SOCIOSPATIAL INEQUALITY:

A MULTILEVEL AND GEO-SPATIAL ANALYSIS OF LATINO POVERTY

A Dissertation

by

CARLOS SIORDIA

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

December 2011

Major Subject: Sociology

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ABSTRACT

Sociospatial Inequality: A Multilevel and Geo-Spatial Study of Latino Poverty.

(December 2011)

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Sociology at its core has always been interested in understanding how society works. Previous studies on social stratification have sought to outline who gets what, when, and why. This project introduces the *where* element to advance our understanding of how resource distribution affects life chances.

The research question is: Does the percent of Latinos in the area of residence have an influence on Latino's individual poverty over and above the influence on poverty of the person characteristics? The study ascertains how micro-level inequality is influenced by macro-level attributes and explores how spatial non-stationarity plays a role in these mechanics. This sociospatial inequality investigation will delineate how individual-level stratifying mechanisms are influenced by context-level structural attributes and how sociospatial non-stationary processes play a role in these mechanics.

The dissertation is conceptually driven by Hubert M. Blalock's 1970 theory on minority relationships. Blalock posited the testable hypothesis that discrimination against oppressed groups increases when their population rises. Using theoretical

propositions inspired by Blalock leads to the testing of the following two formal hypothesis: the multilevel hypothesis (H^1) focuses on macro-level effects, I hypothesize that as the percent of Latinos/as in the area of residence increases, the odds of being in poverty will increase for Latinas/os; on the spatial hypothesis (H^2), I hypothesize that the statistical association between percent Latina/o and percent poverty is spatially nonstationary.

I find that H^1 cannot be falsified. The models reveal, as Blalock predicted, that as the percent of Latinos/as in the area of residence increases, the odds of being in poverty increase for Latinas/os (even after controlling for various level-1, level-2, and GWR-level-2 factors). I also find that H^2 could not be falsified. I find that the statistical association between percent Latina/o and percent poverty is spatially nonstationary.

My multilevel and spatial modeling investigation was unable to falsify Blalock's minority group threat theory. Hierarchical models indicate that as the percent of Latino/a increases, the likelihood of being in poverty for Latinas/os increases. This statically significant relationship holds constant even after spatial nonstationarity level-2 control factors are introduced.

DEDICATION

The dissertation is dedicated to all those who made it possible. To my family: Mother, Father, Brothers, and Sons—thank you for always believing in me. To my colleagues: Thank you for contributing to my academic development. I am deeply grateful to all those before me who have paved the way for opportunities to exist. And to my wife, Laura, who makes everything worthwhile.

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I would like to thank my committee co-chair, Rogelio Saenz, for his guidance and support through my graduate career at Texas A&M University. His patient help and wise insight into field of social demography solidified my interest in the field. In the war of ideas, I would follow him blindly into battle field. Gracias por todo Rogelio!

I would also like to give special thanks my committee co-chair Dr. Dudley L. Poston for always motivating me and showing, by example, that academia is a fun and worthwhile life endeavor. Dr. Poston's excitement and understanding about my work fuelled me with energy. Thank you Dr. William McIntosh for all the support you offered me from year one as a new graduate student. Dr. McIntosh's continued encouragement and extensive experience helped me grow as an academic. I will be eternally indebted to Dr. Douglas F. Wunneburger for planting the seed of interest on all things spatial. Your guidance and support throughout the course of this research has been notable. Dr. Wunneburger's passion and expert authority on spatial analysis sparked in me a deep appreciation for the wonderful universe of spatiality. I'm deeply grateful to each and every one of them. With their help, I have enjoyed and grown in my journey through graduate school.

Thank you to all my colleagues and the department faculty and staff for making my time at Texas A&M University a great experience. Finally, thanks to my mother, father, bothers, and sons, and canine companions for their encouragement and to my wife for her patience and acceptance.

NOMENCLATURE

ACS	American Community Survey
PUMS	Public Use Microdata Sample
PUMA	Public Use Microdata Area
HLM	Hierarchical Linear Model (computer software)
HGLM	Hierarchical Generalized Linear Model
ArcGIS	Geographic Information System (computer software)
GWR	Geographically Weighted Regression
OMB	Office of Management and Budget
ASEC	Annual Social and Economic Supplement
CPS	Current Population Survey

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CHAPTER I

INTRODUCTION

Research Overview

"Inequality—the study of who gets what and why—has been at the heart of sociology since its inception. However, this simple formula fails to acknowledge that ***where*** is also a fundamental component of resource distribution."
Lobao, Hooks, and Tickamyer 2007:1

In September 2010 CBS News alerted our nation that the "ranks of the working-age poor climbed to the highest level since the 1960s…leaving one in seven Americans in poverty." (CBS News: 1) and four months later, in January 2011, they increased the alarmed by informing us that the "number of poor people in the U.S. is millions higher than previously known, with 1 in 6 Americans" struggling in poverty (CBS News: 2). The mass media message is clear: The USA is in financial trouble and many of us are suffering. They conveyed this message by simply talking about the increasing number of people living in poverty. They were not crying wolf. The US is in financial and thus social trouble. Social disequilibrium is affecting both 'people' and 'places' in different ways—they are suffering unequally.

This dissertation seeks to answer how social inequality, as measured by poverty presence, differs by demographic characteristics and social context. In particular, it dependence plays a role in social inequality and will experiment with the idea of spatial non-stationarity by introducing spatially-dependent coefficients in the final models.

This dissertation follows the style and format of *American Sociological Review*.

In short, the dissertation argues and gives quantitative support for the idea that both socioeconomic inequality and percent of minorities in a community rise and fall congruently because there are social structures that bind their movements. I argue and theorize that the primary element perpetuating this positive relationship has to do with systematic discriminatory practices rooted in human nature and structuralized by biased informal interactions and formal organizations. We will now turn our attention to current poverty trends and a short discussion of why we should study poverty. I will close with a ‘full disclosure’ statement.

Poverty in the United States

Despite many governmental and private initiatives, USA poverty levels have seesaw but have on average remained roughly the same over the last decades. Economic recessions and booms have come and gone and social inequality has stubbornly retained its infamous but firm place in American society. For example, data from the Annual Social and Economic Supplement (ASEC) created by the Current Population Survey (CPS) estimates that in 1980, about 13% of the US population lived at or below the poverty line and that by 2009; about 14% of them lived at or below the poverty line. The one percent difference in almost 30 years hides the fact that in 2009 there was a bigger population base—which means there are more people living in poverty than in 1980.

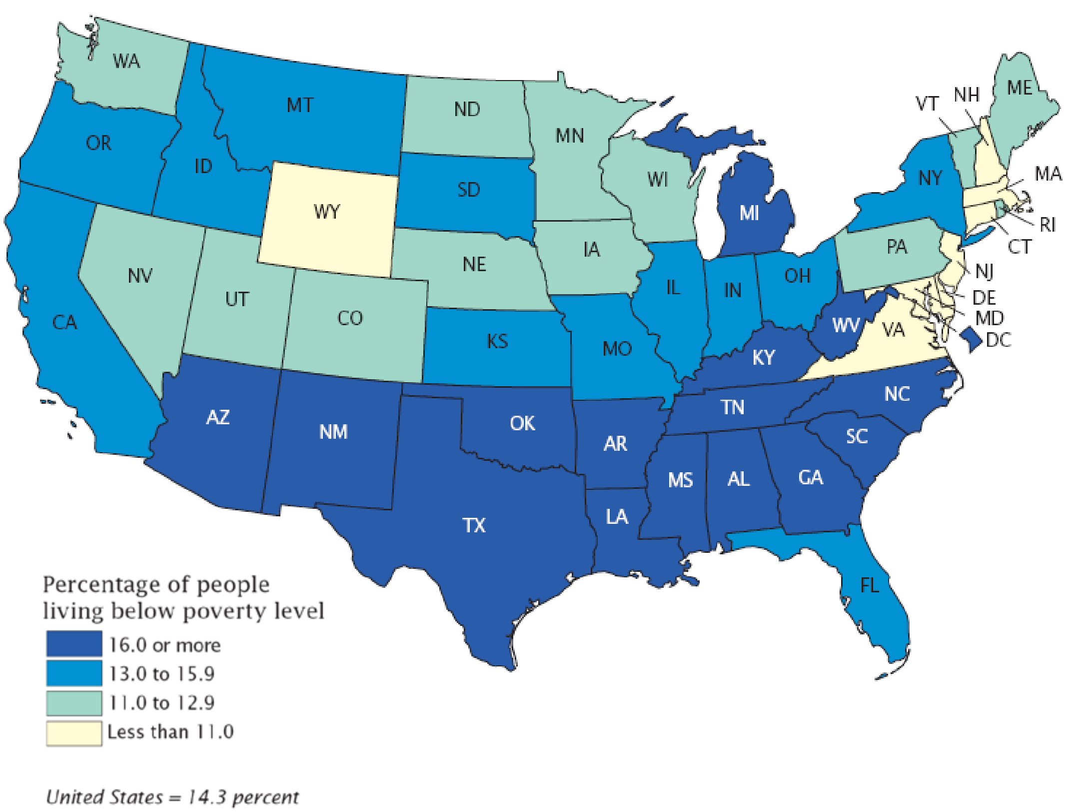
The most recent U.S. Census Bureau report on poverty indicates there are statistically significant annual increases in the poverty rate from 2008 (13.2%) to 2009 when the official poverty rate was at 14.3% (DeNavas-Walt, Proctor, & Smith: 2010).

The 2009 poverty rate was the highest since 1994 but lower than the first official poverty rate estimate in 1959 when the poverty rate was at 22.4%—in absolute numbers, the 2008 (39.8 million in-poverty) population increased to 43.6 million in 2009—the third consecutive annual increase (DeNavas-Walt, Proctor, & Smith: 2010). The number of people in poverty in 2009 is the largest since poverty estimates were first published.

The mainstream story portrayed in the media—by necessity of the medium—oversimplifies the complexity of poverty trends by only telling audiences that we still have many people living in poverty. Public media discourse is usually peppered with the idea that despite the many expensive efforts made over many years, poverty has not been eradicated. It is true; poverty is prevalent in the USA. For example, over the last three decades, the proportion of the population in poverty has fluctuated, but we are where we were 30 years ago and in absolute numbers worse off than we were over half a century ago. While policy makers, media consumers, and academics abstractedly pounder the origins, mechanics, and consequences of inequality (i.e. poverty), people continue to enter, exit, and remain in poverty during their lifetime. Intellectual explorations on the topic at times hide the real every-day pain experienced victims of sociospatial inequality.

Minimalist national-level discussions on poverty are rarely complimented by non-academic complex forums that consider how inequality is simultaneously clustered along social and geographic dimensions. What follows is a overview of these elements.

Let us begin with the geospatial distribution of inequality—"geospatial" is short for geographical-space and "distribution of inequality" will be interchangeably used with sociospatial inequality. Poverty concentrations have an uneven geographical distribution. For example, data from the ASES indicates the top thirteen states poorest states in 2009 contained about 28 million of the approximately 43 million poor. States with the greatest number of people in poverty in order from greatest to least are: California, Texas, New York, Florida, Georgia, Illinois, North Carolina, Ohio, Arizona, Pennsylvania, Michigan, Tennessee, and Indiana. That means that about two-thirds [(28÷43)×100≈65%] of the poor resided in about a quarter [(13÷51)×100≈26%] of the 51 contiguous "mainland" continental US states and Washington D.C. It is clear, even at the state level, that poverty is geographically concentrated (as seen in Map 1 below).



Map 1
Percentage of People in Poverty in the Past 12 Months by State: 2009

Map 1 above (Source: Bishaw & Macartney 2010) visually displays the high geographic concentration of poverty in Southern states. The statistics informing the map make it clear that states are afflicted unequally. On a more theoretical topic, moving from a national to a state level discussion on the distribution of poverty offers substantive insight. This investigation uses geographies that are much smaller than states. Paying attention to “subnational inequality” is “important to social science understanding of stratification processes” (Lobao 2004: 1). By doing so, I paint a more complete and complex picture of how sociospatial inequality operates in continental US.

Poverty is not only geographically clustered; it also concentrates along detectable social dimensions. For example, the “poverty rate of non-Hispanic Whites was lower than the poverty rates for other race groups” (DeNavas-Walt, Proctor, & Smith: 2010:16). Of the 43 million in poverty during the 2009 survey period, non-Latino-Whites and Latinos/as accounted for 71% of all the poor (DeNavas-Walt, Proctor, & Smith: 2010). Racial-Ethnic categorization schemes will be discussed in greater detailed later.

My dissertation will focus on contrasting Latinos/as and Non-Latino-Whites. This makes the vast and complex enterprise more manageable. All other Non-Latino-Minority groups are important and unique in many ways. This is the primary reason why they are not included in the discussion. Each of them deserves and necessitates a detail contrast against the majority group. Only the ‘Latinos versus non-Latino-Whites’ contrast will be included throughout the dissertation.

By using American Community Survey 2005-2009 5-year data, we can estimate the Latino population at 45,476,938 with about 9,765,064 of them having and income in the past 12 months below the poverty level. The same data source estimates that about 18,144,049 non-Latino-Whites (out of a base population of 198,415,102) had an income in the past 12 months below poverty level. In short, within-group comparisons reveal that 21% [= (9,765,064÷45,476,938) × 100] of the Latino population is in poverty while only 9% [= (18,144,049÷198,415,105) × 100] of non-Latino-whites (i.e. the dominant group) is in poverty. The label “dominant” is discussed in greater detail below.

Thus far we have established that social inequality is present in the USA and that it is unequally distributed across geographies and groups of people. So why study poverty?

Why Study Poverty?

Answering the following question is a good starting point for this investigation: Why study poverty as a measure of social inequality? More specifically: Why investigate the geographic and demographic concentration of inequality as measured by poverty status?

The simplest response is that poverty affects everyone—the impoverished, fortunate, and wealthy alike. When resource-inequality gaps increase, both beneficiaries and victims alike are exposed to the risk of social instability created by the disenfranchisement. Because sociospatial inequality has the potential for unjustly and unevenly afflicting all members of society, it merits attention.

Inequality affects all, but is it really an issue in post 2000 USA? Yes, in truth, the gap between the rich and poor has never disappeared and is now rapidly increasing. For example, the wealthiest quintile in the US now holds about 84% of the wealth (Norton & Ariely 2011). It is unfortunate that some investigations suggest individuals dramatically underestimate current levels of wealth inequality (Norton & Ariely 2011).

There are those who argue that inequality is a product of America's open-market capitalism. They argue that "capitalist from the dominant group are the major beneficiaries of prejudice and discrimination in a competitive capitalist economic system" (Becker 1971:21). Others have responded that "stratification and inequality are not created by capitalism" and that "the existence of markets does not guarantee inequality" (Massey 2007:20). Instead, they contend, free-market capitalism only enhances "the *potential* for stratification by increasing the total stock of material resources and multiplying the number of social categories across which they are distributed" (Massey 2007:23). Inequality, in other words, has a greater potential for increasing in free-market capitalist economies because it allows for the concentration of surplus to more readily be spread across a larger set of social categories. But, open-market economies do not necessitate the presence of inequality.

So, inequality affects us all and it is present in our society—but there is nothing in our socioeconomic structure that demands the existence of inequality. Why then should anyone care about understanding poverty? A key element in this discussion is the commonly held belief that great socioeconomic disparities are closely associated with the presence of unstable societies. For example, some attribute current middle-eastern revolutions (as in Egypt and Libya) to the high level of inequality in the country. It could be argued that the proliferation of inequality renders all citizens at risk of subtle or forceful social, military, and/or psychological subjugation. In other words, inequality is deeply interwoven with the social equilibrium necessary for self fulfillment.

There are many reasons why we should expand our understanding on social inequality. But in essence, the prevalence of poverty around the globe signals that as a species, Homo sapiens have not yet found a way to guarantee all their group members an equal set of life chances. Our deliberate and/or unintentional social stratification mechanisms forbid most of us from being equals.

If a democracy is at all possible, then a high level of equality in that society is a necessary condition. The maintenance and proliferation of sociospatial inequality challenges the democratic axiom that all members are equal. Poverty is the evidence of social injustice. It merits attention *and* understanding.

Despite potential cynicism, recent research has also found that individuals from different demographic backgrounds do “desire a more equal distribution of wealth than the status quo” (Norton & Ariely 2011:9). Existing evidence even suggest that individuals have a greater concern for the less fortunate than the more fortunate (Harness & Rabin 2002). If most individuals are interested in creating a more stable and equal world, then investigating poverty as a proxy measure is a worthwhile endeavor in advancing a noble cause. If eradicating inequality is an impossibility, then understanding social stratification may at least offer the opportunity for its mitigation.

Significance

Sociology at its core has always been a discipline primarily interested in understanding how society works—and how this knowledge can help improve our world. Studies on social stratification have sought to outline who gets what, when, and why. Until recent decades, some trailblazing researchers have ventured to include the *where* element in understanding how resource distribution affects life chances.

This work is significant in several ways. Primarily, it utilizes recent mathematical and software developments to address the question of how resources are distributed across individuals and how these dynamics vary by *where* they reside. The project will delineate the geographic and demographic concentration of poverty. By using advanced statistical techniques, the study ascertains how micro-level inequality is influenced by macro-level attributes and explores how spatial non-stationarity plays a role in these mechanics.

The proposed work extends existing research and continues to apply appropriate statistical techniques in a multilevel logistic analysis of context level effects on individual-level poverty. The crucial importance of my relatively recent data is that it assesses the almost universally accepted sociological idea that context affects individuals.

Although this will be discussed in greater detail in the full dissertation, we should note the distinction between the socially constructed meaning given to certain spaces and the geographically defined space created my data limitations. My discussion on sociospatial contexts refers to how geographically bounded areas capture a particular set of structural dynamics. My research pragmatically copes with the ***nesting*** limitations of secondary US Census Bureau microdata and investigates how poverty variance within individuals and areas capture the distribution of inequality.

In summary, the proposed sociospatial inequality investigation will delineate how individual-level stratifying mechanisms are influenced by context-level structural attributes and sociospatial non-stationary processes. In doing so, it will contribute to our knowledge of sociospatial inequality.

Disclosure

In the interest of full disclosure, and in the event that my personal life experience somehow biases this investigation, I would like to admit to my economically destitute childhood. Many years ago, my parents filled our home with tenderness and their hands with calluses as they strived to meet our basic necessities. My four brothers and I often wore shoes and clothes for longer than appropriate and rarely enjoyed the privilege of new expensive toys or the fast food experience many children crave. Our few family trips were confined to a 50-mile radius from our home in *El Valley* (the South most borderland area in Texas between Brownsville and Rio Grande). In spite of the financial challenges my parents struggled with, our home was filled with warmth and security.

When I was a child, I knew the secret to happiness: Follow all the rules, and if you do, all your dreams will come true. As this project will reveal, I think such a view is detached from the truth. There are social structures beyond our individual control that systematically influence our ability to reach our personal goals. We all face different obstacles at different levels of severities. We are not on a level-playing field. By indirectly tracing my psycho-emotional scars—born from what I perceive as unjust social inequality—we will travel through the sociological imagination to expand our understanding of social stratification. Our discussion will focus on the technical as my wounded-child-self joins our journey. Stay with me as I subtly and inadvertently reveal my wounds through a labyrinth of intellectual thought.

CHAPTER II

LITERATURE REVIEW

> "When a person thinks, more than one generation's passions and images think in him."
> Novak 1972:32

The main goal of this investigation is to theorize and investigate *how* and *why* hierarchical and sociogeographical factors are associated with the likelihood of being in poverty. Existing research has established that there are various significant statistical associations between poverty and various micro- and macro-level demographic characteristics. There are two main research questions in this dissertation.

The first and most important research question, which I will call the "*multilevel*" research question, is as follows:

> *Does the percent of Latinos in the area of residence have an influence on individual poverty over and above the influence on poverty of the person characteristics*?

To answer this question, multilevel logistic models are explored with HLM 6.08 software (Raudenbush, Bryk, and Congdon 2004b) using established socio-quantitative logic (see Raudenbush et. al. 2004b). The second "*sociospatial*" and exploratory research question is:

> *Is spatial non-stationarity an important element to account for when investigating poverty*?

Geographically weighted regressions (GWRs) are explored using ArcGIS 10 software (ESRI 2011) and these spatial models are interpreted using existing geocomputational logic (Fotheringham, Brunsdon, and Charlton: 2002).

I find hierarchical and geospatial modeling useful and in determining which factors are statistically significant in predicting individual-level poverty while accounting for local racial-ethnic concentration. This chapter reviews the theory framing the "*how*" and "*why*" in interpretations and final explanations.

In order to answer how and why context matters this enterprise must employ four quasi-truisms. The prefix "quasi" is used because some elements of the assumptions are empirically testable and discussed in this dissertation. I seek to reveal all untestable elements in the theoretical framework guiding the statistical models. The main point is that the theory construction in this project necessitates both because they are crucial for understanding the ensuing sociospatial discourse on inequality.

The first quasi-truism is that *humans are spatial beings*. I believe individuals are most influenced by *proximal events*—proximal in the sense of time (i.e., distinct interactions) and geographic space (i.e., discrete physical location). The term "distinct" is important because genuinely causal relations can only be obtained "between distinct thing or events" (Ball 1978:101). For example (and in general), a murder down the street impacts us more than one that occurs 5,000 miles away. Also, a one-day-old murder is more likely to affect us than one that occurred 5,000 years ago. Our first and fundamental truism is that both time and physical space matters. Geographer Waldo Tobler's seminal first law of geography was written several decades ago: "everything is related to everything else, but near things are more related than distant things" (1970:236). Our first adage would argue that "near" should invoke both time and space.

Secondly, I argue that *human behavior is hierarchically influenced*. People are affected differently by distinct factors at diverse sociospatial-levels. That is, individual level attributes do *not* exist in a sociospatial vacuum: *Context matters*! Individual characteristics are more proximal but not necessarily more relevant than distant community level attributes—both matter equally but in different ways. For example, educational achievement affects an individual's economic potential as a function of their socioeconomic environment (having a Ph.D. in the middle of an abandoned desert is of little economic value). In general, we could say that moderate levels of education are harshest on limiting money-making opportunities in job-deficient markets. Thus, educational attainment at the individual-level affects earned income in ways that interact with local labor markets. The point is that both individual- and context-level factors play different and significant roles in influencing behaviors.

Our third quasi-truism is that *inequality is in part a product of discrimination*. I posit that massive social disparities are not a necessary condition for the survival and evolutionary adaptation of our species. The assumption is partially addressed in the following chapters—but in truth is necessary given available variables in the non-longitudinal data set being used (causality is extrapolated and not directly tested). The crucial point here is that I believe uneven distribution of individuals along socioeconomic-classes exists in part because class-categories (e.g., racial-ethnicity) exist. Neurophysiologically driven heuristics are filtered through prejudiced views that lead humans to create discriminatory categories of people that are then used to unevenly distribute resources across these categories (Massey 2007). This non-pecuniary discrimination-driven process creates social inequality.

The fourth and final quasi-truism is that *poverty-status is a good proxy for measuring discrimination*. I will admit that this view paints individuals who are in-poverty as victims of systematic discrimination. Since the dissertation focuses on the Latino/a racial-ethnic label, the broader argument is that finite social-power creates social stratification by various factors like racial-ethnic discrimination. The goal of social stratification is to control (and concentrate) material and non-material resources. Racial-ethnic discrimination is a good tool for reaching this goal because it can exploit resources away from targeted groups. Thus, poverty is (in part) a product of discrimination and a good proxy measure of it.

This dissertation investigates which characteristics are associated with those who are relegated to the lower rungs of the American socioeconomic hierarchy and how geographic variability (i.e., the *where* element) plays a role in the distribution of resources. This intricate objective requires a multifaceted statistical and theoretical approach. Blalock's (1970) theory—the testable hypothesis that discrimination increases when minority population rises (because their growth amplifies the dominant group's fear against them)—is the cornerstone of this project and our starting point.

After delineating Blalock's work as our guiding theory, we will move on to outline the fundamental assumptions underlying the theory. Subsequently, we will discuss social stratification, power, hierarchical influences, and sociogeographical space.

In brief, the literature review aims at framing our understanding of poverty as occurring in a social structure that systematically creates social categories, allocates people across them and then distributes resources unequally across the stratums.

After introducing Blalock's and Becker's (1971) work on measuring and defining discrimination, we will discuss Gerhard E. Lenski's seminal work in 1966 (I will be using the 1984 book edition) on the distributive processes that create and maintain social stratification. Lenski's work is an excellent source for defining the assumptions in our social stratification theory. Lenski provides us with a philosophy of why individuals and their societies produce social hierarchies. I will use his writings to frame *why* distributive processes are formed and will adapt three postulates to argue that both humans (as individuals) and societies (as their aggregation) are self-seeking units pursuing the maximization of their resources.

The theoretical foundation will also be closely complimented with Douglas Massey's 2007 book on social stratification in the American system. Massey's erudite writing will be instrumentalized to explain *how* social inequality is born, maintained, and expanded. Massey's ideas will help move our conversation to a more modern discourse by scaffolding our views along a more "objective" understanding of human racial-ethnic discrimination. In this part of the chapter, we introduce human's *need* (potentially an evolutionary trait) to categorize as being a key element in understanding the system that begets social strata. By using a set of logical arguments, I will extend his views and argue that internal (i.e., physicalistic) dynamics are products of biological-materialism that *contribute* to the birth, sustenance, and proliferation of equality disequilibrium in our species.

After discussing all these fundamental philosophies and resulting theoretical postulations, I move on to discuss the importance of having a critical sociospatial view of human behavior. The closing sections of the chapter will discuss how social stratification theories on discrimination can benefit from introducing sociospatial elements. In particular, I will discuss the idea of cross-level hierarchical-influences and then explain how spatial non-stationarity is related to this topic.

Defining and Measuring Discrimination

Over four decades ago, Huber M. Blalock Jr. (1970) formulated some empirically testable theoretical propositions on the topic of minority-group relations. The following sections will drill deep into the theoretical underlings of social inequality—the main topic of this project. Blalock's proposed methods for measuring and conceptualizing discrimination—the cornerstone of this dissertation—will now be introduced.

The secondary data being used in this project has no variables on perceived discrimination. Under such limitations, measuring discrimination, Blalock argues (and I concur), must be done indirectly. This indirect measuring necessitates "a set of theoretical assumptions—many of which will be untestable—in order to link the notion of discrimination to actual measures" (Blalock 1970:15). In my case, I assume poverty status is an adequate and appropriate measure of discrimination. The indirectness of the measure requires a theory of social causation, a requirement that inconveniently entangles the measurement process with theoretical considerations. Our literature review will untangle this convolution.

Blalock beautifully ponders how intent operates in causal systems and concludes that when “we attempt to measure discrimination we usually obtain measures of *inequality*” (Blalock 1970:17 italics by original author). My dissertation on social stratification is focused on measuring discrimination against Latinos/as. Existing work supports the “relative group size-inequality hypothesis” (Saenz 1997:207) by showing that Latinos/as residing in communities with heavy co-ethnic concentrations have a labor market penalty (Bean and Tienda 1987; for early work on the Black population see Glenn 1964). I will be using poverty status as a proxy to inequality. Thus, Latinos/as in poverty are seen as victims of inequality. It is important to note that socioeconomic inequality is a resultant of discriminatory behavior *and* “of other factors as well” (Blalock 1970:17). The “other factors” are beyond the scope of this study. I do however acknowledge that social structures are an important component in determining life chances.

The integration of micro and macro approaches is difficult. Theorizing about their bidirectional interaction is deeply challenging. Translating “back and forth between the macro level, where groups are the units of analysis, and the micro level where the focus is on individuals” is complicated (Blalock 1970:21). Following Blalock’s instructions, this quantitative investigation focuses “on individuals as units of analysis while using macro variables as indicators of exposure to different environmental stimuli" (1970:26). In particular, I use statistical models to predict individual-level likelihood of being in poverty after controlling for several individual-level factors and introducing social-environmental variables (e.g., percent Latinos/as in area of residence and spatial dependence in macro attributes). The multilevel and geospatial investigation in effect test how "contextual effects" (Blalock 1970:26) affect individual-level attributes as they predict the status of being in poverty. My work uses the "compositional hypothesis" that percent minority in an area "will tend to affect racial attitudes in a similar manner in all regions" which diminishes the need to postulate a region-specific contextual effect (Fossett and Kiecolt 1989: 822-823).

A great amount of space is dedicated in this chapter to delineating the assumptions of how "individual goals, motives, and needs are major causal agents in social systems" (Blalock 1970:28). For now, there are four main premises to my theory (as adapted from Blalock) that will suffice in advancing our understanding of the ethno-racial discrimination-poverty link.

Discrimination moves from the micro → to the macro → and back to the micro functions as follows. The first premise is that "exposure to large numbers of minority members is a forcing variable that threatened *individual* members of the dominant group" (Blalock 1970:28 italics by original author). In other words, exposure to large numbers of minority persons threatens *individual* members of the dominant group. An idea introduced to academic literature more than sixty years ago by a Texan (Key 1949). The increased presence of minorities poses a political and economic threat. This is particularly true for those who tend towards “individualistic thinking” instead of “structural thinking” (Bobo and Hutchings 1996).

Secondly, “threats combine with personality variables to produce motivation to discriminate” (Blalock 1970:28). Simply put, perceived threats produce discrimination. There are two possible main reasons why minority group threat occurs. Fear can arise amongst majority group members when they perceive minority-group members as posing either an economic or political threat. It is true that “different kinds of persons will not be similarly motivated by the minority percentage variable” (Blalock 1970:31).

For example, majority group members with a high educational attainment may differ in their threat perceptions than their moderate level educated non-Latino-white counterparts. Keep in mind that minority groups may be tempted to retaliate “against discrimination from others by returning the” discrimination, but this would be a mistake “since effective economic discrimination occurs against them” because “majorities have more balanced distribution of labor and capital than they do” (Becker 1971:32). The point is that dominant-group members are framed as responding with discrimination when the local minority population is on the increase and the latter have few resources to resist.

These “perceived competition and power threats” (Blalock 1970:29) are unmeasureable factors in my data. I will simply combine the effects from the “fear of power threat” and the “fear of competition” to hypothesize a positive linear path through the “combined effect on motivation to discriminate” (Blalock 1970:30). As shown in

Figure 1, I expect that as the percent of Latinos/as in an area of residence increases, fears towards them and thus discrimination against them will increase.

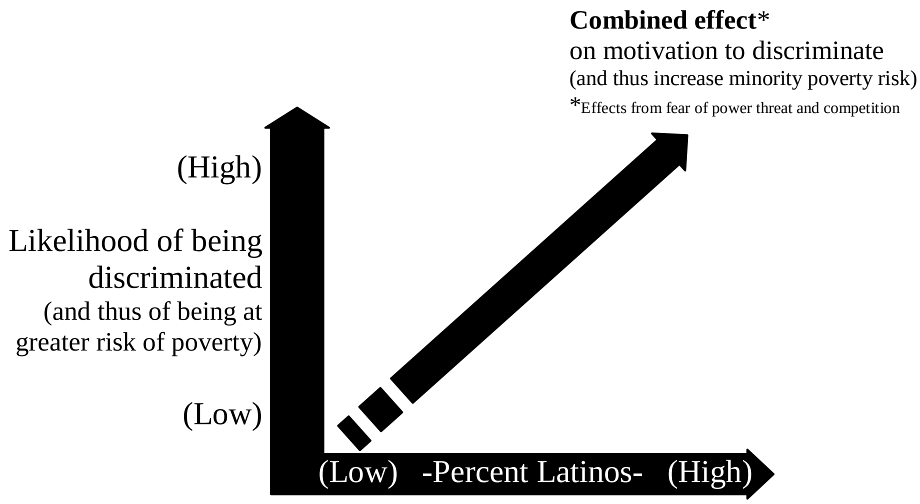


Figure 1
Minority Group Threat Theory: Combined Effect Graph

Previous research has supported this theory. For example, Rogelio Saenz (1997) used U.S. Census data to show that, "there is a positive relationship between the relative size of the Chicano population and the group's poverty rate" (Saenz 1997:205). The positive association between discrimination and minority presence occurs because according to our third premise in the theory, "similarly motivated individuals interact with each other in such a way as to bring about concerted action leading to actual discrimination" (Blalock 1970:28). And there is evidence that Latinos, in particular Mexicans, are seen as a threat to the "American way of life" (Saenz, Filoteo, Murga 2007).

In the words of Herbert Blumer (1958), when historically advantaged group members perceive minority-group members are threatening their entitlements, they manifest their prejudice towards those minorities. Thus, if dominant group members respond similarly and consistently enough to structuralize their discriminatory behaviors, then their individual actions collectively constraint minority-group members threat level.

This idea will be further validated as we move along our discussion on the nature of humans, their societies, and how these elements combine to create systemic and durable discriminatory distributive processes. In passing, I would like the reader to be aware that there is an extensive literature on how contact works. In the most general sense we should keep in mind that "since people discriminate little against those with whom they have only indirect [contact] in the market place, some direct contact must be necessary for the development of a desire to discriminate" (Becker 1971:154).

The main argument—using Blalock as our theoretical touchstone—is that the increased presence of minorities raises the potential for contact and thus the likelihood for the desire to discriminate to escalate. It is also important to note that "contact has other dimensions besides numerical and economic importance; among them are intensity, duration," and level (Becker 1971:155). Early on, the "contact hypothesis" (Allport 1954) focused on how positive interactions improved intergroup relations. Recent work has continued this optimistic approach and found that contact is beneficial (Pettigrew and Tropp 2006)—although its benefits are weaker for minority status groups (Tropp and Pettigrew 2005). Continuing with this positive outlook, some have even found that "the racial threat effect is significantly diminished in areas with greater multiethnic diversity" (DeFinal and Hannon 2009:373). Clearly the influence of contact is complex.

Contact with minorities could actually reduce perceived threat. For example, in post-apartheid Africa, researchers found that "the more contact Whites have with Black people…the less likely they are to resist" policy interventions such as affirmative action (Dixon et. al. 2010:849). The authors do make it clear that interventions challenging in-group privilege are less susceptible to contact effects than those who pose little threat to current in-group power structure.

Another example using a recent police coverage investigation that supports Blalock's power-threat hypothesis finds "that Latino populations did not become threatening until they represented approximately a quarter of the precinct-level populations, at which point precincts significantly increased their levels of police deployment" (Kane 2003:289). More recent work using census tract-level data in Miami-Dade County found that in highly segregated areas "the relative size of the Latino population is a predictor of fear of crime among white residents" (Eitle and Taylor 2008:1102).

The influence of contact is complex. By using Blalock, I am only asserting "that structural barriers blocking minority upward mobility are more insurmountable in those areas where a given minority group accounts for a larger portion of the population" (Saenz 1997:207). My research only focuses on the negative aspects arriving from the perceived threat by majority status members against minority status groups. My data does not allow for sociopsychological testing.

Our fourth and final premise—in moving from the micro to macro and back—states that "discriminatory behavior, when aggregated in some way, leads to" (Blalock 1970:28) minorities being obstructed from resources. As shown in Figure 2 below,

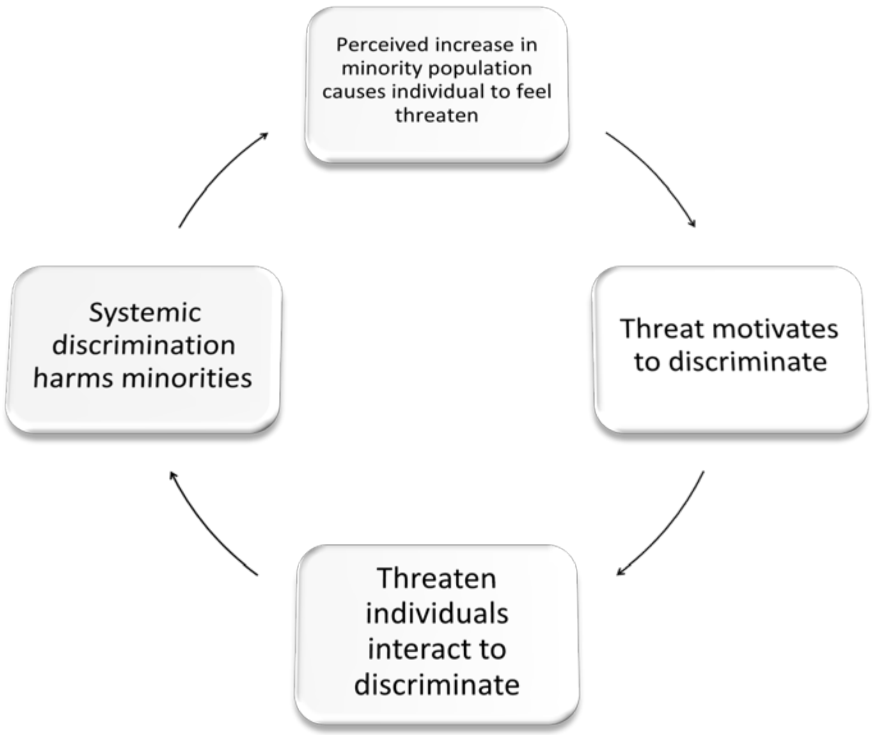


Figure 2
Minority Group Threat Theory:
Discrimination Producing System

aggregate discriminatory behavior harms minorities. This occurs because the more minority individuals there are, the more "direct or potential competition with a given individual in the dominant group" (Blalock 1970:148). In the words of Becker; "tastes for discrimination against non-whites vary directly with their proportion in a community" (1971:123).

