Ginny Garcia

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Mexican American and Immigrant Poverty in the United States

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Nomenclature

IPUMS	Integrated Public Use Microdata Series USA
ACS	American Community Survey
PUMA	Public Use Microdata Area
SPUMA	Super Public Use Microdata Area
OMB	Office of Management and Budget
CIS	Center for Immigration Studies
NCCP	National Center for Children in Poverty
HLM	Hierarchical Linear Model
HGLM	Hierarchical Generalized Linear Model

Chapter 1
Introduction

1.1 An Overview of the Research

It is certainly well-known that racial and ethnic groups tend to be at a disadvantage socially, economically and in terms of overall well-being in the United States. It is the intent of this book to underscore the extent of this disadvantage (by focusing on the extent of poverty) with special emphasis on Mexican Americans and Mexican immigrants in the Southwestern United States. This goal is accomplished by analyzing the poverty of these groups through the use of logistic regression at four levels: *extreme poverty*, *100% poverty* (also known as the poverty threshold), *low income* status (200% of the poverty line), and *relative poverty* (measured as 50% or less of the state median income). A separate discussion is also included which addresses the utility and necessity of a relative measure of poverty in the United States. Additionally, the analyses include the development of a proxy variable for undocumented status. This variable is based on previous research by (Bean et al., 1984) and is an updated extension of their work. The poverty of these groups is also addressed via measures of multiple variables at the contextual level. Here poverty will be predicted using not only individual-level independent variables, but also variables based on the characteristics of the Super-PUMAs[1] within which each individual is located. Thus we are able to achieve an analysis of the individual level characteristics that lead to an increased propensity for differing levels of poverty as well as an analysis of the group level characteristics that increase the likelihood of poverty. The variables to be examined at the contextual level include: percentage of persons in poverty in the area, percentage of Hispanics and immigrants in the area, and the percentage of persons in each major occupational classification (to be described in detail in Chapter 4).

American poverty levels have traditionally been well above those of other industrialized countries even while it boasts the highest Gross Domestic Product of any comparable nation (Smeeding 2006). In fact, many industrialized nations have rates

[1] A Super-PUMA (Super Public Use Microdata Area) is a geographic area with 400,000+ residents (Ruggles et al., 2008). This is the area-based measure used to conduct analyses containing contextual level information.

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that are one half and sometimes as low as one quarter of the rates observed in the United States (Seccombe 2000); the overall average for industrialized nations is around 10% (Rank and Hirschl 1999). As a group, Mexican Americans, and more specifically, Mexican immigrants tend to bear the burden of poverty within this nation the most heavily. For example, Hispanic households have a median net worth that is only about 9% of that of White households (Kochhar 2004). In addition, the overall poverty rate for Americans was 13.2%, while it was 23.2% among Hispanics (DeNavas-Walt et al., 2009). The following pages will briefly introduce the nature of the poverty situation with regard to these two groups, give some discussion of the plight of undocumented Mexican immigrants, as well as contribute some insight as to the strength of contextual effects on the incidence of poverty at any level.

In contemporary times, such incredible rates of poverty seem to beg the question: Why hasn't poverty been eliminated? The "War on Poverty" has been well underway for nearly 50 years, and yet we have seen no real discernible changes in the rates. In fact, we have recently seen an increase in the overall rate to 13.2% in 2008, which is the highest it has been since 1997 (DeNavas-Walt et al., 2009). Several scholars point out that this inability to reduce poverty rates is due to the change in relationship between economic growth and poverty (Danziger 2007). Beginning in the 1970s and continuing through the late 1980s, the unemployment rate rose, growth in real wages stagnated, and income inequality increased (Iceland 2003; Danziger 2007). Accordingly, poverty rates declined modestly in the 1970s and did not change in the 1980s (Danziger et al., 2004). This was largely driven by labor-saving technologies, the globalization of labor markets, and the declining value of the minimum wage (Danziger and Gottschalk 2004). Such economic changes had a particularly negative effect on Hispanics as they were more likely to be concentrated in low-skill occupations (Iceland 2003).

In the 1990s, poverty fell and wages increased for all groups, but there continued to be vast discrepancies between Hispanics and Whites. In 1999, the median family income for Hispanics (adjusted for family size) was 52% of that observed for white non-Hispanic households (Danziger et al., 2004). In comparison, African Americans made considerably larger gains during the same period and had a median family income of 58% of non-Hispanic whites (Danziger et al., 2004). Hispanics have lagged behind Whites and African Americans due to increases in immigration and the resultant low wages earned by recent immigrants who have lower rates of education and skills. It is reasonable to argue that these trends will continue as the share of foreign-born Hispanics increases.

Rising income inequality and a stagnation of earnings in the lower end of the distribution are strongly correlated with a poverty rate that remains disproportionately high in the United States (Smeeding et al., 2000; Hoynes et al., 2006). Of particular import is the fact that due to the unequal distribution of wages in this country, many families are unable to escape poverty (Smeeding 2006). In light of the fact that, "Poverty rates for people in full time working families are particularly high among certain demographic sub-groups such as Hispanics" (Iceland 2000); Mexican immigrants provide a prime vehicle for highlighting the importance of wage deficits as they relate to incidence of poverty. This is especially relevant for immigrants in America and more specifically those in the Southwestern United States (the Southwest region includes two of the top six receiving states for immigration; see Dinan 2005b). An analysis of the Southwestern states is undertaken because these states are a primary area through which to focus in on the indicators and effects of poverty for Mexican Americans and Mexican immigrants.

The Mexican immigrant population deserves special attention in light of the fact that they have shown themselves to be at risk of negative social and economic consequences. Immigrants are at risk because they are faced with a number of obstacles upon entry, including lack of health insurance, language barriers and restrictive policies, subtractive schooling practices, and so on (2006). The issue of poverty itself has been attributed in part to the immigration of less educated workers (Danziger 2007). As this trend continues, it becomes imperative that we focus on policies that increase benefits for low income workers and support those who are willing but unable to find work.

This book analyzes the poverty of Mexican Americans and Mexican immigrants in five states in the Southwest Region (Arizona, California, Colorado, New Mexico, and Texas). Though the Census designates the West South Central as Arkansas, Louisiana, Oklahoma, and Texas, I use a slightly different designation in light of the special considerations to be given to Mexican immigrant populations (Poston et al., 1976; Markides and Coreil 1986). Each of the above mentioned states boasts poverty rates well above the national average of 13.3% (with the exception of California at a rate of 13.1%) (2006). These states are also important to focus on given that they have large Hispanic populations, groups truly impacted by poverty. Another important finding relative to the Hispanic populations in these particular states is that each one is experiencing significant growth in their numbers of undocumented immigrants. It has been noted that approximately 80–85% of the migration to the US in recent years has been comprised of undocumented persons from Mexico (Passel 2005), and that, "the most rapid growth in the number of undocumented migrants has been in states that previously had relatively small foreign-born populations" (2005). Arizona is one of these states where rapid growth in the undocumented population has taken place. As of 2004, each of the above mentioned states had undocumented population estimates of 50,000–85,000 or more, and California reported an estimated undocumented population of 2.4 million (Passel 2005). Much debate exists over the viability of measures used to estimate the undocumented population. As a result of this, included in Chapter 2 is a discussion of the methods most often used in the estimation of this population. The primary focus of this book is not the estimation of undocumented immigrants, but rather to provide the reader with a greater understanding of their characteristics and how their presence contributes to or is affected by the situation of poverty in the United States.

In an effort to further understand the impacts of poverty on this particular population, however, a proxy measure has been developed to measure the presence of undocumented immigrants within the sample of the Mexican immigrant population to be analyzed. This proxy measure is based on the work of Bean, Browning, and Frisbie (1984), in which they developed a fairly reliable method for estimating the size of the undocumented population using a variety of individual characteristics.

These include age concentration in young adult years, high sex ratios, low education and income levels, lack of English proficiency, and those who are of Mexican origin, but not black (Bean et al., 1984). The research in this book presents an updated version of their proxy measure using their original findings and current research relative to the undocumented population. The micro-level variables used in this analysis to create the proxy measure include those of young age, who demonstrate a lack of English proficiency, located in occupations that are saturated with undocumented individuals, have few years spent in the United States, and with low levels of education. These individuals are then further restricted to those who reported their birthplace as Mexico and citizenship status as non-citizen.

