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ESSAYS ON THE SPATIAL CLUSTERING OF IMMIGRANTS AND INTERNAL
MIGRATION WITHIN THE UNITED STATES

Matthew Howard Ruther

A DISSERTATION

in

Demography

Presented to the Faculties of the University of Pennsylvania

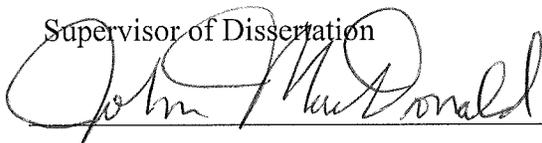
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ESSAYS ON THE SPATIAL CLUSTERING OF IMMIGRANTS AND
INTERNAL MIGRATION WITHIN THE UNITED STATES

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DEDICATION

Dedicated to my family and friends.

ACKNOWLEDGEMENTS

This dissertation would not have been possible without the direction and support of my committee: John MacDonald, Janice Madden, and Emilio Parrado. John was a devoted mentor and my closest ally, supplying endless guidance on the dissertation and offering irrational exuberance when I had none. Janice provided me my first opportunity to do research at Penn, and has since been a professor, adviser, and friend. Emilio got me involved in new lines of research and encouraged me to think in new directions. In addition, the faculty of the Graduate Group in Demography and the staff of the Graduate Group and the Population Studies Center have been excellent resources.

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ABSTRACT

ESSAYS ON THE SPATIAL CLUSTERING OF IMMIGRANTS AND INTERNAL MIGRATION WITHIN THE UNITED STATES

Matthew Howard Ruther

John M. MacDonald

The chapters in this dissertation each look at some aspect of immigration or internal migration in the United States, highlighting the spatial nature of population distribution and mobility. Chapters 1 and 2 focus on the effect of immigrant residential clustering on crime and Chapter 3 explores the internal migration behavior of Puerto Ricans.

In the first chapter, we investigate the effect of immigrant concentration on patterns of homicide in Los Angeles County. We also suggest an alternative method by which to define immigrant neighborhoods. Our results indicate that immigrant concentration confers a protective effect against homicide mortality, an effect that remains after controlling for other neighborhood structural factors that are commonly associated with homicide. Controlling for the spatial dependence in homicides reduces the magnitude of the effect, but it remains significant.

Chapter 2 examines how foreign born population concentration impacts homicide rates at the county level. This chapter utilizes a longitudinal study design to reveal how

changes in the immigrant population in the county are associated with *changes* in the homicide rate. The analysis is carried out using a spatial panel regression model which allows for cross-effects between neighboring counties. The results show that increasing foreign born population concentration is associated with reductions in the homicide rate, a process observed most clearly in the South region of the United States.

In Chapter 3 we explore the internal migration patterns of Puerto Ricans in the United States, comparing the migration behavior of individuals born in Puerto Rico to those born in the United States. Second and higher generation Puerto Ricans are more mobile than their first generation counterparts, likely an outcome of the younger age structure and greater human capital of this former group. Puerto Ricans born in the United States also appear to be less influenced by the presence of existing Puerto Rican communities when making migration decisions. Both mainland- and island-born Puerto Rican populations are spatially dispersing, with the dominant migration stream for both groups being between New York and Florida.

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CHAPTER 1: IMMIGRANT CONCENTRATION AND HOMICIDE MORTALITY: A NEIGHBORHOOD-LEVEL SPATIAL ANALYSIS OF LOS ANGELES COUNTY

Abstract

This paper investigates the effect of immigrant concentration on patterns of homicide in Los Angeles County. The analysis is conducted using homicide death counts from vital statistics records and two methods of measuring immigrant concentration. After statistically controlling for neighborhood structural factors related to poverty, ethnic composition, age composition and residential stability, the independent effect of neighborhood immigrant concentration on rates of lethal violence is isolated. The study also incorporates a measure of the spatial relationships between neighborhoods to account for the spatial dependence of homicide events. The results from the analysis suggest that immigrant concentration confers a protective effect against homicide mortality, an association which remains after adjusting for the spatial clustering of homicide deaths.

1.1 Introduction

Homicide was the fifteenth leading cause of death for Americans in 2007, but ranked second in the number of years of life lost (YLLs) due to the generally younger age profile of homicide victims (Xu et al. 2010). This is true of most large urban counties including Los Angeles, California (Los Angeles County Department of Health Services 2000). Aggregate rankings of the impact of homicide on the county population are important to note, yet these statistics mask the substantial variation in homicide risk that occurs across neighborhood areas. Among the eight geographic regions of Los Angeles County, for example, the South region of the county is disproportionately affected by YLLs from homicide mortality. The South region exhibits increases in disability adjusted life years, of which YLLs are an important component, due to violent acts at roughly twice the rate of any of the seven other county regions.

The existence of a link between residential location and homicide mortality risk is fairly well known, but the underlying processes which perpetuate that link are not fully understood. Variation in risk of homicide among individuals is attributable to a large extent to risk-seeking behaviors including prior criminal behavior (Wolfgang 1958; Lattimore, Linster and MacDonald 1997) and residential location in communities with high rates of interpersonal violence (Sampson and Bean 2006). The structural and social characteristics of a neighborhood itself appear to produce effects that influence community safety independent of individual attributes of persons (Sampson, Morenoff and Gannon-Rowley 2002). While neighborhood effects on crime have been the subject of numerous studies (see e.g., Messner 1983; Land et al. 1990; Parker and McCall 1999; Sampson et al. 2002), less research has focused on the role of immigrant communities on

neighborhood patterns of homicide (for exceptions see Martinez et al. 2008; 2010). Maps 1.1 and 1.2 illustrate the distribution of the foreign born population and the number of homicide deaths, respectively, in Los Angeles County. One striking feature of these two maps is the general discordance between those areas where immigrant concentration is highest and those areas where the greatest number of homicide deaths occur. Map 1.2 also clearly displays how homicide deaths tend to be clustered within a spatial area. This clustering effect is an important consideration, as it implies spatial dependence; that is, the neighborhood-level processes through which immigrant concentration might be related to homicide rates occur within a spatial context.

This study examines the association between neighborhood immigrant concentration and homicide risk. By taking advantage of the detailed geographic information available in death registration data, and by incorporating measures which explicitly account for the spatial clustering of homicide events, this study provides a rarely glimpsed view of local homicide mortality. The paper begins with a brief discussion of theories which articulate mechanisms by which immigrant flows can influence neighborhood homicide rates. Subsequent sections discuss the data and methods for the analysis, the results of the statistical models, the limitations of the study design, and the implications of this research.

1.2 Theoretical Framework

There are notable theoretical explanations for why larger proportions of immigrants in a community could affect the perpetration of homicide incidents. Social disorganization theory is the foundational sociological theory that articulates why change

in the population age structure that accompanies immigrant growth in neighborhoods will positively affect homicide rates. Theories of social capital and collective efficacy also suggest that either a positive *or* a negative relationship might exist between immigrant concentration in areas and homicide. The potential labor market consequences of immigration also imply an ambiguous association.

1.2.1 Why Might Immigrant Concentration Increase Homicide Rates?

Social disorganization theory, first proposed by Shaw and McKay (1942), suggests that a positive association exists between immigration and crime – including homicide. Social disorganization posits that the introduction of immigrants, who tend to settle into high poverty concentration areas, lowers informal social controls as neighborhoods become more culturally heterogeneous and results in the social dislocation of native residents (Sampson 1995). Large immigrant flows into a neighborhood may also adversely impact the level of social capital in the neighborhood (Putnam 2007), as existing native-born residents are replaced or diluted in numbers, thereby reducing the effectiveness of established social networks in deterring crimes of violence that result in homicides (Sampson, Raudenbush and Earls 1997). The reduction of informal social control, the byproduct of the dilution of group cohesiveness, increases the likelihood of conflict and violence (Bursik 1988). Greater levels of immigrant concentration may also interfere with the ability of residents to realize common goals because of ethnic and linguistic heterogeneity, which may hamper violence reduction initiatives (Sampson et al. 1997; Graif and Sampson 2009). Immigrants may also exhibit different normative attitudes regarding the legality of certain behaviors, including resolving disputes

peacefully, which are inconsistent with those prevalent in the host country. These differences in norms may erode over time through acculturation and assimilation (Sellin 1938). To the extent that neighborhoods with high concentrations of immigrants hinder the processes of acculturation and assimilation, neighborhood rates of homicide may be higher in immigrant enclaves.

Increased immigration might also be expected to contribute to intergroup tensions. Conflict theory perspectives imply that diversity creates distrust between ethnic groups, due primarily to competition for resources, and promotes solidarity within each competing ethnic group; this may increase violence between groups and drive up the homicide rate (Blalock 1967). Putnam's (2007) constrict theory suggests that diversity may reduce both within-group solidarity and between-group solidarity, resulting in increased violence overall (Hipp et al. 2009). Immigration also tends to change the age composition of a community, as immigrants are more likely to be young adults in search of work opportunities in the U.S. Neighborhoods with higher concentrations of immigrants are therefore more likely to have a higher proportion of young men, the age range at which criminal offending and homicide victimization is most prevalent (Farrington 1986; Moehling and Piehl 2009). Finally, to the extent that foreign born individuals are at a greater risk of homicide death themselves, larger immigrant populations within a neighborhood could influence the aggregate neighborhood homicide rate. A higher risk of homicide death has been confirmed for new immigrants (less than 15 years) (Toussaint and Hummer 1999), young foreign-born residents of California (Sorenson and Shen 1999), foreign born White, Hispanic and Asian individuals (but not foreign born Blacks) (Sorenson and Shen 1996), and immigrant males over the age of 25

compared to individuals in the same age groups who are native born (Singh and Siahpush 2001).

1.2.2 Why Might Immigrant Concentration Decrease Homicide Rates?

As the proportion of a particular immigrant group in a neighborhood increases, social networks within this group may expand. This suggests that immigration may initially cause increased levels of homicide, but homicide rates may go down once the community reaches a certain concentration or saturation point of immigrants. Ethnic enclaves may generate positive effects on collective efficacy if the enclave group exhibits high levels of informal social controls on its neighborhood residents. Additional benefits of immigrant residential segregation might be network formation and information sharing (Chiswick and Miller 2005), the improvement of social, cultural and economic institutions (Sampson 2008), or the preservation of traditional culture that is more prone to avoiding violence as a means for dispute resolution (Escobar 1998). Halpern (1993) suggests a group density effect of immigrant concentrations for residents among members of the same ethnic group, based primarily on local, rather than national, experience. The local ethnic group effect may result from a reduction in exposure to prejudice and increased social support provided by the homogeneous local network. As a result, tensions and conflict may be less likely to occur, or, when they do occur, are less likely to escalate into violence which results in a homicide. Labor market opportunities for immigrants may also be more plentiful in neighborhoods with higher proportions of immigrants because of the expanded social networks which they provide and because immigrant small-business owners or managers may prefer to employ workers of their

own ethnic group (Zhou and Logan 1989). To the extent that employment opportunities are associated with reduced rates of homicide in neighborhoods, the access to low-skilled job networks for immigrants living in more heavily immigrant areas may reduce the overall propensity for violence in these areas.

1.2.3 Previous Research on the Relationship between Immigration and Crime

Earlier studies that have analyzed immigration and crime at the metropolitan area-level have shown little support for a positive or negative relationship between the two (Butcher and Piehl 1998; Phillips 2002). However, in a more recent study analyzing 2000 census data for 150 metropolitan areas, the proportion foreign born is found to be negatively correlated with homicide rates (Reid, Weiss, Adelman and Jaret 2005). There was no observed relationship between the homicide rate and the proportion Latino foreign-born, proportion Asian foreign-born, or proportion foreign-born with limited English ability. Recent work by Stowell and colleagues (2009) indicates that metropolitan areas experiencing increasing levels of immigration had significantly larger reductions in violent crime (robbery in particular) during the 1990s. Ousey and Kubrin (2009) show that a similarly negative immigration-crime dynamic occurred within U.S. cities between 1980 and 2000.

While neighborhood level research on the relationship between immigration and crime varies in the way immigrant composition is measured and the exact crime outcome studied, this research is largely accordant in the finding that immigrants exert a protective effect against crime. In models controlling for social composition, collective efficacy, and prior homicide rates, Sampson and colleagues (1997) observe no association between

the immigrant concentration in Chicago neighborhoods, measured as an index comprised of the proportion foreign born and the proportion Latino, and the number of homicides; the immigration index was, however, positively correlated with reported violent victimization. Lee, Martinez, and Rosenfeld (2001) find that the proportion of the tract that is comprised of recent immigrants (less than 10 years in the U.S.) is negatively associated with Latino homicide counts in El Paso, but no association between the variables is found in Miami or San Diego. The proportion of the tract that is recent immigrant had no correlation with Black homicide counts in El Paso, a negative correlation with Black homicide counts in Miami, and a positive correlation with Black homicide counts in San Diego. Martinez, Stowell, and Cancino (2008) show that neighborhood homicide counts exhibit a negative association with the proportion of recent immigrants in San Diego, but no relationship between the two is observed in San Antonio. These authors also demonstrate that there is no association between recent immigrants and the number of homicides in neighborhoods in which more than 40% of the population is Latino in *either* city. More recent work by Martinez and colleagues (2010) finds that increases in the proportion of foreign born residents in San Diego neighborhoods, primarily from Mexico, between 1980 and 2000 was associated with significant within-neighborhood reductions in homicide rates. In research by Sampson, Morenoff and Raudenbush (2005), the proportion of the population in a Chicago neighborhood that was first-generation immigrant is negatively associated with self-reported violence in the community; however, this study does not include information on homicides. Using homicide data from the mid-1990's and census data from 1990, Velez (2009) shows that the proportion new immigrants in a census tract is negatively

correlated with the homicide rate only in those neighborhoods in which concentrated disadvantage is high.

In their recent book exploring the variation in crime patterns between white and other ethnically heterogeneous neighborhoods, Peterson and Krivo (2010) find that larger immigrant populations at the neighborhood level are associated with reductions in both violent and property crimes; they report no relationship between immigrant populations at the city level and crime rates. While these authors do not look at the crime of homicide separately, this work is particularly relevant in the context of the current study, as the modeling strategy incorporates as control variables the crime rates and population characteristics of adjacent neighborhoods. The results from this spatial model indicate that the effect of neighborhood immigrant composition on violent crime rates changes little when the spatial controls are added.

Many studies¹ define ethnic heterogeneity in terms of Black and White or other racial groups and few studies distinguish between immigrant versus non-immigrant designations. Aggregating groups together may mask important variation in the effects of immigrant enclaves on homicide. In a study in Israel, for example, ethnic heterogeneity was found to be insignificantly associated with the violent crime rate. After decomposing the ethnic heterogeneity index into the proportion immigrant and the proportion Arab, negative and positive associations, respectively, were found (Herzog 2009). Immigrants are not a uniform group and there may be important manifestations of immigrant incorporation that influence homicide rates in distinct ways.

¹ Shaw and McKay's (1942) research examined differences by native origin and juvenile crime trends in neighborhoods, but they grouped black and foreign born together in their measure of ethnic heterogeneity.

The results from prior research on the immigration-crime link leave important questions unanswered. Metropolitan area and city level studies have failed to establish a definitive association between an increased immigrant concentration and the homicide rate in the area, suggesting that any effect may differ across metropolitan areas. The analysis of large areas may also mask important patterns that occur at smaller geographic levels of analysis. Because immigrant residential patterns and homicides are both social phenomenon that are spatially concentrated, examining these two measures at a lower level of aggregation than metropolitan areas, counties, or cities is important for understanding the social processes by which immigrant residential location may influence homicide rates.

The processes through which immigrant communities exacerbate or alleviate violence may vary between cities or by the ethnic composition of the particular immigrant community, suggesting the need for precision in examining the relationship between immigrant concentration and homicide. For example, immigrant neighborhoods in El Paso, which are largely Mexican-American, might not be expected to have the same set of structural conditions as immigrant neighborhoods in Miami, which are largely Cuban-American. To the extent that a particular ethnic group fosters greater social capital or collective efficacy among its members, a larger protective effect from violent behavior might result. Local area studies which analyze neighborhoods solely within the central city and exclude suburban communities may also underplay the effect of immigrant concentration if certain immigrant groups are selecting into suburban communities. Neighborhood level studies that focus on census tracts within a single city may also have relatively small sample sizes which could reduce the statistical power to

detect significant effects of immigrant communities on homicide patterns.

1.2.4 Study Setting

Although it is the most populous county in the nation, with more than 9.5 million inhabitants, Los Angeles has not been the focal point of any study of the effect of immigration on homicide rates.² This is an unfortunate oversight, since Los Angeles County is in many ways the ideal setting for such research. The county encompasses the entire cities of Los Angeles and Long Beach, as well as numerous smaller cities and rural areas, allowing for results that are not specific to a particular municipal definition. The Los Angeles area is a traditional gateway for immigrants, and is home to large foreign born populations from Mexico, Central and South America, and East and Southeast Asia. The residential patterns of the foreign born population in Los Angeles are varied, with immigrants settling in both urban and suburban neighborhoods throughout the county (see Logan, Zhang and Alba 2002, for a more detailed discussion of the settlement patterns of the foreign born population in Los Angeles). The proportion of the county that is foreign born is also increasing; more than 36% of individuals were foreign born in 2000, compared with 33% in 1990. The presence of this substantial and heterogeneous immigrant pool within a populous and residentially varied region makes Los Angeles an ideal study setting. In addition to the benefits of the geographic setting, this study also attempts to address some of the methodological shortcomings of previous research by including a richer set of measures of immigrant nativity than the proportion foreign born

² Peterson and Krivo's extensive and invaluable National Neighborhood Crime Study (2010) includes within its sample the city of Los Angeles (as well as 3 other cities in Los Angeles County), but the study design excludes over half of the county's population and nearly 40% of the homicide events that occurred in the county in the 1999-2001 period.

measure that is commonly used and to estimate the effect of specific immigrant communities on homicide mortality. This study also relies on official cause-of-death mortality data over multiple years and takes into account the spatial clustering of homicides in the analyses.

1.3 Data and Methods

Death registration data from the Los Angeles Office of Health Assessment and Epidemiology, the unit responsible for producing certificates for all deaths occurring within Los Angeles County, was used in this study. In addition to the precise date and the International Classification of Diseases (ICD) code for each death, the records also include the age, race, gender, and census tract of residence of the decedent. These data do not include the place that the homicide event occurred; the dependent variable is thus characterized as the risk of homicide death for tract residents. While the theories outlined above largely focus on the effect of neighborhood structural factors on the location of homicide events, these determinants have also been shown to affect individual homicide risk (Cubbin, LeClere and Smith 2000; Krueger et al. 2004). A benefit of this design is that the population at risk from homicide mortality, the total neighborhood population, is properly controlled. It is difficult to determine the correct exposure control in an analysis which models the outcome of homicide occurrence in given locations, as the population at risk of becoming a homicide victim may not be adequately reflected by the residential population in business districts and downtown areas with high daily populations and places like bars and transit stops that disproportionately generate violence.

This study uses death registration data from the period 2000 to 2004, focusing on

those deaths that were the result of intentional injury by homicide.³ There were 5,374 homicide deaths in Los Angeles County in the five year period under study. Of these, 294 (5.5%) were missing geographic identifying information and were excluded from the analysis. These excluded cases were somewhat more likely than the geographically identifiable sample to be female and non-Hispanic white, and were slightly older.⁴

This study uses mortality data rather than the FBI's Uniform Crime Reports (UCR) or the Supplemental Homicide Reports (SHR) to illustrate the incidence of violent crime in an area. The analysis of small areas requires the use of these data as both the SHR and UCR can only be aggregated by city, county or metropolitan area and are not available for neighborhoods. It may, however, be instructive to compare the number of deaths reported as homicides on death certificates with the number of homicides reported in official crime statistics. In the period encompassing 2000 to 2004, 5,374 deaths were recorded by the Health Assessment Office as having an underlying cause of homicide, while 5,323 murders were reported by the California Attorney General's Office.⁵ The small discrepancy between these two figures may reflect differences in reporting periods or legal technicalities in the definition of homicides. For example, official crime statistics may report the death as a homicide only after it has been determined by the county medical examiner to be a homicide. The lag between the actual death and the medical

³ The deaths attributable to this cause were those classified to ICD9 codes E960-E969 and to ICD10 codes X85-Y09 and Y87.1. The ICD10 also includes a code for homicides attributable to terrorist acts; however, no deaths during this period were assigned this code.

⁴ The 294 deaths missing geographic info were 81.6% male, 20.4% white, 40.1% Hispanic, 28.2% black, and 4.4% Asian, with an average age of 32.9. The 5,080 deaths in the geographically identifiable sample are 86.7% male, 11.1% white, 49.5% Hispanic, 34.9% black, and 4.3% Asian, with an average age of 29.5.

⁵ California Office of the Attorney General. Retrieved on 03/05/10 from http://stats.doj.ca.gov/cjsc_stats/prof08/19/1.htm.

examiner's ruling may result in some under-counting of homicides in official crime statistics.

This study utilizes census tracts to define neighborhoods. The number of homicides over the five year period was aggregated for each census tract to construct the dependent variable. There were 2,054 census tracts in Los Angeles County in 2000. Those tracts with a population of less than 100 were removed from the analysis, as was any tract in which more than 25% of the population was group-quartered or institutionalized.⁶ The final sample includes 2,003 census tracts, which encompass over 99% of the geographically identifiable homicide deaths. While a small number of homicides were thus excluded because they occurred in sparsely populated or otherwise unusual tracts, these deaths were included in the aggregation of homicides for the spatial lag term which is discussed later.

1.3.1 Measurement of the Foreign Born Population

Previous research studying the effect of immigrant concentration on crime has measured immigrant concentration in a number of ways, including the proportion of a tract that is foreign born (Cagney, Browning and Wallace 2007; Nielsen and Martinez 2009), an index measure of the proportion of a tract that is foreign born and the proportion of the tract that is Hispanic (Sampson et al. 1997; Stowell et al. 2009), and the degree of linguistic isolation (Reid et al. 2005). The present study considers two separate

⁶ In addition, the two tracts which comprise Santa Catalina Island were removed, as were two tracts adjacent to the campus of the University of California-Los Angeles and one tract adjacent to the campus of the University of Southern California. These latter three tracts exhibited population characteristics (primarily the proportion of males in the age range 15-24) that were unrepresentative of the remainder of the tracts in the sample, and would exhibit undue influence on the results.

measures of immigrant concentration: The proportion of the tract that is foreign born and an “enclave intensity” quantity (E), which is defined separately for each country of nativity as:

$$E_i = \frac{(\textit{proportion of foreign born population from country } i)}{(1-\textit{proportion total population that is foreign born})} \quad (1)$$

The index value E is designed to establish more precisely the location of residential enclaves of particular immigrant groups, and to determine whether heterogeneity between different groups is overlooked by aggregation into a broad foreign born category. The numerator of the E statistic, which ranges from 0 to 1, measures the concentration of the group in question relative to the larger immigrant population. The denominator of the E statistic weights the concentration in the numerator based on the relative size of the foreign born population in the tract. This weighting method diminishes the influence of tracts in which the foreign born population is all from the same country, but is comparatively small in magnitude. While the E statistic is theoretically unbounded at the top (and is obviously undefined for a tract composed entirely of immigrants), in the data used here it does not range above 3.5.⁷ In this analysis, E is computed for foreign born populations from Mexico, China, South Korea, and the Philippines, four prominent groups which contain over 60% of the total immigrant population in Los Angeles County.

The importance of the E index is illustrated by a comparison of Map 1.1, which shows the distribution of the total foreign born population in the county, with Maps 1.3-

⁷ The Los Angeles County tract with the greatest proportion of immigrants has a population that is approximately 79% foreign born.

1.6, which show the distribution of various groups by ethnic origin. Dark gray tracts indicate a foreign born population (or *E* index) that is more than two standard deviations above the county mean, while light gray tracts indicate a one standard deviation difference; tracts indicated in white are equal to or less than the county mean. The tracts with the greatest density of Mexican immigrants are those adjacent to the downtown area of the city of Los Angeles, although there are high concentrations of Mexican immigrants scattered throughout the remainder of the county. Foreign born Chinese are concentrated in the independent cities of Alhambra, Monterey Park, and Rowland Heights, among others, in the eastern portion of the county, while clusters of foreign born Koreans exist in the areas west of downtown Los Angeles, in the northern city neighborhoods of Sunland and Tujunga, and in the city of Cerritos on the southern boundary with Orange County. Filipinos comprise significant portions of tracts in the city of Long Beach in the south and the city of Glendale in the north. In general then, the aggregation of all immigrants into a single foreign born group appears to conceal considerable heterogeneity in the neighborhood settlement patterns of distinct ethnic foreign born groups.

1.3.2 Control Variables

All data measuring neighborhood structural characteristics, including the measures of immigrant concentration, were taken from the SF3 file of the 2000 U.S. Census. Characteristics were broadly organized into three groups based on the probable mechanism by which they might reduce or enhance homicide probability: (1) poverty or concentrated disadvantage, (2) residential stability, and (3) demographic composition. The number of possible measures is large and collinearity among these variables is likely

to be problematic. Principal component analysis was used to address the potential collinearity and to reduce the total number of regressors in the estimation equations.

The concentrated poverty index, which is expected to have a positive effect on homicide mortality, is composed of the proportion of the tract that is unemployed, the proportion that is below the poverty rate, the proportion non-Hispanic black, the proportion that is receiving public assistance, the natural log of the median family income, and the proportion of the population that does not have a high school diploma.

Residential stability is evaluated as an index of the proportion of individuals who have been in their current home for more than five years, the proportion of housing units that are occupied, and the proportion of occupied housing units that are owner-occupied. Increased residential stability is expected to contribute to a reduction in the level of crime, as longer term residents and homeowners have a greater stake in maintaining a safe neighborhood. However, the effect of residential stability on neighborhood violence has been shown to interact with the effect of concentrated disadvantage (Smith and Jarjoura 1988; also see Sampson and Wilson 1995). For high-poverty or high-violence neighborhoods residential stability may be the consequence of an inability of residents to move to more affluent or safer areas, such that stability could be positively associated with homicide rates.

The proportion of the tract population that is male between the ages of 15 and 24 is used to convey differences in demographic structure among tracts. This variable accounts for the higher likelihood of homicide in those tracts with a greater density of potential homicide offenders and victims.

The number of homicides within a neighborhood depends on the total number of

potential homicide victims and the degree to which individuals come into contact with one another. The census tracts used in this study exhibit wide variation in geographic size, ranging from .04 to 328 square miles, and population size, ranging from 171 to over 12,000 individuals. To account for this variation, the natural log of the total population and the natural log of the population density are included as control variables.

Social capital and collective efficacy theories predict that the existing ethnic composition of a neighborhood may affect the homicide rate within that area. If immigrants are selecting into a community based on the current prevalence of their ethnic group within that community, it is necessary to separate the immigrant effect from the ethnic group effect. While country-specific ethnicities are not available for the native born population for every census tract, the proportion of the tract population that is native-born Asian and the proportion of the tract population that is native-born Hispanic are included as broad indicators of the potential effect of existing ethnic group composition.

Neighborhood boundaries are arbitrary constructions and the processes through which immigrant concentration might be expected to affect homicide incidence are not spatially isolated within the borders of a particular census tract neighborhood. The spatial independence of neighborhoods, which is an implicit assumption in traditional regression models, does not reflect the reality that neighborhoods are part of a larger social context where nearby communities may produce effects on individual neighborhoods (Morenoff, Sampson, and Raudenbush 2001). The discretionary nature of neighborhood boundaries also means that the rate of homicide in an area may be influenced by retaliatory homicides that have occurred in proximal neighborhoods.

Research is increasingly focusing on the spatial dynamics of neighborhood violence (Morenoff, Sampson and Raudenbush 2001; Graif and Sampson 2009).

A crucial concept in any spatial methodology is that of the spatial weight matrix, which defines the spatial relationship between each unit of analysis – in this case those tracts that neighbor each other. The weight matrix is chosen based on a theoretical consideration of the social process being modeled. Residents of neighborhoods that are more spatially proximal to those neighborhoods with characteristics predictive of violent behavior may themselves be at a higher risk of violence, as neighborhood boundaries are typically unenforceable. To this end, the spatial weight matrix is defined in this analysis such that tracts which are adjacent (contiguous) to one another are considered neighbors and tracts which do not touch are considered non-neighbors.⁸ This spatial analysis is carried out using OpenGeoDa and ArcMap software.

The dependent variable used in this analysis, the count of homicide deaths per tract, is highly clustered in space. The value of the Moran's I statistic, a frequently used measure of spatial autocorrelation, is 0.567 and the p-value ($p < .001$) indicates significant spatial clustering.⁹ Further testing using the OpenGeoDa software suggests that the appropriate model with which to correct for the spatial dependence is a spatial lag model.¹⁰ The spatial lag model includes an endogenous covariate - the neighbor-

⁸ Because the choice of a spatial weight matrix is, to some extent, arbitrary, alternative weighting schemes were also considered. The results from the models which follow are robust to these alternative spatial weights, which included identifying neighbors based on queen contiguity (tracts which share a border or a point), 2nd order rook contiguity (tracts which are adjacent to the origin tract, as well as tracts adjacent to those first neighbors), five nearest neighbors (from/to the centroid), and ten nearest neighbors (from/to the centroid).

⁹ The Moran's I p-value is based on the permutation test detailed in Anselin (2005) and carried out in OpenGeoDa.

¹⁰ The Lagrange Multiplier test in the OpenGeoDa regression diagnostics compares a non-spatial model to a spatial lag model and a spatial error model, and Anselin (2005) provides a decision rule in selecting the

weighted value of the dependent variable. In practice, this is accomplished by averaging the number of homicide deaths in neighboring tracts (as defined by the spatial weight matrix) and then introducing this value as a covariate in the regression model.

1.3.3 Model

The distribution of the number of homicide deaths per tract, shown in Figure 1.1, is noticeably skewed towards 0; over a quarter of the tracts in the county (28.9%) experienced no homicide deaths during the study period. In addition, the number of homicide deaths, as a count variable, takes on discrete nonnegative values only and is left truncated at 0. While linear transformations might be used to remedy the problem of asymmetry, at least in part, the censoring and discreteness of count data requires maximum likelihood estimation procedures.¹¹ The Poisson regression model is a common method to estimate count data, but the Poisson distribution assumes that the conditional mean and variance will be equal. When the data used here were fit with a Poisson model the conditional variance was greater than the conditional mean, violating this basic assumption of the model. The negative binomial regression model, which allows for overdispersion of the distributional variance, provides a more suitable fit for homicide death count data. A zero-inflated negative binomial specification is used in this analysis, due to the large number of zero count tracts.¹²

correct specification. To achieve the normally distributed outcome presupposed by these diagnostics, the dependent variable was transformed by adding 1 to the tract homicide count, dividing by the total tract population, and logging the resulting rate.

¹¹ A Tobit regression model may also be used to estimate censored data. This paper relies on a negative binomial regression model, but a separate analysis using a Tobit regression estimation and a transformed (rate) dependent variable produced substantively similar results.

