temperature and precipitation data. The NCDC climate normals are the source dataset for these variables, which are the expected monthly mean temperatures and annual precipitation averages, as calculated from observations over 1981-2010 (National Climatic Data Center, 2011).

This research does not temporally lag the socioeconomic data serving as pull factors for the migrants because of the temporal scale of the ACS datasets, from which the migration flows and socioeconomic variables are derived. Because that the flows represent five-year aggregates, they span multiple socioeconomic lags. There is no conventional lag period for modeling multi-year migration flows. Data corresponding to the regional and metropolitan scope of this analysis is also limited, with only one earlier ACS 5-year dataset than the one used here (the 2005-2009 dataset). While this dataset could have been used for the socioeconomic variables, given the end of this dataset corresponds to the peak of the Great Recession, there is risk that the behaviors of the migrants who moved in late 2009 and 2010 may not be represented in the demographic dadta. These migrants are captured in the 2006-2010 migrant flows, and their mobility may be inaccurately modeled due to changes in the socioeconomic variables due to the partial recession recovery in 2010. It is for these reasons no temporal lags were used in this analysis.

3.2.3. Results

The results show significant local variation in distance decay parameters, and that the parameters associated with metro-to-metro flows are well explained by the city-level socioeconomic factors included in the second model. County-to-metro flows are not well-modeled, but the variables that significantly impact distance decay at the metro-level are identified. An overview of the distance decay variation calculated from the DSACCD model is presented first. The second-stage socio-economic model results follow, and they show that distance decay parameter, as a measure of attraction, is influenced by unemployment, diversity, education, industry, and climate of the metropolitan area.

3.2.3.1. Local variation in distance decay

The DSACCD model reveals significant spatial variation in distance decay among the 51 destination cities. For metro-to-metro flows, the distance decay parameters ranged from –2.08 for New Orleans, LA to –0.43 for Pittsburgh, PA. County-to-metro flows yielded a different distribution of distance decay parameters, both from each other and the metro-to-metro flows. The estimated distance decay parameters with the contiguous counties included range from –1.55 for Riverside, CA, to –0.41 for Atlanta, GA. Excluding the flows from counties contiguous to each destination metro area, distance decays range from –1.24 for Rochester, NY, to –0.20 for Atlanta, GA.

There is minimal correlation between metro-to-metro distance decay estimates and the county-to-metro estimates (Pearson's $r = 0.10$ for all county flows, $r = 0.28$ for non-contiguous flows). However, there is strong correlation between the two county estimates, with $r = 0.78$. Despite the strong correlation between the two county-to-metro flows, rank tests indicate the distributions are significantly different. Table 7 shows the estimated distance decay parameters for each destination city with their rank from least to most negative. Table 8 presents the Wilcoxon signed-rank test statistics for comparing the three decay distributions. The Wilcoxon test assesses the distribution of two paired observations, with the null hypothesis that the distributions are the same (Wilcoxon, 1945). Wilcoxon test results show all pairs of distance decay parameters are significantly different. This significance is important and validates the evaluation of both sets of county-to-metro flows, because this indicates significantly different migration drivers for each of these flows.

Table 7. Distance decay parameter estimates for the three sets of flows analyzed.

City	**Metro-to-Metro Flows**		**County-to-Metro Flows**		**County-to-Metro Flows (no contiguous flows)**	
	Parameter	**Rank**	**Parameter**	**Rank**	**Parameter**	**Rank**
Atlanta, GA	–0.89	12	–0.41	1	–0.20	1
Austin, TX	–1.26	36	–0.80	16	–0.80	30
Baltimore, MD	–1.65	50	–1.38	49	–0.78	26
Birmingham, AL	–1.30	38	–0.97	29	–0.70	18
Boston, MA	–0.93	16	–1.12	38	–0.73	24
Buffalo, NY	–1.49	45	–1.07	36	–1.03	46
Charlotte, NC	–1.21	32	–0.67	8	–0.55	10
Chicago, IL	–0.63	4	–0.56	4	–0.42	3
Cincinnati, OH	–1.16	28	–0.85	20	–0.56	11
Cleveland, OH	–1.17	31	–1.41	50	–0.98	42
Columbus, OH	–1.64	49	–1.15	40	–1.08	48
Dallas, TX	–1.05	21	–0.67	7	–0.62	16
Denver, CO	–0.74	6	–1.06	35	–0.58	12
Detroit, MI	–0.73	5	–1.37	48	–0.79	28
Hartford, CT	–1.00	19	–1.14	39	–0.71	21
Houston, TX	–1.16	30	–0.82	19	–0.75	25
Indianapolis, IN	–1.29	37	–1.00	30	–0.88	38
Jacksonville, FL	–1.05	22	–0.59	5	–0.51	8

City	Metro-to-Metro Flows		County-to-Metro Flows		County-to-Metro Flows (no contiguous flows)	
Kansas City, MO	–1.13	24	–0.75	13	–0.55	9
Las Vegas, NV	–0.61	3	–0.80	17	–0.70	19
Los Angeles, CA	–0.92	13	–0.95	28	–0.78	27
Louisville, KY	–1.22	33	–0.76	14	–0.61	15
Memphis, TN	–1.35	41	–0.51	3	–0.38	2
Miami, FL	–1.33	40	–0.91	26	–1.01	45
Milwaukee, WI	–1.23	34	–1.17	41	–1.01	44
Minneapolis, MN	–1.37	42	–0.72	10	–0.58	13
Nashville, TN	–1.09	23	–0.63	6	–0.46	5
New Orleans, LA	–2.08	51	–0.81	18	–0.79	29
New York, NY	–0.88	11	–1.00	31	–0.85	35
Oklahoma City, OK	–1.50	46	–0.91	25	–0.70	20
Orlando, FL	–1.16	27	–1.02	33	–0.89	39
Philadelphia, PA	–0.92	14	–1.24	46	–1.12	49
Phoenix, AZ	–0.46	2	–1.21	44	–1.03	47
Pittsburgh, PA	–0.43	1	–0.73	12	–0.49	6
Portland, OR	–0.94	17	–0.87	21	–0.87	37
Providence, RI	–1.46	44	–1.19	43	–0.91	41
Raleigh, NC	–1.15	26	–0.90	24	–0.71	22
Richmond, VA	–1.62	48	–0.92	27	–0.86	36
Riverside, CA	–1.16	29	–1.55	51	–0.91	40
Sacramento, CA	–1.52	47	–1.23	45	–1.24	51
Salt Lake City, UT	–1.31	39	–1.06	34	–1.16	50
San Antonio, TX	–0.93	15	–1.29	47	–0.71	23
San Diego, CA	–1.15	25	–0.78	15	–0.85	33
San Francisco, CA	–0.82	8	–1.18	42	–1.01	43
San Jose, CA	–1.04	20	–1.10	37	–0.85	34
Seattle, WA	–1.25	35	–1.01	32	–0.80	31
St. Louis, MO	–0.78	7	–0.87	22	–0.68	17
Tampa, FL	–1.39	43	–0.72	11	–0.59	14
Virginia Beach, VA	–0.98	18	–0.89	23	–0.83	32
Washington, DC	–0.86	10	–0.43	2	–0.44	4

Table 8. Wilcoxon signed-rank test statistics between the distance decay parameter estimates.

Wilcoxon Tests	Metro-to-Metro Flows	County-to-Metro Flows	County-to-Metro Flows (no contiguous flows)
County-to-Metro Flows	W = 843 **	N/A	W = 786 ***

Wilcoxon Tests	Metro-to-Metro Flows	County-to-Metro Flows	County-to-Metro Flows (no contiguous flows)
County-to-Metro Flows (no contiguous flows)	W = 423 ***	W = 786***	N/A

*** and ** indicate significance at the 99.9 percent and 99 percent significance levels, respectively.

While it is evident there is significant variation in distance decay estimates between the flows, it is also necessary to confirm whether the local distance decay parameter estimates truly vary from the estimated global decay value. Recalling that the non-stationarity test took a ratio of the standard deviation of the estimated local distance decay parameters to the standard error of the global distance decay parameter (Brunsdon et al., 1998), large ratios indicate large amounts of variation relative to the global parameter estimate (while values closer to one indicate less variation). Given the size of the calculated ratios, the non-stationarity tests provide great confidence that there is real variability in distance decay, and the local decay parameter estimates are much more accurate than the global estimate. Table 9 presents the global distance decay and non-stationarity test values.

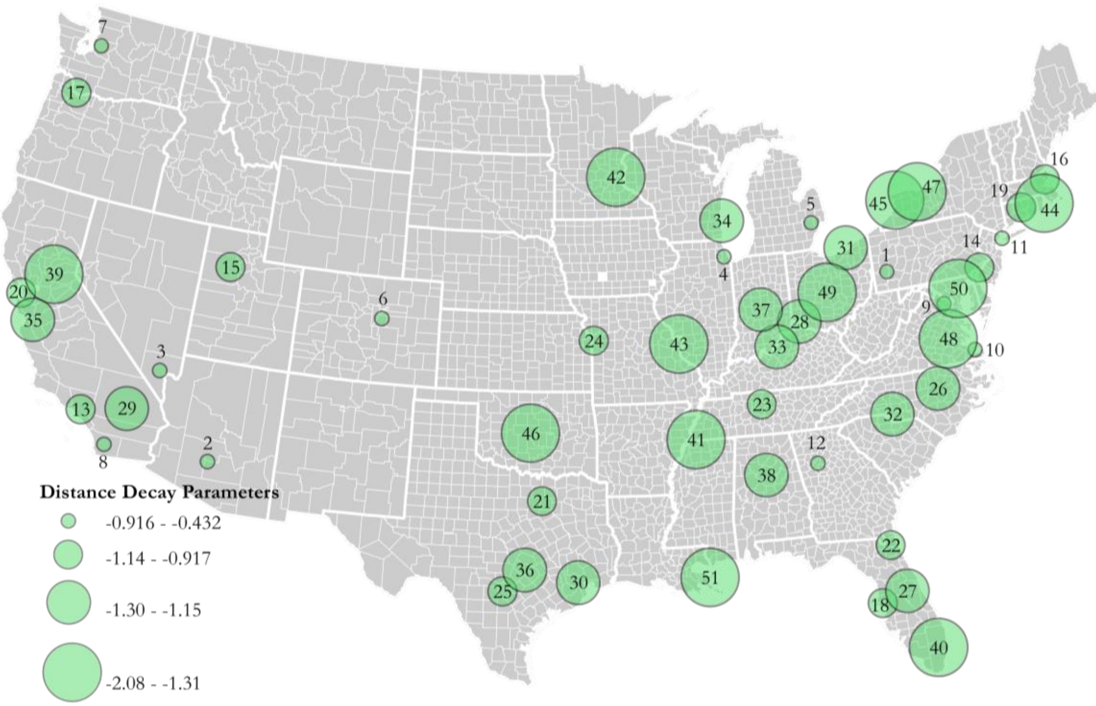

Figure 7: Map of local distance decay estimates. City circle sizes represent distance decay values. The numbers correspond to distance decay rank (smallest to largest) for metro-to-metro flows. The names of these cities is presented in Table 10.

maps the local distance decay estimate for metro-to-metro flows, and Table 10 provides the labels for the cities in

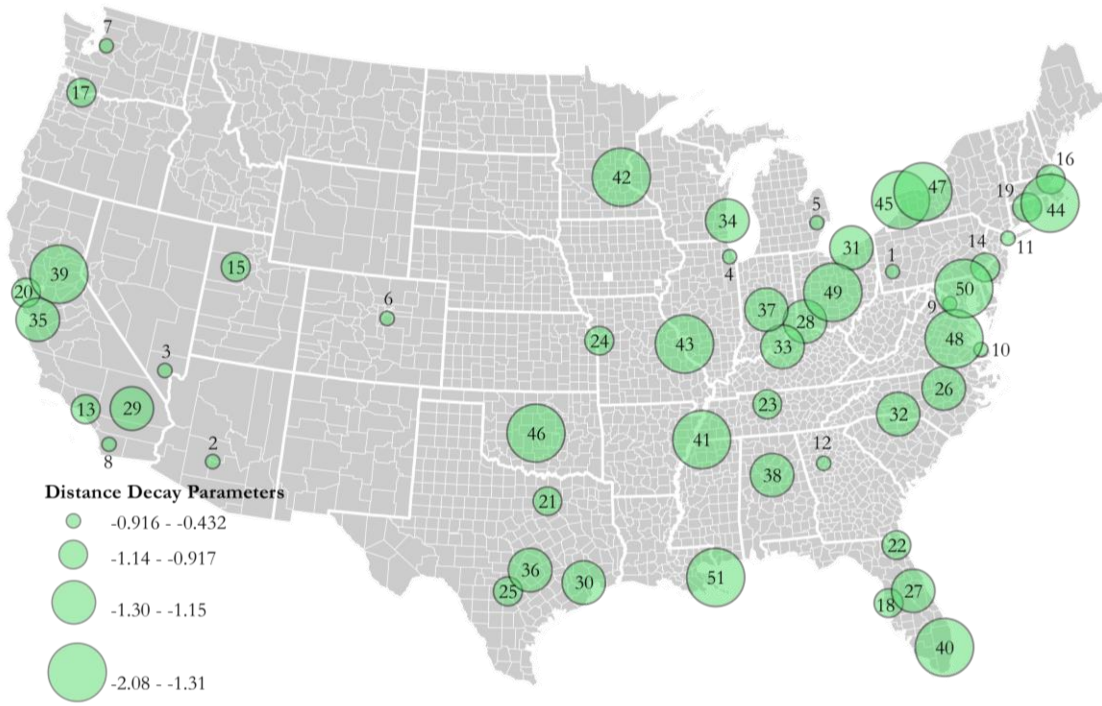

Figure 7: Map of local distance decay estimates. City circle sizes represent distance decay values. The numbers correspond to distance decay rank (smallest to largest) for metro-to-metro flows. The names of these cities is presented in Table 10.

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Table 9. Non-stationarity test values, along with global distance decay and local standard deviation values for each set of flows.

	Metro-to-Metro Flows	**County-to-Metro Flows**	**County-to-Metro Flows (no contiguous flows)**
Global Distance Decay	–0.85 (0.0006)	–0.79 (0.0004)	–0.59 (0.0005)

	Metro-to-Metro Flows	County-to-Metro Flows	County-to-Metro Flows (no contiguous flows)
Local Distance Decay Standard Deviation	0.32	0.26	0.22
Non-stationarity Ratio	531.94	611.46	422.45

Standard errors are in parentheses.

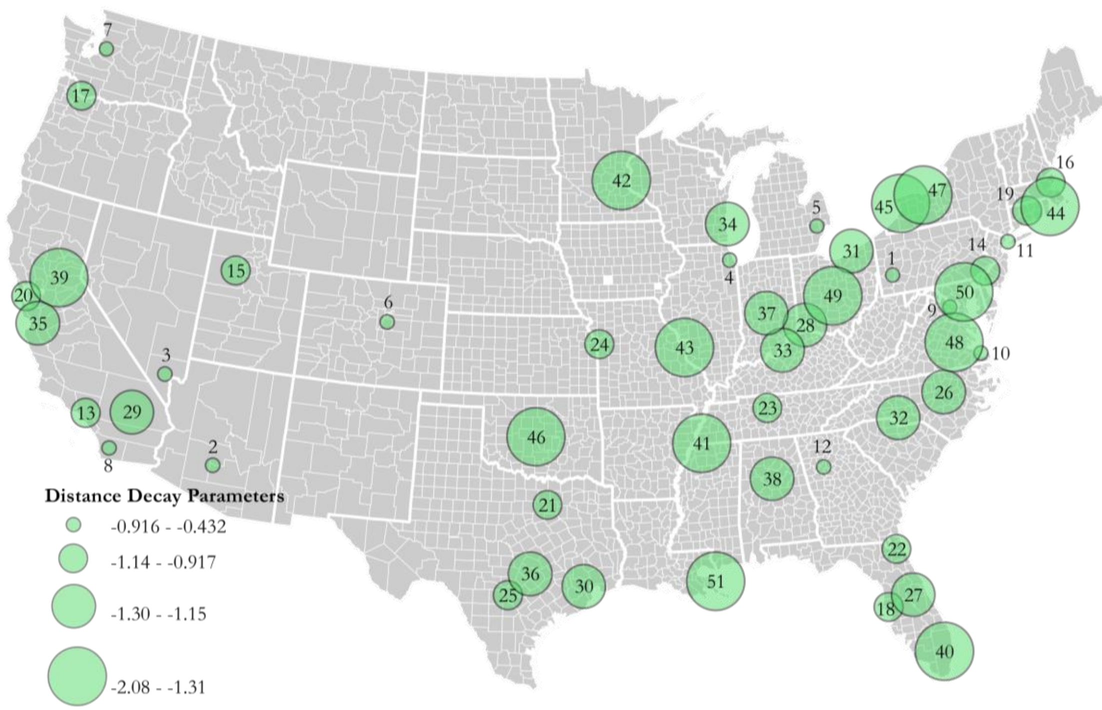

Figure 7: Map of local distance decay estimates. City circle sizes represent distance decay values. The numbers correspond to distance decay rank (smallest to largest) for metro-to-metro flows. The names of these cities is presented in Table 10.