As mentioned above, another interesting observation relative to Mexican immigration is that there has been a great deal of growth of Hispanic populations in states that have not traditionally been considered immigrant receivers. Recent research indicates that new settlement patterns have been observed, much of which is attributable to changes in the industries that primarily employ immigrant workers. Given these changes, I have included a discussion of the regional distribution of these groups as well as a series of maps which display the changes from 1980 to the present. Also provided is a discussion of the implications of such changes and its effects on the poverty status of both Mexican Americans and Mexican immigrants.

1.2 A General Review of Poverty in the United States

Poverty in the US is measured based upon classifications set forth by the Office of Management and Budget (OMB). These poverty thresholds are updated yearly based on inflation rates, however they do not account for differences in cost of living by region. A full description of the poverty measure is presented in Chapter 2 along with the poverty matrix used by the federal government to determine poverty status. Currently, only one measure of poverty exists. It is an absolute measure (meaning that it is unrelated to the income distribution) and only represents those who are on the poverty threshold, or in 100% poverty.

This book points out the necessity for modeling poverty in various ways. Current designations of poverty restrict those identified to individuals who are at 100% of the poverty line or below (this is referred to as the poverty threshold). It is much more accurate to describe poverty in the following terms: *extreme poverty* (50% or below the poverty threshold), *100% poverty* (the current designation used by the Census Bureau and others), and *low-income* (defined as 200% or less of the poverty threshold). The National Academy of Science (NAS) has recently pointed out that the current threshold for poverty is well below what is necessary for the adequate survival of a family. In fact, even the low income classification has proven itself to be insufficient in terms of allowing for necessities. Iceland points out that “about 1 in 8 people of the population under 200% of the poverty threshold reported not having enough food to eat sometimes or often. . .74% between 100 and 200% of the poverty line reported experiencing one or more serious hardships” (2006). An additional relative measure is included in the analyses and is based on the European conception of poverty. This measure is based on a fairly standard measure of half the median income in a given location and is much more reflective of the issue of income inequality.

The poverty threshold in the United States was originally determined based on the finding that families spent approximately one third of their income on food (as of the 1950s), which is far from reality in present times. The creator of the measure herself, Mollie Orshansky, has argued that the measure is outdated and needs revision (Blank 2008). It is also worth mentioning that the official poverty measure does not take into account such expenses as childcare, transportation, or healthcare; and that the tremendous differences in cost of living throughout the US have no bearing on the determination of the poverty threshold (2006).

When analyzing rates for the Southwest, current poverty (100% level) estimates for Mexican immigrants range from a low of 27.7% in California to a high of 40.7% in New Mexico. Regarding those who are in the low-income (200%) category, the statistics are even more alarming and range from 64 to 77% (2006).

Poverty has many devastating effects including lack of access to adequate nutrition and healthcare among other things. Another less regarded notion with respect to poverty is that those who are subjected to it face daily frustration and humiliation seldom experienced by those who are above low-income levels. It has been noted that poverty in childhood has been linked to problems in development that carry over into adulthood. These impacts include attending inferior schools, having less educational motivation in general, living in high-risk neighborhoods, food insecurity, and lack of health insurance (2006). When these findings are coupled with the growth rates of Hispanics in the United States the potential for harmful effects is obvious. Furthermore, the position of the author is that those who are in low-income situations are at the same risk level as those who qualify for poverty in the strict sense (thus vastly increasing the numbers of those who are afflicted).

Another reason promoting this study of poverty is to examine the general belief that those who are poor deserve to be. John Iceland points out that it has long been a tradition in the United States to differentiate between the deserving and undeserving poor (2006). Thus a distinction was made between those who were perceived to be idle or lazy, and those who were unable to support themselves. From a theoretical perspective, this is explained by the prevailing model, neo-classical economic theory, which emphasizes the role of individual traits in the prediction of poverty (Iceland 2006). It effectively negates the influence of structural factors such as wage differentials and instead places the responsibility for the situation of poverty squarely on the shoulders of the affected individuals. In contemporary terms, an overwhelming majority of Americans hold the belief that there is something inherently wrong with nearly all those who are poor, and that they are lazy or simply refuse to work. This type of reasoning is not applicable to the immigrant population where, "virtually all immigrant families are working families. Among children with foreign-born parents, 97% have a parent who works and 72% have a parent who works full-time, year-round" (Dinan 2005a). However, we are continually bombarded by ethnic stereotypes relative to the idea of who is affected by poverty (Iceland 2006). These negative stereotypes then contribute to the general attitude of Americans toward those who are poor, and ultimately their lack of support for federal programs aimed at helping such populations. Hopefully the analyses to be conducted in this book will help call into question the veracity and relevance of these stereotypes.

1.3 An Introduction to Multi-level Models

As sociologists we are dedicated to uncovering the individual and group contexts which may have important impacts on behaviors at the individual level. Thus, a multi-level model allows one to look at group contexts (in this case county and area characteristics) that may influence behaviors associated at the individual level (i.e. likelihood of being in poverty). The macro-data to be analyzed are based on decennial census counts for the entire United States population. As was discussed previously, the analysis will be limited to the Southwest Region as this is the primary receiving area for Mexican immigrants and will be analyzed based on several individual-level variables including immigration and undocumented status, male head of household, and education level, among others. These factors provide important information about the characteristics of individuals who are in poverty. However, in recent decades structural forces such as income inequality have shown themselves to be critical in the determination of poverty status. As a result, I have included a number of contextual level variables created to focus on the importance of the effects of forces located outside the individual in an assessment of the predictors of poverty status. The group-level variables include percentage of agricultural occupations in the Super-PUMA, presence of F.I.R.E (finance, insurance, and real estate) and other industries as a measure of economic advancement, the poverty level for the area itself, and presence of Mexican Americans and immigrants. These variables should act as key determinants of poverty at both the individual and group-level.

Multi-level modeling will be utilized as a means to gain an understanding of the effects of group level contexts on the situation of poverty. The above-mentioned variables should shed a great deal of light about the importance of contextual effects, as well as their interactions with effects at the individual level. It is hoped that these and the analyses described earlier will help us better understand how individual-level predictors and group level contexts are associated with poverty among Mexican Americans and Mexican immigrants.

Chapter 2
Prior Studies

This chapter provides an extensive overview of prior studies and research related to the incidence of poverty among Mexican Americans and immigrants in the United States. It is divided into six sub-sections including a general overview of poverty and how it is defined according to the US government; a discussion of the utility and necessity for a relative measure of poverty; a review of the literature dealing with the micro and macro level predictors of poverty among all groups in the US; a discussion of how immigrants in particular are impacted by poverty; a history of the migration trends between Mexico and the US; a discussion of the most important policies enacted relative to this population and their impacts; and a presentation of the expected contributions to be made by this book. This chapter concludes with a brief accounting of policy changes which have had or are estimated to have the greatest impacts on the Mexican American and immigrant population.

2.1 Defining Poverty

Poverty in its simplest terms is the inability to provide the basic items necessary for human survival. The formal definition of poverty is much more complicated, however. In the US, poverty status is determined by the Social Security Administration (SSA) and has traditionally been based upon questions on the census pertaining to income levels. The original poverty threshold was developed in the early 1960s by staff economist Mollie Orshansky and focused on family food consumption (National Academy of Science and NAS 1995). This threshold was adopted in 1965 for planning purposes and was given official status by the Office of Management and Budget (OMB) throughout the federal government in 1969 (National Academy of Science and NAS 1995). The United States poverty threshold has remained relatively unchanged since its inception in the 1960s.