¹² The *countfit* procedure in Stata compares the Poisson, negative binomial, zero-inflated Poisson, and

The model is estimated separately using each of the immigrant measures, the proportion foreign born and the enclave intensity indices, and is visually represented by the following formulation:

$$Y = \alpha + \beta_1 X^{IMM} + \beta_2 X + \beta_3 \rho + \varepsilon \quad (2)$$

In equation (2), Y is a vector composed of the aggregate number of homicide deaths in each tract, X^{IMM} is a vector of the immigrant concentration or enclave index measure for each tract, X is a matrix consisting of other relevant tract characteristics, ρ is the spatial lag vector relating the average homicide deaths in contiguous tracts, and α , β_1 , β_2 and β_3 are parameters to be determined; the focus is on the magnitude and significance of the β_1 term. The variables used to determine whether a tract homicide count is always 0 are the same as those used to determine the count for those tracts that are not always 0 (i.e. the variable specification for the inflation term is equivalent to the variable specification for the full model). The model will first be estimated without the spatial lag term, to allow for a comparison between the non-spatial model and the model which accounts for the spatial dependence of homicide deaths.

1.4 Analysis

Summary statistics for each of the variables included in the analysis are shown in Table 1.1. The primary dependent variable, the homicide count over the period 2000 to

zero-inflated negative binomial regression distributions on a number of goodness-of-fit statistics (Long and Freese 2006). This procedure suggests that the Poisson model is the most accurate in predicting the actual number of zero counts in the data, but is less successful in predicting the remainder of the count outcomes. The zero-inflated negative binomial model is more effective at predicting count outcomes greater than zero, and was the preferred model based on all goodness of fit tests.

2004, ranges from 0 to 25 with a mean of 2.5 deaths per census tract. Map 1.2 illustrates that the large majority of high homicide tracts are located in the area of South Los Angeles, although there are additional high homicide tracts scattered throughout the county. Foreign born individuals comprise, on average, 36% of the population in the study tracts, ranging from a low of 0% to a high of 79%. As shown in Map 1.1, the foreign born population is fairly widely distributed among tracts and the obvious geographic clustering of predominantly foreign born tracts exhibit greater dispersion than do the high homicide tracts. The *E* index for the Mexican born population is substantially greater than those for the remaining immigrant populations, reflecting the fact that Mexicans are the dominant foreign born group in the county. The Chinese *E* index has the largest maximum value, as the tract with the overall greatest concentration of immigrants is predominantly Chinese. The values of the components of the concentrated disadvantage index vary widely between tracts, with the mean poverty rate somewhat above the U.S. average and the mean proportion black below the U.S. average. There is substantial heterogeneity in the ethnic and age compositions of the tracts.

The results from the estimation of equation (2) are shown in Table 1.2; the first column is the non-spatial model that includes all of the covariates. The coefficient for proportion of the tract that is foreign born is statistically significant and negative, indicating that larger immigrant populations are associated with fewer homicide events. Higher numbers of homicide deaths are predicted by increased poverty, larger populations, and increased population density. Residential stability has a positive correlation with homicide, which may indicate the negative effects of being in a “stable in poverty” trap. There is no observed relationship between the neighborhood homicide

count and the number of young males or the native-born Hispanic population.

The second column of Table 1.2 shows the model with the addition of the spatial lag term. Several coefficients change when this spatial lag term is added to the model, indicating that some of the variation in tract homicide counts is explained by the level of violence in neighboring tracts. Including the spatial lag term as a covariate decreases the value of the foreign born coefficient by over one half, although the coefficient remains significant. While most of the coefficients decrease in magnitude, the general pattern of the covariate's effects remains the same. The positive and significant coefficient on the spatial lag variable itself suggests the existence of a spatial process through which homicides deaths are related.

While the zero-inflated negative binomial model was the preferred count model based on several goodness-of-fit statistics, it may be instructive to see how well the model conforms to the actual distribution of tract homicide counts. Figure 1.2 graphs the predicted probability of specific numbers of homicides occurring in the data set, and compares the observed homicide distribution to that predicted from the zero-inflated negative binomial model. The solid line in Figure 1.2 shows the observed distribution of homicides, while the dashed line corresponds with the predicted probabilities of individual counts. This graph confirms that the selected model does a suitable job of reproducing the underlying unconditional probability distribution of the homicide data.

The coefficient for the proportion foreign born is most easily interpreted by comparing the predicted probabilities from models which allow this variable to fluctuate while holding all other variables constant. Figure 1.3 illustrates how the predicted probability of a tract exhibiting a specific number of homicides changes at the different

deciles of foreign born population. For example, the line representing the probability of a tract exhibiting 4 homicides, designated by the line with circle markers, is downward sloping, indicating that this probability decreases with increased foreign born concentration. The striking feature of this chart is the upward slope of the low count ($X = 1$ or less) lines juxtaposed with the downward slope of the high count ($X = 2$ or more) lines, a pattern which suggests that higher homicide tracts may transition to lower homicide tracts as foreign born populations increase. These transitions may be substantial: A change from a foreign born concentration of 0 (the observed minimum) to a foreign born concentration of 0.80 (the approximate observed maximum), increases the probability of a tract exhibiting a homicide count of 0 by 46%, while decreasing the probability of the tract exhibiting a homicide count of 5 by 66%.

Table 1.3 displays the results from the estimates of equation (2), which include the E indices that quantify the proportion of the immigrant population that is from a specific group. Of the four E indices used in this analysis, only the statistics for the Chinese-born and Filipino-born populations are statistically significant, and both of these coefficients show a negative sign. The magnitudes of these effects are similar to the estimated effect for the proportion born variable in the previous model. While the proportion native Asian variable becomes an insignificant predictor in this model, relative to the proportion foreign born model displayed in Table 1.2, the estimates for the other covariates show little change.

1.5 Discussion

The results from this study suggest that increased immigrant composition, when

broadly defined, is associated with a reduced number of homicides in Los Angeles County neighborhoods. This is true even after controlling for neighborhood heterogeneity in demographic and ethnic composition and economic disadvantage, and adjusting for the spatial clustering of homicide deaths. While specific theories are not tested in this paper, it is important to consider how these results relate to the theoretical framework introduced in framing the analysis.

The negative relationship that is found between immigration and homicide refutes the classic social disorganization theory perspective, which implies that increased immigration should be manifest in a greater number of expected homicide deaths. While it is not possible to determine here the exact causal mechanism through which increasing neighborhood immigrant composition is affecting homicide activity, there is no evidence of a positive link between the two processes. The results here are consistent to some extent with theories of social capital and collective efficacy, in implying that immigrant concentration and immigrant enclaves may increase social connection and community informal social controls against violence. Immigrant clustering in certain neighborhoods may be beneficial if, by providing a common cultural and linguistic background, it increases the predisposition of residents to intervene on behalf of one another. Cultural homogeneity may result in a greater level of informal social control, as ambiguity in social norms and accepted behaviors will be lessened. Linguistic heterogeneity, whether due to a greater propensity for particular groups to speak the language of the host county or due to the clustering of native language speaking immigrants, may produce enhanced levels of trust and social cohesion. There is little evidence in these models to either confirm or contradict labor market theories of the effects of immigration on homicide,

nor is there reason to believe that significant labor market effects could even be found in neighborhood-level studies. Changes in the demographic structure of the population due to the age composition of immigrants certainly explains why a positive relationship between crime and immigration, without appropriate age-standardization, might be found. However, in none of the models estimated was the age composition a statistically significant predictor of homicide counts. In contrast, the immigrant composition is a consistently significant predictor of fewer homicides, suggesting that age composition alone cannot describe the immigration-homicide link.

While the results presented in Table 1.3, which isolates the effect of specific foreign born populations on homicide counts, may appear to promote the idea of violent/less violent subcultures, this is not the intent of the analysis. This decomposition is meant to be a first step in recognizing that the lumping of all foreign born individuals into a single variable is insufficient, particularly if one's goal is to relate this variable to theories of social network formation, collective efficacy, or linguistic isolation. In the context of these theories, there is little justification for the belief that a neighborhood that is 1/3 native and 2/3 Mexican-born would exhibit the same synergies (or antipathies) as a neighborhood that is 1/3 native, 1/3 Mexican-born and 1/3 Chinese-born. Yet, the underlying assumption of uniform foreign born effects is necessary when one collapses all foreign born groups into one measure. In light of the findings for our enclave intensity indices, it is important to keep in mind that we do not know the actual characteristics of the immigrants in this sample. As such, it is not possible to discern dissimilarities between different immigrant groups along the range of the sociodemographic scale.

Immigrants tend to select into neighborhoods with greater levels of economic disadvantage. Within those tracts in the highest quartile of foreign born population the mean poverty rate is 0.28, compared to a rate of 0.09 for the tracts in the lowest quartile. Because the role of economic disadvantage has such a profound effect in studies of homicide and neighborhood violence, it may be instructive to investigate the interaction between poverty and immigrant concentration in this model. Figure 1.4 shows the mean predicted homicide count for groups of tracts, net of the model, at varying levels of poverty and immigrant composition. High poverty tracts are those in the highest quintile of the poverty index; low poverty tracts are those in the lowest. Counts were predicted within each poverty group at three levels of immigrant composition: 0, the observed minimum; 0.36, the observed mean; and 0.79, the observed maximum. Confidence intervals (95%) are included for each predicted count and are designated by the dotted lines.

At low levels of economic disadvantage, there is little difference between the predicted homicide counts of those tracts with large immigrant concentrations and those tracts with smaller immigrant concentrations. While the predicted counts decrease as foreign born populations increase, the lower confidence bound for the low foreign born counts is approximately equal to the upper confidence bound for the high foreign born counts, indicating an insignificant effect. However, at high levels of economic disadvantage, tracts with larger immigrant concentrations have much lower predicted homicide counts, and these differences are substantial. Within these highest poverty tracts, the predicted homicide count at the minimum foreign born value is 4.3, which decreases to 2.2 at the maximum foreign born value.

The results from these spatial lag models suggest the importance of incorporating measures of spatial autocorrelation into neighborhood effects analyses. The coefficient estimate on the spatial lag term, defined here as the average number of homicides in adjacent tracts, is positive and significant, implying that the social processes through which homicides occur do not respect the boundaries of census tracts. Importantly, the inclusion of this spatial term mediates the effect of the immigrant concentration variable, reducing its magnitude by more than one half.

1.5.1 Robustness Tests and Limitations of the Analysis

The spatial lag model assumes that neighboring areas may be correlated with homicide in the tracts of interest, and that the remaining sources of spatial autocorrelation are held constant. This model also assumes that the spatial clustering is exogenous in these equations.¹³ Given that the spatial clustering of homicide is an endogenous variable of neighboring census tracts, and that census tract boundaries themselves are an administrative construction not tied to the social processes that generate homicides, we also examined whether the results would hold using a two-stage negative binomial regression model that controls for the effects of all spatially relevant variables simultaneously. A similar approach was proposed by Land and Deane (1992) using a two-stage least squares estimator where an instrumental variable (IV) in the first-stage estimation of spatial clustering is used to separate out the spatial effect from the main effects of interest in the second-stage estimation. Our model is equivalent to the two-stage version of the negative binomial model developed by Ten Have and Chinchilli

¹³ Ignoring spatial correlation in errors has more to do with loss of efficiency, rather than bias, in our parameters.

(1998), but which relies on the same basic assumption of Land and Dean: That there exists an IV that is correlated strongly with spatial clustering but whose residual error is orthogonal to the main effect being predicted. For this study this implies an IV that predicts the average counts of homicides in surrounding census tracts (spatial lag), but which has no direct causal effect on the homicide death counts in a given tract. This study applies the Los Angeles County Health District within which a tract lies as the IV. The basic assumption underlying this choice of an IV is that Health Districts may be correlated with neighborhood homicide clusters but have no direct causal role in the existence of high homicide counts in any single census tract. This is a tenable assumption, as health districts are not designed based on any particular patterns of homicide. To estimate this two-stage model the spatial lag term is regressed, using negative binomial estimation, on the exogenous control variables and the health district IV's. The resulting adjusted estimates of homicide counts (predicted spatial lag) are then incorporated into the negative binomial model in the second stage as a predictor variable, which in effect controls for all spatial autocorrelation in the residuals from all predictor variables.¹⁴

The results from the first-stage estimation are shown in the first column of Table 1.4. Several of the health district indicator variables are individually significant, and a Wald Test rejects the hypothesis that all of the coefficients on the health district indicator variables are jointly equal to 0 ($p < .001$). This suggests that the instrumental variables are valuable in explaining variation in the spatial lag term. In addition, a likelihood ratio

¹⁴ It should be noted that the standard errors in the second-stage model are not going to be asymptotically correct as this model is not using a simultaneous equations estimator. Ten Have and Chincilli (1998), however, show that even though the two-stage model is not estimated simultaneously this has little consequence on standard errors.

tests indicates that the unrestricted first-stage model which includes the health district variables is preferred over the restricted first-stage model which does not include the health district variables.

The second column of Table 1.4 contains the results from the 2nd-stage estimation of tract homicide counts on the control variables and the predicted values from the first stage. The coefficient estimates for the exogenous variables are essentially the same here as in the spatial regression model shown in Table 1.2 and the substantive story remains the same: The proportion foreign born is negatively associated with the number of homicide deaths in the tract. That the results from this second-stage model are consistent with those obtained from the spatial lag model is further evidence that the spatial clustering of homicide deaths has been properly accounted for, and that the direct effect of proportion foreign born is not sensitive to spatial autocorrelation.

The Moran's I measure of spatial autocorrelation may also be used post-analysis to examine whether spatial autocorrelation remains in the residuals of the model. Although the Moran's I test statistic does not have a numerical interpretation, the statistic always falls between a value of -1 and 1, with values closer to the boundary indicating increased (negative or positive) spatial autocorrelation; a Moran's I of 0 indicates no spatial autocorrelation. A reduction in the spatial autocorrelation of the residuals from the model with no spatial lag to the model which includes a spatial lag, may suggest that the inclusion of the spatial lag variable has sufficiently controlled for the spatial clustering of homicide deaths. The Moran's I value for the residuals from the non-spatial model shown in the first column of Table 2 is .085 ($p < .001$), compared to a value of .016

($p < .05$) for the two-stage model estimated above.¹⁵ While the p-value of the Moran's I statistic from the two-stage model indicates that spatial autocorrelation of the residuals may still be present, the magnitude of this Moran's I statistic is greatly reduced from that obtained in the non-spatial model.

It was noted prior that the distribution of homicide deaths per tract is highly skewed, with a small number of tracts experiencing large numbers of deaths; in fact, nearly 40% of the homicide deaths during this period occurred in just 10% of the tracts, while more than a quarter of the tracts observed no homicide deaths at all. To test whether these outlying tracts were unduly biasing the regression results, the main analysis was rerun after removing those tracts with predicted counts that were in the highest 5% and lowest 5% of all counts. The results from using this restricted sample in the spatial lag regression model from Equation (2) are shown in Table 1.5. The coefficient estimate on the proportion foreign born variable is very close to that obtained in the original regression, as are the estimates for most of the control variables. Based on these results, it does not appear that outliers are driving the observed relationship between the tract foreign born population and the tract homicide incidence.¹⁶

This analysis is limited by the dearth of available data at the neighborhood level. The lack of annual population estimates at the census tract level necessitates the use of decennial demographic information as control variables. Because the dependent variable used in this analysis aggregates homicide deaths from multiple years, inconsistent estimates may occur if the explanatory variables included in the model vary dramatically

¹⁵ Significance levels for the Moran's I values are based on a pseudo p-value determined using a permutation test, as described in Anselin (2005).

¹⁶ The two-stage model was also repeated using the restricted sample and the results were similar to those obtained from the unrestricted sample. These results are available from the author.

over the time period in which homicides are measured. The incorporation of neighborhood structural characteristics at the annual level would allow for a much stronger causal model.

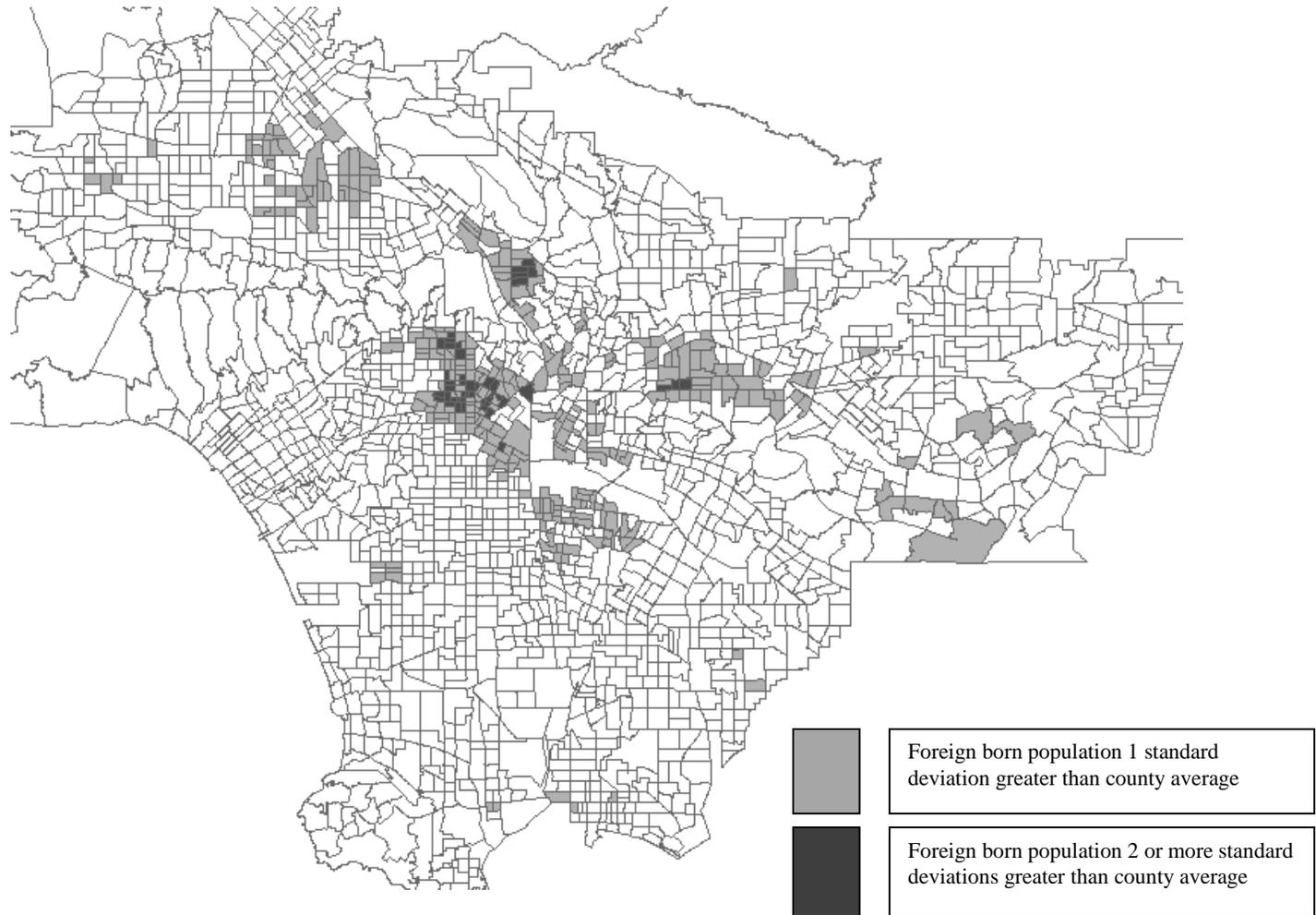
1.5.2 Conclusion

Immigration is the largest component of population growth in the United States today and ethnic enclaves will continue to expand if the precedent of recent immigrant residential clustering upholds. The potential effects of neighborhood clustering of immigrants on homicide mortality has important policy implications. These may include the efficient allocation of police or other public safety resources or the placement of public health facilities or outreach programs. The determination of the processes through which any positive consequences of immigrant clustering occur might suggest policies or treatments that could be enacted in non-immigrant neighborhoods. Subsequent research which questions the role of neighborhoods on individual health may wish to incorporate some measure of immigrant concentration as an explanatory variable.

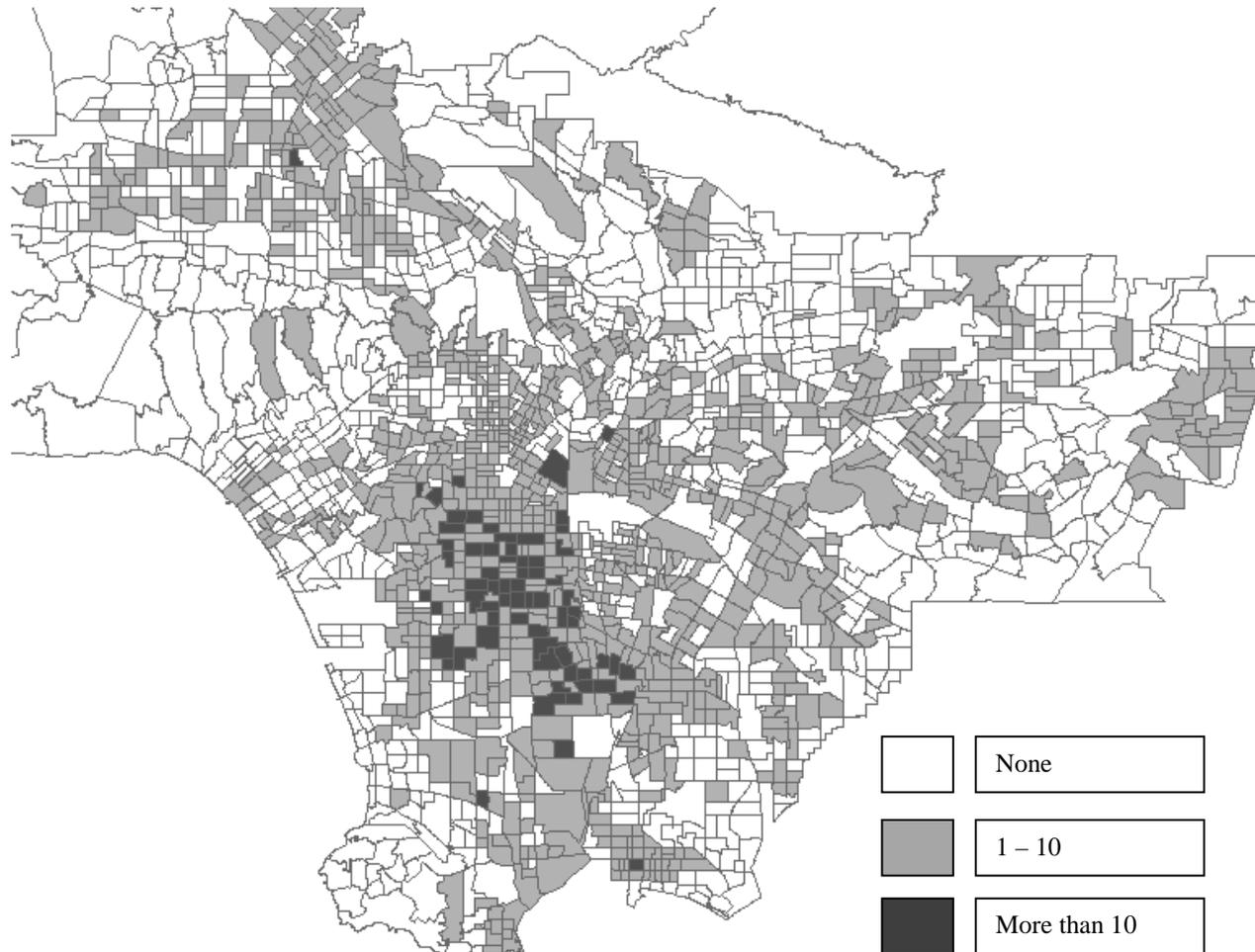
Consistent with the prior research on neighborhood patterns of violence and immigration conducted in other cities, this paper finds a significant and robust effect of foreign born populations on homicide events in the previously understudied area of Los Angeles. There is also evidence that this effect may differ based on the predominant immigrant group in the neighborhood, although there is insufficient information regarding the characteristics of the various groups to suggest the mechanism behind this variation. This research adds to the existing literature in proposing a method of measuring immigrant enclaves that allows the effect of distinctive foreign born

populations to be isolated, and highlights the importance of properly accounting for spatial autocorrelation in neighborhood-level studies. It also showcases the use of death registration data in homicide research, providing an effective way to study homicide mortality at the local level.

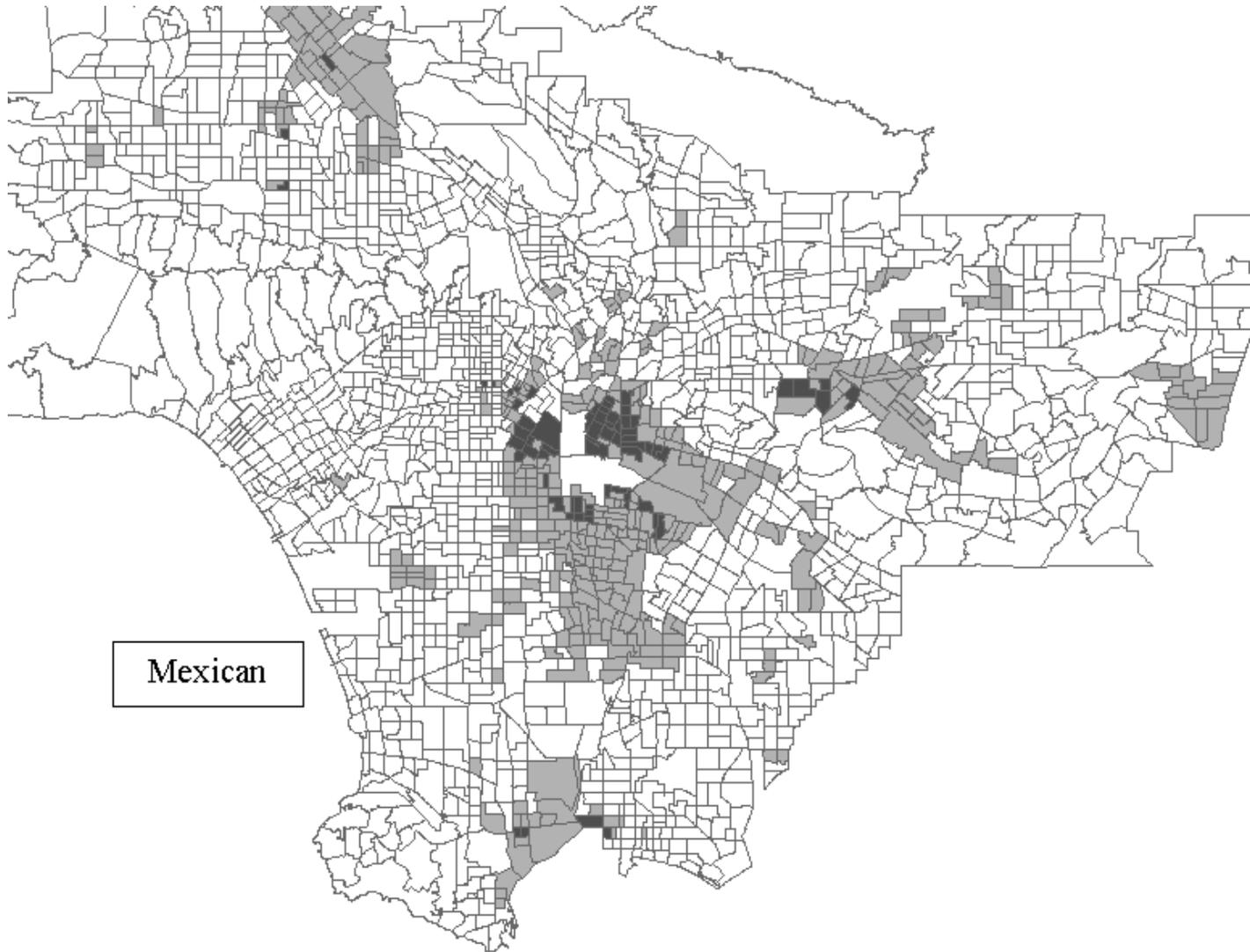
Map 1.1: Distribution of Foreign Born Population in Los Angeles County



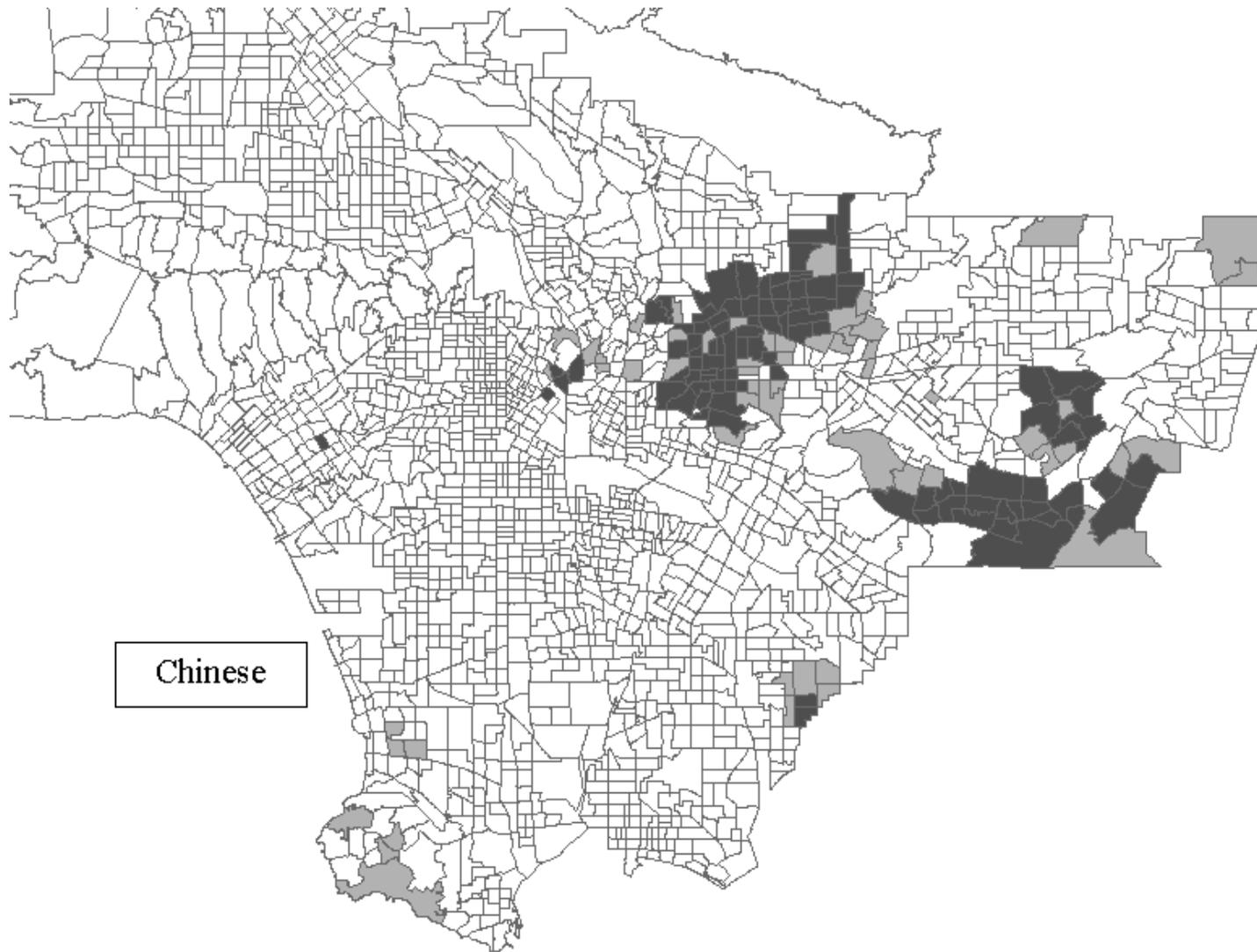
Map 1.2: Distribution of Homicide Deaths in Los Angeles County (2000-2004)