Recent work validates the idea that in-group cooperation varies positively with intergroup competition (Burton-Chelley, Ross-Gillespie, and West 2010). The more "others" threaten us, the more we cooperate—and in the case of precondition prejudice, discrimination is born. Consequently, large minority populations represent a threat that fuels the prevailing stratification system by allowing "the majority group to erect "formidable structural obstacles" (Saenz 1997:207).

Fear of minorities occurs because dominant-group members are "linked" to minority-group members in five general ways that intertwine their means for achieving goals. First, if minorities are serious economic or political competitors, then "discrimination may serve as a means of restricting or eliminating such competition" (Blalock 1970:41). Next, minority avoidance could either help "achieve status objective or…reduce the likelihood of uncomfortable contact" (41). Our third link posits that minorities may be exploited as a means toward status objectives and our fourth link outlines that shared-prejudice which is acted on can help obtain or consolidate political power. Lastly, dominant-group members' links to minority-groups members increase fear because psycho-emotional frustration may lead some toward direct aggression towards minorities. In summary, I hypothesize that as the minority percentage increases discriminatory behavior will increase to handicap minorities.

During the same time that Blalock (1970) was advancing his ideas, Gary S. Becker (1971) joined the academic literature on discrimination. Early in his book, Becker introduces the idea that discrimination in economic environments is "an expression of tastes or values" (1971:13)—where individuals have a "taste for discrimination" (Becker 1971:14). This monograph operates from an economic framework that analyzes discrimination based on *non-pecuniary* considerations (see Becker 1971:153).

Non-monetary factors like racial-ethnic categories are the only factors appropriate for measuring discriminatory behavior. For example, an individual who offers a job to person A over person B because the latter does not meet basic educational requirements is not said to be discriminating. The hiring entity is using a market-related category (i.e., education) to differentiate between the two applicants. If instead, the supervisor were to select between two people purely on their racial-ethnic category, then we could assume they have a taste for discrimination. I argue that "these tastes are the most important immediate cause of actual discrimination" (Becker 1971:153). I focus on non-pecuniary discrimination by spotlighting the Latino/a racial-ethnic factor and my work embraces the idea that causality can only be understood through an "organism-environment system" (Lickliter 2009) framework.

The bottom line is that the "necessary condition for effective discrimination against N is that N be an economic minority; a sufficient condition is that N be a numerical minority; a necessary and sufficient condition is that N be more of an economic minority than a numerical majority" (Becker 1971:27). Since my analysis of discrimination uses a minority-majority framework and given that my dependent binary-variable is poverty status, I believe "the concept of economic minorities is somewhat more important here than that of numerical ones" (Becker 1971:27). Thus, a Latina who resides in a 80%-Latino/a concentrated community is still a minority because her economic status is more important than her numerical one.

As mentioned earlier, the main goal of the research is to investigate how individuals differ as they are exposed to differing environmental stimuli by examining and describing how discrimination affects life chances—and how such associations vary by differing social habitats. Thus far I have argued that economic inequality is a product of discrimination, that using poverty-status as a micro-level proxy to inequality is appropriate, and that percent-Latinos/as as macro-level factor adequately measures their minority threat against majority non-Latino-whites. These are the fundamentals of how I will be testing Blalock's minority group threat hypothesis. We now turn our attention to theorize *why* people discriminate.

First Postulate: Human Nature

My guiding theory (as adapted from Blalock) on how racial-ethnic discrimination systematically creates and maintains social inequality has many general assumptions on the nature of humans and society. Before we begin our discussion on how an individual's location along the social hierarchy alters his/her life chances, we must outline how (and briefly why) humans—and their ensuing societies—have the potential for stratifying individuals along resource varying positions.

Lenski offers us three main postulates on a general theory of social stratification. We will be better equipped to understand Blalock's discussion on discrimination and economic outcomes if we outline how humans have the *potential* for stratifying others (and themselves) along various social categories. We will first discuss the nature of humans.

Our first postulate deals with the fundamental nature of humans. Lenski posits that "*man is a social being obliged by nature to live with others as a member of society*" (1984:25 italics by original author). This postulate is an axiom in sociology. The idea is so basic to sociology, that it seems absurd to mention it as our fundamental proposition. There are, however, several reasons why the idea—that Homo sapiens are social beings—is important.

Foremost, social hierarchies are impossible in a universe with a single inhabitant. In addition, a multi-inhabitant universe could only create differing social strata if inhabitant-interaction is present. Thus, ordering groups/people along different categories that offer differential access to resources requires at least three elementary conditions: (1) habitat must contain *others*; (2) people must have the *ability* to interact with others; and (3) inhabitants must have a *need* to interact with others. Our first proposition argues that our species dwells in a multi-inhabited universe where agents have both the ability and need to interact with others.

The proposition does more than just subtly stating the necessary conditions for the creation of social agents. Our first premise on human nature also incorporates a view that society shapes a person's "character and personality in ways over which he has no control and of which he is often unaware" (Lenski 1984:26). Over 200 years ago, Adam Smith wrote that by endowing humans with an original desire to both please and avert offending their brethren, nature formed humans as social (1790). In the words of Peter Berger, society "shapes our identity, our thoughts and our emotions"—to the point that the "structures of society become the structures of our own consciousness" (1963:121). These arguments gracefully introduce the idea that the aggregating mechanisms, by which individuals form a society, countereffect people in unique ways.

Societal influence on individuals highlights an important two-way interaction between m*i*cro and m*a*cro units. As per our previous logic, the potential for the formation of a society is present when the three fundamental conditions are met. When individuals coalesce to form a macro-unit (i.e., society), the aggregating apparatus creates and contains the potential for the macro-unit to counter-influence the constitution of individuals. In other words, micro units shape the formation of the macro, and the macro in turn reacts (through the aggregating system) to shape micro units in ways that would be otherwise impossible.

For example, belonging to a minority group (e.g., being a Latino/a) increases the risk of having poor mental (e.g., depression) and physical health (e.g., contracting HIV) because marginalized statuses increase the chances of experiencing discrimination. HIV is highly stigmatized and associated with marginalized groups and minorities who contract HIV are more likely to have experienced depression before contracting the virus (Gonzalez et. al. 2009). Consequently, individual-group interactions lead marginalized individuals—who experience depression and contract HIV—to be at a higher risk of experiencing social isolation to the degree that it further increases their depression (Simoni et. al. 2011). Thus, depression can be amplified in the micro-unit (i.e., minority person) when the macro-context (i.e. society) pushes them into the isolating margins of society. The cross-level interaction creates special outcomes for the individual.

The sociological maxim, that humans are social beings obliged to form societies, assumes several sub-premises with various implications. In the simplest of terms, the main argument is that human behavior does not exist in a vacuum. Instead, our species transverses its existence in a universe filled with other people. We each contribute to forming both our physical and social environments. The sum of the parts, in turn, shapes our individual dispositions and proclivities. Such is our first and most fundamental proposition on how social inequality is possible.

These views primarily capture how *nurture* plays a role in human nature. Our current discourse conveys the phenomena under discussion as if it existed in an abstract world where units navigate through intangibles to assert their micro boundaries and macro formations. Such a metaphorical view could be unintentionally deceptive, because the framing of the discourse hides the fact that all these things are only possible in a material/physical world. For example, when it comes to my discussion of space, we must understand that the "initial basis or foundation of social space is nature—natural or physical space" (Lefebvre 1991:402). I believe the only things empirical sciences can investigate exist in matter—the physical world.

Human nature is a physical phenomenon and all its interactions occur in a bio-chemical world. I embrace this physicalism and will thus turn our attention to discuss how human's *nurture* interacts with our biological materialism (i.e. physical *nature*).

First Postulate Clarification: Biological Materialism

In this section, I briefly disclose my epistemological views on the biological base of human nature: biological materialism. While it is important to recognize the eminent role of biological materialism in understanding human behavior, it is beyond the main focus of this project. The following section is only aimed at briefly clarifying that while the topic of human behavior in this dissertation is spoken of in non-material terms, the author is cognitively theorizing about such events as occurring in a yet immeasurable physical realm.

This brief sub-section has three goals: (1) make it clear that the author believes all human behavior occurs in the physical world; (2) introduce the importance of having a sociobiological perspective; and (3) briefly explain how the material base does not necessarily equate to biological materialism. All this is being mentioned because subsequent discussion on the meaning of the findings will include implications for sociobiological ideas.

Ideas, feelings, memories, decisions, and other such human phenomena occur in the physical world. Every human behavior is the result of a physical event (see Clark 2010). For example, many scientific studies on gene-environment interactions have found that properties of serotonin transporter genes can be moderated by environmental adversity/stress (Uher and McGuffin 2010). Some investigations have even focused on how the serotonin transporter gene 5-HTTLPR and stress in the environment cause depression and have found that “an individual’s response to environmental insults is moderated by his or her genetic makeup” (Caspi et al. 2003:386). More recent investigations in this area have found that there is even a large heritable effect on preferences in consumer decision making (Simonson and Sela 2011).

I belief all human behavior has the potential for being investigated in such a biological way. For example, in studying social inequality with a focus on racial-ethnic factors, we could include a discussion on phenotypic plasticity. Although this is not necessary for the development of my theory, we could simply highlight in passing that in "many organisms the same genotype can give rise to many different phenotypic variants whose appearance or behavior depends on its environmental setting" (Pérez, Alfonsi, and Muñoz 2010: 864). Or in discussing our complex brain and neural networks, we could argue that they are more accessible to scientists than "the vast universe itself" (Wurzman and Giordano 2009: 369). The point is that our growing technology and science will eventually allow us to investigate behavior using biological measures.

The human nature we have been discussing operates in a bio-chemical world. There are no mystical entities playing a role in human behavior. All sensing, information processing, and decision making of biological systems (e.g., humans) occurs in a physical world. It is true that a full and adequate naturalistic account of human phenomena would have to include a discussion on how "concepts have no a priori connections to physical or functional concepts" (Levin 2008:402). The debate would outline how biological products are imbued with meaning by social context—a truly worthwhile endeavor beyond the scope of this investigation.

Agency and structure are important ideas in sociology that normally exclude a sociobiological discussion. The two concepts are closely aligned with ideas of body and mind. Hobbes (1839) first introduced the term “agency” to sociology over 170 years ago. The agency/structure debate remains unresolved because many still think of them as being “opposite natural kinds” (Fuchs 2001:24). They are in fact variable devices observers use to explain human phenomenon. As a proponent of biological materialism, I would contend the “mind” is not a phantom navigating within our physical body. There is no such thing as a ghost in the machine (see Feinberg 2009). Nurturing (i.e., socialization) does not occur in a purely abstract world—our socialization occurs in a physical world. For example, our psychological dispositions are formed and maintained in our biological body that inhabits a house, a climate, and so forth. Non-physical human attributes are inherited relics from a time where talking about a “soul” in academia became frowned upon. In its stead, mind/will became the operate word. I argue neither is necessary or relevant for empirical investigation of physical events like human behavior.

The main argument is that if nurture influences human behavior, it is because it interacts *through* and *with* nature (i.e., physical materialism) to alter the constitution of our biological being. For example, when investigating how food consumption influences our biological constitution, research has found a poor diet can create the obesity that begets diabetes (see Lazar 2005; Jiménez-Corona et. al. 2010), and that in turn, a low-carbohydrate diets can help improve type-2 diabetes patients (Farrés et. al. 2010). In this example, nurturing towards poor diet develops negative physical conditions which are in turn only alterable through other eating behaviors—that is, nurture influences nature and vice-versa.

Thus far we have established the physicalism of all human phenomena. Why does a sociobiological perspective matter? Why mention biological materialism in an investigation of poverty (i.e., social stratification) while discussing human nature?

On the first question, sociologists must learn to appreciate the fact that a "human being is a complex organism consisting of sixty trillion cells with six billion base pairs of DNA information" (Sakurada 2010:56). The humans, we social scientists investigate in mainly non-biological means, are "dynamic systems carrying out 10^{16} (ten quadrillion) cell divisions through" their life-time (Sakurada 2010:56). A human is a complex physical organism.

Social scientists must join the discourse on how biology informs our understanding of human behavior. All behaviors are in part produced by "micro-geography of synaptic connections, cellular interactions and electrochemical flows that operate in a dispersed fashion and below the level of consciousness" (Papoulias and Callard 2010:35). The sociobiological perspective matters. My research demands that I mention biological materialism in the investigation of poverty because our biological constitution is the *necessary* material and eventual physical depository for whatever nature produces to influence human behavior.

Human events must be investigated with a physicalistic philosophy that highlights the importance of sociobiology—the "systematic study of the biological basis of all social behavior" (Wilson 1975a:4). Why is this discussion so rare in sociology? The simple answer is that biological determinism fell into disfavor from the social sciences many decades ago. Many factors played a role. One contributor to the silencing of sociobiology was the rigidity/deterministic world view it creates. I will now succinctly explain how the material base does not necessary equate to biological determinism.

Discussions of biological determinism in sociology sometimes create an uncomforting view of human behavior as being fixed in an agency-void existence. Such a concern is now more easily challenged by emerging findings in epigenetics—where genetic determinism is altered in meaning by the introduction of phenotypic plasticity (Pérez, Alfonsi, Muñoz 2010). Epigenetic investigations seek to explain how individual-environment interactions physiologically influence gene expression. Epigeneticist study how gene activity is regulated within cells. The field theorizes how and why “functional changes of genes” occur “without accompanying the sequence changes of DNA” (Sakurada 2010:61).

For example, some research has found that both parent’s genes and their lived experiences influence their offspring’s makeup (Young 2008). We now understand our DNA does not fully determine our biological constitution. There is a deeper set of bio-mechanics (epigenetics) that regulates the mode, time, and intensity of genetic expressions—all of which influences our biological material base. This is because superimposed “upon the DNA sequence is a layer of heritable [epigenetic] information that we have only just begun to read and appreciate” (Bernstein, Meissner, and Lander 2007:669).

In short, the uncomforting fixity of biological determinism detested by some social scientists can now find some consolation in the fact that epigenetic studies offer us a better understanding of how we have a previously unknown "plasticity in the face of ecological variation" (Scott-Phillips, Dickins, and West 2011:39). Stored epigenetic chemical information shows us "how the genome is made manifest across a diverse array of developmental stages, tissue types, and disease states" (Bernstein, Meissner, and Lander 2007:669). Our DNA is not our final destiny. There is a deeper level of biological determination that influences our DNA's influence on us. Our epigenetic constitution interacts with the environment to influence, through an ordered chaos, the material base from which all human behavior flows.

Although it is beyond the scope of this investigation, I believe both agency and structure (and how they interact) are important. Briefly defined, agency refers to the potential for randomness in human behavior—and structure as the habitat that both limits and fuels this fascinating randomness. The mathematical philosophy of my stochastic models both assume and depend on the fundamental probability theory assumption that even if an initial condition is known, randomness is possible and certain outcomes have a higher probability of occurrence over others. By making use of multilevel models, this project frames the discussion on poverty along a path that must render a clear view of how individual-level characteristics interact with structural-level attributes—as they relate to poverty status.

Truth be told, "despite the great progress that has been made in the" rapidly developing area of epigenetics, it is "probably many years away from providing insights into the heritability of choice and judgment" (Simonson and Sela 2011:952). The fact that existing research and theories limit us from talking about *how* (much less *why*) physical behavior operates in the biological base is not an acceptable excuse for not noting the importance of physicalism in sociology. Progress in the is being advanced by recent theoretical, mathematical, and computational progress. Our ability to instantiate the details of physicalism in all human behavior are now visible in the horizon. This short discussion on biological materialism is crucial to our understanding of human nature.

Given current limitations on the topic, why is the discussion of biological materialism necessary in discussing the nature of humans as it pertains to social stratification? Understanding human behavior requires that we investigate micro-level events in *context*. Society is the context. Social habitat is deeply intertwined with the elements that constitute the individual. Put more clearly, to properly understand behavior, we must investigate *why* and *how* it works (Scott-Phillips, Dickins, and West 2011). Investing how it works at the biological level is beyond the scope of this dissertation. Some have even said that sociobiological views are no more than a “novel philosophical approach” to studying human behavior (Marks 1980: 28). However, it is important that we continue to think of all ensuing discussion in terms of how all concepts operate in the biological constitution of the person.

Thus far we have established that Homo sapiens—by nature and nurture—are social creatures. We will now turn our attention to why they are self-seeking units.

Second Postulate: Self-Seeking Units

Our first postulate explains that humans are social beings. After important deliberation on how self-interest plays a role in the social creature, Lenski concludes that "*when men are confronted with important decisions where they are obliged to choose between their own, or their group's, interests and the interest of others, they nearly always choose*" their own (1984:30 italics by original author). The view, he accepts, is skeptical about the innate goodness of man. In essence, our second postulate argues that individuals and their formed groups will seek their interest before others. This is a key element in the logic of my analysis.

Some have argued that the "presumption of individual-interest as the root of human behavior is a model derived from a classical evolutionary genetics" that was formulated and applied within a "culture of narcissism" (Marks 1980: 49, also see Lasch 1979), and that such an approach glorifies ego and frames the social world in biological terms that lead to erroneous egocentric views. More recent arguments have highlighted the fact that in academic discourse, "which holds dear enlightenment notions of an inexorable march to perfection," the darker aspects of humans are treated as regrettable anomalies by pathologizing them as problematic behaviors and thereby "removing them from the ambit of normalcy" (Ak 2009: 726).

Unfortunately, our cognitive dissonance does not eradicate the fact that "*societies, like individuals, are basically self-seeking units*" (Lenski 1984:42 italics by original author). Some have even argued that *society* is but "a metaphor for multiple interest groups vying for" power (Kane 2003: 290; also see Chambliss and Seidman

1982). Our second postulate on human nature also signals that “prohibition runs deep into the consciousness” of our species-being and even though we may be free to choose, what we” can choose from is already chosen; not specifically by anyone but by default and by virtue of what is discursively available” (Ball 1978:29). The unpleasant truth is that individuals, and the groups they create, are above all self-seeking units.

While writing on this topic, Blalock reminds us that after having generalized “economic man” to that of “status-seeking man,” we must abstain from minimizing “the importance of other types of goals” and from assuming that status and economic factors constitute a single “master motive” (Blalock 1970:39). Thus, even though I spend all my time talking about economic related outcomes, please keep in mind that there are other non-economic motives (e.g., sex) driving human behavior.

Thinking of humans as selfish beings may be considered highly pessimistic by some, but Lenski points out that division of labor in complex societies hides the unsettling truth behind our second postulate. For example, in the U.S., our highly bureaucratized existence easily veils our group- and individual-selfishness by limiting us from seldom seeing the consequences of our economic and political actions (Lenski 1984:31). In 2010, our labyrinthine U.S. political system became even more perplexing when the Supreme Court decided that for-economic-profit corporations were “individuals” protected under the First Amendment (Stevens 2010).

Exercising power sparingly is desired and can be done by “securing consent” by “translating power into strategic action” that avoids “having to coerce recalcitrant bodies” (Wolin 1960: 33). Our Supreme Court is an institution founded on the belief that elites must rule of necessity through organized means. Our aim at democracy is to create a representative government. In our indirect democracy, this representative institution is necessary because “social order require[s]d explicit planning and organization” (Mosca 1939:47).

The main point is that our intricate social organization leads most of us to only interpret successes and failures—in “objective” and “level-playing-field” markets—as the result of “impersonal forces, or forces so complex that the influence of any single individual” is negligible (Lenski 1984:31). For example, and thinking of a conceptual billiard table:

> “…to skew the table is simultaneously to advantage and disadvantage players dependent upon their relation to the table and the moves they wish to make. It disturbs the equilibrium upon which the rules of the game may fairly be applied, by skewing the rules to the advantage of whosoever has management of the skewed table. Of course, only in pure games of skill or chance is it ever the case that games are played on a ‘level table’ or a ‘level playing field’. Social games rarely if ever correspond to the ideal condition of pure games per se. The rules will not be as static and idealized as in chess or some other game but will instead be far more fragile, ambiguous, unclear, dependent upon interpretation, and subject either to reproduction or transformation dependent on the outcome of struggles to keep them the same or to change them this way or that” (Clegg 1989: 209).

The main argument is that despite the many attempts to hide our unsettling selfishness, they persist. Let us remember that to “assume that the absence of grievance equals genuine consensus is simply to rule out the possibility of false or manipulated consensus by definitional fiat” (Lukes 1974:24). Our selfish drives operate in an unjustly imbalanced playing field.

Humans and social groups as selfish agents have also been discussed from a biological perspective. Some have even argued that humans are biologically programmed to be self-seeking units. For example, Richard Dawkins argued several decades ago that some of our genes survived for millions of years in a highly competitive world and that if “you look at the way natural selections works, it seems to follow that anything that has evolved by natural selection should be selfish” (1976:4).

More recent biologically oriented discussions framing our self-seeking nature have used variations of game theory to argue that “group selection is consistent with individuals maximizing their own long-run reproductive interests or those of close relatives” (Bergstrom 2002:85). In clarifying that self-interest is not always in conflict with group-interest, some have contended that “individual self-interest is consistent with behavior that maximizes group success” in stable environments (Bergstrom 2002:68).

This dissertation investigates poverty—a financial outcome of individual economic behavior in varying social structures. Poverty is viewed as a byproduct of individual behavior as it navigates a stratified world. Our second postulate simply disputes that both individuals and groups seek to meet their needs before those of others. Economic behavior has biological basics—at the very least is biological instantiated.

Existing work argues that a desire for social status is biologically “innate” (Robson 2001). Considering behaviors as influenced by genes (Lehmann and Rousset 2010) is a radical proposition by some standards—and beyond the scope of this study. Suffice it to say that a discourse of humans and societies as selfish entities can be advanced with social abstracts framed on biological materialism. The prevalence and persistence of poverty is directly associated with existing self-seeking mechanisms.

Thus far we have established that humans are social creatures and that both they and their groups are self-seeking units. What other postulate is necessary for understanding the formation of social stratifying systems? Our first two postulates are necessary but not sufficient. We need a proposition that captures how humans have an insatiable appetite for resources. We now turn our attention to discussing our species insatiability for limited material resources.

Third Postulate: Insatiable Appetite for Finite Resources

Thus far it has been established that humans are social creatures who first seek to meet their (or their group's) self-interest. The third postulate pertains to human's strife for resources. Objects of desire (i.e., resources) have both a *utilitarian* and *status* value. Shelter from the natural elements has utilitarian value. Driving a multi-million dollar Lamborghini or Bugatti has status value. In general, we could say those in poverty concentrate their efforts in attaining utilitarian resources while those out of poverty devote their attention to increasing their status symbols.

There is a deleterious synergism between these resource-seeking movements: Utilitarian resource attainment if severely hindered by desire for status proliferation—because the latter can only occur by exploiting others from their resources. In simpler words, those with power seeking more status-wealth must do so at the expense of the weaker members pursuing basic utilitarian resources. This leads to a vicious cycle that can doom society towards a system that continually widens the gap between those in the top and the bottom.

Lamentably, status striving leads *demand* to constantly exceed *supply*, because "those of lower status constantly strive to equal those of higher status and those of higher status always seek to preserve the difference" (Lenski 1984:31). In other words, "have nots" want to become the "haves" (see Milanovic 2011) and the latter will do anything to retain their privileged status.

Lenski points out there are a few abundant resources like oxygen to breathe, but most are in short supply and that unlike other species on earth, "*man has an insatiable appetite for goods and services*" (1984:31 italics by original author). In sum, our species insatiable appetite for resources creates a perverse system of behaviors that ultimately makes satiation impossible. As a consequence, our third and final postulate necessary for discussing Blalock's theory of discrimination is then that humans have an insatiable appetite for resources.

Our third fundamental view on human nature necessitates expansion. My dissertation contributes to the existing literature by expanding on this last postulate. In recent times, largely as a byproduct of the environmental movement, humans have begun to understand and accept the fact that material resources are *finite*. This means that oxygen—or earth for that matter—need not last at infinitum. Organisms have the power to affect their habitat in such a way that even the most fundamental elements are altered in self-harming ways. Humans could collectively behave in such a way as to eradicate the existence of oxygen in earth.

Expanding the third postulate to include that resources are finite requires that we pay heed to the two fundamental messages: first, all life on earth is interdependent; secondly, resources have a finite nature (Deesen 2009). Thus, when you combine “the interdependence of all life on earth” with “the finite nature of the resources on which” interdependent life depends (Deesen 2009:70), you see that individual behavior reverberates across the web of our species’ existence. Consequently and in light of bounded resources, human’s insatiable appetite for limited resources exacerbates social inequality—and thus the systematic structural-maintenance of poverty.

Distributive Systems

Using our three postulates, we would deduce that human nature can be summarized as follows: Humans are social, self-seeking units, who are continually struggling for limited resources. If the three postulates are acceptable, “then it follows logically that *a struggle for rewards will be present in every human society*” (Lenski 1984:31-32 italics by original author). That is, stratifying social structures may be unavoidable—which is why formal mitigation mechanisms are necessary.

When thinking about the nature of society and how it operates as a structure that unevenly distributes resources, Lenski admonishes us to think “of distributive systems as reflecting *simultaneously* system needs and unit needs, with each often subverting the other” (1984:34 italics by original author). In other words, limited resources are distributed along detectable mechanisms that unevenly feed the needs of both the group and the individual. Social inequality is created and grows when either special groups or individuals within a population hoard resources in the distributive system.

The coordination of society in which distributive systems operate can be reduced to two basic elements. The first goal is to create and maintain social harmony. For example, we could argue that societies "are directed toward *the maintenance of the political status quo within the group*" (Lenski 1984:41 italics by original author). I believe—and our recorded history could be said to support—that attaining perfect equilibrium in social harmony is impossible. Thus, such a goal may be rephrased in more realistic terms as "*the minimization of the rate of internal political change*" (Lenski 1984:44 italics by original author). Thus, the first goal in the coordination of any group is to maximize social harmony.

The coordination of society requires that harmony be maximize along with social resources. More formally, the second element necessary in the coordination of a society is aimed at the "*maximization of production and the resources on which production depends*" (Lenski 1984:42 italics by original author). Distributive processes must then navigate through an environment where social harmony and production are being maximized.

The priority given to each of the two main societal goals differs by place and time, where "*the goal of maximizing production has priority in relatively unstratified societies" and "the goal of minimizing political change has priority in societies in which power and privilege are monopolized by a few*" (Lenski 1984:42 italics by original author). I believe the U.S. fits the latter status because the increasing concentration of power and privilege is birthing an American quasi-oligarchy that includes organizational entities. Thus, our proliferating wealth accumulation by a few is forcing our society to first seek the minimization of internal conflict (i.e., harmony maximization) above all else.

This discussion is important because prioritizing harmony over production affects our resource distributive system in an adverse way by clamping down on production and increasing formal and informal constraints against a revolt from those at the bottom. Sadly, our rapid and sustained industrialization and technological revolution in a quasi-free market capitalist economy has “enabled an unprecedented increase in material well-being, dramatically widening the absolute distance between the top and the bottom of human social structures” (Massey 2007:4). It was noted long ago that capitalism is a deeply geospatial project, that it has achieved its intended growth, even though we “cannot calculate at what price, but we know the means: *by occupying space, by producing space*” (Lefebvre 1976:21 italics by original author). We will return below to the discussion of space.

How then does our understanding of human nature and distributive systems inform our view of social stratification? To answer this, we now turn our attention to how social, self-seeking, resource hungry beings—operating in a harmony, production maximizing environment that distributes resources differently across social stratums—contribute to the creation of categorical inequality.

Categorical Inequality

Up to now, we have discussed the three fundamental postulates on the nature of humans and their societies and how these postulates operate in an environment where the two main goals of societal coordination take place. My arguments up to now paint a picture of a social, selfish, insatiable resource seeking humans (or groups) who in combination with a desire to maximize sociopolitical harmony and production create structures that systematically distribute resources unequally. In this section, we employ Douglas S. Massey's (2007) theoretical perspectives to outline how uneven distribution of resources varies across different social categories and geographies.

Poverty, the central topic of my dissertation, is being used as the dependent variable in all the statistical models as a proxy measure of inequality. As mentioned earlier, those in poverty are thought of as being victims of social inequality. These views assume that poverty is *in part* a byproduct of social stratification.

What is social stratification? In the words of Massey, social stratification is "the unequal distribution of people across social categories that are characterized by differential access to scarce resources" (2007:1). For my project, I am arguing that poverty exist as a consequence of distributing people unequally across different resource access stratums. Those who possess the correct combination of acquired and attained social attributes are relegated to advantaged (i.e., resource rich) social categories and their least fortunate counterparts are hurled towards the ever growing group of disadvantaged (i.e., resource poor group). Historically, non-Latino-whites have been the majority-status group in the U.S. and Latinos/as the structurally hindered minority-status group (see Acuna 1988).

Before outlining Massey's excellent modern appraisal of social stratification, we must first understand where he joins the discourse. In general, social science can be said to bifurcate theory along structural or individual level explanations (see Poston et. al. 2010; Saenz, Cready, and Morales 2007). Delineating poverty causing mechanisms at the individual level usually confines researchers to explanations of how an individual's attributes affects his/her life chances. On the other hand, structural level causal explanations usually render theorists mute on how "agency" plays a role in economic outcomes.

As a side note, if agency is free will and it is thought of as a sovereign entity that is completely disconnected from all external influence, then I think this "agency" is a myth. I belief all ideas/emotions (i.e., biochemical events) are directly influenced by bio-material and social forces (for example, see Thaler and Sunstein 2008). A full discussion of agency is beyond the scope of this investigation. The term agency is however used in the dissertation and it is meant from the more sociobiological perspective. Agency is a species-level descriptive being used as a mentalistic and anthropomorphic symbol to describe neurobiological events (Thompson and Deer 1996; also see Williams 1966).

There are three classical and mainstream social theories on poverty. Amongst the oldest and based on individual-level economic views is the one advanced by Gary S. Becker in 1964. Becker's *human capital* theory frames poverty as a product of differing investments on skills that directly influence labor market performance (i.e., poverty status). This "approach assumes that individual tastes, preferences, and abilities lead people to make differential investments in education and skill development" and that "differential investments ultimately translate into greater and lesser rewards in the labor market" (Poston et. al. 2010:142). For example, if a person invests in formal education and attains a Ph.D., then she/he will be able to reap a high economic payback in the formal labor market.

During the same time period, Oscar Lewis (1966) was developing what remains a controversial theory. Lewis believed a *culture of poverty* could explain how people are socialized towards differing values and that culture is the primary factor determining a person's ability to attain resources. In essence, the "culture of poverty thesis suggests that people growing up poor are socialized to internalize values that prevent them from participating in the economic mainstream" and as a result are separated from the middle class—which perpetuates their impoverishment (Poston et. al. 2010:142).

For example, a child who grows up in a poor family unit may have a detectable vernacular, way of dressing, walking, and values that lead him/her to stay away (or be pushed out) from advanced formal education. The child's behavior then lowers his/her chances of reaping benefits from the formal sector. On this topic, Blalock wrote that socialization "affects the child's behavior and value system, leading ultimately to social and economic inequalities" (1970:194). In different words, multigenerational transference of money, status, and positions are influenced by "demographic processes because families influence subsequent generations through differential fertility and survival, migration, and marriage patters" (Mare 2011:1). The point is that the culture of poverty theory emphasizes values and neglects to expand on how structural disadvantages play a role in the connection between values and resources.

Essentially, the poverty-culture perspective "argues that children of poor families are socialized into a culture of poverty with a set of values and beliefs that prevents them from recognizing and taking advantage of opportunities" (Lee, Singelmann, and Yom-Tov 2008:517). Others have eloquently argued that there are no specific values or cultural behaviors that create poverty (see Valentine 1968). By advancing a more structural perspective, they reframe the causal path and explain "that children who grow up in poor families have less access to human capital, which makes them less competitive in the labor market and, in turn, more likely also to end up poor" (Lee, Singelmann, and Yom-Tov 2008:517).

For example, a child born in a poor family unit is likely to reside in a poor neighborhood where they are ill-prepared by financially depleted schools. Their inability to enter college because of limited financial resources and poor training then become insurmountable obstacles. Because of existing social structures, and by no fault of their own, they were born in poverty and are very likely to remain in poverty for the rest of their lives.

Within the framework of the structural perspective, Blau and Duncan (1967) advanced the *status attainment* approach for understanding poverty. They pointed out that both *achieved* skills—which Becker only focused on—and *ascribed* characteristics are linked to life chances. Educational attainment is one of many achieved characteristics. Skin color is one of many ascribed traits. Both achieved and ascribed characteristics of individuals and their familie's matter. These factors are important in Massey's explanation of social stratification. According to Massey, categorical inequality is present because all "human societies have a social structure that divides people into categories based on a combination of achieved and ascribed traits" (Massey 2007: 1).

The main point is that both ascribed and achieved "factors are linked to outcomes such as income and occupation" (Poston et. al. 2010:142). For example, person A may obtain a PhD while person b stops their formal education after he/she gets her/his high school diploma. Assume for a moment that person A, who has a PhD, is a "detectable" minority who is not socially connected to resource-rich networks and person B comes from a wealthy family made up of majority-status group members. It is possible that person A with his/her Ph.D. will end up making as much money during her/his lifetime as person B with his/her high school diploma will in his/her lifetime. The main point is that achievements operate in a symbol saturated and stratified universe. Ascribed characteristics matter.

Human capital, culture of poverty, and status attainment all circle around individual and structural explanations of poverty. Massey makes use of all these ideas in explaining categorical inequality. Inequality is in part responsible for the creation, maintenance, and sometimes growth of poverty. Inequality could be thought of metaphorically as the gap between social hierarchies. More formally, inequality is "the degree of variability in the dispersion of people among ranked social categories" (Massey 2007:2).

Lamentably, and despite drastic social transformations over the last few thousands of years, inequality producing processes have been solidified by durable social stratification mechanics. This is so because regardless of structure or agency factors, distributive processes persist. There are two main mechanics for the maintenance of categorical inequality: 1) "the allocation of people to social categories"; and 2) "the institutionalization of practices that allocate resources unequally across these categories" (Massey 2007:6). In simpler words, humans categorize each other and then resources are distributed unequally across those created categories. For example, in majority "white" U.S. society, phenotypes at the "light" end of the spectrum have more access to resources than those towards the center "brown" or extreme "black" end (see Arce, Murguia, and Frisbie 1987; Frank, Redstone, and Lu 2010).

It is also important to note that the above stratification perpetuating systems are fueled by exploitation and opportunity hoarding (Tilly 1998). Both of these combine our self-seeking and insatiable resource appetite postulates. Tilly's ideas expand our postulates with important details.

In *Durable Inequality,* Charles Tilly (1998) explains that exploitation occurs when group X deforces resources produced by group Y. The unjust appropriation of resources then obstructs group Y's ability to maximize their investments. A simple and calamitous example is slavery in the U.S. From about 1619 until 1865, when the 13th

Amendment was passed, non-Latino-whites exploited (for a quarter of a millennia) the labor of African slaves to build their wealth (see Feagin 2006).

Consequently, slaves' ability to maximize their physical labor investments was obstructed by the laws (i.e., social structure) that protected slave holders. Their traumatic abuse was later "followed by discrimination and continued economic exploitation" (Meerman 2005:551). Minorities' overt economic discrimination diminished during the Civil Rights revolution. Poverty then became a new tool in the development of their economic serfdom.

The second component that solidifies categorical inequality is opportunity hoarding. As adapted from Tilly's definition, opportunity hoarding is enabled through a socially defined process of exclusion that allows group X to limit, either through obvious force or penalty infringement, group Y access to scarce resources. In other words, when given the chance, people (or groups) will hoard opportunities for themselves at the expense of others. This view supports our earlier premise on the nature of humans.

A sad example of opportunity hoarding comes from the story of current prisoner and former American stock broker Bernard Madoff. His ponzi scheme defrauded thousands of investors from more than $60 billion dollars (Tresniowski 2011). Madoff's crimes also burdened his two sons, Andrew and Mark, with numerous civil lawsuits. While Andrew got away from it all, Mark Madoff wanted to continue working in the financial world. His fight ended on Dec. 11, 2010. After writing an e-mail to his wife, Mark "slipped a cord around his neck, tied it to a ceiling beam and hung himself" as his

2-year-old son slept in a nearby room (Tresniowski 2011:58). Opportunity hoarding has deleterious consequences for both individuals and societies.

It is important that we note that both exploitation and opportunity hoarding are supported through emulation and adaptation. The latter two generalize the influence of the first two. Adaptation occurs at the micro-level, where individual's behaviors are oriented towards perceived ranked categories and emulation operates at a more macro/group-level, whereby x_{group^i} copies from group y_{group^j} or transfers the socially emulated distinctions from i^{th} geographical location to j^{th} place.