This measure came under criticism in the 1990s in a widely published report by the National Academy of Science (NAS). Their findings indicated that, "the current measure no longer provides an accurate picture of the differences in the extent of economic poverty among population groups or geographic areas of the country, nor an accurate picture of trends over time" (National Academy of Science and NAS

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1995). The current measure of poverty is in fact an absolute measure (meaning that it is fixed at a specific point in time and is only updated based on price changes rather than changes in standard of living) and many analysts feel that a relative measure (one that is updated regularly and takes into account geographic variations in cost of living as well as changes in living standards) is much more suitable to the current situation with respect to families in poverty. Additionally, many experts argue that the current poverty threshold is in fact inadequate in terms of allowing for the basic necessities such as food and housing (Lichter and Crowley 2002). The Office of Management and Budget uses the poverty threshold (what is considered and will be referred to as 100% poverty), which is obtained by multiplying the cost of the Economy Food Plan by three.[1] This particular plan was initially chosen given that it was the least expensive of the four food plans presented (Fisher 1997).

In the United States, poverty status is determined by comparing a person's total family income to the poverty threshold for a family of that size and composition. The poverty thresholds are revised annually and include adjustments based on inflation rates (see Fig. 2.1 for national poverty estimates as of 2008). Thus, the official

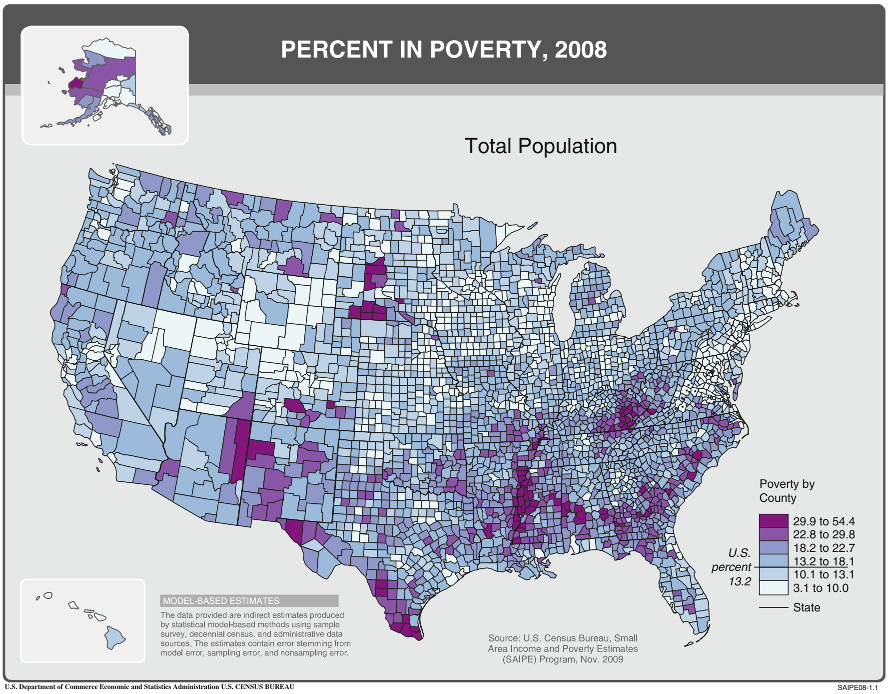

Fig. 2.1 Percent of total population in poverty 2008

[1]This is based on the finding made by the USDA's 1955 Food Consumption Survey which showed that families of three or more spent approximately one third of their total income on food.

poverty definition derived by the census is obtained by estimating money income before taxes to determine whether a family is above or below the poverty threshold. If they are deemed to be below the threshold then that individual and every member of the family is considered to be in poverty (2007).

The American Community Survey (ACS), the government survey that provides the data to be used in this work, bases its poverty thresholds on information obtained pertaining to income variables.[2] In the ACS data, each individual and/or household is assigned a value based on their income level. This income level is then multiplied by an appropriate factor in order to obtain a numerical value between 1 and 500. Thus if a family scores 100 based on this scale it is considered to be on the poverty threshold, or 100% of poverty.

As was mentioned previously, the current poverty threshold has been deemed inadequate in a number of respects. For example, the National Academy of Science (NAS) points to at least six deficiencies in the current measure, namely, (1) the need for a distinction between working families with childcare expenses and non-working families, (2) variations in medical costs across population groups, (3) geographic variation in cost of living expenses, (4) changes in the standard of living and what is considered necessary, (5) changes in family characteristics and structure, and (6) changes in governmental policy which have had direct impacts on disposable income (1995: 2–3). However, given that this is the only real measure for poverty in terms of research reported on income levels in the ACS, it will be used as a general indicator of well-being for families in the United States. The Census Bureau itself states that "they [thresholds] are intended for use as a statistical yardstick, not a complete description of what people and families need to live" (2007). In an attempt to gain a fuller understanding of the extent of poverty throughout the US, this research uses three absolute levels of poverty: extreme poverty, the poverty threshold, and low income.

In real numbers, the current poverty threshold amounts to approximately $22,000 for a family of four (see Table 2.1). Families living at or below this level of income are considered a part of the 100% *poverty* group. Poverty rates are further separated into groups including those in extreme poverty and low-income families. Those in *extreme poverty* are categorized as living with incomes at or below 50% of the US poverty threshold. Those in *low-income* families live at or below 200% of the US poverty threshold. This definition of low income derives from the Urban Institute's conception of the working poor and low-income households that maintain 200% or

[2]Poverty statistics in ACS products adhere to the standards specified by the Office of Management and Budget in Statistical Policy Directive 14. The Census Bureau uses a set of dollar value thresholds that vary by family size and composition to determine who is in poverty. Further, poverty thresholds for people living alone or with nonrelatives (unrelated individuals) vary by age (under 65 years or 65 years and older). The poverty thresholds for two-person families also vary by the age of the householder. If a family's total income is less than the dollar value of the appropriate threshold, then that family and every individual in it are considered to be in poverty. Similarly, if an unrelated individual's total income is less than the appropriate threshold, then that individual is considered to be in poverty.

Table 2.1 Poverty Thresholds for 2009 by size of family and number of related children under 18 years

	Related children under 18 years								
Size of family unit	None	One	Two	Three	Four	Five	Six	Seven	Eight or more
One person (unrelated individual)									
Under 65 years	11,161								
65 years and over	10,289								
Two people									
Householder under 65 years	14,366	14,787							
Householder 65 years and over	12,968	14,731							
Three people	16,781	17,268	17,285						
Four people	22,128	22,490	21,756	21,832					
Five people	26,686	27,074	26,245	25,603	25,211				
Six people	30,693	30,815	30,180	29,571	28,666	28,130			
Seven people	35,316	35,537	34,777	34,247	33,260	32,108	30,845		
Eight people	39,498	39,847	39,130	38,501	37,610	36,478	35,300	35,000	
Nine people or more	47,514	47,744	47,109	46,576	45,701	44,497	43,408	43,138	41,476

Note: The poverty thresholds are updated each year using the change in the average annual Consumer Price Index for All Urban Consumers (CPI-U). Since the average annual CPI-U for 2009 was lower than the average annual CPI-U for 2008, poverty thresholds for 2009 are slightly lower than the corresponding thresholds for 2008.
Source: U.S. Census Bureau.

less of the poverty threshold (Orthner et al., 2004). These families have proven to be at risk for the same negative influences as those who are in the lower poverty groups. Such negative impacts include food insecurity, lack of access to adequate healthcare, poor social adaptation, inability to obtain quality childcare, inability to afford suitable housing, lowered educational opportunities, and higher likelihood of experiencing poverty in adulthood (for affected children) (Orthner et al., 2004). Mexican Americans and immigrants are at an increased risk for negative factors given that they face unique consequences such as restricted access to safety net programs in addition to the risks mentioned above. These risks, as well as their predictors, will be presented alongside a discussion of the repercussions of poverty for many groups including Mexican Americans and immigrants in the following sections.

2.2 Relative Measures of Poverty

A discussion of poverty would be incomplete without the inclusion of a review of relative measures. Unlike the United States, a great number of European countries have long used relative measures and have made a great deal of progress in developing much more useful and appropriate indicators as a result (Blank 2008). It is also worthwhile to note that the conception of poverty is quite different in European and Scandinavian nations. In such countries, the debate is focused on the level of income at which individuals experience social exclusion (Atkinson et al., 2002; Smeeding 2006). This conception is based on a series of social indicators set forth by such agencies as the United Nations and are used to, "measure levels of living and social and economic factors considered to influence levels of living" (1989). In the case of this measure, poverty, or rather, at risk of poverty is measured by considering the annual net household income in relation to national median income (those who fall below 60% are considered to be at risk of poverty) (EUROSTAT 2010). The following provides an overview of relative measures including a full description of how it is applied as well as how it is derived in various locations.