Table 10: City names corresponding to the ranks/numbers in

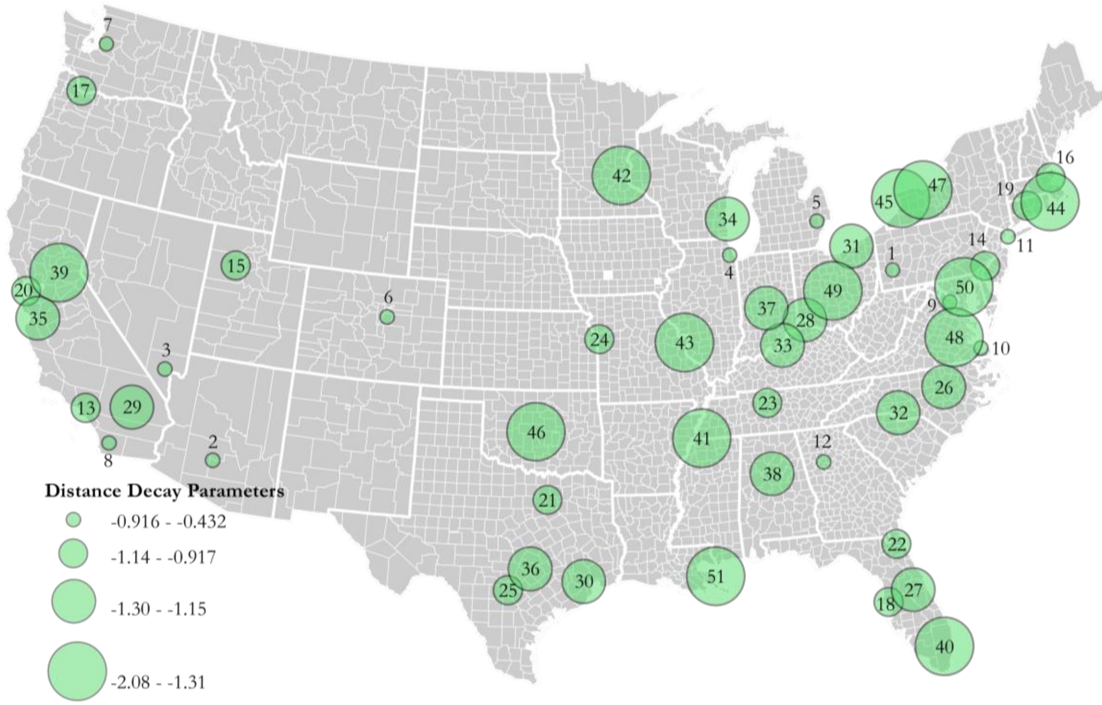

Figure 7: Map of local distance decay estimates. City circle sizes represent distance decay values. The numbers correspond to distance decay rank (smallest to largest) for metro-to-metro flows. The names of these cities is presented in Table 10.

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ID	City	ID	City	ID	City
1	Pittsburgh, PA	18	Tampa, FL	35	San Jose, CA
2	Phoenix, AZ	19	Hartford, CT	36	Austin, TX
3	Las Vegas, NV	20	San Francisco, CA	37	Indianapolis, IN
4	Chicago, IL	21	Dallas, TX	38	Birmingham, AL
5	Detroit, MI	22	Jacksonville, FL	39	Sacramento, CA
6	Denver, CO	23	Nashville, TN	40	Miami, FL
7	Seattle, WA	24	Kansas City, KS	41	Memphis, TN
8	San Diego, CA	25	San Antonio, TX	42	Minneapolis, MN
9	Washington, DC	26	Raleigh, NC	43	St. Louis, MO
10	Virginia Beach, VA	27	Orlando, FL	44	Providence, RI
11	New York, NY	28	Cincinnati, OH	45	Buffalo, NY
12	Atlanta, GA	29	Riverside, CA	46	Oklahoma City, OK
13	Los Angeles, CA	30	Houston, TX	47	Rochester, NY
14	Philadelphia, PA	31	Cleveland, OH	48	Richmond, VA
15	Salt Lake City, UT	32	Charlotte, NC	49	Columbus, OH
16	Boston, MA	33	Louisville, KY	50	Baltimore, MD

ID	City	ID	City	ID	City
17	Portland, OR	34	Milwaukee, WI	51	New Orleans, LA

3.2.3.2. Explaining distance decay

Regression results indicate a model with good explanatory power for the metro-to-metro distance decay parameters. A R^2 of 0.64 was calculated for the model, with no indications of non-normal error distributions. The Moran's I tests of the models' residuals showed no significant spatial autocorrelation for any of the tested conceptualizations of spatial relationships for all three models. Initial model results showed significant multicollinearity among the per capita income variables. To address this, the separate per capita incomes were replaced with the overall per capita income for the city, which both corrected multicollinearity and improved model fit. The full regression results are presented in Table 11, with variance inflation factors (VIF) describing multicollinearity. Moran's I test results are presented in the Appendix.

Contrary to the initial hypothesis, population is found to be highly significant with a negative relationship with distance decay, indicating that – when other variables are controlled for – larger cities are less resistive to migrant flows. Two of three unemployment variables, Hispanic and African American, were significant. Interestingly, Hispanic unemployment had a negative coefficient, indicating cities with higher Hispanic unemployment had lower distance decay values. The African American unemployment variable's coefficient was positive and significant, indicating that cities with higher African American unemployment have greater distance decay. Taken as a whole, these unemployment results suggest that higher Hispanic unemployment does not decrease a city's attraction to migrants, while higher African American unemployment does. Replacing these demographic unemployment rates with an aggregate unemployment rate for the city yielded a poorer model fit and an insignificant relationship between unemployment and distance decay. Thus, the significance of these variables indicates important correlations with distance decay that are worth investigating.

These unemployment results may signify several underlying social constructs at play. First, Hispanic unemployment rates include native-born and immigrant employment numbers. While the Great Recession generally leveled unemployment between natives and foreign-born (U.S. Bureau of Labor Statistics, 2013a), before the recession Hispanic immigrants had significantly lower unemployment rate than their native-born brethren (Kochhar, 2006). This trend continued through the Great Recession: despite more than a doubling of the foreign-born Hispanic unemployment rate, it remained lower than the native-born Hispanic unemployment rate (Kochhar, Espinoza, & Hinze-Pifer, 2010). This is likely due to the unique economic accesses afforded to native-born Hispanics (i.e., easier access to the primary labor market) while immigrant Hispanics must leverage their network association to obtain employment in niches, often in the secondary labor market (see Section 3.3) (Waldinger, 1994). Additionally, Hispanic migrant workers, in high-unemployment periods, may leave for work elsewhere if unemployed, thus reducing that demographic's unemployment rate. Thus, if the data were to allow segregation of Hispanic native and immigrant unemployment numbers, there may have been different relationships to distance decay. (A further investigation of foreign-born employment during this period is performed in Section 3.3.) Second, long-term unemployment may be contributing to the directionality of the relationships. Unemployed African Americans are the more likely to be part of the long-term unemployed than Hispanics, who, next to Asians, are the least likely group to be among the long-term unemployed (U.S. Bureau of Labor Statistics, 2010). Data show that long-term unemployment rose equally as fast as regular unemployment during the Great Recession period, rising above four percent by December 2009 from sub-one percent levels as recently as April 2008 (U.S. Bureau of Labor Statistics, 2011). Therefore, while African American unemployment may have a positive relationship with distance decay, the correlation may be a surrogate for the relationship between long-term unemployment and distance decay. While the data available for this research limits the ability to empirically test this hypothesis, further exploration of this relationship is warranted in future research.

Foreign-born diversity has a significant positive relationship with distance decay, indicating that, controlling for other factors, migrants are pulled less to cities with more diverse foreign-born populations. The foreign-born diversity metric, which measures the uniformity of presence of immigrant groups in the city, is not correlated with a city's foreign-born population percent. Smaller diversity values indicate dominance by one or a few immigrant groups, whereas larger diversity values indicate more equal presence of nationalities. This result is likely a result of the nature of the flows described in Section 3.1, and it serves to highlight the differences between the analysis here of in-migration (focusing on raw migrant counts) and the analysis of in-migration rates (which are normalized by the destination's population). Generally speaking, the raw in-migration counts were much greater for Southern and Southwestern cities, which are generally less diverse by virtue of larger Hispanic populations. Exceptions to this Southern trend are large in-flows to Chicago, Washington, and New York. Greater diversity will also increase the number of immigrant niches in an urban economy (Wang & Pandit, 2007), which can limit the opportunities for employment in those niched sectors to co-ethnics of the dominant immigrant group (Logan et al., 2003). This could deter migration among the larger population to cities for employment in these sectors. A further investigation of immigrant populations and their diversity, to include their impact the native workers in these 51 cities, is presented in Sections 3.3 and 3.4.

Two education variables have significant influence on distance decay values, confirming a portion of the initial hypothesis. Migrants are pulled less to cities with larger relative numbers of high school dropouts and pulled more to cities with larger relative numbers of high school graduates. The percent of the population with a graduate degree was not significant. The insignificance of the graduate degree variable may symbolize a partial educational convergence among these metropolitan areas, particularly given the economic turmoil and recalibration caused by the Great Recession. As college-educated workers lost employment during the recession, they may have been drawn to urban areas where their competition for employment opportunities was less (i.e., places with fewer college degree holders and more people who capped at high school graduation).

Contrary to the initial stated hypothesis regarding education/health care employment, the variable has a significant negative relationship with distance decay. Despite the education and health care sectors being the only sectors with overall growth during the recession, percent employment in these sectors was not a draw for migrants. The growth among these two sectors may not be spatially homogeneous and might rather be occurring in metropolitan areas with less employment in these sectors (i.e., convergence is occurring). In this case, people migrating for employment in these sectors would be drawn to cities with lower overall employment in these sectors, as they would be experiencing the most growth and in most need of workers. In the contrary case that healthcare and education were not converging across space, the significant negative coefficient may signify that this sectoral growth is occurring from within the bounds of the metropolitan area (i.e., is not being augmented by migrant workers). Those pursuing education and training for employment in these sectors would be much more likely to find and accept employment in the same city, thus reducing the need for migrant workers to support the sectoral growth.

Precipitation also has a significant positive relationship with distance decay, indicating the migrants are drawn to cities with lower annual precipitation levels. While this may be a chance correlation resulting from the confluence of other factors, the relationship is in line with conventional theories of migration, which state that climate plays an important role in destination selection (Greenwood, 1969). Previous research has shown that climate and other location-fixed amenities associated with cities, such as beautiful scenery or successful sports teams, influence the migration decision, but as secondary factors correlated to economic success (Graves, 1980). The directionality may also be tied to the larger raw migration flows into the Southwestern U.S. described above. Given the general lack of rainfall in this area, and the West in general (the correlation coefficient between precipitation and presence in the Western Census Region is $r = -0.79$), migration flows in the West may be driving this result.

The model did not perform as well in explaining the distance decay parameter variation for the two county-to-metro flows. While the county-to-metro flow models had poorer fits than the metro-to-metro flow models, it is the general lack of significant variables that drives the conclusion of poor performance. While it is not surprising that these two flows have different drivers and attraction elements from each other, and from the metro-to-metro flows, it is surprising that only one of the variables had a significant coefficient in the county-to-metro models, particularly given ten were significant in the metro-to-metro model. This does, however, reinforce the observation made in Section 3.1.4 that significant push and pull factors identified for a given scale of analysis (i.e., metro-to-metro flows) may not have the same relationship at other scales (i.e., county-to-metro flows). The county-to-metro model with contiguous flows had a R^2 of 0.24, while the model for county-to-metro decays that excluded contiguous flows had a R^2 of 0.33. Both had the same single significant variable: education/health care employment. As in the metro-to-metro models, this variable is positive, which, again, signifies convergence among the sectoral growth and locally supplied labor to support this growth.

Table 11. Full regression results the metro-to-metro model, and the two county-to-metro models, with model diagnostics.

	VIF	**Metro-to-Metro Decay**	**County-to-Metro Decay**	**County-to-Metro Decay (no contiguous)**
Intercept		1.79 (6.36)	1.49 (7.50)	4.02 (5.85)
Population (log)	3.58	–0.40 *** (0.08)	0.00 (0.09)	0.00 (0.07)
Rent (log)	8.79	0.34 (0.43)	0.24 (0.51)	-0.26 (0.40)

	VIF	Metro-to-Metro Decay	County-to-Metro Decay	County-to-Metro Decay (no contiguous)
Rent Variation	2.17	–0.89 (0.69)	–0.19 (0.81)	–1.19 (0.63)
Unemp. (White)	3.45	–3.60 (4.33)	1.14 (5.12)	–3.12 (3.99)
Unemp. (Hispanic)	3.32	–7.94 ** (2.28)	4.12 (2.69)	2.30 (2.10)
Unemp. (Af. Am.)	2.91	6.50 ** (1.86)	–0.58 (2.20)	0.09 (1.71)
Per Capita Income (log)	10.26	0.01 (0.68)	–0.22 (0.81)	0.00 (0.63)
Diversity – Pct. Foreign-born	8.79	0.78 (0.93)	–0.14 (1.09)	0.88 (0.85)
Diversity – Origins	4.23	1.21 * (0.53)	–0.27 (0.63)	–0.06 (0.49)
Diversity – Bohemian Index	2.54	–0.07 (0.16)	–0.06 (0.19)	–0.03 (0.15)
Education – no HS	3.87	7.18 *** (1.73)	–0.52 (2.05)	–1.19 (1.59)
Education – HS	5.44	–4.89 ** (1.49)	–0.10 (1.76)	–1.95 (1.38)
Education – GD	11.07	–3.22 (3.06)	0.76 (3.62)	–3.91 (2.82)
Industry – Con./Man.	2.08	–1.38 (1.33)	–0.03 (1.57)	–1.47 (1.23)
Industry – Service	1.93	0.02 (1.41)	–0.18 (1.67)	–2.03 (1.30)
Industry – Ed./Health	3.07	5.59 ** (1.69)	4.10 * (2.00)	4.44 ** (1.56)
Climate – Temp. Var. (log)	3.87	0.15 (0.08)	–0.04 (0.09)	–0.08 (0.07)
Climate – Precip.	3.01	0.22 * (0.09)	–0.18 (0.10)	–0.03 (0.08)
Adjusted $\boldsymbol{R^2}$		0.64	0.24	0.35
Observations		51	51	51
Breusch-Pagan stat		17.31	18.28	17.19
p-value		0.50	0.44	0.51
Jarque-Bera stat		0.46	4.52	2.00
p-value		0.80	0.10	0.37

Standard errors are in parentheses. ***, **, and * indicate significance at the 99.9 percent, 99 percent, and 95 percent confidence levels.

3.2.4. Discussion

This spatial interaction research shows that distance decay, derived from the elemental version of DSACCD gravity model (that is, the explanatory factors other than mass, distance, and spatial structure are excluded), can be used to identify the elements of attraction associated with migration between metropolitan areas. Previous research has used origin- and destination-specific gravity models to demonstrate the variation in distance decay across a set of destinations (Fotheringham, 1981; Plane, 1984), but none has utilized this method to derive attractivity metrics for the specific destinations. Other research has used various incarnations of the gravity model show relative attraction between cities (Baxter & Ewing, 1981; Tobler, 1979, 1983), but these methods fail to account for distance decay variation, and also fail to identify the characteristics driving the variations in relative attraction.

This research finds that migration distance decay varies significantly across the 51 metropolitan areas, and the estimations are highly dependent upon the flows being modeled. Different distance decay distributions for metro-to-metro flows and the two county-to-metro flows suggest that metro-level and county-level migration are substantially different phenomena. The context dependence of distance decay parameters, and vast differences between the parameters estimated for a given city by each set of origins, reinforces the need to contextualize all migration analysis. Part of this context, however, is the accuracy of the flow data itself. As discussed above, over 80 percent of the origin-destination pairs in the Census migration dataset have margins-of-error greater than the corresponding flow: this inaccuracy is no doubt having influence on the estimated decay parameters. Because there is no 'right' distance decay parameter for destination, one can only understand the exactness of distance decay parameter estimate in the context of its relationship to other variables. Distance decay, regardless of the flow, represents the friction distance imparts on migration, but because of the formulation of the model as destination-specific, the estimated friction factor inherits the influence of the elements of attraction to the destination. Thus, the distance decay coefficient can be regressed against to determine the common elements of attraction for a given set of flows. The performance of this second-stage model not only serves to allow for estimation of the influence of metropolitan elements of attraction on distance decay, but it helps to assess the validity of the distance decay element itself.