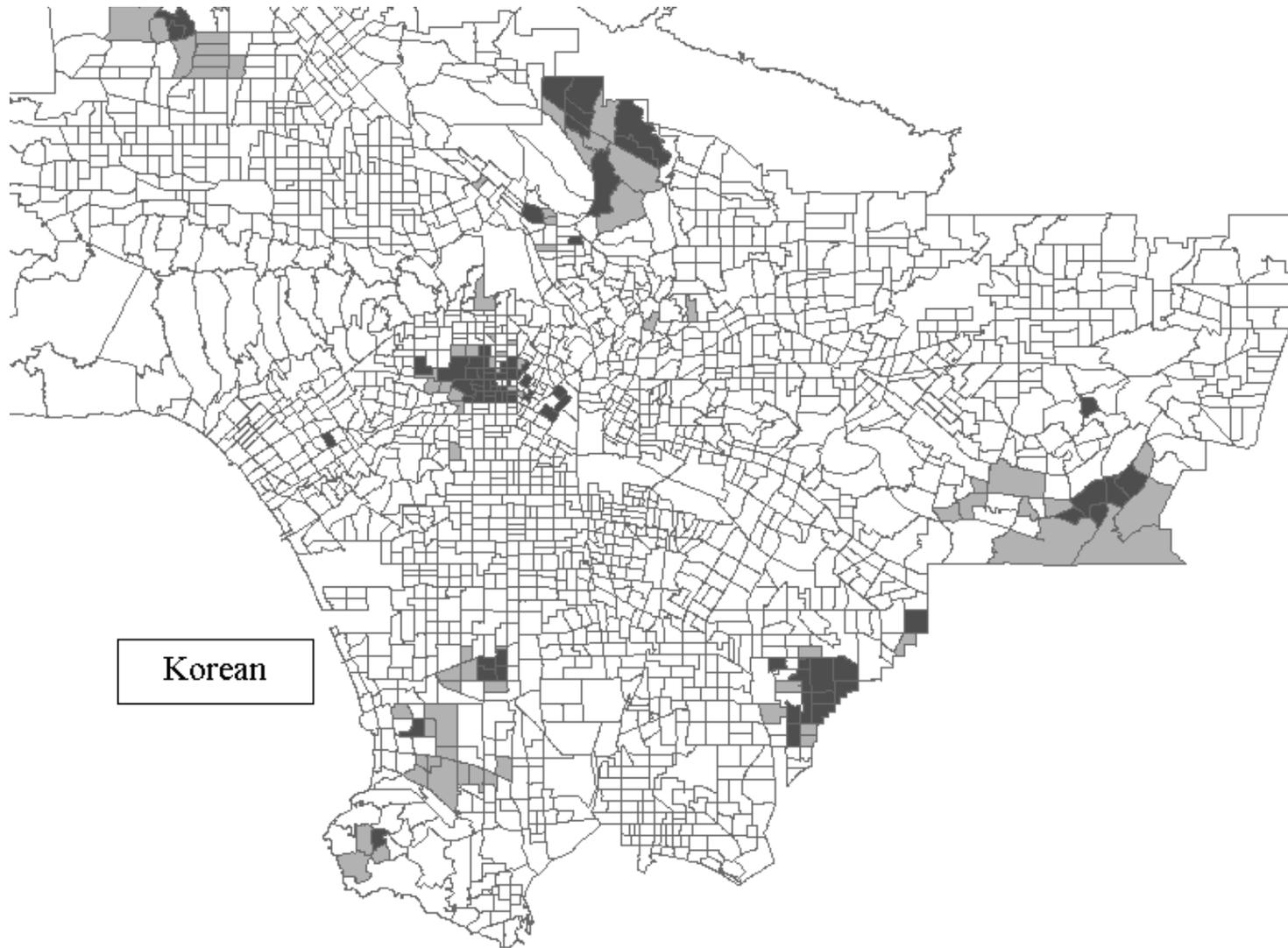
Map 1.3: Distribution of Foreign Born Population by E Index – Mexican



Map 1.4: Distribution of Foreign Born Population by E Index – Chinese



Map 1.5: Distribution of Foreign Born Population by E Index – Korean



Map 1.6: Distribution of Foreign Born Population by E Index – Filipino

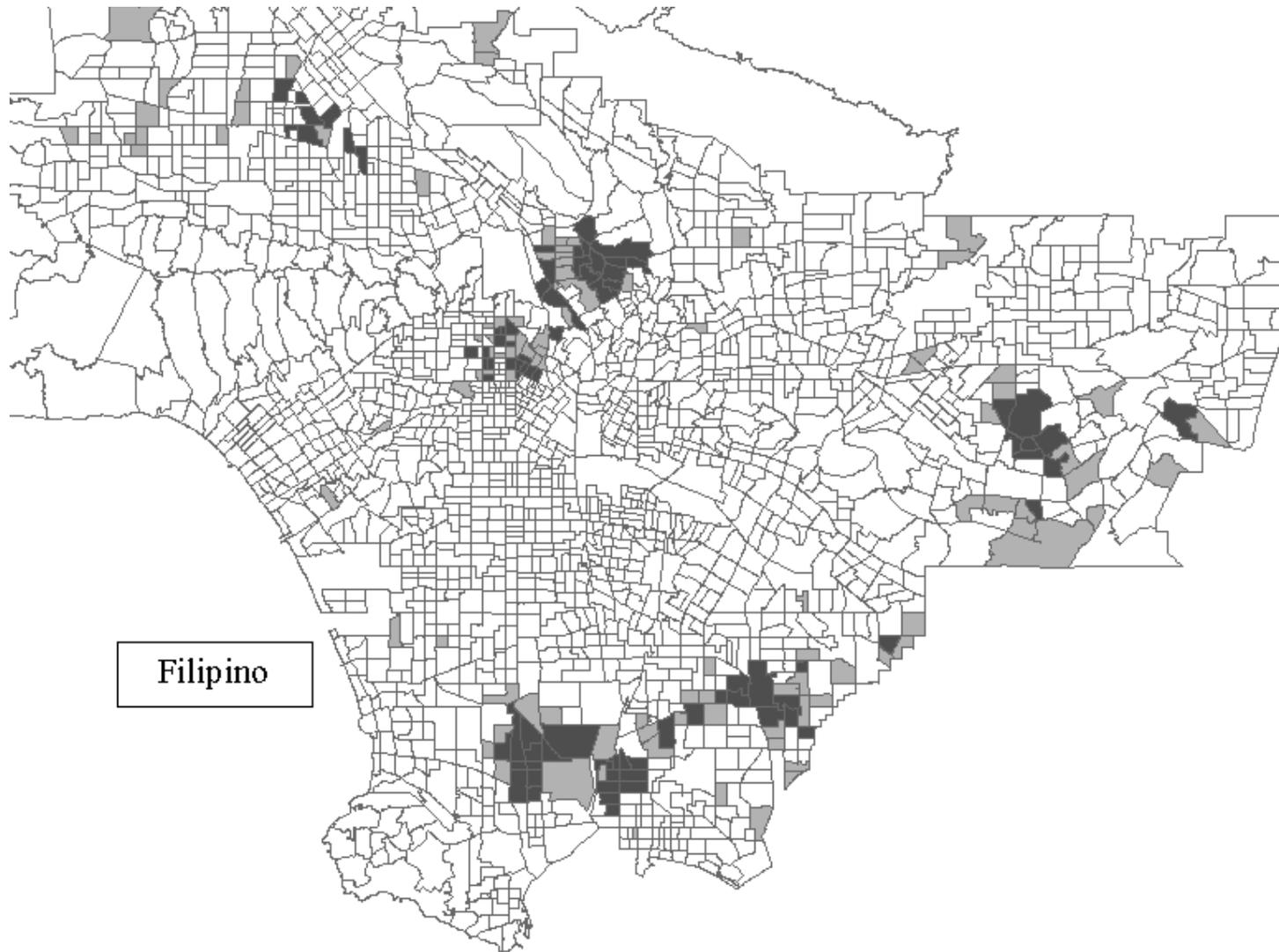


Figure 1.1: Distribution of Homicide Counts per Tract

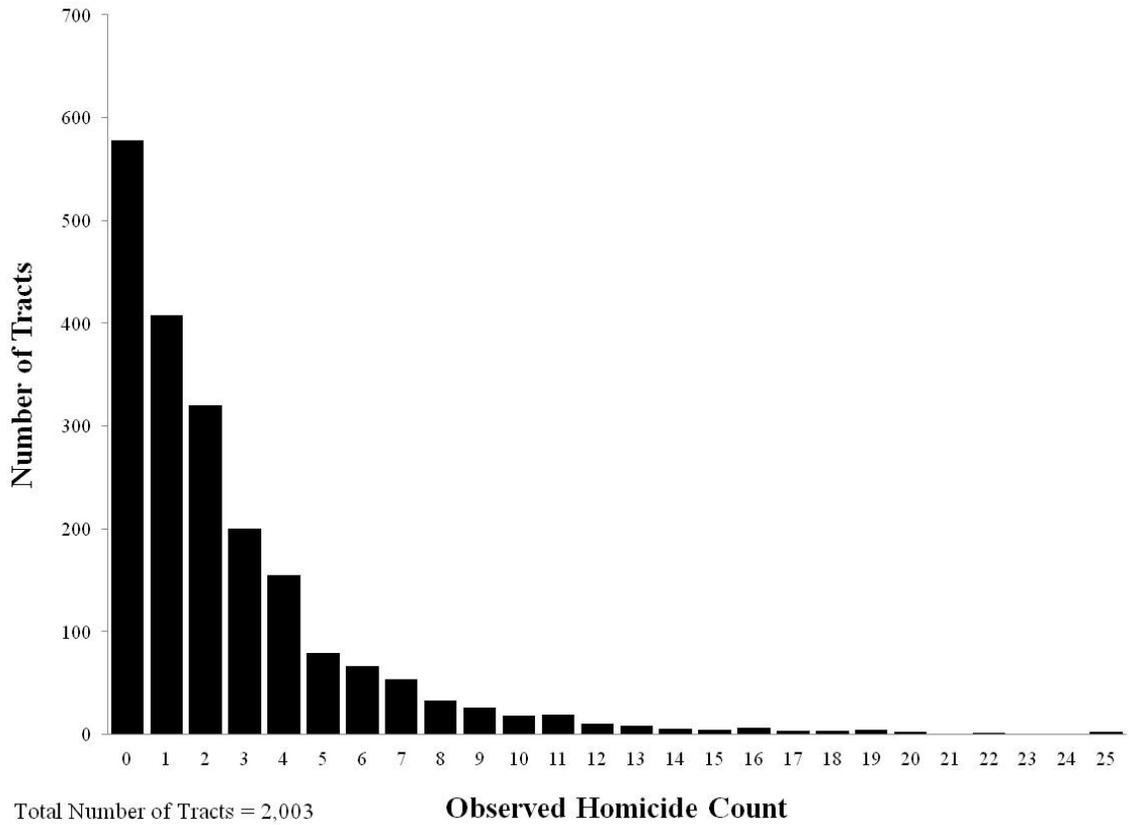


Table 1.1: Summary Statistics for Tract Structural Covariates

	Mean	Standard Deviation	Minimum	Maximum
<i>Dependent Variable</i>				
Homicide Count (2000-2004)	2.5	3.2	0	25
<i>Immigrant Composition Variables</i>				
Proportion Foreign Born	0.36	0.16	0.00	0.79
E Index – Mexican ¹	0.70	0.58	0.00	2.88
E Index – Chinese	0.10	0.23	0.00	3.46
E Index – Korean	0.07	0.17	0.00	2.13
E Index – Filipino	0.10	0.14	0.00	1.39
<i>Concentrated Disadvantage Index Components</i>				
Mean Family Income	52,171	29,365	11,144	200,001 ²
Unemployment Rate	0.09	0.05	0.00	0.44
Poverty Rate	0.18	0.12	0.00	0.70
Proportion Non-Hispanic Black	0.09	0.16	0.00	0.91
Proportion Families Receiving Public Assistance	0.13	0.09	0.00	0.72
Proportion No High School Diploma	0.11	0.11	0.00	1.00
<i>Residential Stability Index Components</i>				
Occupancy Rate	0.96	0.03	0.57	1.00
Proportion Housing Owner-Occupied	0.50	0.27	0.00	1.00
Proportion Residents in Same House 5 Years	0.53	0.11	0.02	0.81
<i>Other Variables</i>				
Proportion Native Hispanic	0.22	0.14	0.00	0.67
Proportion Native Asian	0.04	0.04	0.00	0.41
Proportion Male Age 15 to 34	0.07	0.02	0.02	0.23
Total Population	4,687	1,701	171	12,399
Population Density (Persons/Square Mile)	12,633	10,696	2	99,080
<i>Spatial Variable</i>				
Neighbor Homicide Count (2000-2004)	2.5	2.6	0	17.2

¹ Calculation of the E indices excludes the single tract which has no foreign born population.

² Mean family income is top-coded in the SF3 data.

Table 1.2: Coefficients from the Regression of Homicide Deaths on Proportion Foreign Born and Tract Structural Covariates

	Homicide Count	Homicide Count
Proportion Foreign Born	-1.29 *** (.19)	-.55 ** (.19)
Proportion Native Hispanic	-0.34 (.20)	-.01 (.19)
Proportion Native Asian	-2.79 *** (.67)	-2.07 *** (.64)
Poverty Index	0.37 *** (.02)	0.22 *** (.02)
Residential Stability Index	0.16 *** (.02)	0.07 ** (.02)
Proportion Male Age 15-24	2.69 (1.62)	1.64 (1.53)
Logged Population	0.86 *** (.06)	0.85 *** (.06)
Logged Population Density	0.07 * (.03)	0.02 (.03)
Spatial Lag		.10 *** (.01)
Constant	-6.67 *** (.55)	-6.65 *** (.537)
<i>Overdispersion parameter (alpha)</i>	0.15 *** (0.02)	0.10 *** (0.02)
<i>Number of observations</i>	2,003	2,003

Zero-inflated negative binomial regression. Dependent variable is the total number of homicide deaths from 2000 to 2004. Spatial lag term is average number of homicides in adjacent census tracts. Robust standard errors in parentheses. *** $p < .001$; ** $p < .01$; * $p < .05$

Figure 1.2: Probability of Obtaining Homicide Count X: Observed vs. Predicted

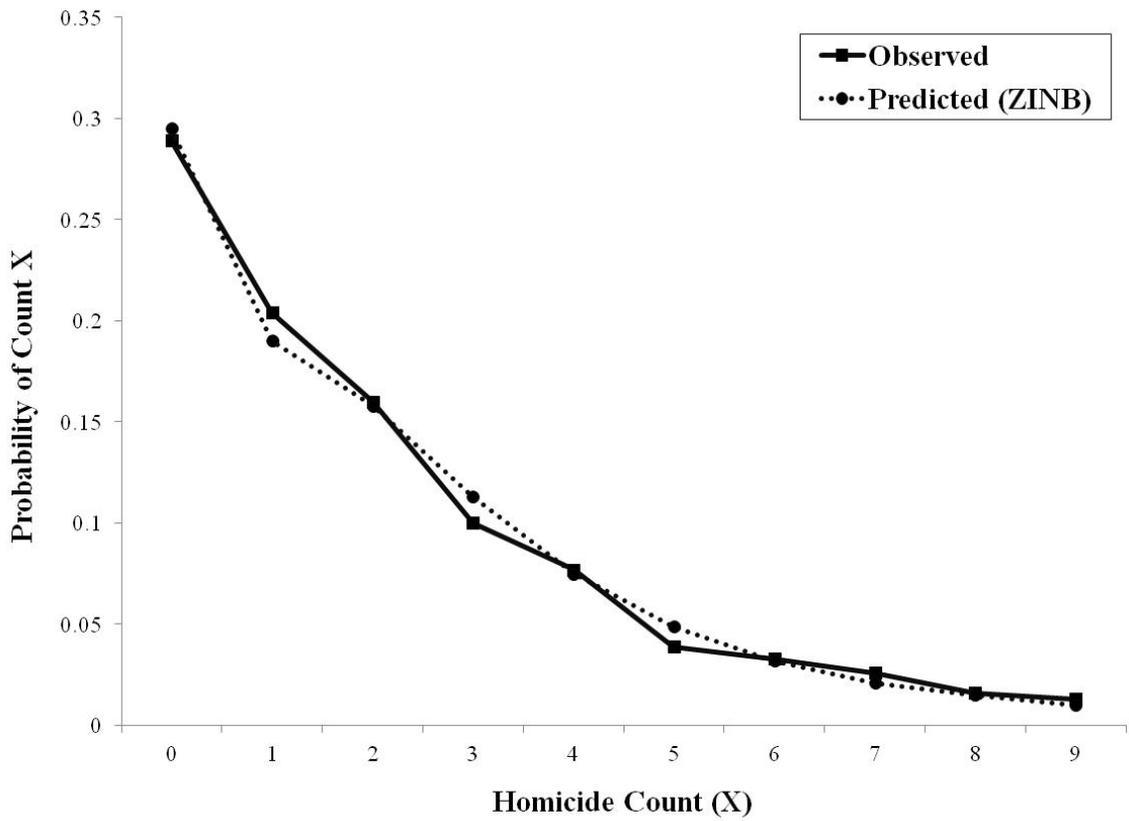


Figure 1.3: Probability of Homicide Count X at Proportion Foreign Born Deciles

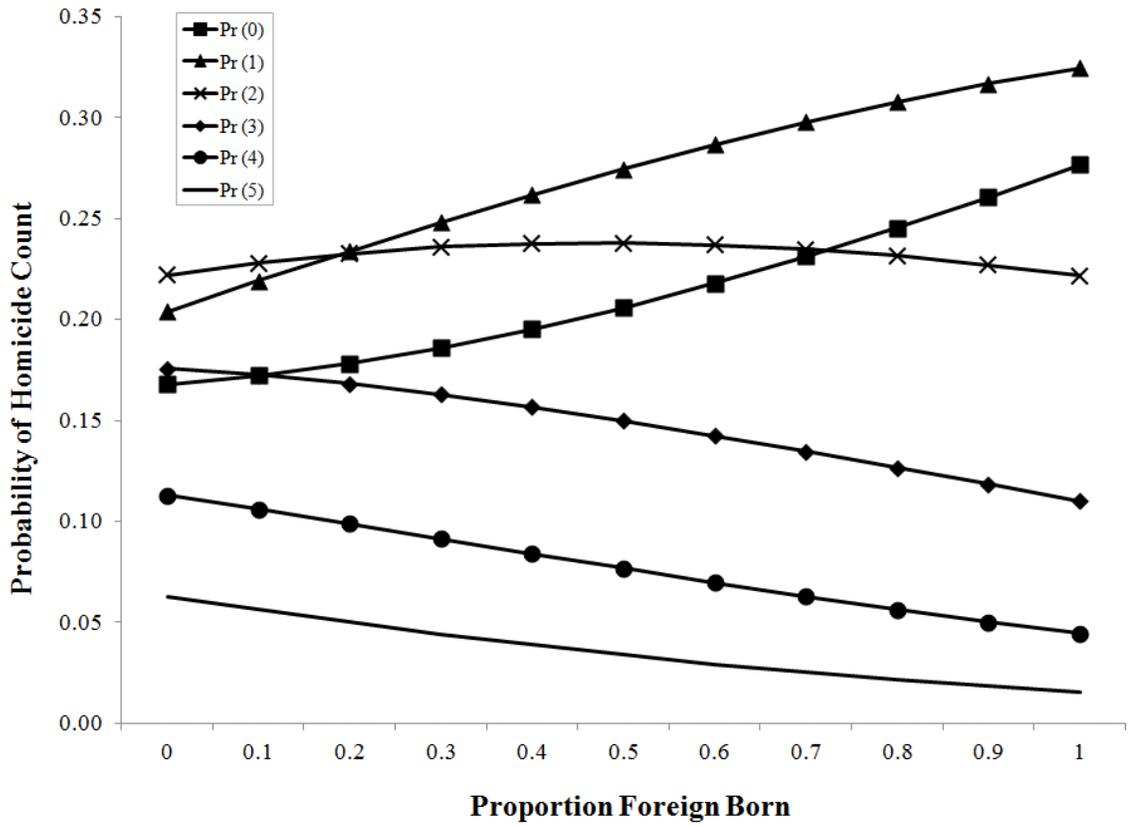


Table 1.3: Coefficients from the Regression of Homicide Deaths on Enclave Indices and Tract Structural Covariates

	Homicide Count
E Index – Mexican	0.10 (0.07)
E Index – Chinese	-0.58 ** (0.21)
E Index – Korean	0.00 (0.10)
E Index – Filipino	-0.45 * (0.18)
Proportion Native Hispanic	-0.43 (0.24)
Proportion Native Asian	-0.59 (0.76)
Poverty Index	0.20 *** (0.02)
Residential Stability Index	0.08 *** (0.02)
Proportion Male Age 15-24	-0.70 (1.47)
Logged Population	0.89 *** (0.06)
Logged Population Density	-0.02 (0.03)
Spatial Lag	0.10 *** (0.01)
Constant	-6.58 *** (0.53)
Overdispersion parameter (α)	0.10 *** (0.01)
<i>Number of observations</i>	2,003

Zero-inflated negative binomial regression. Dependent variable is the total number of homicide deaths from 2000 to 2004. Spatial lag term is average number of homicides in adjacent census tracts. Robust standard errors in parentheses. *** $p < .001$; ** $p < .01$; * $p < .05$.

Figure 1.4: Predicted Homicide Counts for Low/High Poverty Tracts

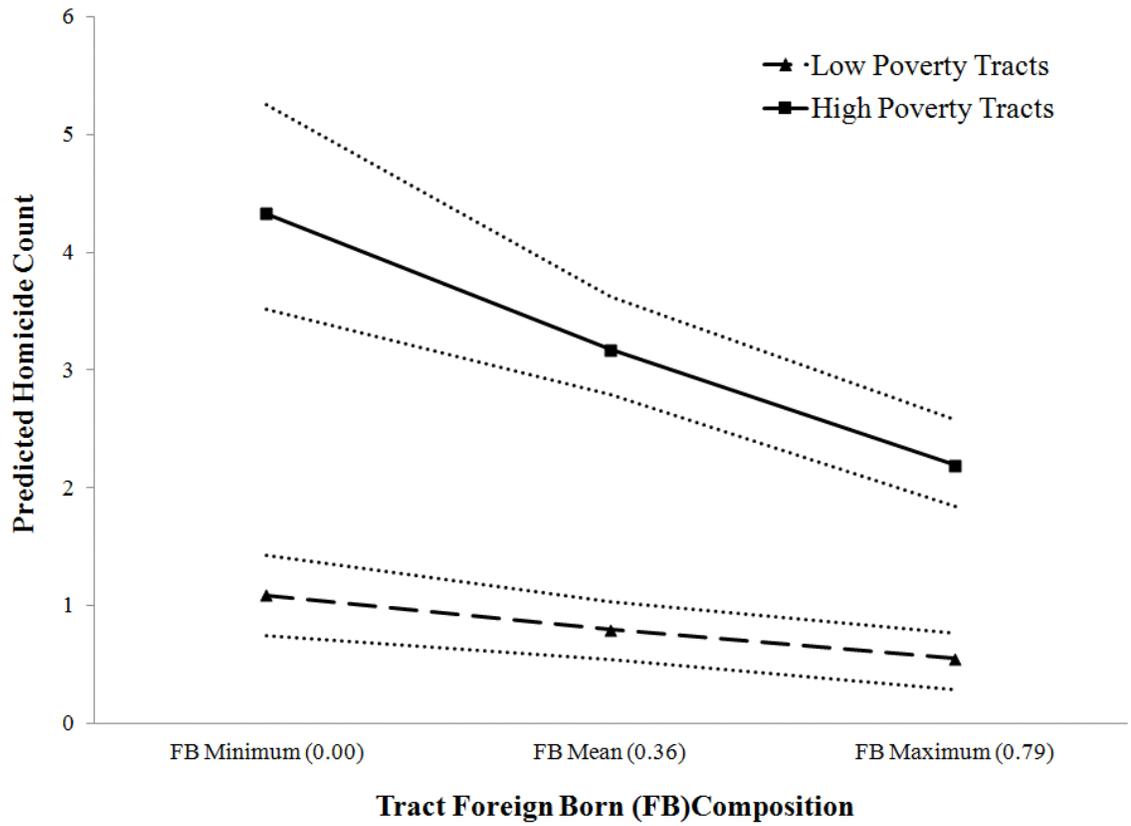


Table 1.4: Coefficients from the Two-Stage Regression of Homicide Deaths on Proportion Foreign Born and Tract Structural Covariates

First-stage		Second-stage	
Proportion Foreign Born	-0.52 ** (0.19)	Proportion Foreign Born	-0.56 ** (0.20)
Proportion Native Hispanic	0.79 *** (0.21)	Proportion Native Hispanic	-0.16 (0.20)
Proportion Native Asian	-0.35 (0.52)	Proportion Native Asian	-2.38 *** (0.64)
Poverty Index	0.20 *** (0.01)	Poverty Index	0.21 *** (0.02)
Residential Stability Index	0.10 *** (0.02)	Residential Stability Index	0.07 *** (0.02)
Proportion Male Age 15-24	2.69 * (1.12)	Proportion Male Age 15-24	1.23 (1.52)
Logged Population	0.05 (0.04)	Logged Population	0.83 *** (0.06)
Logged Population Density	0.03 (0.03)	Logged Population Density	0.02 (0.03)
Health Districts 1-26	† ***	First-Stage Predictors	0.11 *** (0.01)
Constant	-0.34 (0.36)	Constant	-6.46 *** (0.53)
		<i>Overdispersion parameter (alpha)</i>	0.13 *** (0.02)
<i>Number of observations</i>	2,003	<i>Number of observations</i>	2,003

Zero-inflated negative binomial regressions. Dependent variable in second-stage model is the total number of homicide deaths from 2000 to 2004. **Health Districts 1-26** represents a series of dummy variables for each of 26 health districts. **First-Stage Predictors** are expected counts from first-stage model predicting the spatial lag variable. Standard errors in parentheses. *** $p < .001$; ** $p < .01$; * $p < .05$.

† Individual health district results are suppressed.

Table 1.5: Coefficients from the Regression of Homicide Deaths on Proportion Foreign Born and Tract Structural Covariates with Outlying Tracts Removed

	Homicide Count
Proportion Foreign Born	-0.52 * (0.21)
Proportion Native Hispanic	0.21 (0.20)
Proportion Native Asian	-1.50 * (0.69)
Poverty Index	0.23 *** (0.02)
Residential Stability Index	0.05 (0.02)
Proportion Male Age 15-24	-0.16 (1.46)
Logged Population	0.86 *** (0.07)
Logged Population Density	0.00 (0.03)
Spatial Lag	0.14 *** (0.01)
Constant	-6.68 *** (0.61)
<i>Overdispersion parameter (alpha)</i>	0.09 *** (0.02)
<i>Number of observations</i>	1,803

Zero-inflated negative binomial regression. Dependent variable is the total number of homicide deaths from 2000 to 2004. Spatial lag term is average number of homicides in adjacent census tracts. Robust standard errors in parentheses. *** $p < .001$; ** $p < .01$; * $p < .05$.

CHAPTER 2: THE EFFECT OF FOREIGN BORN POPULATION GROWTH ON COUNTY HOMICIDE RATES: A SPATIAL PANEL APPROACH

Abstract

This paper examines the impact of changes in a county's foreign born population on changes in the county's homicide rate over the years 1970 to 2000. The analysis is carried out using restricted cause-of-death data from the National Center for Health Statistics and a spatial Durbin panel regression model which accounts for both the spatial clustering of homicide deaths and unobserved heterogeneity between counties. Geographic clustering of high homicide counties is apparent in the South region of the United States in each of the four decades under study, and this clustering appears to diminish over time. Increases in the foreign born population concentration are associated with reductions in the homicide rate, a process observed most clearly in the South region. This foreign born impact is primarily the result of spillover, the effects of growth in the immigrant population in one county on homicide rates in its neighbors, suggesting that the decrease in violence will be greatest in places where large numbers of high-immigrant counties are clustered.

2.1 Introduction

The U.S. homicide rate exhibited substantial variation in the latter part of the 20th century, climbing from 7.9 (homicides per 100,000 people) in 1970 to 10.2 in 1980, before falling to a low of 5.5 in 2000.¹⁷ Within the broader national trend, however, there existed substantial geographic heterogeneity in both the level and progression of homicide rates (Harries 1985; Baller et al. 2001). There are a number of theories which describe those structural characteristics of places which affect homicide (Messner 1983; Hawley and Messner 1989; Land, McCall, and Cohen 1990; Bursik and Grasmick 1993). One such structural variable, the absence or presence of large immigrant populations, has been the focus of a renewed research interest (Sampson 2008) and is the subject of the present study.

In the period from 1970 to 2000, the U.S. immigrant population increased threefold, rising from less than 10 million to more than 30 million. Foreign born individuals comprised 4.7% of the total U.S. population in 1970; by 2000 this number had risen to 11.1%. This large and growing population segment might be expected to exert substantial influence on social processes. Theories that link increased immigration to homicide and other crime rates are well-documented, and have focused on social disorganization and social control (Shaw and McKay 1942; Bursik 1988; Sampson, Raudenbush, and Earls 1997), intergroup tensions (Blalock 1967; Hipp et al. 2009), labor market outcomes (Borjas 2003; Card 2005), and changes in demographic composition (Farrington 1986; Moehling and Piehl 2009).¹⁸ Overall, the expected relationship

¹⁷ Source: Federal Bureau of Investigation Uniform Crime Reports. Retrieved on 8/15/2011 from <http://www.ucrdatatool.gov>.

¹⁸ Mears (2001) provides a thorough accounting of the theoretical bases and practical concerns of the

between immigration and homicide is ambiguous, particularly at larger geographic scales, as many of the existing theories focus on neighborhood-level processes. Macro-level research on the immigration-homicide link has been inconsistent, with the most common findings an inverse or null relationship (Butcher and Piehl 1998; Phillips 2002; Reid et al. 2005; Ousey and Kubrin 2009; Stowell et al. 2009). The dissonance in these studies may be the result of differences in the unit of analysis (e.g. cities vs. counties vs. metropolitan areas), particular methods for characterizing the foreign born population (e.g. proportion foreign born vs. an indexed value which includes proportion foreign born and proportion Hispanic), or a time-variant effect of foreign born populations on homicide rates.