Although the details of the following are beyond the scope of this study, it is worth noting that categorical inequality is only possible when the roots of social stratification are present—namely the ability to cognitively construct the elements that allow the boundarization of individuals into different groupings. Heuristics, mental shortcuts (Read and Grushka-Cockayne 2011), are said to have evolved from the need to conserve energy. Some have argued that Homo economicus benefits and necessitates "adaptive rationality" (Haselton et. al. 2009) to survive complex physical and social environments.

Categorization sustaining "rule of thumb" systems afford our species a fast decision making structure that affords us approximate solutions (Rozoff 1964). They simultaneously render us weak to challenge the exploitation and opportunity hoarding that fuels the solidification of systemic stratification.

We could also argue from the sociobiological perspective that humans are neurophysiologically wired "to construct general categories about the world in which we live and then to use them to classify and evaluate the stimuli we encounter" (Massey 2007:9). A key point in this discussion is on how biology interacts with the social environment. The bio-chemical creation of social categories in each individual unit is ultimately and physically expressed in social settings. This occurs because group "identities and boundaries are negotiated through repeated interactions that establish working definitions of the categories in question" (Massey 2007:15).

Regardless of location on the multidimensional social hierarchy continuum, we can say all people "actively participate in the construction of the boundaries and identities that define" our system of stratification (Massey 2007:16). This means that there is hope for change. A change that can only occur when we understand how "power" underlies everything we have been talking about. We now turn our attention to how power operates in distributive processes to create categorical inequality.

Power in the Distribution of Resources

Before discussing sociological space we must briefly highlight how power is a subtle but crucial topic in our discussion on the distribution of resources. Sociology is interested in understanding power—a fleeting concept that seems to resist being defined. Our postulates above argue that humans are social, motivated by self-interest, and that the objects of their desire are in short supply. These elements function in an environment where humans create categories and distribute resources unequally.

These social, self-interested agents pursuing limited resources create self-seeking societies interested in maintaining their existence. How does resource distribution function under such circumstances? The answer is deceptively simple: Resources are distributed on the basis of power.

What is power? Weber (1947) defined power as the ability of one person (or group) to carry out their will over another. Lenski argues, and I agree, that "*power will determine the distribution of nearly all of the surplus possessed by a society*" (1984:44 italics by original author). From the classical pluralist model, power can be defined as "A has power over B to the extent that he/she can get B to do something B would not otherwise do" (Dahl 1957: 202-203). The point is that power equals control.

Explaining the distribution of resources only requires that we determine the distribution of power. The pattern of distribution can lead us to discover the causes of a given social power structure. Although this will be discussed in latter sections, it is important to note the "geometry of power," the idea that power itself always has a physical and abstract geometric form—that is, social power is geographical (D. B. Massey 2005 and 2009). Some have even written on how geographies are recreated to resist global hegemony (e.g., Katz 2006) and how laws have spatial impacts in communities (see Wunneburger, Olivares, Maghelal 2008). All these ideas have recently been revived to full rigor from academic interest that lead to a "rematerialization" of human geography—a discourse on the way in which the material and the social intertwine and interact to influence the creation and maintenance of power (Bakker and Bridge 2006:5).

Sociospatial stratification, in terms of categorical inequality, could argue that social hierarchies result:

> …whenever those in power enact policies and practices to give certain groups more access to markets than others; offer competitive advantages to certain classes of people within markets, invest more in the human capital of certain groups than others; and systematically channel social and cultural capital to certain categories of people (Massey 2007:23).

Consequently, large patterns of discrimination can lead to systematic investment that shapes “the geography and built environment” in such a way as to create socially and spatially discriminatory” processes (Soja 2010:x).

My discussion on power is short but suffices in answering the following: How does race and ethnicity play a role in power as it determines the distribution of resources? Lenski uncomplicated the answer by untangling the mechanics between status groups and distributive process. He explains that when membership in a racial or ethnic group “begins to have an appreciable influence on men’s access to important rewards which are in short supply,” then it becomes necessary to consider them a class or status group (Lenski 1984:396).

Calling racial-ethnic groups classes means “that they are groups of people who stand in common position with respect to some attribute which functions as a resource in the distributive process” (Lenski 1984:396). My dissertation uses this logic in singling out the contrast between non-Latino-whites and Latinos/as. In my view, Latinas/os are a group whose “common position” in the American social structure relegates them to the lower echelons. This means that, in general, Latinos/as are not part of the mainstream classes. Even those who are highly educated and wealthy must first prove themselves to the dominant class as an unthreatening element.

The “Latino/a” label is prominent in our American inequality because stratification of racialized groups is salient in the minds of U.S. members because “the very struggle to reduce this form of inequality has often had the effect of increasing men’s awareness of it” (Lenski 1984:402). The label is ambiguous because the core group may be easily detectable (e.g., a bilingual Mexican-origin 3rd generation Tejano), while the outer boundaries are more porous (e.g., a mono-English Spain-born Californio). In other words, the Latina/o umbrella term includes many individuals who may not have a deep affinity with the group. The label, at best, is a way of recognizing U.S. residents who have an affiliation/ancestry with a Spanish-speaking culture/group.

A discussion on power and ethnicity is important because people should be aware that some groups may be seeking a parallel social existence—where they retain their language and various cultural practices while participating in America’s democracy (i.e., cultural pluralism). Some have argued that minority assimilation to mainstream culture is (and should be) the ultimate goal of any minority group (see Chavez 1991). Such a philosophy posits that in order for a group to attain social harmony, all members must become culturally similar to one another by holding the same values (which are attained by developing a similar culture). Thus, the term assimilation is used in positive terms to signal how new group members move from their undesirable habits towards embracing the sacred mainstream values. This theoretical stance is problematic (see Johnson 1997; Telles, Ortiz, Moore 2008). This view hides the formal and informal way power operates to force (potentially unjustifiable) duplication.

In simple terms, talking in terms of assimilation is a polite way of hiding the dangerous fact that minorities are “coming into the game after it has already begun, after the rules and standards have already been set, and having to prove oneself according to those rules and standards” (Young 1990:164). Minorities must adapt to an existing game that disadvantages them from the outset. This occurs because assimilation in effect “perpetuates cultural imperialism by allowing norms expressing the point of view and experience of privileged groups to appear neutral and universal” (Young 1990:165).

The main point is that “the aim of assimilation is to unite people around a common good, but the common good is often defined in a way that fulfills the interest of perspectives of the dominant groups” (Piatelli 2009:4). The hostile “downside of an inclusivity based on assimilation denies the reality of oppression and blinds privileged groups to their own group specificity, thereby resulting in *exclusive* versus inclusive environments” (Piatelli 2009: 4, italics by original author). Assimilation in the United States is oppression because it fosters an exclusive social environment. Minority-status groups like Latinos/as are thus made victims under such socio-political and -economic regimes.

Racial struggles in the U.S. have heightened the sense of racial/ethnic identity. Any real reduction in the degree of status group inequality need not be psycho-emotionally connected to the salience of racial/ethnic group labels. The bottom line is that racial-ethnic categories still matter and Latinos/as are a social class. Understanding how Latinas/os are systematically distributed along the U.S. social hierarchy is important since their group salience is likely to increase as their population continues to proliferate.

Power is complex and a full discussion elsewhere is warranted, because eloquent words remind us that to legitimate the power of the established “is an appeal to a justice transcending any one man or group” while protecting the “present interests of the established” is but “an excuse for enforcement of the order from which they so notably benefit” (Novak 1972: 30). Criticizing current forms of power is easy. Understanding where depart from the humane to the discriminatory is much harder.

How do all these matters come into play with geosocial space? By *geosocial* I only mean geographical social space. From a geospatially conscious perspective, we could highlight that the geographic distribution of power “affects society and social life just as much as social processes shape the spatiality or specific geography” of any habitat (Soja 2010:5). Lefebvre’s words vitally capture how power saturates space in the following passage:

> It would be mistaken in this connection to picture a hierarchical scale stretching between two poles, with the unified will of political power at one extreme and the actual dispersion of differentiated elements at the other. For everything (the 'whole') weighs down on the lower or ‘micro’ level, on the local and the localizable—in short, on the sphere of everyday life. Everything (the 'whole') also depends on this level: exploitation and domination, protection and—inseparably—repression. The basis and foundation of the 'whole' is dissociation and separation, maintained as such by the will above… (1991:366).

The power that frames inequality is spatial and has both abstract and material consequences that alter societies and their physical environments. We now turn our attention to how power, through spatial non-stationarity, influences the distribution of individuals along the American social hierarchy.

Spatiality of Time and Space

Before we begin discussing spatial non-stationarity (i.e. the fact that near things influence each other more than distant things), there are several things that require our attention. In this section, I will be introducing how space is socially constructed, what sociospacial factor I am referring to in my investigation, and why including a space element in any sociological investigation is important.

Critical spatial thinking, at its roots, arises "from the belief that *we are just as much spatial as temporal beings*" (Soja 2010:16 italics by original author). A quest for descriptive, analytic, and global geospatial knowledge could be termed "spatiology" (Lefebvre 1991:404). The spatiological view would advance on the premise that our existential spatiality and temporality are essential and equally powerful in explaining human behavior—that they are "interwoven in a mutually formative relation" (Soja 2010:16). That is, in talking about human behavior we are talking about space. We must note how "space and place are different aspects of a unity—that is, two facets of a dialectical process just as the wave and particle aspect of matter is assumed in quantum physics" (Merrifield 1993:527). Human behavior has a bidirectional relationship with both physical and abstract space.

For example, living in Antarctica—where they have long periods of no sunlight and freezing weather—has both anatomical and psychological effects. Our physical habitat directly influences our behavior by providing material potential—if you want to swim you need a body of water. Our environment can also be altered to suit our needs—deforestation in early times helped build our cities and has kept us warm. The bottom line is that social space is important and its hegemony operates at the micro, meso, and macro level. We could say “its effects may be observed on all planes and in all interconnections between them” (Lefebvre 1991:412).

The spatiality of time and space within our species is simply based on the fact that we are temporal beings (see Heidegger 1962; Massey 1992: and Laclau 1990 for the non-temporality of space-time). By temporal I mean that we are most influenced by what is most immediate—in time and space. This is because our “biography defines our individual lived time” which makes us irreversibly contemporary and unavoidably temporary (Soja 2010:15).

The most proximal social behavior work, related to this topic, comes from economics. Many years ago, economist began to talk about the intertemporally inconsistent preferences of individuals in their consumption (Goldman 1979; Ryder and Heal 1973) and intergenerational altruism (Phelps and Pollak 1968). The idea is simple to understand, people’s behavior is differentially influenced by the pass, present, and future. Each time element exerts both a different degree and type of influence.

Humans are affected by all three time frames, but “when considering trade-offs between two future moments, present-biased preferences give stronger relative weight to the earlier moment as it gets closer” (O'Donoghue and Rabin 1999:103). Put differently, humans are more influenced by what is most immediate. Our species is biased towards preferring the present; we have present-biased preference. We are more likely to pursue immediate gratification even if it jeopardizes our future well-being. Both our immediate physical environment and time-interactions matter more than distant spaces and transactions. This is why "the distribution of space is an outgrowth of social structure" (Baldassare 1978:31).

Robert E. Park, gave his ASA presidential address and told his audience:

> It is because social relations are so frequently and so inevitably correlated with spatial relations; because physical distances so frequently are, or seem to be, the indexes of social distances, that statistics have any significance whatever for sociology. And this is true, finally, because it is only as social and psychical facts can be reduced to, or correlated with, spatial facts that they can be measured at all (1926:18).

This is why including a study of space is necessary. Investigations on social phenomena that neglect the significance of "spatial facts" make sociology less significant. An analysis of space must supplement all social demographic analyses. My investigation explores how sociospatial factors play a role in the prediction of poverty status.

Almost a century after Park shared his wisdom, most social science research primarily gives attention to "social processes and social consciousness as they develop over time" rather than focusing on spatial developments (Soja 2010:2). That is, most investigations only focus on the events that unfold around geographical space—they do not seek to understand if and how the distribution of events over space matters. A focus on the geographical distribution of events has "been treated as a kind of fixed background, a physically formed environment that, to be sure, has some influence on our lives but remains external to the social world" (Soja 2010:2). Such a theoretical approach privileges "time" over "space' and powerfully shapes the sociological imagination by limiting its implications (as Park long ago warned us).

Space and time, along with their "socially constructed extension as geography and history," are most fundamental "qualities of the physical and social worlds in which we live" (Soja 2010:15). Time is a term being used as a substitute for a more complex concept. By time, I mean to invoke how *distinct transactions* are cognitively linked to create a continuum that shapes our identities and thus how we navigate the social world. Which is why Soja tells us that it "is over time that we also create our collective selves, construct the societies and cultures, polities and economies within which our individual experiences are expressed and inscribed" (2010:15).

Henri Lefebvre deals with, amongst other things, developing and "*orientation*" towards our understating of the production of social space (1970:423). In Donald Nicholson-Smith's 1991 translation, Lefebvre writes that social space is a social product (1970:26). He admits the proposition borders on being tautological and requires a detail explanation. A full discussion on this matter is beyond the scope of the current project. Instead, I will simply delineate and adapt Lefebvre's ideas.

Social space, as explained by Lefebvre, is indistinguishable mental and physical space. Thus "such a social space is constituted neither by a collection of things or an aggregate of (sensory) data, nor by a void packed like a parcel with various contents, and that it is irreducible to a 'form' imposed upon phenomena, upon things, upon physical materiality" (Lefebvre 1991:27). In simpler words, our physical space is filtered by our morphing mental constitutions and our neurophysiologic self is a part of the material habitat.

In this project, I too argue that social space is socially created. The productive process of space is defined by how individual members interact with each other and their physical environment, and how these interactions transform the process over time. This assumes that if "space is produced, if there is a productive process, then we are dealing with *history*" (Lefebvre 1991:46, italics by original author). The U.S. has had a history (i.e. a high quantity of distinct transactions) were "many social groups" have been "excluded from markets as a matter of both formal policy and informal practice" (Massey 2007:23). Our social space is riddled with inequalities.

Unequal distribution of resources by social statuses and geographical locations amplifies the inequality gap. Social inequality has unjust "consequential geographies" (see Soja 2010). Consequential geographies are "the outcome of social and political processes," and "are also a dynamic force affecting these processes in significant ways" (Soja 2010:2)—they are the spatial expression of stratification. For example, poorly resourced environments (e.g. deep-poverty counties or low-agricultural rural areas) hinder individual's life chances above and beyond their attained and ascribed characteristics. Toxic environments (e.g., high-crime communities or chemically hazardous waste depositories) can even threaten quality of life beyond the effects of the micro- or macro-social elements.

There are two overlapping and interactive elements to sociospatial inequality. The first, at a m**a**crogeographical level, "results from the external creation of unjust geographies through boundary making and the political organization of space" (Soja 2010:8). The second, at a m**i**crogeographical level, factor in sociospatial inequality results when "unjust geographies arise endogenously or internally from the distributional inequalities created through discriminatory decision making by individuals, firms, and institutions" (Soja 2010: 9). In effect, inequality is geo-localized either through formal (e.g. policy driven boundaries) or informal (e.g., racially biased behavior) means.

Our discussion can be complimented by the extensive work of many others. For example, a few years ago Lefebvre wrote:

> Every space is already in place before the appearance in it of actors; these actors are collective as well as individual subjects inasmuch as the individuals are always members of groups or classes seeking to appropriate the space in question. This pre-existence of space conditions the subject's presence, action and discourse, his competence and performance; yet the subject's presence, action and discourse, at the same time as they presuppose this space, also negate it. The subject experiences space as an obstacle, as a resistant 'objectality' at times as implacably hard as concrete wall, being not only extremely difficult to modify in any way but also hedged about by Draconian rules prohibiting any attempt at such modification. Thus the *texture* of space affords opportunities not only to social acts with no particular place in it and no particular link with it, but also to a spatial practice that it does indeed determine, namely its collective and individual use: a sequence of acts which embody a signifying practice even if they cannot be reduced to such a practice" (1991:57, italics by original author).

The point is that sociogeographies are important because it "is within space that time consumes or devours living beings, thus giving reality to sacrifice, pleasure to pain" (Lefebvre 1991:57). Non-spatiological investigations on inequality are thus, as Park argued many decades ago, less sociologically relevant than their counterparts that include a sociospatial element.

It is important to note that an appropriate spatiological study is not "directed at space itself, nor does it construct models, typologies or prototypes of spaces; rather, it offers and exposition of the *production of space*" (Lefebvre 1991:405, italics by original author). In my study, the sociospatial exploratory component is meant to capture what could be considered a science of space or "spatio-analysis" that stresses "the *use* of space, its qualitative properties" where a critique of established knowledge/knowing is the essential goal (Lefebvre 1991:405). In other words, when I say that minority concentration in the area of residence matters, in actuality I am saying that the historical processes that have culminated to form the existing social and physical environment matter when trying to understand how individual level attributes are statistically associated with the likelihood of being in poverty.

The formation of social categories used in the distribution of resources plays a role not only in the social and cognitive spheres, "social boundaries can be made to conform to geographic boundaries through" (Massey 2007: 18-19) systematic processes that make social differentiating more efficient and effective (see Massey 2005). Consequently, inequality is facilitated by investing or disinvesting in **either** geographic places or groups of people (see Massey and Denton 1993). The overlapping of social and spatial boundaries increases the efficiency of stratifying systems.

The core argument in this discussion is that everything that is social "is simultaneously and inherently spatial, just as everything spatial, at least with regard to the human world, is simultaneously and inherently socialized" (Soja 2010:5-6)—which is why the sociospatial element is included in my investigation.

In this section we established that space is socially constructed and the many reasons why social demographic investigation should incorporate a spatiological component into analyses. We have also defined spatial non-stationarity throughout the chapter as the fact that near things influence each other more than distant ones. We now turn our attention to a more formal discussion of the topic.

Spatial Non-Stationarity

The idea of "stationary process" was discussed long ago, in 1954, by University of Cambridge statistician Peter Whittle. He was amongst the pioneers who observed that new estimation techniques were necessary to model non-stationary fields. In discussing one-plus dimensional fields, he pointed out that spatial processes have statistical dependence that extends in all directions (Whittle 1954).

Several decades earlier, E. G. Ravenstein wrote on the pattern of migration flows (1876, 1885, 1889). His work dealt with migration movements as a function of distance. Others later adopted his approach and even termed more abstract investigations of movements as "social physics" (Zipf 1946). To be sure, modeling spatial dependence has been at the forefront of sociological thought for many generations. For example, early work focusing on Mexican-Americans and their income differential also controlled for region in order to account for "definite regional differences in terms of wages, dollar value, and possible hiring practices" (Poston and Alvírez 1973:701).

By invoking Waldo Tobler's (1970) first law of geography that "everything is related to everything else, but near things are more related than distant things," I argue that investigating poverty requires we expand our understanding of how social phenomenon disintegrates as a function of geographical distance. In more statistical terms, my theory is that spatial non-stationarity is necessary because it can help us *explicitly* investigate how space plays a role in the modeling process. The concept is meant to convey how statistical associations are "not fixed over space" (Brunsdon, Fotheringham, and Charlton 1998:431).

A more technical and full discussion on how regression coefficients are functions of their geospatial locations will be given in the methods chapter of this dissertation. The explanations will focus on delineating how variation of each of the elements of β over space operates. By using geographically weighed regressions, I employ the use of a "nonparametric estimate of $\beta_j(\rho_i)$ " (Brunsdon, Fotheringham, and Charlton 1998:432) to capture the space function.

The core question in spatiology is: How and why does an area attribute vary from one place to another? In my project I ask: How is racial-ethnic concentration spatially dependent when predicting poverty levels? A necessary proposition in such an endeavor is that statistically significant sociospatial variations are casually related. Thus, the "central problem in locational or distributional studies" is to "describe and account for significant features of the distribution" (Duncan, Cuzzort, and Duncan 1961:21). My project undertakes this endeavor.

The main goal in Chapter II was to theorize *how* and *why* hierarchical and sociogeographical factors are associated with the likelihood of being in poverty. Subsequent chapters explore data for support of the proposed theory by answering the following two questions:

> *Does the percent of Latinos in the area of residence have an influence on individual poverty over and above the influence on poverty of the person characteristics*?

and,

> *Is spatial non-stationarity an important element to account for when investigating poverty*?

At the micro-level, the hypothesis being assumed is that Latinos/as have greater odds of being in poverty than their non-Latino-white counterparts. The questions more formally stated in hypothesis form are:

> *At the macro-level, I hypothesize that as the percent of Latinos/as in the area of residence increases, the odds of being in poverty will increase for Latinas/os.*

and within the exploratory question,

> *I hypothesized that the statistical association between percent Latina/o and percent poverty is spatially non-stationary. In particular, I expect positive GWR coefficients in historically saturated Latino/a areas and negative betas in economically-healthy new destinations.*

CHAPTER III

METHODOLOGY

> "It is because social relations are so frequently and so inevitably correlated with spatial relations…that statistics have any significance whatever for sociology."
> Park 1926:18

The quantitative methods employed in the analysis of secondary data will now be discussed. This chapter outlines and explains the various models used to investigate Blalock's group threat theory. It offers a detail discussion on the implications of using quantitative analysis, with ACS data, given our selected sample and variables. After discussing the source and quality of my ACS data, I deliberate details of the final sample being used in study—at which point detail logic of my dependent and independent variables is given.

The models will be introduced in the same order they are given in Chapter IV. I first give a general rationale for using hierarchical Bayesian statistics. I then explain the random-coefficient equation before introducing the full pre-GWR intercepts-and-slopes-as-outcomes model. At this point, I motivated the use of spatial models by arguing the existence of spatial non-stationarity and how geographically weighted regressions are capable of capturing such phenomenon. While discussing the exploratory spatial analysis, I present some of the challenges facing spatiology.

After both the pre-GWR multilevel and spatial models are discussed, I move on to explain the creation of my exploratory hybrid multi-geospatial model. It is here that the final hybrid-HLM model is given. The hybrid model is the main focus of my dissertation. I conclude Chapter III by reminding the reader of my two formal hypotheses under investigation and how their working can be refined in more technical terms to capture the various forms of modeling being employed in my work.

Quantitative Analyses

Before discussing the data, sample, variables, and models, we must briefly point out some implications when using quantitative social research. As a quantitative social demographer I employ the use of statistics. In doing so, I partake of the many implicit assumptions found in probability theory. In particular, my models view human phenomenon as evolving in a stochastic process. This means that I believe probability distributions can capture the indeterminacy of human behavior. The statistical techniques used in this project work on the axiom given in the stochastic process assumption—that even if an initial condition is known, there are many possible destinations and some paths may have a higher probability of selection over others. In terms of human behavior, my use of statistics means that I believe we cannot predict future behavior with certainty, but we can "attach probabilities to the various possible future states" (Bartholomew 1967:1).

All my statistical models assume a Bernoulli scheme on a Markov chain. Markov chain refers to a system that moves from one state to another in a chain-like fashion. This statistical philosophy can only be applied to a stochastic process where the next state depends only on the current state and not on the past. A Bernoulli process is necessary when modeling a binary dependent variable—because it helps measure a discrete-time stochastic process that only uses two values (i.e., 0 and 1). My multilevel dependent variable of poverty status only has two conditions: 1=in poverty, and 0=not in-poverty. The Bernoulli process assumes that past outcomes provide no information about future outcomes. The process of estimating probabilities in my logistic model is thus memoryless.

In addition to assuming that next states do not depend of past states (the Markov chain assumption), the Bernoulli scheme further assumes that the next state is even independent of the current state. These philosophies on stochastic processes underlie the probabilistic laws structuring the legitimacy of my statistical techniques. Sociology adapted the use of stochastic models from the natural sciences.

Some have argued that the laws governing natural/material events do not apply to human behavior and that “to treat human beings as subject to ‘laws’ seems to be depriving them of freedom of choice” (Bartholomew 1967:5). It has been pointed out that social phenomena are too complex “by saying that social situations are far too complicated to allow mathematical study and that to ignore this fact is to be led into dangerous over-simplification” (Bartholomew 1967:6)—a warning that should be engraved in the minds of quantitative researchers.

I agree with those who point out that it “is precisely because man is a free agent that his behavior is unpredictable and hence must be described in probabilistic terms” (Bartholomew 1967:5). The truth is “that there is no alternative to simplification,” because the basic limiting factor is not the mathematical or software apparatus available but “the ability of the human mind to grasp a complex situation” (Bartholomew 1967:6). The legitimate use of stochastic models in social sciences has been around for several decades (see Coleman 1964; Kemeny and Snell 1962). Stochastic models of social phenomena have many functions.

My focus will be on giving insight into understanding poverty as a proxy to inequality (a product of discrimination). This means that my research could be characterized by some as being “pure” science. Pure science, because, as Melvin (1927:198) told us long ago: “He who would collect and classify sociological facts and draw consequential deductions there from cannot be too much concerned about their immediate application.” In truth, most social scientists seek discovery of facts as ends in themselves (Tyndall 1901). Stemming from current antinomies in the field, “scientific knowledge is at once theoretical and empirical, pure and applied, objective and subjective, exact and estimative, democratic (open for all to confirm) and elitist (experts alone confirm), limitless and limited (to certain domains of knowledge)” (Gieryn 1983:792). From these views, I approach my study as a pure scientist with the understanding of the power it has for application.

Keep in mind that the “suggestion that mathematical methods may lead to the manipulation of social systems is often viewed with misgivings by sociologists and others who have a concern for individual freedom,” a problem that arises “whenever new knowledge places power in the hands of its discoverers”—because it “can be used for good or ill” (Bartholomew 1967:4). My worthwhile project then is to search for general probabilities/solutions with the use of stochastic models. Some have argued that no model is perfect, but some are useful (Box 1987). Most of what I have stated above is given with the intent of disclosing all the "imperfections" (Freedman 2008) in my quantitative research. I am, in effect, admitting to the arguably high level of detachment my enterprise has from daily life. However, I feel justified (and think it a worthwhile endeavor) to quantitatively investigate complex human behavior, because in the end, all the centuries of social sciences have only developed investigative techniques that require us all to be "content with approximation" (Bartholomew 1967:7).

Source of Secondary Data

My quantitative social demography analysis is conducted using a Public Use Microdata Sample (PUMS) from the American Community Survey (ACS) administered by the U.S. Census Bureau during the 2005-2007 survey time-period. The term "time-period" is a Census term used to highlight the fact that responses are collected during the whole time period and not only in one or two months during each of the target years. There is substantial documentation available on the ACS methodology elsewhere (Census 2008).

The ACS is an ongoing yearly survey that helps the U.S. government allocate more than hundreds of billions of dollars in federal and state funds every year. For example, in fiscal year "2008, 184 federal domestic assistance programs used ACS-related datasets to help guide the distribution of $416 billion, 29 percent of all federal assistance" and about $389 billion (69%) of all federal grant funding (Reamer 2010:1). Its' primary purpose is to help the U.S. Congress determine funding and policies for a wide variety of federal programs (Census 2009b). The randomly selected national sample has extensive documentation available (Census 3). The microdata being used in this research includes several population characteristics. The main benefit of microdata is that it allows researchers the flexibility to prepare customized variables for the formation of tabulations and regressions.

The data source has an acceptable level of validity and reliability. Perhaps a short history of its inception and subsequent creation will help the reader contextualize the data source. Almost three decades ago, and after deciding that a “rolling sample design” (Kish 1981) was more appropriate for detailed demographic data than the decennial format, the U.S. Census Bureau was authorized (but not funded) in 1985 and again in the early 1990s to use the method.

Several years after the rolling sample design idea was introduced, the U.S. Census Bureau received Congressional funding to proceed. The Bureau selected one of three tested “rolling sample design prototypes” (Alexander 1993). The main benefit of a rolling sample, it argued, is that for less money, it creates more up-to-date estimates on key demographic characteristics of the population. A recent report validated the government’s effort to be more cost-effective by concluding that the “nation receives a very substantial return on its investment in ACS-related datasets” (Reamer 2010:1).

A national evaluation on the reliability of ACS estimates, compared to decennial estimates, is yet to be given (Citro and Kalton 2007; Diffendal, Petroni, and Williams 2004; Salvo and Lobo 2006; Salvo, Lobo and Love 2003). To be sure, “if the ACS is to serve as a *superior* replacement for the decennial census and a model for local data collection in the 21st century, increases in sample size and follow-up are crucial," especially for areas with low mail response (Salvo, Lobo, Willet, and Alvarez 2007:17 italics given by original author).

The project was first tested in 2005 and entered full implementation (i.e., the inclusion of group quarters in the sampling universe) by 2006. Please note that no "group quarter" data is used in my analysis and that there are limitations in the ACS because of its statistical and demographic measurement processes that employ controls from the Population Estimates Program in the Bureau (see Hogan 2008). Although a detailed discussion on these matters is beyond the scope of the current project, it will suffice to say that the ACS's use of the 2000 Census Master Address File challenges the idea that the housing unit stock is nationally representative (see Swanson 2006). There are also discussions on how "place of residence" complicates the sample (see National Research Council 2006). The many challenges and opportunities were noted since before its full inception (see Alexander and Wetrogan 2000).

After several years of implementation, the Bureau compiled single-year files to create three-year period data—and has more recently created five-year files. Each single- and multi-year file has benefits and drawbacks. One-year estimates have no survey instrument *consistency* problems (e.g., questions or format changes). They, however, only offer small samples that can only be used to estimate population demographics of large geographies like nation and states.

Three-year samples are three times as big and have the ability to estimate much smaller geographies like counties. The data collected over 36 months is less current than the 1-year data but more current than the 5-year file. There are some problems with using three-year files. The main one is that questions and survey formats have changed over the years. Consequently, all multi-year files require public data users to understand how (if at all) questions are compatible across years—which are why comparisons across ACS survey years must be made with caution (see Hogan 2000).

Five-year estimates are the largest and are useable at the track level—please refer to the above cited work on the covariance inflation factor issues with small geography estimates using ACS data. The consistency of the variables being used in this research (e.g., the race question) is most turbulent in this five-year file. There are more recent 3-year files, but the 2005-2007 survey time-period is consistent on all the questions I am using to create my variables. The main reason why I am using the 2005-2007 file is because in 2008 the ACS changed the format of the survey instrument and some of the key questions. In particular, the race and ethnic questions seem to have altered the way many respondents identified themselves. Thus, I have chosen the 2005-2007 three-year data because it affords a large sample and variable consistency.

Public Use Microdata Sample

Prominent social science research has used Census Public Use Microdata Sample (PUMS) files to investigate poverty through a multilevel framework (Cotter 2002; DiPrete and Forristan 1994). As a reminder, my project uses the 2005-2007 ACS Public Use Microdata Sample (ACS 05-07 PUMS). PUMS files allow researchers like me—who are in the public domain—to access individual-level data (i.e., micro-level data).

The three-year file being used is capable of creating population estimates for areas with as little as 20,000 people. The details for the custom estimates I create at the PUMA level are given below. Understanding the ACS data file requires some technical explanations. Extensive PUMS documentation is available elsewhere (Census 2009a).

One-year ACS PUMS files give analysts access to a 1% sample. A one-year file represents about 40% of the internally available data with some minor alterations on sensitive variables. Unlike the decennial census in which the sample represented approximately 1 in 6 households (i.e., 17% of the population), the ACS represents approximately 1-in-40 households (i.e., 2.5% of the full U.S. population) within a given year-period. This is approximately 1.3 million housing unit records and about 3 million person records (this excludes group quarter records). As explained above, the ACS provides the public with one-, three-, and five-year PUMS files. The three-year 2005-2007 PUMS file contains the same sample found in each of the 1-year files for the years: 2005, 2006, 2007.

The ACS 2005-2007 PUMS file being used in this research contains 3% of the housing units during the 2005-2007 survey time-period. For the sake of clarity, I am using the three year file because it is the most appropriate for my research. The three-year file is more precise than the one-year files and more stable than the five-year file. The instability present in the five-year file has to do with all the changes on the format of the survey and the questions in the survey. That is, the five-year file aggregates individuals across five years—even though they responded to slightly different survey instruments and questions. The three-year file being used here allows for the analyses of individual-level characteristics while accounting for PUMA attributes (i.e., contextual effects).

Because of confidentiality requirements by federal law, the ACS protects the microdata in various ways. PUMS files have a very unique way of being created—they follow clear federal laws—it has to do with protecting survey participants' personal information. The confidentiality of respondents is protected though a series of statistical and administrative processes. The publicly released microdata is "disguised" enough to protect individuals and at the same time allow the information to be current, useful, and valuable to public users.

Of the methods employed to insure respondent confidentiality, limiting the ability of public users to geographically locate respondents is one of them. The U.S. Census Bureau protects the identity of individuals by introducing small demographic alterations to the sample and only allowing their physical location (at the time of taking the survey) to be detected in geographical polygons with at least 100,000 people or more. Consequently, Public Use Microdata Areas (PUMAs) are the smallest geographic unit available for nesting individuals when using PUMS.

We will now turn our attention to delineating the PUMA geography.

Public Use Microdata Areas

Figure 3 below displays where PUMAs are located on the Census geographic hierarchy. A PUMA is a statistical geographic area defined by the U.S. Census Bureau

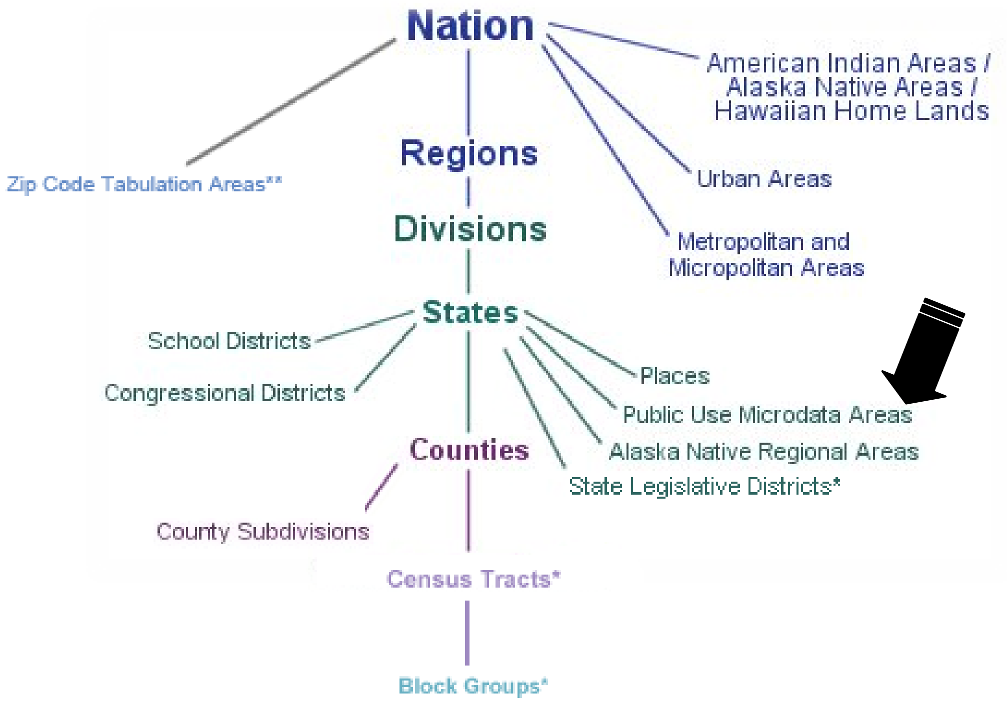


Figure 3
Location of Public Use Microdata Area in the Census Geography Hierarchy

for public dissemination. Statistical areas are defined by the Bureau, state, regional, or local authorities, and include small geographies like census tracts. Statistical areas, in general, experience less boundary changes than do legal areas because they are designed to have stable geographic boundaries. Since the ACS does not update previously released estimates to reflect subsequent boundary changes, PUMS data can be used to address such a limitation. ACS PUMA boundaries are identical to those in the 2000 5% census sample (see Ruggles et al. 2010).

It is important to note that the primary purpose of statistical areas is to tabulate and present census data (U.S. Census Bureau 2009a). The PUMA polygons being used in the analysis are not theory driven—they are driven by quantitative considerations and laws. To be sure, PUMAs are “units specially delineated for statistical purposes” (Duncan 1957:27). In a sense, their creation is driven by geometry and population concentration. The technique is unable to embrace complex socio-theoretical propositions.

For example, PUMA boundary creation does not take into account social process—even though “the spatial is socially constituted” and social space itself “is created out of the vast intricacies,” incredible complexities, and through “networks of relations at” the micro-, meso-, and macro-level (Massey 2007:80). PUMA boundaries ignore such dynamics. Consequently PUMA boundaries are, for the most part, without social meaning and could thus be argued to be politically insignificant.

Micro-level data from the Bureau is however governed by such geographical limitations—which is why I use “context” or “area effects” instead of talking about “community” (Selnick 1996) influences on x-individual-level factors as they relate to poverty. Note that that PUMAs are special, non-overlapping areas that partition states. Since states governments do influence the formation of the PUMA boundaries, they hold some (although ambiguous) meaning too many users.

These sample driven Census geographies do have several detectable characteristics. All U.S. Census Bureau geographies are built on the *block* geographic element. PUMA polygons are nested within states, cover the entire U.S., contain at least 100,000 persons per unit, are built on counties, census tracts, and are contiguous. The

Census provides maps showing how PUMAs overlap with other geographies (U.S. Census Bureau 6).