Whereas absolute measures remain constant and do not take into account such factors as varying cost of living by geographic location or economic growth, relative measures do just that. In *Measuring Poverty: A New Approach*, the authors state, "A relative approach to deriving poverty thresholds recognizes the social nature of economic deprivation and provides a way to keep the poverty line up to date with overall changes in a society" (Citro and Michael 1995).

Little contention over the adoption of a relative measure in the EU has been observed; though the choice of a relative threshold at which to set the measure has generated some problems (Atkinson et al., 2004).The adoption of a measure that considers those under 60% of the median as at risk of poverty is meant to encompass those in the low income category. Thus, the final report set forth by the commission also included secondary indicators that included those with incomes below 40 and 50% (Atkinson et al., 2004). Though the data provided by the ACS on poverty do not take into account any alternative measures, I have included a fairly straightforward calculation of a relative measure[3] based on available household income data and the United Nations' standard measure of 50% of the median income (this level is accepted by a number of poverty scholars as a standard measure of relative poverty) (Iceland 2000; Lichter and Crowley 2002). To underscore the variation in incomes by geographic location, I have based the relative measure on state level median incomes. Hence, the lowest median income in the five Southwest states is New Mexico at $40,629 while the highest is California at $56,645. In terms of how relative and absolute measures compare: in 2000, the US poverty threshold was approximately 27% of the median family pretax cash income and 32% of post tax disposable income (Smeeding 2006). Astoundingly, the current threshold has fallen from 48 to 29% of the median income for a family of four between 1960 and 2000 (Smeeding 2006). Based on estimates for 2008, the absolute poverty threshold for a family of four in the United States is approximately $22,000 while a relative measure based on 50% of the national median income would be $26,087 (2008). Another important point of separation between the United States' conception of poverty and that in the European Union is that gross income is used to calculate poverty status in the US, while disposable income is the basis for the European measure (Notten and de Neubourg 2007). This is much more relevant to the measurement of poverty given that a fair assessment should be based on identifying those whose standard of living is low in comparison to the society they live in (Notten and de Neubourg 2007).

As mentioned above, the current measure of poverty in the United States is sorely lacking; most notably in its inability to account for vast differences in cost of living throughout the country. Most all scholars of poverty agree that the US measure is outdated and should be revised. Some of the greatest concerns raised relative to the current poverty threshold include variations in out-of-pocket medical expenses, changes in policy that have affected disposable income, changes in standard of living, and cost of housing variations by geographic area (Michael and Atkinson 1997). As a result of changes in incomes overall, it is necessary to assess whether the current measure allows for the full participation in society of individuals who are in poverty.

Overall, relative measures are a much more accurate indicator of income inequality given that a more spread out distribution tends to have a larger share of the population who makes less than half the median income (Smeeding 2006). In other words, countries with greater income inequality will have higher rates of relative poverty. Thus, the overall goal of the European measure is to aid in the reduction of such disparities (Burkhauser 2009). Given the current threshold's numerous criticisms, something more akin to such a measure is quite necessary in the US. Recent reports indicate that though the nation's productivity rose by nearly 20% between 2000 and 2007, poverty rates rose substantially and low and middle income families

[3] The measure for relative poverty considered in the analyses is limited by the fact that the estimates are based on average household median incomes made available by the Census. It is meant to provide a general estimation of relative poverty and has been applied to all households regardless of age/household size given the similarities in family structure.

did not share at all in the economic prosperity generated during this period (Holzer 2009). Given that most of the gains in income have been experienced at the upper end, the relative poverty rate is only slightly affected and highlights the immense amount of income inequality present in the US.

As mentioned previously, the original poverty threshold was developed in the 1960s and there has been little to no change in the measure since. A number of reasons exist which explain the inability to update and/or implement alternative measures. A comprehensive discussion of which is provided by Rebecca Blank and includes the following: (1) the Executive Office of the President is in charge of the measure and this means that any changes made to the measure are directly attributable to them rather than to an outside statistical agency, (2) the length of time the measure has gone without change has actually hindered the process of change given that so many agencies/programs are dependent upon the current measure, and (3) the conception of poverty itself is vague and requires assumptions about the nature of need in this country (2008). Another reason for support of absolute measures in the US is mentioned above. Relative measures give a much more accurate depiction of income inequality in an area. Hence, a country that is focused on economic freedom is much more likely to support an absolute measure (Blank 2008).

Evidence suggests that both relative and absolute measures are called for in the assessment of poverty given that absolute measures help to establish a benchmark for those who cannot attain a minimum standard of living, while relative measures identify those whose standard of living is low in comparison to others in the society in which they live (Notten and de Neubourg 2007). In addition, using a relative measure of poverty brings to light the level of inequality that exists in a society. The analyses contained in this book use several derivations of the absolute poverty measure and a relative measure based on a standard calculation of 50% of the median income by state. Given that the US has experienced a great deal of economic growth over the past few decades, yet the majority of this growth has been concentrated in the top fifth of earners, this may well serve to lessen the strength of arguments that would target unwillingness to work as the source of poverty and direct it toward the staggeringly uneven distribution of resources in this country.

2.3 The Micro and Macro Level Predictors of Poverty

An immense amount of literature is available with respect to the individual level predictors of poverty. This section provides an overview of that research in combination with an introduction to the group level, or contextual level, predictors of poverty. Very little research has been focused on the impacts of group level factors upon the incidence of poverty. Thus, this section provides some discussion of the work that has been done and makes estimations relative to the expected outcomes of the group level predictors included herein. Even less work has been focused on multi-level analyses of poverty. In such analyses, both individual and group level variables are combined in an effort to understand the effects of each diagnostic on its own as well as the interaction effects that may occur between the two levels.

Many studies have focused on the individual level risk factors which lead to poverty. In fact, a wealth of literature has surfaced in response to the growing numbers of families who are in poverty, but who also maintain at least part-time working status. This group has come to be known as the working poor. This research maintains a focus on married couple households where at least one child is present. Thus, the research which has been reviewed focuses specifically on households which maintain similar characteristics. Though a review of the characteristics of those in poverty will implicitly describe many Americans, special attention will be given to Mexican Americans and immigrants in the Southwest as this is the population of interest.

A number of individual level characteristics describe the impoverished population. Most often, work and education related findings are presented in reference to degree of risk present. The information presented below will provide a snapshot of the most commonly cited variables associated with poverty status.

As was previously stated, the working poor have emerged as a group who despite maintaining employment is still at significant risk for poverty. For instance, approximately 11.7% of the population was in poverty in 2001, and a little over 20% of those individuals maintained employment for 27 weeks or more throughout the year (Mosisa 2003). Of married couple families with at least one child present, approximately 7.3% were listed as below the poverty level (Mosisa 2003). These numbers are increasing and minorities are overrepresented in the category of working poor; in fact they experience poverty at rates nearly double those of their white counterparts. Additionally, it may be argued that these numbers are significantly understated as they do not include those who are low income (200% poverty). In the coming chapters, this analysis explores variables pertaining to labor force participation as well as number of children present as they impact the likelihood of reporting to any of the four measures of poverty. These two variables have been shown to dramatically impact the experience of poverty given that members of the workforce are less likely to be in poverty and each additional child in a household represents an additional burden and an accordingly increased risk of poverty. Moreover, because one my contentions is that Mexican Americans and immigrants are in poverty while maintaining full time employment, labor force participation becomes a very important tool in the analysis of poverty for these groups.