Research on the immigration-crime relationship is increasingly focusing on the possible spatial interactions between distinct neighboring spatial units. This spatial dependence, along with the geographic heterogeneity inherent in most crime data, may present complications when modeling the relationship between crime rates and the structural characteristics of a place. Debarsy and Ertur (2010) distinguish between spatial heterogeneity which arises from the absolute physical location of an entity in space, possibly due to spatial instability in the effects of exogenous covariates, and heterogeneity which results from spatial interactions between an entity and its neighboring entities. “Absolute” spatial heterogeneity may be dealt with in a straightforward manner by including regional indicators and interactions between the regional indicators and the remaining covariates in the analysis. “Relative” spatial heterogeneity, however, will require special estimation procedures, as the interactions between neighboring geographic units violate the assumption of most models of

independent observations.

Analyses of homicide and other crime rates which explicitly include spatial effects have been conducted both at the neighborhood-level (Morenoff, Sampson, and Raudenbush 2001; Messner and Anselin 2004; Graif and Sampson 2009; Ye and Wu 2011) and at the macro-level (Messner 1983; Baller et al. 2001; Deane et al. 2008). This work has largely been cross sectional in nature, and no study has looked at the association between immigration and homicide using a panel analysis to control for unobserved heterogeneity between different geographic units. This research builds on the work of Baller et al. (2001), which investigates the spatial relationship between homicide and structural characteristics at the county level, and which suggests that, within certain regions, the clustering of homicide events is related to the clustering of unmeasured variables. In particular, this research will evaluate the spatial clustering of homicide rates in U.S. counties and assess whether this spatial clustering is likely to produce biased parameter estimates of the effect of structural factors on homicide rates. A spatial panel regression model will be used to estimate the impact of county social and demographic characteristics on county homicide rates, with a primary emphasis on how changes in the foreign born population are associated with changes in homicide rates. While spatial panel data models have been described and estimated in the econometrics literature, they are less often seen in other social science disciplines, and have not been used before in an examination of the immigration-homicide association.

Compared to cross sectional data, panel data tend to exhibit less collinearity among variables, and panel analysis is better suited to estimate changes in the independent variables by controlling for unobserved heterogeneity between different

units (Baltagi 1995). In a cross sectional analysis of homicide rates, unobserved heterogeneity between counties may bias coefficient estimates. The problem of omitted variable bias may be especially salient when looking at an outcome such as homicide, which may be the result of complicated social or family dynamics or difficult to measure but likely county-variant factors. The inclusion of a county fixed effect (FE) controls for time-invariant county-specific measures, such as drug market activity, which are unobserved or otherwise excluded from the model, but which might be expected to affect the homicide rate. One important assumption underlying the FE model is that the unobserved heterogeneity between counties is time-invariant, an assumption which may become less credible as the time between successive panels increases. A FE model is also unable to produce coefficient estimates for variables which are time-invariant, or for variables that have little within-county variation over time, as these variables will be collinear with the county specific effect.¹⁹

The next section briefly details the development of statistical models to deal with spatially dependent data, and describes the innovative spatial panel regression model that will be used in this paper. Section 3 introduces the county homicide data and control variables to be analyzed and section 4 shows the results from the analysis. This is followed by a discussion of the results and some extensions and limitations of the model.

2.2 Methodology

¹⁹ A random effects (RE) model may also be used to account for unobserved heterogeneity in panel data, but the RE model rests on the assumption that the unobserved variables are uncorrelated with the observed variables (Allison 2009). This restriction is unnecessary in the FE model, although this flexibility comes with a loss of efficiency in the FE model estimation. While the RE model offers the advantage of being able to estimate coefficients for time-invariant covariates, the use of such a model with a known, finite sample is conceptually less appealing.

2.2.1 Spatial Models

In modeling county homicide rates, the rate in any particular county might be expected to depend upon the rates in neighboring counties, the result of a diffusion process of violence (Baller et al. 2001) and the unseen boundaries between neighboring counties. This diffusion process may be envisioned as the free flow between neighboring counties of violent individuals, weapons, or ideas. The homicide rate in a specific location may also be dependent on the rates of neighboring locations if an observed causal variable clusters in space. For example, to the extent that handgun availability is a causal mechanism for increased homicide rates, regions with large clusters of high homicide counties may exist as a result of the clustering of counties with less strict handgun legislation. To account for such a diffusion mechanism, a spatial autoregressive model (SAR), which institutes as an additional covariate a weighted value of the homicide rates in neighboring counties, may be used (Anselin and Hudak 1992; Anselin and Bera 1998).

Spatial dependence may also be the result of spatially interacted error terms, an outcome which may arise from the clustering of unobserved or unmeasured variables that are highly correlated with the dependent variable (Baller et al. 2001). Homicide rates may be higher in counties possessing an ideology more accepting of violent behavior, yet cultural norms are extremely difficult to measure or model. The purpose of a spatial error model (SEM), then, is to incorporate into the error term a weighted average of the error terms of neighboring counties, thus accounting for the spatial interdependence of the error structure (Anselin and Hudak 1992).

While the SAR and SEM models were originally formulated for cross sectional data, they have been extended with panel specifications (Anselin 1988; Elhorst 2003; Anselin, Le Gallo and Jayet 2006). Elhorst (2003) proposes a panel data model with a spatially autoregressive dependent variable of the form:

$$y_{it} = \beta_i x_{it} + \delta \sum_{j=1}^N w_{ij} y_{jt} + \mu_i + \tau_t + \varepsilon_{it} \quad (1)$$

where for each $i = \{1, 2, \dots, N\}$ spatial units over the period $t = \{1, 2, \dots, T\}$, the demeaned values of x_{it} and y_{it} are used in a model estimated by OLS or maximum likelihood. The term w_{ij} defines the relationship between any two spatial units i and j , and μ_i and τ_t are spatial and time fixed effects. The parameter δ estimates the endogenous spatial interaction, or the relationship between the outcome variables in neighboring units. Although the spatial fixed effect itself cannot be consistently estimated for a fixed T , this is not a problem in the case where the effects of interest are the estimated trends in the explanatory variables, as the inconsistency of the estimates of the spatial fixed effects does not bias the estimates of the remaining variables (Elhorst 2003).

The panel SEM model is specified according to the following form:

$$y_{it} = \alpha + \beta_i x_{it} + \mu_i + \tau_t + v_{it},$$

$$v_{it} = \rho \sum_{j=1}^N w_{ij} v_{ijt} + \varepsilon_{it} \quad (2)$$

As in the panel SAR model above, μ_i is a spatial specific effect, τ_t is a time specific

effect, and the term w_{ij} defines the relationship between any two spatial units i and j , but in the SEM this relationship affects only the error term v_{it} . The parameter ρ estimates the error spatial interaction, or the relationship between the error terms in neighboring units.

Lagrange Multiplier (LM) tests, which use the OLS regression residuals to identify the source of spatial dependence, were first proposed by Burridge (1980) and Anselin (1988) for the cross sectional case. Robust forms of these tests, which test for a spatial lag process in the presence of spatial error correlation and vice versa, were developed by Anselin et al. (1996) for use when the simple tests present an ambiguous outcome. Panel data analogues to these LM tests have been developed by Baltagi, Song, and Koh (spatial error model and spatial random effects) (2003), Anselin et al. (2006), Debarsy and Ertur (spatial fixed effects) (2010), and Elhorst (spatial and time fixed effects) (2010).²⁰

Anselin (1988) suggests a model which contains, as additional right-hand side variables, spatially lagged values of the independent variables; this specification has come to be known as a spatial Durbin model (SDM) (LeSage and Pace 2009). This model allows for indirect spatial interactions, with the exogenous explanatory variables influencing not only the dependent variable within their own spatial unit, but within neighboring spatial units as well. The SDM is represented by the following form:

$$y_{it} = \alpha + \beta x_{it} + \delta \sum_{j=1}^N w_{ij} y_{jt} + \theta \sum_{j=1}^N w_{ij} x_{jt} + \mu_i + \gamma_t + \varepsilon_{it} \quad (3)$$

²⁰ These LM tests, as well as the estimation of various spatial panel models, may be carried out using MATLAB code provided by J. Paul Elhorst (www.regrooningen.nl/elhorst/software.shtml) and Donald J. Lacombe (community.wvu.edu/~djl041/matlab.html).

As in the SAR model, the parameter δ estimates the endogenous interaction between neighboring spatial units. The second summation term characterizes the exogenous interaction between spatial units, or the relationship between the endogenous variable in a place and the exogenous covariates in neighboring places, with θ denoting this spatial interaction.²¹ For example, the foreign born composition in a single county is theorized to have a direct effect on the homicide rate in that county, as well as an indirect effect on the homicide rate in each other county. Because this indirect effect is conditional upon the neighbor weight matrix (w_{ij}), it will be equal to 0 for all cases where one county is not considered a neighbor of the other. This spatial spillover accounts for the population dynamics between neighboring counties, which are often nested within larger social and labor markets. Put another way, to the extent that the foreign born population has a beneficial (detrimental) effect on homicide rates, the benefit (detriment) might be expected to accrue not only to the host county, but also to neighboring counties through which the population may pass through. Like the SAR, the SDM model may be solved using maximum likelihood estimation (Elhorst 2003; Elhorst and Fréret 2009; Lee and Yu 2010).

In the case where $\theta = 0$, the SDM model simplifies to a SAR model, as only the original exogenous variables and the endogenous spatial interactions remain in the equation. Likewise, in the case where $\theta + \delta\beta = 0$, the SDM model simplifies to a SEM model (Burrige 1981; Elhorst 2010). These hypotheses may be tested to infer whether

²¹ While the addition of a spatially correlated error term would seem an improvement to the SDM, Manski (1993) has shown that the inclusion of all possible spatial interaction terms results in a model that is not identified (Elhorst 2010). Lesage and Pace (2009 pp. 155-158) suggest that the exclusion of a spatially correlated error term, which results in a potential loss of efficiency, is less precarious than the exclusion of either the spatially lagged dependent variable or the spatially lagged exogenous covariates, which may result in biased parameter estimates.

the unrestricted Durbin model better describes the underlying spatial process than does either of the more restrictive spatial lag or spatial error models. A complete model selection procedure for spatial panel data, outlined by Elhorst (2010), is thus as follows:

1. Using the panel LM tests and robust panel LM tests described above, compare a non-spatial model to the SAR and SEM specifications. If neither of the spatial models has a significant LM test statistic, then the presence of spatial autocorrelation in the model residuals is non-problematic, and the non-spatial model can be used.
2. If the SAR model is the preferred specification from Step 1, compare the SDM model to the SAR model by testing the hypothesis that $\theta = 0$. If this hypothesis is rejected, then the SDM model is preferred over the SAR model and should be used. In the case that this hypothesis is unable to reject, the SDM model simplifies to the SAR model and this latter model should be used.
3. If the SEM model is the preferred specification from Step 1, compare the SDM model to the SEM model by testing the hypothesis that $\theta + \delta\beta = 0$. If this hypothesis is rejected, then the SDM model is preferred over the SEM model and should be used. In the case that this hypothesis is unable to reject, the SDM model simplifies to the SEM model and this latter model should be used.

LeSage and Pace (2009, pp. 155-158) describe in detail the potential consequences in estimating a SAR model, a SEM model, or a SDM model when the true spatial process underlying the data is different than that which is hypothesized. In the

case that the true spatial process is one in which spatial dependence exists between the dependent variable in one unit and the exogenous covariates in neighboring spatial units, both the SAR and SEM models may produce biased coefficient estimates, as neither the SAR model nor the SEM model includes these spatially dependent exogenous covariates. If the excluded covariates are correlated with other variables included in the model, omitted variable bias may arise. This is likely to be a salient issue, as many of the commonly used indicators of social conditions (e.g. poverty rate or foreign born composition) tend to be clustered in space, thus implying correlation between the values in neighboring spatial units.

When the true spatial process is one in which the outcome variable is spatially correlated only with the exogenous covariates within the same spatial unit (SAR) or in which there exists a spatially correlated error term (SEM), the SDM model will continue to produce unbiased coefficient estimates. Although in the SEM case the coefficient estimates from an SDM specification will be inefficient, inference regarding these estimates will still be correct (LeSage and Pace 2009, pp. 158). It is a reasonable inference, then, that except under circumstances in which the SAR or SEM model is an unequivocally better fit to the underlying spatial process, the SDM model may be the preferred option. The potential loss of efficiency from the misspecification of an SEM model as an SDM model (which is reduced as sample size is increased) is arguably preferable to the potential bias from omitted variables that may arise from the misspecification of an SDM as either of the other spatial models.

2.2.2 The Spatial Context of Homicide

The inclusion of a spatially lagged dependent variable is consistent with prior literature that explores the diffusion process of homicide (Baller et al. 2001). Would-be offenders in county B may observe the high (or low) number of homicides in neighboring county A and determine that homicide is (is not) an acceptable resolution to interpersonal conflicts. The number of homicides in a particular county might also be influenced, through a retaliatory process, by the number of homicides in neighboring counties, if there exists a contentious relationship between factions in the neighboring counties. There is often little demarcation in the urban form between adjacent counties, particularly on the denser East Coast, and the daily life of many residents may be carried out on both sides of a county border. The arbitrariness of these borders may have implications for the homicide totals in each county, as an attack that occurred in one county could have conceivably been carried out in the adjacent county.

The inclusion of spatially lagged independent variables accounts for any potential relationship between the structural factors associated with homicide in a target county and the homicide rates in neighboring counties. As an example, consider a county which houses a large number of establishments that sell guns. While the ready availability of weapons might be expected to affect homicide rates in the host county, it may also influence homicide rates in neighboring counties, as individuals in those counties have easy access to these same businesses. The exclusion of the spatially lagged independent variables could also result in biased parameter estimates for the remaining model variables, if there are unmeasured spatial processes that operate between the neighboring counties that are correlated with the included control variables (LeSage and Pace 2009; Elhorst and Fréret 2009). In the above example, the presence of a large number of gun

stores may be correlated with the existence of an underlying violent subculture, yet this latter variable is unobserved or unmeasured. To the extent that the violent subculture diffuses to neighboring counties, its exclusion from the regression equation may produce biased coefficient estimates unless the number of gun stores in neighboring counties is controlled.

Incorporating spatially lagged endogenous and spatially lagged exogenous variables into the model presents a challenge in the interpretation of the coefficient estimates. The raw coefficient estimates (β in equation (3) above) include feedback, as the effect of each exogenous variable on the county homicide rate is reintroduced into the regression equation through the spatially lagged dependent variable. An illustration of the relationship between neighboring spatial units a and b in the SDM is shown in Figure 2.1. Each exogenous covariate (X_a) in unit a will encompass both a direct effect, the impact of the variable on the outcome (Y_a) within its own spatial unit, and an indirect effect, the impact of the variable on the outcome (Y_b) in neighboring spatial units. The inclusion of the outcome variable in the neighboring spatial unit as an additional explanatory variable is the source of the feedback loop, as X_a affects Y_a both directly and through the path $X_a \rightarrow Y_b \rightarrow Y_a$. Methods to estimate both the direct and indirect effects from models which incorporate spatially lagged independent and dependent variables are described in LeSage and Pace (2009). Notationally, the impact of a change in an explanatory variable k on the outcome y for a sample of n spatial units is given by:

$$\frac{\partial y}{\partial x_k} = (I_n - \delta W)^{-1} (I_n \hat{\beta}_k + W \hat{\theta}_k) \quad (4)$$

In this equation, $\hat{\delta}$ is the estimated coefficient of spatial dependence, $\hat{\beta}_k$ and $\hat{\theta}_k$ are the estimated coefficients for explanatory variable k and the neighbor weighted variable k , respectively, W is the spatial weights matrix, and I_n is the identity matrix. The right hand side of this equation is characterized by a symmetrical $n \times n$ matrix, with the diagonal elements representing the direct effect of a change in k in a spatial unit on the y in that spatial unit. The off-diagonal elements represent indirect effects of changes in k in all other spatial units on y in each spatial unit. LeSage and Pace propose summarizing the information contained in this matrix by averaging the diagonal elements of the matrix to determine the average direct impact of a change in k and averaging either the summed column or row elements of the matrix to determine the average indirect impact of a change in k .

It is worth noting that in a non-spatial regression, in which there is neither a spatially lagged dependent variable nor spatially lagged covariates, both the $\hat{\delta}$ and $\hat{\theta}_k$ terms are assumed to be equal to 0. In this case the off-diagonal elements of the $n \times n$ matrix on the right hand side of the equation will all be 0 and each diagonal element will be $\hat{\beta}_k$. Thus, the non-spatial regression has no indirect impacts and the average direct impact is equal to $\hat{\beta}_k$, identical to the usual interpretation of coefficient estimates.

2.3 Data

This paper considers the relationship between immigration and homicide mortality at the county level. Counties are administrative units defined at the state level and may perform a variety of governmental functions, although the exact functions vary widely between different states. The choice of geographical unit is quite relevant in a

spatial analysis, as the spatial relationship may vary depending on the geographic scale. In their county-based study, Baller et al. (2001) note that their chosen analytical scale could either be too large or too small, obscuring important geographic variation or possibly creating it. The same caveat clearly applies here, although there is theoretical justification for why counties are an appealing geographic scale for this type of research. Although they may encompass several different municipalities, counties often serve in important administrative roles, including judicial review, taxation assessment, economic development, and housing authority. The interpretation of some causal mechanisms often used in homicide studies, such as labor market mobility or housing and residential stability, may be better modeled at the county level than at a smaller municipal geography. There is also precedence for the use of counties in studies of the structural determinants of homicide (Baller et al. 2001; Messner and Anselin 2004). In a broad sense, the use by researchers of a number of different geographic scales in studies with similar theoretical foundations and variable compositions allows for post-hoc analysis of the strengths and limitations of each scale.

While county boundaries tend to remain stable over time, there are occasions when a single county will split or when two independent counties will merge. The U.S. county composition in 2000 is the template for this analysis, with modifications made if prior decade data on any county were not available.²² Due to their geographic isolation, counties in Alaska and Hawaii are not considered here. There are a total of 3,104

²² Specifically, data from a county that existed in prior decades but did not exist in 2000 was aggregated (over the whole study period) with data from the county by which it was subsumed, while data from a county that did not exist in any prior decade but did exist in 2000 was aggregated with data from the county from which it was formed. The number of these modifications was small, with only a handful of counties (n=13) exhibiting boundary changes between 1970 and 2000.

counties and four observations per county, for a total sample size of 12,416 county-decades used in the present analysis.

The dependant variable is the homicide rate, defined here as the average number of homicide deaths per county over the three year period centered on each decadal census (e.g. 1999-2001 for the 2000 decade) divided by the total county population from the census. The three year average is used to provide smoothed rates, in which the influence of exceptionally high or low homicide years is minimized. Homicide rates were calculated for each decade from 1970-2000. Homicide deaths were identified based on the ICD code for cause of death in restricted mortality cause-of-death files from the National Center Health Statistics, which contain a record for every death that occurred in the United States. These restricted files also include both the county of residence of each homicide victim and the county of occurrence of the homicide itself; this latter variable is used to construct the homicide counts. The benefit of this restricted data is that it includes the county of occurrence for all deaths, regardless of the population of the county; the unrestricted version of the data identifies only the county of occurrence if the county population is greater than 100,000. The restricted data thus allows for a full accounting of the spatial distribution of homicides, crucial for this study which incorporates spatial interactions. Total county populations were obtained from the National Historical Geographic Information System (Minnesota Population Center 2004), as were all the remaining variables, except where noted. The primary independent variable of interest, immigrant concentration, is measured as the proportion of each county that is foreign born.

The covariates included in the model are consistent with those that have been used

in prior studies of the immigration/homicide relationship, and serve as evidence against alternative hypotheses of homicide variation. Controls for economic disadvantage, widely associated with an increased incidence of homicide, include the proportion of the population that is below the poverty level, the mean family income (standardized to 2000\$), the proportion of the population that does not have a high school diploma, the proportion of families that are female-headed, and the proportion of the county population that is non-Hispanic black.

Homicide rates might also be expected to fluctuate based on the demographic composition of a county. The adult to child ratio, calculated as the total population 18 years or older divided by the total population under the age of 18 is used as a proxy measure of informal social control. The proportion of the population that is male and between the ages of 15 and 24 is included to control for county-level heterogeneity in the age-gender group at the highest risk of homicide offending and homicide victimization.

Residential stability is expected to contribute to reduced homicide rates. Counties in which large segments of the population are transient may incur less residential investment, and counties with large numbers of long term residents may have better developed informal social controls (e.g. neighborhood watch groups) and have existing relationships with police and policy makers. Stability is evaluated as the proportion of county residents who lived in the same house 5 years prior.

The majority of homicides are committed with firearms and the magnitude of this number changed little during the period from 1970 to 2000.²³ The stability of firearm homicide deaths over time may obscure geographic variation in the incidence of such

²³ In the full NCHS data, the percentage of homicides committed with firearms was 67.7% in 1969-1971, 64.7% in 1979-1981, 66.0% in 1989-1991, and 64.7% in 1999-2001.

deaths, and geographic heterogeneity in firearm prevalence could therefore be an important explanatory variable behind geographic fluctuations in homicide rates. Greater firearm availability increases the risk that a firearm is impulsively used in a domestic altercation, or that a firearm is present during robberies or other crimes that may result in death. Firearm availability is likely the outcome of state regulations, such as required background checks or waiting periods for purchase, and there may be regional variation in the acceptability of guns and gun ownership. While the actual prevalence of firearms may be difficult to ascertain, Azrael, Cook, and Miller (2004) have advocated that the proportion of suicide deaths that were committed using a firearm be used as a proxy for gun ownership. This measure, also constructed using the NCHS mortality data, is employed here to account both for differences between counties in gun ownership and differences within a county in gun ownership over time.

The substantial drop in crime rates during the 1990's was potentially influenced by increased policing, highlighting the importance of controlling for police force size in this analysis (Levitt 2004). Data on the number of sworn officers per police agency were obtained from the FBI's Law Enforcement Officers Killed and Assaulted program. These data were aggregated to the county level based on the Agency Identifier Crosswalk available from the National Archive of Criminal Justice Data (2005).

Finally, controls are added for the total population and the proportion of the county that is classified as urban, to account for differences in density and urban form, as well as dummy variables for each decade. The inclusion of the decade indicator variables accounts for national-level trends (not county-specific) in the data, which may be the result of broad demographic or social changes. The panel structure of the data will also

be exploited through the incorporation of a county (spatial) fixed effect.

A weight matrix is a required element for all spatial analyses and the results from any analysis are dependent upon the specific matrix chosen. The definition of neighbor may vary depending on the scale of the geographic area under study, the expected process under consideration, and the precise question that is being asked. As the neighbor definition, and by extension the weight matrix, is central to the estimation of the spatial regression models, its construction should be theoretically sound. In most instances, however, scholars defer to Tobler's first law of geography (Tobler 1970), and define neighbors as those entities that are the most spatially proximal, with neighbor importance decreasing with distance. However, it is noted that spatial proximity is certainly not the only, and may not always be the most desirable, way in which to define neighbors.²⁴

This research, which focuses on the spatial interaction between counties, utilizes a rook contiguity weight matrix, in which adjacent counties are considered neighbors. The weight matrix is time-invariant since, by construction, county borders do not change over the three decades of the study. The weight matrix has diagonal elements equal to zero, indicating that a county is not a neighbor of itself, and is row-standardized. In a practical sense, row-standardization ensures that the effects of the spatially weighted variables on individual counties are comparable, and are not inflated for counties with many contiguous neighbors. Non-adjacent counties are considered non-neighbors and do not explicitly contribute to calculations involving the origin county. It is fairly plain to see, however, that non-adjacent counties may indirectly affect one another through their effect on intermediary counties. This is the process of diffusion through which a spatial process

²⁴ Tita and Radil (2011) present an analysis which relies on a spatial weight matrix with an explicitly conceptual definition based on gang rivalries.

might be expected to occur. According to this weighting method, more than half of counties had 6 or more neighbors, and approximately 95% of counties had four or more neighbors.²⁵

2.4 Results

2.4.1 Descriptive Statistics

Table 2.1 displays decadal summary statistics for the dependent and independent variables considered in the model, as well as panel statistics on the pooled data. The substantial heterogeneity that exists between counties is reflected by the large standard deviations for the majority of the covariates in each decade. The final three columns of Table 2.1 show the overall mean for the pooled data and the mean variation between counties and within counties. The final column, which illustrates for each variable the average change over time within a county, is of primary concern in this analysis:

Variables which do not change over time are unable to be estimated using the spatial fixed effect framework. While some of the deviations reported in the last column of Table 2.1 are of a small magnitude, they are substantial when compared to the overall group mean. Ultimately, the estimated standard errors for variables which vary little over time may be too large, which may result in an inability to reject the implicit hypothesis that the coefficient estimates for these variables is 0.

The use of the spatial panel model described above is founded on the assumption that county homicide rates exhibit spatial autocorrelation, an assumption based on a

²⁵ Two island counties (Nantucket, MA and San Juan, WA) were considered contiguous with the nearest physical county to which they had ferry service. These two counties experienced no homicides during the study period.

number of previous studies (Baller 2001, Graif and Sampson 2009). To test for the presence of spatial autocorrelation, the Moran's I statistic was calculated for each decade; the evolution of this measure over time is shown in the bottom row of Table 2.1. While the value of the Moran's I decreases somewhat over time, the statistic is significant in each of the four decades, suggesting a continuing presence of spatial autocorrelation.²⁶

2.4.2 Local Indicators of Spatial Association

The global Moran's I statistics report the presence of spatial dependence in the data, but do not indicate the pattern of the dependence or specify which counties are contributing heavily to the overall dependence. To reveal clusters of high or low homicide counties, it is necessary to use a local indicator of spatial association, one of which is the local Moran's I. The local Moran's I is a decomposition of the global Moran's I into the contribution of each county, and comparisons between the local Moran's I values for individual counties may indicate clustering of high homicide counties with other high homicide counties or low homicide counties with other low homicide counties (Anselin 1995). Maps 2.1-2.4 indicate clusters of low homicide counties in gray and clusters of high homicide counties in black; counties in white are not part of significant clusters in each decade. Consistent with the mapping strategy employed by Baller et al. (2001), low homicide counties near to high homicide clusters and high homicide counties near to low homicide clusters are regarded here as non-clustered.

In all of the four decades under study, high homicide rates are clustered in

²⁶ The statistical significance of the Moran's I values were determined using the random permutation test outlined by Anselin (2005) carried out with the GeoDa software.

southern counties, with some smaller clusters existing in California in 1980 and in the Chicago area in 2000. The overall pattern of high county homicide clustering appears similar between decades, although there is a noticeable change between 1970 and 2000 for several counties in Florida and eastern Texas from high homicide clustered to non-clustered. Low homicide counties are clustered in the northeast and the north-central parts of the country; these clusters also show little change over time.

In this presentation of the homicide rate clustering suggested by the local Moran's I, it is important to recognize that these maps are based on the univariate distribution of homicide rates, and do not take into account other structural variables that may vary between counties. The high homicide rates exhibited by southern counties would, *ceteris paribus*, suggest that the South is particularly dangerous, yet clustering is likely the consequence of the clustering of other variables, observed or unobserved, that are associated with increased levels of homicide. While these maps convey information about relative levels of homicide risk in various parts of the country, they are not designed to account for these other factors; for this, regression modeling is used.

2.4.3 Non-Spatial Model and Tests for Fixed Effects

The first step in the analysis is to test whether the inclusion of county fixed effects and/or time fixed effects is warranted, based on a comparison of model fit statistics. To this end, the data is pooled and non-spatial OLS models are run without fixed effects, with county fixed effects, with time fixed effects, and with both county and time fixed effects. The likelihood ratio (LR) statistics for the specification with county fixed effects ($\chi^2 = 6674.4$, $p < .001$) and the specification with time fixed effects ($\chi^2 = 246.7$, $p < .001$)

are both significant with respect to the base model with no fixed effects. In addition the LR tests of the specification with both county and time fixed effects indicates that this model is significantly improved over the model with only county fixed effects ($\chi^2 = 203.9, p < .001$) or the model with only time fixed effects ($\chi^2 = 6631.7, p < .001$). As the interest in this analysis is on isolating the effect of changes in within-county foreign born populations on within-county homicide rates, the use of county fixed effects is warranted, and the spatial panel analysis which follows will incorporate both spatial and time period effects.²⁷

To highlight how the focus on within-county change alters the interpretation of the model parameters, a between-county fixed effects model was estimated and compared to the specification with within-county fixed effects. The coefficients from these two models are shown in Table 2.2. The between-county effects model estimates the effect of each exogenous variable using the county mean of the variable for all time points, thus leveraging differences in structural covariates between counties but not differences in structural covariates over time. In the period 1970-2000 the mean effect of a county's foreign born population on its homicide rate is insignificant, while the mean effects of most of the other covariates on the homicide rate, excepting the proportion young and

²⁷ In cases where the unobserved heterogeneity between counties is the result of the clustering of unobserved or unmeasured variables at the regional level, researchers will often include regional indicator variables as crude controls to reduce bias in the remaining covariates. A fifth pooled model including time fixed effects and region indicators is also estimated, to assess whether the improvement in model fit achieved through the addition of county fixed effects compensates for the large number of degrees of freedom lost through the inclusion of these additional parameters. The specification which includes regional indicators and time fixed effects is nested within the specification which includes county and time fixed effects, and the LR test of the two models indicates that the spatial fixed effects model is preferred. A comparison of the Information Criterion of these two models reveals that the model with county fixed effects is likewise preferred based on the AIC, while the model with regional indicator variables only is preferred based on the BIC. This is unsurprising, as the BIC penalizes additional parameters more heavily than does the AIC. Overall, these test statistics are inconclusive in highlighting a preferred model fit, so we proceed with the model with county fixed effects, which more closely aligns with the original aim of the research.

male and the proportion of housing owner occupied, are positive. Focusing on the mean value of an explanatory variable over the whole period, however, ignores any trend in the variable over time, an oversight that may be especially salient in the case of a foreign born population which was substantially increasing between 1970 and 2000. A comparison of the between-effects and the fixed-effects specifications reveals that many of the structural factors used in homicide studies have explanatory power in predicting differences in homicide rates between counties, but not necessarily within counties. Given that this paper is interested in the dynamics of population change via immigration, a focus on the within-county effects is thus warranted.