This two-stage regression process modeled the contributors to metro-to-metro flows showing that specific elements of unemployment, diversity, education, industry, and climate are key attractions to migrants coming from other cities. The model, however, performed more poorly at identifying the pull factors associated with county-to-metro flows. While this does not preclude the two-stage process for use on these types of flows, it does indicate the variables selected may not be important elements of attraction for migrants when analyzing county-to-metro flows. The poor performance of the models may also be signifying the inexactness of the distance decay estimates derived from the county origins: many of these flows, having not originated from metropolitan areas, are small, inherently having much larger margins of error.

If the estimated distance decay parameters for county-to-metro flows are generally 'accurate', there are several possible explanations for the poor performance of the model. Perhaps the migrant decision-making process is unique at different scales due to qualitative differences between the types of migration flows. A migrant considering a metropolitan destination may consider a unique set of pull factors depending on the scale of his origin. Central to this thought is how the migrant conceptualizes the origin with respect to weighing the pull factors and comparing the benefits of destinations: does a migrant whose origin is rural associate only his county as the origin, or is it a larger region? Does the migrant of urban origin consider his home county, both the urban and suburban characteristics of his home metro area, or perhaps even a larger region of origin? These questions are difficult to answer empirically, but exploratory research into the various scales of migration origins and destinations may yield important insights into these questions.

While a significant amount of previous research has sought to identify and explain the pull factors that influence migrant destination selection, none has sought to do so in the context of different drivers among different flows (save for differences between internal and international migrants). This research has illuminated that the elements of attraction are potentially different for different types of flows, and scholars should investigate this further. Furthermore, this novel method of analyzing destination attraction utilizing distance decay parameters expands our understanding of the importance and applicability of the spatial interaction model as a tool for analyzing migration.

3.3. Niche Formation

Now that we have an understanding of the distance-decay variation associated with internal migration patterns over the 2006-2010 period, and the drivers associated with interurban flows, we now transition to an analysis of the international migrant populations of these metropolitan areas. Studying the spatial mobility of international migrants is quite difficult because of the unique physical, administrative, and political barriers (i.e., the intervening obstacles discussed in the Section 2.1) each migrant must overcome to arrive and gain legal status in the U.S. While internal migrants face challenges unique to their own situation, mobility within the U.S. is generally free from restriction, with the primary cost/obstacles being economic (e.g., transportation, housing, job search, etc.). While the difficulties of spatially analyzing international migrant mobility to the U.S. abound, a critical node in the canon of international migration research is understanding the economic behaviors of these international migrants once they arrive in the U.S.

Building off previous research such as Ellis et al.'s (2007) and Wright et al.'s (2010) assessment of intra-urban geography and the uniformity of niching across a metropolitan area, this research seeks to discover the broad patterns of immigrant group niching and to characterize the homogeneity and heterogeneity of group niching. Just as Ellis et al. (2007) hypothesize that a sector may be a niche for different groups in different parts of a city (because of proximity of place of work to residence), it is hypothesized here that groups will exhibit a substantially heterogeneous pattern of niching across space due to the local variation in economy, demographics, and immigrant assimilation. It is also hypothesized that immigrant groups will exhibit substantial spatial variation in their propensity to niche, showing that some metropolitan areas have more niche-forcing factors than others.

To test these hypotheses, this section's research question – Does migrant propensity to form niches and niche composition vary over space, and what factors contribute to these variations? – must be answered using sub-questions. First, are all immigrant groups equally prone to niche formation, and does this vary across space? Second, are immigrant groups consistent in their niche industries across space, or are their niches heterogeneous? Third, what factors contribute to an immigrant group's propensity to form different niches in different cities? And fourth, are some cities more or less prone to niche formation than others?

3.3.1. Methods

3.3.1.1. Niche identification

A location quotient is a basic ratio of local concentration in some category as it compares to a larger benchmark area. Location quotients are used throughout economic and geographic research as a typical method for economic base analysis (Krikelas, 1992), investigating urban centers (Leslie & Ó hUallacháin, 2006; Leslie, 2010), and characterizing employment niche presence (Ellis et al., 2007; Wang & Pandit, 2007). Location quotients here are used to assess the concentration of each immigrant group in each industry, with the benchmark the industry concentration at the city level. Nearly all conventional scholarly research into niche formation utilizes the location quotient to characterize overrepresentation in an industry. Location quotients for each group-industry combination within a city are calculated as:

$$LQ = \frac{n_r / N_p}{n_{r-city} / N_{p-city}}$$

where n_r is the number of migrants of a specific ethnicity working in an industry, N_p is the total number of migrants of that ethnicity in the city, n_{r-city} is the total number of people working in the industry in the city, and N_{p-city} is the sample population for the city. A location quotient of 1 indicates an immigrant group's presence in an industry is on par with the overall population's presence in that industry. A location quotient greater than 1 indicates a higher concentration than the city as a whole; a location quotient less than one indicates a lower concentration.

The city is used as the base population distribution rather than the U.S. or an aggregation of the study cities' data as there is substantial variation in the regional economies of the U.S. (Armington & Acs, 2002). The distribution of migrant ethnicities is also highly variable across U.S. regions (Bartel, 1989), likely both a cause and function of the regional economic variation. By looking at immigrant niches from a regionally specific metropolitan perspective, it is possible to explore how these local variations in economies and immigrant populations affect the propensity of immigrant groups to form niches and alter their industry distribution. A location quotient of 1.5 is used as the threshold for niche formation, as it is a convention used by scholars elsewhere (Ellis et al., 2007; Waldinger, 1996; Wang & Pandit, 2007; Wang, 2004; Wright et al., 2010).

3.3.1.2. Propensity to niche

Immigrant group propensity to niche, the Niche Index, is calculated using a diversity index. The Niche Index, P_n, calculated for each immigrant group for each metropolitan area, measures the degree of concentration of a particular entity and allows for cross-metropolitan comparisons of concentration. Analogous to the Herfindahl-Hirschman Index (HHI) frequently used in economics research to assess market share and the effect of mergers and acquisitions (Rhoades, 1993), and the Simpson Diversity Index in ecological research to understand species diversity within a landscape (McIntosh, 1967), P_n is used here to assess whether one immigrant group is more or less concentrated than others within the metropolitan economy. It is calculated as:

$$P_n = \sum_{i=1}^{M} s^2$$

where s is the share (proportion) of each immigrant group population found within an industry, and M is the number of industries (or the labor market). The proportion, s, is calculated as n_r/N_p, where n_r is the number of residents of a particular group employed in an industry and N_p is the total number of residents of that group.

If an immigrant group was equally represented across all industries, P_n would equal $1/M$, indicating perfect dispersion (and, consequently, no clustering). Larger values of P_n indicate the immigrant group has higher representation in some industries than others, while a P_n value of 1 indicates perfect clustering in a single industry (that is, 100 percent of an immigrant group's population is employed in a single industry). This can also be thought of as the probability that any two randomly selected people within an immigrant group would be employed in the same industry. This metric is used as an indicator of the propensity of an immigrant group to form a niche in a particular metropolitan area. Immigrant groups with higher Niche Index values can be thought of as being less diverse across the employment landscape: they are significantly under-represented in some industries while significantly over-represented in others. As it is independent of group size, this metric also enables cross-metropolitan comparisons of an immigrant group to better understand how their propensity to form niches varies across space.

3.3.1.3. Spatial variation in metropolitan propensity to niche

The third goal of this section of the dissertation is to statistically assess the variation in the Niche Index across space, and specifically whether some cities are significantly more prone to niching than others. Because the Niche Index is constrained by $1/M$ and 1 and is a modified form of a proportion, the Beta regression is utilized to estimate the effects of each city. Beta regression has been shown to be a superior method for regressing proportional dependent variables, compared to other potential methods such as OLS regression with a logit-transformed dependent variable and logistic regression (Ferrari & Cribari-Neto, 2004; Kieschnick & McCullough, 2003; Smithson & Verkuilen, 2006). The Beta regression assumes the observed dependent variable follows the Beta distribution, which has a probability density function of:

$$\pi(y; p, q) = \frac{\Gamma(p+q)}{\Gamma(p)\Gamma(q)} y^{p-1}(1-y)^{q-1}, 0 < y < 1$$

where $p > 0$ and $q > 0$ are distribution shape parameters, and Γ signifies the gamma function (Ferrari & Cribari-Neto, 2004; Smithson & Verkuilen, 2006). The expected value of y is:

$$E(Y) = \mu = \frac{p}{p+q}$$

and the variance of y is:

$$Var(Y) = \frac{\mu(1-\mu)}{(\phi+1)}$$

where $\phi = p + q$ is a precision parameter of the distribution.

Distribution shape parameters and coefficient estimates are derived using Maximum Likelihood Estimation (MLE) with a link function to estimate μ and ϕ by maximizing the sum of log-likelihoods across all observations. The chosen link function is logit, following the suggestions of Kieschnick and McCullough (2003) and Smithson and Verkuilen (2006). Model goodness-of-fit is estimated using a pseudo-R^2 value, which is defined as the square of the correlation coefficient between the estimated linear predictor value ($\hat{\eta}$) and the link-transformed observed value ($g(y)$) (Ferrari & Cribari-Neto, 2004). Beta regression coefficients, when exponentiated, can be interpreted as an odds ratio between the original model's logit transformed expected mean (μ) and the new model's logit-transformed expected mean (μ') (Smithson & Verkuilen, 2006), such that for the ith covariate:

$$e^{\beta_i} = \frac{\mu'/(1-\mu')}{\mu/(1-\mu)}$$

The distribution of the Niche Index was assessed against the Beta probability distribution, as well as the normal and logistic distributions, using standard goodness-of-fit statistics to ensure accurate model selection. The results, shown in Table 12, indicate the Beta distribution is not rejected as a fitting distribution, while the other two potential distributions are significantly rejected.

Table 12. Goodness-of-fit statistics for Niche Index as a Beta probability distribution.

	Kolmogorov-Smirnov	Anderson-Darling	Chi-Squared
Statistic	Beta = 0.037 Normal = 0.123 Logistic = 0.133	Beta = 0.255 Normal = 4.389 Logistic = 4.359	Beta = 1.946 Normal = 24.311 Logistic = 15.429
p-value	Beta = 0.986 Normal = 0.029 Logistic = 0.014	N/A	Beta = 0.963 Normal = 0.001 Logistic = 0.031
Critical Value ($\boldsymbol{\alpha}$ = 0.05)	0.116	2.502	14.067
Observations	136	136	136
Reject?	Beta = **No** Normal = Yes Logistic = Yes	Beta = **No** Normal = Yes Logistic = Yes	Beta = **No** Normal = Yes Logistic = Yes

A detailed description of the aspects of Beta distribution and further information on Beta regression can be found in Ferrari and Cribari-Neta (2004).

The Niche Index value for each immigrant group in each city is the dependent variable, and the cities are included as dummy independent variables. Two Beta regressions were executed: one where New York City is omitted as the reference city and one where Los Angeles is the reference city. These two cities are regularly assessed within the immigrant niche literature due to their size, ethnic diversity, and economic diversity. By isolating New York and Los Angeles as reference categories, statistical significant will demonstrate variation in niching propensity relative to each of these research foci.

3.3.1.4. Drivers of niche propensity

The final goal of this research into immigrant niches is to better understand the factors influencing spatial variations in immigrant groups' propensities to niche. With the Niche Index as the dependent variable, a multivariate Beta regression is performed with a logit link function, as described above. Ten types of independent variables are considered. These are discussed below.

(1) The size of the immigrant group's sample population within each metropolitan area is included as an independent variable to assess the relationship between group size and niching propensity. Logan et al. (2000) show that population size and growth affects, both positively and negatively, the strength and growth of ethnic economies and niches. They show that Cubans in Miami have many more niches than in New York and Los Angeles due to their larger population in Miami.[3] However, between 1980 and 1990 in all cities, there was both expansion and contraction in niches. Size, theoretically is a confounding variable. From one perspective, a smaller group population might suggest an increased need to form niches because of more restricted social capital networks and fewer opportunities for employment elsewhere in the primary or secondary labor markets. Alternatively, a larger group population might suggest increased opportunities for niche formation because of a larger social capital networks, more awareness of potential employment opportunities, and group entrenchment in more areas of the metropolitan economy. Thus, smaller group populations may likely lead to fewer, stronger niches (where "strong" is defined as extreme overrepresentation), while larger group populations may likely lead to more, but weaker, niches. Because propensity to niche is defined based on employment shares rather than a measure of overrepresentation, group size should have a negative effect on a group's

[3] Logan et al. (2000) compare white, blacks, and eight ethnic minorities across 17 U.S. metropolitan areas. Though not the focus of their research, they successfully show that there is both significant crossover and diversity among a group's niches across space.

propensity to niche. This variable is logged in the regression to reduce issues with heteroskedasticity.

(2) The percentage of males in the immigrant group is included as an independent variable to test whether, overall, immigrant groups that have a greater share of men are more prone to niched employment. Migration patterns of women and men are different, which alters their access to the same social capital resources and influences their occupational selections (Grasmuck & Grosfoguel, 1997; Schrover et al., 2007). While most minorities are unfortunately subject to some level of racism or prejudice that restricts their access to the primary labor market and within the secondary labor market, women are dually subjected to racism and sexism, or what Castles & Miller (2009) refer to as gendered racism. As a result of this, research has shown that male and female migrants not only occupy different niches, but that men are more prone to niche employment than women (Wright & Ellis, 2000). It is hypothesized that the same relationship will manifest here: a larger percentage of males leading to a higher propensity to niche.

(3) Metropolitan area population is included to assess whether larger cities supply migrants with more diverse, and expanded access to, employment opportunities to counter the need to form niches. It is possible that larger cities would be more diverse and less prejudiced (Glaeser et al., 1992), contributing to expanded access to employment, and it is suspected that larger cities will be less prone to niche formation. This variable is logged in the regression to reduce issues with heteroskedasticity.

(4) The percent foreign-born of each metropolitan area is included as an independent variable to test, more directly, whether a diverse city leads to greater or lesser propensity to

form niches. Ottaviano and Peri (2006b) demonstrate that cultural diversity has a positive relationship on productivity, wages, and rental prices for a city. The diversity created from larger relative immigrant populations in a city should decrease the need for immigrant groups to form niches, as increased diversity implies increased tolerance of foreign-born labor and a greater permeation of foreign-born labor throughout both the primary and secondary labor markets.

(5) Each metropolitan area's average percent unemployment for 2006-2010 was included as an independent variable to test whether urban unemployment influences an immigrant group's propensity to form niches. It is expected that higher unemployment negatively affects niching propensity, as this increases the demand for employment throughout the urban economy. This increased demand and, perhaps, desperation leads workers to take jobs and work in industries of lesser pay and preference, diluting mono-ethnic niches with other immigrant groups and domestics.

(6) The change in a metropolitan area's percent unemployment between 2006 and 2010 is also included as an independent variable, to test whether niching propensity is affected by economic downturns. This variable is expected to have a negative relationship between unemployment change and niching propensity, in line with the effect of overall percent unemployment: areas with greater increases in unemployment will likely have their niche industries diluted by desperate workers of all ethnicities as employment opportunities dwindle (Mosisa, 2002).

(7) The percent of poor English speakers is included to assess the importance of language as a barrier to entry into the broader labor market. This percentage represents both

poor and non-English speaking immigrants. Wright et al. (2010) and Wang (2004) find a significant negative relationship between good English skills and niche employment. The same relationship is expected here: higher percentages of poor/non-English speakers should have a significant positive effect on niche propensity.

(8) The percent of recent immigrants is included as an independent variable to test for the importance of assimilation as a springboard into the primary labor market. Recent immigrants are defined as those who have arrived in the year 2000 or later. Research has been shown that more tenured immigrants are less likely to be employed in niches (Hudson, 2002; Wang, 2004; Wright et al., 2010). A significant positive relationship is hypothesized between this variable and niche propensity: immigrant groups with larger proportions of new migrants will experience higher propensities to niche than other immigrant groups.

(9) A 'group dominance' variable that represents the immigrant group's representation among the immigrant community in the city. Of the immigrant groups in a city with samples large enough to be included in the study, this variable is calculated as the percentage each immigrant group composes of the total immigrant sample size for the city. For example, if only one immigrant group has a sample size large enough for inclusion in a particular city, this group will have a value of 1.0 for this variable. If three immigrant groups are included for a city and they have equal sample size representation, each will have values of 0.33 for this variable. This variable is included to test whether the relative size of the immigrant group is an important contributor to its propensity to form niches. An insignificant relationship to niche propensity is expected: while there is potential for larger, more dominant immigrant groups to be less prone to niche formation in a city due to their

relative prevalence in the labor market, this relationship may be negated in smaller cities with smaller foreign-born populations.

(10) Lastly, three regional dummy variables are included to test if there is a regional bias in niche propensity. Given the largest U.S. growth in new immigrant populations has been in the South over the past decade (J. H. Wilson & Singer, 2011), including these dummy variables allows us capture, at the regional vice metropolitan level, the effect of this foreign-born population growth and other region-specific factors on a group's propensity to niche. Dummy variables are assigned to each city indicating which of the four Census regions it falls within: Northeast, South, Midwest, or West. The Northeast region is held out of the regression as the reference region.