As a group, Mexican Americans and immigrants are at a significantly higher risk of being in poverty than whites, thus Mexican ethnicity will be used as a variable from which to draw conclusions. These groups also tend to be concentrated in low-skill and low-wage occupations and have generally lower rates of education (Suro et al., 2005). One of the most oft-cited reasons for poverty is that of lower educational attainment. This book employs a measure of education at the individual level that is based upon the educational attainment levels set forth by the US Census Bureau. It is reported that Hispanics are subject to less rigorous standards in curriculum, they score lower on standardized tests, and enter college with less frequency than their white peers (Suro et al., 2005). There exists a real wage gap for less educated workers in the US The lack of gains in earnings for this segment of the population since the 1970s explains the country's inability to lessen poverty and is directly applicable to immigrants who have low skills and education (Danziger 2007). Across the board, those with less education have done far worse than those who have more than a high school degree (Danziger 2007). These gaps in education will likely translate into a significant issue as this very large segment of society enters the workforce (it is estimated that Hispanic population growth will account for 46% of total population growth between 2000 and 2020) (Suro et al., 2005). The impacts will likely be felt in the form of an inability of this population to command an income that will be sufficient to remain above the poverty threshold. Hence, the education measure employed should provide a general idea of the extent to which educational attainment impacts the incidence of poverty as well as the general education levels of the population of interest.

Another key predictor of poverty for all groups in society is occupational classification. Given that Hispanics tend to be younger and less skilled than their non-Hispanic White counterparts, they are more often represented in low-wage occupations. This contributes significantly to incidence of poverty and low income status. Moreover, the Pew Hispanic Center reports, "foreign born Latinos earn the least of all workers in the labor force," (Suro et al., 2005). This study employs a classification of occupations that is based on this assumption. Douglas and Saenz have developed an occupational classification scheme which divides the Census Bureau's lengthy occupation structure into those that are "Mexican immigrant" jobs and those that are not (2008) (see Appendix A for full listing of included occupations). This binary variable is utilized as a measure that is specific to the Mexican immigrant population; however, it is also very useful in analyses of the Mexican American population as it acts as a general predictor of low status employment.

A number of variables will be implemented at the individual level and include: educational attainment, ethnicity, number of children present in the household, labor force participation, and employment in a "Mexican immigrant" or low status job. This analysis also explores the effect of citizenship status for the Mexican Americans in the sample population. The Mexican immigrants will be analyzed in light of the above mentioned variables in addition to the effect of undocumented status through the use of a proxy variable as well as the amount of time spent in the United States.

In turning to a discussion of the Hispanic population as a whole, it is worthwhile to note that the wealth of Hispanic households is significantly lower than that of their White counterparts; though this gap in wealth is largely attributable to the immigrant population. In a recent study conducted by the Pew Hispanic Center, it was determined not only that Hispanics earn substantially less than other workers, but also that they were not able to close this earnings gap during the economic expansion in the 1990s (Kochhar 2004). In fact, during the period of 1999–2001 the worth of Hispanic households fell by about 27%, while the worth of White households increased by about 2% during this same time frame (see Fig. 2.2) (Kochhar 2004). It is further noted that this estimate may well be understated given the fact that much of the immigrant population is not reflected in the sample. Hispanic households are

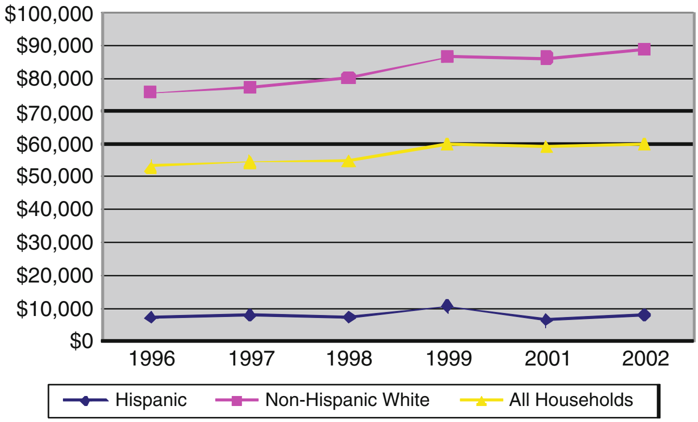

Fig. 2.2 Median net worth of households: 1996–2002

facing incredible burdens and do not have access to even the most basic of financial securities such as a bank account. Additionally, it was found that while White households felt relatively small impacts as a result of the economic recession[4] in 2001, Hispanic households have yet to recover and the distribution of resources in this country have become progressively more skewed since 2002 (Kochhar 2004). Finally, the impacts of the recession were shown to have a direct correlation with education levels for the non-Hispanic population. Those that had more than a high school education actually realized gains during the recession. On the other hand, college-educated Hispanics earned less in 2001 ($50,097) than they did in 1996 ($51,146) (Kochhar 2004). Interestingly, non-Hispanic immigrants have fared quite well in the time period following the recession and have continually increased their net worth from 1996 to 2002. This more than illustrates the need for a thorough evaluation of the extreme gap in earnings and earnings potential for both Hispanic natives and immigrants. Many would argue that the gap is attributable to the young age, and low skill and education level of these populations, but clearly there is more to the story.

More recent contributions to the literature base have focused on the incidence of poverty based on aggregate measures. For example, studies have been undertaken which estimate the incidence of poverty in a particular geographic region with respect to the poverty rate, education level, or unemployment rate of that area overall. These studies point out those contextual level factors may play as a big a role in predicting such outcomes as do the individual factors discussed above. In such studies, it is pointed out that geographic regions such as Appalachia, the Mississippi Delta, and Texas Borderland tend to display very high rates of poverty on the whole

[4]The National Bureau of Economic Research measured the duration of the recession as lasting from March to November of 2001. This recession had the largest impacts upon Hispanic and Black households, eroding about one quarter of their wealth within 2 years (Kochhar 2004).

(Slack et al., 2009). Additionally, regional studies have shown that in such contexts, a large presence of minorities is often detected as is a high concentration of rural inhabitants (Slack et al., 2009).

The focus of this book is on the Southwest given that this is a region that has remained economically deprived and is typified by a concentration of Mexican Americans and immigrants (see Fig. 2.3). As part of this work the presence of Mexicans as well as Hispanic immigrants is analyzed in an effort to determine the extent to which the presence of ethnic minorities increases the risk of poverty for a given area. One of the most important aggregate level measures of poverty status is that of the percentage of persons in poverty in a given geographic area. Thus, the proportion of those in poverty is calculated as a relative, weighted average for each area (Super-PUMAs containing 400,000 or more persons) and should display the effect of which higher rates of group-level poverty contribute to poverty incidence overall. Another key indicator of poverty at the aggregate level is the occupational classification observed within each geographic sub-unit. Thus, as greater concentrations of such occupations as Finance, Insurance, and Real Estate (FIRE) exist within an area, a negative correlation has been observed in relation to poverty status (Singelmann 1978; Parisi et al., 2003; Rupasingha and Goetz 2007; Slack et al., 2009). Accordingly, it has been observed that greater concentrations of those employed in agricultural occupations leads to