2.4.4 Spatial Models

Having established the preferred fixed effect specification, the most suitable spatial model can be identified using the three step procedure suggested by Elhorst (2010) and explained above. The panel LM test of the spatial lag and spatial error specifications indicates limited support for a lag specification over an error specification, although this choice is somewhat ambiguous. In the simple version of these tests, both the LM lag value (91.5, $p < .001$) and the LM error value (80.5, $p < .001$) are highly significant; the same is true for the robust version of the tests (LM lag=40.8, $p < .001$; LM error=29.9, $p < .001$). Although a preference for a spatial lag specification may thus be based on the assumption that coefficient estimates derived from this model are unlikely to be biased, further testing reveals that a spatial Durbin model is preferred over either a spatial lag model or a spatial error model. A Wald test ($\chi^2 = 42.8$, $p < .001$) of the restricting assumption that $\theta = 0$ (from equation (3)) suggests the rejection of this

hypothesis, indicating that the SDM does not simplify to a SAM and justifying the choice of the SDM. Likewise, a Wald test ($\chi^2 = 49.0, p < .001$) of the restricting assumption that $\theta + \delta\beta = 0$ (from equation (3)) points to rejection of the SEM model in favor of the SDM. Thus, there is some assurance that the SDM is the preferable model with which to proceed.

While these objective test statistics indicate a preference for an SDM specification, it is worth noting that the underlying structure of the SDM is also conceptually appealing. The inclusion of spatially lagged independent variables allows social processes to cross borders, and the impacts of structural features of the population are therefore not limited to a single spatial unit. For example, a county with a very low rate of poverty that is surrounded by counties with high rates of poverty may still suffer some of the social effects of increased poverty due to its close proximity to the high poverty counties. This spillover effect is absent from both the SAR and SEM models, although the SAR model would include some feedback effects through the spatially lagged dependent variable.

The results from the estimation of the panel SDM described in Equation 3, in which the county homicide rate is a function of the structural covariates in the county, the lagged homicide rate in neighboring counties, and the lagged values of structural covariates in neighboring counties, are shown in Table 2.3. As detailed above, the coefficient estimates of the SDM, reported in the first column, are not directly interpretable, owing to the feedback effects present between neighboring counties. Feedback exists due to the introduction of the spatially lagged homicide rate, which itself is determined in part through the values of the variables in the target county, as well as

the introduction of the spatially lagged covariates. The direct effect is calculated as the average, over all spatial units, partial derivative of the homicide rate with respect to changes in the covariate value in that county, while the indirect effect is the average, over all spatial units, partial derivative of the homicide rate with respect to changes in the covariate values in *all* other counties (Lesage and Pace 2009). The total effect is the sum of these direct and indirect effects.

The direct effects shown in column 2 indicate that increases in a county's black population and increases in the gun ownership rate (proportion of suicides in which a firearm are used) are associated with higher homicide rates within that county. The differences between the coefficient estimates in column 1 and the direct effect estimates in column 2 are small in this model, suggesting that the feedback effects are minimal. While there is no significant direct effect of a county's foreign born population on its homicide rate, a sizable negative indirect effect is present between the two variables, suggesting homicide reductions in those counties which neighbor counties experiencing increases in foreign born concentration. A similar negative effect is seen in the proportion of the population that is residentially stable, while positive homicide spillover is associated with an increasing black population, growth in the proportion of the population without a high school diploma and increasing rates of gun ownership.

The total impact of growth in the foreign born population on homicide rates is negative, as shown in the 4th column of Table 2.3. This total includes the direct effect of the foreign born population on rates in a county, as well as the indirect effect from growth in the foreign born population in neighboring counties. Residential stability is likewise correlated with decreased rates of homicide, while variables commonly used as proxies

for economic disadvantage, the proportion of the population that is black and the proportion of the population without a high school diploma, are associated with higher rates of homicide. None of the other economic disadvantage variables (poverty rate, mean family income, proportion of household female-headed) demonstrate a significant impact on homicide rates, either direct or indirect. Because a panel analysis focuses on within-unit change, the lack of a significant relationship between the homicide rate and some of the measures of economic disadvantage is likely the result of these measures exhibiting little change over time, or exhibiting non-uniform change over time.²⁸

2.4.5 Comparison of Spatial Models

Table 2.4 contains a comparison of the estimated impacts from the preferred SDM model with the impacts from an SAR model and the coefficients from an SEM specification. It is important to note that a direct comparison of the SEM model, which does not involve feedback, with the others is inappropriate, as the SEM model does not allow for feedback effects; these coefficients are provided here for illustrative purposes. The total estimated impacts from the SDM and SAR models are consonant in sign and significance, although the SDM impacts are in most cases of a much greater magnitude. A comparison of the indirect impact estimates suggests that the differences in magnitude of the total effects are the result of much greater indirect impacts occurring in the SDM model. This is unsurprising, as the indirect impacts in the SDM model encompass effects

²⁸ While collinearity between measures of economic disadvantage is often an issue in cross-sectional studies, it is less likely to be relevant in a time series analysis which analyzes differenced, rather than absolute, values of the measures. With the exception of the poverty rate and the mean family income (which are inextricably linked and which have a fairly high differenced bivariate correlation ($\rho=0.61$)), the correlations between the differenced values used here are quite low.

from the explanatory variables in neighboring counties as well as spillover effects from the spatially lagged dependent variable; the indirect impacts in the SAR model reflect only these latter spillover effects. The SEM model includes no spatially lagged variables, and the coefficients from that model can be interpreted as would coefficients from a standard regression model. In this case the coefficients from the SEM model are quite similar to the total effects estimates from the SDM model.

2.4.6 Model Diagnostics

The residuals from the model estimated above are distributed approximately normally, and there is no evidence of outlying values based on a comparison of the leverage values for each individual observation. In a spatial panel model, however, our primary concern with the residuals may be whether: 1) they show evidence of serial autocorrelation and 2) they exhibit any remaining spatial dependence.

When repeated observations on a single spatial unit are made over time, the residuals from a regression model may exhibit serial autocorrelation, with the residual in time t dependent upon the residual in time $t-1$. The presence of serially autocorrelated residuals indicates that some important time-varying covariate has been excluded from the model, and the remaining coefficient estimates may therefore be biased. To test for the presence of serial correlation in the model residuals, researchers often rely on the Durbin-Watson statistic, commonly used following estimation of single time-series data and extended to the panel data case by Bhargava, Franzini, and Narendranathan (1982). The panel Durbin-Watson statistic from this model has a value of 1.966, not statistically significant at a p-value of 0.05, suggesting that serial autocorrelation is not present in the

model residuals.

If a non-spatial model is used to estimate spatially correlated data, and if the source of the spatial correlation is not a covariate that is included in the model, the model residuals are likely to be spatially correlated. This residual spatial correlation is the basis for the LM testing procedure highlighted above and indicates that the spatial dependence in the data has not been appropriately controlled. To the extent that the residuals from a model do not exhibit any remaining spatial dependence, it may be inferred that the spatial interactions within the data have been accounted for. While residual spatial autocorrelation may be assessed using the Moran's I statistic, this calculation is distinct from the calculation of the Moran's I statistic for individual variables, such as that shown in the bottom row of Table 2.1.

The Moran's I values for the residuals of the baseline non-spatial model shown in the 4th column of Table 2.2, estimated separately for each decade, are each significant at the $p < .001$ level, indicating that the spatial dependence in the data is not simply a product of spatially clustered model covariates. A comparison of these values to the Moran's I values for the residuals from the SDM model estimated in Table 2.3, which are not significant in any decade, suggests that the spatial panel model, which includes the spatially interacted dependent variable and covariates, has successfully accounted for the spatial dependence in the homicide data.²⁹

2.4.7 Spatial Heterogeneity

²⁹ The Moran's I values for the non-spatial, pooled OLS model residuals are 0.050 for 1970, 0.056 for 1980, 0.040 for 1990, and 0.050 for 2000, each of which is statistically significant. The comparative values from the SDM residuals are 0.001, 0.005, -0.003, and -0.004, none of which are statistically significant at standard levels.

In addition to spatial dependence, geographic data may exhibit spatial heterogeneity, with the effects of covariates varying between spatial units or regions. Spatial heterogeneity is difficult to distinguish from spatial dependence, as both may manifest as spatial clustering of model errors, and thus may confound the LM tests for spatial effects. Upon finding evidence of distinct spatial regimes, Baller et al. (2001) pursue a disaggregated modeling strategy, estimating separate cross sectional models for Southern and non-Southern U.S. counties. A similar approach is used here, with independent panel models run for each of the four U.S. Census regions (Northeast, Midwest, South, and West).³⁰ The focus on the four regions, rather than a South/non-South dichotomy, is motivated by the clustering observed in the LISA maps presented earlier. While the South region clearly exhibits spatial clustering of high homicide counties, there is similar clustering in the West region, although it is perhaps not as conspicuous. Moreover, the clustering of low homicide counties appears to be a phenomenon that is concentrated largely in the (upper) Midwest. Aggregating the West region with the Midwest region in a “non-South” group may obscure heterogeneity in the model estimates for each of these regions. The regional panel models are estimated in the same manner as the full model with county and time fixed effects, and with the spatial weight matrix corresponding to contiguous neighbors within that region.^{31,32}

³⁰ While geographically weighted regression (GWR) (Fotheringham, Brunson, and Charlton 1996) may also be applied to data which exhibits spatial heterogeneity, the use of GWR with panel data has not been fully developed. In this homicide data, it is not immediately clear whether the assumption of coefficient stability across time (taking into account coefficient instability between spatial regimes) is tenable. The disaggregation technique used here allows the estimated impacts to vary between regions, but not within region.

³¹ Counties which share inter-regional borders are not considered neighbors under this methodology.

³² Elhorst (2009) uses a spatial panel model with distinct spatial regimes which estimates each regime simultaneous, but the regimes in that case are time-variant. Census regions, being time-invariant, cannot be estimated using a fixed effect specification, although a hybrid model, such as that proposed

The panel LM tests for the appropriate spatial model indicate that a SDM is the preferred specification in the South, Northeast, and West regions. In the Midwest region, none of the LM statistics is significant at all, suggesting that a non-spatial model is sufficient for this region. This is somewhat surprising, given the clear pattern of low homicide clustering in the Midwest in the LISA maps. It is important to recall, however, that whereas the LISA maps are based on the observed homicide rates, the LM statistics are based on the residuals of the base OLS model. The non-significant clustering in the model residuals implies that the clustering of homicide rates in the Midwest was the result of the clustering of the observed covariates, and that the inclusion of these covariates renders a spatial regression model unnecessary.³³

Table 2.5 displays the results from the estimation of a non-spatial panel regression for the Midwest region, as well as SDM panel models for the remaining regions. The effects of the structural covariates appear to vary substantially by region, with the strongest effects seen in the South region. The large coefficient estimates for the Southern region do not appear to be an artifact of the Southern explanatory variables exhibiting greater within-county variability over time, although homicide rates in the South did, on average, decrease more than rates in the other regions. The lack of significant coefficients in the Northeast region may possibly be related to the smaller sample size in this region, which has fewer counties, or to the greater stability of structural covariates in this region.

by Allison (2005), may be feasible.

³³ It is also the case that the pattern of spatial autocorrelation among county homicide rates differs within each region when the region is considered independently, relative to its pattern when it is considered as part of the whole U.S. However, each region (including the Midwest) continues to exhibit significant clustering of county homicide rates when it is analyzed independently of the other regions.

Overall, these disaggregated models highlight a general pattern of coefficient instability across regions, and suggest that a national focus may overstate the impact of what may in fact be a regional phenomenon. The full model results displayed in Table 2.3 appear to be largely a reflection of changes happening in the South.

2.5 Discussion

The aim of this paper is to demonstrate how *changes* in a county's population share of foreign born individuals are reflected in *changes* in the county's homicide rate. The importance of focusing on within-county change can be seen by contrasting the results from the between-county analysis with the results from the within-county analysis. County-level heterogeneity in many of the structural covariates commonly associated with increased violence, such as greater economic disadvantage, larger numbers of single family households, and increased residential instability, appears to explain much of the variation in homicide rates in the between-county model. Foreign born concentration is not a significant predictor of homicide rates in this model. The absence of a relationship between the foreign born population share and the homicide rate may be due to immigrants truly not exerting an influence on homicide rates, or it may be the case that the influence of this population segment is obscured by the cross-county differences in other covariates with which it may be highly correlated. The within-county model, however, presents a more compelling test for the effect of immigration on homicide levels, as *increases* in the foreign born population are associated with *decreases* in the county homicide rate, and because the foreign born population has changed more dynamically than other county-level population attributes. The unobserved county-level

amenities (or disamenities) which may be drawing immigrants to a specific county are unimportant in this model, at least to the extent that these factors are time-invariant.

While the time-invariance of the unobserved heterogeneity between counties is an unanswered question, the covariates used in this study are consistent with those used in prior research, and explain a substantial portion of the between-county variation in homicides. In general, the estimates of the total impacts from the SDM model in Table 2.3 are quite similar to the coefficient estimates from the non-spatial model shown in the last column of Table 2.2, although the impacts are of a much greater magnitude. This is likely related to the failure of the non-spatial model to account for either spillover effects or feedback effects, effects which may be quite substantial. The importance of accounting for spillover may perhaps be seen most clearly in the estimates of the impacts of the foreign born variable. While the share of a county's immigrant population does not have a direct effect on the homicide rate within that county, there is evidence that it has a significant effect on neighboring counties. This implies that the greatest reduction in homicide rates may be occurring in regions where there is clustering of counties with rapidly increasing foreign born populations.

The consequences of these large spillover effects are quite salient in light of current population dynamics of the United States, and the implications for continued homicide reductions are encouraging, especially perhaps in the South region.

Researchers have illustrated an inclination for the U.S. foreign born population to live in residential clusters, whether described at the neighborhood or the municipal or metropolitan level (Baird et al. 2008; Kritz, Gurak and Lee 2011), which suggests a continued expansion of the existing foreign born destinations on the East and West coasts

and in Florida. In addition, demographers have shown that newly developed immigrant communities are arising in Dallas, Atlanta, and other cities in the U.S. South (Newbold 1999; Singer 2004). As the region with the highest homicide rates, the South may be the area best poised to benefit from increasing immigrant concentrations, although it largely remains to be seen whether the new immigrant communities contribute heavily to intergroup tensions in the region.

With the exception of the proportion of the county that did not graduate from high school, the impacts of the variables measuring poverty and economic disadvantage are insignificant in the SDM model, showing neither direct nor indirect impacts. This is possibly the result of these structural covariates exhibiting minimal within-county variation over time, as structural factors that remain nearly constant from one decade to the next are unlikely to be statistically significant using a FE specification.

2.5.1 Alternate Weight Matrices

Because the estimation of a spatial regression model is critically dependent on the neighborhood weight matrix, the SDM model was re-estimated under alternative constructions of the weight matrix \mathbf{W} . These alternative weighting schemes included a 2nd order rook matrix, which defines as neighbors the counties contiguous to the target county as well as the counties contiguous to *those* neighboring counties, and a fixed distance matrix, which define as neighbors all counties within 100 miles of the target county. The coefficient estimates from these alternate models are quite similar to those from the original SDM model.³⁴ These alternate neighbor weights, like the rook matrix

³⁴ These results are available from the author.

used in the main analysis, are based only on the relative geographical positions of each county. In the future, it may be informative to construct a neighbor matrix with a stronger theoretical basis, such as interstate highway links, metropolitan areas, or media markets, as these definitions of what constitutes a neighbor may better represent the actual spatial interactions between counties.

2.5.2 Limitations

Although panel data has many positive qualities, allowing for analyses which control for unobserved heterogeneity between counties and which effectively isolate the impacts of within-county covariate change, this panel analysis requires considerable assumptions about the data. Perhaps chief among these is the assumption that any unmeasured heterogeneity between counties is time-invariant. In the 30 years encompassed by this study, many counties have certainly undergone significant social and demographic change, and to the extent that this change is measured by the included covariates it is fully accounted for in the model. It is those changes which are unmeasured and which may be correlated with homicide rates (i.e. changes in religiosity, attitudes, or beliefs) that are problematic. We have attempted to include measures which proxy these large cultural transformations, but unaccounted for county-specific trends may still persist. A related drawback is the use of data measured at decadal intervals, which results in long periods between panels and relatively few observations for each spatial unit. This ten year gap in the measurement of data points may obscure variation in the measured variables which occurs during the intercensal period, and increases the possibility that unmeasured characteristics of counties exhibit change between panels.

The limited number of observations available for each county could result in imprecise coefficient estimates, as the FE method uses only within county variation in model estimation. Unfortunately, this choice is necessitated by data availability at the county level.

The costs or benefits of increased foreign born populations on social processes may depend on specific factors within the immigrant population, and richer measures of the characteristics of the foreign born population may better explain the relationship between immigrant composition and homicide rates. Examples may include the degree of linguistic isolation of the group, the presence of violent subcultures within the sending country, or the precise sociodemographic characteristics of the immigrant population. It is also not possible to determine the level of integration of the foreign born population within the host county. We cannot tell, for example, whether immigrants living in a particular county reside within enclaves within that county or whether their residential patterning is more random. To the extent that residence in an enclave protects against negative crime outcomes, perhaps by mitigating “culture shock” or through the provision of better labor force opportunities for new immigrants, more precise residential clustering data would be advantageous. In effect, this returns to the question of the appropriate geographic unit of analysis for the study of the social process of homicide, and the use of county aggregate data may conceal important geographic variation in structural characteristics and homicide rates within the county.

County level homicide rates are typically skewed and there are many counties with no homicides at all during the study period. While the skewness in the dependent variable can be ameliorated by using a logged rate, this method requires a transformation

of the data so that those counties with zero homicides can be preserved. Osgood (2000) illustrates that such a transformation may result in incorrect inference regarding the significance of the explanatory variables and advocates the use of count models in such situations. While the inclusion of spatial interaction effects in count models of panel data has been theoretically described, there are no examples of such models having been estimated in applied work on homicide rates, and this is an avenue in which further research is warranted.

2.5.3 Conclusion

This paper illustrates that growth in the foreign born population at the county level is associated with a reduction in the rate of homicide, which suggests a protective effect of immigrant populations. While this finding is consistent with prior macro-level research on the immigration-crime association, this study offers two important analytical improvements over much prior research. First, the focus on within-county change implicitly controls for unobserved heterogeneity between counties, reducing the concern that the observed effect on homicides is the result of unmeasured and omitted variables. The coefficient estimates from this panel study, interpreted as the effects of temporal change in the explanatory variables, are also better suited to describe population dynamics than are estimates from similar cross sectional studies. Secondly, this analysis implements an innovative framework which allows the effect of social processes to extend beyond county borders. Accounting for the spatial interactions between counties results in estimates of both a direct and an indirect effect for each variable, corresponding to the variable's impact on the origin county and the impact on all neighboring counties,

respectively. The estimated impacts of foreign born population concentration on homicide rates obtained here indicate that a unit increase in foreign born population is associated with a 4% decrease in the homicide rate, averaged over all spatial units. The bulk of this foreign born impact appears to be a spillover effect, highlighting how the geographic clustering of population characteristics, not taken into account in many traditional studies, may be an important consideration in future research in criminology.

Figure 2.1: Spatial Durbin Model Framework

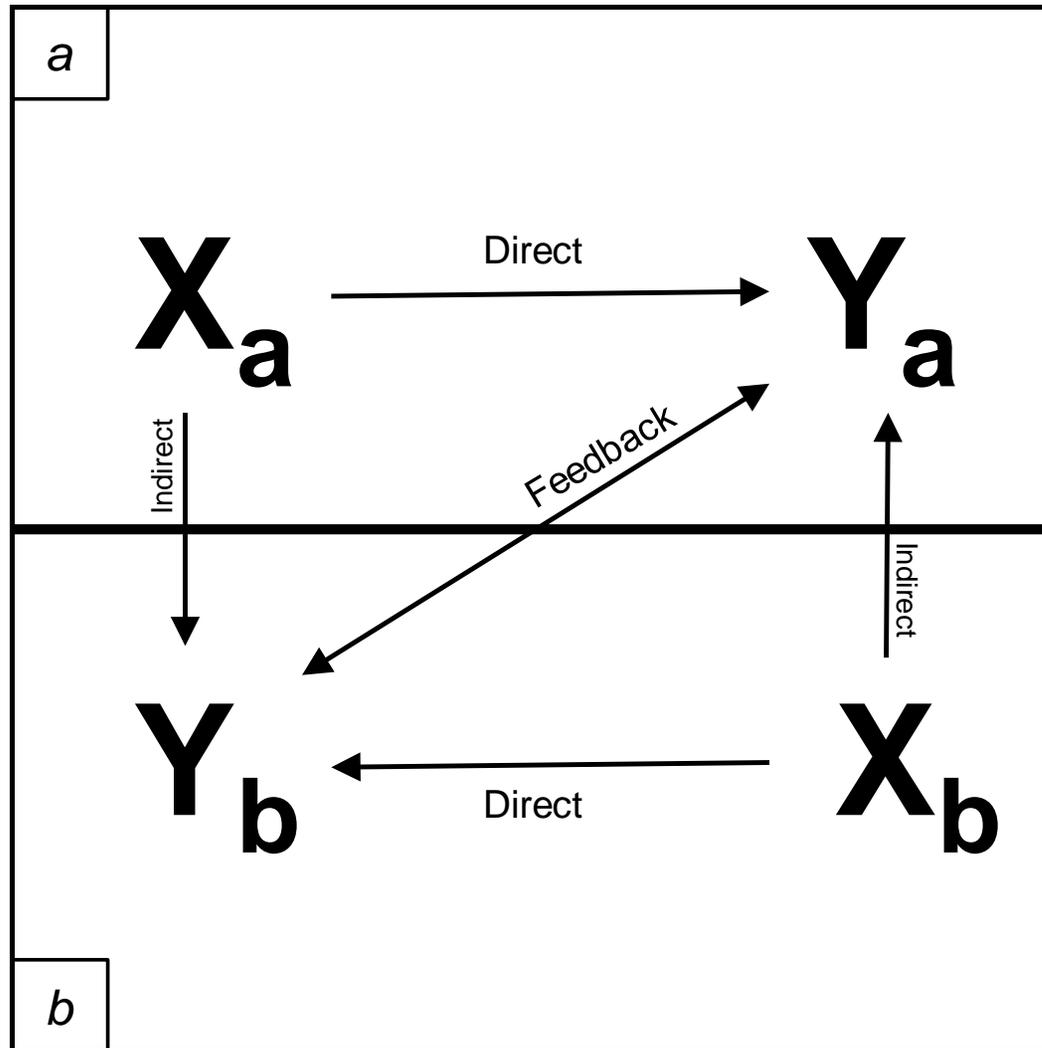
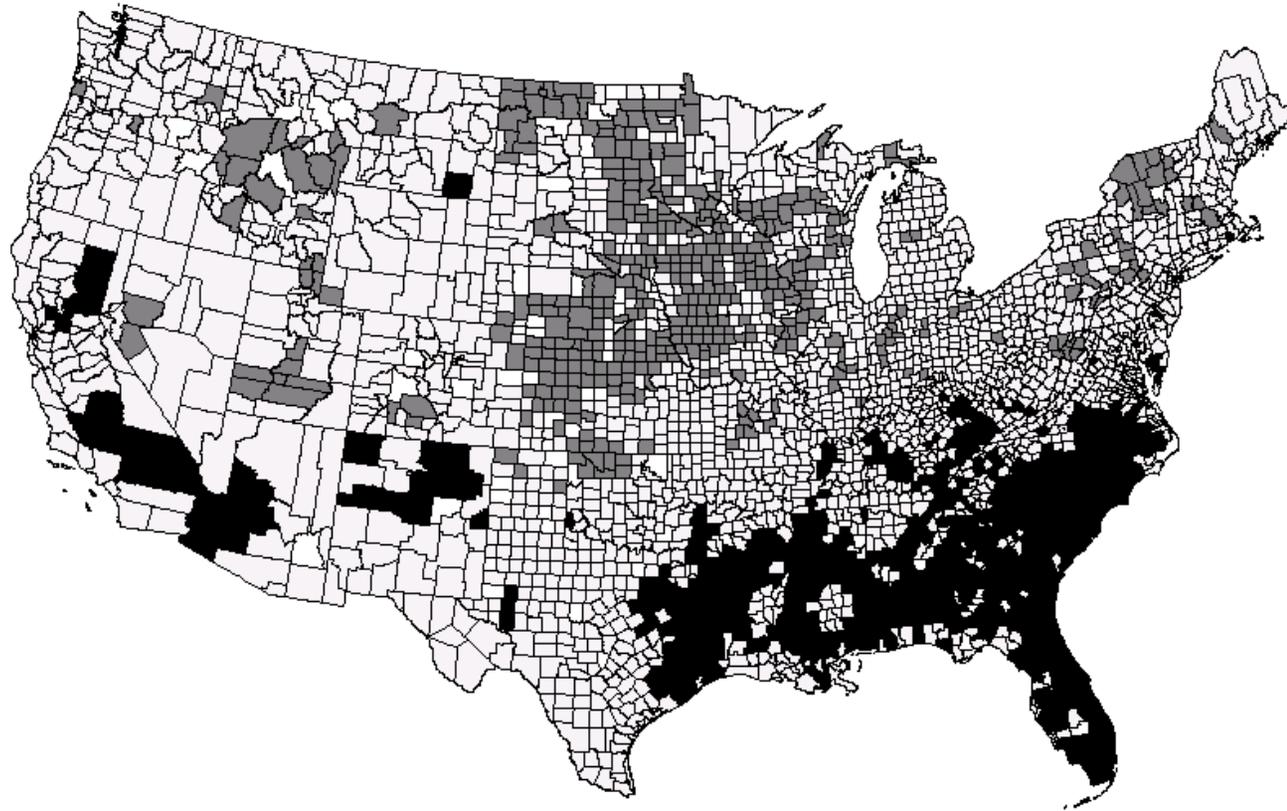


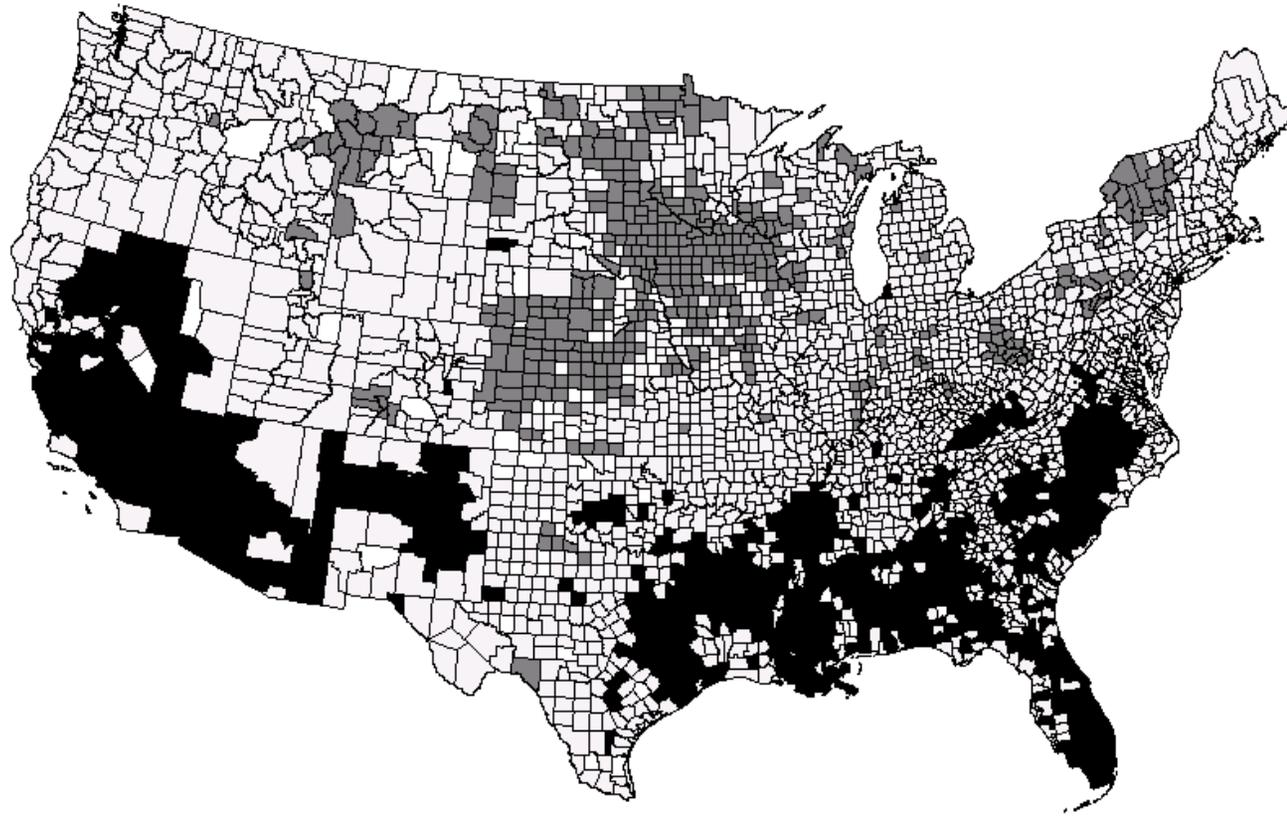
Table 2.1: Summary Statistics for County Structural Covariates

	1970		1980		1990		2000		Overall Mean	Average SD Between-unit	Average SD Within-unit
	Mean	SD	Mean	SD	Mean	SD	Mean	SD			
Homicide Rate (per 100,000)	6.40	7.37	7.03	7.20	6.23	6.74	4.40	4.90	6.01	5.22	4.20
Proportion Foreign Born	0.02	0.02	0.02	0.03	0.02	0.04	0.03	0.05	0.02	0.03	0.02
Prop Black	0.09	0.14	0.09	0.14	0.09	0.14	0.09	0.15	0.09	0.14	0.02
Total Population (000's)	65	229	72	237	80	265	90	294	77	254	42
Proportion Urban	0.35	0.29	0.36	0.29	0.37	0.30	0.40	0.31	0.37	0.29	0.06
Dependency Ratio	1.89	0.36	2.45	0.46	2.79	0.52	2.99	0.52	2.53	0.43	0.46
Proportion Male 15-24	0.08	0.03	0.09	0.02	0.07	0.02	0.07	0.02	0.08	0.02	0.01
Poverty Rate	0.17	0.11	0.16	0.07	0.17	0.08	0.14	0.07	0.16	0.08	0.03
Mean Family Income (2000\$)	38	8	40	8	44	10	51	12	44	9	6
Proportion Families Female-Headed	0.05	0.02	0.06	0.03	0.05	0.02	0.09	0.03	0.06	0.02	0.02
Proportion in Same House 5 Years	0.57	0.09	0.57	0.09	0.59	0.08	0.59	0.07	0.58	0.08	0.03
Suicide/Gun Ratio	0.66	0.27	0.70	0.25	0.71	0.22	0.66	0.24	0.68	0.17	0.18
Sworn Officers (per 100,000)	77	101	134	112	155	199	181	273	137	159	103
	I_M	p-val	I_M	p-val	I_M	p-val	I_M	p-val			
Spatial Autocorrelation (Moran's I)	0.479	<.001	0.426	<.001	0.432	<.001	0.335	<.001			