The independent variables with a description and their null hypothesis are summarized in Table 13.

Table 13. Independent variables in multivariate regression model for niche propensity.

Variable	**Description**	**Expected Sign/Significance**
Sample Population	Log of the sample population of an immigrant group within a city.	(–), significant
Percent Male	Percent of males in an immigrant group.	(+), significant
Metropolitan Population	Log of the metropolitan area population estimate for the study period.	(–), significant
Percent Foreign-born	Percent foreign-born of the metropolitan population for the study period.	(–), significant
Average Percent Unemployment	Average percent unemployment for the metropolitan area for the study period.	(–), significant
Unemployment Change	Change in percent unemployment for the metropolitan area between 2006 and 2010.	(–), significant
Percent Poor English	Percent of immigrant group that speaks English poorly or not at all.	(+), significant
Percent New Entry	Percent of immigrant group that arrived in the U.S. in 2000 or later.	(+), significant

Variable	Description	Expected Sign/Significance
Group Dominance	Immigrant group percent of the city's foreign-born sample.	(–), insignificant
Regional Dummy	Dummy variable representing city's location in one of the four Census regions: Northeast, South, Midwest, and West	(Varying), significant

3.3.2. Data

This research utilizes U.S. Census Bureau's 2006-2010 5-year Public Use Microdata Samples (PUMS) data (U.S. Census Bureau, 2010b). The PUMS data are individual-level anonymized sample data collected as part of the Census Bureau's ACS (U.S. Census Bureau, 2010c). This research began with a focus on the same 51 U.S. cities with populations over 1 million researched in the previous sections of this dissertation. For these 51 cities, the counties that compose each are identified using the 2009 U.S. Census Bureau Combined Metropolitan Statistical Area (CMSA) definitions (U.S. Census Bureau, 2009b). Finally, these metropolitan county definitions are used to filter the PUMS data to the Public-Use Microdata Areas (PUMAs) that corresponded to the metropolitan study areas.

To ensure adequate sample sizes within the cities, analysis is limited to only cities with at least one immigrant group with a sample population greater than or equal to 1000. This reduced the study to 26 metropolitan areas. Within each of the 26 metro areas, only those immigrant groups whose sample population is 1000 or greater are included for analysis, following Waldinger (1996). Because niche identification focuses on intra-group proportions, inclusion of a minimum sample size is critical to preventing small-sample biases. This methodology, however, constrains one's ability to assess immigrant group niching across cities, as not all groups meet the sample threshold in all cities. Regardless, the ability to assess the niching behavior of 42 unique immigrant groups across 26 cities remains, leading to 136 group-city observations. The 26 metropolitan areas included in this study are presented in Table 14 and shown in Figure 8 with their foreign-born sample size. The immigrant groups are presented in Table 15 along with the number of cities where they meet the sample criteria. While the remaining cities represent a strong sample for this analysis, it must be noted that 9 of the 26 sampled cities have only one immigrant group that meets the sampling criteria. This research will draw conclusions about the relationships between these one-immigrant group cities and the multi-immigrant group cities, and these conclusions will be based on valid statistical observations and estimates. However, as with any data-specific research, the results are highly contingent upon not only the sampling scheme chosen here, but also the sampling scheme of the source dataset (PUMS in this case).

Table 14. Study cities and the number of immigrant groups included in their sample.

City	Immigrant Groups	City	Immigrant Groups
Atlanta, GA	3	Philadelphia, PA	1
Austin, TX	1	Phoenix, AZ	1
Boston, MA	4	Portland, OR	1
Charlotte, NC	1	Riverside, CA	2
Chicago, IL	6	Sacramento, CA	2
Dallas, TX	4	Salt Lake City, UT	1
Denver, CO	1	San Antonio, TX	1
Detroit, MI	1	San Diego, CA	3
Houston, TX	5	San Francisco, CA	8
Las Vegas, NV	2	San Jose, CA	6
Los Angeles, CA	17	Seattle, WA	5
Miami, FL	14	Tampa, FL	2
New York, NY	36	Washington, DC	8

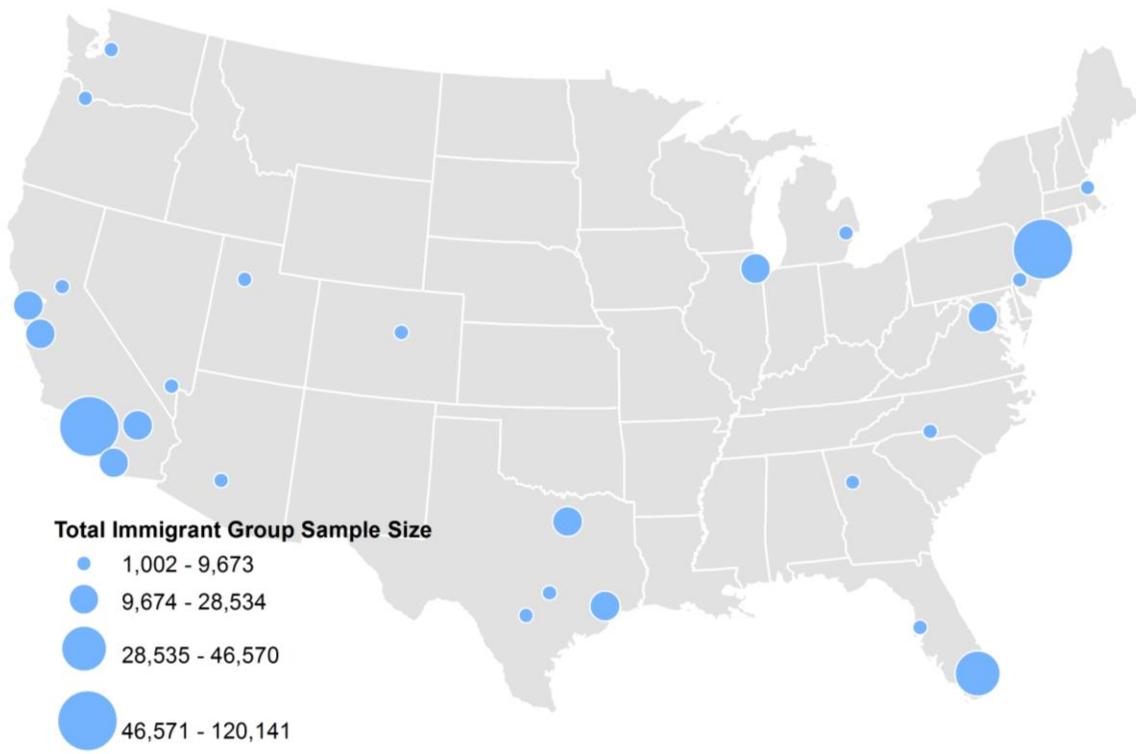

Figure 8. Map of the 26 metropolitan areas represented by their total immigrant group sample size used in this study.

Table 15. Immigrant group countries included in the study and the number of cities where they meet the sample size criteria.

Immigrant Cntry	Cities	Immigrant Cntry	Cities	Immigrant Cntry	Cities
Argentina	1	Greece	1	Mexico	23
Armenia	1	Guatemala	4	Nicaragua	1
Bangladesh	1	Guyana	1	Pakistan	1
Brazil	3	Haiti	2	Peru	3
Canada	4	Honduras	3	Philippines	12
China	7	Hong Kong	3	Poland	2
Colombia	2	India	12	Portugal	1
Cuba	3	Iran	1	Russia	1
Dominican Republic	3	Ireland	1	Taiwan	4
Ecuador	1	Israel	1	Trinidad & Tobago	1
Egypt	1	Italy	1	Ukraine	1
El Salvador	6	Jamaica	2	United Kingdom	1
England	1	Japan	2	Venezuela	1
Germany	2	Korea	5	Vietnam	9

The data of interest for niche identification are the North American Industry Classification System (NAICS) industry code for each resident and the place of birth for each resident of the metropolitan area. The NAICS industry codes categorize businesses based on the type of work they perform based on various levels of specificity. Two-digit NAICS codes represent broader industry categories whereas three- and four-digit NAICS codes represent more specific sub-categories of business (U.S. Census Bureau, 2013b). Previous research into immigrant niching has been less than consistent in their aggregation of economic sectors (Wang, 2004). Some researchers look at a fixed set of occupations while others look at a subset of sectors within the overall economy. The two-digit NAICS industry codes are used to define sectors in which niches can occur. Sectors also provide a more appropriate level of niche assessment than occupation: occupations can span multiple industries and are better suited to understanding the division of labor than the clustering of ethnicities, and industries also capture co-ethnics working in different occupations but in the same work place (i.e., industry) (Ellis et al., 2007; Waldinger, 1996). The sectors, as defined by the 2007 two-digit NAICS industry codes, are listed in Table 16. As discussed above regarding sampling, the decision to analyze the employment data using the two-digit NAICS rather than lower-level, more specific, industry codes influences these results. Though the two-digit industry codes are convention in the niche analysis literature, this research is limited to using them due to concerns about sample size if disaggregated to three-digit or four-digit industry codes.

Table 16. Industry sectors analyzed for immigrant niche identification.

Code	Description	Size*	Code	Description	Size*
11	Agriculture, Forestry, Fishing and Hunting	0.74%	53	Real Estate and Rental and Leasing	2.09%
21-22	Mining, Quarrying, and Oil and Gas Extraction; Utilities	0.45%	54-55	Professional, Scientific, and Technical Services; Management of Companies and Enterprises	5.86%
23	Construction	10.53%	56	Administrative and Support and Waste Management and Remediation Services	6.57%
31-33	Manufacturing	13.55%	61	Educational Services	5.12%
42	Wholesale Trade	3.82%	62	Health Care and Social Assistance	12.27%
44-45	Retail Trade	9.90%	71	Arts, Entertainment, and Recreation	1.50%
48-49	Transportation and Warehousing	4.61%	72	Accommodation and Food Services	9.83%
51	Information	1.89%	81	Other Services (except Public Administration)	7.15%
52	Finance and Insurance	4.12%			

* Size as a percent of the total sample population.

In addition to the NAICS codes, the PUMS data also provide the variables for assessing the Niche Index. The variables *percent male*, *percent poor English*, *percent new entry*, and *group dominance* were calculated using the PUMS data. The unemployment variables, *average percent unemployment* and *unemployment change*, were calculated from U.S. Bureau of Labor Statistics' Smoothed Seasonally Adjusted Metropolitan Area Estimates (U.S. Bureau of Labor Statistics, 2013b). This dataset provides monthly unemployment rates for each metropolitan area. The *average percent unemployment* variable is calculated as the average monthly unemployment rate from January 2006 to December 2010 for each city. The *unemployment change* variable is calculated as the difference between the 2010 average monthly unemployment rate and the 2006 average monthly unemployment rate.

3.3.3. Results

3.3.3.1. Niche identification

A quick look at sector niche totals, shown in Table 17, reveals that immigrant groups prefer to form their niches in specific industries, regardless of city. Of the 361 niches identified across 17 sectors in this analysis, 50 percent of them (179) are found in 4 sectors: Construction (49 niches), Accommodation and Food Services (45 niches), Administrative Support (43 niches), and Other Services (42 niches; this sector includes auto repair, barber shops and nail salons, and dry cleaning services). Another 40 percent of the niches (146) can be found in the 6 additional sectors: Manufacturing (36 niches), Agriculture (28 niches), Health Care (24 niches), Professional Services (22 niches), Wholesale Trade (19 niches), and Transportation and Warehousing (17 niches). The Finance and Insurance sector had 11 niches, while Information and Real Estate sectors were both identified with 7 niches. Retail Trade and Arts/Entertainment sectors claimed five and four niches, respectively, Mining/Oil and Gas only two niches, and Education Services lacked any niches.

Table 17. Sector niches totals across 26 cities and 42 immigrant groups.

Code	Description	Niches	Code	Description	Niches
11	Agriculture, Forestry, Fishing and Hunting	28	53	Real Estate and Rental and Leasing	7

Code	Description	Niches	Code	Description	Niches
21-22	Mining, Quarrying, and Oil and Gas Extraction; Utilities	2	54-55	Professional, Scientific, and Technical Services; Management of Companies and Enterprises	22
23	Construction	49	56	Administrative and Support and Waste Management and Remediation Services	43
31-33	Manufacturing	36	61	Educational Services	0
42	Wholesale Trade	19	62	Health Care and Social Assistance	24
44-45	Retail Trade	5	71	Arts, Entertainment, and Recreation	4
48-49	Transportation and Warehousing	17	72	Accommodation and Food Services	45
51	Information	7	81	Other Services (except Public Administration)	42
52	Finance and Insurance	11			

The number of niches identified in each city appears highly dependent upon the number of immigrant groups and the total immigrant sample size of the city. Pearson's correlation coefficient between the number of niches and the number of immigrant groups in a city is $r = 0.99$ and between the number of niches and immigrant sample size is $r = 0.89$. However, normalizing the number of niches in a city by the city's immigrant sample size reveals some substantial outliers among the cities. Clear spikes can be seen in Charlotte and Salt Lake City, while troughs are also noticeable in Chicago, Los Angeles, Phoenix, and Riverside. Charlotte's and Salt Lake City's small average group sample size (1002 and 1228, respectively, each with one immigrant group) and relatively large number of niches contribute to these spikes. Conversely, cities with fewer niches per 1000 immigrants have larger average immigrant sample sizes, indicating an inverse relationship between group size and niche formation.

New York, with the largest number of immigrant groups and thus the most diverse population of the study cities, showed the largest number of niches with 102. New York only had two sectors with no identified niches: Mining/Oil and Gas (a very small industry in New York, representing only 0.6 percent of employment) and Educational Services (which occupies a much larger 11 percent of city employment). Detroit, on the other hand, had the fewest niches with one. Nine cities, including Detroit, had samples that consisted of only one immigrant group, however the number of niches found in these cities range from one (Detroit) to five (Salt Lake City and San Antonio). While at first glance one may take this to be a function of the cities and their economies, further investigation into the immigrant groups themselves reveals striking niche patterns across space.

Focusing on the seven immigrant groups represented in five or more study cities, consistent niche behavior is observed across most cities. Figure 11 and Figure 12 in the Appendix highlight the niches of these seven immigrant groups graphically.

- Chinese immigrants are sampled in seven cities and occupy 14 niches in these cities. In six of seven cities, they have niches in Accommodation/Food Services, and in four of ten cities they have niches in Manufacturing.
- Salvadorians are sampled in six cities, occupying 22 niches. In all six cities, they niche in Construction and Administration Support sectors. Salvadorians occupy niches in Accommodation/Food Services in all but one city, and in Other Services in four of their six cities.

- Indians occupy 23 niches in 12 cities. In all cities they form niches in the Professional/Scientific/Technical Services sector. Their other 11 niches are not consistent across the cities.
- Koreans occupy 10 niches across five cities. Their niche pattern is less well-defined; however in four of their five cities they form niches in Other Services.
- Mexicans are sampled into 23 cities and occupy 97 niches. In all cities, Mexicans form niches in the Construction and Administrative Support sectors. In all but one city, Mexicans niche in the Agriculture industry, and in 19 of 23 cities they form niches in Accommodation/Food Services.
- Filipinos occupy 18 niches in 12 cities. In all twelve cities, Filipinos niche in the Health Care industry. In four of 12 cities, Filipinos niche in Transportation/Warehousing.
- Vietnamese immigrants are sampled into nine cities and occupy 20 niches. In all cities, they form niches in Manufacturing and in Other Services.

These descriptive results are contrary to the initial hypothesis of heterogeneous niche sectors for an immigrant group in different cities. The results suggest niche formation is a fairly homogeneous phenomenon across space, supporting the conclusion of Ellis et al. (2007) that immigrant workers concentrate in a limited number of industries. The seven immigrant groups exhibit high sectoral consistency across their respective cities. However, sectoral consistency cannot be assessed for the 35 other immigrant groups represented in the study due to limited representation across multiple cities. While this pattern is highly evident in this subset of data, it is based upon only one-sixth of the immigrant groups analyzed in this research, and an even smaller sample of the total number of immigrant groups residing and working in the U.S. Despite the limiting extent to which these results can be extrapolated, the sectoral homogeneity demonstrated for these seven immigrant groups provides an important benchmark for understanding the spatial consistency for any set of immigrant groups. Sectoral consistency, however, does not speak to the probability that an immigrant group will form a niche in a given city. The Niche Index is assessed next, which provides a more holistic view of immigrant sectoral clustering.

3.3.3.2. Propensity to niche

The Niche Index was calculated for the 136 unique group-city combinations. The Indian population in San Jose received the highest propensity to niche at 0.23, indicating Indians are highly clustered in San Jose. The 0.23 index value can be interpreted as a 23 percent chance that any two San Jose Indians would be employed in the same industry. The lowest calculated Niche Index value was for Venezuelans in Miami, at 0.07, indicating nearly perfect dispersion across the 17 industries. The mean niche propensity across all observations is 0.12, while average propensity by city ranges from 0.21 (Charlotte) to 0.09 (Miami). The Pearson's correlation coefficient between a city's average Niche Index and the number of immigrant groups sampled in a city is $r = -0.37$. The correlation coefficient between average Niche Index and city sample size is $r = -0.42$. Thus, larger immigrant groups, and the simple presence of other immigrant groups in the city, expands the labor market opportunities for a given immigrant group, driving down their propensity to niche.