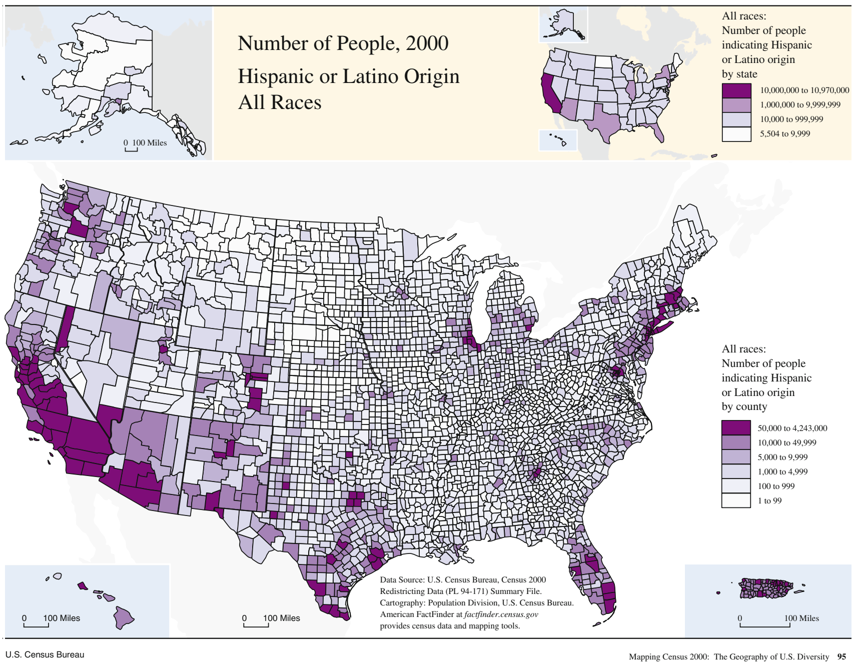

Fig. 2.3 Number of Hispanic or latino origin by county, 2000

greater incidence of poverty at the contextual level (Albrecht et al., 2000; Slack et al., 2009; Fontenot et al., 2010). A full spectrum of occupations (nine major industries have been identified by the Census Bureau) is included and should demonstrate the relationships had by each relative to aggregate poverty measures. In addition, a measure of industrial diversification (Gibbs and Poston 1975) is included based on findings that regions that exhibit higher levels of industrial diversification tend to have higher levels of urbanization and technological development and in turn more robust economies (Gibbs and Martin 1962). This measure (M1) is based on work by Gibbs and Poston, which posited that such a measure would allow for the analysis of both structural and distributive differentiation within a population (1975). Finally, prior research has shown that rural areas tend to display higher rates of poverty than highly urbanized areas (Brown et al., 2003). Therefore, a weighted measure of metropolitan status, which is based on the metropolitan statistical areas presented by the US Census Bureau, is included for each Super-PUMA in order to generate its impact on aggregate level poverty rates.

The literature on multi-level analyses of poverty is somewhat limited. Much of the research initiated in multi-level analyses has addressed fertility characteristics with respect to group level contexts (Casterline 1985; Entwisle and Mason 1985; DiPrete and Forristal 1994). Very few studies exist which have focused specifically on the phenomenon of poverty and those that do have not focused on Mexican Americans and immigrant poverty in the Southwest region. Indeed, much of the work on social stratification has been dedicated to the effects of community level (or higher) characteristics on social mobility and/or status attainment (DiPrete and Forristal 1994).

Multi-level analyses are dedicated to examining the relationship between personal characteristics and the incidence of poverty at a personal level, and also the effects on poverty of contextual characteristics. In a study conducted by Cotter, the main focus was on underscoring the fact that the strength of individual level predictors may not play as large a role in the incidence of poverty as does the context within which it occurs (2002). This study's main focus was on the incidence of rural poverty and attempted to delineate the role of contextual factors in determining poverty status (Cotter 2002). In such accounts, it is argued that these structural forces are great enough to determine poverty status irrespective of individual characteristics. Thus, poverty is estimated based on a combination of individual and contextual level characteristics.

Multi-level analyses are uniquely equipped to examine why poverty affects certain groups much more heavily than others (Cotter 2002). Instead of using only individual level information to predict poverty among individuals or place-based characteristics to estimate aggregate poverty measures, this type of analysis allows for an examination of both simultaneously. Thus in this analysis I have employed the usage of individual level characteristics such as ethnicity and undocumented status in conjunction with contextual level characteristics such as the M1 measure and percentage of poverty in a given area.

In summary, it has been found that Hispanic households make less than 10% of the earnings of their non-Hispanic white peers (Kochhar 2004). Every effort has been made to understand this gap through the use of not only traditional individual level variables, but also group level factors. Individual analyses may be lacking in that the focus remains solely on predictors generated within an individual; while exclusively aggregate level analyses lack an indication of why poverty rates vary by area. Through the use of both levels a clearer, more focused description of poverty for Mexican Americans and immigrants in the Southwest is provided.

2.4 The Immigrant Situation

It is the intent of this book to emphasize the current impacts of poverty on Mexican immigrants as well as bring to light recent immigration trends and their short and long-term impacts. As a group, Mexican immigrants tend to be heavily and adversely impacted. In fact, they remain at an incredible economic disadvantage while maintaining full time employment. Accordingly, it becomes necessary to ask why Mexican immigrants tend to fare so much more poorly than other population groups.

Mexican immigrants maintain poverty rates well above those of their native counterparts. Recent findings published by the Center for Immigration Studies indicate that, "about one in four Mexican immigrants live in poverty, compared to about one in ten natives" (CIS 2001: 1). The results of this study indicate that 25.3% of Mexican immigrants are in poverty in the Southwestern United States in comparison to about 14% of native born individuals (a finding that is consistent with recent reports on Mexican immigrant poverty levels) (ACS 2006a). It is also pointed out that these rates may well be understated given that immigrants' US born children are not actually calculated in the figures for immigrants, but rather for natives (CIS 2001). These rates have broad ranging impacts not only for immigrants themselves but also for the population as a whole. Immigration rates are increasing at an incredibly fast pace (to be discussed in detail below), which does not bode well for the future prospects of such a large segment of society. In addition, this may well translate into a general inability to help those in low-income situations in the face of such vast numbers in need (CIS 2001).

Most interestingly, the National Academy of Science has determined that recent poverty trends indicate an increase in the number of working families who are in poverty (NAS 1995). This issue seems to coincide directly with the astounding growth in Mexican labor force participation. Recent studies indicate that Hispanics account for a significant proportion of the labor force and are the second largest group behind Whites in the United States (Suro et al., 2005). Moreover, many studies have highlighted the finding that Mexicans immigrants earn significantly less than their non-Hispanic white counterparts (Trejo 1997; CIS 2001). This wage deficit is substantial and the Center for Immigration Studies reports that the average Mexican immigrant's income is approximately 57% of that of non-Hispanic whites (2001). Stephen Trejo's report on Mexican earnings argues that this wage differential is due to relatively young age of workers, deficiencies in English language proficiency, and lower education levels (1997; see also Crowley et al., 2006).

Additionally, a report entitled *Poverty among Working Families* indicates that, "poverty rates for people in full-time working families are particularly high among certain demographic sub-groups such as Hispanics" (Iceland 2000).

It appears Mexican immigrants are in poverty and low income situations for a number of reasons. The most oft-cited explanation for very high rates of Mexican immigrant poverty is that of low education levels and lack of English proficiency among immigrant workers. Another contention is that, "Mexican immigrants are often steered into a limited number of economic sectors, saturating the low-skill, low-wage labor market and depressing hourly wages" (Crowley et al., 2006). Douglas and Saenz have also argued that there are particular occupations most likely to be saturated with Mexican immigrants (2008) (see Appendix A). These particular occupations tend to be of low status and are typically undesirable to natives. The classifications set forth in their study are used as the basis for a predictor of poverty with respect to type of occupation in some of the logistic regression models to be presented in later chapters. Whereas agricultural jobs have been the traditional mainstay for Mexican immigrants, we are now seeing an increase of Mexican workers in meat-packing, manufacturing, and service industries (Crowley et al., 2006). Chapter 3 provides a discussion of this phenomenon and its effects, which include significant movement of recent immigrants into rural destinations and increases in employment rates in low-wage, high-risk positions. Furthermore, many of the occupations that immigrants tend to secure do not offer employee benefits such as health insurance (Douglas-Hall and Koball 2004) or child care and offer little to no job safety or room for advancement.

A host of negative impacts are felt in response to being relegated to the lower levels of the social hierarchy. We see all those impacts associated with low income and poverty status as well as unique impacts faced by this group in particular. As was mentioned earlier, poverty and low income status lead to a host of negative consequences including restricted access to quality schools and affordable housing, lack of access to healthcare, inability to meet basic needs for the family, and increased likelihood of remaining in or returning to poverty, among others. In addition to these negative effects many impacts have been identified as applying directly to immigrant populations. These include: (1) the inability to afford adequate housing or more than 50% of income spent on housing, (2) low levels of parental education which has been shown to negatively influence educational attainment of children, (3) no health insurance coverage for nearly half the relevant population and resultantly high levels of poor health, (4) decreasing levels of participation and/or barred restriction to government assistance based on fear of repercussions such as deportation, and (5) living in crowded housing situations (Douglas-Hall and Koball 2004). These issues are particularly salient for immigrants in the South as this is where wage levels are lowest and public benefits are least utilized (Douglas-Hall and Koball 2004).