My project uses ACS 2005-2007 three-year PUMS that only allows me to nest individuals into PUMA polygons. I want to reiterate this so that the reader has a clear understanding once the discussion gets more complex: individuals are nested in PUMAs. The dissertation extends existing research by applying appropriate statistical techniques in a multilevel logistic analysis of context level effects on individual-level poverty. By nesting micro-level data in macro-level PUMA polygons, my investigation into sociospatial inequality delineates how individual-level stratifying mechanisms are influenced by context-level structural attributes. I also explore how sociospatial non-stationary processes are statistically associated with these relationships.

There are many limitations associated with using PUMAs as nesting polygons for people included in my analysis. This is primarily due to the ambiguous nature of the polygon—as explained above. This topic is fully discussed is the section below where we discuss the challenges spatiology faces. It is important to note that I am using micro-level demographic characteristics in the level-one equation. Subsequently, I aggregate those same characteristics from the same subjects to produce macro-level attributes (e.g., percent of Latinos in area of residence). This means that when I attempt “to explain individual-level dependent variables using combinations of individual- and group-level independent variables” (Blalock 1984), I must employ relatively new theoretical frameworks.

Please keep in mind that this government-created data does not reveal "unofficial behavior" like criminal activity—and the various "social-organizational processes that lie behind neighborhood demography" (Raudenbush and Sampson: 1999:2). This point is important because I presume "collective aspects of community life" (including deviant behavior) all contribute to the social processes constituting the neighborhood (see Mayer and Jenks 1989). My data and polygons do not fully capture this collective process. These are theoretical and methodological issues that need attention and more proper forms of data.

Existing research and theories on how the micro interacts with the macro have existed for over five decades (see Blau 1960; Davis 1961; Robinson 1950). Sociologists have been dealing with this issue for many generations. According to Blalock (1984) when dealing with "contextual-effects models," we must pay attention to the following:

> a) the proper choice of contextual unit,
>
> b) situations involving either nested or overlapping contexts,
>
> c) the causal ordering of micro- and macro-level variables and how this relates to the question of self-selection, and
>
> d) the nature of the specification problems that may arise whenever group means are used as indicators of the "true" contextual variables thought to belong to the correctly specified model (Pg. 335).

Unfortunately, these issues can only be tackled with a great deal of conceptual ambiguity. In my case:

a) My data forces me to choose the PUMA polygon as the "proper" contextual unit. The drawbacks are explained in the challenges in spatiology section below.

b) I believe contextual social processes are overlapping and are thus attempting to account for this by developing a hybrid multilevel logistic model that accounts for spatial non-stationarity. More technically, I believe the PUMA polygon boundaries I use are highly inadequate in correctly capturing "community nodes." This is why a spatial model is employed—(more on this below).

c) As explained in my literature section, I believe the micro precedes the macro-formations. I have not, nor will I, discussed self-selection at length. Self-selection deals with, among other things, how individuals select their context once their micro-level attribute is in existence. For example, a Latino who is in-poverty may be more likely to seek out residency in communities with other Latinos who are also economically deprived because of financial necessity (i.e., cheap rent) or choice. In this example, the micro preceded the macro. Self-selection is complex and my data renders me with little room for exploring the phenomena.

d) My multilevel models do use means to estimate parameters and control for any potential statistical heterogeneity—but not for highly localized social heterogeneity. The latter is accounted for with a spatial model. The estimates produced by the latter are then used as data to account for local social heterogeneity.

In order for me to argue that "individual-effect variables should be introduced before contextual-effect variables" I must "specified the direction of the causation between the two" (Blalock 1984:368). This is my primary argument in this regard: I propose that the contextual-effect variables employed in this study (e.g., percent Latino) have not been continuously operative throughout my subject's life. To put it differently, context is fluid and is thus a dynamic factor influencing and being influenced by the individuals who inhabit the environment. This is why I first introduce individual-level effects, and then account for how the produced PUMA-level attribute interacts with the micro-level factor.

Figure 4 below may help with clarification. The figure displays how macro and micro interactions are conceptualized. Some social science research only models effects within context-level units (the blue line in Figure 3) between time-1 and time-2 (i.e., $t_1$and t_2). These are macro-only-level investigations. Other sociologists investigate associations within individual-level units (the red line in Figure 3) from $t_1$and t_2. These are micro-only-level investigations.

Sociology was created as an academic discipline to understand how context interacts with the individual (all the black lines in Figure 3). These could be called micro- and macro-level investigations. In my multilevel models, I first introduce the attributes of "individual *X* at t_1" and then introduce "context t_2" at level-2. By doing this, I am ignoring the effects "context t_1" on individual *X* at t_1. The model then privileges the theoretical effects of individual *X* at t_1 on "context t_2" (the micro to macro interaction) and then explains the macro-level effects as if context t_2 is influencing individual *X* at t_1 (the macro to micro at t_2).

This approach is used because I belief co-ethnic distributions in area of residence become more volatile in larger geographies. As argued before, humans are temporal; they perceive their context in the most immediate form (e.g., their local community). I belief micro-level context fluctuations have less perception equilibrium, followed by meso-level perceptions, and macro-level perceptions of community, which have the most stability. Thus, I argue that the micro precedes the macro—because individual level characteristics are more immediate than macro-level attributes. It may be that self-selection becomes a factor in latter ages—when economic resources are available and social tastes are more settled.

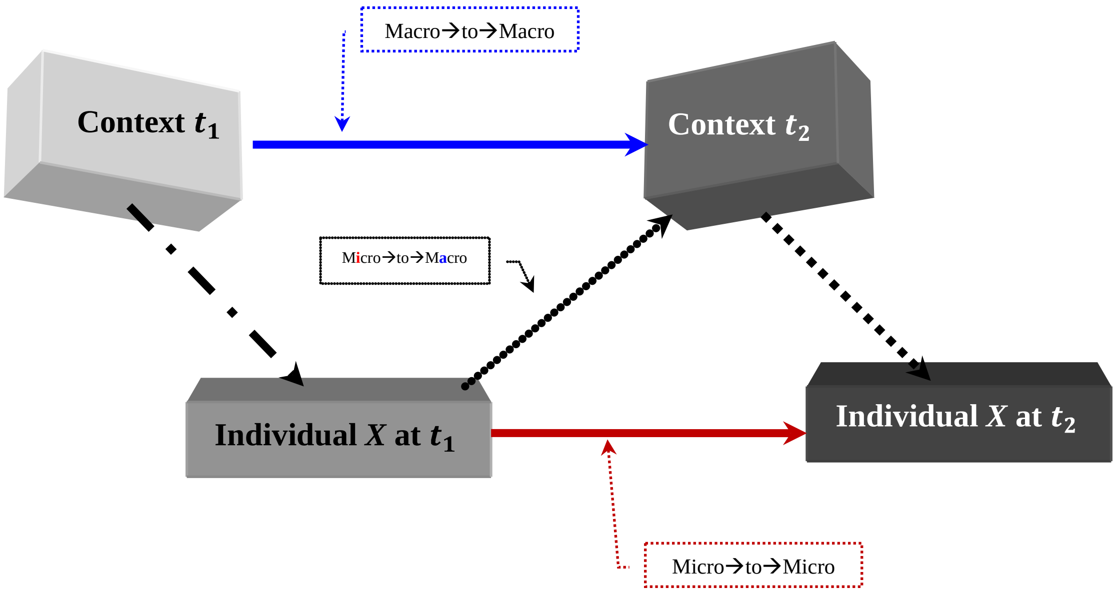


Figure 4
Theoretical Hierarchical Causality System

Despite these challenges, some have argued that "the presence of conceptually similar dependent variables at both levels increases the likelihood of conceptually similar explanatory processes and structures at both levels" (Liska 1990:299). Linking the micro to the macro seeks to remedy the problems created by only-macro research approaches that are distant from individual action and by only-micro approaches which neglect the influence of context (Sampson 1988 and 1991). In truth, capturing "system behavior" (Coleman 1986) remains a complicated goal.

When discussing theoretical complexities of this nature, it is important to understand that the micro and macro "are temporary poles bracketing a continuum, with social entities moving along this continuum over time" (Fuchs 2001). The micro and macro are not distinct elements. Linking them does not require building a conceptual bridge between them; rather, it requires an understanding of how people navigate along the multidimensional continuum they bracket. These are all worthwhile topics but beyond the scope of the current study. It is important to keep in mind that it "is not the geographic focus of a study that determines the applicability and value of the findings, but rather the quality of the data gathered, the quality of the analyses of that data, and the insight generated from the study" (Besser 2002:8).

On a more technical note, the U.S. Census Bureau releases PUMA geography related information by using a combination of numeric or alphanumeric codes—by using a *geocode* system. I use this geocode system to link micro-level observations (with their id number) to their PUMA of residence. The system is also important when linking PUMA level measure s to polygons in ArcGIS. I use Topological Integrated Geographic Encoding Referencing (TIGER) Shapefiles from the Census to conduct all my mapping and spatial analysis. In brief, a shapefile is a popular geospatial vector data format used in geographic information system (GIS) related software. In general, shapefiles provide open specification for data interoperability. More technically, they spatially describe geometries by using points, polylines, and polygons. Full details on ".shp" files are made available elsewhere (ESRI Shapefile Technical Description 1998) and a broader explanation of how geographies are released through U.S. Census Bureau TIGER/Line Shapefiles is also available (U.S. Census Bureau 2007).

A TIGER shapefile is an extract from the Census Bureau's Master Address File (MAF) database that contains selected geographic and cartographic information. The MAF/TIGER database is useful when mapping PUMS data in PUMA polygons using any form of Geographic Information System (GIS) software (in my case ArcGIS). My 2007 TIGER/Line Shapefiles contain the geographic boundaries as of January 1, 2007, that includes a Census 2000 vintage geography. It is beyond the scope of this study to explain how the Boundary and Annexation Survey (BAS) has made some alterations to the boundaries. Suffice it to say that my PUMA polygons are representative of the data being used in the analysis.

Before moving on to discuss the sample being used, it is important that the reader understand that even though "PUMAs are not ideal, they represent a scale falling somewhere between large MSAs and counties" and are customarily used (McCall 2000:420).

Sample

In this section, I outline the logic for sample selection. The research will only include "reference" persons—age 20 to 64—who currently reside in one of the mainland contiguous states (and DC). The main reason why states like Alaska and Hawaii are excluded in the sample is because the spatial models require that all polygons a cohesive area with no geographically empty spaces. Using non-geographically connected states like the ones mentioned above would prohibit the use of spatial models.

The sample only includes Latinos/as, single-race non-Latino-blacks, and single-race non-Latino-whites (for a detail discussion on the demography of race and ethnicity see Saenz and Morales 2005). These categories are discussed below. "Reference person" is a Census technical term used to label the variable that can identify the relationship of an individual within the house unit to the person responding in the survey. There are several “modes” of participation with the survey (Census 2009c), but for the most part, the reference person is the only survey respondent directly engaged with answering the survey questions for themselves and all other household members.

My primary micro-level variable of interest is individuals’ racial-ethnic identity. Since reference persons are the ones who are actually participating in the survey—all others are likely given their racial-ethnic labeling by the reference person and are thus not directly connected with the primary variables of interest: race and ethnicity. I use ethnicity along with race because previous research has found that “people with specific ethnic self-conceptions” use different self-images in the course of interaction with others (Saenz and Aguirre 1991:17). Because self-identification on both the race and ethnic variable matter so deeply, I only use reference persons in my sample. More technically, if a micro-unit has a “00” value on the relationship (REL) variable, they are retained in the sample and all others are deleted. This technique is prevalent in existing research (e.g., Garcia 2008).

Individuals between the ages of 20 and 64 are selected into the sample because this age range best captures the time when a person is more likely to enter and exit the labor market. That is, the age range captures most of the working-age reference person population in the microdata. In addition to this age selection, only reference persons who reside in one of the mainland states and DC are included in the sample. The main reason for this decision is that my spatial models require that polygons be adjacent to one another. All the above decisions lead to a sample that contains 2,526,896 individual-level units (i.e., reference people) who are nested across 2,054 context-level units (i.e., PUMAs).

Level-1 HLM Dependent Variable

My dependent binary variable is *poverty status*. I am predicting the likelihood of being in poverty. My measurement follows existing academic standards (see Garcia 2008; Poston et. al. 2010; Saenz 1997). Poverty in the ACS is calculated using standards specified by the Office of Management and Budget (OMB) in their Statistical Policy Directive 14 (U. S. Census Bureau 4). The original poverty thresholds were first developed back in 1963 by Mollie Orshansky of the Social Security Administration (Orshansky 1965). The official measure uses money income before taxes and does not include capital gains or noncash benefits like food stamps. The Census calculates a family's total income and compares it to the dollar value thresholds set in the directive (see Bishaw and Macartney 2010). The Census then uses the thresholds, which vary by family size and composition, to assign a poverty status.

The poverty thresholds do not vary geographically and as such do not account for the relative cost of living. The thresholds are however annually updated for inflation using the Consumer Price Index (CPI-U). For example, in 2007 a household with four people (where two are related children under 18 years of age) had a poverty threshold of $21,027. If hypothetical household A has a combined income of $22,000 per year, then they are not in poverty. Simply put, if a family's total income is less than the family's poverty threshold, then both the individual and the family are labeled as being in poverty.

On a more survey methodology note, since people respond throughout the year in ACS data, income items specify periods covering the last 12 months. Thus, the poverty threshold is determined by multiplying the base-year poverty thresholds by the monthly inflation factor based on the 12 monthly CPIs and the base-year CPI (U.S. Census 2). Note that poverty status is not determined for the following people: institutionalized, in group quarters, in college dormitories, and unrelated individuals under 15 years old. Consequently, these groups of individuals are excluded from the numerator and denominator when calculating poverty rates.

The binary categorization of “in poverty” versus “not in poverty” only allows the estimation of a poverty proportion. The problem is that proportions only capture the amount of people living below the poverty threshold. Using an *income-to-poverty ratio* is more sophisticated because it measures *depth of poverty* (DeNavas, Bernadette, Smith 2010: 18). The classical ratio measure of poverty commonly uses a 1.0 level, which indicates the person is at or below 100% of poverty.

Extensive research has been conducted on the measurement of poverty (Citro and Michael 1995) and to the development of experimental measures (see Garner and Betson 2010; Short 2011; Provencher 2011). Many criticisms on the current measure of poverty have led several researchers to argue that using a 1.5 ratio represents a more realistic view of poverty that accounts for the cost of living found across geographical variability. The 1.5 ratio can be thought of as grouping individuals that are *near*, *at*, or in *deep* poverty. Research using this approach has been done at the macro level (see Jargowsky and Bane 1991; Timberlake 2007) and micro level (Wertheimer 1999; Garcia 2008; Seccombe 2000). If we take this approach, 2009 data shows that while the Latino/a population had 33% of their group at a 1.5 income-to-poverty ratio, non-Latino-Whites only had 13% of their group at or below 1.5 ratio (DeNavas, Bernadette, Smith 2010: Pg.18).

By using poverty ratios, we can see the fact that Latinos were three times more likely to be near, at, or in deep poverty than their Non-Latino-White counterparts. It is clear, even with a crude racial-ethnic categorization scheme and different poverty ratios that poverty is *demographically* concentrated in minorities. A core argument in this dissertation is that social stratification is occurring across geographic and demographic dimensions—and that persistent and deep concentrations of poverty are detectable. Not all people are suffering equally in North America.

As outlined earlier, the ratio captures 'depth' of poverty. The ratio is computed using the poverty threshold discussed above. For example, a household with two people under the age of 65 and with one related child under the age of 18 has a 2006 threshold of $13,896. This family unit would need this amount of money to provide for food and all other basic sustenance requirements. Let us assume this hypothetical family unit of three had a combined yearly income of $30,000. To obtain the poverty ratio one would divide $30,000 by $13,896. This division would yield a quotient of 2.158. To obtain the final poverty ratio one multiplies the quotient by 100 and get a rounded number of 216.

Thus, the family unit would be said to have an annual income that is more than twice their assigned poverty threshold.

My research uses the ratio of income to poverty as the dependent variable. In the ACS PUMS, persons' poverty status is given with the variable: POVPIP. The percent of poverty status value ranges from 0 to 501. Following existing research (Poston et. al. 2010), reference persons with a POVPIP score ranging from 0 to 99 will have a "1" in my *in-poverty* dependent variable. More technically, reference persons with a poverty statistic of less than 100 (i.e., if POVPIP <= 100 then in poverty) are given a "1" on my dependent variable and all others a zero.

Poverty is a hypothetical and abstract variable that researchers use. I use poverty as an "intervening variable in the analysis" (Blalock 1970:144) for measuring discriminatory behavior. Poverty is an instrumental abstract construct that is believed to capture a "real" condition some humans experience. As such, poverty cannot be observed directly. Poverty can only be measured indirectly by means of money related indicators. This "unobservable construct" is a latent variable (see Bollen 2002). I can only infer the existence of poverty (i.e., socioeconomic deprivation) by the properties of monetary variables like personal income. Traits like hair color exist among people; constructs on the other hand exist in the minds of researchers (Loevinger 1957:642).

Such a technique weakens the "relative deprivation" premise (see Sen 1981; Duclos and Gregoire 2002). Relative measures are most "commonly used by researchers in Europe" who "define poverty as a condition of comparative disadvantage, to be assessed against some relative, shifting, and evolving standard of living" (Iceland

2003:501). Some have argued that comparing poverty across distributions may involve ‘‘different standards of minimum necessities’’ (Sen 1981:21) and ‘‘that *absolute* deprivation in terms of a person’s capabilities relates to *relative* deprivation in terms of commodities, income and resources’’ (Sen 1984:326). Although solutions to this problem have been given (see Foster, Greer, and Thorbecke 1984), they have not led to an academic consensus opting out of the classical form of measuring poverty (i.e., with an individuals’ personal or household income).

In ratio terms, people in poverty will have a ratio below 1.0 with respect to income to poverty—they have no income above their assigned poverty threshold. The multilevel logistic equation models the likelihood of having a 1 (i.e. of being in poverty) versus being out of poverty (having a zero on the dependent variable)—the reference category. The spatial model uses percent in poverty by PUMA as the dependent variable and will be further discussed in the GWR section below.

Level-1 HLM Independent Variable

The racial-ethnic category of Latino/a is my independent variable of interest. As stated above, the sample includes reference persons in the mainland from the three most common racial-ethnic groups: Latinos/as, non-Latino-blacks, and non-Latino-whites. My interpretation will focus on contrasting how Latinos differ in their odds of being in poverty when compared to non-Latino-whites. Consequently, non-Latino-whites will the reference category in both racial-ethnic variables in the multilevel equations.

The fabrication of these arbitrary labels is restricted by the available identity variables in the data. They represent only what the reader infers from their creation. In my analysis, I consider these racial-ethnic categories adequate proxies for capturing the respondents' social identity within their communities. This self-perceived status is of the utmost interest since it pertains to my investigation of how majority-group members respond to minority-group people—and ultimately influence (in part) their life chances.

The ACS, as required by OMB, collects on five race categories and allows a "Some Other Race" category (for a detail discussion on race see Appendix B in Grieco 2009). The 2007 survey includes 15 separate response categories and 3 write in areas. Respondents who only selected one race are referred to as "single race" or "only one race" population. My reference person sample only comes from this single race population.

The OMB defines Hispanic or Latino as "a person of Cuban, Mexican, Puerto Rican, South or Central American, or other Spanish culture or origin regardless of race" and the 2007 questionnaire includes the following "Hispanic origin" response categories:

a) No, Not Spanish/Hispanic/Latino
b) Yes, Mexican, Mexican Am., Chicano
c) Yes, Puerto Rican
d) Yes, Cuban and
e) Yes, other Spanish/Hispanic/Latino.

The "Hispanic" label is a much contested category (see Aguirre and Turner 2011; Idler 2007; Priestley 2007) since the umbrella term includes a very identity-fluid group of people (see Rodriguez 2000). I have thus decided to use the label Latino/a.

The three groups in the sample are then coded by first considering their Latino status and then their single-race. In the ACS PUMS file, the Latino variable is HISP and the race variable is RAC1P. If the reference person has a value greater or equal to “1” on HISP then he/she is coded as being Latina/o—that is, they have a one on the dummy Latino factor in the multilevel model. If the unit has a zero on HISP and a “1” on RAC1P then she/he has a “1” on the non-Latino-white binary label. If a person is not Latino and has a “1” on RAC1P then he/she has a one on the binary non-Latino-white variable, and if they have a “2” on RAC1P, then they have a one on the non-Latino-black dummy factor. Just to be clear, my sample then includes all origin-type Latinos of all races and only uses single-race non-Latino-blacks and -whites. Consequently, Non-Latino other-than-black or –white (e.g., non-Latino Native-American) and non-Latino multiracial (e.g., non-Latino black-and-white) respondents are excluded from the analysis—they make up a relatively small part of the full microdata sample.

Level-1 HLM Covariates

I include several covariates in the various models. My main micro-level independent variable is *Latino status*. There are various micro-level controls introduced in the hierarchical logistic model. Aside from coding Latino status, I isolate non-Latino-Blacks by introducing their status at level-1. Both Latinos and non-Latino-Blacks (here after only referred to as black) are compared to non-Latino-Whites (here after only referred to as white). As stated previously, my study will only focus on comparing Latinos versus non-Latino-Whites.

Research has shown that minorities are more likely to be in poverty. I am not testing this hypothesis—rather, it is taken as a given. The primary hypothesis under investigation is how the minority-concentration at the macro level influences this racial-ethnic variable as it relates to the likelihood of being in poverty. That is, this research analyses the extent to which a reference person racial-ethnic characteristic is affected by the Latino/a-concentration in their PUMA of residence, above and beyond the effects of the individual socio-economic and other demographic characteristics.

Time in the U.S. has previously been found to have an influence on earnings (e.g., McManus, Gould, and Welch 1983). Others have introduced similar factors to account for experience in the United States (e.g.,Van Hook, Brown, and Kwenda 2004), I however, am accounting for age at time of arrival because I belief immigrants are equally influence by their home-land experiences. By combining AGEP (person's age) and the YOEP (a person's year of entry) variables, I also account for individuals' nativity status and age at time of entry to the U.S. by including an "age at time of immigration" variable. Those with a zero on this variable are native born and all others immigrants, with the number representing their age at time of entry to the U.S.

I will statistically control it using two variables, because language has been consistently shown to be an important predictor of earnings in previous studies (e.g., Poston 1994, McManus, Gould, and Welch 1983). I use the ENG (English speaking ability) ACS PUMS variable. Language is measured by creating three categories: Only speaks English, bilingual (speaks English very well, well and another language), and mono-other (speaks English not-well or not at all). The only-English group (i.e., monolingual) will be the reference category. I will thus compare bilinguals and no-English to only-English speakers.

Education is a key factor in predicting poverty status. Researchers continue to find that increases in formal education reduced the odds of being in poverty (Awan et al. 2011). Others have also shown that accounting for the context of that education matters (e. g. Van Zandt and Wunneburger 2010:292). I accounted for it by using the SCHL (educational attainment) microdata factor. Only one binary factor is created for the sake of simplicity and because it attains the desired goals—to control for how education influences the odds of being in poverty. If a reference person has at least a high school diploma (and beyond), they get a “1” on the education variable and those with less than this level of educational attainment get a value of “0”.

Several other covariates are introduced. By using AGEP (person’s age), I also control for age with an interval variable. Younger people are expected to have higher odds of being in poverty. Current work continues to validate the expectation that males are less likely to be in poverty than females (Awan et al. 2011). Consequently, I statistically control for it by using the SEX (whether male or female) variable (males=1). I too expect males should have lower odds of being in poverty.

Existing work paints a clear picture when it comes to marital status. Married individuals tend towards being “healthier, work more, and earn more” than those who are not married (Poston 1994:487). Because others have found that non-married families are more socioeconomically fragile than married ones (Hummer and Hamilton 2010), I use the MAR (marital status) variable to code those who are married as “1” and all others (never married, divorced, separated, widowed) as "0". Those who are married should have a lower likelihood of being in poverty.

If a person has ever served in the military they get a "1" on the related binary variable—I use the MIL (military service) variable in PUMS. Military experience may also be introduced in the models. The military experience variable may be more relevant for the native-born male group and may have selectivity for less educated people. Others have included military experience variables because individuals with military experience "tend to do better socioeconomically than those who have not served" (Poston 1994:488). I expect those with some military experience to have lower odds of being in poverty. Lastly, I use the DS (disability status) variable to account for a person's disability status—if a person has a disability, he/she gets a value of "1" while those without a disability are assigned a "0". Those with a disability should be more at risk of being in poverty.

Level-2 HLM and Geographically Weighed Regression Covariates

Because previous research has shown that when it comes to investigating poverty, "contextual factors" matter and need to be included in any analysis (see Cotter 2002; Garcia 2008; Poston et. al. 2010), I include several macro-level controls. In truth, "sociologists have a stake in place no matter what they analyze" (Gieryn 2000:463)—which is why "recent methodological advancements have merely encouraged and brought refinement to the expanding body of spatially oriented population research" (Voss 2007:457).

Similar to what others have done (see Lewin, Stier, and Caspi-Dror 2006) I am using multilevel models in HLM to analyze the extent to which reference-person poverty is affected by PUMA of residence attributes, above and beyond the effect of individuals' socio-economic and demographic characteristics. Following existing research that uses macro-level controls (e.g., Fontenot et. al. 2010; Poston et. al. 2010), and accounts for racial-ethnic composition (Moller, Alderson, and Nielsen 2009), at the PUMA-level, in the pre-GWR multilevel model I introduce three factors:

a. Percent of Latinas/os in PUMA
b. Percent of blacks in PUMA
c. Percent of individuals, over the age of 25, with a bachelors education and beyond in PUMA.

The post-GWR "*hybrid-multilevel*" model adds the following:

d. Latino GWR coefficient in PUMA
e. Black GWR coefficient in PUMA
f. Bachelors education and beyond GWR coefficient in PUMA.

The latter will be made clearer as we move into the subsequent sections explaining the spatial modeling theory and techniques.

I will focus on investigating if and how "percent Latina/o in PUMA of residence" influences the statistical association between the Latino individual-level status and the likelihood of being in poverty. My interest is on how this socio-environmental attribute interacts with the micro-level Latino status. I account for the racial-ethnic composition of place because recent investigations concluded that racial diversity is a key determinant in shaping the spatial form of a community as it relates to poverty (e. g.

Dwyer 2010). The cross-level interaction between Latino status and percent Latino is the main element under investigation.

Percent black is introduced to fully control for the level of minority concentration in the area of the respondent residence. This is due to the fact that high levels of minorities are closely associated with high levels of poverty. Percent of individuals with a “high” education (i.e., BA and beyond) is used as a proxy to account for local socioeconomic structures (see McCall 2000). Controlling for “local” labor market conditions allows me the ability to theorize that I am considering how local monetary opportunities influence an individual’s characteristics as it related to the likelihood of being in poverty.

I would like to mention in passing that no “standard” variables, at either level-1 or level-2, will be *centered*. Standard variables are percent Latino, black, and BA-plus. Only GWR shifted coefficient factors are centered on their grand mean. This will be discussed in greater detail in the next chapter. The main point is that with non-GWR variables, I am avoiding this technique with regular variables because “centering around the group mean amounts to fitting a different model from that obtained by centering around the grand mean or by using the raw scores” (Kreft, de Leeuw, and Aiken 1995). Explaining how centered variables alter the meaning of the gammas is probability not in the best interest of our current enterprise. Consequently, none of my raw variables at any level are ever centered.

We no turn our attention to a deeper explanation of multilevel modeling.

Generalized Hierarchical Linear Modeling

The use, appropriateness, and desirability of multilevel models in sociology have been discussed at length elsewhere (Skrondal and Rabe-Hesketh, 2004; Snijders and Bosker, 1999; Goldstein, 1995; Hox, 1995; Di Prete and Forristal, 1994). Hierarchical Bayesian models of poverty have been shown to be of great benefit (e.g., Fabrizi, Ferrante, Pacei, and Trivisano 2011). The fundamental premise behind the use of hierarchical and spatial models is that human societies in general arrange themselves into nested hierarchies (see Moellering and Tobler 1972). All this helps explain why, when it comes to racial inequality, racially shaped hierarchies account in part for neighborhood inequality (Sampson and Sharkey 2008).

In general, hierarchical models allow researchers to account for context using correct error measurements. Almost two decades ago, Scott and Holt (1982) explained that “intra-unit correlation” seriously under-estimates the variability of estimates with ordinary least square techniques that result in false-positives. More technically, multi-level models “represent a considerable improvement over single-level models estimated by ordinary-least squares” because “ML models allow relationships to vary in time and space according to context” (Jones 1991:148). In this section, I describe the statistical approach being employed in the analyses.

A driving motivation behind this investigation is that most seminal work on poverty has been lacking in one respect: the appropriate recognition and modeling of hierarchical data. If social context matters and I think it does, then accounting for individuals’ socio-environmental influences is not only important but necessary. In reality, once “you know that hierarchies exist, you see them everywhere" (Kreft, de Leeuw, & van der Leeden 1994). More generally, my basic "argument is that through its opportunity structure, the place of residence affects the ability of households to raise their economic status and avoid falling into poverty, above and beyond the human resources and work behavior of its residents" (Lewin, Stier, and Caspi-Dror 2006:178). My research operates from this academic world view.

In this research, I nest individuals in their PUMA of residence at the time of survey participation. Clustering reference persons by PUMA make classical regression techniques inappropriate since individuals are contextually dependent by PUMA. This dependency could potentially bias my standard errors leading me to conclude false significance (Hox 1995). Since my theoretical position is that people are hierarchically influenced, I must employ models that account for this interesting dimension.

The existing literature has already made the case for how traditional "one-layer" statistical techniques lead to biased parameter estimates and deflated standard errors (Kreft and de Leeuw 1998; Snijders and Bosker 1999). The substantive part of the argument is that hierarchical statistical models allow for the decomposition of the total variance of the dependent variable in both the *between*- and *within*-contexts (Flaherty 2010).

My proposed research will use HLM software to specify and investigate a hierarchical Bayesian logistic model that accounts for the multi-dimensional human experience. There are many advantages to using HLM (Kreft, de Leeuw, and van der Leeden 1994) and recent advances in the software have further solidified the benefits

(Bryk and Raudenbush 1992). It has been convincingly argued that "true multilevel statistical tools provide advantage over traditional methods, such as allowing for random intercepts and coefficients" (Flaherty 2010).

When modeling individual-level data while accounting for context, HLM is the preferred method of analysis (Raudenbush and Bryk, 2002). The user friendly software estimates equations that help explain cross-level statistical associations (Poston and Duan 2000). As explained elsewhere (see Poston 2002) the technique accounts for the fact that individuals are dependent at the context level. Classical ordinary least square regressions assume both micro- and macro-level factors come from simple random samples (Arnold 1992).

In a metaphorical sense, the technique runs a single regression for each level-2 unit and combines (using averages) them to calculate the given "population-average" estimates. The individual regressions by nesting unit are the "within-PUMA" equations. The subsequent use of their resulting intercepts and coefficients are the "across-PUMA" equations. The variance around each parameter at level-1 is taken into account in the regression at level-2 (Arnold 1992). In short, both intra-PUMA and inter-PUMA coefficients have their own error measurements where "maximum likelihood and generalized least squares estimation procedures are used to generate the HLM coefficients and variances" (Poston 2002).

On a more technical note, since I have more than 100 level-2 units (i.e., 2,054), I will be interpreting the coefficients with "robust standard errors" in the HLM outputs (Mass and Hox 2004a; Mass and Hox 2004b). In simple terms, the use of HLM software empowers my research by giving me the ability to understand how the micro-level Latino status is *on average* associated with the likelihood of being in poverty across and within PUMAs, as I control for the various macro-level factors.

Multilevel Logistic Models

This section outlines the procedural and my final multilevel models. All HLM models require that the researcher first determine if there is in fact any statistically significant variation in the binary poverty-status dependent variable occurring between the 2,054 level-2 nesting units. Having significant variation of the dependent variable across PUMAs reduces the model to a classical model (Gelman and Hill 2007: Raudenbush and Bryk 2002).

Decomposing the variability into between and within PUMAs requires that we calculate the "intra-class" correlation coefficients (ICC). I first execute the following simple two-level random intercept model:

$$Prob(InPoverty = 1|\beta) = \varphi$$

$$Log[1 - \varphi)] = \eta$$

$$\eta_{ij} = \beta_o$$

$$\beta_o = \gamma_{00} + u_0$$

The results show that the level-2 variance τ_{00} (i.e., u_0) has a value of 0.425 with a statistically significant chi-square value of 94,208 9(p-value=0.000). This means that I can accept the null-hypothesis and can safely conclude that there are significant differences among the 2,054 PUMA's average log-odds of being in poverty. The intra-class correlation coefficient (ICC)—representing the proportion of the variance in poverty-status between PUMAS—can be calculated for linear multilevel models (according to Guo and Zhao 2000) as follow:

$$\rho = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_e^2}$$

and according to Snijders and Bosker (1999), and Long (1997), a proper substitute to calculate ICC for a nonlinear multilevel modes is (also see Li 2005:208):

$$\rho = \frac{\tau 00}{\tau 00\ + \pi^2/3}$$

which in my case is

$$= \frac{0.42818}{0.42818 + 3.14159^2/3.}$$

and computes to 0.115163 (*100=11.5%). ICC can range from 0 to 1 (or in percent form from 1% to 100%) with higher values representing a stronger clustering effect of the dependent variable.

In my case, this means that about 11% of the variance in poverty occurs between PUMAS. As per Hox (2002), ICC is “the proportion of the variance explained by the grouping structure in the population” (p. 15). In a broad sense, ICC is the average relation between individual’s poverty statuses within their PUMA. Barcikowski (1981) showed that the type I error rate could be inflated when a very small ICC (e.g., .01) occurred. My 0.11 ICC is sufficiently strong to conclude that I do not have a Type-I error and I think this between-PUMA variance on poverty status may be due to the fact that poverty is so deeply concentrated in a few PUMAs.

After concluding that a multilevel analysis of poverty is both statistically appropriate and necessary, I move away from the “unconditional model” (i.e., the baseline model above) to a “conditional model” where I first introduce all the level-1 factors and then add the PUMA-level controls. Here is the individual-level structural part of the HLM full-model logistic equation with no PUMA-level controls:

$$
\begin{aligned}
\eta_{ij} &= log\left[(\phi_{ij} \div 1) - \phi_{ij}\right] = \\
&\beta_{oj} + \beta_{1j}(Nativity)_{ij} + \beta_{2j}(Bilingual)_{ij} + \beta_{3j}(MonoOther)_{ij} + \\
&\beta_{4j}(Age)_{ij} + \beta_{5j}(Male)_{ij} + \beta_{6j}(Disable)_{ij} + \beta_{7j}(Married)_{ij} + \\
&\beta_{8j}(Served)_{ij} + \beta_{9j}(HSplus)_{ij} + \beta_{10j}(Latino)_{ij} + \beta_{11j}(NLBlackd)_{ij} + r_{ij}
\end{aligned}
$$

where η_{ij} is the predicted log-odds of being in poverty (which can be interpretable with “percent change” numbers by converting *population-average* estimate, through the exponentiation of the coefficient, to odds ratio);

i and *j* refer to the i^{th} reference person in j^{th} PUMA;

β_{0j} is the intercept in j^{th} PUMA;

β_{1j} through β_{11j} are the eleven average slopes for Nativity, Bilingual, MonoOther, Age, Male, Disable, Married, Served, HSplus, Latino, and NL-Black variables, in j^{th} PUMA; and

r_{ij} is the error term for the i^{th} reference person in j^{th} PUMA.

I will first discuss an HLM model where no level-2 control variables are introduced. The above model reveals the simple form of the level-1 (i.e., individual-level) equation being used in the first HLM model. After discussing the outcomes of this simple model, I will then introduce the "pre-GWR" hierarchical model. This second model will have the same level-1 structure and introduces three level-2 (i.e., PUMA-level) factors into the equation. The introduction of PUMA-level factors would add on to the equation above and render the following complex level-2 equation (written in more HLM friendly terms):

$$\beta_{oj} = \gamma_{00} + \gamma_{01}(\%Latino) + \gamma_{02}(\%NLBlack) + \gamma_{03}(\%BAplus) + u_0$$

$$\beta_{1j} = \gamma_{10} + \gamma_{11}(\%Latino) + \gamma_{12}(\%NLBlack) + \gamma_{13}(\%BAplus)$$

Subsequent betas 2 through 10 continue until you get to

$$\beta_{11j} = \gamma_{110} + \gamma_{111}(\%Latino) + \gamma_{112}(\%NLBlack) + \gamma_{113}(\%BAplus)$$

where γ_{00} is the "king" intercept of the full model;

γ_{01} is the intercept by percent Latinos;

γ_{02} is the intercept by percent Non-Latino-Blacks;

γ_{03} is the intercept by percent with a BA and beyond;

γ_{k0} (k^{th} ranging from 1-11) are the *direct effects* of the individual-level factor;

γ_{k1} are the *indirect effects* of percent Latino on the micro level association;

γ_{k2} are the *indirect effects* of percent NL-Black on the micro level association;

γ_{k3} are the *indirect effects* of percent with BA-plus on the micro level association;

and where u_o is the error measurement for all intercepts (no other Taus are included so that cross level interactions are assumed to be similar across all PUMAs).