Given these aspects of the Niche Index calculations, we now turn our attention to whether the two urban pillars of niche research, New York and Los Angeles, have immigrant groups with significantly different propensities to niche than each other and the remaining 24 cities.

3.3.3.3. Spatial variation in metropolitan propensity to niche

Beta regression results indicate that New York and Los Angeles do not significantly differ from each other in their immigrant groups' propensity to niche. The results also show that all cities which are significantly different from either New York or Los Angeles are significantly *more* prone to sectoral clustering than those two cities. Ten study cities are significantly more prone to niching than both New York and Los Angeles, two cities are significantly more prone than only LA, and fourteen cities are not significantly different from either of the reference cities. These relationships are shown in Table 18. The model has a reasonably good fit with a pseudo-R^2 of 0.44 and a log-likelihood of 315.20. Interpreting the coefficients requires exponentiating Euler's constant (e) to the coefficient value to get the odds-ratio of being clustered in that city as compared to the reference city. That is, $e^{\beta_i} = {p_i}/{(1 - p_i)}$. The exponentiated Intercept estimates are the odds associated with Los Angeles's and New York's propensity to niche. Using Atlanta as an example, one can see that $e^{0.52757} = 1.69$ is an immigrant's odds of being clustered reference Los Angeles, and $e^{0.433766} = 1.54$ is an immigrant's odds of being clustered reference New York. This indicates that, relative to both New York and Los Angeles, immigrants in Atlanta are greater than one-and-a-half times more likely to be employed in a niche. Looking at it as percentages, the results could be interpreted as an Atlanta immigrant is 54 percent more likely to be clustered in a sector than a New York immigrant, and 69 percent more likely to be clustered in a sector than a Los Angeles immigrant. Figure 9 shows a map of the 26 cities symbolized by the number of niches identified in each and its statistical difference between New York and Los Angeles. The full regression results and calculated odds are presented in Table 19.

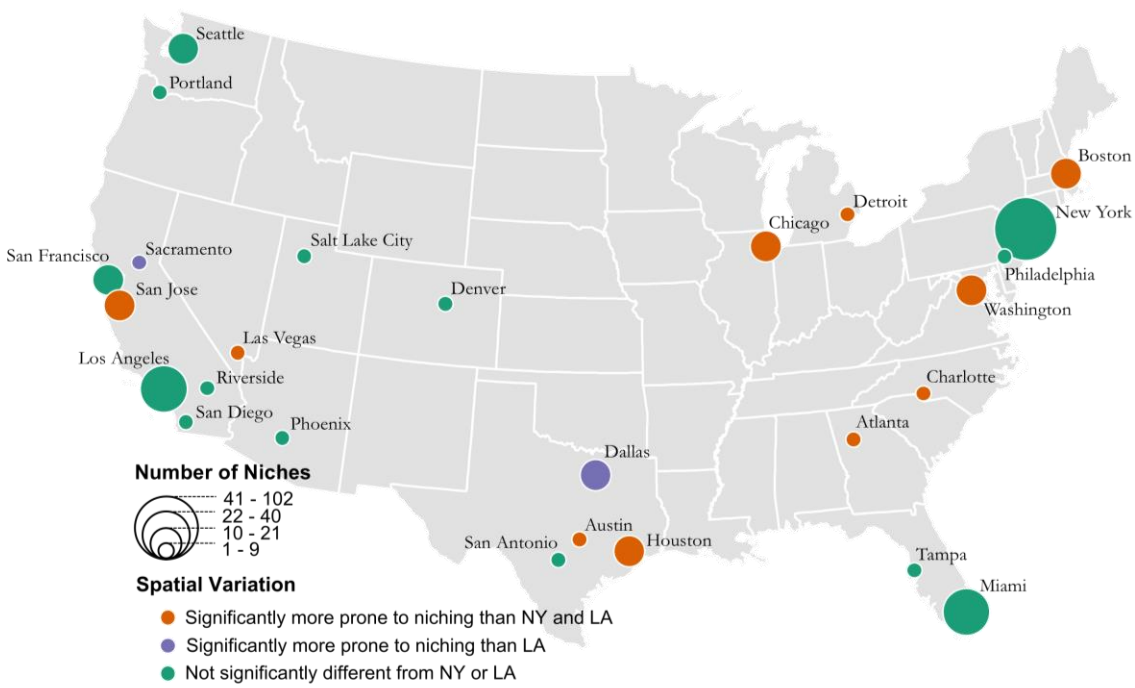

Figure 9. Map of the study cities depicting the number of niches identified in each (by size), along with the spatial variation in niche propensity (by color).

Table 18. Number of study cities whose propensity to niche is significantly different from the reference cities, New York and Los Angeles.

	Not significantly different from LA	**Significantly more prone to niching than LA**
Not significantly different from NY	14 Denver, Los Angeles, Miami, New York, Philadelphia, Phoenix, Portland, Riverside, Salt Lake City, San Antonio, San Diego, San Francisco, Seattle, Tampa	2 Dallas, Sacramento
Significantly more prone to niching than NY	0	10 Atlanta, Austin, Boston, Charlotte, Chicago, Detroit, Houston, Las Vegas, San Jose, Washington

Table 19. Beta regression results for spatial variation in Niche Index.

Variable	**Model Coefficient (LA as ref)**	**Odds (LA as ref)**	**Model Coefficient (NY as ref)**	**Odds (NY as ref)**
Intercept	–2.19	0.11	–2.10	0.12
Atlanta	0.53***	1.69	0.43***	1.54
Austin	0.59**	1.80	0.50*	1.64
Boston	0.34**	1.40	0.25*	1.28
Charlotte	0.89***	2.43	0.79***	2.21
Chicago	0.31**	1.36	0.21*	1.24
Dallas	0.30*	1.35	0.20	1.23
Denver	0.40	1.49	0.31	1.36
Detroit	0.63**	1.87	0.53**	1.70
Houston	0.34**	1.41	0.25*	1.28
Las Vegas	0.42**	1.52	0.33*	1.38
Los Angeles	N/A	N/A	–0.09	0.91
Miami	–0.06	0.95	–0.15	0.86
New York	0.09	1.10	N/A	N/A
Philadelphia	0.23	1.26	0.14	1.15
Phoenix	0.22	1.25	0.13	1.14
Portland	0.18	1.19	0.08	1.09
Riverside	0.32	1.37	0.22	1.25
Sacramento	0.33*	1.39	0.23	1.26
Salt Lake City	0.33	1.39	0.24	1.27
San Antonio	0.08	1.08	–0.02	0.98
San Diego	0.24	1.27	0.15	1.16

Variable	Model Coefficient (LA as ref)	Odds (LA as ref)	Model Coefficient (NY as ref)	Odds (NY as ref)
San Francisco	0.10	1.11	0.01	1.01
San Jose	0.64***	1.89	0.55***	1.72
Seattle	0.14	1.15	0.05	1.05
Tampa	0.11	1.12	0.02	1.02
Washington	0.40***	1.49	0.31***	1.36
Pseudo-R^2		0.44	0.44	
Log-likelihood		315.20 (df=27)	315.20 (df=27)	
Observations		136	136	

***, **, and * indicate significance at the 99.9 percent, 99 percent, and 95 percent levels, respectively.

These results indicate significant spatial variation in the propensity to niche, insofar as it can be measured relative to Los Angeles and New York. Metropolitan areas both nearby and far away from these two immigrant gateways are significantly more prone to niche formation. On the other hand, the results signify a majority of the cities evaluated are not significantly different from either of these two cities. Nor do the results highlight any spatial clusters that are significantly different from the two reference cities, indicating that individual city characteristics, and characteristics of the distinct immigrant populations in those cities, are driving the propensity differences rather than regional trends.

3.3.3.4. Drivers of niche propensity

Beta regression results for the drivers of niche propensity indicate four significant variables. Table 20 provides the full regression results, as well as the odds ratios calculated from the model coefficients. Model fit is reasonable and in-line with most research on immigrant niches. A pseudo-R^2 of 0.36 is calculated, improving upon previous attempts to model drivers of niche formation (Wang, 2004). Log-likelihood for the model is 304.10 with 14 degrees of freedom.

Table 20. Beta regression results for immigrant group propensity to niche.

Variable	**Model Coefficient**	**Odds**
Intercept	1.34	3.82
Sample Population (log)	0.10**	1.11†
Percent Male	0.40	1.50
Metropolitan Population (log)	–0.26***	0.77†
Percent Foreign-born	–0.44	0.64
Average Percent Unemployment	2.72	15.25
Unemployment Change	–0.23**	0.80
Percent Poor English	–0.39**	0.68
Percent New Entry	0.52	1.68
Group Dominance	–0.25	0.78
South Region (dummy)	–0.04	0.96
Midwest Region (dummy)	0.10	1.10
West Region (dummy)	–0.07	0.93
Pseudo-$\boldsymbol{R}^2$	0.36	
Log-Likelihood	304.10 (df=14)	
Observations	136	

***, **, and * indicate significance at the 99.9 percent, 99 percent, and 95 percent levels, respectively.
† indicates the odds ratio should be interpreted as a function of change by multiple of the dependent variable rather than unit increases of the dependent variable.

Both size variables are significant, though with opposite effects. The sample population variable is positively significant, contrary to expectations that it would have a negative effect. This may indicate that niches are more ‘career-focused’, as suggested by Waldinger (1994), rather than initial short-term opportunities that allow immigrants easy entry to the metropolitan labor force. As new immigrants enter the labor force in a niche industry, the more tenured immigrants are not leaving the niche industries for employment in the broader labor market. This supports previous research findings that larger immigrant groups work to reinforce the niching process by providing a pipeline for employment in sectors already rich with that immigrant group (Bailey & Waldinger, 1991; Portes & Sensenbrenner, 1993). The significant negative relationship of the city population variable confirms the initial hypothesis that larger cities will, due to their broader economies and inherent population diversity, drive down niche propensity.

Change in unemployment over the study period is a significant variable and has a negative relationship with propensity to niche. This confirms the stated hypothesis that cities with greater growth in unemployment over the study period would experience lower propensities to niche. As jobs are lost within an immigrant niche, those immigrants seek out employment in non-niche sectors, leading to decreases in Niche Index values. Percent poor English is also significant with a negative relationship to the Niche Index, again contrary to expectations. A positive relationship was expected: that larger percentages of non- and poor-English speakers would lead to higher Niche Index values. These poor English speakers would be more reliant on co-ethnics to obtain employment, which would likely be in established niches, thus reinforcing these existing niches. On the contrary, the results show that larger percentages of non- and poor-English speakers drives down the propensity to niche. It is speculated that this negative relationship may be explained by looking at the immigrant population arriving since 2000 in these cities. At an aggregated level, weak positive correlation is seen between the *percent new entry* and *percent poor English* variables, with a Pearson's correlation coefficient of $r = 0.25$. This signifies either that a substantial portion of the more tenured immigrant population remains poor English speakers, or that a substantial portion of the new immigrants speak English reasonably well. Either situation would drive down the Niche Index: more tenured immigrants would have more exposure to local primary and secondary labor market opportunities and would thus have greater opportunities to find employment outside of niches; new immigrants with good English-speaking skills will be able to rely less on co-ethnics to find employment, and they will be able to more quickly assimilate with the local culture.

This mixed relationship within the immigrant populations may also be the source of the significance level of the *percent new entry* variable. This variable has a positive relationship, as expected, but just missed the 0.05 significant cut-off with a p-value of 0.056. Suspicious that multicollinearity between the variables measuring poor English and high levels of new immigrants was reducing significance for this variable, the model was tested with the *percent poor English* variable removed. The resulting sign and significance level of the *percent new entry* is consistent with its original coefficient.

The remaining four covariates were more clearly insignificant in their relationship to the Niche Index, as were the regional dummy variables. *Percent males* and *average percent unemployment* both had positive but insignificant coefficient estimates, while *percent foreign-born* and *group dominance* both had negative and insignificant relationships. With the exception of *average percent unemployment*, each of these was directionally in-line with initial hypotheses. The regional dummy variables are also insignificant, indicating that there are not broader regional drivers of niche propensity, and reinforcing that the propensity to niche is highly contingent upon the unique urban socio-economic character, and the particular characteristics of the immigrant groups themselves.

The lack of significant relationships for these variables indicates several things. First, immigrant populations dominated by a particular gender are no more prone to niching that populations dominated by the other gender. While previous research has demonstrated that immigrants of the different genders cluster in different industries (Hudson, 2002; Wright & Ellis, 2000), these results suggest that neither is significantly more prone to clustering. Second, average unemployment for a metropolitan area has no significant effect on the niche propensity of the immigrant groups within that metro area. This is perhaps indicative of the structural nature of an 'average' measure, suggesting the immigrants formed their niches in the context of an understanding of the overall unemployment picture within a metro area. Third, the relative size of the overall foreign-born population of a metro area, and the relative size of the specific immigrant group population, does not affect an individual immigrant group's propensity to niche. As previously mentioned, the results here indicate that absolute size, rather than relative size, has a significant positive effect on niche propensity. Viewed in the context of the homogeneous nature of niche formation by a group within a city, it is clear that larger absolute numbers clearly reinforce the sectoral clustering. Viewed in the context of the opposite effects of immigrant group sample size (positive) and city population (negative) on Niche Index values, it is reasonable to suspect that combining these two measures would lead to an insignificant result. Fourth, there is no significant spatial clustering or regional characteristics driving Niche Index values for an immigrant group. The spatial variation hypothesized and demonstrated in propensity to niche appears to be limited to the metropolitan level.

Exploratory analysis showed that removing the regional dummy variables from the model increased the significance of the percent new entry variable to the 0.05 level. This is likely due to the uneven destination space of the recent immigrant populations, and the overwhelming growth of those foreign-born populations in the greater Southeastern U.S., mainly at the expense of the Pacific West (J. H. Wilson & Singer, 2011). Correlations between *percent new entry* and the regional dummy variables reinforce this: $r_{NE} = -0.08$, $r_S = 0.37$, $r_{MW} = -0.009$, and $r_W = -0.28$.

Interpreting the Beta regression coefficients of the variables, as described in the previous section, requires exponentiating the coefficients over e. However, because two of the significant variables are logged and two are not, a discussion of the different relationships is warranted. Under normal circumstances, one would interpret the model coefficients to be the change in the log odds given a one unit increase in the predictor variable. Transforming these coefficients to odds, a one unit increase in the predictor variable should produce a $(odds - 1) * 100$ percent increase in the odds. Using unemployment change as an example, a one percent increase in the amount of unemployment change (that is, more unemployment) leads to a 20 percent *decrease* in the odds of being clustered in a sector.

For the logged variables, the percentage increase is now associated with multiples of the predictor variable rather than unit increases. Using the sample population variable as an example, the results indicate that a doubling of the sample population would *increase* the odds of being clustered in a sector by 11 percent. Looking at the negative coefficient for metropolitan population, one can interpret the estimates to say that a doubling of the metro population leads to a 23 percent *decrease* in the odds of being clustered in a sector.

3.3.4. Discussion

This section of the dissertation investigates the phenomenon of niche formation and whether this phenomenon is consistent across metropolitan areas. In addition to utilizing the traditional method of identifying niches, the location quotient, a new method called the Niche Index is introduced. The Niche Index characterizes the probability that an immigrant group member is employed in a niche, or an immigrant group's propensity to niche. The Niche Index provides a view of immigrant niching not seen in the literature to date. This research demonstrates the heterogeneity of niching propensity across space relative to New York and Los Angeles, and it is statistically shown that metropolitan population and immigrant group populations drive the propensity to niche.

The results of this research show immigrant niches to be a complex phenomenon that has both homogeneous and heterogeneous tendencies across space. Fifty percent of all immigrant niches identified in this research were found in four sectors (Construction, Administrative Support, Accommodation and Food Services, and Other Services). Among the immigrant groups with ample representation across multiple cities, sectoral niches are highly consistent across metropolitan areas. Of these seven immigrant groups, five had at least one niche in the same sector across all their cities, while two had niches in the same sector in all but one of their cities. Along with these consistencies, significant differences are found in the propensity to niche across cities. Ten cities are significantly more prone to niching than both New York and Los Angeles, the major foci of most niche research. Significant among the drivers of niching propensity are the immigrant group population and the metropolitan population at large, however these influence the propensity in opposite ways: metropolitan population negatively, immigrant group population positively. The change in metro-area unemployment and the percent of poor/non-English speakers among the immigrant group also influence negatively the propensity of that group to niche.