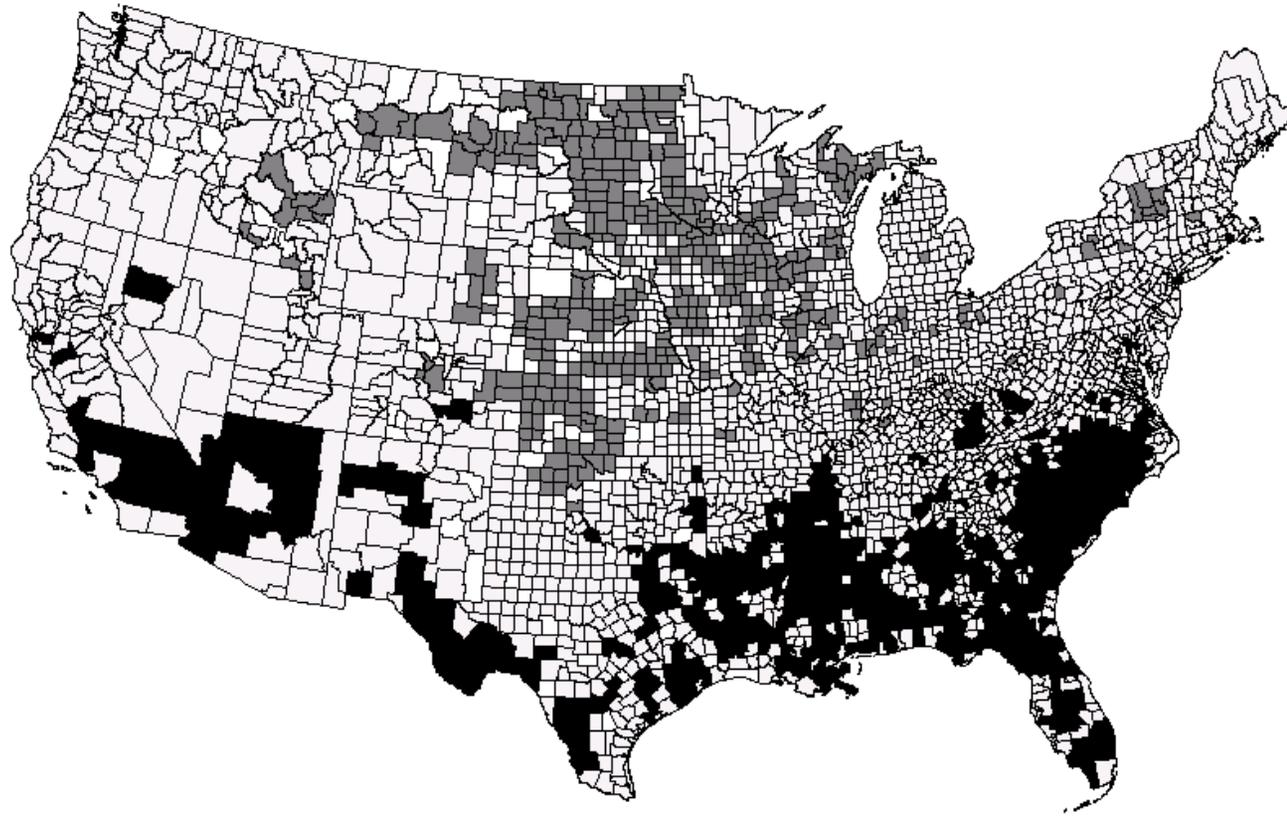
Map 2.1: Homicide Rate Clusters, 1970 (Contiguous Neighbors Weight)



Map 2.2: Homicide Rate Clusters, 1980 (Contiguous Neighbors Weight)



Map 2.3: Homicide Rate Clusters, 1990 (Contiguous Neighbors Weight)



Map 2.4: Homicide Rate Clusters, 2000 (Contiguous Neighbors Weight)

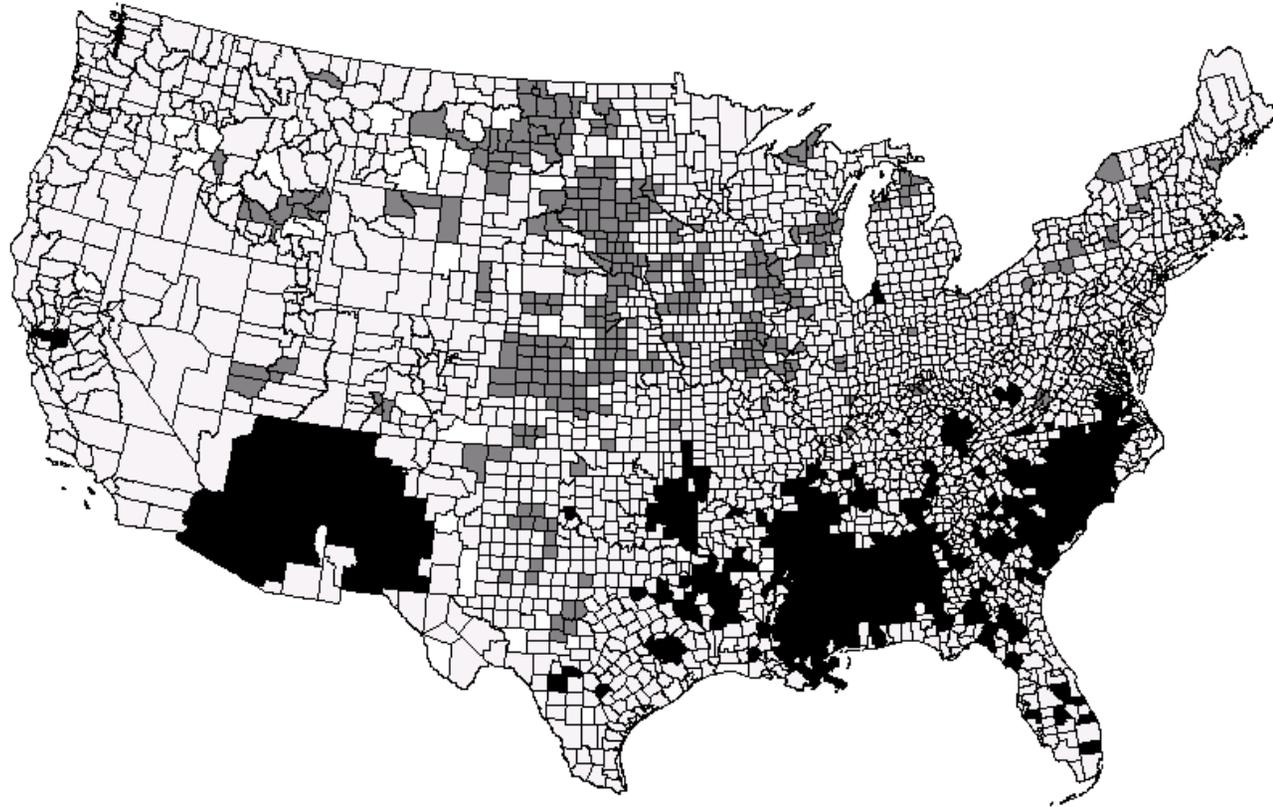


Table 2.2: Coefficients from Regressions of County Homicide Rates on Model Covariates with Fixed Within-County Effect and Between-County Effect

Variable	County Fixed Effects			County Between Effects		
	Coeff		t-stat	Coeff		t-stat
Prop Foreign Born	-2.210	***	-4.63	-0.534		-1.70
Prop NH Black	1.779	***	4.70	1.123	***	10.89
Total Population	-0.089		-1.79	0.174	***	16.18
Adult/Child Ratio	-0.067	*	-2.09	0.044	*	2.15
Prop Male 15-24	-0.117		-0.40	-5.121	***	-10.35
Poverty Rate	0.06		0.23	1.408	***	5.19
Mean Family Income	0.165		1.45	0.167		1.61
Prop Female-Headed	-1.017		-1.81	8.709	***	11.51
Prop No High School	0.971	***	4.03	2.599	***	18.92
Prop Same House	-0.814	***	-4.08	-3.385	***	-22.99
Suicide Gun Rate	0.168	***	4.72	0.381	***	6.93
Police Rate	0.000		-1.04	0.000	**	2.68
Prop Urban	-0.013		-0.14	0.003		0.07
N			12,416			12,416
r2			0.649			0.688
ll			-11167.70			-1892.34
ll_0			-17673.42			-3698.15
aic			28575.41			3812.67
bic			51746.84			3916.65
rank			3120			14

Dependent variable is logged homicide rate. Fixed effects model includes time effects. ***p<.001 **p<.01 *p<.05.

Table 2.3: Coefficients and Estimated Impacts from Spatial Panel Regression of County Homicide Rates on Model Covariates

Variable	Coefficients		Direct Effects		Indirect Effects		Total Effects				
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat			
Prop Foreign Born	-0.617	-1.06	-0.648	-1.14	-3.636	**	-2.58	-4.284	***	-3.28	
Prop NH Black	1.503	***	3.83	1.532	***	4.12	2.968	1.58	4.501	*	2.46
Total Population	-0.039	-0.61	-0.036	-0.57	0.049		0.34	0.013		0.10	
Adult/Child Ratio	-0.060	-1.54	-0.060	-1.56	-0.029		-0.31	-0.089		-0.99	
Prop Male 15-24	0.427	0.57	0.468	0.64	2.807		0.98	3.276		1.15	
Poverty Rate	-0.335	-1.10	-0.329	-1.13	0.339		0.38	0.011		0.01	
Mean Family Income	0.043	0.34	0.044	0.35	0.145		0.36	0.189		0.48	
Prop Female-Headed	-0.838	-1.32	-0.826	-1.30	1.933		0.96	1.106		0.57	
Prop No High School	0.451	1.51	0.469	1.63	1.519	*	2.11	1.987	**	2.98	
Prop Same House	-0.325	-1.49	-0.351	-1.62	-2.241	***	-3.35	-2.592	***	-3.91	
Suicide Gun Rate	0.131	***	3.70	0.136	***	3.95	0.450	1.86	0.586	*	2.39
Police Rate	0.000	-0.40	0.000	-0.39	0.000		0.28	0.000		0.18	
Prop Urban	-0.071	-0.69	-0.070	-0.66	0.334		0.74	0.264		0.59	
W * Prop Foreign Born	-2.444	*	-2.19								
W * Prop NH Black	1.815		1.34								
W * Total Population	0.044		0.39								
W * Adult/Child Ratio	-0.005		-0.06								
W * Prop Male 15-24	1.935		0.89								
W * Poverty Rate	0.332		0.50								
W * Mean Family Income	0.089		0.31								
W * Prop Female-Headed	1.603		1.08								
W * Prop No High School	0.972		1.75								
W * Prop Same House	-1.528	**	-2.97								
W * Suicide Gun Rate	0.288		1.69								
W * Police Rate	0.000		0.32								
W * Prop Urban	0.271		0.83								
W * Homicide Rate	0.282	***	10.05								

Dependent variable is logged homicide rate. Model includes spatial (county) fixed effects and time (year) fixed effects.
 ***p<.001 **p<.01 *p<.05

Table 2.4: Comparison of Estimated Impacts from the Spatial Durbin Model, Spatial Autoregressive Model, and Spatial Error Model

Variable	SDM		SAR		SEM				
	Impact	t-stat	Impact	t-stat	Coeff	t-stat			
<i>Direct</i>									
Prop Foreign Born	-0.648	-1.14	-1.894	***	-3.81				
Prop NH Black	1.532	***	4.12	1.711	***	4.61			
Total Population	-0.036	-0.57	-0.078		-1.58				
Adult/Child Ratio	-0.060	-1.56	-0.058		-1.75				
Prop Male 15-24	0.468	0.64	0.904		1.27				
Poverty Rate	-0.329	-1.13	0.026		0.10				
Mean Family Income	0.044	0.35	0.138		1.20				
Prop Female-Headed	-0.826	-1.30	-0.967		-1.76				
Prop No High School	0.469	1.63	0.857	***	3.48				
Prop Same House	-0.351	-1.62	-0.747	***	-3.70				
Suicide Gun Rate	0.136	***	3.95	0.152	***	4.19			
Police Rate	0.000	-0.39	0.000		-0.54				
Prop Urban	-0.070	-0.66	-0.039		-0.39				
<i>Indirect</i>									
Prop Foreign Born	-3.636	**	-2.58	-0.272	***	-3.46			
Prop NH Black	2.968		1.58	0.246	***	4.03			
Total Population	0.049	0.34	-0.011		-1.54				
Adult/Child Ratio	-0.029	-0.31	-0.008		-1.71				
Prop Male 15-24	2.807	0.98	0.130		1.25				
Poverty Rate	0.339	0.38	0.004		0.10				
Mean Family Income	0.145	0.36	0.020		1.17				
Prop Female-Headed	1.933	0.96	-0.139		-1.71				
Prop No High School	1.519	*	2.11	0.123	**	3.18			
Prop Same House	-2.241	***	-3.35	-0.107	***	-3.30			
Suicide Gun Rate	0.450	1.86	0.022	***	3.73				
Police Rate	0.000	0.28	0.000		-0.54				
Prop Urban	0.334	0.74	-0.006		-0.38				
<i>Total</i>									
Prop Foreign Born	-4.284	***	-3.28	-2.166	***	-3.81	-3.83	***	-5.14
Prop NH Black	4.501	*	2.46	1.956	***	4.60	3.47	***	4.30
Total Population	0.013	0.10	-0.089	-0.089		-1.58	-0.03		-0.34
Adult/Child Ratio	-0.089	-0.99	-0.067	-0.067		-1.75	-0.05		-0.83
Prop Male 15-24	3.276	1.15	1.034	1.034		1.27	0.88		0.51
Poverty Rate	0.011	0.01	0.030	0.030		0.10	-0.01		-0.01
Mean Family Income	0.189	0.48	0.158	0.158		1.20	0.30		1.38
Prop Female-Headed	1.106	0.57	-1.106	-1.106		-1.76	0.45		0.41
Prop No High School	1.987	**	2.98	0.981	***	3.48	1.85	***	4.65
Prop Same House	-2.592	***	-3.91	-0.855	***	-3.69	-1.69	***	-3.81
Suicide Gun Rate	0.586	*	2.39	0.174	***	4.18	0.27	**	2.64
Police Rate	0.000	0.18	0.000	0.000		-0.54	0.00		-0.82
Prop Urban	0.264	0.59	-0.044	-0.044		-0.39	0.32		1.44

Dependent variable is logged homicide rate. Model includes spatial (county) fixed effects and time (year) fixed effects. ***p<.001
**p<.01 *p<.05

Table 2.5: Estimated Impacts from Spatial Panel Regression of County Homicide Rates on Model Covariates by Separate Region

Variable	Northeast		Midwest		South		West		
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	
<i>Direct</i>									
Prop Foreign Born	-0.676	-0.46	3.613 **	2.70	-0.583	-0.64	-2.364	-1.52	
Prop NH Black	3.231	1.76	2.627	1.72	1.001 *	2.25	2.297	0.51	
Total Population	-0.454 *	-2.10	0.092	0.63	-0.247 **	-2.61	0.350 *	2.10	
Adult/Child Ratio	-0.142	-1.18	-0.104	-1.29	-0.066	-1.27	-0.032	-0.29	
Prop Male 15-24	-2.401	-0.96	-1.787	-1.12	0.137	0.14	7.001 *	2.43	
Poverty Rate	2.015	1.44	-0.198	-0.33	-0.427	-1.08	0.187	0.20	
Mean Family Income	0.218	0.57	0.048	0.20	0.029	0.16	0.080	0.24	
Prop Female-Headed	-0.820	-0.46	-1.110	-0.94	-1.914 *	-2.14	0.343	0.16	
Prop No High School	-0.911	-0.88	-1.127	-1.86	1.114 **	2.66	0.893	0.98	
Prop Same House	-0.993	-1.26	-0.435	-1.01	-0.480	-1.53	-0.204	-0.37	
Suicide Gun Rate	-0.174	-1.20	0.123 *	2.50	0.133 *	2.37	0.199	1.73	
Police Rate	-0.001	-1.04	0.000	-0.66	0.000	-1.61	0.001 *	2.77	
Prop Urban	0.050	0.17	-0.173	-0.76	-0.076	-0.56	-0.038	-0.13	
<i>Indirect</i>									
Prop Foreign Born	-1.968	-0.94	-2.301	-0.97	-3.446 *	-2.43	4.335	1.66	
Prop NH Black	5.303	1.22	-2.443	-0.79	2.233 **	2.72	-4.672	-0.44	
Total Population	0.555	1.36	-0.124	-0.61	0.098	0.65	-0.016	-0.05	
Adult/Child Ratio	0.309	1.38	-0.044	-0.32	0.063	0.77	0.000	0.00	
Prop Male 15-24	4.053	0.58	5.788	1.86	-1.920	-0.94	-15.150 *	-2.46	
Poverty Rate	-5.174	-1.50	0.414	0.36	0.093	0.12	0.618	0.31	
Mean Family Income	-1.022	-1.53	0.468	1.11	0.514	1.49	-1.426	-1.80	
Prop Female-Headed	-2.593	-0.83	-1.536	-0.67	0.856	0.56	4.417	0.90	
Prop No High School	1.664	0.81	0.272	0.26	1.208	1.74	-2.334	-1.16	
Prop Same House	-0.204	-0.15	0.055	0.07	-1.708 **	-2.87	-1.362	-1.15	
Suicide Gun Rate	-0.108	-0.30	0.020	0.16	-0.083	-0.58	0.300	0.91	
Police Rate	-0.002	-1.52	0.001	0.61	-0.001	-1.35	0.002 *	2.43	
Prop Urban	0.135	0.26	0.244	0.54	0.380	1.40	0.928	1.29	

Table 2.5 continued

<i>Total</i>									
Prop Foreign Born	-2.644	-1.36	1.313	0.59	-4.029	**	-3.22	1.971	0.86
Prop NH Black	8.534	1.75	0.184	0.06	3.234	***	3.89	-2.375	-0.21
Total Population	0.101	0.25	-0.031	-0.19	-0.149		-1.14	0.333	1.18
Adult/Child Ratio	0.167	0.75	-0.148	-1.22	-0.003		-0.04	-0.032	-0.15
Prop Male 15-24	1.653	0.23	4.001	1.34	-1.783		-0.83	-8.149	-1.25
Poverty Rate	-3.160	-0.84	0.216	0.19	-0.334		-0.46	0.805	0.41
Mean Family Income	-0.805	-1.24	0.516	1.25	0.543		1.53	-1.346	-1.74
Prop Female-Headed	-3.413	-1.08	-2.646	-1.15	-1.059		-0.69	4.760	0.89
Prop No High School	0.753	0.37	-0.855	-0.91	2.322	***	3.60	-1.441	-0.69
Prop Same House	-1.198	-0.92	-0.379	-0.46	-2.188	***	-3.59	-1.566	-1.29
Suicide Gun Rate	-0.282	-0.69	0.142	1.09	0.050		0.31	0.499	1.35
Police Rate	-0.003	-1.78	0.000	0.28	-0.001	*	-2.07	0.003	**
Prop Urban	0.185	0.35	0.071	0.14	0.304		1.08	0.891	1.12
N =	868		4,220		5,684			1,644	

Dependent variable is logged homicide rate. Model includes spatial (county) fixed effects and time (year) fixed effects. ***p<.001 **p<.01 *p<.05

CHAPTER 3: THE SPATIAL MOBILITY AND MIGRATION CHARACTERISTICS OF PUERTO RICANS IN THE UNITED STATES, 1995-2000

Abstract

This paper investigates the internal migration patterns of Puerto Ricans in the United States, comparing the migration behaviors of Puerto Rico-born and U.S-born Puerto Ricans. Puerto Ricans born in the U.S. are younger than their island-born counterparts, have higher levels of human capital, and are more likely to be part of the labor force and less likely to live in poverty. These second and higher generation Puerto Ricans are also more likely than Puerto Ricans born in Puerto Rico to migrate within or between states, although the individual and contextual characteristics associated with internal migration are similar for the two groups. Puerto Ricans born in the U.S. appear to be less influenced by the absence or presence of co-ethnics when making migration decisions, and display increased migration to new destinations. Within both groups, however, the most significant migration stream is between New York (and other northeastern states) and Florida.

3.1 Introduction

The past two decades have witnessed substantial growth in the Puerto Rican population in the United States. The U.S.-based Puerto Rican population grew by nearly 25% during the 1990's, and increased by more than 36% between 2000 and 2010 (Guzman and McConnell 2002; United States Census Bureau 2011). At the time of the 2000 Census, Puerto Ricans comprised approximately 10% of the more than 35 million Hispanics living in the U.S., and during the 2000's, the number of Puerto Ricans in the United States surpassed the number living in Puerto Rico (Duany 2003; Pew 2009). Despite the size and growth of the U.S. Puerto Rican population, there is relatively little contemporary research which focuses specifically on this group, as the accelerated growth in the populations of other Hispanic groups may have overshadowed the growth in the Puerto Rican population. While more than a third of the total U.S. Puerto Rican population was born on the island of Puerto Rico, there is precious little research which compares this immigrant segment to its mainland-born counterpart.³⁵ This distinction may be quite important, as the cultural, educational, and labor market experiences of these two groups is likely to be markedly different.

While there is precedence for research on the social characteristics of Puerto Ricans within the U.S. (Hernandez-Alvarez 1968; Ortiz 1986; Tienda 1989; Ramos 1992; Meléndez 2007), few studies have focused on the spatial mobility of Puerto Rican migrants. In addition to expanding in size, there is evidence that the U.S. Puerto Rican population is dispersing from its traditional settlements in the Northeastern region of the

³⁵ We refer to Puerto Ricans born on the island of Puerto Rico as "island-born" or "Puerto Rican-born", to distinguish these individuals from Puerto Ricans born within the 50 states. This latter group is referenced throughout this paper as "Puerto Rican-origin", "U.S.-born", "mainland-born", or "2nd and higher generation Puerto Rican".

country (Belanger and Rogers 1992; Foulkes and Newbold 2000). It is not known, however, whether the ongoing deconcentration of the Puerto Rican population is a result of internal migration of the mainland-born population, internal migration of the island-born population, or the initial location decision of the newly arrived island-born population. This paper aims to add to this literature by describing the current patterns of domestic migration of Puerto Ricans and by comparing the migration behavior of those individuals born on the island to those individuals born in the U.S.

In the next section we describe prior research on the internal migration behavior of U.S.-based Puerto Ricans. This is followed by sections detailing the data and methodology used in the analysis, the analysis itself, and a discussion of the results.

3.2 Background

Prior to 1950, nearly all Puerto Ricans in the United States lived in New York City, with out-migration from New York beginning in earnest during the 1950's (Hernandez-Alvarez 1968). Hernandez-Alvarez shows that while island-born Puerto Ricans displayed overall greater mobility than 2nd generation Puerto Ricans during this time, 2nd generation Puerto Ricans were more likely to make interstate moves. Through a comparison of the flow of Puerto Ricans arriving from the island with the flow arriving from other states, he suggests that the concentration of Puerto Ricans in the U.S. is largely a function of island-mainland migration, rather than later secondary migration. The geographic pattern of interstate migration among the U.S. population born in Puerto Rico continued during the 1960's and 1970's, with significant secondary migration from New York to other Northeastern and Southern states (Ortiz 1986; McHugh 1989). In

terms of magnitude, however, interstate migrants still comprised only 7% of the existing Puerto Rican-born population in the U.S. in 1980. In an analysis of Puerto Rican migration patterns over the period 1985-1990, Foulkes and Newbold (2000) find that the mainland-born Puerto Rican population exhibits a greater overall propensity to make an interstate move relative to the island-born Puerto Rican population. These authors show that greater educational attainment and English fluency are associated with an increased tendency to migrate across state lines, while interstate migration decreases with age.

Research on the internal migration patterns of foreign born populations and native born Hispanic populations may provide insight on the migration behavior of Puerto Ricans. Although they likely do not confront the same legal or labor market obstacles faced by non-citizen foreign born residents, island-born Puerto Ricans are culturally similar to immigrants from other Spanish-speaking Caribbean nations. Having grown up in the U.S., 2nd and higher generation Puerto Ricans may exhibit migration behavior more in line with the native born population. In most cases, studies on the secondary migration of foreign born populations in the U.S. exclude Puerto Ricans or group Puerto Ricans with other foreign born Latinos (Frey and Liaw 1999; Newbold 1999; Parrado and Kandel 2010; Kritz, Gurak and Lee 2011). Newbold (1999) found that, in the period 1985-1990, internal migration of the foreign born population did not lead to increase spatial concentration of the foreign born population as a whole. The spatial patterns of immigrant concentration which arose from the simultaneous in-migration of new foreign born and secondary migration of existing foreign born were largely dependent on the specific immigrant group in question. Although his sample did not include individuals from Puerto Rico, Newbold's results for other Caribbean nations exhibited little

consistency in patterns of interstate migration. While immigrants from Cuba were more likely to migrate to states with existing Cuban populations, the foreign born Dominican population was more likely to move away from co-ethnics. Frey and Liaw (1999) show that those states experiencing net out-migration of foreign born Latinos (which includes Puerto Ricans) from 1985 to 1990 were also experiencing net out-migration of native born Latinos. However, interstate migration was not broken down by single nativity groups, and any migration behavior specific to Puerto Ricans was likely diluted by the presence of the larger Latino groups, most notably Mexicans.

There are plausible reasons why we might expect the spatial mobility of island-born Puerto Ricans to differ from that of mainland-born Puerto Ricans. Although island-born Puerto Ricans are U.S. citizens by birth, they may face greater cultural and linguistic obstacles in the U.S., relative to Puerto Ricans who are born in the mainland (Duany 2003). Foreign born Puerto Ricans are likely to possess lower levels of human capital, which may translate into having fewer resources with which to undertake migration. Ramos (1992) looks at migration and return migration between Puerto Rico and the U.S. during the period 1970 to 1980, for the population born in Puerto Rico and the U.S., with a focus on the explanatory power of human capital accumulation in predicting migration behavior. His descriptive results indicate that although working age Puerto Rican males born in Puerto Rico and residing in the U.S. tend to be older than their mainland-born counterparts, they have lower levels of human capital and earn lower wages. On the other hand, island-born Puerto Ricans may have fewer familial or social ties which keep them tied to any particular area, and might therefore display a greater propensity for interstate migration.

Puerto Ricans born in Puerto Rico are more likely than Puerto Ricans born in the 50 states to return to the island, a process of circular migration that has been documented by Duany (2003). Ramos (1992) shows that the mainland-born Puerto Rican population that migrates to the island is small relative to the population that stays in the U.S., and is a more select group in terms of education and earnings. Puerto Rican-born individuals residing in the U.S. and expecting to return to the island may thus be less inclined to commence with internal migration, instead opting for the return trip.³⁶

Other factors that might influence the internal migration patterns of Puerto Ricans are the contextual characteristics of the current place of residence, as well as the characteristics of other potential destinations. These may include the industrial composition of the labor market, increased opportunities for employment, or the absence or presence of co-ethnics. As part of a Hispanic minority that may be subject to discrimination, Puerto Ricans may wish to remain in, or move to, areas which have existing large populations of Puerto Ricans or other Hispanic groups. Such areas may allow for increased within-group social networking and better access to cultural and community organizations. The presence of co-ethnics is likely to be more relevant to island-born Puerto Ricans, who are likely less acculturated than are Puerto Ricans born in the U.S. Researchers have shown that immigrants who make a secondary move are likely to migrate into areas with existing concentrations of immigrants (Belanger and Rogers 1993; Neuman and Tienda 1994; Newbold 1999; Foulkes and Newbold 2000).

Based on the current state of knowledge on the migration behavior of Puerto Ricans, the analytical plan of this paper has two components. First, we will describe the

³⁶ As will be explained below, the structure of the Census data used in this analysis makes it impossible to determine precisely the extent of this circular migration.

geographic distribution and mobility of Puerto Ricans born in the U.S. and those born in Puerto Rico, with a focus on migration between states during the period 1995-2000. The focus on interstate migration is based on White and Meuser's (1988) observation that interstate movers represent the most select group of migrants, and is consistent with prior studies on the internal migration of foreign born populations (Kritz and Nogel 1994; Nogle 1997; Gurak and Kritz 2000; Newbold and Foulkes 2000). Next, we will analyze the migration decisions of Puerto Rican individuals to determine the individual- and place-level characteristics which are associated with migration, and assess whether the effects of the characteristics vary by place of birth. This analysis will be carried out using a multinomial logistic model which allows for multiple outcomes, so while the emphasis will again be on interstate migration, we will also consider the effect of the covariates on intrastate migration.

The primary aim of this study is to highlight the context of Puerto Rican migration. The second aim is to provide perspective on how this migration might be expected to affect future origin and destination states. With birthrates at or below replacement levels, internal migration is the primary component of population growth and loss for most states. The sociodemographic structure of the in- and out-migrating population will have consequences for states in terms of social services, schools, tax revenue, and political environment.

3.3 Data

The source of data for this paper is the 5% Public-Use Microdata Sample (PUMS) from the 2000 U.S. and Puerto Rico Censuses (Ruggles et al. 2010). These files contain

sociodemographic information on individuals and households, including prior place of residence, making them suitable for a study of migration flows and the characteristics of migrants. In addition, the use of the Puerto Rican Census allows for the identification of individuals who lived in the U.S. in the prior period and now reside in Puerto Rico, an important benefit in the examination of migratory flows. In contrast to immigration from foreign countries, for which return migration or circular migration is unrecorded and potentially problematic, the return migration of Puerto Ricans from the U.S. is well-documented in the Puerto Rican Census. PUMS data are weighted to create a nationally representative population.

While the PUMS data is commonly employed in studies of the patterns of migration, there are limitations to its use, most notably in the level of geographical detail that is available. The smallest identifiable geographic unit of migration in PUMS data is the Migration Public-Use Microdata Area (Mig-PUMA), which consists of one or more contiguous counties. Mig-PUMAs defy conventional geographic definitions, often encompassing multiple municipalities and crossing metropolitan area boundaries. Mig-PUMAs do not, however, cross state boundaries, and it is possible to isolate those individuals who move within a state from those who move between states.³⁷

Puerto Rican individuals were identified using the variables denoting place of birth and Hispanic origin. Individuals born in Puerto Rico and listing a Hispanic ethnicity of Puerto Rican are designated Puerto Rican-born, while individuals born in the

³⁷ Although it is also possible to distinguish between migrants who move within a Mig-PUMA and migrants who move between Mig-PUMAs within the same state, these movements are not considered here. This is largely an analytical convenience, founded in White and Meuser's (1988) suggestion that the differences between within-county movers and between-county movers have become less distinct as suburbanization has increased.