Before explaining the final hybrid-multilevel model we must discuss the geographically weighted regression approach, why spatial modeling is necessary, and reminder the reader of what spatial non-stationarity is and how it is at the core of this discourse.

Spatial Modeling

Geographically weighted regression (GWR) is a modeling technique used to explore spatial non-stationarity (Brunsdon, Fotheringham, and Charlton 1998). As discussed before, spatially stationary phenomenon is one that has no influence on neighboring entities (for a more detailed discussion on the topic see Charlton, Fotheringham, and Brunsdon 1997). A discourse on spatial autocorrelation, a form of spatial dependence often exhibited in geographical data, has been ongoing for several decades. The ideas were formally introduced during the 1950s (Geary 1954, Moran 1950) and mathematically solidified a few years later (see Cliff 1975, Cliff and Ord 1969, 1973, 1981).

What is spatial nonstationarity? An example may help define the abstract. In a rough sense, the legality of same-sex marriage in Iowa is spatially stationary as it pertains to the influence such a law has on the geographically adjacent states of Illinois, Minnesota, Wisconsin, Missouri, Nebraska, and South Dakota. Since none of the neighboring states have made same-sex marriage legal, we could argue that Iowa's state law has had no *spatial effect* on its geographically neighboring entities. We could say that *spatial homogeneity* is present at the state-level with regards to legalization of same-sex.

Spatial homogeneity assumes "that all members of the population have the same chance of affecting and being affected by each other" (Strang and Tuma 1993:615). From our example, we expect Illinois and Nebraska to be affected in the same way by Iowa's state law: no influence is expected since same-sex marriae remains illegal in both states. In more technical terms, we could say attribute-X in point-C has the same effect (or lack thereof) on points A, O, and N—hence the geographical association between the points is irrelevant.

Unfortunately, most social phenomena are not spatially stationary. Spatial homogeneity is rarely (if ever) present in social processes. This is because in general, members of human populations have different chances of being affected and affecting each other. For example, the loud music my next door neighbor plays affects me more than the loud music being played twenty blocks away or that was played twenty years ago. The main point is that "statistical issues in spatial analysis of a response variable"—were the "focus on the almost ubiquitous phenomenon that two measurements taken from geographically close locations are often more similar than measurements from more widely separated locations" (Beale et. al. 2010:247). Both social context and geographical location matter.

These beliefs stem from the view that interdependence of data at different geographic locations exist because "movement of people, goods, information, and the like over space makes what happens in one location influence what happens at the other places" (Namboodiri 1991:222). This means that "spatial probability models can be used for providing a convenient summary description of a geographic pattern" (Namboodiri 1991:219).

PUMA interdependence is present because what happens in one affects other PUMAs as a function of distance. This interdependence is theoretically grounded on three points first given by Morenoff, Sampson, and Raudenbush (2001:522). They are here adapted as follows:

1. The artificial boundary of PUMAs in part creates interdependence.
2. Clusters of poverty concentrations create PUMA interdependence.
3. Poverty is based on social interaction and is thus subject to diffusion processes.

The good news is that “the concept of spatial autocorrelation has been developed to deal with the tendency toward interdependence among spatial data” (Namboodiri 1991:221). This builds on the view that one “of the main reasons for studying demography is that population structure and change are intertwined with social, economic, and political structures and changes, and the study of demography is essential to understanding these linkages” (Namboodiri 1991:1). My GWR models account for the PUMA interdependence (i.e., spatial autocorrelation).

Human’s temporality creates spatially heterogeneity by allowing our influences (and ability to affect others) to vary as a function of physical space and time. This is why individuals who are physically near each other influence each other more than distant ones. In most (if not all) instances, members in human populations have different chances of affecting and being affected by each other—and the same can be said of their aggregated macro-level boundarized attributes (i.e., polygons with group attributes).

My main argument on spatial processes is that the statistical association between PUMA- poverty and percent of Latinos in that PUMA is spatial non-stationarity. In other words, I am arguing that there are areas of the country where the statistical association will be positive and other areas where the increase presence of Latinos will be statistically associated with lower poverty PUMA poverty rates. In simpler terms, I am arguing that my level-2 factors are spatially non-stationary as they relate to poverty status and consequently need to be explored using GWR.

The “main characteristic of GWR is that it allows regression coefficients to vary across space, and so the values of the parameters can vary between locations” (Mateu

2010:453). GWR accounts for spatial non-stationarity—"a condition in which a single global model cannot explain the relationship between some sets of variables" (Brunsdon, Fotheringham, and Charlton 1996:281)—as is my case where a local model would not suffice. GWR allows me to explore "spatial nonstationarity by calibrating a multiple regression model which allows different relationships to exist at different" (Leung, Mei, Zhang 2000:9) geographical points (by PUMAs) across the mainland. My GWR will account for the *poverty-Latino* statistical spatial non-stationarity.

Geographers have used multilevel modeling to account for space variation (e.g., Jones 1991). Many more statistical geographers however argue for the use of geographically weighted regression approach to account for spatial heterogeneity (e.g., Ali, Partridge, and Olfert 2007; Fotheringham 1997; Fotheringham, Charlton, and Brusdon 1996). GWR's reliability as a spatial predictor has been shown (Harris, Brunsdon, and Fotheringham 2011) and a discussion on the various statistical methods for exploring varying coefficient models can be found elsewhere (e.g., Fan and Zhang 2008; Fotheringham, Charlton, and Brunsdon 1997).

More specifically, the GWR approach has been used and shown to have value when investigating poverty (see Deller 2010; Longley and Tobon 2004). For example, research on county-level poverty data shows that spatial autocorrelation may be present and admonishes "social scientists to examine spatial autocorrelation in their data and to explicitly correct for spatial externalities" (Voss, Long, and Hammer 2006:369). Recent work on poverty and obesity in Taiwan concluded "GWR revealed that there were local variations in the poverty-obesity relationship and that poverty was only significantly associated with obesity in less-developed areas" (Wen, Chen, and Tsai 2010:257). Clearly GWR can help us better understand the spatial non-stationarity nature of poverty.

GWR has also been used to explore racial-ethnic related topics. For example, researchers have even found that race and ethnicity are significantly related to cancer risks in Florida by using GWR and have pointed out that using such a technique is important because "conventional regression can hide important local variations in statistical relationships relevant to environmental justice analysis" (Gilbert and Chakraborty 2011:273). The social "environmental-racial order" matter because when it comes to inequality it affects "the distribution of material wealth, rights, and privileges" (Wilsem 2007: 236).

By including a "spatial" element in the dissertation, I acknowledge the obvious and logical observation that socio-spatial environments influence each other as a function of geographical distance. The framing of human behavior through a multileveler's prism requires that the reearcher ponder, discuss, and investigate if and how attributes in nesting units (i.e., PUMAs) spatially influence each other. When possible, GWR "should be used for regional scale spatial analysis because it is able to account for local effects and shows geographical variation in the strength of the relationship" (Ogneva-Himmelberger, Pearsall, and Rakshit 2009:478).

Several decades ago we were eloquently informed that "whether or not the investigator initially lays emphasis on [spatial] variation," his/her study of spatially non-stationary phenomenon (like poverty) would be rendered "incomplete unless at some point this source of variation is explicitly taken into account" (Duncan, Cuzzort, Duncan 1961:Pg.102). My dissertation pays heed to their advice and explores this topic using a geographically weighted regression in ArcGIS. Maps throughout this dissertation are created using ArcMap with ArcGIS® software by ESRI. ArcGIS® and ArcMap™ are the intellectual property of ESRI and are used herein under license [Copyright © ESRI, all rights reserved] (for more information about ESRI® software, please visit www.esri.com).

Existing research and theory highlights how human behavior varies by physical space (Fotheringham, Stewart, and Brunsdon 1999). Some social scientists argue that most quantitative analyses assume statistical estimates to be stationary over geographical space. As a consequence, such models only produce and review *global* estimates. This "global approach" could unfortunately mislead researchers into believing that to investigate statistical relationships with a single parameter estimate is sufficient.

Traditional non-spatially conscious research implicitly assumes that the nature of statistical-relationships under investigation is the same for all points within the entire study area. Under such a view, that would mean that the influence of percent of Latinos in the area of residence on neighboring PUMAs does not exist, and is thus inconsequential. Our multilevel models suggest otherwise and capture this variation. About 11% of the micro-level poverty status variable is explained between-PUMAs. The polygons do capture something about poverty.

Implicit in this is my belief that poverty is spatially non-stationarity. I am arguing that PUMA poverty concentrations are spatially non-stationary because polygon-attributes of neighboring PUMAs are more influential than the influence exerted by those polygon-attributes found in distant PUMAs. For example, a South Texas PUMA with 50% of its residence in poverty will affect and be affected more by the economic conditions of other neighboring South PUMAs than Chicago-PUMAs. In this example, Chicago-PUMAs may have a similar level of poverty as in the Texas-PUMAs. The difference is that Chicago-PUMAs are geographically distant and thus exert a lower level of influence than other geographically proximal Texas-PUMAs.

The multilevel models do not, however, account for how neighboring PUMA attributes influence each other. That is, even though HLM helps us account for PUMA level influences, it does not take into account how spatial non-stationarity is playing a role. If a relationships exhibits spatial non-stationarity (as poverty and Latino concentration do), then social scientists must account for local estimates, because, as stated earlier, local forms of spatial modeling provide evidence on the nature of spatial variations in relationships. That is, they (e.g., GWR) expand our understanding on the spatial distribution of local relationships.

My main argument is that the statistical relationship between poverty and Latino concentration varies by geographic space and that their spatially dependent (i.e., local-associations) should be investigated. In sum, my GWR model posits that concentration of poverty varies by space—that the social process is spatially non-stationary. Consequently, a global/single parameter estimation technique of the relationship between percent Latinos in PUMA and the poverty status requires the use of a local-parameter modeling technique like GWR—otherwise the global parameters may be very misleading locally.

Challenges in Spatiology

Before outlining our final GWR model, we must understand the challenges spatiology faces. When discussing the formation of space and the measuring of such phenomenon, it is appropriate to quote Lefebvre at length:

> "Social relations, which are concrete abstractions, have no real existence save in and through space. Their underpinning is spatial. In each particular case, the connection between this underpinning and the particular case, the connection between this underpinning and the relations it supports call for analysis. Such an analysis must imply and explain a genesis and constitute a critique of those institutions, substitutions, transpositions, metaphorizations, anaphorizations, and so forth, that have transformed the space under considerations" (1991:404).

When dealing with the spatiality of social space, spatiologist must address how to measure "the degree of areal concentration of a sub-population with respect to the total population of which it is a part" (Duncan, Cuzzort, and Duncan 1961:8). Spatiology must undertake the task of explaining how inferences about statistical relationships drawn from areal data must be understood. Robinson long ago warned us about the aggregation problem (1950). Inferring individual level relationships from macro-level correlations is inappropriate.

The view that time, space, and matter are "inextricably connected" has imbue all things spatial with a sense of primordiality that heavily influences most spatial analysis (Soja 1989:79). At the core of the spatial argument in this dissertation is the idea that although space “in itself may be primordially given,” its organization and meaning “is a product of social translation, transformation, and experience” (Soja 1989:79-80).

When Soja describes his “socio-spatial dialectic” construct, he explains that “social and spatial relations are dialectically inter-reactive, interdependent; that social relations of production are both space-forming and space-contingent” (1989:81). The socio-spatial dialectic view is premised on Lefebvre’s argument that “space and the political organization of space express social relationships but also react back upon them” (1970:25). In other words, “the spatiality of whatever subject you are looking at is viewed as shaping social relations and societal development just as much as social processes configure and give meaning to the human geographies or spatialities in which we live” (Soja 2010:4). This fundamental idea, that social and spatial dimensions of human life mutually influence each other, is what motivates the use of a spatial model in this project.

The obstacle with these theories is that any empirical investigation must first deal with “the difficulty in finding an appropriate measure” of community (Becker 1971:123). We could, for example, ask: “is an individual’s discrimination determined primarily by the relative number of non-whites working with him in the same plant or by their relative numbers in his community, county, state, region, or some more complicated sociogeographical area” (Becker 1971:123)? If we find this to be true, we could then argue that “tastes for discrimination … are positively associated with the percentage of non-whites” in each geographical unit (Becker 1971:123).

A full discussion of the modifiable areal unit problem (MAUP) is beyond the scope of this study, but the main point researchers in this field have given is that using smaller geographic units could eventually lead to “reduction ad absurdum” (Duncan, Cuzzort, and Duncan 1961:35). Earlier on the issue of scale, others concluded that in geographical investigations, “every change in scale will bring about the statement of a new problem, and there is no basis for presuming that associations existing at one scale will also exist at another” (McCarty, Hook, and Knos 1956:16). Hence, evaluations of the results “depend a good deal on the investigator’s judgment as to the plausibility of the assumptions underlying the model” (Duncan, Cuzzort, and Duncan 1961:73).

PUMAs, like many other Census created polygons, were “devised for purposes other than the specific ones of the investigator” (Duncan, Cuzzort, and Duncan 1961:33) . PUMAs are thus merely instrumental devices. The meaning of the polygon character is imposed by me the investigator. As a student of areal structure, I “must take into account the discrepancy between [my] hypothetical constructs and [my] actual results which [are] generated by the necessity of working with systems of areal units for which data are available” (Duncan, Cuzzort, and Duncan 1961:99). I do not lay emphasis on the shapes of PUMA polygons.

It is thus “important to realize how the meaning of an areal datum involving comparison of area units depend on the attitude taken toward areal units” (Duncan, Cuzzort, and Duncan 1961:50). In effect, researchers need to answer: What element entered into the determination of the polygon boundaries? The answer depends on how “areal units represent a subdivision of the total territory” (Duncan, Cuzzort, and Duncan

1961:50) or the full territory and not a sample. In my case, PUMAs are not conceptualized as communities and include the full mainland territory.

In truth, given that the data is cross-sectional, the complex modeling being employed can only serve to describe statistical relationships between models. As a reminder, given the literature review in the previous chapter, we can conclude that humans in superordinate positions act to preserve their position (Blalock 1970:191). I argue that in the United States, non-Latino-whites are in superordinate position vis-à-vis minorities. My main hypothesis is driven by the theory that in the U.S., non-Latino-whites will act towards minorities in such a manner as to preserve their privileged position (Blalock 1970:191). In effect, I am arguing that “certain independent variables” like the percent of minorities in PUMA of residence can lead to discrimination by superordinate groups “which in turn produces inequalities” (Blalock 1970:18). This “successful discrimination” occurs “by reducing the effectiveness of minority competition, usually does away with the need for further discrimination” (Blalock 1970:148).

There are “instances where the so-called “minority” may be in a numerical majority” and in such cases, it is assumed that they remain “in a subordinate position and that it has been set apart on the basis of racial and or ethnic characteristics” (Blalock 1970:145). For example, Latinos/as are the majority groups in South Texas PUMAs. In such instances, I am assuming “the degree of discrimination is close to some maximum level because it is perceived as necessary to prevent intimacy” and this will create “a very weak association with minority percentage because of the lack of variation in the dependent variable" (Blalock 1970:146). Thus, in South Texas poverty is extremely high because Latinos are discriminated against at a maximum.

The truth is "that the perspective of the investigator conditions the selection of data and choice of analytical framework in studies of areal differentiation" (Duncan, Cuzzort, and Duncan 1961:21). In my study, "areal units are merely instrumental devices for classifying areal data and facilitating their analysis" (Duncan, Cuzzort, and Duncan 1961:24). This is in stark contrast to investigations were the geographic "unit character is inherent and not imposed by the investigator" (Duncan, Cuzzort, and Duncan 1961:24).

This dissertation is nesting individuals in different geometrical polygons. It then estimates an attribute of importance for that polygon (i.e., percent minority in area). The subtle goal in this is to develop a synthetic movement. In longitudinal data, the movement tracks an individual as his/her characteristics vary (or not). When such data is unavailable, then nesting renders a proxy measure of movement.

Let us now turn our attention to the actual GWR model being employed.

Geographically Weighted Regression Model

GWR models are estimated using ArcGIS 10 (ESRI 2011). To be clear, these models are being used in an exploratory manner. The use of spatial cluster analysis in sociology has been present for over two decades (e.g., Anselin 1980; Anselin and Rey 2002, 2010). The intent is to validate/explore if/how statistical variations over space exist when it comes to measuring the statistical association between poverty rates and

Latino concentrations. Existing work validates “the importance of specifying known spatial effects in order to accommodate local context” (Ali, Partridge, and Olfert 2007:517). By using GWR, this sociospatial investigation on inequality (as measured by poverty) estimates parameters by using a weighted function based on *geographical distance* so that “near” locations have a greater influence on the estimate.

My units of analysis in the spatial model are PUMAs. The 2,054 PUMAs being used make up the U.S. mainland and the District of Columbia. All the variables in the model are created using the same ACS 2005-2007 IPUMS data described above. The universe is all individuals in the microdata. PUMA estimates were created using the person weight variable PWGTP in the microdata file. Thus, numerators contain the population of interest and denominators include them and all other people. For example, when calculating for the percent of Latinos/as, I develop the weighted estimate for their population in PUMA-x (i.e., the numerator) and then develop the estimate for the full population of all the people in PUMA-x (i.e., the denominator) and divide the first by the latter estimate. This means that all my PUMA-level attributes are nationally representative of the U.S. mainland for the 2005-2007 survey-period.

My dependent variable in the GWR model is percent of non-group quarter people (with a poverty score) in poverty by PUMA. Including group-quarter populations is complicated and their population is minute relative to the full sample. The independent variable of interest is percent of Latinos/as in a given PUMA. I control for percent of non-Latino-blacks to account for the minority population in the area of residence (Latinos/as and non-Latino-blacks make up most of the minorities in almost all

PUMAs). The percent of individuals with a bachelor's degree and beyond is also controlled for as a proxy for local market wellbeing.

Moving on to a more technical discussion of the GWR model, in OLS, error terms are generally assumed to be independent normally distributed random variables with zero means and constant variance. This model in its *unconstrained* form is not implementable for investigating spatial processes because the number of parameters increases with the number of observations. We need a technique for estimating a parameter "drift" (Leung, Mei, and Zhang 2000). Brunsdon et al (1996; 1997) and Fotheringham et al (1997a, 1997b) have suggested a geographically weighted regression (GWR) technique. In which the parameters are estimated by a *weighted least squares* procedure. As mentioned earlier, the weighting system is *dependent on the location* of PUMAs within their geographical space. In effect, I use spatial weights that have an adaptive distance decay function.

As a reminder from our earlier discussion, GWR allows *local* rather than *global* parameters to be estimated. The GWR model captures the heterogenic nature of poverty by allowing the equation to "alter over space to reflect the structure within the data" (Brunsdon, Fotheringham, and Charlton 1996:281). The typical output from a GWR model is a set of parameters that can be mapped in the geographic space to represent nonstationarity. That is, each PUMA is given a coefficient value (on other values like p-values) on each of the variables being used on the equation. I use these GWR created-values (i.e., beta coefficients for each PUMA) to map how each of the variables is associated with the percentage in-poverty in the PUMA dependent variable. I use

ArcGIS (in particular ArcMap) to map all the findings from my spatial nonstationarity investigation.

Compared with other methods, the GWR technique in ArcGIS appears to be a relatively simple but useful geographically oriented method to explore spatial nonstationarity. Based on the GWR model, not only can variation of the parameters be explored, but significance of the variation can also be tested.

Before outlining the final GWR model, the reader must be aware that these exploratory techniques are at the forefront of statistical science. Inferences from spatial modeling are still being debated (Anselin 2005; Ripley 1981; 1988). Specialist in the field have pointed out that in “order to carry out statistical inference, a notion of a superpopulation or spatial random process is required” where the we would have to assume the existence “of a stochastic process that may generate many possible spatial patterns” and where the main objective of the analysis would be “to characterize the spatial process by means of the observed spatial pattern” (Anselin 2005:255).

From a certain point of view, we could argue that “GWR analysis serves as an exploratory geographic analysis tool to detect local anomalies” (Qiu and Wu 2010:80). This is why a recent investigation concluded “that the ecological importance of regression coefficients cannot be evaluated with confidence irrespective of whether spatially explicit modeling is used or not” (Bini et al. 2009:193). Consequently, researchers should always be “explicit about the uncertainty of models and more cautious in their interpretation” (Bini et al. 2009:193).

Since I use PUMAs as spatial units that "are contiguous and exhaust the space" under investigation, the "notion of *interpolation* is impractical" and we would most benefit from understanding spatial prediction as extrapolation (i.e., to infer/project from know data to unknown area), where model estimates from observed spatial patterns could be applied "to another set of spatial units, outside the observed set, or for a different time period (Anselin 2005:255). P-values are then given to stay within existing statistical protocols—but are ambiguous since my 2,054 PUMAs in effect reflect the full universe under observation.

The GWR model being employed was developed by Brunsdon, Fotheringham, and Charlton (1996). In order to better understand our final GWR, we will start by describing a basic ordinary least square (OLS) linear regression model. If the standard regression equation in my investigation of poverty is given by:

$$y_i = \beta_0 + \sum_K \beta_K x_{Ki} + \varepsilon_i$$

where y_i is the percent in poverty at PUMA i,

β_0 is a constant term (i.e., the intercept), and

β_k measures the relationship between the independent variable x_k and y for the set of i locations (i.e., PUMAs), and

ε_i is the error associated with PUMA i.

The above equation “results in one parameter estimate for each variable included” (Cahill & Mulligan 2007). With GWR in ArcGIS we can estimate *local* parameters instead of estimating single parameters for each variable. By estimating a parameter for each data location (i.e. PUMA) in the mainland contiguous U.S., the GWR equation would only alter the above equation as follows:

$$y_i = \beta_{0i} + \sum_K \beta_{Ki} x_{Ki} + \varepsilon_i$$

where β_{0i} is the constant term for the corresponding explanatory variable at PUMA i, and

β_{Ki} is the value of the parameter for the corresponding explanatory variable at point i, and where

ε_i is $i \in C = \{1,2, \ldots, n\}$ and where *C* is the index set of locations of *n* observations (i.e., PUMAs).

In the GWR model, a continuos surface of parameter values is estimated under the assumption that locations nearer to i will have more influence on the estimation of the parameter $\widehat{\beta_i}$ for that location (Fotheringham, Brunsdon, and Charlton 2000). In short, GWR asumes parameters are functions of the locations on which the observations are obtained (Brunsdon et. al., 1996; Fotheringham, Brunsdon, and Charlton, 2002; Fotheringham et. al., 2001). My final GWR using PUMA polygons with all the independent variables (in simple form) is:

$$\%InPoverty_i =$$

$$\beta_{0i} + \sum_{1} \beta_{1i}\%Latinos_{1i} + \sum_{2} \beta_{2i}\%NlBlacks_{2i} + \sum_{3} \beta_{3i}\%BAplus_{3i} + \varepsilon_i$$

Before concluding this section and giving the final post-GWR hierarchical hybrid-model, I want to disclose the important but yet under examined "bandwidth" detail in the modeling of spatial processes with GWR. The distance function being use to create the spatial weights uses a band-width to determine the polygons exerting an influence on the parameter estimation. I explored different alternatives for selecting a bandwidth. In particular, I explored a Local Moran's I cluster analysis, and multiple mile-distances and number of neighbors techniques to increase the R^2.

A large bandwidth can produce parameters with little spatial variation. On the other hand, a small one can produce large local variation (i.e., exaggerated variance). There is no existing standard for selecting a bandwidth when using PUMAs. Hence, I am justified in exploring different alternatives. After extensive exploration, I decided to use an adaptive kernel with a neighbor bandwidth that minimizes the Akaike Information Criterion (AIC) (for details, see Fotheringham, Brunsdon, and Charlton 2002). Roughly defined, a "kernel" is a weighting function used in the estimation of our GWR model. Kernel widths are necessary when using non-parametric estimation techniques like GWR. In the simplest of words, the kernel specifies the number of data points in the local sample used to estimate the GWR parameters.

The second formal hypothesis under investigation, leads me to expect that the geographically weighted statistical association between percent poor and percent of Latinos in PUMA-of-residence will have a detectable and statistically significant spatial pattern. In particular, I expect “regions” (i.e., mid-East) with low-Latino concentrations will have a negative statistical association with percent in poverty and that regions (i.e., Southwest) with high-Latino concentrations will have a positive GWR statistical associations between percent in-poverty and Latino concentration.

Hierarchical and Geospatial Hybrid Modeling

The final HLM hybrid-model combines the results from my GWR outputs with my HLM model. After exploring a pre-GWR multilevel model, I fit a spatial model then use the from this GWR model as data in my final HLM-hybrid equation. The reason for this is to account for spatial non-stationarity. The hybrid model then accounts for contextual factors and their spatial non-stationarity as they relate to the poverty factor (i.e., the dependent variable).

It is not very common to develop regression models using estimate variables. I have yet to find a single study that develops a multilevel model using GWR estimates at level-2. This dissertation is the first, to my knowledge, that incorporates user-friendly statistical software like HLM and ArcGIS and combines their use.

A proximal technique I have found is something coined as “two-stage” modeling, where researchers first fit a model and then use the estimate from the model as data in another regression (Gelman 2005). The special issue on “Multilevel Modeling for Large Clusters" in the journal *Political Analysis* (Volume 13, Issue 4), in 2005 contains the various articles using this two-stage approach. The most similar work introduces a "spatial lag" variable in an HLM model to account for spatial dependence at level-2 (Morenoff, Sampson, and Raudenbush 2001). Only "unit-specific" estimates are given with the approach and thus results are somewhat difficult to consume. None of these works employ the use of GWR. Thus, without such blazed paths, I am relegated to both the benefits and burdens afforded to the use of new approaches.

Including GWR estimates in the final HLM-hybrid has ambiguous implications for the interpretation of the results. In particular, my introduction of the spatial estimates in the HLM model does not account for the errors associated with the GWR model fit. However, as I explained earlier, the level-2 area in my spatial analysis is the full geographic universe under investigation and not a sample from it. Hence, I have crudely concluded that not introducing the GWR error term in the HLM hybrid-model is statistically tolerable. The current hybrid approach is thus methodological acceptable.

In practical terms, I take the GWR coefficients and treat them as data in the hybrid-multilevel model. The spatial models produce a value for each of the PUMA polygons for each of the variables in the model. I take these values as GWR-Level-2 PUMA-attributes that show spatial non-stationarity and insert them into the level-2 data used in the final hierarchical model. For example, PUMA values for $\beta_{1i}\%Latinos_{1i}$ are inserted into the level-2 equation to control for the spatial non-stationarity of the percent-Latinos with the poverty outcome.

Multi-Geospatial Hybrid Models

Here are my final hybrid models controlling for spatial dependence in a hybrid multilevel logistic model. The final "post-GWR" multilevel hybrid model looks the same at level-1 as given before and level-2 is expanded as follows:

$$\beta_{oj} = \gamma_{00} + \gamma_{01}(\%Latino) + \gamma_{02}(\%NLBlack) + \gamma_{03}(\%BAplus)$$
$$+\gamma_{04}(LatCoef) + \gamma_{05}(BlackCoef) + \gamma_{06}(BACoef) + u_0$$

until

$$\beta_{11j} = \gamma_{110} + \gamma_{111}(\%Latino) + \gamma_{112}(\%NLBlack) + \gamma_{113}(\%BAplus)$$
$$+\gamma_{114}(LatCoef) + \gamma_{115}(BlackCoef) + \gamma_{116}(BACoef)$$

where *LatCoef* is the GWR coefficient for the PUMA-level association between percent in-poverty and percent Latino,

BlackCoef is the GWR coefficient for the PUMA-level association between percent in-poverty and percent non-Latino-black, and

BACoef is the GWR coefficient for the PUMA-level association between percent in-poverty and percent with a bachelors degree and beyond.

This is how the values produced by the GWR equation are used as data in the hybrid HLM final model. The main cross-level statistical association in our discussion will remain focused on the association between the level-1 Latino status and the level-2 Latino concentration. As a reminder, the two hypotheses under investigation are (with minor extensions to include our methodological discussion):

> *At the macro-level, I hypothesize that as the percent of Latinos/as in the area of residence increases, the odds of being in poverty will increase for Latinas/os—even after controlling for various level-1, level-2, and GWR-level-2 factors.*

and within the exploratory question,

> *I hypothesized that the statistical association between percent Latina/o and percent poverty is spatially non-stationary. In particular, I expect my exploratory analysis to show that the association between percent in-poverty and percent-Latino is positively correlated in areas where Latinos have been historically concentrated and negatively associated in economically-healthy new Latino-destinations.*

CHAPTER IV

ANALYSES

> "The potential exists, of course, for substantively meaningful
> spatial effects in many of the phenomena studied by social scientists...
> such models can make important contributions to our understanding
> of how events in one area can transcend geographic boundaries
> to influence outcomes in other areas"
> Tolnay, Deane, and Beck 1996:812

Analyses of the different models are presented in this chapter. I begin by discussing the descriptive statistics in all the models. Subsequently, we move on to discuss the findings of the pre-GWR hierarchical model with no level-2 controls and then the results when said controls are introduced. In the latter model, we will discuss how hypotheis-1 (H^1) is supported. After this is done, we explore how the GWR results give support to hypothesis-2 (H^2). Finally, we investigate how the post-GWR multilevel hybrid logistic model continues to validate H^1.

Descriptive Statistics

This section delineates the descriptive statistics for the sample used in multilevel models. Table 1 below displays the descriptive statistics for the sample being used in all HLM models. The table provides the following figures for each of the individual-level variables: the mean, standard deviation, minimum, and maximum values. From the table, we see that amongst all (Latinos, black, and white) the 2,526,896 reference

Table 1
Level-1 HLM Descriptive Statistics:
Micro-Level Variable Mean, Standard Deviation, and Extreme Values

Variable	*Mean*	*Std. Dev.*	*Minimum*	*Maximum*
Level-1				
HLM Dependent Variable				
Poverty 100	0.10	0.30	0	1
Level-1				
HLM Independent Variables				
Latinos	0.11	0.31	0	1
Non-Latino-Blacks	0.10	0.30	0	1
Non-Latino-Whites (reference)	0.79	0.41	0	1
Level-1				
HLM Control Variable				
Age at Immigration	2.99	7.65	0	66
Bilingual	0.10	0.30	0	1
Mono-Other	0.03	0.17	0	1
Age (years)	45.18	11.75	20	65
Male	0.57	0.49	0	1
Disable	0.14	0.35	0	1
Married	0.58	0.49	0	1
Served	0.15	0.35	0	1
High School Plus	0.90	0.30	0	1

persons in the U.S. mainland (at level-1), about one-tenth of them are in poverty (i.e., below the 100% poverty line). The minimum and maximum values on the “poverty 100” variable indicate its binary coding.

In Table 1, we see that Latinos (of all races) and non-Latino-blacks (hereafter only referred to as blacks) make up about one-tenth of the persons in the micro-level sample. Non-Latino-whites (hereafter only referred to as whites) are the reference category. A background investigation on the sample shows a clear picture of how poverty rates are distributed in the full sample and the three sub-groups. In the full sample, there are 98 people in poverty for every 1,000 reference persons. Whites only have 75 in poverty for every 1000 of their group, compared to Latinos at 173 and with blacks at 203 being in poverty—for every 1000 people within each their racial-ethnic group.

The table also illustrates that on average the sample was 3 years of age at time of arrival (native born are 0 in this variable). Please note that this value is heavily skew by massive amount of people with a zero (i.e., who are native) in the sample. Further investigation on this variable shows that 87% of all individuals in the sample are native-born. Reference persons are on average 45 years of age. About 57% of them are male, 14% have some form of disability, 58% are married, and about 15% have served in the military at some point in their lifetime. Approximately 90% of them have a high school degree and beyond.

When it comes to language, 10% are bilingual and 3% are mono-other (i.e., speak very little or no English). This means that about 87% of the reference persons only speak English—they are mono-English (the reference category). Unfortunately, the bilingual variable offers little insight on the details of bilingualism, because most of the bilinguals are whites. From our variable, we cannot know if the person speaks Spanish, Polish, or German—aside from speaking English well, or very well. Consequently, the bilingual variable only informs us that the individual can speak English and another language.

Table 2 below presents all the multilevel level-2 and GWR descriptive statistics. For the GWR sample, we see that from the 2,058 PUMAs about 12% of their population is in poverty (i.e., at a poverty ratio of 100 or below). For both HLM and GWR samples, Latinos made up, on average, 14% of the PUMA population and blacks 13%. Further investigation also revealed that on average the PUMAs had a 66% percent of whites (the racial-ethnic reference category in both GWR and HLM models). When it comes to formal educational attainment, on average, 19% of the population had a bachelor's degree and beyond.

Table 2 demonstrates that the same HLM level-2 variables used in the pre-GWR multilevel equation are introduced in the GWR spatial analysis. Results from the GWR equation are discussed at length below. After being executed in ArcGIS, the GWR equation creates coefficient values for all PUMA polygons and for each of the three independent variables in the equation. The values reflect the beta values for each of the variables as they are associated with i^{th} PUMA polygon.

The GWR raw coefficient variables display the values as produced by the equation. As can be seen, the minimum values indicate that there are PUMAs where the statistical relationship between x-variable (e.g., percent Latinos at -1.21) and the percent in poverty is negative. Inserting these negative values, however, creates convergence problems in HLM.

Table 2
Level-2 HLM and GWR Descriptive Statistics

Variable	*Mean*	*Std. Dev.*	*Minimum*	*Maximum*
GWR Dependent Variable				
Percent in Poverty	0.12	0.06	0.01	0.41
Level-2 HLM Control Variables and GWR Independent Variables				
Percent Latinos	0.14	0.18	0	0.98
Percent Non-Latino-Blacks	0.13	0.17	0	0.98
Percent with a BA and beyond	0.19	0.1	0.02	0.68
GWR Raw Coefficients Variables				
Raw GWR Latino Coefficient	0.14	0.24	-1.21	0.83
Raw GWR NL-Black Coefficient	0.23	0.16	-0.66	0.94
Raw GWR BA+ Coefficient	-0.19	0.17	-0.83	0.17
HLM Level-2 GWR Control Variables				
Shifted GWR Latino Coefficient	1.35	0.24	0	2.04
Shifted GWR NL-Black Coefficient	0.89	0.16	0	1.60
Shifted GWR BA+ Coefficient	0.64	0.17	0	1.00
PUMA Square Miles	1,517	4,375	1.34	92,749
PUMA Perimeter	160	180	6.57	1,546
PUMA Total Population	144,419	39,134	85,853	394,346

In order to account for the nonstationarity value of the PUMA, these raw outputs were shifted to start at zero. The shifted scales are used in the final hybrid model and are centered on their grand mean. GWR factors are centered for two main reasons. The first is that their scales have been shifted. The second is that GWR coefficients are only introduced as controls for spatial nonstationarity and their interpretation is not the main focus of the dissertation.

In the case of the raw Latino GWR coefficient, the lowest value is -1.2094. In order to shift this value to start at zero, I subtract -1.2094 from all the raw Latino GWR values and then take their absolute value (to avoid negative numbers). This creates a scale that ranges from 0.000 to 2.0428. Thus, on average, PUMAs have a 1.35 value on this shift GWR Latino coefficient. Note that within the shifted scale, the raw GWR coefficient value of zero is between 1.2095 and 1.2091, in which 1.2095 and above signals a positive association between the percent-Latino independent variable and the percent-poverty dependent variable, and in which 1.2091 and below indicate a negative association.

Consequently, we could interpret the 1.35 as indicating that on average, there is a positive relationship between percent-Latino and percent-poverty within PUMAs. A positive association signals that as the percent of Latinos increases, the percent of reference persons in-poverty increases—holding all else constant. The PUMAs that contain a negative association are of particular interest in this research because they signal the instances when the PUMA-level attribute is associated with lower levels of PUMA-poverty.

In the case of the black variable, the lowest value is -0.6599. When shifted, the black scale goes from 0.00 to 1.60—with an average PUMA having a 0.89 value on this scale. The raw GWR coefficient value of zero on this shifted scale is between 0.6604 and 0.6595, in which 0.6604 and above signals a positive association between the percent black and percent-poverty, and in which 0.6595 and below indicate a negative association. We could thus interpret the mean as indicating that on average (0.89), there is a positive association between percent black and percent in poverty within PUMAs. This spatially weighted positive association indicates that as the percent of blacks increases the percent of reference persons in poverty decreases—net of all other effects.

The lowest GWR coefficient value for BA-plus is -0.8317. When shifted, the BA-plus scale ranges from 0.00 to 1.00 and the average PUMA contains a 0.64 on this scale. The shifted BA-plus scale contains a zero between 0.8328 and 0.8315, in which where 0.8328 and above signals a positive association between the percent with a BA and beyond and percent-poverty, and in which 0.8315 and below indicate a negative association. Since on average, PUMAs have a value of 0.64 on this variable, we could say the most prevalent spatially weighted statistical association is negative. This means that for most of the U.S. mainland, the increase in the percent of people with a bachelor's degree and beyond is accompanied by a decrease probability of poverty—ceteris paribus.