These results both confirm and contradict some of the initial hypotheses of this research. Larger metropolitan populations drive down immigrant propensity to niche, as the cultural and economic diversity inherent in larger cities provides more economic opportunities to immigrants on the whole. However, larger immigrant groups drive up niche propensity, as these groups are likely utilizing their own sectorally specific labor market knowledge to provide initial employment opportunities for co-ethnics, thus feeding and reinforcing the existing niche industries. Greater metro-area unemployment growth leads to decreased propensity to niche, supporting the contention that as jobs are lost across the economy, these unemployed residents (both native and immigrant) seek employment in any available industry, thus diluting immigrants' economic clusters. Greater proportions of poor- and non-English speakers also lead to lower propensity to niche, which suggests that the majority of poor/non-English speakers are among the more tenured of the group while new immigrants to be better skilled in the English language, both serving to have a negative effect on niche propensity.

While the results of this research support some of the conclusions of other scholars (Ellis et al., 2007; Waldinger, 1994), the results also demonstrate that there is significant insight into the niching phenomenon by expanding beyond the limited geographies of the existing research (New York and Los Angeles, predominantly). Immigrant groups in ten of the 26 study cities are significantly more prone to niching than those in New York and Los

Angeles, a function of both the composition of the immigrant groups themselves and the demographic and economic history (and present) of the place. Conversely, 14 of the 26 are not significantly different New York and Los Angeles, indicating that these two cities may be representative of a given set of cities, just not all classes of cities in which niches will form. Additionally, the sectoral consistency across space is demonstrated quite strongly, and confirms suggestions in previous research. However, these results limited to the analysis of only the seven immigrant groups who were present in five or more cities. The results of this research encourage broader exploration of the spatial consistencies and inconsistencies of the niche phenomenon, and more comparative research on niching between metropolitan areas.

3.4. Foreign-born Population Impact

Immigrant niches are a fundamental element of foreign-born labor, and labor in general, in the metropolitan economy. By examining niches across the 51 study cities, this dissertation research has shown the industries where immigrants cluster and the metropolitan attributes that drive a group's propensity to niche. But the previous analysis does not address the labor market relationship between foreign-born and domestic workers. The impact of immigrants on local economies is another critical element in the analysis of international migration in the U.S. This final piece of research assesses the impact of foreign-born populations on the economic and occupational stature of native-born workers in large U.S. metropolitan areas, specifically during the period surrounding the recent economic downturn. Given the conclusions of previous scholars that native-born unemployment is negligibly affected by immigration, and the debate among researchers on foreign-born labor's impact on native wages, this analysis should fill an important research gap: the impact of foreign-born labor during a specific economic cycle. The recent Great Recession in America, part of the larger global financial crisis that the world's economies are still recovering from, provides an opportunity to assess whether the previous findings of minimal impact by immigrants on native-born worker wages and unemployment holds true during a time of economic turmoil.

3.4.1. Methods

Multivariate OLS regression is used to estimate growth (or change) of several economic variables between the 2005-2007 period and 2009-2011 period. The same large metropolitan areas are used again: those with a total population greater than one million, of which there are 51 in the United States. To assess economic growth characteristics of native-born workers, three variables are examined: change in percent unemployment, change in median household worker income, and change percent of individuals living in poverty. Median household worker income is determined by dividing the median household income for the metro area by the average number of workers per household. For simplicity, as the hypothesized impacts of each independent variable are discussed below, only the expected impact on native unemployment growth will be stated. However, it is hypothesized the same relationships exist for native poverty growth as for native unemployment growth given the high positive correlation between the two variables themselves (r=0.78). It is also expected the opposite dependent variable relationships to occur for native income growth due to the negative correlations between the income growth and unemployment growth (r=–0.46) and poverty growth (r=–0.59).

There are thirteen independent variables. The independent variables of primary interest are percent foreign-born in 2005-2007 and the diversity of the foreign-born population during the same period. Foreign-born and diversity figures for the start time of this analysis are used to allow us to assess the impact of immigrants on economic changes that occur between the two periods. The percent foreign-born is calculated as simply the proportion of the metropolitan population that has a country of birth other than the United States. Foreign-born diversity is calculated in accordance Ottaviano and Peri's (2006b) method, which is similar to the Gini-Simpson diversity index (Jost, 2006) and represents the probability that any two individuals selected from the foreign-born population have different countries of birth. It is also very similar to the Niche Index presented in Section 3.3, which models clustering rather than diversity. Diversity here is calculated as:

$$D = 1 - \sum_{i=1}^{n} p_i^2$$

where p_i is the proportion of the metro area's foreign-born population that is born in country i, and $i = 1, 2, \dots, n$ is a list of 97 potential countries of origin and 'other' categories provided by the data. The diversity index has a range of 0 to 1, where an index value of 0 indicates all of the foreign-born were borforeign-bornn in the same country and a value of 1 indicates perfect dispersion across all countries. Following from the results of Ottaviano and Peri (2005, 2006a, 2006b), both percent foreign-born and diversity are expected to have negative impacts on native unemployment growth. They show that cities with greater diversity are more productive, and hence immigration is a net benefit to urban and the U.S. economy (Ottaviano & Peri, 2006b), and it is expected that this will manifest in the analysis through better urban responses to the recession.

As an alternative measure of diversity, Florida's (2002a) Bohemian Index is included as an independent variable. While this does not measure the impact of foreign-born populations and cultures, it attempts to capture the diversity of cultural opportunity within a metropolitan area, as measured by the area's representative employment in the arts (Ó hUallacháin & Leslie, 2005). The Bohemian Index is calculated as a location quotient for the arts employment within each metropolitan area, as compared to the nation as a whole. Florida (2002a) showed that metropolitan areas with high concentrations of Bohemians were strongly correlated with areas of high human capital and high technology. It is included here to test whether metros with higher concentrations of Bohemians fared better than their counterparts. If Florida's correlations to high human capital and technology hold, a negative relationship is expected: cities with higher concentrations of Bohemians will experience less unemployment growth through either a stronger response to the recession or a quicker recovery.

The percent growth of the foreign-born population between the two periods is also included, defined as the raw growth between the two periods as a percentage of the 2005-2007 foreign-born population, as an independent variable. This allows for capturing the effect of new migrants (or those that have departed) on the economic changes and draw conclusions about changing migrant levels during the recession. Wilson and Singer (2011) show that during the 2000s decade, metropolitan migrant populations grew fastest in cities with smaller foreign-born percentages. The data concur with this: a $r = -0.53$ correlation coefficient is calculated between the 2005-2007 percent foreign-born of a city and the percent of foreign-born growth between 2005-2007 and 2009-2011. Thus, with the majority of new migrants going to smaller cities (both in terms of total and relative foreign-born population), to the goal is understand their impact on the natives in these places. A negative relationship is expected between foreign-born population growth and unemployment growth due to the higher internal mobility of immigrants than natives (Bartel, 1989): metro areas that experience greater job losses will have significantly fewer gains (or greater losses) of immigrants because of their willingness to move for employment opportunities.

The estimated total population of each metropolitan area for the 2005-2007 period is included to control for city size. Larger cities tend to have greater diversity of economic opportunities and a larger number of social services (Wheeler, 1988). These characteristics may prevent native-born workers from becoming unemployed or slipping into poverty. City population is expected to have a negative correlation with unemployment growth because of these factors.

A measure of the spatial structure surrounding the city is included as an independent variable to capture two spatial effects: the impact of agglomeration economies (Rosenthal & Strange, 2001) and the flexibility with which ease of mobility (both native and foreign-born) might affect native labor forces during the recession. The Spatial Interaction Regression analysis in Section 3.2 controlled for spatial structure when estimating distance decay parameters using this same method, because spatial structure has strong implication for how and where people move within in region. This measure of spatial structure, presented by Hansen (1959), is considered a measure of accessibility of the city. Accessibility for a city i is calculated as:

$$A_i = \sum_{\substack{j=1 \\ j \neq i}}^{n} p_j / d_{ij}$$

where p_j is the population of another city j in the set of places, d_{ij} is the distance between city i and city j, and $j = 1, 2, \dots, n$ are the study cities. Metro areas with high accessibility are indicative of urban agglomerations (e.g., the U.S. mid-Atlantic Interstate 95 corridor), whereas metros with lower accessibility values are more isolated (e.g., Seattle, WA or Oklahoma City, OK). Spatial structure is expected to have a positive correlation with unemployment gains due to the competition and complementarity inherent in agglomeration economies (Rosenthal & Strange, 2001; Storper & Scott, 2009). Additionally, while accessibility has been shown to be directly tied to economic development (Vickerman, Spiekermann, & Wegener, 1999), accessibility also provides firms broader access to human capital and, likewise, human capital broader access to firms. Thus, an unemployed worker in highly accessible areas is competing for new jobs not just with his urban co-residents, but also with residents in nearby cities that are part of the agglomeration economy. This variable is logged because of heteroskedasticity.

Unemployment due to the recession of 2007 to 2009 was not equally dispersed across the economy: the construction and manufacturing industries were much more severely affected than other industries (U.S. Bureau of Labor Statistics, 2010) and also slower to recover than other sectors (Levine, 2012). Additionally, a select group of the service sectors experienced significantly higher job loss than the rest (U.S. Bureau of Labor Statistics, 2011). To ensure the employment structure of each metropolitan area is accounted for, the percent of employment in three sector categories are captured as independent variables: (1) major employment losses: construction and manufacturing sectors; (2) moderate employment losses: wholesale trade, retail trade, transportation and warehousing, information, financial, and professional services sectors; and (3) employment gains: health care and education sectors. These are same employment structure variables used in Spatial Interaction Regression. The results there showed percent employed in health and education has a negative relationship with distance decay, potentially indicating spatial convergence of education/healthcare employment. While the other employment groupings were not statistically significant in the Spatial Interaction Regression, the significance of education/healthcare variable has implications here because it suggests that internal migrants were not drawn to cities with high employment in these sectors, despite their growth during the recession period. Thus, the competition for these jobs is generally internal to the metropolitan area. The immigrant niche analysis showed that 24 immigrant groups across 26 cities held niches in the healthcare sector (NAICS 62), but none had niches in the education sector (NAICS 61). Table 21 presents the sectors in each employment category and the unemployment growth within each sector.

Table 21. The employment structure categories and the unemployment growth (for native-born workers) of economic sectors during the recession with their NAICS codes (U.S. Bureau of Labor Statistics, 2011).

Major Employment Loss		**Moderate Employment Losses**		**Employment Gains**	
Sector	**Emp Change**	**Sector**	**Emp Change**	**Sector**	**Emp Change**
Construction (23)	–19.8%	Wholesale Trade (42)	–7.6%	Education and Health Care (61-62)	+3.3%
Manufacturing (31-33)	–14.6%	Retail Trade (44-45)	–6.7%		
		Transportation and Warehousing (48-49)	–7.3%		
		Information (51)	–7.6%		
		Financial (52)	–5.8%		
		Professional Services (53)	–8.9%		

Education levels of an area are a driving force behind employment growth (Acs & Armington, 2004). The regression models control for the education structure of the native-born population by focusing on the education extremes. Independent variables for the percent of natives with less than or equal to a high school diploma and the percent of natives with greater than or equal to a bachelor's degree in the 2009-2011 period are included. It is important to control for the high end of the education spectrum because higher educated employees are significantly less likely to lose their jobs during the recession, and they gained jobs after the recession much more quickly than those with lesser education (Levine, 2012). The latter rather than earlier period is used because the education levels obtained as of 2009-2011 should have a direct impact on the changes in economic variables between the two periods; that is, an employee who received a graduate degree by the end period will be more likely to be employed and have a higher income, influencing the employment and income differentials.

Regional differences are expected with regard to changes in unemployment. The southeast and Pacific west U.S. were generally the worst at retaining employment, while the plains states between the Mississippi River and the Rockies, and the northeast U.S., more successfully retained employment (Friedhoff, Kulkarni, & Berube, 2012). Regional differences in recession affects can be somewhat attributed to the historical and prevailing economic structures of the metropolitan areas within them, as well as the extent of the housing bust in the metropolitan areas (Wial & Shearer, 2011). To compensate for these regional differences, the U.S. Census Bureau's region-level geographic boundaries are used (U.S. Census Bureau, 2012c). Dummy variables capture the metropolitan area's presence in a region, and the Northeast region is excluded as the dummy variable reference area. Table 22 summarizes these dependent and independent variables.

Table 22. Expected sign and significance of independent variables for each model.

	Expected Sign and Significance		
Dependent Variables	Model 1: Native Unemp. Growth	Model 2: Native Income Growth	Model 3: Native Poverty Growth
Percent Foreign-Born	(–) significant	(+) significant	(–) significant
Diversity	(–) significant	(+) significant	(–) significant
Foreign-Born Percent Growth	(–) significant	(+) significant	(–) significant
Bohemian Index	(–) insignificant	(+) insignificant	(–) insignificant
City Population	(–) insignificant	(+) insignificant	(–) insignificant

	Expected Sign and Significance		
Dependent Variables	Model 1: Native Unemp. Growth	Model 2: Native Income Growth	Model 3: Native Poverty Growth
Accessibility (log)	(+) significant	(–) significant	(+) significant
Low Education	(+) significant	(–) significant	(+) significant
High Education	(–) significant	(+) significant	(–) significant
Const./Manuf. Emp.	(+) significant	(–) insignificant	(+) significant
Select Serv. Emp.	(+) significant	(–) insignificant	(+) significant
Educ./Health Emp.	(–) significant	(+) insignificant	(–) significant
South (dummy)	(+) significant	(–) significant	(+) significant
Midwest (dummy)	(+) insignificant	(–) insignificant	(+) insignificant
West (dummy)	(+) significant	(–) significant	(+) significant

3.4.2. Data

This research utilizes U.S. Census Bureau ACS three-year estimates for 2005-2007 and 2009-2011 (U.S. Census Bureau, 2007, 2012a). The ACS three-year estimates aggregate survey sample data collected from 2005-2007 and 2009-2011, respectively, to derive their variable estimates (U.S. Census Bureau, 2008). ACS multiyear estimates cannot be interpreted as referring to a specific year within the interval, but should be interpreted as the average estimate over the period in question (U.S. Census Bureau, 2009a). The ACS three-year estimates provide a more accurate estimate due to larger sample sizes than the one-year ACS, and they offer a more reliable estimate by smoothing out annual anomalies across a three-year period. As with the ACS data used in the previous sections, however, this data is a sampled dataset with a sampling error. Given the dataset are three-year versus five-year samples, the margin-of-error for the statistical estimates is greater than the five-year data previously used. The use of five-year datasets for this portion of the research is restricted by the goal of assessing the change in unemployment, income, and poverty across the recession period. The available five-year datasets for this period would be greatly smoothed and would overlap temporally (2005-2009, 2007-2011), with a substantial portion of the samples being used to estimate the data for each period.

The focus is on the foreign-born and native populations of the same 51 largest U.S. cities studied in previous sections of this dissertation. The MSA population variables are derived from the 2005-2007 three-year estimate,[4] which, using the same threshold of a population of one million or greater, yields the same study sample of 51 metropolitan areas. The 2005-2007 foreign-born percentages range from a high of 37 percent in Miami to a low of 3 percent in Pittsburgh. The percent foreign-born of the study cities, and their diversity statistic (calculated using the above described method), are presented in Table 23.

Table 23. Percent foreign-born population of the study cities for the 2005-2007 period.

City	Percent Foreign-born	Diversity	City	Percent Foreign-born	Diversity
Miami, FL	36.89%	0.88	Raleigh, NC	10.43%	0.87
San Jose, CA	36.29%	0.89	Charlotte, NC	8.99%	0.89
Los Angeles, CA	34.55%	0.80	Minneapolis, MN	8.72%	0.95
San Francisco, CA	29.55%	0.91	Detroit, MI	8.61%	0.95
New York, NY	28.06%	0.97	Philadelphia, PA	8.56%	0.97
San Diego, CA	22.96%	0.74	Baltimore, MD	7.51%	0.97
Riverside, CA	21.92%	0.59	Oklahoma City,	7.08%	0.78

[4] No U.S. MSAs rose above or fell below the one-million population threshold between the 2005-2007 and 2009-2011 periods.

City	Percent Foreign-born	Diversity	City	Percent Foreign-born	Diversity
			OK		
Houston, TX	21.28%	0.75	Jacksonville, FL	6.90%	0.96
Las Vegas, NV	21.21%	0.76	Milwaukee, WI	6.54%	0.86
Washington, DC	20.07%	0.96	Nashville, TN	6.51%	0.91
Dallas, TX	17.67%	0.66	Columbus, OH	6.16%	0.95
Chicago, IL	17.59%	0.81	Rochester, NY	6.10%	0.97
Sacramento, CA	17.36%	0.89	New Orleans, LA	6.02%	0.93
Phoenix, AZ	16.79%	0.58	Richmond, VA	5.86%	0.96
Boston, MA	15.88%	0.97	Kansas City, MO	5.64%	0.85
Orlando, FL	15.75%	0.96	Cleveland, OH	5.63%	0.97
Seattle, WA	15.32%	0.94	Virginia Beach, VA	5.53%	0.94
Austin, TX	14.05%	0.69	Indianapolis, IN	5.17%	0.86
Atlanta, GA	12.62%	0.91	Buffalo, NY	4.88%	0.96
Providence, RI	12.55%	0.89	Memphis, TN	4.33%	0.87
Denver, CO	12.53%	0.73	Saint Louis, MO	4.00%	0.95
Portland, OR	12.08%	0.88	Louisville, KY	3.60%	0.92
Tampa, FL	12.03%	0.95	Cincinnati, OH	3.50%	0.95
Hartford, CT	11.60%	0.95	Birmingham, AL	3.26%	N/A*
Salt Lake City, UT	11.36%	0.79	Pittsburgh, PA	3.01%	0.96
San Antonio, TX	11.04%	0.88			

* Country-of-origin statistics were not available for Birmingham, AL as part of the 2007 ACS 3-year data.