United States and listing a Hispanic ethnicity of Puerto Rican are designated Puerto Rican-origin. Persons of Puerto Rican origin that were born outside of the U.S. were excluded from the analysis, as were persons born in Puerto Rico who indicated a Hispanic ethnicity other than Puerto Rican.³⁸

Migration is defined based on the respondent's place of residence 5 years ago. Any individual who listed residence in a different house 5 years ago and residence in the U.S. in 1995 and 2000 is designated an internal migrant, with internal migrants further subdivided into those who moved within the same state and those who moved to a new state. The structure of the Census migration question does not allow the identification of multiple movements during the period 1995-2000. We are also unable to identify Puerto Rican individuals who moved out of the U.S. to foreign nations during the period, which will inflate the estimates of net migration in the analysis of migration flows. For the analysis of migration flows, out-migrants are defined as those persons living in Puerto Rico in 2000 who lived in the U.S. in 1995 and in-migrants as those persons living in the U.S. in 2000 and Puerto Rico in 1995. While out-migrants and in-migrants are included in the analysis of migration flows, they are not considered in the regression analysis of the secondary migration decision, which focuses on the internal migration behavior of Puerto Ricans. Motivations for migration between the island and the mainland may be very different than those for secondary migration, and the characteristics of international migrants are likely to be different from those of internal migrants (Ramos 1992; Duany 2002; Massey and Sana 2003; Feliciano 2005).

³⁸ Approximately 2% of the U.S. Puerto Rican population not born in Puerto Rico was born in a foreign country. More than 90% of the U.S.-resident population that was born in Puerto Rico listed a Hispanic origin of Puerto Rico.

3.3.1 *Model of Secondary Migration Decision*

The internal migration decision of Puerto Ricans residing in the U.S. may be a function of the individual-level characteristics of the migrant, as well as place-level attributes of the migrant's current or desired location. To simultaneously estimate the influence of these factors on the migration decision requires a model which allows discrete, but unordered, outcomes. Multinomial logistic regression, which is conceptually similar to repeated logistic regressions between all potential pairing of outcomes, is commonly used to estimate models predicting nominal outcomes. Relative to fitting a series of logistic regressions, which would result in the use of a separate sample for each pair of outcomes, the MLNM estimates all pairings simultaneously using the full sample (Long and Freese 2006). The multinomial logistic model has as the dependent variable the preferred alternative for each individual, denoted here as the actual migration decision that each individual made. The coefficient estimates reflect the impact of the included covariates on the preferred migration outcome, relative to the base outcome.

The multinomial logistic regression equation is given by the equation:

$$\ln \Omega_{m|b}(X) = \ln \frac{\Pr(y = m|X)}{\Pr(y = b|X)} = X\beta_{m|b} \text{ for } m = 1 \text{ to } J \quad (1)$$

where m represents the set of possible outcomes and b is the outcome against which the

others are compared, X is the matrix of covariates and β the matrix of estimated effects (Long and Freese 2006). In this analysis, the base outcome is “no migration”, represented by continued residency in the same house, while the alternative outcomes are “interstate migration” and “intrastate migration”. The multinomial logistic regression will give two sets of coefficient estimates, one for each alternative outcome, which indicate the effects of the covariates on the probability of each alternative migration outcome relative to non-migration.

The covariates included in the model are based on prior studies of migration and the internal migration of foreign born populations (Greenwood 1985; Nogle 1997; Kritz, Gurak and Lee 2011). The covariates comprise three general categories: Individual-level demographic variables, individual-level socioeconomic and human capital variables, and place-level factors. Demographic characteristics which may impact the migration decision include the migrant’s age, gender, marital status, the presence of children in the household, and housing tenure. Human capital is measured by the highest level of education that the respondent has completed, mean household income, labor force participation, and English language proficiency. One additional control variable, year of immigration to the U.S., was included for the population born in Puerto Rico only.³⁹

Researchers have noted that contextual factors are important predictors of migration outcomes and should be considered in the residential migration decision, as individuals may be drawn to (or repelled from) particular areas based on the social composition of the area or the labor market opportunities available in the area

³⁹ Although this analysis does not control for the respondent’s race, separate model specifications that included indicators for race did not substantively alter the results. Individuals coded as white were slightly more likely to undertake an intrastate move, but no significant results were obtained for race coded as black or non-white.

(Greenwood 1985; Massey 1990; Scott, Coomes, and Izyumov 2005). To the extent that states or PUMAs exhibit differential levels of those place-level characteristics that are important to secondary immigrants, interstate or intrastate migration might be expected to vary. Prior research has identified general economic conditions and the presence of co-ethnics as factors that are salient in the study of the internal migration of Puerto Ricans (Foulkes and Newbold 2000). General economic conditions are assessed at the mig-PUMA level using the unemployment rate, the poverty rate, and the percentage of the population that has a college degree. Less favorable economic conditions within a mig-PUMA are expected to exert a positive influence on migration outcomes, as individuals seek out better employment prospects in more vibrant places. The presence of co-ethnics is measured at the mig-PUMA level as the percentage of the population that is Puerto Rican, including both island-born and mainland-born persons, as well as the percentage of the population that is Hispanic. Large co-ethnic populations within a mig-PUMA are expected to discourage out-migration and encourage in-migration, as individuals relocate to be nearer to those with similar cultural backgrounds and language. While they did not look at Puerto Ricans in particular, Kritz and Nogle (1994) found that state-level nativity concentrations for nearly all foreign born groups were associated with decreased out-migration of the nativity group in question. Two measures of the industrial composition of the mig-PUMA, the percentage of the population employed in manufacturing and the percentage of the population employed in construction, are included as additional covariates.

The value of each contextual variable was calculated in the year 1995, using the full 2000 PUMS data, by assigning each individual to the mig-PUMA in which they

resided in 1995. This reduces the potential endogeneity that may result by measuring place-level characteristics after the migration event has occurred. Place-level influences on migration behavior are incorporated into the model by including, for each individual and for each contextual covariate, the difference in the covariate value for the mig-PUMA in which the individual lived in 2000 and the covariate value for the mig-PUMA in which the individual lived in 1995; for individuals who did not move, this differenced value is 0. Including this differenced value simultaneously accounts for both the migration “push” from the current place of residence and the migration “pull” from other destinations. The odds ratios of the coefficients on these differenced values are thus interpreted as the effect of moving to a place with “more” of the covariate (e.g. greater Puerto Rican concentration, higher poverty, increased unemployment, etc.).

While no restrictions were imposed on the sample for the examination of population stocks and migration flows, the multinomial logistic analysis is limited to non-group quartered individuals between the ages of 25 and 64 who are listed as the head of household. Constraining the analysis to this age group minimizes the confounding effects of education-related and retirement migration, while the focus on household heads reduces the influence of interdependent spousal and children relocation decisions. This restriction results in a migration sample of 20,156 respondents born in Puerto Rico and 16,064 respondents born in the U.S.

3.4 Analysis

3.4.1 Interstate Migration

An estimated 1.3 million Puerto Rican-born individuals were living in the U.S. in

2000, including approximately 150,000 who had moved from the island during the prior five year period (Table 3.1). While not included in the total here, an estimated 72,392 island-born individuals migrated from the mainland back to Puerto Rico, representing a net migration loss for Puerto Rico. Among the island-born population that lived in the U.S. in both 1995 and 2000, 54% lived in the same house in both years, a figure approximately equal to that of the U.S. population as a whole.⁴⁰ Of those individuals who relocated within the U.S., 19% migrated to a new state, while the remaining 81% moved within the same state.

In 2000, over 85% of the Puerto Rican-born population resided in just 8 states (NY, FL, NJ, MA, PA, CT, IL, and CA), with over one-quarter living in New York alone. Florida was the top destination for new in-migrants from Puerto Rico between 1995 and 2000, as well as the top destination for internal migrants during the period. Of the Puerto Rican-born population that migrated internally between 1995 and 2000, over 30% listed residency in Florida in 2000, nearly 4 times as many as listed the 2nd most popular destination of Pennsylvania (8%). The proportion of the Puerto Rican-born population that is “new” in 2000, defined as the proportion living in a different state or in Puerto Rico in 1995, is highest in the southern states of Virginia, Georgia, Texas, and Florida, as well as in the state of Rhode Island.

The population of Puerto Rican-origin individuals is substantially larger than the population born in Puerto Rico, at slightly more than 2 million, and appears to be somewhat more mobile. Only 46% of the 2nd or higher generation population reports living in the same house in 1995 and 2000, and 21% of those who moved reported

⁴⁰ 2000 United States Census, Summary File 3.

moving to a new state. Because the Puerto Rican-origin individuals were born in the U.S., they might be expected to have fewer social or business ties on the island, and may thus exhibit reduced migratory behavior between the mainland and the island. This is borne out in the data, with fairly small 2nd and higher generation populations, 32,087 and 22,419 respectively, migrating from Puerto Rico to the U.S. and vice versa. These flows represent less than 2% of the total mainland-born Puerto Rican population in 2000.

While somewhat more mobile overall, the Puerto Rican-origin population does not appear to be much more geographically dispersed than the Puerto Rican-born population, with over 81% of the population residing in those same 8 states listed above. The trend for the origin population may be towards greater dispersion, however, as only 58% of internal migration during the period 1995-2000 was towards one of the 8 most populous states; the corresponding figure for the island born population was 68%. Florida was the top receiving state for internal migrants, with 21% of the between-state migrants residing there in 2000, while smaller populations moved to New York, New Jersey, and Pennsylvania. The states with the largest proportions of “new” 2nd or higher generation Puerto Ricans were all located in the U.S. South, similar to the pattern exhibited by the Puerto Rican-born population.

The migration flows shown in Table 3.1 present a one-sided picture of the dynamics of Puerto Rican internal migration, as they fail to account for the population that is moving out of each state. Table 3.2 displays net migration flows, both between other states and between the island of Puerto Rico, for those states which exhibited

significant Puerto Rican migration flows.⁴¹ For both the Puerto Rican-born and the Puerto Rican-origin populations, domestic migration was dominated by migration flows in two states, New York and Florida. New York exhibited the greatest net loss of island-born Puerto Ricans, with nearly 20,000 more Puerto Rican-born persons moving from New York to other states than moved from other states to New York between 1995 and 2000. New Jersey, Illinois, and Massachusetts, which, like New York, are traditional destinations for Puerto Rican individuals, also showed net population loss, albeit to a much lesser extent. Florida was by far the largest gainer from domestic migration of the Puerto Rican-born population during the period, with a much smaller increase exhibited by Pennsylvania. Net migration of island-born Puerto Ricans between Puerto Rico and the individual states was somewhat more evenly dispersed, with several states experiencing positive net migration from the island, although Florida had the largest net gain in population.

The pattern of migration of the mainland-born Puerto Rican population is quite similar to that of the island-born population, with the increased migration flows of this mainland-born group reflecting its greater size. New York lost more than 40,000 mainland-born Puerto Ricans to other states between 1995 and 2000, with smaller net losses occurring in New Jersey, Illinois, and California. Florida gained more than 25,000 mainland-born Puerto Rican residents from other states, with additional significant population gains occurring in Pennsylvania and several Southern states. As expected, net migration of Puerto Rican-origin individuals to the island of Puerto Rico was negligible.

⁴¹ Because these migration estimates are based on a weighted sample, they may be surrounded by generous confidence intervals, an issue most salient for those states with very small migration flows; as such, the very small migration flows (e.g. those less than 1,000) may not be significantly different from 0. The purpose here is to highlight broad migration trends, rather than provide exact population estimates.

3.4.2 The Spatial Distribution of Puerto Ricans

Maps 3.1 and 3.2 show the distribution of the Puerto Rican-born and Puerto Rican-origin populations in 2000. In these maps, states with large Puerto Rican populations in 1995 (greater than 25,000) are highlighted in gray. In addition, icons represent population change over the period 1995 to 2000, with stars indicating those states with population gains and circles indicating those states with population losses. The map showing the population born in Puerto Rico confirms that this population segment is concentrated in a few states in the Northeast, as well as other states which are historically large immigrant-receiving states and which have large populations overall (Frey 1996). Growth in the Puerto Rican-born population is also strongest in those states which have existing large Puerto Rican-born populations, suggesting that Puerto Rican natives may be migrating to be nearer to co-ethnics. Only two states which do not already have large existing populations of Puerto Rican natives, Texas and Ohio, exhibit fast growing Puerto Rican-born populations. The map displaying the distribution of the population of Puerto Rican origin suggests that this population is somewhat more dispersed than that of Puerto Rican immigrants. Internal migration of the Puerto Rican-origin population is evident in several states in the South and Southeast, including three, Virginia, North Carolina, and Georgia, which do not have historically large Puerto Rican populations. California, Illinois, and Massachusetts, exhibit large but non-increasing populations of Puerto Rican origin.

Aggregation of populations to the state-level obscures variation in the distribution of the Puerto Rican population within states. To allow for a more nuanced view of the

spatial concentration of Puerto Ricans within the United States, Maps 3.3 and 3.4 show the distribution of island-born Puerto Ricans and 2nd and higher generation Puerto Ricans, respectively, by mig-PUMA. As noted above, mig-PUMA's are composed of a single county or a small group of geographically contiguous counties. These maps illustrate three levels of concentration, with Puerto Ricans comprising a small proportion (less than 1%) of the population of the light gray mig-PUMA's and a large proportion (more than 1%) of the population of the mig-PUMAs shaded in black; unshaded mig-PUMA's contain no Puerto Rican population.

Similar to the state-level maps, these maps indicate that both the population born in Puerto Rico and the population of Puerto Rican-origin are geographically concentrated, and that the residential patterns of the two populations largely overlap. The somewhat greater dispersion of the population of Puerto Rican origin is likely the result of the relative size of this group, which is approximately 2/3 larger than the native-born Puerto Rican population. For both groups, the largest concentrations exist in the New York metropolitan area, central and southern Florida, and eastern Pennsylvania. There are also notable populations of both groups in the former Rust Belt cities of Cleveland, Buffalo, Rochester, and Springfield, Massachusetts. While there are few mig-PUMA's outside of Florida and the Northeast with large island-born Puerto Rican populations, some Southern areas, which include the cities of Clarksville, TN, Savannah, GA, and Wilmington, NC, have a significant number of 2nd and higher generation Puerto Ricans. These maps also indicate that, although the bulk of the Puerto Rican population is concentrated in a relatively small number of mig-PUMA's, there is at least some level of Puerto Rican representation in the majority of the mig-PUMA's across the nation.

This examination of the domestic migration of Puerto Ricans in the United States illustrates two main points. First, the migration of Puerto Ricans, both those individuals born in Puerto Rico and those individuals born in the U.S., appears to be dominated by out-flows from New York and in-flows to Florida. In fact, in the period 1995-2000, Florida gained an estimated 9,339 island-born migrants and an estimated 15,950 mainland-born migrants from New York alone. Secondly, the rates of interstate migration for individuals born in Puerto Rico (7.5%) and Puerto Rican individuals born in the U.S. (9.4%) are similar to the rate for the U.S. population as a whole (8.4%).⁴² The somewhat higher rate of interstate migration for the Puerto Rican population born in the 50 states is possibly a result of the social or demographic characteristics of that segment of the population, which are investigated next.

3.4.3 Characteristics of Secondary Puerto Rican Migrants

Summary statistics on the sociodemographic characteristics of Puerto Rican migrants in the U.S. are displayed in Table 3.3. This table (and all further analyses) were restricted to individuals between the ages of 25 and 64 who were designated in the survey as the head of the household, to remove the effect of interdependence between household members in the migration decision. Statistics are shown for the entire migration sample, as well as stratified by migration outcome, for migrants born in Puerto Rico and migrants born in the U.S. separately.

Among those individuals born in Puerto Rico, secondary migrants tend to be younger and have spent fewer years in the U.S., yet also have greater levels of human

⁴² 2000 United States Census, Summary File 3.

capital and labor market participation. They also have, on average, lower household incomes than do those individuals who do not change residence. Interstate migrants are younger than intrastate migrants and have increased levels of schooling and labor market participation. There are no statistical differences in employment status between the different migration outcomes. It is worth noting that the mean number of years in the U.S. for this population born in Puerto Rico (27.6) is quite high, implying a mean age of arrival in the U.S. of approximately 18.⁴³ The sociodemographic pattern of migrants versus non-migrants among the Puerto Rican population born in the U.S. is similar to that of the population born on the island. mainland-born Puerto Rican migrants tend to be younger than their non-migrating counterparts, and have higher levels of educational attainment and labor force attachment. Within the Puerto Rican-origin population that migrates, interstate migrants are more likely to have graduated high school and are more likely to have a college degree, relative to intrastate migrants, but there is no difference in the mean age of these two groups.

Although our intention is to compare internal or secondary migrants, it may be informative to look at some basic characteristics of those individuals who moved from the United States to Puerto Rico during the period 1995-2000. Immigrant Puerto Ricans who returned to the island had slightly higher levels of education than the population which remained in the U.S., but were less likely to speak English fluently, less likely to be part of the labor force, and more likely to live in poverty. Mainland-born Puerto

⁴³ The mean age of arrival does not account for the possible bias caused by circular migration between the U.S. and Puerto Rico. In addition, a small number of individuals (n=10) indicated residence in the U.S. of a number of years greater than their age; these individuals were coded as arriving at age 0.

Ricans who moved to Puerto Rico displayed overall lower levels of human capital.⁴⁴ As expected, return migration to Puerto Rico was higher for those individuals born in Puerto Rico relative to those born in the U.S, although the emigration of neither group was very large.⁴⁵

Heterogeneity within and between the Puerto Rican-born and Puerto Rican-origin populations in those characteristics associated with migration behavior may imply differences in migration outcomes for the two groups. The mainland-born Puerto Rican population is significantly younger than the island-born population, suggesting that the increased migration exhibited by this group may be a function of age. However, the island-born population has higher levels of education and a higher average income, which are additional factors predictive of residential migration. To isolate the independent effects of each of these population characteristics, regression analysis is used.

3.4.4 Multinomial Logistic Regression Analysis

Multinomial logistic regression is commonly used to model ordinal outcomes for which the difference in outcomes has no numerical interpretation. Such is the case in many migration analyses, where the choice of residence may be one of many mutually exclusive options. In this analysis, the migration outcome is one of three alternatives: No migration, intrastate migration, and interstate migration.

The results from the multinomial logistic regression are presented in Table 3.4 by

⁴⁴ While these individuals emigrated at some point between 1995 and 2000, the covariates are measured in Puerto Rico in 2000, and the context of labor force participation and poverty may be different in Puerto Rico than in the United States.

⁴⁵ Of the population living in the U.S. in 1995, a little more than 4% of individuals born in Puerto Rico had returned to the island by 2000, compared to less than 1% of the population born in the U.S.

migration outcome, separately for those individuals born in Puerto Rico and those individuals born in the U.S. Coefficients are reported as odds ratios, or the change in the odds of the migration outcome associated with a change in the covariate. In addition to the usual tests for significant individual coefficients, this table indicates those covariates for which the coefficients on alternative outcomes (intrastate migration or interstate migration) differ within a group and those covariates for which the coefficients vary between the Puerto Rican-born and the Puerto Rican-origin groups.⁴⁶

For both island-born and mainland-born Puerto Ricans, males are more likely than females to undertake any migration, although the magnitude of this effect may be confounded by the fact that males are more likely to be listed as the head of household. The gender effect is larger for migration to a new state than for migration within the same state, with island-born Puerto Rican men 64% more likely than Puerto Rican women to move to a new state, relative to staying in the same house.

The migration propensities for both nativity groups decline with age, although there are subtle differences within the various cohorts. Puerto Rican-born individuals between the ages of 35 and 44 are approximately half as likely to migrate relative to Puerto Rican-born individuals between the ages of 25 and 34, whether the migration decision is intrastate or interstate. Puerto Rican-origin individuals in the same 35-44 age group, however, while still less likely to migrate than the younger cohort, are significantly less likely to move within-state than to move between-states. This is surprising, as it is the only age group for which interstate migration is preferred over

⁴⁶ Differences in coefficients among alternatives for each group were identified using a Wald Test, while differences between the coefficient estimates of the two groups were assessed through an interaction of a Puerto Rican-born indicator with each remaining covariate in an analysis of the combined sample.

intrastate migration, and suggests that individuals in this age group may be exerting substantial influence on the trend in interstate migration.

Married Puerto Ricans are no more likely than their single counterparts to make an intrastate move, but married individuals are considerably more likely than single individuals to make an interstate move among both the island-born and mainland-born populations. Increased migration propensity is observed among those respondents who are divorced, separated or widowed, while the presence of children in the household is associated with a decreased likelihood of migration.

Not surprisingly, homeownership is related to a decreased propensity to change residences between 1995 and 2000, although it is not possible to ascertain whether the individual was a homeowner prior to the move. Both island-born Puerto Rican homeowners and Puerto Rican homeowners born in the U.S. were, relative to renters, more likely to have migrated within-state than to a new state in the prior five years, although mainland-born Puerto Rican homeowners were more likely to have made an intrastate move than their immigrant counterparts.

There is no measurable impact of increased educational attainment on within-state migration for either of the Puerto Rican groups, although college educated individuals in both groups are more likely to make interstate moves. The effect of a college degree is quite large, with a Puerto Rican-born college graduate three times more likely to make an interstate move than an individual with less than a high school education. The importance of education in explaining migration behavior might also account for the mostly insignificant effects observed for the income variables, with which education is correlated.

Among individuals born in Puerto Rico, English fluency does not show a significant impact on the migration decision, likely the result of this effect being conditional on educational attainment. Puerto Ricans born in the U.S. who speak English well are more likely to make an interstate move than are those who do not speak English well. Finally, for Puerto Ricans not born in the U.S., length of time spent on the mainland appears to have a dampening effect on migration behavior, with longer tenured cohorts exhibiting reduced propensities to move from their current residence. There are no differences in the effect of immigration year on intrastate versus interstate migration.

The effects of the structural covariates on intrastate migration are similar between Puerto Rican-born individuals and Puerto Rican-origin individuals, with both groups displaying increased odds of moving to mig-PUMAs with a greater existing concentration of Puerto Ricans and to mig-PUMAs with higher employment in the construction industry and decreased odds of moving to mig-PUMAs with greater poverty. While island-born Puerto Ricans are less likely to make an in-state move to a mig-PUMA with a higher unemployment rate, this coefficient is not significant for mainland-born Puerto Ricans. In making interstate moves, both Puerto Rican groups exhibit remarkably reduced odds of moving to a mig-PUMA with a higher rate of unemployment, but somewhat increased odds of moving to a mig-PUMA with a higher rate of poverty. Island-born Puerto Ricans are also significantly more likely to make an interstate move to a mig-PUMA with a larger concentration of existing Puerto Ricans; the same is not true for Puerto Ricans born in the 50 states.

While the significance levels for specific coefficients vary between the population born in Puerto Rico and the population born in the U.S., the general pattern of parameters

is quite concordant between the two groups. Only two variables, one identifying individuals in the age group 35-44 and the other denoting the language ability of respondents, exhibit a statistically different impact on the island-born population versus the mainland-born population. While the fact that English fluency is more predictive of migration for mainland-born Puerto Ricans than for island-born Puerto Ricans may seem counterintuitive, the relevance of language acquisition to this former group may be greater as the expectation for English fluency may be greater. Although the number of mainland-born Puerto Rican heads of household who report not speaking English well is small (n=255, 2% of the sample), this population segment is likely unique. In terms of the contextual factors associated with migration, island-born and mainland-born Puerto Ricans differ in their response to the level of unemployment and the proportion of the populace with a college degree. Both groups are less likely to make an interstate move to a mig-PUMA with a higher unemployment rate than their origin mig-PUMA, although Puerto Ricans born on the island are significantly less likely to do so than are Puerto Ricans born in the U.S. Island-born Puerto Ricans are also less likely to make an interstate move to a mig-PUMA with a greater proportion of college graduates; this effect is not seen in mainland-born Puerto Ricans.

Although the characteristics which predict internal migration show little variation between Puerto Ricans born in Puerto Rico and Puerto Ricans born in the 50 states, it may be helpful to compare these estimates to those from other segments of the population. To that end, intrastate and interstate migration of the non-Hispanic white population, the U.S.-born Hispanic population (excluding Puerto Ricans), and the foreign born population was analyzed over the period 1995-2000, using the same sample

restrictions and model specification as in the Puerto Rican analysis. The results from these estimations are shown in Table 3.5 for the outcome of interstate migration only, along with the previous results for island-born and mainland-born Puerto Ricans.

While males of all five groups are more likely than females to make an interstate move, the odds are significantly higher among both of the Puerto Rican groups than for the other groups. This may be related to the restriction of the sample to heads of household, as the head of household is less likely to be male in either of the Puerto Rican groups than in the other groups. Homeownership discourages interstate migration for all of the population segments, but its effect is not as strong among island-born Puerto Ricans and mainland-born Puerto Ricans as it is for the Hispanic group or for the foreign born group. Although the proportion of interstate movers who are homeowners is similar between the Puerto Rican groups and the foreign born and Hispanic groups, the proportion of the total population that are homeowners is much higher in these latter two groups. Compared to other U.S.-born Hispanics, married Puerto Ricans are much more likely to make an interstate move than are single Puerto Ricans (1.54 vs. 1.11). The age gradient of interstate migration is the steepest for the non-Hispanic white population, suggesting the overall increased mobility of the Puerto Rican populations, as well as the foreign born and native Hispanic populations. While Hispanics and foreign born individuals share the preference of island-born Puerto Ricans to move to areas with greater concentrations of Puerto Ricans, non-Hispanic whites display a significant disinclination to make such a move.

Overall, mainland-born Puerto Ricans are the most mobile of the five population segments observed here (Figure 3.1), with this group displaying the highest rates of both

intrastate and interstate migration. While native-born Hispanics exhibit within-state migration rates similar to that of mainland-born Puerto Ricans, they appear much less likely to make an interstate move. Island-born Puerto Ricans, however, have much lower rates of migration than the other groups, with the exception of non-Hispanic whites.

3.5 Discussion

The results from the analysis of interstate migration indicate that the destinations for internal Puerto Rican migrants are largely the same as those for new Puerto Rican immigrants, consistent with research on the migration dynamics of the broader Hispanic population (Lichter and Johnson 2009). The interstate migration of Puerto Ricans, both those individuals born in Puerto Rico and those individuals born in the U.S., is primarily bimodal, with large out-migration from New York accompanied by substantial in-migration to Florida. Historical settlement patterns for Puerto Ricans in the U.S., wherein the large majority of the population used to reside in New York, is likely one driving force behind this state's significant sending status. Second and higher generation Puerto Ricans, themselves the children of prior generation Puerto Rican immigrants into New York, may be leaving the state in search of better opportunities elsewhere. The data in Table 3.3 indicate that, among both Puerto Rican groups, interstate migrants have higher levels of human capital and are better situated economically than non-movers. This may have implications for the economic and political health of Puerto Rican communities in states, such as New York, which exhibit negative net migration of Puerto Ricans. The finding that island-born Puerto Ricans are less likely than their mainland-born counterparts to move towards areas with lower concentrations of Puerto Ricans is

consistent with Foulkes and Newbold's (2000) results for the same groups over the period 1985-1990. They show evidence that, unlike island-born Puerto Ricans and native born and foreign born Cubans and Mexicans, Mainland-born Puerto Ricans are no less likely to move out of their origin county as the share of co-ethnics in their origin county increases. It may be the case that, like other immigrant groups that may tend to cluster in enclaves, island-born Puerto Ricans derive benefit from living near co-ethnics, a benefit that is not realized by the Puerto Ricans born on the mainland. These results also suggest that the deconcentration of the Puerto Rican population may be a consequence of the dispersion of the 2nd and higher generation Puerto Rican individuals.

Mainland-born Puerto Ricans ages 35-44 are more likely to migrate between states as they are within the same state, an outcome which may in fact be a consequence of the increasing suburbanization of this group. One of the drawbacks in defining migration only in terms of intrastate or interstate is that these definitions disregard geographical distances within and between states. Foulkes and Newbold (2000) note that the historical settlement patterns of different Hispanic groups have implications for whether a move is classified as intrastate or interstate, as Puerto Ricans tend to live in the spatially compact Northeast and Mexicans tend to live in the relatively vast West. Puerto Ricans who move within the New York metropolitan area, from the city of New York to Jersey City for example, will be classified as interstate movers, while a similar move for a Mexican between the city of Los Angeles and Orange County would be classified as intrastate. Future research may instead wish to focus on the distance over which the migrant moves, as this measure may better reflect the social and economic impact of the migration event.

One limitation of this analysis is that the measurement of the contextual variables at the level of the mig-PUMA may insufficiently describe the true character of the origin and destination areas, and that unmeasured or unmeasurable factors may be drawing migrants to new destinations or keeping them in their current place. While we attempt to measure the effect of the presence of co-ethnics on the migration decision, it is difficult to simultaneously incorporate the characteristics of both the sending and the receiving state into this individual-level migration framework, as the number of potential interstate movements is large, and the number of Puerto Rican individuals making the transition between any two given states is quite small. The exception, of course, is migration between the states of New York and Florida, which accounts for nearly 13% of all interstate moves. The fact that such a substantial proportion of interstate migration occurs between these two states suggests that a more nuanced analysis of this particular migration stream may be appropriate.

While the use of Census PUMS data allows for a large, nationally representative sample, the migration information available in the data has limitations. The structure of the migration question on the Census allows only the identification of single movements, and the five year span encompassed by the question may mask multiple migration events, particularly among a population that has been shown to be highly mobile. This problem is alleviated somewhat in the recent data being released from the American Community Survey (ACS), for which the period of migration that is observed is a single year. However, there is still some uncertainty among researchers on how to deal with this ACS migration data, as the one year period to which the ACS question refers may occur at any point during the five year period covered by the survey (see Rogers, Raymer, and

Newbold (2003) and Franklin and Plane (2006) for a discussion of the ACS migration data). The five year duration over which migration is measured may be particularly relevant in the context of Puerto Ricans, as these individuals may exhibit high levels of circular migration or return migration which is unaccounted for.

3.5.1 Conclusion

The geographic concentration of Puerto Ricans in the Northeastern United States appears to have diminished in recent years, with both mainland-born and island-born individuals displaying increased dispersion out of New York and its immediate surroundings. This is particularly true of 2nd and higher generation Puerto Ricans, who are showing up in large numbers in several Southern states. In general, the Puerto Rican population born on the mainland is a highly mobile group, exhibiting intrastate and interstate migration rates larger than those of island-born Puerto Ricans. This increased migration propensity appears to be at least partly the consequence of characteristics of this group, which is younger and more highly educated than the island-born Puerto Rican group. Overall, we see few differences in those characteristics which predict internal migration between Puerto Ricans born in Puerto Rico and Puerto Ricans born in the U.S.

Table 3.1: Puerto Rican Population by State and Prior Residence, 2000

Puerto Rican Born					
	Pop 2000	Residence in 1995			% "new"
		Same State	Diff State	Puerto Rico	
New York	361,224	328,269	6,944	19,817	0.08
Florida	238,447	159,840	29,799	42,842	0.31
New Jersey	141,094	122,400	6,177	10,162	0.12
Massachusetts	93,569	71,874	4,799	14,150	0.21
Pennsylvania	92,086	69,379	7,870	12,572	0.23
Connecticut	85,882	67,541	4,858	11,212	0.19
Illinois	55,508	48,982	1,966	3,329	0.10
California	34,562	27,836	3,931	2,174	0.18
Texas	28,520	18,594	3,939	5,236	0.33
Ohio	23,854	17,801	1,705	3,875	0.24
Remaining States	139,915	86,438	25,142	22,835	0.36
U.S. Total	1,294,661	1,018,954	97,130	148,204	0.19

Note: States listed had a Puerto Rican-born population of at least 20,000 in 2000; all other states are aggregated in the "Remaining States" group. Excludes Puerto Ricans born in foreign countries. Columns do not sum to the total due to births during the period and the exclusion of individuals living in foreign countries in 1995.