Before moving on to discuss the findings in the pre-GWR multilevel model, please note in passing that the average PUMA contains about 1,517 square miles, has a 160 mile polygon perimeter, and about 144,419 people per unit.

Pre-GWR Multilevel Logistic Model

We will now turn our attention to our pre-GWR HLM model. Before moving on the technical discussion of the model and findings, it is important to note that all the hierarchical models I use with my HLM 6.0 software have many of the same assumptions:

a) they assume that all function forms are linear at each level;
b) that level-1 residuals are normally distributed;
c) and level-2 random effects have a multivariate normal distribution;
d) with regards to homoscedasticity, that level-1 residual variance is constant
e) on independence, that level-1 and level-2 residuals are uncorrelated
f) and finally, that observations at the highest level (i.e., PUMA's attributers) are independent from each other

After several diagnostic tests, I find that all the assumptions from *a* through *e* are sufficiently met for both of my HLM models.

The crux of my dissertation lies with the fact that I think most multilevel models violate the *f* assumption by not accounting for the spatial nonstationarity in the higher order units. Throughout this project, I have made the argument that my PUMAs are *not* independent from each other. This violates assumption *f*. In particular, I argue that PUMA-level characteristics are spatially dependent. Regarding theory, I propose that not unless polygon independence is ascertained, all social scientist using nesting units with multilevel models should assume that assumption *f* is being violated and that a statistical or data solution should be sought.

Although important, a full discussion on how temporal and spatial diffusion play a role in creating inter-PUMA dependence is beyond the scope of this study. I note in passing that existing research does tackle this issue (see Land and Deane 1992; Land, Deane, and Blau 1991). My investigation explores *spatial diffusion*, but frames it in terms that are best suited for a discussion that captures how diffusion occurs over time (i.e., temporal diffusion). The differences between spatial and temporal diffusion mechanics and processes matter.

For example, researchers on this topic have found that time can bind diffusion patterns "by limiting the paths through which risks and resources flow"—in more conceptual terms, we could say that like "switches on a railroad track," timing has the ability to influence "network flow to particular subsets of the network" (Moddy 2002:43). In terms of inequality, we could say that resource distribution is affected by both time and temporal diffusion systems.

For example, economic resource flows could be affected by one's *place* within one's social network. Using Figure 5 below, if subject *A* is economically afflicted by an event, subject *E* within the network may be less likely to feel the effects compared to subject *B*. Individuals' resource equilibrium is also affected in relation to the *time* when the external effect enters the network. Extending our hypothetical example above, we could find an event where even though subject *B* is more proximal to *A*'s economic downturn, *B*'s current strong economic liquidity will make him/her less susceptible to the negative vibe in the network (introduced by *A*) than the effect it will have on distant subject *E* because the latter is financially challenged after a recent family economic devastation.

These arguments primarily point out that "when predicting social outcomes, we are better served by integrating the insights of the social capital and social networks literatures" because "the most promising bridge is to combine the *structure of networks* with the *content of social capital* to better understand social reality" (Moody and Paxton 2009:1500). This worthwhile and necessary endeavor is beyond the scope of the current study.

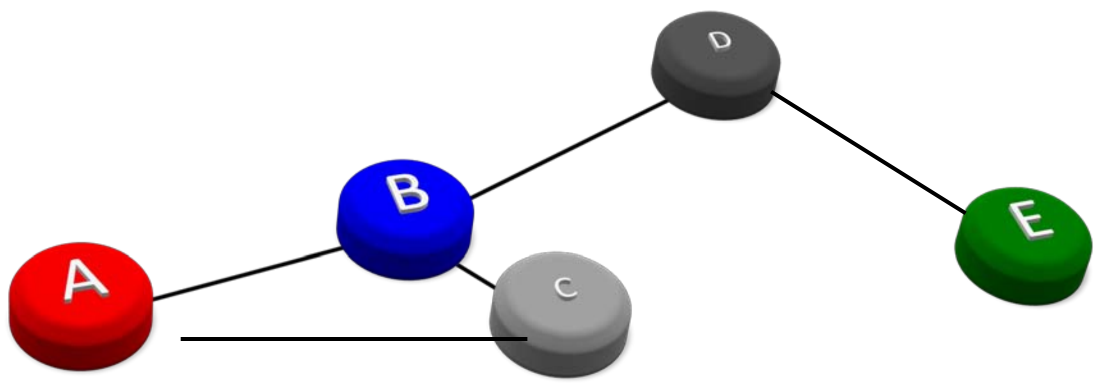


Figure 5
Simple Hypothetical Social Network

After discussing how my PUMA-level attributes are spatially dependent, we can now turn our attention to our first multilevel logistic model. Using the HLM format of summarizing the specified model in equation format, our first multilevel logistic model is as follows, at level-1 (i.e., the individual-level), with the binary poverty status dependent variable, no centered factors, no weighting, and a Bernoulli distribution, the random-coefficient model (see Hofmann 1997) is as follows:

$$Prob\left(Y = \frac{1}{\beta}\right) = \rho$$

$$log\left[\frac{\rho}{1-\rho}\right] = \beta_0 + \beta_1(AgeAtImmigration) + \beta_2(Bilingual) + \beta_3(MonoOther)$$

$$+ \beta_4(Age) + \beta_5(Male) + \beta_6(Disable) + \beta_7(Married)$$

$$+ \beta_8(Served) + \beta_9(HighSchool) + 10(Latino) + \beta_{11}(NLBlack).$$

where $\beta_1(AgeAtImmigration)$ in the respondents age at time of entry to the U.S. (native born have a "0" on this variable);

$\beta_2(Bilingual)$ is bilingual speaking status (fluent in English and some other language have a "1" in this variable);

$\beta_3(MonoOther)$ captures low English speaking ability (those with a "1" in this variable speak English very little or not at all), the reference category for both language variable is mono-English (people who only speak English);

$\beta_4(Age)$ is an interval variable capturing the respondents age;

$\beta_5(Male)$ controls for the respondent's sex type (females have a "0" in this variable);

$\beta_6(Disable)$ accounts for an individual's disability status (persons with disability have a "1");

$\beta_7(Married)$ shows marital status (never married, divorced, separated, widowed individuals are in the reference category);

$\beta_8(Served)$ is the military service control (if never served in military then has a "0");

$\beta_9(HighSchool)$ the educational binary variable (where "1" means person has a high school education and beyond);

$\beta_{10}(Latino)$ the primary micro-level variable of interest (all Latinos—such as Mexicans, Puerto Ricans, Cubans, Salvadorians, etc.—of all races have a "1" in this variable); and finally,

$\beta_{11}(NLBlack)$ wich controls for ethnic-racial status (if non-Latino and of single-black race, then person has a "1" in this factor), the reference category for the racial-ethnic variables is non-Latino-white (individuals who do not identify as having a Latino ethnicity and who are of a single- and white-race).

And where level-2 is:

$$\beta_0 = \gamma_{00} + u_0$$

$$\beta_1 = \gamma_{10}$$

and where the betas continue until you reach

$$\beta_{11} = \gamma_{110}.$$

Table 3
Results from the Pre-GWR Multilevel Logistic Model with No Level-2 Controls

Variable	***Gamma***	***% Change***	***P-Value***	***Odds Ratio***	***Logit Coef***	***Std. Error***
Intercept	γ_{00}	-20.2%	0.000	0.798	-0.226	0.018
Independent Variable						
Latino	γ_{100}	32.4%	0.000	1.324	0.28	0.014
Control Variables						
Non-Latino-Black	γ_{110}	90.9%	0.000	1.908	0.646	0.011
Age at Immigration	γ_{10}	1.1%	0.000	1.011	0.011	0.000
Bilingual	γ_{20}	10.8%	0.000	1.108	0.102	0.013
Mono-Other	γ_{30}	70.5%	0.000	1.705	0.533	0.019
Age	γ_{40}	-3.7%	0.000	0.963	-0.037	0.000
Male	γ_{50}	-41.9%	0.000	0.581	-0.542	0.006
Disable	γ_{60}	276.8%	0.000	3.768	1.326	0.007
Married	γ_{70}	-70.0%	0.000	0.299	-1.204	0.009
Served	γ_{80}	-10.4%	0.000	0.896	-0.109	0.011
High School Plus	γ_{90}	-63.3%	0.000	0.367	-1.002	0.008

Our random coefficient model outputs (above) indicate that our variance component for τ_{00} is 0.21816 (p-value 0.000). Table 3 displays the population-average outputs with robust standard errors (more on this below). From the table, we see that Latinos have 33% greater likelihood of being in poverty than their white counterparts. Blacks have a 91% greater likelihood of being in poverty than whites. Both γ_{100} and

γ_{110} confirm customary findings: minorities are more at risk of being in poverty than their non-minority counterparts.

From Table 3, we can also see that as age at time of immigration increases, the odds of being in poverty increase. Bilinguals and mono-others are also more likely to be in poverty than mono-English speakers. As age increases the odds of being in poverty are reduced and males, married people, those who have served, or have a high school education and beyond are also less likely to be in poverty. Disable people are almost 3 times more likely to be in poverty than non-disable respondents.

The random coefficient model has shown above that all level-1 variables are statistically significant and operating as expected. In our second HLM pre-GWR model we introduce level-2 variables. This intercepts-and-slopes-as-outcomes model (see Hofmann 1997), sets the residual parameter variance (tau) to zero for all level-1 coefficients except the intercept γ_{00}—where u_0 signals that a residual parameter is included in the equation. Please note that the random level-1 coefficient reliability estimate for β_0 is 0.903 and has τ_{00} variance component of 0.13052 (p-value 0.000). Keeping the exact same level-1 part of the equation given above, we now have, at level-2 (i.e., the PUMA-level), the following:

$$\beta_0 = \gamma_{00} + \gamma_{01}(\%Latinos) + \gamma_{02}(\%NLBlacks) + \gamma_{03}(\%BAPlus) + u_0$$

$$\beta_1 = \gamma_{10} + \gamma_{11}(\%Latinos) + \gamma_{12}(\%NLBlacks) + \gamma_{13}(\%BAPlus)$$

$$\beta_2 = \gamma_{20} + \gamma_{21}(\%Latinos) + \gamma_{22}(\%NLBlacks) + \gamma_{23}(\%BAPlus)$$

$$\beta_3 = \gamma_{30} + \gamma_{31}(\%Latinos) + \gamma_{32}(\%NLBlacks) + \gamma_{33}(\%BAPlus)$$

$$\beta_4 = \gamma_{40} + \gamma_{41}(\%Latinos) + \gamma_{42}(\%NLBlacks) + \gamma_{43}(\%BAPlus)$$

$$\beta_5 = \gamma_{50} + \gamma_{51}(\%Latinos) + \gamma_{52}(\%NLBlacks) + \gamma_{53}(\%BAPlus)$$

$$\beta_6 = \gamma_{60} + \gamma_{61}(\%Latinos) + \gamma_{62}(\%NLBlacks) + \gamma_{63}(\%BAPlus)$$

$$\beta_7 = \gamma_{70} + \gamma_{71}(\%Latinos) + \gamma_{72}(\%NLBlacks) + \gamma_{73}(\%BAPlus)$$

$$\beta_8 = \gamma_{80} + \gamma_{81}(\%Latinos) + \gamma_{82}(\%NLBlacks) + \gamma_{83}(\%BAPlus)$$

$$\beta_9 = \gamma_{90} + \gamma_{91}(\%Latinos) + \gamma_{92}(\%NLBlacks) + \gamma_{93}(\%BAPlus)$$

$$\beta_{10} = \gamma_{100} + \gamma_{101}(\%Latinos) + \gamma_{102}(\%NLBlacks) + \gamma_{103}(\%BAPlus)$$

$$\beta_{11} = \gamma_{110} + \gamma_{111}(\%Latinos) + \gamma_{112}(\%NLBlacks) + \gamma_{113}(\%BAPlus)$$

where γ_{00} is the intercept where all level-2 predictors equal zero;

γ_{01} is the change in the intercept for a one-unit change in "percent-Latino" (first-order effect). Similar interpretations can be given to γ_{02} and γ_{03} by simply exchanging the level-2 factor.

u_0 is the variance (i.e., τ_{00}) for each PUMA mean around the average level-1 variable (this is the variance component). u_0 is our only random effect;

γ_{10} is the slope of the association between the level-1 factor "age at immigration" and the binary dependent variable of poverty status—where all level-1 and level-2 factors equal zero. In conceptual terms, we can explain that γ_{10} is the average regression slope relating "age at immigration" to poverty-status for PUMAs where all level- 1 and level-2 predictors=0. This is also a first-order effect which is commonly referred to as the "direct effect." Thus, γ_{10} can be interpreted as the direct effect of the individual's characteristic as it relates to their odds of being in poverty—holding all other level-1 and level-2 factors at zero. By simply substituting the level-1 independent variable given above, similar interpretations can be given for γ_{20} through γ_{110};

γ_{11} is the change on the level-1 statistical slope for every one-unit increase on the level-2 factor. That is, γ_{11} is the change on the "age at immigration" variable for a one-unit change on the "percent Latino" factor. Explained differently, γ_{11} captures how the regression slopes, between "age at immigration" and poverty-status, are moderated by the "percent Latino" macro-variable. This is our first of 30 cross-level interactions. Here again, we can simply substitute the level-1 independent variable "age at immigration" (e.g., with "male") and offer comparable interpretations for γ_{21} through γ_{111};

γ_{12} is the change in slope , on the "age at immigration" level-1 variable, for a one-unit change on the "percent non-Latino-black" level-2 variable. You can replace the level-1 independent variable given above (e.g., insert "bilingual") to attain analogous interpretations for γ_{22} through γ_{112};

γ_{13} is the change in slope , on the "age at immigration" level-1 variable, for a one-unit change on the percent with a bachelors degree and beyond level-2 factor. As before, by simply exchanging the level-1 age at immigration independent variable—with for example age, corresponding interpretations can be given for γ_{23} through γ_{113};

The output using a non-linear model with a logit link function, being interpreted in this project, come from the section titled *population average model* in the HLM raw text outputs (see Raudenbush, Bryk, and Congdon 2000). In particular, the coefficients in all the following tables come from the *final estimation of fixed effects* found in the *population-average model with robust standard errors* section of the outputs. Fixed effects are variable coefficients that are constant across groups (e.g., mean intercept and slope across level-2 units). Random effects are coefficient that can vary across groups (e.g., error terms at both levels).

Our pre-GWR model, with 2,526,896 level-1 units nested in 2,054 level-2 units, converged after two iterations with a likelihood function value of -3.556673E+006. As in the null-model (i.e., intercepts only or unconditional model) used to calculate the intra-class correlation, τ_{00}(i.e., u_0) remains significant with a x^2 (i.e., chi-square) value of 25,878 (p-value=0.000). This means that individuals within PUMAs are not independent from one another. Using a single-layer regression would be inappropriate since the units under observation violate the independence principal assumption in non-hierarchical multivariate regressions.

Before moving on to the discussion of the pre-GWR HLM findings, it is important to recall why both multilevel and spatial models are employed: I argue that spatial dependence is a substantive phenomenon that requires both theoretical and methodological attention (see Tolnay, Deane, Beck 1996). This is despite the fact that spatial dependence can be treated as a nuisance—in the form of a spatial error model (Anselin, 1988). As others have done my theoretical approach specifies spatial dependence as a substantive phenomenon rather than as a nuisance (Morenoff, Sampson, and Raudenbush 2010).

Table 3 contains the results of our pre-GWR multilevel logistic model. Table 4 is long and complex. Thus, and explanation of the contents and layout of the table will help. Note that the labels for each column can be found in the top-most row. The left-most column contains all the variables. These are broken down into three sections: intercept, independent variables, and control variables. Each of the independent variables is followed by all of the level-2 factors associated with the level-1 variable. For example, right below the "Latino" micro-level variable, one will find all the three associated macro-level factors included in the equation. All the independent variables have the same three macro variables: percent Latino, percent black, and percent with a bachelor's degree and beyond.

Furthermore, the "gamma" column is introduced to help the reader follow during the interpretations of the various coefficients. The "percent change" column will be the primary source of all interpretations. The "p-value" is given to determine the statistical significance of the gammas, the odds ratio values are given to show how "1" is subtracted from these values and then converted to percent form to create our primary column of interest (i.e., %-change).

The logit coefficient and standard error values are given for reference. Only statistically significant values at or below an α of 0.05 are discussed. All statistically non-significant outcomes are included for reference.

The results show that *Latino* is significant (p=0.000) with a logit-coefficient of 0.21 and an odds ratio value of 1.231 ($exp^{0.21} = 1.231$). Thus, Latinos have about a 23% greater likelihood of being in poverty than whites—ceteris paribus. This confirms a common hypothesis (not being formally tested here) that Latinos are more likely to experience poverty than non-minority group members. We could say that when it comes to predicting the likelihood of poverty, being a Latino/a is a disadvantage.

There are two statistically significant cross-level-interactions (CLI) with our level-1 *Latino* variable. The CLI with γ_{101} (coefficient 0.21, α 0.002), as predicted by Blalock, indicates that the "Latino disadvantage" increases as the percent of Latinos in the PUMA of residence increases—holding all else constant at zero. In more technical terms, this means that for every increase of 0.01 of *percent Latino* in a PUMA, the slope of *Latino* status on the log odds of being in-poverty are increased by 0.0021.

The reason why the value is moved two decimal places to the rights is that the *percent black* variable is measured as a proportion that ranges from 0.00 to 0.98 (see Table 2). This means that a one unit change in the *percent Latino* variable would result

Table 4
Pre-GWR Multilevel Logistic Model Results with Level-2 Controls

Variable	***Gamma***	***% Change***	***P-Value***	***Odds Ratio***	***Logit Coef***	***Std. Error***
Intercept	γ_{00}	84.9%	0.000	1.849	0.614	0.046
% Latino	γ_{01}	-72.5%	0.000	0.275	-1.292	0.097
% NL-Black	γ_{02}	-31.1%	0.000	0.689	-0.372	0.085
% BA-Plus	γ_{03}	-96.4%	0.000	0.036	-3.319	0.231
Independent Variable						
Latino	γ_{100}	23.1%	0.000	1.231	0.200	0.04
% Latino	γ_{101}	24.5%	0.002	1.245	0.210	0.06
% NL-Black	γ_{102}	64.9%	0.000	1.649	0.500	0.10
% BA-Plus	γ_{103}	-14.5%	0.353	0.855	-0.150	0.16

Table 4 (continued)						
Variable	*Gamma*	*% Change*	*P-Value*	*Odds Ratio*	*Logit Coef*	*Std. Error*
Control Variables						
Non-Latino-Black	γ_{110}	74.6%	0.000	1.746	0.550	0.03
% Latino	γ_{111}	8.4%	0.255	1.084	0.080	0.07
% NL-Black	γ_{112}	14.6%	0.072	1.146	0.130	0.07
% BA-Plus	γ_{113}	39.7%	0.024	1.397	0.330	0.14
Age at Immigration	γ_{10}	1.1%	0.000	1.011	0.011	0.001
% Latino	γ_{11}	-0.1%	0.707	0.999	0.000	0.002
% NL-Black	γ_{12}	-2.1%	0.000	0.979	-0.021	0.002
% BA-Plus	γ_{13}	1.3%	0.022	1.013	0.013	0.005
Bilingual	γ_{20}	17.2%	0.000	1.172	0.158	0.039
% Latino	γ_{21}	-17.3%	0.002	0.827	-0.189	0.059
% NL-Black	γ_{22}	-18.0%	0.009	0.820	-0.198	0.075
% BA-Plus	γ_{23}	6.7%	0.623	1.067	0.064	0.132
Mono-Other	γ_{30}	23.6%	0.002	1.236	0.211	0.064
% Latino	γ_{31}	24.0%	0.012	1.240	0.214	0.085
% NL-Black	γ_{32}	-12.9%	0.228	0.871	-0.138	0.114
% BA-Plus	γ_{33}	368.7%	0.000	4.687	1.544	0.228
Age	γ_{40}	-3.9%	0.000	0.961	-0.039	0.001
% Latino	γ_{41}	1.3%	0.000	1.013	0.012	0.001
% NL-Black	γ_{42}	0.3%	0.126	1.003	0.002	0.001
% BA-Plus	γ_{43}	-0.3%	0.533	0.997	-0.003	0.005
Male	γ_{50}	-54.4%	0.000	0.456	-0.784	0.016
% Latino	γ_{51}	27.7%	0.000	1.277	0.244	0.030
% NL-Black	γ_{52}	14.9%	0.000	1.149	0.138	0.031
% BA-Plus	γ_{53}	194.5%	0.000	2.945	1.080	0.074
Disable	γ_{60}	279.1%	0.000	3.791	1.332	0.018
% Latino	γ_{61}	-40.0%	0.000	0.600	-0.510	0.036
% NL-Black	γ_{62}	-19.9%	0.000	0.801	-0.221	0.036
% BA-Plus	γ_{63}	92.2%	0.000	1.922	0.653	0.086

Table 4 (continued)						
Variable	*Gamma*	*% Change*	*P-Value*	*Odds Ratio*	*Logit Coef*	*Std. Error*
Control Variables (continued)	γ_{70}					
Married		-73.1%	0.000	0.269	-1.313	0.020
% Latino	γ_{71}	145.5%	0.000	2.455	0.898	0.035
% NL-Black	γ_{72}	67.5%	0.000	1.675	0.515	0.037
% BA-Plus	γ_{73}	-48.7%	0.000	0.513	-0.668	0.099
Served	γ_{80}	-10.9%	0.000	0.891	-0.115	0.029
% Latino	γ_{81}	-16.5%	0.008	0.835	-0.179	0.066
% NL-Black	γ_{82}	-15.3%	0.005	0.847	-0.166	0.058
% BA-Plus	γ_{83}	47.2%	0.005	1.472	0.386	0.137
High School Plus	γ_{90}	-64.7%	0.000	0.353	-1.042	0.022
% Latino	γ_{91}	51.6%	0.000	1.516	0.415	0.038
% NL-Black	γ_{92}	-1.3%	0.731	0.987	-0.012	0.037
% BA-Plus	γ_{93}	-18.1%	0.080	0.819	-0.200	0.114

in a change in the log-odds of 0.21. But a change of 0.01 in the same variable results in a change in the log-odds of 0.0021. The main point is that Blalock's group threat theory finds support here.

The same association is present in the CLI with γ_{102} (coefficient 0.5, α 0.000), where an increase in the presence of blacks further aggravates the Latino disadvantage. Both γ_{101} and γ_{102} directly support hypothesi-1 (H^1). Just as Blalock's group threat hypothesis predicted, the concentration of minorities significantly alters the odds of being in poverty. As hypothesized, I find that as the percent of minorities increases, the odds of being in poverty increases for Latinos/as. H^1 finds support in the intercepts-and-slopes-as-outcomes HLM model.

The rest of the variables are discussed briefly, with a special focus on how the percent of minorities in the area of residence alters the odds of being in poverty. With the *black* (γ_{110}) variable, we see that blacks have a 75% greater likelihood of being in-poverty (p=0.000) than their white counterparts. The only statistically significant CLI is with *percent-BA-plus*. The coefficient indicates that as the percent of individuals with a bachelor's degree and beyond increases, the odds of being in-poverty increase for blacks.

Moving on to the rest of the control variables, we see that *age at immigration* is statistically significant (p=0.000). Within immigrants, with every one unit increase of age at time of entry to the U.S., there is a 1.1% greater likelihood of being in poverty. The variable is relevant for the immigrant population and captures two general trends: immigrants have greater odds of being in-poverty than native born, and the older the immigrant is at the time of arrival, the greater the odds of experiencing poverty. Both γ_{12} (i.e., the *age-at-immigration* and *non-Latino-black* CLI) and γ_{13} (i.e., the *age-at-immigration* and *percent-BA-plus* CLI) are statistically significant. Where γ_{13} shows that as the percent of individuals with a bachelor's degree and beyond increases, the "poverty-immigration" slope slows down. This means the "immigrant penalty" increases in PUMAs that contain a highly educated population. On the other hand, γ_{12} shows that as the percent of blacks increases, the odds of being in poverty are reduced for immigrants.

When it comes to language, bilinguals have a 17% (γ_{20}, p=0.000) chance of being in-poverty than individuals who only speak English. An increase in the Latino (γ_{21}) and black concentration (γ_{22}) reduces the odds of being in poverty for bilinguals. Bilinguals are less penalized in minority concentrated PUMAs. *Mono-others* (γ_{30}) also have 24% greater odds of being in poverty than mono-English speakers—where residing in a heavily concentrated Latino PUMA (γ_{31}) further increases the negative effects and living in a highly-educated PUMA (γ_{33}) significantly magnifies the mono-other disadvantage.

As expected, with each unit increase in *age* (γ_{40}), the odds of being in poverty decrease by 4%. The "age benefit" seems to be greatest in heavily Latino populated PUMAs (γ_{41}). When it comes to sex, males (γ_{50}) are 54% less likely to be in poverty than females. The benefit of being "male" increases as the percent of Latinos (γ_{51}), blacks (γ_{52}), and highly educate people (γ_{53}) increase. Disabled (γ_{60}) persons are three times more likely to be in poverty than their non-disabled counterparts. The "disability penalty" is reduced as the percent of Latinos (γ_{61}) and blacks (γ_{62}) increases. Disabled individuals suffer a greater disadvantage as the percent of highly educate people (γ_{63}) increases.

Married (γ_{70}) respondents also have 73% lower odds of being in-poverty compared to their divorced, widowed, or never married counterparts. This "marriage benefit" increases in areas with many Latinos (γ_{71}) and blacks (γ_{72}) and decreases in highly educate areas (γ_{73}). I find that those who have served in the military (γ_{80}) have lower (11%) odds of being in poverty than individuals who have never served. This benefit is reduced (reversed) in Latino (γ_{81}) and black (γ_{82}) concentrated areas and is increased in highly educated PUMAs (γ_{83}). Finally, when it comes to education (γ_{90}), the pre-GWR model indicates that those with a high school education and beyond are less likely to be in poverty than their moderately educated counterparts. This benefit increases in Latino (γ_{91}) heavy PUMAs and is reduced in highly educated areas (γ_{93}).

Blalock's minority-group threat theory led me to formalize the following pre-GWR-H^1 hypothesis: I hypothesize that as the percent of *Latinos/as* in the area of residence increases, the odds of being in poverty will increase for Latinas/os—even after controlling for various level-1, level-2. Gamma 101 (γ_{101}) in pre-GWR model is statistically significant and consequently fails to rejects my hypothesis. Blalock's proposition—a minority-group's proliferation increases discrimination against them—is validated with our findings.

Geographically Weighted Regression

The previous section highlighted the pre-GWR HLM-findings. After showing that the increase in the minority population increases the odds of being in poverty for Latinos, I concluded that H^1 is supported. I now want to determine if after accounting for spatial nonstationarity, we can still find support for H^1. Our GWR model will help us produce data to account for spatial nonstationarity in the final hybrid-HLM model.

In this section, we give an overview of the GWR findings. As a reminder, the dependent variable is percent of people living in-poverty in a given PUMA. The independent variables are percent of Latinos, blacks, and people with a bachelors degree and beyond by PUMA. I use ArcGIS to specify the model even though GWR 3.0 software is available (see Wen, Chen, Tsai 2010; Fotheringham 2011).

Our formal exploratory hypothesis (H^2) is as follows: I hypothesized that the statistical association between percent Latina/o and percent poverty is spatially non-stationary. In particular, I expect my exploratory analysis to show that the association between percent in-poverty and percent-Latino is positively correlated in areas where Latino/a have historically been concentrated and negatively associated in new Latino-destinations. This hypothesis is in part inspired by previous findings that illustrate how "communities' sustenance activities are useful in explaining local" phenomenon (Saenz and Colberg 1988:334).

Before moving on to the GWR model, I will provide my general spatial metadata in Table 5. By doing this, I am abiding by the minimum mandatory elements as required by the Federal Geographic Data Committee (FGDC) Content Standard for Digital Geospatial Metadata (FGDC-STD-001-1998), which include the identification and reference information sections. The main goal of Table 5 is to provide the reader basic information on the source, validity, and reliability of the data used in the GWR model.

After providing basic spatial metadata information, basic GWR model results are given. Since the descriptive statistics for the GWR sample are given above in Table 2, only model evaluation diagnostics are given. Table 6 below gives the model descriptive outputs. The model uses an inverse distance and Euclidian distance. All interpretations are guided by ESRI online help instructions (ESRI-July 2011).

Table 5
Spatial Metadata

	Description
Title	By Carlos Siordia (csiordia@tamu.edu) during 2011 at Texas A&M University in College Station from U.S. Census Bureau 2007 TIGER/Line Shapefile source data (approximate resolution at 400 by 600), in miles with a North American Albers Equal Area Conic projected coordinate system on a GCS North American 1983 geographic coordinate system with a NAD83 datum.
Abstract	The spatial data set was created to conduct statistical analyses. It contains information on poverty-, racial-ethnic-, and education-concentrations by PUMAs. The geographical area being covered is made up of mainland PUMAs. The data set compliments the study by accounting for poverty-Latino spatial nonstationarity.
Spatial Extent/Coordinate System (Projection):	Shapefile feature class using an automatic data frame extend (with an average 1:27,064,159 value). The geographic coordinate system is GCS North American 1983 with a NAD83 datum. The projected coordinate system in miles is North American Albers Equal Area Conic ("polygon" geometry type with a "degree" angular unit). The prime meridian is in Greenwich.
Bounding coordinates	Horizontal in decimal degrees: *West:* -128.477280 *East:* -64.998987 *North:* 51.306925 *South:* 22.956769 and in projected coordinates: *Left:* -1393.208558 *Right:* 1325.012221 *Top:* 828.446654 *Bottom:* -1059.503873
Data Quality	The primary source of the data and shapefile is the U.S. Census Bureau. PUMA's attributes were created using ACS 2005-2007 PUMS files. Polygon-line information for the 2007-PUMAs was downloaded from http://www.census.gov/cgi-bin/geo/shapefiles/national-files and projected in ArcGIS.

Table 6
Geographically Weighed Regression Results

Variable	*Value*
Neighbors	60
Residual Squares	1.99
Effective Number	384.58
Sigma	0.035
AICc	-7737.64
R^2	0.77
R^2 ***Adjusted***	0.72

When executing a GWR model, one of the first things the researcher must do is decide which *bandwidth* to use. My approach has been established in academia (see Deller 2010). In a GWR model, the weight given to data point *n* for location *i* works on a function with a Gaussian weighting scheme, where the distance between observation *i* and location *j* (i.e., the bandwidth) is estimated by minimizing the Akaike Information Criterion (AICc)—my AICc is -7,738. This follows existing logic that “fixed bandwidths” are inappropriate when using census enumeration units because their population-density driven formulation forces them to vary in size (Mennis and Jordan 2005; Mennis 2006).

The adaptive kernel I am using selects an optimal number of neighboring PUMAs for the analysis which rely upon contiguity (rather than distance) to specify a number of nearest neighbors that ensures a constant size of local samples (Zhuang 2006). My spatially adaptive kernel is “produced by sorting the distances of the sample points from the desired regression point *i* and setting the bandwidth so that it includes only the nearest *N* observations, where the optimal value of *N* is found from the data" and where the "weight is computed by using the specified kernel and setting the value for any observation whose distance is greater than the bandwidth to zero and excluding them from the local calibration" (Gilbert and Chakraborty 2011:278). This is the preferred method for producing adaptive kernels (Fotheringham, Brunsdon, and Charlton 2002).

The spatial weighting scheme I am using was selected to allow for the bandwidth to adapt itself. Table 5 indicates I have a polygon bandwidth of 60. This means that for each regression point, *i*, there is a 60-neighbor area of influence—observations within the bandwidth have a greater influence on the estimation of the parameters in i^{th} PUMA than those outside the bandwidth.

After using the AICc to identify the optimal distance number of neighbors of 60—the bandwidth is a function of the 60 nearest neighbors so that each PUMA parameter is based on the same number of features. I now proceed to quickly outline the other statistical output. The residual squares value of 1.99 in Table 5 is the sum of the squared residuals in the model, where smaller values indicate closer fit of the model to the observed data.

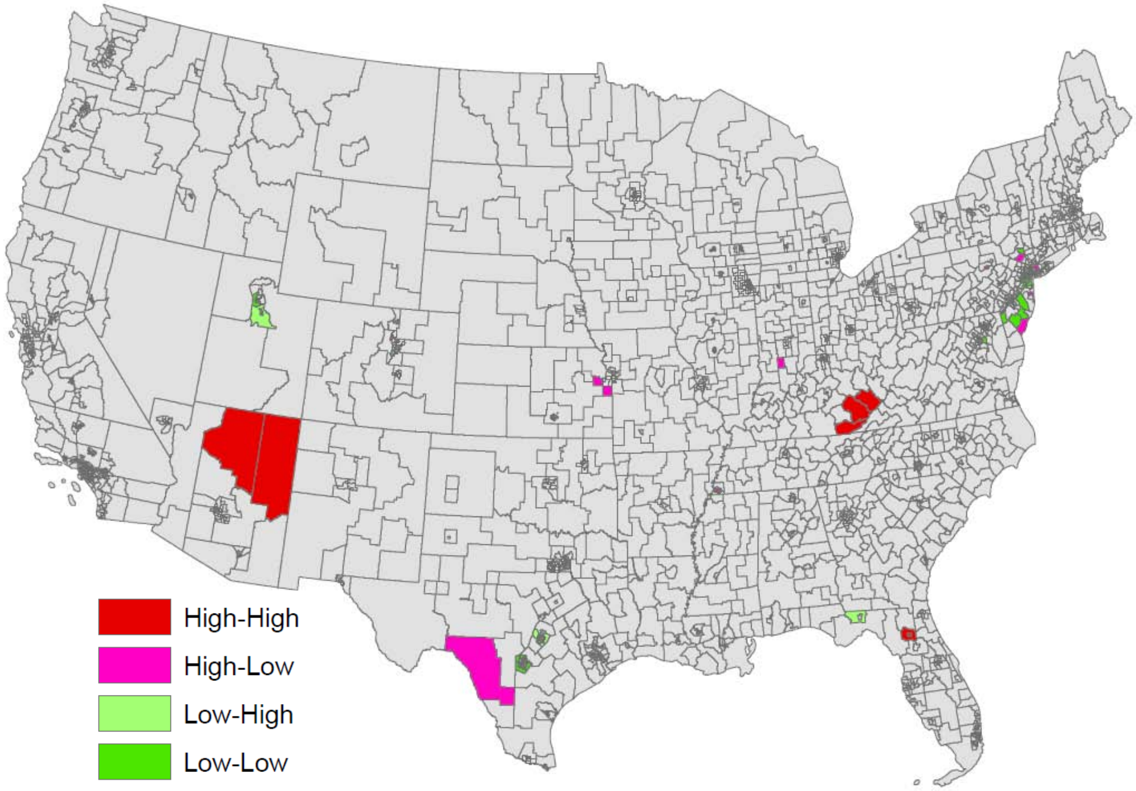
Our effective number of 385, which is influenced by the bandwidth, reflects the tradeoff between the variance of the fitted values and the bias in the coefficient estimate. The effective number is used to compute other diagnostic measures. Our sigma value of 0.035 is the square root of the normalized residual sum of squares—it is the estimated standard deviation for the residuals and is used for AICc computations. As discussed before, AICc is the measure of the model performance (but not an absolute measure of goodness of fit).

The R^2 value of 0.77 is the measure of goodness of fit. Our GWR model is accounting for about 77% of the dependent variable variance. Because the denominator for the R^2 is not altered by the introduction of an explanatory variable but the numerator is, an adjusted-R^2 can be used. Our adjusted-R^2 value of 0.72 reflects our model fit after we normalize the numerator and denominator by their degrees of freedom. After compensation for the number of variables in our GWR model, we can still have an acceptable degree of fit as we explore the variance of percent in-poverty between mainland PUMAs.

Before moving on to discussing GWR maps, we must make sure that over and under predictions are randomly distributed. Thus, I conducted a spatial autocorrelation (Moran's I) analysis on the GWR regression residuals to ensure they are spatially random. The local Moran's I index is popularly used (Anselin, 1995; Getis and Ord, 1996) and detail explanations of it with ArcGIS have been given elsewhere (see Zhang et. al. 2008).

Map 2 below shows the results of a Local Moran's cluster analysis on the standardize residuals from the GWR model. Note that all maps are extracted from PDF images to present findings. No standard geo-referencing applies to their visual representation since they are warped through the extraction process and final presentation formatting.