The economic variables of interest are the change in native-born percent unemployment, change in native-born median household worker income, and change in native-born percent in poverty. These are calculated as the difference between the 2005-2007 and 2009-2011 ACS estimates for the variables. Not all metropolitan areas experienced drastic unemployment increases during the study period. The mean native-born unemployment growth across all 51 cities was +2.5 percent, however the unemployment distribution ranged from an increase of +4.9 percent in Las Vegas, NV to an increase of +0.8 percent in Oklahoma City, OK and Houston, TX. Average native-born worker income growth varied greatly across the study cities as well, with Washington, DC experiencing the most growth at +$5,417 while Orlando, FL experienced the most income decline at –$2,156. The mean income growth for native-born workers across all cities was +$2,471. Poverty growth for native-born workers ranged from a high of +4.1 percent in Riverside, CA to a low of +0.5 percent in Memphis, TN, with an average growth of poverty across all cities of +1.9 percent. Figure 10 presents the native-born worker unemployment, income, and poverty growth for each city, categorized by region.

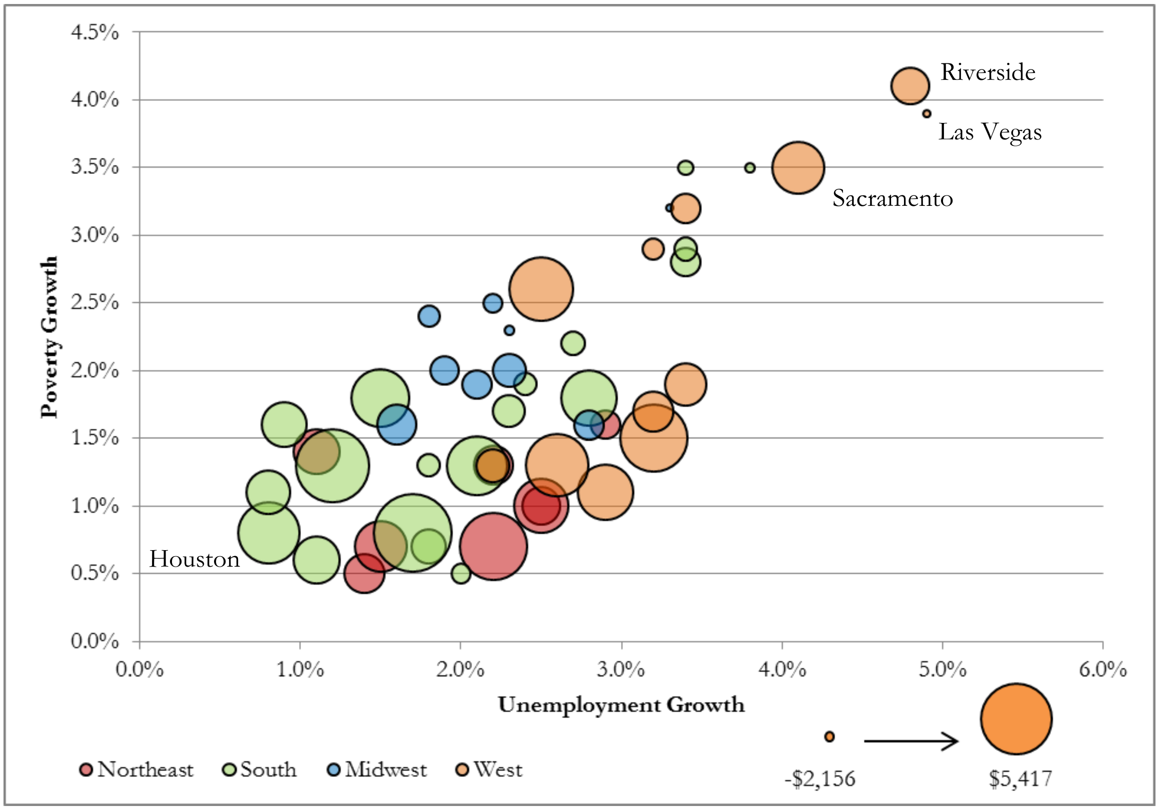

Figure 10. Chart representing the relationship between native-born unemployment growth (x-axis), poverty growth (y-axis), and income growth (relative circle size), and the region of each city (circle color).

Regionally, the variance of unemployment growth is lowest in the Midwest (0.0024 percent) and highest in the South (0.0121 percent). This is principally due to the successes of the four cities in Texas, as well as Oklahoma City, OK and New Orleans, LA, during the recession: native-born unemployment in these six cities increased by an average of +1.1 percent, while the other 15 southern cities averaged +2.8 percent unemployment growth for native-born workers. The South also has the highest variance in average native-born worker income growth, with over five times the variance of the Northeast. Poverty growth for native-born workers was the most variable in the West, which had eight times the variance of the Northeast.

Despite this variance, Moran's I tests for spatial autocorrelation reveal significant positive autocorrelation for each of the dependent variables across space. As in the previous sections, tests for autocorrelation were performed using multiple conceptualizations of spatial relationships/weights in an attempt to capture any broader spatial trends evident in the data. These conceptualizations are inverse distance weighting, inverse distance squared weighting, five nearest neighbors, ten nearest neighbors, and fixed distance bands at 500km, 1000km and 1500km. For all but one of the tested conceptualizations of spatial relationships, significant positive autocorrelation was identified, indicating there is some spatial dependence among these variables and spatial regression techniques may be necessary. Table 24 presents the global Moran's I autocorrelation results for inverse distance weighting; the results for the other spatial relationships tested are presented in the Appendix. Tests were also performed on the regression residuals to determine whether spatial regression was a necessary alternative for any of the current OLS models. These are discussed in the Results section.

Table 24. Global Moran's I spatial autocorrelation test results for the three independent variables.

	Native-Born Unemployment Growth	**Native-Born Income Growth**	**Native-Born Poverty Growth**
Moran's I	0.668 ***	0.497 ***	0.502 ***
Z-Score	7.692	5.823	5.799
p-value	0.000	0.000	0.000

*** indicates significance at the 99.9 percent level.

3.4.3. Results

Contrary to initial hypotheses, the percent foreign-born in a city at the outset of the recession is highly correlated with negative outcomes for native-born workers during the recession. Rather than having more stable native-born employment, income, and poverty, cities with larger proportions of foreign-born saw statistically higher unemployment and poverty growth, and statistically lower income growth. Foreign-born diversity had a less-consistent impact across the models, and foreign-born growth had no impact on native-born worker outcomes during the recession. The model results indicate reasonably good fits, with adjusted R^2 values of 0.63 for Model 1 (unemployment growth), 0.53 for Model 2 (income growth), and 0.57 for Model 3 (poverty growth). Breusch-Pagan tests for heteroskedasticity and Jarque-Bera tests for normality of errors reveal no concerns regarding distribution of the residuals. The VIF was calculated for reach independent variable to assess for multicollinearity: only among the two education variables is there collinearity, which is to be expected. Dropping either of these variables leads to poorer model fit statistics, and dropping the high-education variable leads to substantive changes to the significant variables. Moran's I tests for spatial autocorrelation of the models' residuals indicated no significant spatial dependence for any conceptualization of spatial relationship. The full results of the regressions and tests are presented in Table 25, and Moran's I test results are presented in the Appendix.

Table 25. Full regression results, including normality tests.

	VIF	Model 1: Native Unemp. Growth	Model 2: Native Income Growth	Model 3: Native Pov. Growth
Intercept		–0.142 (0.068)	19,400 (11,900)	–0.081 (0.071)
Percent Foreign-born	3.28	0.061 ** (0.018)	–11,500 *** (3,140)	0.050 * (0.019)
Diversity	1.73	0.027 * (0.009)	–2,190 (1,730)	0.014 (0.010)
Foreign-Born Percent Growth	2.25	–0.012 (0.013)	1,410 (2,310)	–0.009 (0.013)
Bohemian Index	3.78	0.010 (0.007)	–1,520 (1,140)	0.011 (0.007)
City Population	3.35	–6.98e–10 (4.99e–10)	0.0003 ** (8.71e–05)	–1.10e–09 * (5.22e–10)
Accessibility (log)	2.57	0.016 ** (0.004)	–1,050 (774)	0.013 ** (0.005)
Low Education	14.25	–0.090 (0.0549)	–4,480 (9,400)	–0.127 * (0.056)
High Education	13.76	–0.179 ** (0.051)	17,900 • (8,930)	–0.221 *** (0.054)
Const./Manuf. Emp.	1.99	0.046 (0.038)	–5,780 (6,670)	0.033 (0.039)
Select Serv. Emp.	3.67	0.130 * (0.049)	–17,000 • (8,550)	0.127 * (0.051)
Educ./Health Emp.	4.14	–0.155 * (0.071)	18,500 (12,300)	–0.143 • (0.074)
South (dummy)	7.57	–0.007 (0.005)	749 (842)	–0.006 (0.005)
Midwest (dummy)	3.92	–0.005 (0.004)	–855 (742)	0.003 (0.004)
West (dummy)	10.37	–0.002 (0.006)	1,620 (1,130)	–0.007 (0.007)
Adjusted R^2		0.63	0.53	0.57
Observations		51	51	51
Jarque-Bera stat		1.38	1.83	0.78
p-value		0.50	0.39	0.68
Breusch-Pagan stat		16.31	13.18	12.65
p-value		0.29	0.51	0.55

Standard errors are in parentheses. ***, **, *, and • indicate significance at the 99.9 percent, 99 percent, 95 percent, and 90 percent levels, respectively.

A potential explanation for this unexpected correlation between percent foreign-born and poor recession outcomes for natives is the demographic of the unemployed. While the recession impacted workers across all education and skill levels, a majority of job losses were within industries that employ the largest percentages of foreign-born workers: construction, manufacturing, and retail (U.S. Bureau of Labor Statistics, 2011). These are industries which employ both native-born and foreign-born workers, and they have a greater likelihood of immigrant niches (Hudson, 2002). As these sectors laid off workers, if companies that had invested in hiring immigrants (through work Visa sponsorships) may have been disinclined to layoff immigrant workers first: these laid-off immigrant workers would likely have to return to their home country, and thus the company risks not being able to rehire them when the economy stabilizes. An additional consideration is that, as these industries slowly rehired following the recession, many businesses restructured their pay and benefits packages for new workers (Dickler, 2012; Plumer, 2013; Society for Human Resource Management, 2010). Native-born workers looking to re-enter the labor force in the same or similar job they lost, may have seen the prospect of lower pay and benefits than when the left, and passed on employment opportunities. These, in turn, may have then been filled by foreign-born workers (Kochhar, 2012). If these foreign-born workers were willing to re-join the labor force for lower wages, this would both drive up unemployment (and tangentially poverty) growth and drive down income growth for native-born workers. A third consideration stems from the results of the previous section's niche analysis. Unemployment growth is shown to be negatively correlated with propensity to niche, indicating that with higher unemployment immigrants diversify in the labor market rather than remain clustered in niches. This may introduce competition between immigrants and native-born workers that was not present prior to the sharp unemployment increases, which may further reinforce native-born unemployment.

The positive significance of diversity in the unemployment model may be further support the suggestions above of a hesitation by employers to layoff immigrants. As shown in the analysis of the Niche Index, a greater diversity of immigrant groups is negatively correlated with a propensity to niche, indicated a greater distribution across the metro economy. As the economy was beset by the recession and layoffs occurred, immigrants were likely retained in industries across the economy because of workplace investments in them.

The foreign-born growth variable was in line with the hypothesized direction but was insignificant across all three models. Foreign-born growth was expected to be negatively correlated with native-born unemployment and poverty growth, and positively correlated with income growth, due to the increased propensity of immigrants to migrate internally for employment opportunities. The insignificance is not due to historical 'gateway' cities receiving large numbers of 'first-stop' international migrants despite the economic conditions: including a 'gateway city' dummy variable in the regression does not make this variable significant. This is likely due to the general small increases in foreign-born growth over the period.

The second measure of diversity, the Bohemian Index, was opposite the initial hypothesized direction, but was insignificant across all three models. It was expected that cities that encouraged and embraced the cultural diversity afforded by the Bohemian sectors would experience more stability during the recession, but the opposite may be true (although not statistically significant). Bohemian employment may have been indirectly impacted by the recession, as disposable income waned and residents' desire for culture and entertainment was abridged in favor of saving 'rainy day' funds. Additionally, many Bohemians supplement their incomes with part-time work in the service sector (Florida, 2005), which experienced moderate unemployment growth during the recession.

City population did not influence unemployment growth, but it does have a positive impact on income gains and a negative impact on poverty gains. The significance of city population to income gains has been shown in the past (Hoch, 1972), and may be due to any number of externalities and endogenous factors. These results also support the previous hypotheses regarding poverty – that the social services provided by larger cities may stem the growth of poverty, even in the face of unemployment gains.

An interesting finding from the models is confirmation of the significance of spatial structure/accessibility on unemployment and poverty growth. Significance of this variable is likely tied to the increased opportunities for worker mobility and competition between nearby cities. As discussed in Section 3.2 and above, spatial structure is a central influence on the larger mobility of patterns of a region. This competition could be between native-born workers relocating from nearby cities or rural areas in search of employment, or it could be related to the local mobility of the foreign-born, who are more prone to move for employment opportunities than their native-born peers (Card, 2001). It is unclear given the data whether there was a permanent realignment of workers among nearby cities, but this is worth exploring in subsequent research.

The education and employment variables generally confirmed the hypothesized relationships. The percent of population that are highly educated is a stronger predictor of economic outcomes than the percent with low education. Despite the overwhelming unemployment growth in the construction and manufacturing sectors, this variable was not significant in any of the models, likely due to the uneven distribution of these industries across the study cities. Louisville, KY, for example has 21 percent of its native-born workforce in construction/manufacturing, while New York, NY, only has 11 percent; Louisville, however, had a slightly lower unemployment growth than New York (2.4 versus 2.5 percent, respectively). All study cities have sizeable employment in the service sectors, thus the consistency of the relationship between this employment variable and recession outcomes is significant across the models.

Contrary to initial hypotheses, the regional dummies for the South, Midwest, and West were not significantly different from the Northeast reference region, which is not surprising given the within-region variability discussed earlier. The coefficient signs were also different than expected, which is potentially due to urban variability within the regions. While smaller geographic regions, such as the nine U.S. Census geographic Divisions, would likely provide less in-region variability, sample sizes would need to expand beyond 51 cities to ensure a sufficient number of samples fell within each region.

3.4.4. Discussion

This section of research sheds light on the relationship between the presence and diversity of foreign-born populations on the economic impacts of native-born labor during an economic downturn. The principal concern for this section is the role of the foreign-born population, and the diversity of that population, on the economic outcomes of native-born workers across the recession period. Results show that, despite initial hypotheses to the contrary, cities with larger proportions of foreign-born residents had native-born workers who fared worse over the course of the recession: they experienced greater unemployment growth, less income growth, and an expansion of poverty. It is also found that higher education is a significant driver of improved outcomes for native-born workers during a recession, while metropolitan accessibility has the opposite effect due to inter-city competition for jobs.

This negative impact of the foreign-born is potentially a reflection of three phenomena: fewer and less-attractive employment opportunities, and structural issues at play regarding the hiring and retention of immigrant workers, and the further expansion of immigrant employment outside of niches. As the 'Great Recession' ended and employment opportunities slowly expanded, businesses in many cases adjusted their benefits and pay packages due to the lingering uncertainty in the economy (Society for Human Resource Management, 2010). When facing the decision of returning to the labor force with lower pay and fewer benefits, many native-born workers may have opted to hold out for better opportunities. While native-born and foreign-born unemployment numbers were generally on par throughout the recession, industries may have been slower to let go immigrant workers for whom they had invested financially through employment Visas, housing arrangements, language training, etc. Additionally, the sectors which experienced the most employment losses, construction and manufacturing, are home to an overwhelming majority of the immigrant niches, which may have insulated many immigrants from employment losses while their native-born counterparts lost their jobs in the primary sector. However, results of the analysis of the Niche Index shows that unemployment growth is negatively correlated with propensity to niche, thus indicating that niches are diluted and immigrant employment is broadened with increased overall unemployment growth. This may lead to increased competition for employment with native-born workers.