Puerto Rican Origin					
	Pop 2000	Residence in 1995			% "new"
		Same State	Diff State	Puerto Rico	
New York	657,019	548,307	15,648	5,527	0.04
Florida	228,247	144,749	40,973	7,836	0.25
New Jersey	220,837	169,303	15,842	2,756	0.10
Pennsylvania	138,591	98,502	12,344	2,129	0.13
Connecticut	107,985	79,771	7,035	2,414	0.11
Massachusetts	102,836	75,336	6,592	2,155	0.10
California	102,076	78,917	9,510	669	0.11
Illinois	94,712	76,663	4,179	1,404	0.07
Ohio	40,741	29,855	3,445	443	0.12
Texas	39,178	24,429	7,498	869	0.26
Remaining States	299,100	176,932	68,787	5,885	0.30
U.S. Total	2,031,322	1,502,764	191,853	32,087	0.13

Note: States listed had a Puerto Rican-origin population of at least 30,000 in 2000; all other states are aggregated in the "Remaining States" group. Columns do not sum to the total due to births during the period and the exclusion of individuals living in foreign countries in 1995.

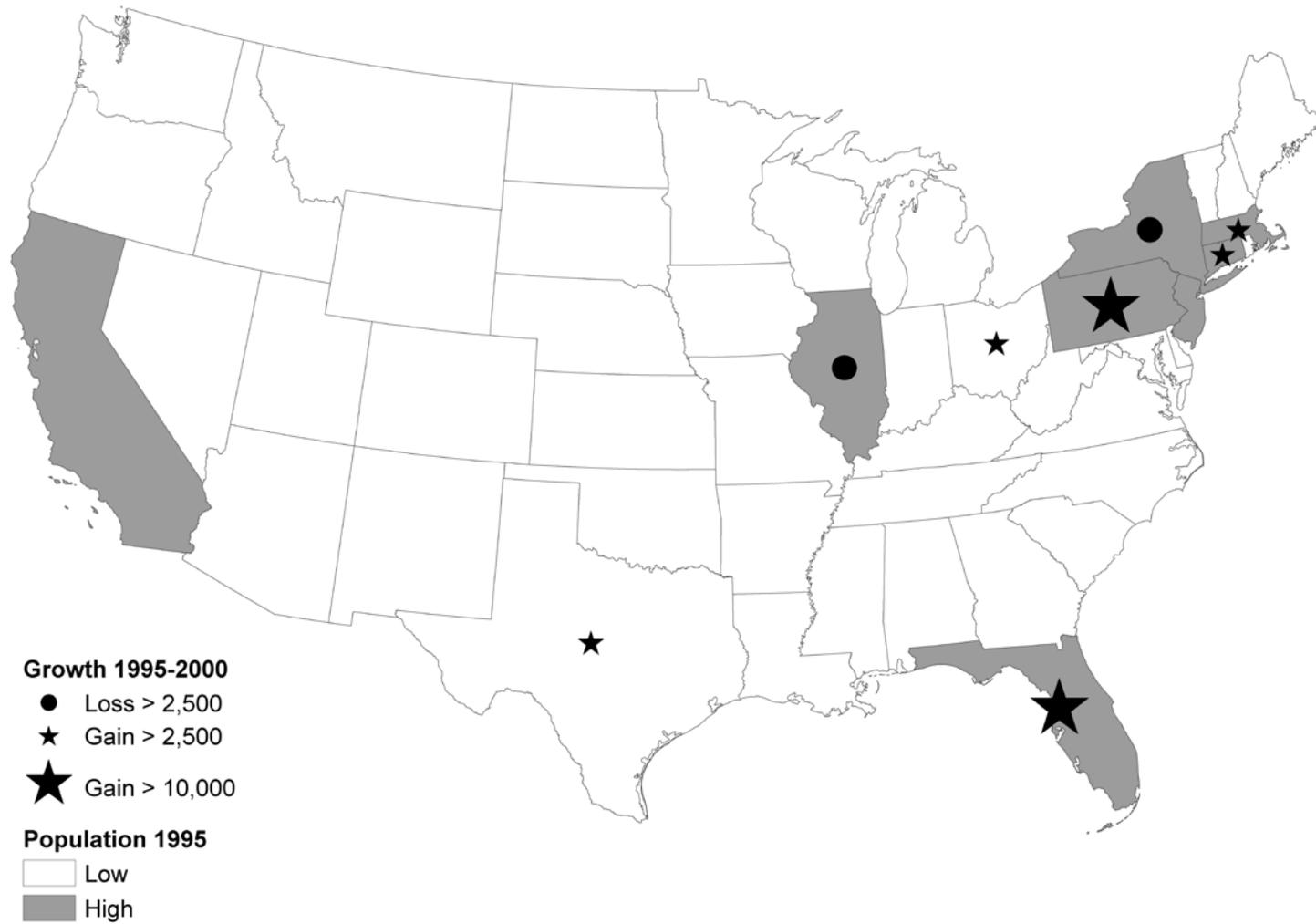
Table 3.2: Net Puerto Rican Migration by State, 1995-2000

Puerto Rican Born			
	Net Migration Between		PR-Born Population in 2000
	Other States	Puerto Rico	
Florida	20,009	30,488	238,447
Pennsylvania	2,873	9,007	92,086
Texas	868	4,357	28,520
Connecticut	73	6,574	85,882
Ohio	53	2,716	23,854
Massachusetts	(1,551)	9,565	93,569
New Jersey	(4,781)	2,818	141,094
New York	(19,411)	(485)	361,224

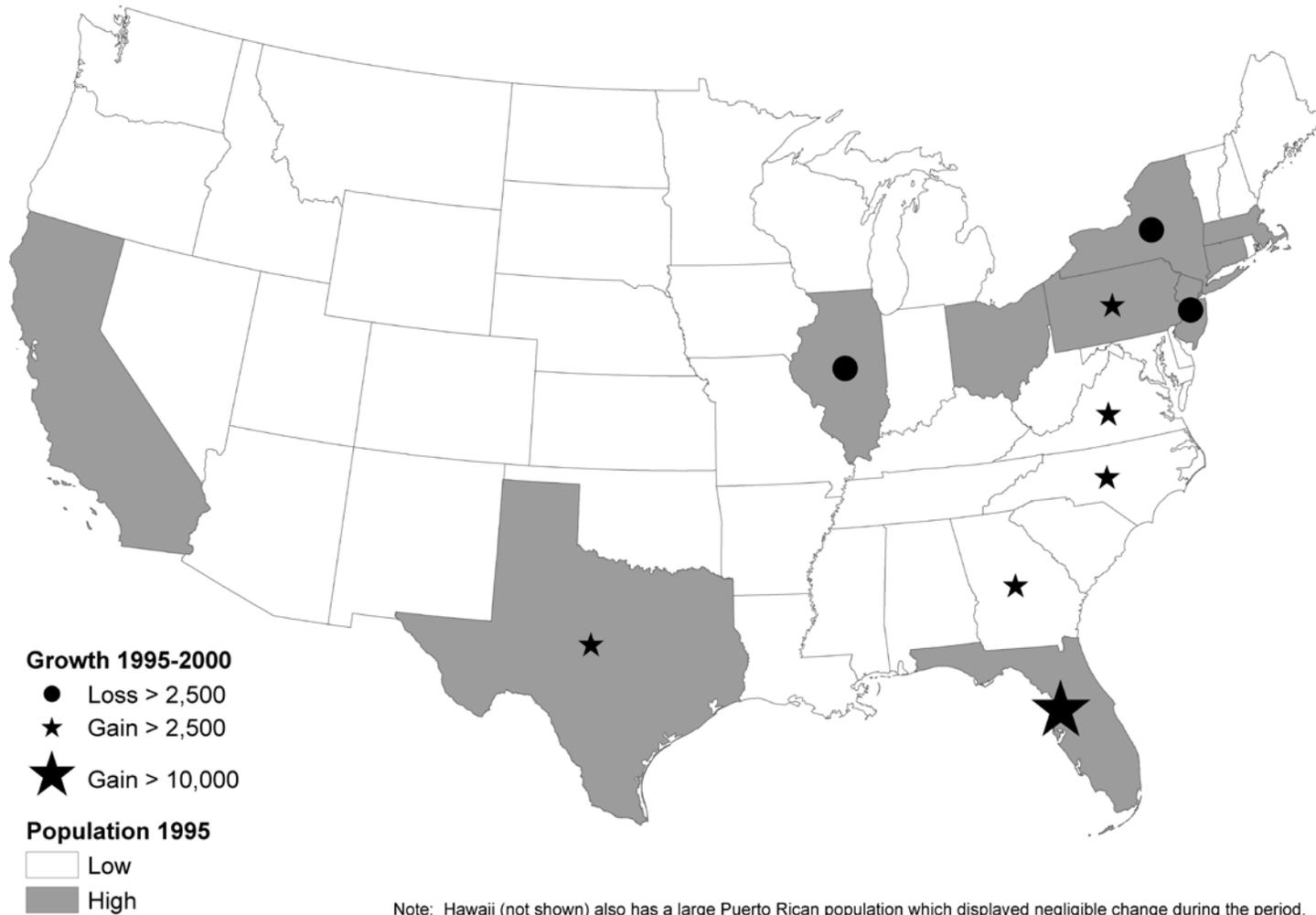
Puerto Rican Origin			
	Net Migration Between		PR-Origin Population in 2000
	Other States	Puerto Rico	
Florida	25,149	5,909	228,247
Georgia	3,052	238	20,398
North Carolina	3,012	307	20,126
Virginia	2,884	101	25,881
Pennsylvania	2,735	717	138,591
Illinois	(2,777)	(86)	94,712
New Jersey	(3,768)	(761)	220,837
New York	(43,205)	(1,112)	657,019

Note: States listed had minimum net migration of +/- 2,500 between other states or Puerto Rico between 1995 and 2000. Parentheses indicate net population loss.

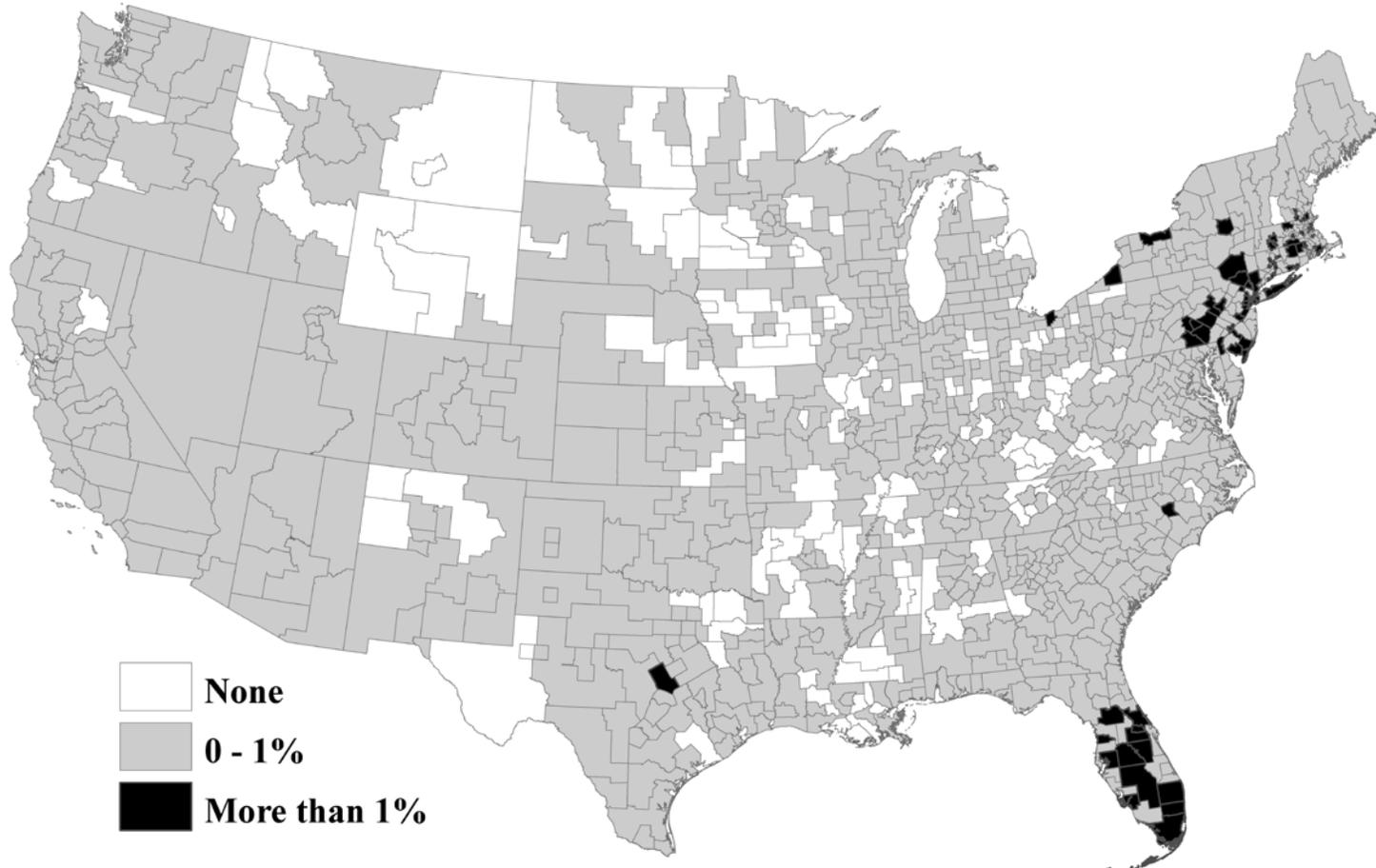
Map 3.1: State-Level Distribution of Population Born in Puerto Rico, 1995-2000



Map 3.2: State-Level Distribution of Population of Puerto Rican Origin, 1995-2000



Map 3.3: PUMA-Level Distribution of Population Born in Puerto Rico, 2000



Map 3.4: PUMA-Level Distribution of Population of Puerto Rican Origin, 2000

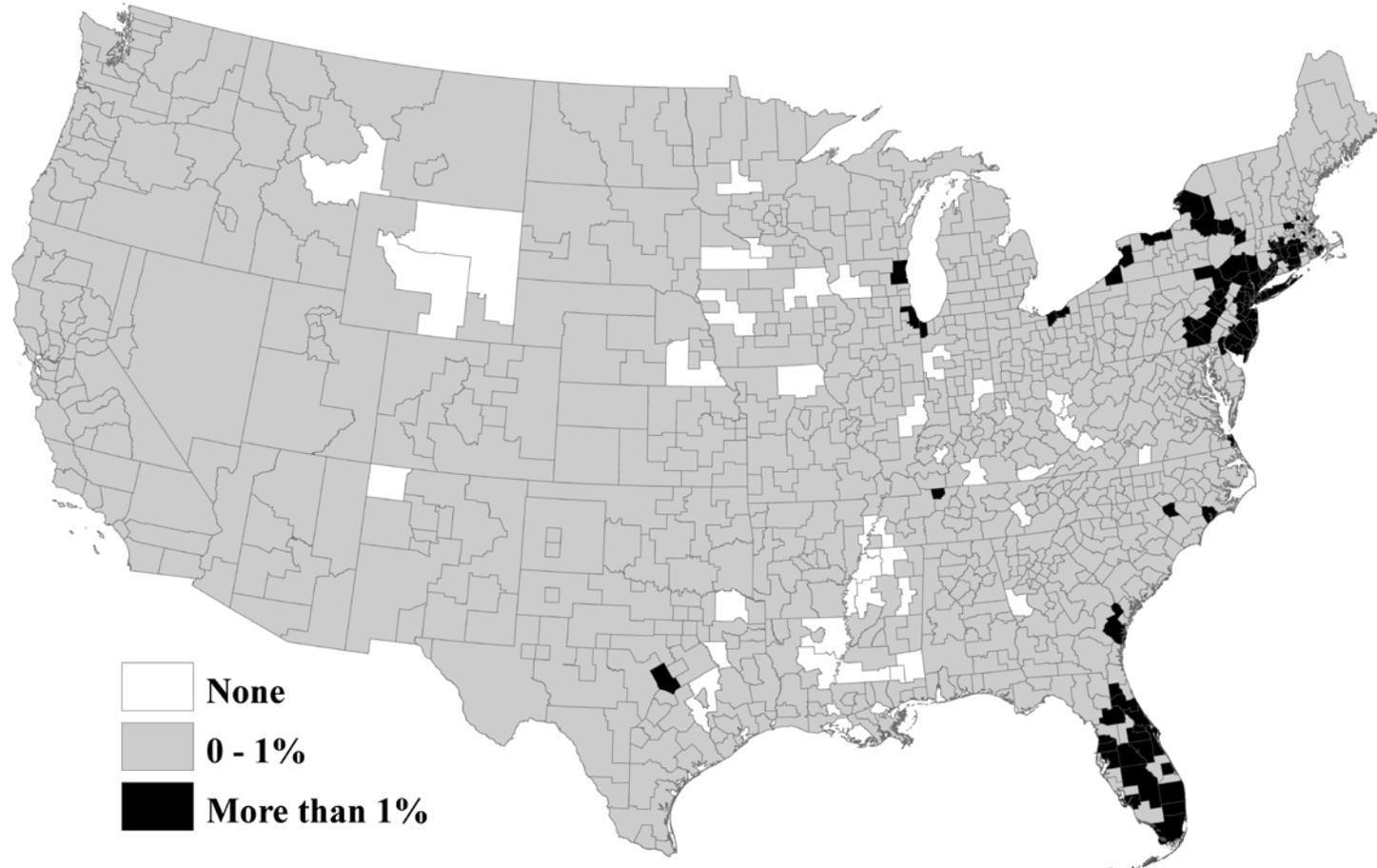


Table 3.3: Characteristics of the Puerto Rican Population in the U.S. by Migration Outcome, 1995-2000

	Born in Puerto Rico				Born in the U.S.			
	Non Mover	Movers		Total	Non Mover	Movers		Total
		Same State	Diff State			Same State	Diff State	
Mean Age	48.2	42.4	40.8	45.4	40.1	35.1	35.1	37.3
% Male	55%	53%	62%	55%	53%	52%	61%	54%
Mean Years in USA	30.3	24.6	23.5	27.6	--	--	--	--
% Speak English	80%	81%	87%	81%	98%	98%	99%	98%
% Single	17%	23%	21%	20%	26%	32%	27%	29%
% Married	51%	43%	51%	48%	48%	42%	49%	45%
% Homeowner	43%	31%	32%	37%	45%	34%	31%	38%
% Any Children	63%	62%	61%	62%	68%	64%	60%	65%
% High School Grad	54%	58%	69%	57%	79%	79%	86%	80%
% College Grad	10%	11%	22%	11%	15%	15%	23%	16%
% in Labor Force	57%	63%	69%	60%	75%	80%	83%	78%
% Poverty	27%	28%	23%	28%	20%	19%	17%	19%
Mean HH Income	43,154	38,227	43,987	40,553	49,577	46,296	48,817	47,817
Unweighted N	10,994	7,545	1,617	21,102	6,842	7,308	1,914	16,200
Weighted N	245,607	169,266	35,985	450,858	157,187	166,521	43,410	367,118

Sample-weighted population characteristics of Puerto Rican-born and Puerto Rican-origin individuals age 25-64 listed as head of household and living in the United States. Migration measured over the period 1995-2000. Excludes persons moving between Puerto Rico and the United States.

Table 3.4: Odds Ratio Estimates from Regression of Migration Outcome on Individual- and Place-Level Covariates

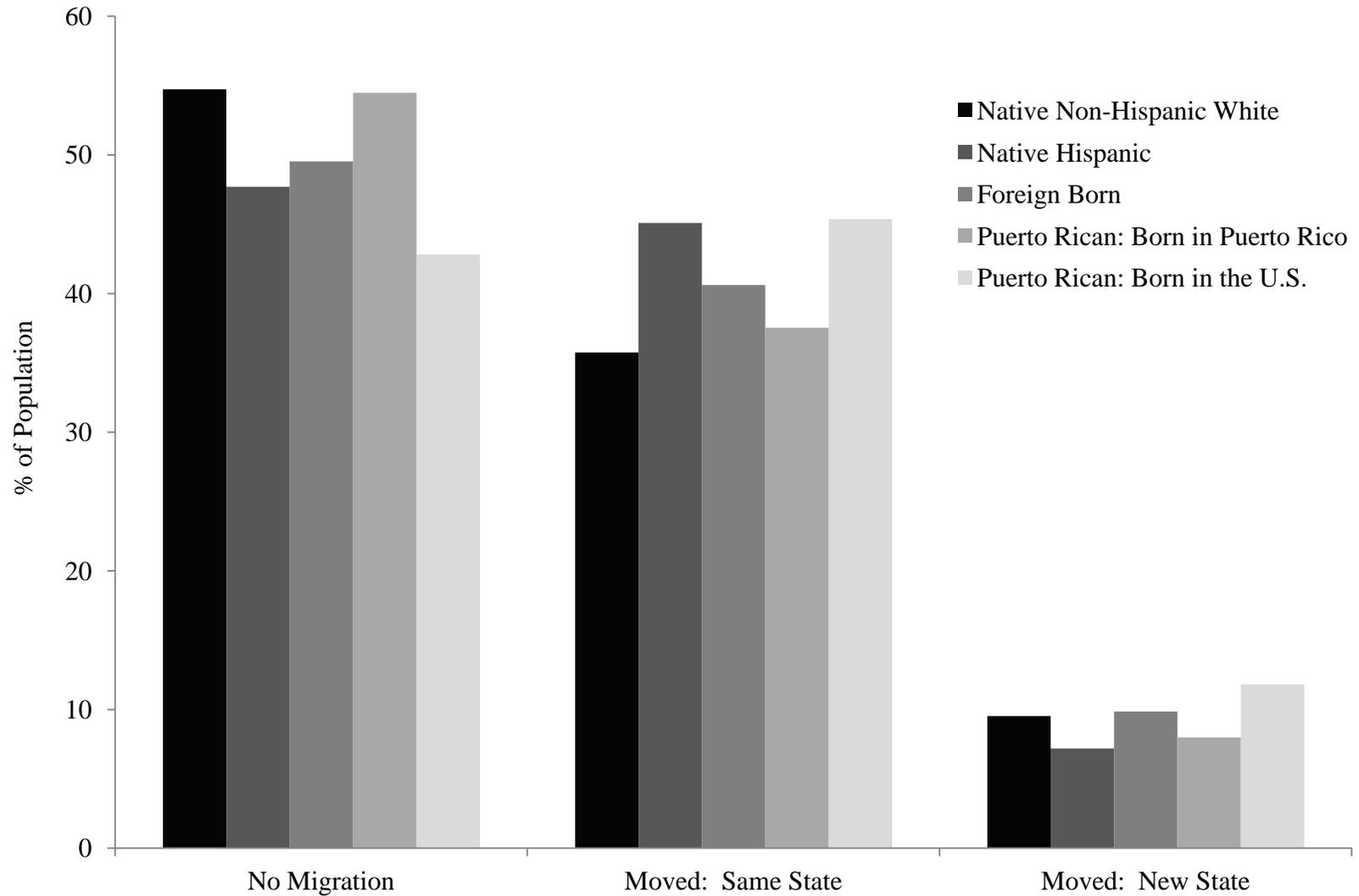
	Puerto Rican-Born				Wald Test 1/2	Puerto Rican-Origin				Wald Test 3/4	Difference: Born vs. Origin			
	1		2			3		4			Intra	Inter		
	Intrastate vs. No Migration		Interstate vs. No Migration			Intrastate vs. No Migration		Interstate vs. No Migration						
Male	***	1.209	(0.05)	***	1.643	(0.12)	*	1.118	(0.05)	***	1.558	(0.11)	*	
Speaks English Well		0.927	(0.04)		1.075	(0.10)		1.234	(0.18)	*	1.880	(0.53)	*	*
Labor Force	***	1.184	(0.05)		1.104	(0.08)		***	1.267	(0.06)	**	1.272	(0.10)	
Homeowner	***	0.665	(0.03)	***	0.472	(0.04)	*	***	0.745	(0.03)	***	0.444	(0.03)	*
Age 35-44	***	0.525	(0.03)	***	0.502	(0.04)		***	0.405	(0.02)	***	0.500	(0.03)	
Age 45-54	***	0.310	(0.02)	***	0.250	(0.03)	*	***	0.225	(0.01)	***	0.194	(0.02)	*
Age 55-64	***	0.233	(0.02)	***	0.175	(0.02)	*	***	0.167	(0.02)	***	0.143	(0.03)	
Married	*	0.890	(0.05)	*	1.221	(0.11)	*	1.011	(0.06)	***	1.540	(0.13)	*	
Divorced	***	1.240	(0.06)	**	1.325	(0.12)		***	1.330	(0.07)	***	1.615	(0.14)	*
Has Any Children	***	0.770	(0.03)	***	0.753	(0.05)		***	0.799	(0.04)	***	0.687	(0.05)	*
High School Grad		0.934	(0.04)		1.018	(0.09)		0.968	(0.06)		1.141	(0.11)		
Some College	*	1.106	(0.06)	***	1.743	(0.15)	*	1.055	(0.06)	***	1.882	(0.17)	*	
College Grad		1.105	(0.07)	***	3.448	(0.37)	*	1.121	(0.08)	***	3.156	(0.35)	*	
Income 2nd Quartile	**	1.145	(0.06)		1.003	(0.08)		1.111	(0.06)		1.036	(0.09)		
Income 3rd Quartile		1.020	(0.06)		0.883	(0.09)		1.057	(0.07)		0.893	(0.09)		
Income 4th Quartile		0.963	(0.06)	*	0.784	(0.09)		1.064	(0.07)		0.816	(0.09)	*	
Immigrated 1980-1990	**	0.827	(0.05)	*	0.809	(0.09)								
Immigrated 1970-1980	***	0.737	(0.05)	***	0.677	(0.07)								
Immigrated Pre-1970	***	0.620	(0.04)	***	0.611	(0.07)								
% PUMA Puerto Rican	***	1.027	(0.01)	*	1.046	(0.02)		**	1.019	(0.01)		1.025	(0.02)	
% PUMA Hispanic	**	0.992	(0.00)		1.013	(0.01)	*	***	0.993	(0.00)		1.002	(0.01)	
% PUMA Unemployed	*	0.937	(0.03)	***	0.413	(0.04)	*	0.994	(0.03)	***	0.612	(0.05)	*	*
% PUMA Poverty	*	0.974	(0.01)	***	1.197	(0.04)	*	***	0.961	(0.01)	**	1.090	(0.03)	*
% PUMA College Degree		0.987	(0.01)	*	0.955	(0.02)		0.992	(0.01)		1.010	(0.01)		*
% PUMA Manufacturing		0.988	(0.01)		0.981	(0.02)		1.006	(0.01)	**	1.053	(0.02)	*	*
% PUMA Construction	**	1.109	(0.04)	***	1.876	(0.16)	*	***	1.091	(0.03)	***	1.669	(0.12)	*
N					20,156						16,064			

Multinomial logistic regression model. * p<.05, ** p<.01, *** p<.001

Table 3.5: Odds Ratio Estimates from Regression of Interstate Migration (versus No Migration) on Individual- and Place-Level Covariates for Native and Foreign Born Groups

	Non-Hispanic White		Native-born Hispanic		Foreign Born		Puerto Rican-Born		Puerto Rican-Origin	
	β	SE	β	SE	β	SE	β	SE	β	SE
DV = Interstate Move										
Male	1.090	(0.007)	1.244	(0.029)	1.176	(0.019)	1.651	(0.122)	1.558	(0.109)
Speaks English Well	1.245	(0.050)	0.920	(0.021)	1.076	(0.020)	0.992	(0.090)	1.880	(0.532)
Labor Force Participant	0.814	(0.006)	1.206	(0.027)	1.162	(0.020)	1.101	(0.080)	1.272	(0.103)
Homeowner	0.171	(0.001)	0.313	(0.006)	0.343	(0.005)	0.471	(0.036)	0.444	(0.032)
Age 35-44	0.282	(0.002)	0.417	(0.009)	0.393	(0.006)	0.459	(0.039)	0.500	(0.034)
Age 45-54	0.130	(0.001)	0.222	(0.006)	0.183	(0.004)	0.211	(0.019)	0.194	(0.021)
Age 55-64	0.108	(0.001)	0.141	(0.005)	0.126	(0.003)	0.141	(0.015)	0.143	(0.026)
Married	1.503	(0.013)	1.110	(0.030)	1.197	(0.024)	1.241	(0.114)	1.540	(0.133)
Divorced	1.456	(0.013)	1.235	(0.037)	1.187	(0.027)	1.332	(0.124)	1.615	(0.142)
Any Children	0.643	(0.004)	0.648	(0.014)	0.630	(0.009)	0.762	(0.053)	0.687	(0.047)
High School Grad	1.205	(0.014)	1.091	(0.027)	1.186	(0.025)	1.029	(0.089)	1.141	(0.110)
Some College	2.165	(0.024)	1.527	(0.038)	1.649	(0.033)	1.799	(0.158)	1.882	(0.175)
College Grad	4.073	(0.046)	2.962	(0.085)	3.618	(0.070)	3.697	(0.387)	3.156	(0.349)
Income 2nd Quartile	0.992	(0.007)	1.006	(0.022)	0.941	(0.017)	0.996	(0.083)	1.036	(0.091)
Income 3rd Quartile	0.998	(0.008)	0.922	(0.025)	0.910	(0.018)	0.864	(0.084)	0.893	(0.087)
Income 4th Quartile	1.162	(0.010)	0.954	(0.030)	0.929	(0.020)	0.752	(0.084)	0.816	(0.090)
Difference Puerto Rican %	0.958	(0.003)	1.018	(0.008)	1.027	(0.005)	1.045	(0.021)	1.025	(0.018)
Difference Hispanic %	0.992	(0.001)	0.963	(0.002)	0.976	(0.001)	1.013	(0.009)	1.002	(0.008)
Difference Poverty Rate	1.095	(0.003)	1.126	(0.013)	1.018	(0.008)	1.197	(0.045)	1.090	(0.033)
Difference Unemployment	0.761	(0.006)	0.586	(0.017)	0.769	(0.017)	0.415	(0.041)	0.612	(0.055)
Difference College Degree %	0.999	(0.001)	0.962	(0.006)	1.007	(0.004)	0.956	(0.017)	1.010	(0.015)
Difference Manufacturing %	1.016	(0.002)	1.003	(0.006)	1.031	(0.004)	0.981	(0.024)	1.053	(0.020)
Difference Construction %	1.499	(0.008)	1.600	(0.036)	1.685	(0.026)	1.871	(0.157)	1.669	(0.117)
N	2,837,135		300,821		423,349		20,156		16,064	

Figure 3.1: Migration Behavior of Population Age 25-64, 1995-2000



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