Map 2
Local Moran's I Clustering of GWR Standardize Residuals



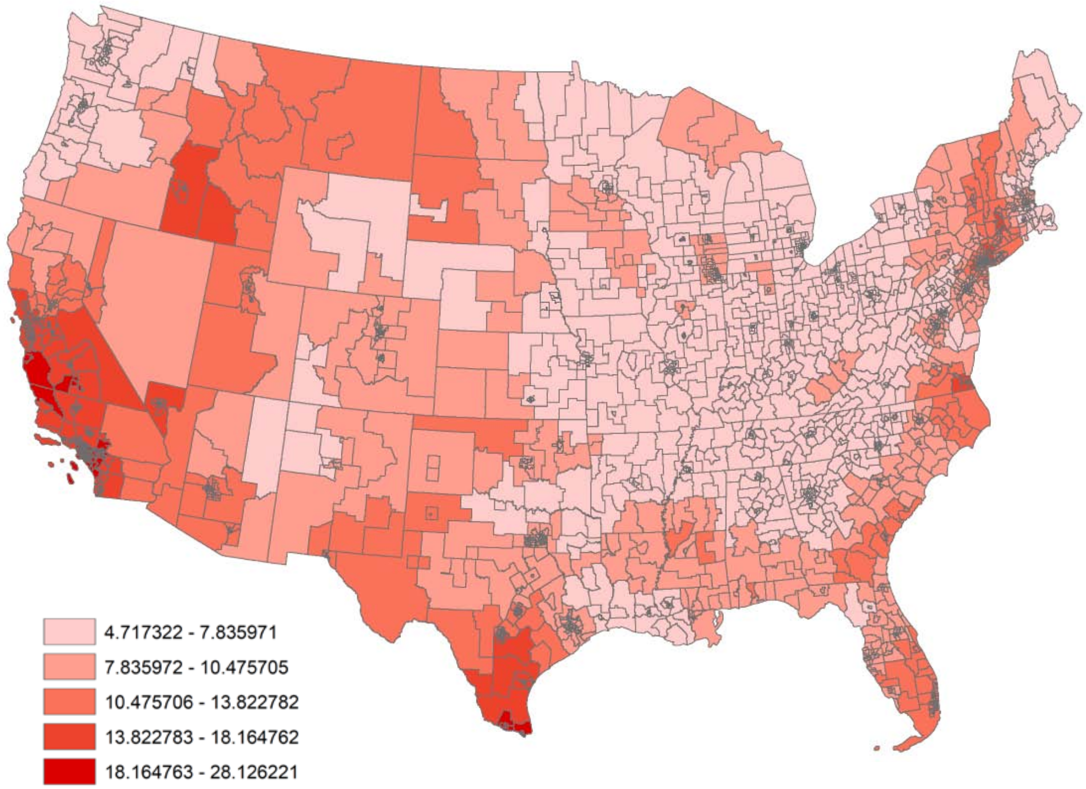
For the most part, no significant clustering of concern is present. High-High areas (i.e., red polygons) signal that high-residual values are significantly clustered—these are most present in rural areas. Low-Low areas (i.e., green polygons) indicate the presence of low-residual value clustering—they are most present in metro areas. Most of the clustering items are in the hyper-metro areas like Los Angeles in California and Houston in Texas. I conclude predictions are randomly distributed. We can now move on to evaluate additional outputs given by ArcGIS.

Map 3 below shows the condition number distribution. This diagnostic evaluates local collinearity. If strong local collinearity is present, results may become unstable.

Results associated with condition numbers larger than 30, may be unreliable. Map 3 below signals that all conditional values range from 4 to 28 and thus are acceptable. Deep red areas in California and South Texas are the most unstable and the mid-East region (light red) is the most stable. In general, there is no strong local collinearity in my GWR model.

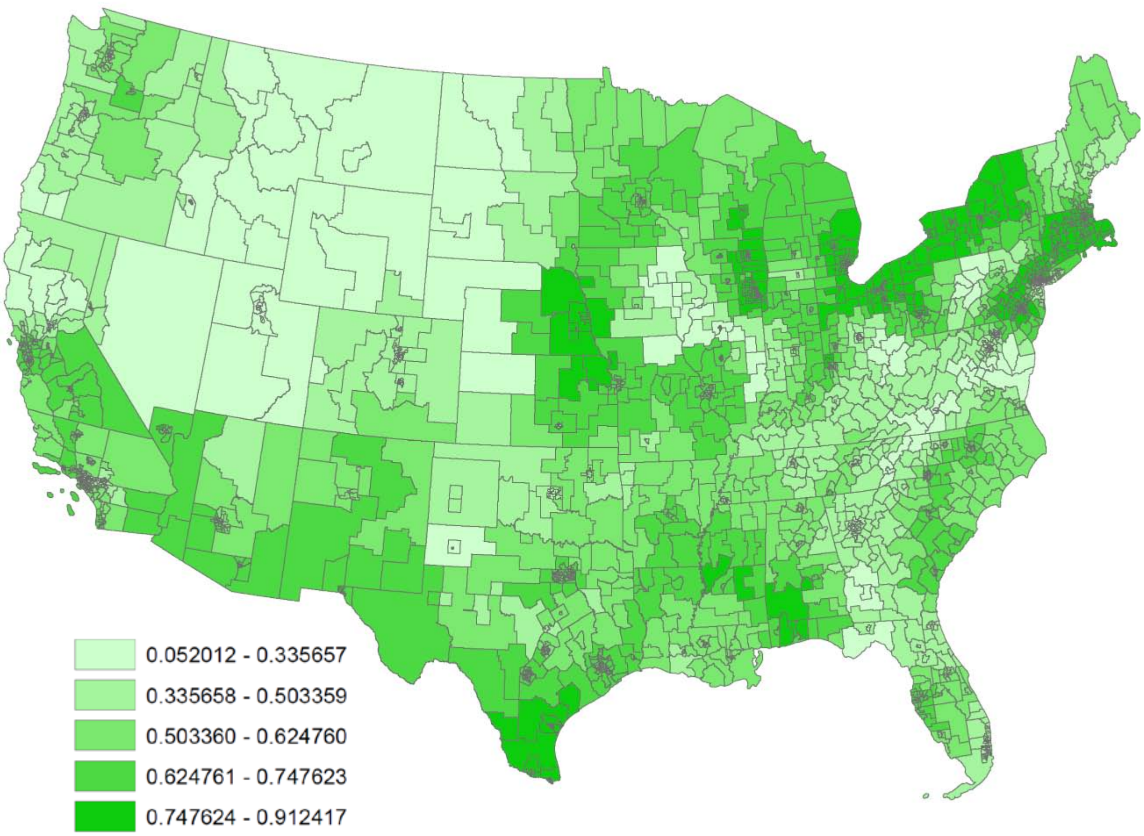
Since the map above indicates that the GWR model is stable, we can move on to Map 4 to display Local R^2 values. Values on this diagnostic can range between 0.0 and 1.0. As explained earlier, the number indicates how well the local regression model fits observed *y* values (i.e., poverty rates). My R^2 values range from 0.05 to 0.91. The very low values (e.g., below 0.30 in very light green) indicate the local model is performing poorly. The map below shows the distribution of the Local R^2 values. The GWR predicts well (dark green reflects high values) in most of the heavily populated areas and predicts poorly in rural regions. Previous research has found that minorities' poverty rate varies by metropolitan status (Saenz 1991). Perhaps a rural/urban variable would help better specified the model.

Map 3
GWR: Condition Number Distribution



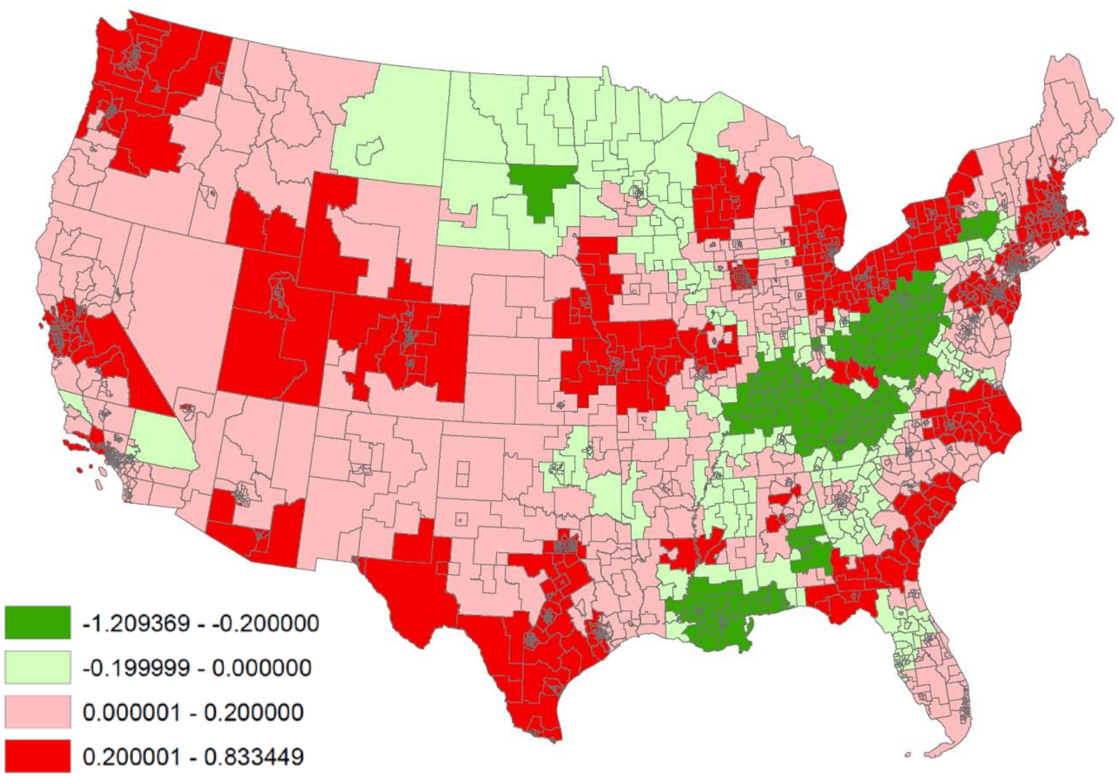
I then mapped and evaluated predicted values, residuals, and cold-to-hot standardized residuals. After finding no problems with these diagnostics, I moved on to map the coefficient values for all three predictors in the model. By mapping the individual spatial parameters of percent-Latino we can observe the spatial patterns in Map 5. In this mapping, the green polygons signal a negative statistical relationship between percent Latino and percent in poverty (all else held constant). I use green to indicate that a positive event is occurring—in green areas, as the percent of Latinos increases, the percent of poverty is decreases. Red tone polygons indicate a positive (i.e., undesired) association. Positive value polygons in Map 5 signify a cluster of units where as the percent of Latinos increase, the percent in-poverty increases.

Map 4
GWR: R^2 Distribution



Our formal exploratory H^2 that the statistical association between percent Latina/o and percent poverty is spatially non-stationary is confirmed in Map 5. I find that $\beta_{1i}\%Latinos_{1i}$ is significantly heterogeneous and ranges from negative (-1.21) to positive (0.83) values (see Table 2). More specifically, H^2 stated that the positive correlations would be present in areas where Latinos have been historically concentrated (e.g., Texas, California, and New York) and that negatively associations would exist in new Latino-destinations (e.g., Tennessee, Kentucky, West Virginia)—this too is generally confirmed in Map 5.

Map 5
Percent Latino GWR Coefficient

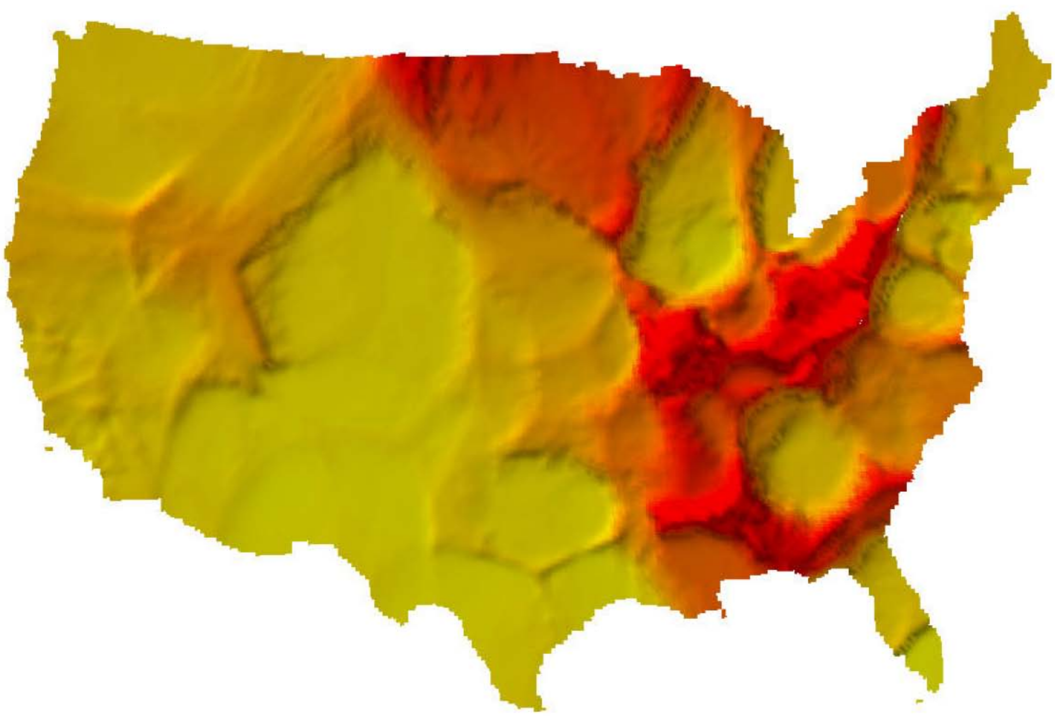


The GWR Latino coefficient $\beta_{1i}\%Latinos_{1i}$ can be represented using quasi-3-dimensional maps. Positive values represent "low altitude" areas and negative coefficients represent "high altitude" mountain-like areas. The 3-D Map 6 displays the spatial nonstationarity of β_{1i}—where red areas (high negative numbers) indicate that as the percent of Latinos increases, the percent in-poverty decreases.

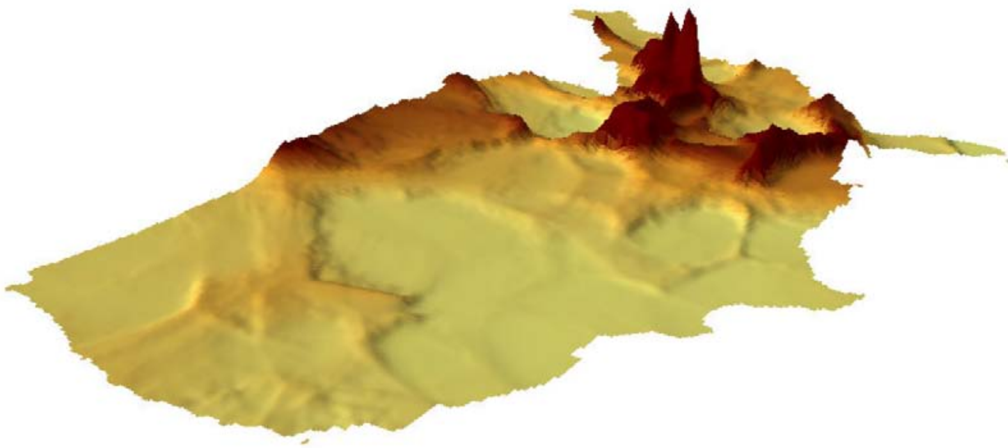
From the angle in 3-D Map 6, we can appreciate the fact the West Virginia area has the strongest negative values—the more Latinos the greater the likelihood of having low poverty levels, ceteris paribus.

From the angle in 3-D Map 7 below, we can see the impact Alabama and Mississippi. These new Latino-immigrant destinations indicate that as the percent of Latinos increase, the odds of having lower levels of poverty decreases, holding all else constant. This association is in stark contrast to the "low altitudes" in the South Texas region where the increasing presence of Latinos is accompanied by increasing levels of poverty.

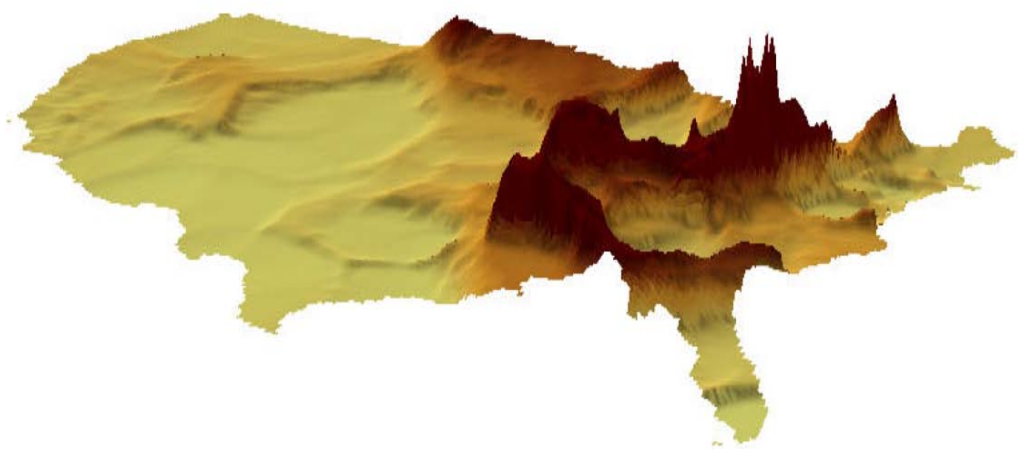
Map 6
Percent Latino GWR Coefficient (3D Angle-1)



Map 7
Percent Latino GWR Coefficient (3D Angle-2)



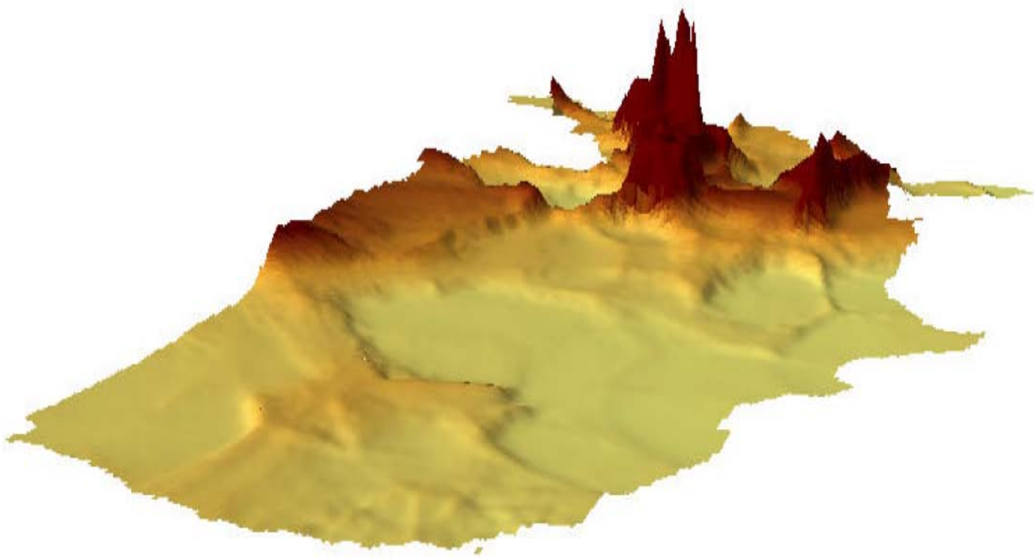
Map 8
Percent Latino GWR Coefficient (3D Angle-3)



From our final quasi-3-d maps, Map 8 and 9, we can see that in the Montana, the Dakotas, and Iowa area, an increasing presence of Latinos is accompanied by a decreasing level of poverty, net all other effects. In an indirect way, this finding supports H^1—for the most part, the more Latinos present the higher the level of poverty.

An implicit assumption here is that majority group-members are aware of aggregate circumstances (i.e., the high presence of minorities) and that this knowledge creates fear that minority proliferation will worsen economic and safety conditions.

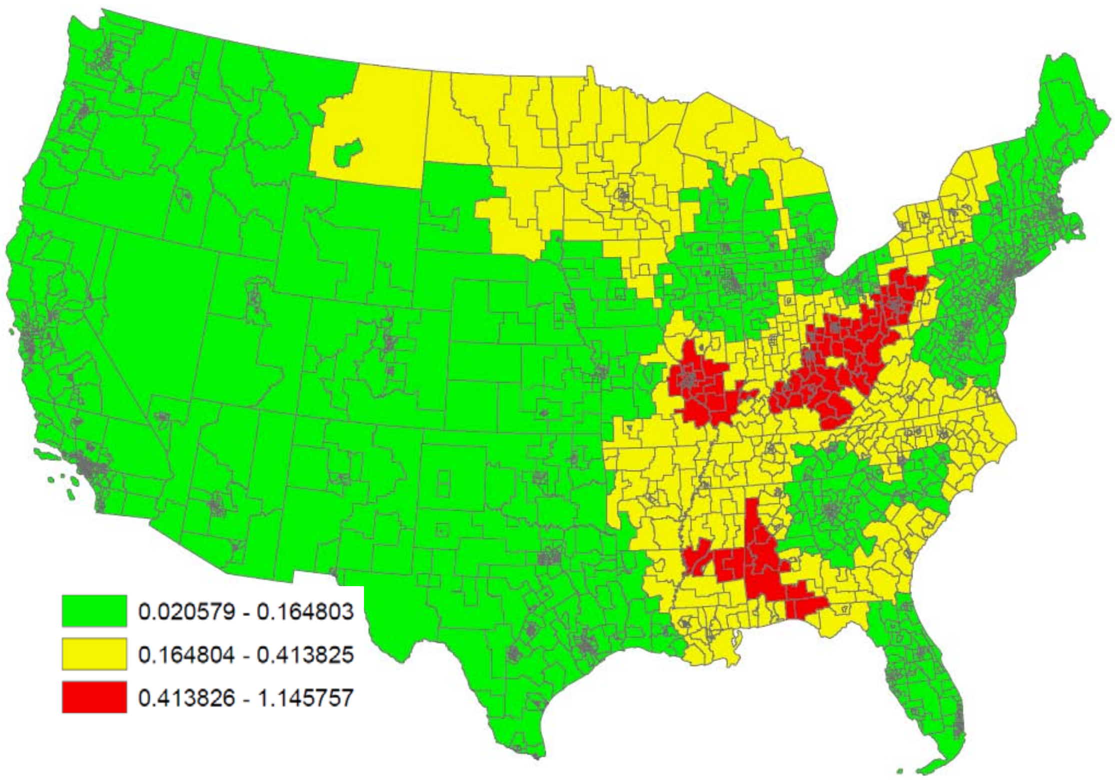
Map 9
Percent Latino GWR Coefficient (3D Angle-4)



It is worth noting in passing that many majority group-members may not simply be concerned about "managing dangerous classes" (Feeley and Simon 1992), but more focused on regulating "those perceived as menacing material resources such as jobs and welfare" (King and Wheelock 2007: 1272). Blalock's minority-group threat theory again finds support in the exploratory spatial modeling.

Before moving on to display the other coefficients, let us examine Map 10. The map below shows how the Latino coefficient's standard error (cSE) is distributed. These values measure the reliability of each coefficient estimate. Confidence in GWR estimates is high in areas with low cSE values. Polygons with high cSE values may indicate problems with local collinearity and are consequently of low confidence.

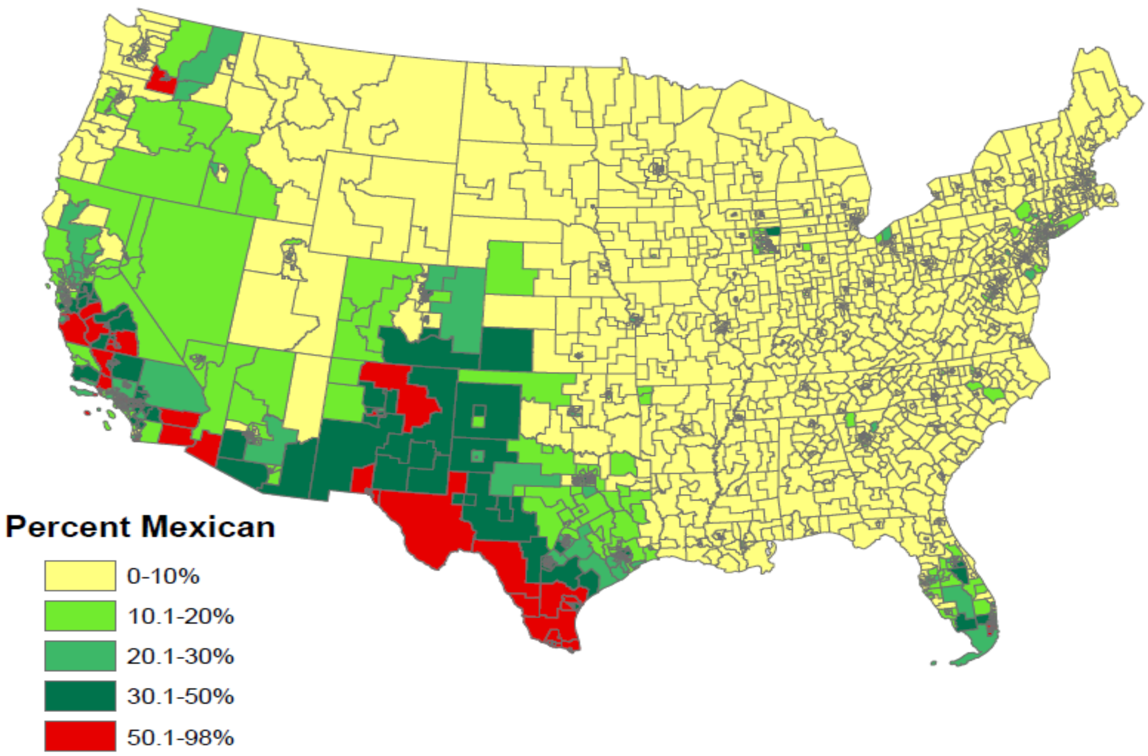
Map 10
Percent Latino GWR Coefficient Standard Error



As can be seen from the map above, confidence in our Latino GWR-coefficient is high in most of the PUMAs. The SE ranges from 0.02 to 1.15. The stability of the coefficient is most volatile in western Alabama, mid-east Mississippi, West Virginia, Kentucky, southern Illinois, and eastern Missouri. The errors seem highest in PUMAs with positive GWR Latino-coefficient values. Map 11 is given only for reference.

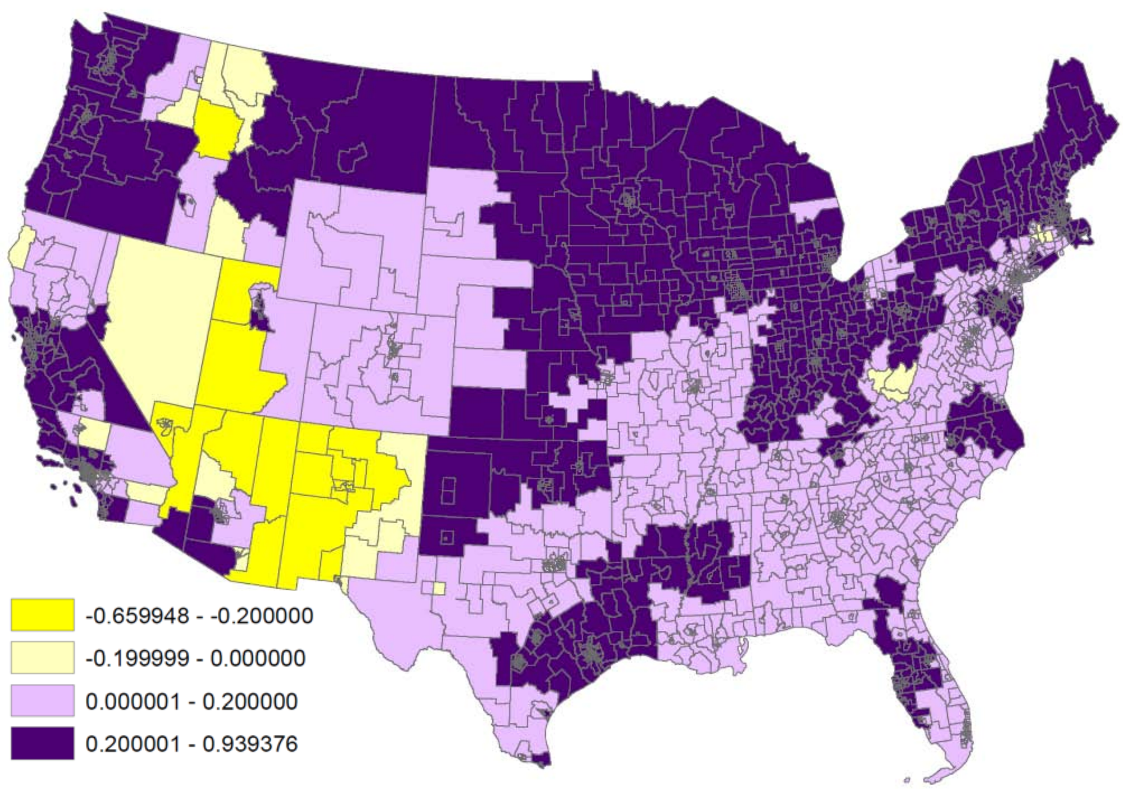
Map 12 below shows the distribution of $\beta_{2i}\%NlBlacks_{2i}$—where values range from -0.66 to 0.94. In New Mexico and Arizona (yellow areas), an increasing presence of blacks is closely associated with lower levels of poverty, ceteris paribus. Dark purple areas indicate that an increasing presence of blacks is accompanied by an increasing level of poverty in the PUMA.

Map 11
Percent Latino by PUMA Polygon



My findings concur with what others have found: Blalock's assumptions in his racial threat theory are supported. For example, researchers investigating the desire to punish from a group threat and social control perspective found that "whites who live in places with a growing African American population are more punitive largely because they perceive African Americans as a threat to economic resources. The assumptions of racial threat theory were thus supported" (King and Wheelock 2007:1272). These findings are not surprising because almost 40 years ago investigations on percent Black and lynchings supported Blalock's theory (Reed 1972).

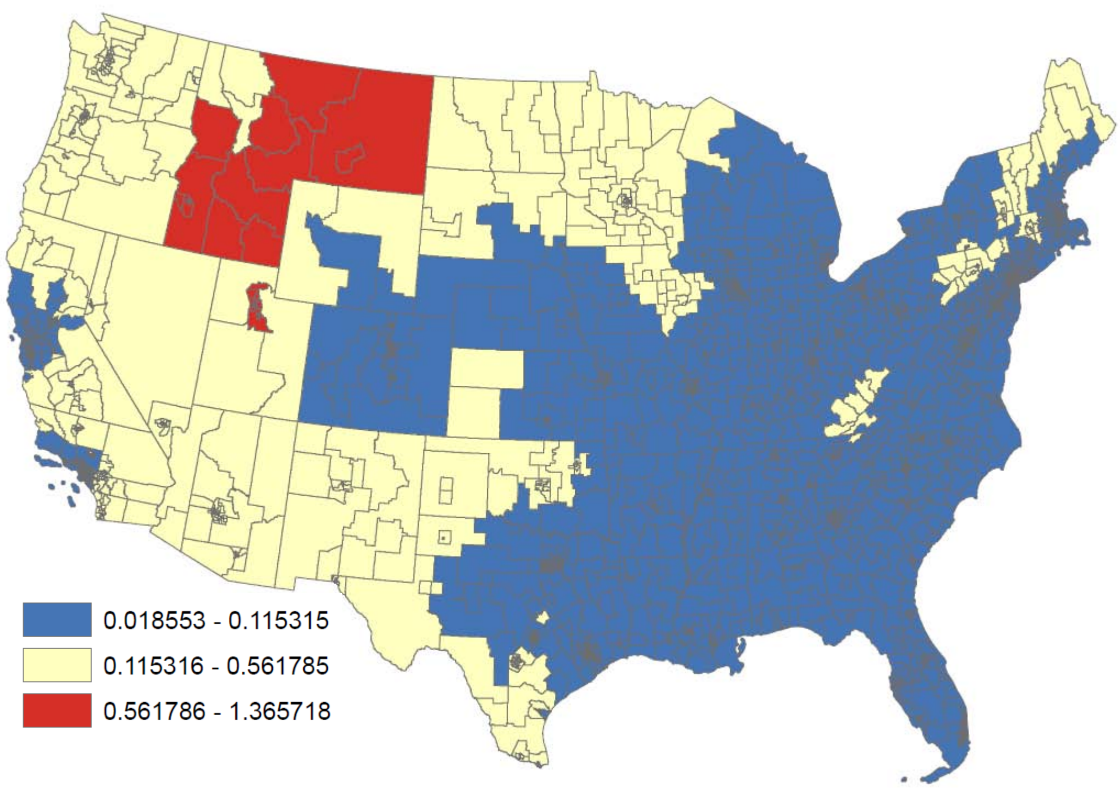
Map 12
Percent Non-Latino-Black GWR Coefficient



Map 13 below displays the black GWR coefficient stability. As illustrated in this tri-color map, the variable is most unstable (red areas) in Montana and Indiana and most stable (in blue) in most of the East mainland. The SE range here is from 0.02 to 1.37

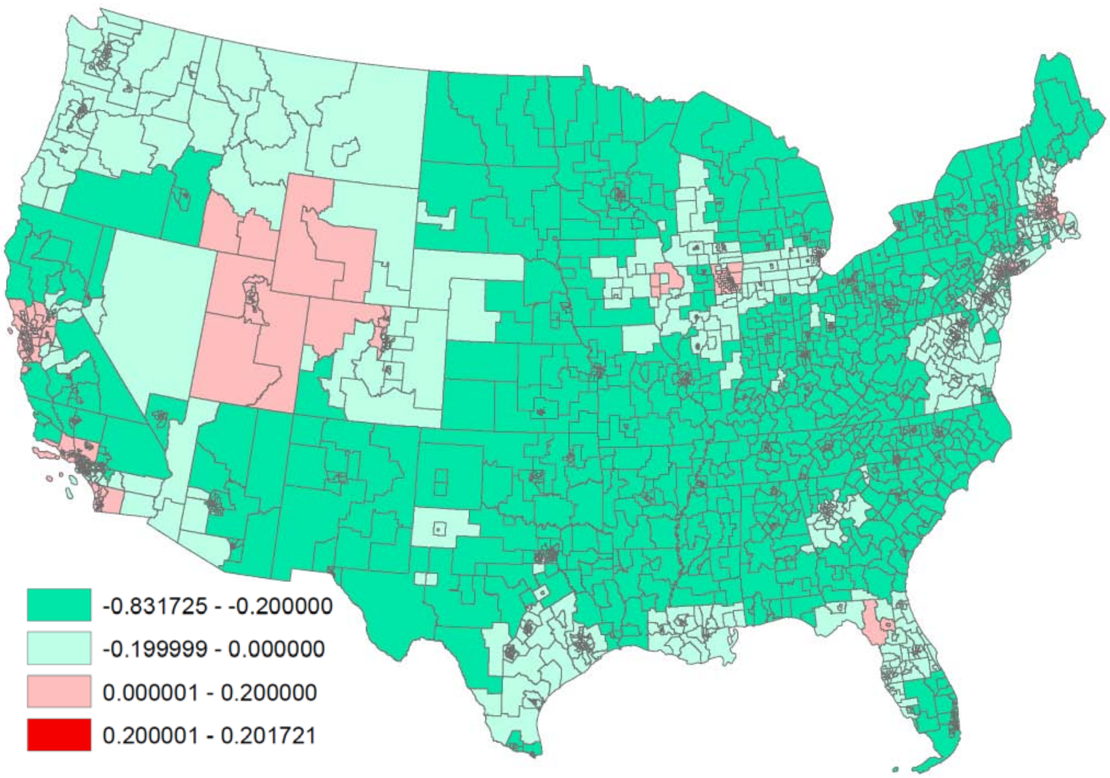
(similar range as in the Latino coefficient). I conclude that the coefficient is stable in most PUMAs.

Map 13
Percent Non-Latino-Black GWR Coefficient Standard Error



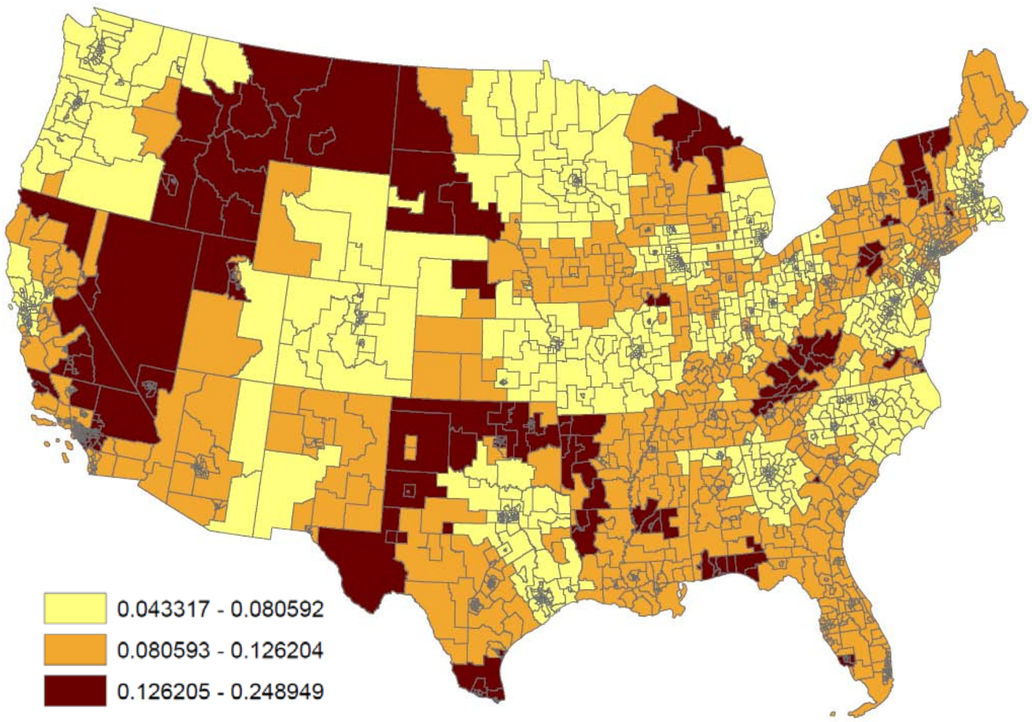
Map 14 below demonstrates the distribution of $\beta_{3i}\%BAplus_{3i}$—where values range from -0.83 to 0.17. For the most part, net of all other effects, as the percent of people with a bachelor's degree and beyond increases, the percent of people in-poverty decreases. Although not visible in this map, opposite associations are present in deep metro areas (deep red polygons) and in Utah, Wyoming, Colorado, and Indiana (light red areas). Deep metro areas like Houston, Texas indicate that the increase presence of highly educated populations is also accompanied by high levels of poverty. The opposite statistical association is present in most rural areas.