The Great Recession provided an ideal opportunity to validate much of the previous research on immigrant impacts on native-born workers, but in the context of a short-run economic event. Scholars had previously performed longer-range impact studies that may have smoothed out the effects of immigrant populations during previous economic downturns. This research shows the correlations drawn in previous research between productivity and foreign-born populations and diversity (Ottaviano & Peri, 2006b) are not bellwethers for economic performance during a recession. Many previous studies of immigrant impacts address the substitutability of new immigrant populations for low- or comparably skilled native labor (Borjas, 2003; Chiswick, Chiswick, & Miller, 1985; Grossman, 1982). The results of this research cannot refute the previous conclusions on the topic, but it is suggested here that the negative impacts for native-born workers are potentially tied to both structural conditions and competition. However, given that the focus of this research is on the entire immigrant population and not those newly arrived, the evidence of complementarity observed by some also cannot not be wholly rejected or endorsed (Chiswick et al., 1985; Friedberg & Hunt, 1995; Grossman, 1982).

From a policy perspective, cities must work to ensure both their native-born and foreign-born workers are minimally affected during times of economic turmoil. Given the significance of higher education in stemming unemployment growth for native workers, which is supported by much previous research (cf. Mincer, 1991), cities may better prepare themselves for the next recession by helping their residents, native-born or otherwise, invest in educational opportunities. If low-skilled immigrants continue to dominate the new-migrant groups, promotion and subsidizing of education for native-born workers should lead to greater complementarity of the urban labor force and more stability during recessionary periods.

4. CONCLUSIONS

This research explored four broad, yet interdependent, research questions related to the migrant and migration to large U.S. cities for the 2006-2010 period. With the aim of illuminating the period trends in migration in the U.S., results showed that high in- and out-migration rate counties were generally not located in one of the 51 largest U.S. cities. Generally speaking, high rates of migration were concentrated west of the Mississippi while low rates of migration were concentrated east of the Mississippi, generally indicating the West to be a more mobile region. Additionally, analysis showed that much of traditional migration theory regarding the impact of age, education, and gender were consistent over the 2006-2010 period for county-level out-migration. Increases in education among residents were generally correlated with increases in out-migration rates. The age-migration curve observed during this period was also consistent with what would be hypothesized. Metropolitan out-migration rates were much higher than in-migration, signifying and overarching exodus from the largest U.S. metro areas for smaller cities or rural locales.

A key discovery is the difference in some relationships between county-level flows and large metropolitan flows. Metropolitan-area flows showed a different relationship to education and gender levels than county flows, which suggests metro area migrants behave differently than migrants overall, and that migration is subject to ecological fallacy. Migration scholars should embrace the disparities in flow relationships between metropolitan and county flows: a focusing of research on this dichotomy will shed light on both the different migration behaviors observed at different research scales and the impacts and implications of aggregating migration data for analysis.

The second analytical section assessed of the spatial variation of distance-decay parameters and their use in measuring destination attraction in spatial interaction modeling. Results showed that, when modeling spatial interaction as destination-specific, distance decay varies greatly across space, but the distribution of this variation is highly dependent upon the flows being modeled. County-level flows yield a different decay parameter distribution from metro-level flows. The distance decay for a destination holds great relative value – it sheds light on the spatial impacts of the place relative to all other destinations – but scholars should always contextualize the parameter by the flows that drive it.

It was also shown that the elements of attraction in a city can be modeled as a linear regression against the estimated distance decay parameters, and the model performed well when looking at metro-to-metro flows. The model results indicated that specific elements of a city's unemployment, diversity, education, industry, and climate are significant attractants of migrants from other cities. The poor performance of the model in identifying any of the metropolitan attributes as attractants to migrants from county-level flows reinforces the discovered disparity of relationships identified when evaluating migration trends.

This research demonstrated a novel approach to spatial interaction, using the proven principles of the gravity model and expanding the role of the distance-decay parameter beyond what was done in previous research. Rather than building a traditional gravity model that incorporates all the explanatory variables within it, the approach presented here separates these two parts into independent models. By formulating the spatial interaction model as destination-specific and deriving the distance-decay parameters using only the basic gravity model elements of origin mass, origin accessibility, and distance, the estimated distance-decay coefficients inherit the influence of all elements of destination attraction (no other variables describing the destination are included because they are constants in a destination-specific model). Thus, the distance-decay coefficient itself can be utilized as a relative measure of attraction among the destinations. But distance-decay can also be used to estimate the contributions of a set of destination characteristics to that relative attraction, using the distance-decay parameter as the independent variable for OLS. The unequal performance of the model for the different flows is likely a symptom of the phenomenon rather than the method. As discussed above, the results, both in the Spatial Interaction Regression analysis and in the 'trends' section, indicate a potential different set of push and pull factors for migrants depending on the scale of analysis. Given this, a refinement of the model specifically for county-to-metro flows would likely yield a better model fit and demonstrate the applicability of the method for county-level origins.

The third research topic questioned the spatial variation in immigrant niche behavior, and explained niche formation using a unique metric. The results showed niche behavior to be highly consistent sectorally across space, and in general focused on a select group of industries: construction, administrative support, accommodation and food services, and 'other services'. The propensity of immigrant groups to form niches, however, does vary across space, at least as related to New York and Los Angeles, the focal points of most niche research. This is significant, because much of niche theory is based on research performed using data from New York and Los Angeles. Looking at the drivers of an immigrant group's propensity to niche, larger cities drive down the propensity to niche, while larger immigrant group populations counteract this and drive up the group's propensity to migrate. English language proficiency and percent unemployment change are also shown to drive down a group's propensity to niche.

Though the results of this dissertation do not call into question the existing foundations of immigrant niche theory, this research suggests a spatially broader look at niching would both reinforce its soundness, and illuminate local or regional uniquenesses in the phenomenon. Nearly all research to date has focused on the location quotient for niche identification (as does this paper), but little research has sought to answer questions regarding propensity to niche. The Niche Index introduced in this dissertation provides a relative scale on which to compare the probability of immigrant group niche employment. This is found nowhere else in the niche literature, but its use is substantiated through good model fit when modeling the expected drivers of niche formation.

The fourth research topic investigated the impact of immigrant population and diversity on native-born labor over the recession period: specifically, how did natives fare with unemployment, income, and poverty. Despite hypotheses to the contrary, the results show that the presence of greater proportions of immigrants was significantly correlated with the greater economic decline among native workers, which may be a function of structural issues associated with immigrant worker retention, and immigrant niche presence in the hardest hit sectors. The results also show that urban accessibility contributed to economic decline, likely due to increased competition for limited employment resources, while higher education and higher employment in education and health care led to less economic decline among native workers. From the perspective of foreign-born impact, the results here contradict those of previous research which suggests immigrants have either little to no impact, or a positive impact, on native workers. Previous research, however, was not concerned with the short-term impacts during the recession, which places the findings of this research squarely in a research gap needing to be filled. While this dissertation does not contend that immigrants are a negative impact on the U.S. or metropolitan economy, the results show that, because of the wide-ranging effects of the recession, there native unemployment grew more extensively in cities with higher proportions of immigrants. The recession's impacts on native workers involves a highly complex set of interdependent variables, some of which may correlate to foreign-born population percent. It is important to remember that correlation, in all of these analytical results, does not mean causation.

The results of any analytical project are highly dependent upon the datasets employed, the sampling schemes chosen, the methods selected, and the author's understanding of the phenomenon. The research presented here is no different. While every effort has been made to be thorough with regard to prevailing theories and existing evidence, something may have been missed that would improve or alter the conclusions of this research. Additionally, as discussed throughout this dissertation, the data selected for these analyses are at once the best available and beset by accuracy concerns. Every effort has been made minimize the error whenever possible, but the truest test is showing whether the results are in line with existing research and our understanding of the migration phenomenon – and if not, providing a reasonable justification for the deviance. This research has done exactly this, supporting convention within the migration research canon, and breaking it when necessary.

Outside of the academic research realm, the results presented in this dissertation have important implications for public policy. As cities compete for migrants from other cities, education (and specifically high-school education) is shown to be an important attractor. Cities should focus resources on ensuring their populace has a high school diploma or equivalent, as this expands their employment opportunities and decreases the likelihood they will be involved with criminal activity. Hand-in-hand with high school education, cities should also focus resources on improving the unemployment rates for African Americans. Additionally, cities should seek to attract a diverse population of immigrants: not only does a diverse immigrant population broaden the cultural appeal and increase the cultural capital of the city, it expands the entrepreneurial opportunities within the city as these micro-cultures are sustained, and it expands the skill-base in the city's economy.

While the analyses in this dissertation do not show any negative impacts on the economy by the presence of niches, niches fundamentally represent the inability of immigrant groups to spread throughout the entire economy, limiting the groups' overall potential economic contribution, reinforcing economic segregation, and crowding out employment opportunities for native workers in these niche sectors. Despite the overarching negative impacts of the recession, the results of this research show that it may have served a useful purpose by expanding the economic footprint of migrants out of their niches and into any available jobs. The results also show, however, that this may have increased competition between immigrant and native-born workers, which may led to increased unemployment and poverty growth for the natives. Education, again, was shown to stem this negative impact. Thus, cities should continue to promote, expand opportunities for, and subsidize education when possible to lessen the negative impacts of economic downturns on all ethnic groups in the metro labor market.

Taken as a whole, this dissertation research both fills gaps in the migration research canon and introduces novel methods for analyzing and understanding migration and the migrant. The four research areas investigated represent four critical, omnipresent nodes in migration research that inform our understanding of the U.S.'s internal and international migrant, and our understanding of the impacts of both on our economies and populations. The methods and results presented in this dissertation not only highlight new dimensions of internal and international migration, they also expand the ability of future researchers to describe, contextualize, and explain migration and the migrant.

		Niche Index	11	21 22	23	31 33	42	44 45	48 49	51	52	53	54 55	56	61	62	71	72	81
China	Boston	0.13					N												N
	Chicago	0.12																N	
	Los Angeles	0.09					N											N	
	New York	0.10				N	N											N	
	San Francisco	0.09				N												N	
	San Jose	0.19				N							N						
	Washington	0.15											N					N	
El Salvador	Dallas	0.11			N									N				N	
	Houston	0.10			N									N				N	N
	Los Angeles	0.09			N									N					N
	New York	0.10			N	N								N				N	N
	San Francisco	0.09			N									N				N	N
	Washington	0.15			N									N				N	
India	Atlanta	0.13											N						
	Boston	0.16											N						
	Chicago	0.12											N			N			
	Dallas	0.13								N			N			N			
	Detroit	0.17											N						
	Houston	0.12											N			N			
	Los Angeles	0.11									N		N						
	New York	0.11									N		N						
	Philadelphia	0.12				N							N						
	San Francisco	0.15				N							N						
	San Jose	0.23								N			N						
	Washington	0.18		N							N		N						
Korea	Chicago	0.10																	N
	Los Angeles	0.09					N												
	New York	0.10					N	N											N
	Seattle	0.10																N	N
	Washington	0.10						N										N	N

Figure 11. Niches by city for immigrants with representation across five or more cities: China, El Salvador, India, and Korea, along with each group's Niche Index.

		Niche Index	11	21 22	23	31 33	42	44 45	48 49	51	52	53	54 55	56	61	62	71	72	81
Mexico	Atlanta	0.20	N		N									N				N	
	Austin	0.17	N		N									N				N	
	Charlotte	0.21	N		N									N				N	
	Chicago	0.14			N	N								N				N	
	Dallas	0.13	N		N									N				N	
	Denver	0.14	N		N									N				N	
	Houston	0.13	N		N									N				N	
	Las Vegas	0.15	N		N									N					
	Los Angeles	0.11	N		N	N								N				N	
	Miami	0.12	N		N									N					
	New York	0.13	N		N									N				N	N
	Phoenix	0.12	N		N									N				N	
	Portland	0.12	N		N									N				N	
	Riverside	0.10	N		N	N								N					
	Sacramento	0.11	N		N									N				N	
	Salt Lake City	0.13	N		N	N								N				N	
	San Antonio	0.11	N		N	N								N					N
	San Diego	0.09	N		N									N				N	N
	San Francisco	0.11	N		N									N				N	N
	San Jose	0.11	N		N									N				N	N
	Seattle	0.13	N		N									N				N	
	Tampa	0.14	N		N									N				N	
	Washington	0.17	N		N									N				N	
Philipinnes	Chicago	0.22														N			
	Houston	0.22														N			
	Las Vegas	0.14														N			
	Los Angeles	0.16														N			
	New York	0.21														N			
	Riverside	0.17									N					N			
	Sacramento	0.16														N			
	San Diego	0.14							N							N			
	San Francisco	0.12							N							N			
	San Jose	0.16							N							N			
	Seattle	0.12		N					N							N			
	Washington	0.12														N			
Vietnam	Atlanta	0.15	N			N													N
	Dallas	0.15				N													N
	Houston	0.13	N			N													N
	Los Angeles	0.13				N													N
	San Diego	0.14				N													N
	San Francisco	0.10				N													N
	San Jose	0.18				N													N
	Seattle	0.12				N													N
	Washington	0.11				N													N

Figure 12. Niches by city for immigrants with representation across five or more cities: Mexico, Philippines, and Vietnam, along with each group's Niche Index.

Table 26: Moran's I tests for spatial autocorrelation of county and metropolitan in- and out-migration rates.

Conceptualization of Relationship	County In-Migration	County Out-Migration	Metro In-Migration	Metro Out-Migration
Inverse Distance	0.124	0.147	0.309	0.463
p-value	0.000	0.000	0.000	0.000
Inverse Distance Squared	0.144	0.169	0.370	0.473
p-value	0.000	0.000	0.000	0.000
5 Nearest Neighbors	0.156	0.186	0.368	0.513
p-value	0.000	0.000	0.000	0.000
10 Nearest Neighbors	0.136	0.171	0.259	0.425
p-value	0.000	0.000	0.000	0.000
500km Distance Band	0.058	0.084	0.287	0.429
p-value	0.000	0.000	0.003	0.000
1000km Distance Band	0.029	0.049	0.150	0.388
p-value	0.000	0.000	0.001	0.000
1500km Distance Band	0.012	0.027	0.055	0.238
p-value	0.000	0.000	0.028	0.000

Table 27: Moran's I tests for spatial dependence of residuals for Metro-to-Metro and County-to-Metro distance-decay models.

Conceptualization of Relationship	Metro-to-Metro Flows	County-to-Metro Flows	County-to-Metro Flows (No Contig.)
Inverse Distance	–0.156	–0.045	–0.031
p-value	0.128	0.776	0.902
Inverse Distance Squared	–0.163	–0.045	–0.052
p-value	0.180	0.807	0.761
5 Nearest Neighbors	–0.105	–0.057	–0.050
p-value	0.270	0.631	0.692
10 Nearest Neighbors	–0.094	–0.108	–0.081
p-value	0.153	0.087	0.230
500km Distance Band	–0.116	–0.112	–0.086
p-value	0.351	0.365	0.511
1000km Distance Band	–0.050	–0.069	–0.030
p-value	0.556	0.330	0.842
1500km Distance Band	–0.042	–0.045	–0.043
p-value	0.512	0.460	0.492

Table 28: Moran's I tests for spatial autocorrelation of the dependent variables for Native Unemployment, Income, and Poverty Growth models.

Conceptualization of Relationship	Native Unemp. Growth Model	Native Income Growth Model	Native Pov. Growth Model
Inverse Distance	0.668	0.497	0.502
p-value	0.000	0.000	0.000
Inverse Distance Squared	0.703	0.537	0.539
p-value	0.000	0.000	0.000
5 Nearest Neighbors	0.645	0.419	0.491
p-value	0.000	0.000	0.000
10 Nearest Neighbors	0.431	0.247	0.306
p-value	0.000	0.000	0.000
500km Distance Band	0.667	0.585	0.549
p-value	0.000	0.000	0.000
1000km Distance Band	0.481	0.245	0.261
p-value	0.000	0.000	0.000
1500km Distance Band	0.247	0.029	0.056
p-value	0.000	0.149	0.027

Table 29: Moran's I tests for spatial dependence of residuals for Native Unemployment, Income, and Poverty Growth models.

Conceptualization of Relationship	Native Unemp. Growth Model	Native Income Growth Model	Native Pov. Growth Model
Inverse Distance	0.0715	–0.105	–0.043
p-value	0.304	0.344	0.795
Inverse Distance Squared	0.103	–0.084	0.086
p-value	0.248	0.546	0.535
5 Nearest Neighbors	0.011	0.002	–0.011
p-value	0.687	0.778	0.903
10 Nearest Neighbors	0.022	–0.038	–0.004
p-value	0.412	0.723	0.755
500km Distance Band	0.056	0.042	0.038
p-value	0.459	0.547	0.57
1000km Distance Band	–0.003	–0.023	–0.034
p-value	0.736	0.957	0.785
1500km Distance Band	–0.053	–0.051	–0.044
p-value	0.338	0.958	0.487

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CURRICULUM VITAE

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