Many would argue that poverty for Mexican immigrants is a relatively short term, or episodic, experience. Some evidence suggests that over time Mexican immigrants fare significantly better with each successive generation and resulting acculturation and increase in skills (Crowley et al., 2006). For example, Crowley and colleagues point out that in 2000, 36% of Mexican children were in poverty compared with 23% of third-generation Mexican children (2006). This is in addition to the fact that Mexicans are more often members of married-couple households, thus lowering their overall risk of poverty. However, findings from the Center for Immigration Studies (CIS) indicate that while significant gains are made in terms of income and poverty levels over time, this population still lags well behind natives (even after considerable assimilation time) (2001). The CIS findings indicate that though Mexican immigrants do make some progress, their earnings level never approaches that of natives (CIS 2001). "Even Mexican immigrants who have lived in the country for more than three decades still have an average income that is only 70% that of the average native" (CIS 2001: 5). Thus arguments which would indicate that poverty for immigrants is short term (i.e. episodic) may not be applicable in an economy with increasingly fewer opportunities for advancement for those individuals without a significant amount of skill and education. Moreover, we are seeing a rise in the number of undocumented Mexican immigrants who have shown themselves to be at an even greater disadvantage than legal immigrants. As an example, illegal Mexican immigrants average about 40% of the earnings of natives (CIS 2001) and are faced with an even greater number of barriers to economic and social success overall.

In light of the previous findings relative to Mexican immigrant poverty rates it is quite necessary to discuss the recent immigration trends for this particular population. Both documented and undocumented rates of immigration are seeing increases previously unprecedented. Much of the rising immigration rate can be attributed to Latin America and more specifically, Mexico. This is a trend that developed rapidly in the 1970s and has persisted to the present. As for documented migration from Mexico, we have witnessed steady growth between 1970 and 2000. In fact, Suro and Passel report a growth rate of 436% between these years, which translates to approximately 11,515,000 immigrants (2003). It is also expected that we will see considerable gains in the number of Latinos in the workforce as well as in the education system (Suro and Passel, 2003). As for the undocumented population, we have also witnessed incredible growth. It is estimated that there were approximately 11.1 million[5] undocumented Mexicans residing in the United States in 2005 (Passel 2006). It is further estimated that between 80 and 85% of the migration from Mexico has been undocumented in recent years (Passel 2005). Passel reports that each year a significant gain in undocumented migration is experienced and that overall an average annual growth rate of about 8% is recorded (Passel 2005). Not surprisingly, the bulk of this population is concentrated in several key states including California and Texas. More recently however, states such as Colorado and Arizona are experiencing rapid population growth due to immigration (Passel 2005) and we are witnessing a significant dispersal of this population throughout the United States (for a full discussion of Latino settlement patterns see Chapter 3).

[5]The "residual method" is used to estimate the undocumented migrant population and is obtained by subtracting the estimated legal-immigrant population from the total foreign-born population. The residual value is then treated as the source of data for the unauthorized population.

The foregoing discussion makes clear the significant difficulties faced by Mexican immigrants. This unique population has displayed an undeniable inability to succeed within such a complex and volatile economic situation in many instances. This group usually is ineligible for public assistance, unable to secure high paying or desirable jobs, and for the most part relegated to the lowest rungs of the socio-economic ladder. Additionally, this is a group that maintains a very high employment rate despite the fact that they earn the lowest wages of all workers in the labor force (PEW 2005). Their incidence of poverty is substantial and does not seem to be lessening even in light of sufficient assimilation time.

One last noteworthy point relative to the undocumented population is the issue of remittances and their impacts upon Mexican immigrant poverty. Remittances refer to money sent by migrant workers to family members in their sending country (International Monetary Fund and IMF 1993; Congressional Budget Office and CBO 2005). In recent discussions, the question was raised as to whether immigrant poverty levels were in fact understated given that remittances would be an additional expense included in household expenditures. In response to this particular inquest, a two-fold response is presented. First, it has been determined that foreign-born Latinos do remit with great frequency. The Pew Hispanic Center reports that about 40% of this population sent remittances on a regular basis (Suro et al., 2005). However, the value of the remittances is unknown as is the extent of remittance behavior among later generations of immigrants. Thus, given that poverty rates are calculated prior to making any deductions it seems fairly safe to proceed on the assumption that while the current measure may be flawed, it certainly does not underestimate the extent of poverty among immigrants. Though not directly considered in this analysis, this is a valid and worthwhile contention that should be considered in future studies dealing with poverty rates for immigrant populations.

2.5 A History of Mexico-US Migration

In light of current trends with respect to Mexican immigration levels, it will be useful to detail the history of United States bound Mexican immigrants. As a result of the historical relationship between the two countries it is natural to see a saturation of Mexican Americans and immigrants in the Southwestern region, which accounts for nearly 70% of the immigrants in this country (Douglas-Hall and Koball 2004). As for the relationship between Mexico and the US, Massey and colleagues point out that "the USA has invaded Mexico three times; it annexed one-third its territory; it is the primary source of capital for Mexican investment; it is Mexico's largest trading partner and Mexico is the second most important trading partner for the USA" (67: 2005). Obviously, there exists a deep and well-established relationship between Mexico and America. Let us now investigate how this relationship has developed over time.

Initial movement occurred en masse after the Mexican Revolution (1910) and was largely driven by the need for labor in the Southwest (Donato 1994). This movement continued in a steady pattern until the 1930s when Mexicans were targeted for xenophobic sentiment and deported in large numbers. The Immigration Act of 1924 was exceptionally restrictive and put national origins quotas into effect (mainly in an attempt to give preference to Northern and Eastern Europeans, the ancestors of whom were already well-established in the US). The anti-immigrant sentiment which was prevalent at this time was largely the result of job competition and a belief that America was being overrun with migrants of inferior stock (Espenshade and Hempstead 1996). However, once a renewed need for agricultural labor surfaced, Mexican migration was resumed on a grand-scale (Donato 1994).

Though the United States has always experienced a great deal of migratory movement; migration scholars have identified three major eras of arrivals to the United States. These major periods of movement include the *bracero* period which lasted from 1942 to 1964, the post-*bracero* period which lasted from 1965 through 1986, and the post-IRCA period, also referred to as the *New Era of Migration*, which began in 1987 and continues to the present (Donato 1994; Durand, Massey and Parrado, 1999).

As was mentioned previously, Mexican migration increased dramatically as a result of the *bracero* program (1942–1964) initiated by the United States in response to a need for temporary agricultural labor. During this regime a more tolerant attitude toward immigration was detectable, and the US imported foreign workers from Mexico over a period of approximately 22 years (Durand, Massey and Parrado, 1999). The 1952 Immigration and Nationality Act reversed the national origins quotas and moved toward a policy of family reunification (Espenshade and Hempstead 1996). These changes in attitude were a reflection of America's emergence as a world super power, a booming postwar economy, and increasing education levels (Espenshade and Hempstead 1996; Massey 1995).

The total number of temporary workers recruited during this time approximated 4.6 million (Durand et al, 1999). The nature of this period of migration was cyclical and encouraged movement between the United States and Mexico. Thus Mexican workers were imported on a temporary basis and had a tendency to maintain ties with the home country. Very little illegal migration occurred during this time, and the little that did occurred in response to the inability to obtain a *bracero* contract (Reichert and Massey 1980). The importance of this particular period is that it set a precedent for migration to the United States, in that it created not only a desire for the extra earnings in the form of remittances but also a habitual pattern of seasonal migration.

When the *bracero* program was terminated in 1964 several key changes with respect to immigration were noted. First, only those who had familial ties to green card holders were eligible to work in the United States (Reichert and Massey 1980). Thus for individuals who did not maintain ties to US citizens, illegal migration became the only means through which to gain employment in the United States. Additionally, women and children increasingly joined the ranks of Mexican migrants (Reichert and Massey 1980). Other scholars note that the increased number and divergent composition of immigrants during the post-*bracero* period coincided with three developments (Bean et al., 1987; Massey, 1981). These developments included the passage of an amendment to the Immigration and Nationality Act in 1965 (this lifted the restrictions based on the national origins quota system and eliminated the ban on Asian entry but placed a cap on immigration from the Western hemisphere of 20,000 per country); legislation which allowed refugees to enter the country with greater ease; and an apparent increase in undocumented migration (Bean et al., 1987). Traditionally, migration to the United States was dominated by Europeans. However in recent years (post 1970s) an astonishing shift toward Latin American and Asian migration has been experienced. This trend appeared in direct response to the repeal of immigration laws in the 1960s which favored Northern and Western Europeans (Massey et al., 2006).