Map 14
Percent Bachelors-Plus GWR Coefficient



Our next map (Map 15) illustrates the BA-Plus GWR coefficient standard error distribution. From the map we see that the variable is most unstable in dark brown areas like Montana and Indiana and most stable in yellow and orange polygons. Most of the mainland is stable. Note that the SE range goes from 0.04 to 0.25.

Map 15
Percent Bachelors-Plus GWR Coefficient Standard Error



When compared to the Latino cSE range of 0.02-1.15 and the black cSE of 0.02-1.37, the BA-plus cSE is the most stable of all the predictors. A metro/non-metro binary variable may help improve the model and would help account for the fact that "Latinos have deep rural roots" (Saenz and Torres 2003:57). The inclusion of binary variables in GWR equations creates havoc for model convergence. Besides, previous research has found no significant differences on the economic returns of Mexican workers (Saenz 2000)—the biggest group in the Latino population (our focus minority group).

This section has delineated our GWR findings. After careful evaluation, I find that H^2 is supported. There are two parts to this hypothesis. In the first part, I support H^2 because I find that the statistical association between percent Latina/o and percent poverty is spatially non-stationary. In the second part, I find general support for H^2 because the association between the percent in-poverty and percent-Latino is in general positively correlated in areas where Latinos have historically been concentrated and negatively associated in new Latino-destinations.

Let us move on to use the GWR coefficients as data in our final hybrid-multilevel model. By doing so, I argue, I am accounting for spatial nonstationarity.

Post-GWR Multilevel Logistic "Hybrid" Model

Our final hybrid model is now discussed. After conducting the GWR model in ArcGIS, I take the information given to each of the PUMAs for each of the GWR independent variables and use them as data in the hybrid-HLM equation.

At level-1, the model remains as before:

$$Prob\left(Y = \frac{1}{\beta}\right) = \rho$$

$$log\left[\frac{\rho}{1-\rho}\right] = \beta_0 + \beta_1(AgeAtImmigration) + \beta_2(Bilingual) + \beta_3(MonoOther)$$

$$+ \beta_4(Age) + \beta_5(Male) + \beta_6(Disable) + \beta_7(Married)$$

$$+ \beta_8(Served) + \beta_9(HighSchool) + 10(Latino) + \beta_{11}(NLBlack).$$

And at level-2, it changes with the introduction of the "shifted" and then grand-mean centered GWR coefficients (i.e., GwrLatino, GwrNLBlack, and GwrBAPlus), as follows:

$$\beta_0 = \gamma_{00} + \gamma_{01}(\%Latinos) + \gamma_{02}(\%NLBlacks) + \gamma_{03}(\%BAPlus)$$
$$+\gamma_{04}(GwrLatino) + \gamma_{05}(GwrNLBlack) + \gamma_{06}(GwrBAPlus) + u_0$$
$$\beta_1 = \gamma_{10} + \gamma_{11}(\%Latinos) + \gamma_{12}(\%NLBlacks) + \gamma_{13}(\%BAPlus)$$
$$+\gamma_{14}(GwrLatino) + \gamma_{15}(GwrNLBlack) + \gamma_{16}(GwrBAPlus)$$

until we reach β_{11} where it look like this:

$$\beta_{11} = \gamma_{110} + \gamma_{111}(\%Latinos) + \gamma_{112}(\%NLBlacks) + \gamma_{113}(\%BAPlus)$$
$$+\gamma_{114}(GwrLatino) + \gamma_{115}(GwrNLBlack) + \gamma_{116}(GwrBAPlus)$$

From the final estimation of variance components of this hybrid model (where the GWR coefficients are centered on their grand mean), I find that the variance component (τ_{00}) is 0.11521 with a SD of 0.33943 and a p-value of 0.000. Table 7 below displays the population-average output with robust standard errors for our final hybrid-HLM model. Interpretations are only given for gammas associated with the primary level-1 variable of interest: *Latino*.

From Table 7 below, we see that after we control for spatial nonstationarity, the individual-level *Latino* attribute remains statistically significant (p-value=0.000).

Latinos/as are 25% more likely to be in poverty than their white counterparts (i.e., Latinos are more at risk of poverty than whites)—holding everything else at zero. This post-GWR model, here being interchangeably called a *hybrid-model* because it incorporates GWR produced data, indicates that even after controlling for spatial stationarity, Latinos retain their greater likelihood of being in poverty when compared to

Table 7
Post-GWR Multilevel Logistic Hybrid-Model Results

Variable	*Gamma*	*% Change*	*P-Value*	*Odds Ratio*	*Logit Coef*	*Std. Error*
Intercept	γ_{00}	44.4%	0.000	1.444	0.367	0.0477
% Latino	γ_{01}	-58.8%	0.000	0.412	-0.886	0.0974
% NL-Black	γ_{02}	-22.0%	0.005	0.781	-0.248	0.0874
% BA-Plus	γ_{03}	-91.4%	0.000	0.087	-2.447	0.2302
Latino GWR-Coefficient	γ_{04}	-19.1%	0.002	0.809	-0.212	0.0660
NL-Black GWR-Coefficient	γ_{05}	4.3%	0.671	1.043	0.042	0.0996
BA-Plus GWR-Coefficient	γ_{06}	-67.0%	0.000	0.330	-1.109	0.1009
Independent Variable						
Latino	γ_{100}	25.3%	0.000	1.253	0.225	0.048
% Latino	γ_{101}	18.3%	0.019	1.183	0.168	0.071
% NL-Black	γ_{102}	59.8%	0.000	1.598	0.469	0.100
% BA-Plus	γ_{103}	-19.0%	0.225	0.810	-0.209	0.172
Latino GWR-Coefficient	γ_{104}	56.7%	0.000	1.567	0.449	0.082
NL-Black GWR-Coefficient	γ_{105}	20.3%	0.042	1.203	0.185	0.091
BA-Plus GWR-Coefficient	γ_{106}	-7.0%	0.426	0.930	-0.072	0.090

Table 7 (continue)

Variable	*Gamma*	*% Change*	*P-Value*	*Odds Ratio*	*Logit Coef*	*Std. Error*
Control Variables						
Non-Latino-Black	γ_{110}	69.6%	0.000	1.696	0.528	0.038
% Latino	γ_{111}	19.0%	0.019	1.190	0.174	0.074
% NL-Black	γ_{112}	18.7%	0.020	1.187	0.172	0.074
% BA-Plus	γ_{113}	49.3%	0.010	1.493	0.400	0.155
Latino GWR-Coefficient	γ_{114}	3.7%	0.430	1.037	0.037	0.047
NL-Black GWR-Coefficient	γ_{115}	50.4%	0.000	1.504	0.408	0.082
BA-Plus GWR-Coefficient	γ_{116}	-22.6%	0.001	0.774	-0.256	0.071
Age at Immigration	γ_{10}	1.0%	0.000	1.010	0.010	0.0017
% Latino	γ_{11}	0.2%	0.418	1.002	0.002	0.0022
% NL-Black	γ_{12}	-2.0%	0.000	0.980	-0.020	0.0027
% BA-Plus	γ_{13}	1.7%	0.006	1.017	0.017	0.0059
Latino GWR-Coefficient	γ_{14}	-0.8%	0.003	0.992	-0.008	0.0028
NL-Black GWR-Coefficient	γ_{15}	0.1%	0.832	1.001	0.001	0.0034
BA-Plus GWR-Coefficient	γ_{16}	-0.4%	0.291	0.996	-0.004	0.0035
Bilingual	γ_{20}	21.2%	0.000	1.212	0.192	0.0432
% Latino	γ_{21}	-23.8%	0.000	0.762	-0.272	0.0646
% NL-Black	γ_{22}	-20.4%	0.005	0.796	-0.228	0.0792
% BA-Plus	γ_{23}	-3.1%	0.826	0.969	-0.032	0.1439
Latino GWR-Coefficient	γ_{24}	30.6%	0.000	1.306	0.267	0.0630
NL-Black GWR-Coefficient	γ_{25}	-9.7%	0.218	0.903	-0.102	0.0824
BA-Plus GWR-Coefficient	γ_{26}	2.0%	0.813	1.020	0.020	0.0826
Mono-Other	γ_{30}	33.9%	0.000	1.339	0.292	0.0685
% Latino	γ_{31}	6.0%	0.516	1.060	0.058	0.0898
% NL-Black	γ_{32}	-19.5%	0.070	0.806	-0.216	0.1194
% BA-Plus	γ_{33}	262.7%	0.000	3.627	1.288	0.2401
Latino GWR-Coefficient	γ_{34}	72.4%	0.000	1.724	0.545	0.1192
NL-Black GWR-Coefficient	γ_{35}	-1.4%	0.910	0.986	-0.014	0.1251
BA-Plus GWR-Coefficient	γ_{36}	16.8%	0.242	1.168	0.156	0.1329

Table 7 (continue)						
Variable	***Gamma***	***% Change***	***P-Value***	***Odds Ratio***	***Logit Coef***	***Std. Error***
Control Variables (continued)						
Age	γ_{40}	-3.6%	0.000	0.964	-0.037	0.0011
% Latino	γ_{41}	0.9%	0.000	1.009	0.009	0.0019
% NL-Black	γ_{42}	0.2%	0.388	1.002	0.002	0.0017
% BA-Plus	γ_{43}	-1.2%	0.031	0.988	-0.012	0.0055
Latino GWR-Coefficient	γ_{44}	0.1%	0.377	1.001	0.001	0.0015
NL-Black GWR-Coefficient	γ_{45}	0.0%	0.828	1.001	0.001	0.0023
BA-Plus GWR-Coefficient	γ_{46}	1.2%	0.000	1.012	0.012	0.0024
Male	γ_{50}	-54.3%	0.000	0.457	-0.784	0.0184
% Latino	γ_{51}	27.0%	0.000	1.270	0.239	0.0325
% NL-Black	γ_{52}	14.8%	0.000	1.148	0.138	0.0325
% BA-Plus	γ_{53}	194.5%	0.000	2.945	1.080	0.0779
Latino GWR-Coefficient	γ_{54}	0.6%	0.812	1.006	0.006	0.0251
NL-Black GWR-Coefficient	γ_{55}	-0.5%	0.891	0.995	-0.005	0.0373
BA-Plus GWR-Coefficient	γ_{56}	0.9%	0.827	1.009	0.009	0.0397
Disable	γ_{60}	285.8%	0.000	3.858	1.350	0.0202
% Latino	γ_{61}	-40.9%	0.000	0.591	-0.526	0.0376
% NL-Black	γ_{62}	-20.4%	0.000	0.796	-0.228	0.0370
% BA-Plus	γ_{63}	81.3%	0.000	1.813	0.595	0.0904
Latino GWR-Coefficient	γ_{64}	5.7%	0.060	1.057	0.056	0.0296
NL-Black GWR-Coefficient	γ_{65}	8.0%	0.080	1.080	0.077	0.0440
BA-Plus GWR-Coefficient	γ_{66}	2.4%	0.600	1.024	0.024	0.0454
Married	γ_{70}	-74.0%	0.000	0.260	-1.347	0.0224
% Latino	γ_{71}	154.9%	0.000	2.549	0.936	0.0383
% NL-Black	γ_{72}	69.6%	0.000	1.696	0.528	0.0388
% BA-Plus	γ_{73}	-42.4%	0.000	0.576	-0.551	0.1015
Latino GWR-Coefficient	γ_{74}	-8.2%	0.008	0.918	-0.085	0.0317
NL-Black GWR-Coefficient	γ_{75}	-6.9%	0.132	0.931	-0.071	0.0471
BA-Plus GWR-Coefficient	γ_{76}	-6.3%	0.165	0.937	-0.065	0.0470

Table 7 (continue)						
Variable	***Gamma***	***% Change***	***P-Value***	***Odds Ratio***	***Logit Coef***	***Std. Error***
Control Variables (continued)						
Served	γ_{80}	-11.7%	0.000	0.884	-0.124	0.0330
% Latino	γ_{81}	-13.2%	0.043	0.868	-0.141	0.0698
% NL-Black	γ_{82}	-13.2%	0.020	0.868	-0.142	0.0608
% BA-Plus	γ_{83}	47.4%	0.008	1.474	0.388	0.1448
Latino GWR-Coefficient	γ_{84}	2.6%	0.543	1.026	0.026	0.0422
NL-Black GWR-Coefficient	γ_{85}	21.5%	0.005	1.215	0.195	0.0690
BA-Plus GWR-Coefficient	γ_{86}	-4.1%	0.545	0.959	-0.042	0.0696
High School Plus	γ_{90}	-62.3%	0.000	0.377	-0.976	0.0244
% Latino	γ_{91}	35.8%	0.000	1.358	0.306	0.0402
% NL-Black	γ_{92}	-5.4%	0.153	0.946	-0.055	0.0385
% BA-Plus	γ_{93}	-34.4%	0.001	0.656	-0.422	0.1170
Latino GWR-Coefficient	γ_{94}	4.5%	0.167	1.045	0.044	0.0315
NL-Black GWR-Coefficient	γ_{95}	-4.2%	0.383	0.958	-0.043	0.0487
BA-Plus GWR-Coefficient	γ_{96}	32.1%	0.000	1.321	0.279	0.0491

their non-minority counterparts. This finding validates the widely held belief that even after controlling for a series of factors, Latinos are more at risk of being in poverty than their majority group-member counterparts.

Our results from the hybrid-model also support H^1. Our γ_{101} is significant at 0.02 and shows, as predicted by Blalock, that as the percent of Latinos/as in the area of residence increases, the odds of being in poverty increase for Latinas/os—even after controlling for various level-1, level-2, and GWR-level-2 spatial nonstationarity factors.

This holds true with the *%-NL-Black* CLI (γ_{102}, p-value 0.000), where the "Latino disadvantage" increases as the percent of black increases. Blalock's group threat theory is validated by both the pre- and post-GWR hierarchical models.

Summary

The first hypothesis under investigation (H^1) is confirmed. Using Blalock's group threat theory, I had hypothesized that as the percent of Latinos/as in the area of residence increased, the odds of being in poverty will increase for Latinas/os. The pre-GWR model supports H^1. The HLM model accounting for spatial nonstationarity also supports H^1.

The second hypothesis (exploratory in nature), H^2, is confirmed. In the first part of H^2, I had hypothesized that the statistical association between percent Latina/o and percent poverty would be spatially non-stationary. Our GWR findings support the first part of H^2. On the second part of H^2, I hypothesized that association between the percent in-poverty and percent-Latino would be positively correlated in areas where Latinos have been historically concentrated and negatively associated in new Latino-destinations. The GWR results also support this second part of H^2.

CHAPTER V

CONCLUSION

"The potential exists, of course, for substantively meaningful
spatial effects in many of the phenomena studied by social scientists...
such models can make important contributions to our understanding
of how events in one area can transcend geographic boundaries
to influence outcomes in other areas"
Tolnay, Deane, and Beck 1996:812

In concluding the dissertation, I first summarize the theory used in framing the analysis. After making it clear that both hypotheses under investigation are unfalsifiable, important implications are outlined. Subsequently a discussion of Blalock's ideas on minority-group threat theory is given before concluding with some suggestions for future research.

Summary of Findings

The project began by arguing and providing evidence for how social disequilibrium asymmetrically affects people and places. Chapter I outlined the growing gap between the wealthy and poor. From the time I began writing this dissertation until now, a report by the Pew Research Center noted that the "median wealth of white households is 20 times that of black households and 18 times that of Hispanic households" (Kochhar, Fry, and Taylor 2011:1). The report highlights how the gaps "are the largest since the government began publishing such data a quarter century ago" (Kochhar, Fry, and Taylor 2011:1).

The fundamental argument underlying this investigation is that social suffering occurs on an unequal basis. In citing Rogelio Saenz's (1997) research on the Chicano population, I found justification for focusing on on how Latinos/as are affected by wealth distributing mechanisms. In reviewing the literature in Chapter II, I use Blalock's race-relations writings as the cornerstone of my investigation and expanded the foundation of the theories by utilizing Gerhard E. Lenski's (1984) theory of power. I summarized that the unjust and systematic uneven distribution of resources is based on human's three primary dispositions that result in making Homo sapiens self-seeking, social-units, with an insatiable appetite for finite resources.

After concluding a review of existing ideas and investigations, a formal hypothesis was anchored on Hubert M. Blalock's (1970) seminal minority-group threat theory. Douglas S. Massey's (2007) modern take then helped frame how our species' basic constitution exacerbates social inequality by systematically altering how resources are distributed along different categories. The Blalock theoretical grounding was thus centered with the help of Saenz's, Lenski's, and Massey's valuable academic work.

The primary goal of this project has been to explore how hierarchical and sociogeographical factors influence a Latino's likelihood of being in poverty. The presence of poverty is interpreted as being partially the product of racial-ethnic discrimination by those controlling resources (i.e., majority-group whites). Moving beyond how individual level characteristics predict likelihood of poverty, the dissertation answers how the percent of Latinos/as in the area of residence has an influence on Latino’s poverty over and above the influence on poverty of the person characteristics. I have clearly shown in Chapter IV that accounting for racial-ethnic context matters and that Blalock’s predictions are accurate: the increase of the Latino (i.e., oppressed group) population increases the odds of being in poverty for Latinos.

As explained in Chapter III, in combination with the multilevel hypothesis, I explored how spatial non-stationarity plays a role in predicting context-level poverty rates. After offering an extensive argument for why spatial nonstationarity should be accounted for, I hypothesized that the statistical association between percent Latina/o and percent poverty would be spatially non-stationary. Of particular interest to this work was how the Latino GWR-coefficient would be associated with the poverty percent GWR-dependent variable. In the latter case, I predicted positive GWR statistical associations in historically concentrated Latino/a regions and negative betas in new destination areas.

There are several significant statistical findings. Foremost, the null hierarchical model in Chapter III indicates there are significant differences among individual’s average log-odds of being in poverty *between* PUMAs. In particular, I find that about 12% of the variance in poverty occurs between PUMAs. As such, about 12% of the variance in poverty can be explained by the PUMA grouping structure in the U.S. mainland population. This finding alone requires that poverty be investigated using hierarchical modeling.

I would like to mention in passing why hypotheses are being defined in terms of their falsifiability. I concur with Clegg's notion that formal hypothesis statements are not "timeless truths but are provisional, expressed in a propositional form as hypotheses which are always in principle subject to empirical disconfirmation" (Clegg 1989: 45). More technically, scientifically testable hypotheses are "conjectures which are systematically grounded but which remain open to refutation" where they remain until "either the establishment of a counterfactual empirical regularity or the demonstration of an irregularity" is given "where one was previously not established which would occasion the refutation of a conjecture" (Clegg 1989: 45, also see Popper 1965). Nothing can be proven, only refuted or unfalsified. I use this approach in drawing conclusions regarding my hypotheses.

The variance component remained significant in all models. In Chapter IV, the random coefficient model demonstrated that Latinos had greater odds of being in poverty when compared with their white counterparts—controlling for several individual-level characteristics. This statistically significant association remained even after introducing PUMA-level controls in the intercepts-and-slopes-as-outcomes hierarchical model; Latinos have a greater likelihood of being in poverty than their white counterparts. This last model tested H^1 and found no evidence to reject it because the PUMA's increase in Latino population increases a Latino's odds of being in poverty. The same was true with the increase in the black population. Blalock's minority threat theory could not be falsified. As minority concentration increases, minorities' odds of experiencing disadvantage increases. This pattern supports Blalock's idea that his is the result of oppressed groups becoming a threat to the existing power structure as their numbers grow.

In exploring sociospatial inequality, as measured by the existence of economic poverty, I theorized that racial-ethnic discriminatory micro-level processes eventually aggregate to create and sustain macro-level structures that lead to the preservation of inequality. In framing this view, I explained that social phenomena have material consequences that alter both societies and their physical environments. In other words, social power navigates the abstract world through a series of micro-level interactions that eventually have macro-level consequences that in the end serve towards the solidification of inequality-creating social and physical structures.

The GWR model tested for H^2 and found no evidence to reject it. The GWR model indicated the statistically significant presence of spatial nonstationarity. Spatial modeling outputs indicate that the increased presence of Latinos does not always equal an increase in the percent of local poverty. Using GWR created PUMA coefficients as data in a final hybrid hierarchical model, I found no evidence to reject H^1 since Latinos retained their greater odds of poverty when compared to whites and the rising presence of Latinos (and blacks) increased their odds of being in poverty. Thus, even after accounting for spatial nonstationarity, Blalock's predictions prove useful. The quantity of minorities in an area has an effect on their life chances.

General theories were particularized to be used with Blalock's minority group threat hypothesis. This dissertation is unable to falsify Blalock's minority group threat propositions. The findings support the idea that both socioeconomic inequality and percent of minorities in a community rise and fall congruently—because there are social structures that bind their movements. Using Blalock's logic, I find support for the theory that the primary element perpetuating this positive relationship has to do with systematic discriminatory practices rooted in human nature and structuralized by biased informal interactions and formal organizations.

In summary, H^1 cannot be falsified. I find that as the percent of Latinos/as in the area of residence increases, the odds of being in poverty increase for Latinas/os, even after controlling for various level-1, level-2, and GWR-level-2 factors. My multilevel and spatial modeling investigation was unable to falsify Blalock's minority group threat theory. Hierarchical models indicate that as the percent of Latino/a increases, the likelihood of being in poverty for Latinas/os increases. This statically significant relationship holds constant even after spatial nonstationarity level-2 control factors are introduced. I interpreted this cross-level-interaction as being the product of ethno-racial discrimination: Latinas/os are more at risk of poverty as their numbers increase because their population growth increases local discriminatory practices against them.

Finally, H^2 could not be falsified. I find that the statistical association between percent Latina/o and percent poverty is spatially non-stationary. Geary's and Moran's mid-1950s ideas on spatial autocorrelation, later made testable by Cliff and Ord in the 1960s find support in the geographically weighted regression advanced by Charlton, Fotheringham, and Brunsdon. In general, the geographically weighted statistical association between the percent of householder in poverty and the percentage of the population in the area that is Latino are positively correlated in historically concentrated Latino/a areas and negatively associated in new Latino-destination PUMAs.

Discussion

Writing about inequality is difficult. Seeking its cause is primarily driven by the desire to blame somebody. A general belief is that if the source of a problem is found, then a solution is possible. For those who still belief a solution is achievable, finding the source of inequality is the first step towards developing a response.

Even within the ranks of the optimist, solving structural injustices is overwhelming. Which is why some argued that instead of "focusing exclusively on how individuals and families manage the adversity associated with poverty" it is more important to "alleviate the stress and resulting crisis in the first place" (Seccombe 2002: 391). They explain that research endeavors should instead "be attuned to what causes poverty and how structural conditions and economic policies (or their absence) affect the objective and subjective experience of impoverishment" (Seccombe 2002: 391). In other words, understand how the problem is created and then alter that process so as to negate its initial formation. If we are proactive and stop the problem from ever developing, then we need not solve it at a later, in a potentially more complicated and expensive point in time.

Micro-level behavioral patterns do influence financial outcomes. As explained in Chapter II, individual-level factors are founded on biological materialism and arise from both internal life experiences and external influences. It is the latter that this dissertation has focused on. I have delineated how structural patterns, fueled by racism among those controlling resources, negatively influence Latino's life chances. In wrestling with the structure/agency debate, I have concluded that structure matters most and that individuals in poverty exhibit the same basic economic behaviors as other most fortunate people, "except that in poverty, with its narrow margins for error, the same behaviors often manifest themselves in more pronounced ways and can lead to worse outcomes" (Bertrand, Mullainathan, and Shafir 2004:419), because when people are at the edge of a precipice, even the smallest of wind gust matter.

As with all academic investigations, there are some limitations with the present study. I will only focus on two of them. The first concerns the measure of poverty and how it relates to discriminatory practices. This topic was discussed at length during the literature review in Chapter II. I only want to bring attention to the assumed connection between an individual's current income and his/her communities' level of discrimination.

The non-longitudinal data being used in this project does not allow me to investigate how the various factors associated with financial outcomes have varied over time. For example, assume Jos**é** is in poverty. My variables only tell me Jos**é's** other *current* demographic characteristics and context-level attributes. I will know how much education he currently has, if he is currently married, if he considers himself a Latino or not, how many Latinos resided in his PUMA during the survey period, and so forth. I will not be able to understand the factors that played a role in the past to determine Jos**é's** current level of education or marital status.

The data only allows me a one-time slice of information on José. This static and limited image of José means that several assumptions are being made on how his demographic and contextual characteristics are interrelated. The main point is that I am assuming that racial-ethnic discriminatory practices are partially responsible for José's current poverty status. My theoretical framework assumes that micro-level prejudices coalesce to influence the formation of unjust and systematic discriminatory systems. From these views, José is most influence by the structure he is randomly born into. I am privileging the idea that structure is the most powerful force shaping José's ultimate life chances. Existing variables within my cross-sectional data do not allow me explore such longitudinal events.

Existing research does verify that minority concentration has effects on majority-group members. For example, researchers investigating community trust found that the increase in percent Hispanic was associated with reducing interracial trust among whites (Rudolph and Popp 2010: 83). Others have found that as the size of a minority group increases, majority-group members are more likely to feel their social, economic, and political privileges are at risk (Oliver and Wong 2003). The term "minority groups" has its own problems and could more correctly be interchanged for "oppressed" groups (Meyers 1984).

Similar studies have discovered that white people "are influenced by the percentage white in a community (net of the community's social class characteristics) and very unlikely to consider [residing in] communities where they are anything but the strong majority" (Krysan and Bader 2007:699). In general, findings indicate that caution toward minority-group members is a function of minority-group size (Harpham 2008:53). In my dissertation, Blalock's minority group threat hypothesis creates the expectation that inter-racial/ethnic discrimination will increase as a function of racial/ethnic heterogeneity. Previous and current evidence make it clear that my assumptions are not borne out of pure speculation. They are very probable and I thus conclude their inclusion in the theory is reasonable and beneficial.

The second major limitation highlighted here concerns the non-theoretically driven boundaries of PUMA polygons. PUMA polygons rarely (if ever) represent a community. It is worth noting that the term "community" is highly elusive and possesses many interpretations (Bell and Newby 1974; Bernard 1973; McLain and Jones 1997). Attempts to define community have been in existence within sociology for more than a century (e.g., Tonnies 1905).

Even though there is a lack of consensus, some agree that there are three basic elements that can help define a community: shared geography, common ties, and social interaction (Bernard 1973). Common locality (i.e., residing in geographic proximity) is necessary but not sufficient (Selznick 1996). Participating in a local economic hub is the second central component of classifying a community because it captures how individuals share in the conflict over access to and control of resources. Lastly, demarcating a community requires accounting for shared history, knowledge, beliefs, ethics, customs, etc. (Bernard 1973). Although somewhat ambiguous, the porous and continually morphing geographical boundaries of communities could be said to be established as a function of physical proximity, economics, and shared culture.

Defining the geographical boundaries of communities is difficult—and may even be impossible. Previous research has shown that social relations transcend most spatial boundaries (Leach et al 1997). Others have offered more complete reviews on the challenges of defining community (e.g., Kepe 1999). Community is the ideal areal unit for most "sociospatiological" investigations. It has yet to be systematically defined. We are still working on simpler topics like: what is a nation? Defining political boundaries should be easier than deciphering the informal demarcations of communities. This is not so.

For example, the U.S. recognizes the Sovereign Military order of Malta—whose territory only includes two buildings in Rome—as a sovereign government and sanctions the 0.44 km^2 that is Vatican City as a nation. If this seems extreme, consider the fact that the U.S. government distinguishes Bouvet Islands as a political entity—even though the recognized Norway-dependent island is only an uninhabitable Antarctic volcanic knoll in the South Atlantic. Ironically, the penguins in Bouvet Island have their own zip code (Anonymous 2010) while South Ossetia, with its 3,900 km^2 area and about 70,000 people is not consider a sovereign entity by the U.S. There is no global consensus on what constitutes a nation. How far off are we from being able to boundarize communities?

After extensive contemplation, I consider the non-theoretically driven boundaries of PUMA polygons acceptable. Then truth is that when researchers investigate spatial communities, "the main decision is whether to use an officially recognized area, such as an electoral ward or postcode area, or to qualitatively explore respondents' constructions of community and then to use the most meaningful definition in the quantitative survey" (Harpham 2008:53). Either way, the final decision of what constitutes a community will remain arbitrary until the matter is more systematically and scientifically established. In my case, I abstained from calling PUMA areas communities. PUMAs in deeply populated areas may be more likely to capture what could be understood as a community. I leave it to the reader to determine how PUMA's relate to their own idea of a community.

The main point in this discussion is that the drawing of political boundaries like nations, states, counties, cities, and school and voting districts are themselves potent political acts (see Newton 1975:18) with all sorts of implications for all community members. Blalock wrote that "power is a multiplicative function of two very general types of variables, total resources and the degree to which these resources are mobilized in the services of those persons or groups exercising the power" (1960:53). He extended his logic and explains that "if [non-Latino] whites are to maintain a constant power advantage over [minorities] their degree of mobilization relative to that of [minorities] must not only increase with percentage [minorities], but it must rise at an increasing rate" (Blalock 1956:56). Embedded in his argument is the idea that all these processes must occur in self-containing areas (i.e., communities).

Power can only be maintained through these mechanics if control over resources is localized. In the post civil rights U.S., dominant-group discrimination against Latinas/os is primarily "maintained by a series of uncoordinated though similar individual acts" (Blalock 1956:58). Institutionalized racial-ethnic discrimination has conceptual and practical limitations. Alternative multilevel frameworks like the one employed in this research are most helpful because they "takes us beyond an approach which privileges institutional factors and instead recognize the significance of micro-racialisation expressed at the individual level and the macro-racialising tendencies of late modernity" (Philips 2010:187).

There are elaborate ideological systems justifying racist behavior. The main point is that when the power threat increases, dominant-group members will mobilize their "resources through organizational and ideological techniques" to the point that "power relationships are likely to take on more and more the form of a conscious struggle between groups" (Blalock 1956:58). All these events happen in communities. The problem is that Blalock (1956) never defined what a community is—and consequently "where" dominant-group members increase their degree of resource mobilization. Blalock's power threat hypothesis offers no tools for operationalizing the geographical boundaries of communities (i.e., locus and boundaries of resource control).

When it comes to sociospatial inequality, PUMA's geographical boundaries mandate that social theory adapt itself to suit their sample-driven construction. In order to account for the limitations and existing theories I now summarize my theoretical propositions. Following Blalock's approach (1970:191), I too will explain the inequality borne out of racial-ethnic discrimination by deriving at a lower- and sociospatial-order proposition from a combination of general propositions:

Universal Proposition: Homo sapiens are social, self-seeking units whose appetite for finite resources is insatiable.

General Proposition: Because of their universal disposition, humans in superordinate positions will act in most cases in such a manner as to preserve their privileged status.

Specified Condition: In the U.S., non-Latino-whites have historically been in superordinate positions v**is-**à**-vis** Latinas/os (and all other oppressed groups).

Lower-Order Proposition: In the U.S., non-Latino-whites act toward Latinos/as in such a manner (i.e., discriminatingly) as to preserve their privileged position.

Sociospatial-Order Proposition: U.S. non-Latino-whites will seek to exercise their power over those most geographically proximate to them so as to maximize their level of influence.

Future Research

The primary concern of this sociospatial inequality research has been to study "who gets what and why" and to "acknowledge that *where* is also a fundamental component of resource distribution" (Lobao, Hooks, and Tickamyer 2007:1). Working from the idea that social relations are frequently and inevitably "correlated with spatial relations" (Park 1926:18) I have conducted multilevel and spatial analysis.

Although challenging, it is easier to investigate how individuals behave differently under changing social environments than to detect how communities are affected by social structures and by the interactions among ecosystem residents. The investigation ends with many potential future research questions and suggestions. The following discussion only focuses on how community geographical boundaries are perceived and how macro-level attributes are estimated by individuals.

Of primary interest would be to conduct studies on how individuals construct their community geographical boundaries. Such investigation could use surveys and open-ended questions to explore the many factors and psychological mechanics involved in determining how individuals perceive their community. The main question would be if there are generalizeable patterns that determine how most people define a community. The second question would focus on determining if it is possible to determine the geographical boundaries of communities. I suspect little generalization from individual's responses would be available to inform existing multilevel theories.

Another important investigation could explore how people develop their perceptions of local macro-level demographic factors. Future studies could focus on investigating the reliability and process through which people develop their macro-level perceptions. For example: are most individuals able to correctly ascertain the local minority concentration? Even if their estimate of local minorities is wrong, how do they arrive at such estimates? What factors (e.g., family, media, etc.) do they use to determine the various macro-level attributes of what they perceive as their community?

In short, future research should investigate the theoretical essence driving hierarchical spatial modeling: people feel they belong to a community, they know the geographical boundaries of said community and the social characteristics of their environment—and behave accordingly. The first may be easier than the latter two. I suspect standardizing community geographical boundarization will prove nearly impossible since people may vary greatly in their perceptions of where the community starts and ends. The latter element may show some credence for the belief that individuals are able to detect the composition of their social environments.

Conclusion

Humans are a keystone species—they have a disproportionate effect on their environment relative to their biomass. Our species affects many taxa by our presence. We impact other plant and animal organisms in ways that significantly alter our local ecosystem. Our actions sculpt the physical and social environment we inhabit. We each influence the various aspects that go into the creation of our social environment. I belief humans have the potential for both motivation and intent. Consequently, I believe humans have the ability to predict and change the future.

Blalock's prediction using the power threat and minority presence function has not been falsified. If Blalock's theories are correct and Latino's proliferation in the U.S. continues, then fear, conflict, and discrimination will continue to rise. Consider that "conflict enhances group solidarity, clarifies group boundaries and strengthens the individual-group linkage through ego-emotion commitment and overt action" to the point that "in-group identity is extended to the larger social system through the extension of communication, the enlargement of the network of social interactions and ideological evolution to national core values" (Himes 1966:10). If fear gives rise to conflict and the latter to discrimination, then it may be that Latinos will continue to gain group solidarity—a solidification that may render their group as a political, social, and economic key player in North America.

One of the major contributions of this dissertation lies in the hierarchical, spatial, and hybrid modeling of minority-group status related variables in the prediction of poverty. I have been unable to falsify my argument that Latinos are at a disadvantage when compared to whites. I argue the difference is the product of discrimination. Many years ago, Novak wrote that "when a person thinks, more than one generation's passions and images think in him" (1972:32). So it is with me—my perceptions and interpretations join the collective formation of the plural author describing the process by which oppressed groups become the recipients of their disadvantages.

I began the dissertation by highlighting my previously held naïve belief that if people follow all the rules, all their dreams will come true. My personal disposition has framed the project in such a way so as to show that life chances are deeply rooted on events beyond our control. I did not choose to be born a Chicano in deep economic poverty. Many factors existed before I could even began to walk that systematically influenced my ability to reach my personal goals.

We are not born into a level-playing field because some of us have more access to resources than others. By using my sociological imagination, I have argued that sociospatial inequality is unjust. I have given quantitative evidence for the existence of Latino victimization. Latinos are and will continue to be a force in the formation of North America. Even after a labyrinth of intellectual thought, the question remains simple: How will the Latino population continue to change the U.S.? And the argument remains equally simple: If Latinos are increasingly alienated, all U.S. residents will suffer the consequences.

American democracy is founded on the popular sovereignty principal. The philosophical principal argues that the sovereignty of a governing body depends on the consent of its people. Consent can only be given by participation and the latter requires the formation of social contracts that in turn create social power. If fear continues to rise and produce discriminatory behaviors that unjustly victimize Latinos, then Latinos may eventually learn to abstain from participating in the U.S. democracy experiment. In the end, human's own selfish driven desires challenge the creation of social harmony. Perhaps it's time we reconsider the treatment of oppressed minorities.

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