It was undocumented migration that began to increase rapidly during this period given the caps on entry, coupled with the fact that migrants could enter and depart with relatively little difficulty, and employers were none too worried over the use of undocumented workers. It was during the latter part of this period, however that serious concerns began to arise over the issue of undocumented migration (Bean et al., 1987). Throughout the 1970s and 1980s blue collar workers experienced economic insecurity on a grand scale (Durand et al., 1999). Durand and colleagues state that "after 1973, wages stagnated, unemployment rates rose, income inequality grew, and the distribution of wealth became progressively more skewed" (1999: 520). Eventually that stagnation filtered out onto the white collar workers as well. During the 1980s the issue of undocumented migration seemed to reach a critical mass and was transformed from a debatable political issue into a question of national security (Durand, Massey and Parrado, 1999). President Reagan argued in 1985 that the United States was losing control of its borders and in a sense set the stage for the nativist sentiment that followed. Widespread hostility toward immigrants became evident and several studies have shown that these negative attitudes coincided directly with economic insecurity (Espenshade and Hempstead 1996). Eventually, these concerns over both documented and undocumented migration culminated in the passage of the 1986 Immigration Reform and Control Act (Warren and Passel, 1987).

This act, commonly referred to as IRCA included a number of provisions designed ultimately to drastically curtail the rate of undocumented migration from Mexico (White et al., 1990; Durand and Massey 1999). These provisions included: (1) employer sanctions for those who knowingly hired undocumented migrants, (2) an amnesty offered to long-term undocumented residents who could prove they were continuous residents since January 1982 and were able to demonstrate an understanding of US policy and the English language, (3) increased resources to border patrol efforts, and (4) a special legalization program directed at agricultural workers in California and Texas (Durand, Massey and Parrado, 1999). This legislation was specifically designed to change the composition and flow of migration, though its main objective was to severely reduce illegal immigration. For all intents and purposes, IRCA was largely successful in that it did severely reduce the amount of undocumented migration. However the extent to which it reduced the flow of undocumented migration is another matter. The federal government reclassified many illegal immigrants as legal temporary residents which resulted in the appearance of fewer undocumented migrants, but it is lesser known as to whether undocumented migration did in fact recede (White et al., 1990). In fact, Passel's work on undocumented migration indicates that though an immediate drop in immigration was detected in response to IRCA's enactment, rates began to rise sharply in the early 1990s and have continued to increase rapidly to the present (Passel 2006).

Interestingly, several migration scholars have pointed out that the latent effect of this act has been a marked change in the nature of immigration; meaning that those migrants who were once temporary and maintained ties to their homeland are now bound to the United States given their heightened fear of deportation upon exit and re-entry (Durand et al., 1999). In fact, their findings indicate that the likelihood of returning home reached historic low levels in the 1990s (Durand et al., 1999). Furthermore, given that IRCA maintained a family reunification program, another after effect was an actual increase in immigration levels.

The period following the passage of IRCA has come to be known as the *New Era of Migration* (Durand et al., 1999) in which the constitution of the immigrant population has been transformed from temporary, seasonal, geographically concentrated, and predominantly male into a long-term, urbanized, and geographically dispersed population. This has been compounded by the fact that in 1996 the Mexican government passed legislation which allowed for dual citizenship, thus opening the door to unprecedented levels of potential for naturalization among Mexican citizens (Durand et al., 1999). The past two decades have been characterized by increasingly nativist sentiment (Espenshade and Hempstead 1996) fueled by a stagnating economy, the belief in a possible threat to national security in the post 9–11 era, and a perceived feeling of competition for employment (even though immigrants do tend to be concentrated in jobs that are undesirable to natives). The following pages describe the post-IRCA period with a special emphasis on the policies enacted and their impacts on the immigrant population.

2.6 Post-IRCA and Policy Implications

Much of the discussion in previous pages has focused on a general overview of the immigrant situation in the United States. Most importantly, these major periods in history and the key acts mentioned had led to an alarming level of economic inequality for Mexican Americans and Mexican immigrants. The period following IRCA was one of heightened awareness of external and internal threats and Mexican immigrants came to be viewed as responsible for many of the ills faced by the average American (Durand, Massey and Parrado, 1999). In the early 1990s Proposition 187 surfaced in California and with it came restrictions that would prevent undocumented migrants from attending school or receiving any sort of public assistance including medical, welfare, or otherwise (Espenshade and Hempstead 1996). This proposition was very well received (it passed with a 3–2 margin) and soon reached the national level. The strong anti-immigrant stance associated with this legislation culminated in the passage of two acts: the Illegal Immigration Reform and Immigration Responsibility Act, and the Personal Responsibility and Work Reconciliation Act of 1996, or the Welfare Reform Act (Durand, Massey and Parrado, 1999).

The Illegal Immigration Reform and Immigrant Responsibility Act of 1996 set forth some of the harshest measures ever enacted against illegal immigration (Fragomen 1997). With it came provisions for increased border enforcement, stricter measures relative to employer sanctions including new investigators dedicated to enforcement, increased penalties for smuggling, new allowances for deportation, changes to welfare requirements, and changes to refugee/asylum procedures (Fragomen 1997). First, as part of the increased border patrol protocol, at least 1,000 new agents were to be hired each year for at least 5 years after the implementation of the new policy. Next, employers who acted in "good faith" in terms of hiring illegal immigrants were to be given the benefit of the doubt unless they were repeat offenders, and more importantly, the list of I-9 documents which were acceptable for employment verification was substantially limited. Third, immigrants who were once granted asylum were now only allowed asylum in the instance that an acceptable third country could not be found; and applications for asylum now had to be filed within 1 year of arrival for consideration. Changes were also made to the refugee classification and included those who were forced to abort a pregnancy, undergo sterilization, or who were victims of female genital mutilation. As for deportation procedures, border officials were granted the authority to deport any individuals upon arrival who either failed to provide documentation or provided false documents, and allowed for the deportation of any individual who engaged in high speed flight from an immigration checkpoint or who was convicted of domestic violence, among other crimes, upon entry (Fragomen 1997). This authority to deport applied in a blanket sense and did not need to be accompanied by any sort of hearing or procedure. Finally, a key change was made in the documentation relative to an immigrant's arrival in the United States. The new law maintained that the arrival be specified as an admission (meaning it was inspected by a border patrol agent and approved) rather than as an "entry".

In combination with the myriad of restrictions aimed at revamping illegal immigration protocols was a major overhaul of the welfare system. This was referred to as the Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA) of 1996, or Welfare Reform Act, which was originally established to limit cash assistance to families and promote entrance into the workforce. However, those most largely affected were immigrants, a majority of whom have already been determined to be part of the full-time workforce. This act specifically created new restrictions targeted at immigrants and given its scope its intentions are quite clear. The provisions of this act extend to any of the following: grants, loans, or licensures; retirement, health, or welfare benefits; any form of public housing assistance; post-secondary education; food assistance; or unemployment benefits (Fragomen 1997). With the exception of only a few select groups of immigrants, e.g., asylees and war veterans, immigrants are barred access to any public benefit for their first 5 years of residence in the United States. Additionally, they are banned in the case of two federal programs indefinitely: Supplemental Security Income (SSI), and food stamps (Fragomen 1997; Alden-Dinan 2005). This act was a key departure from past policy in that it made eligibility directly related to citizenship verification. Another key provision of this act was that the federal government decided to provide each state with block grants to be used toward individual welfare programs. These state level programs include Temporary Assistance for Needy Families (TANF), social service, and Medicaid (Fragomen 1997). Thus, each state now had the authority to completely prohibit immigrants from receiving such benefits. This becomes particularly noteworthy for states in the Southwest such as Texas and California given that they have traditionally been trendsetters in making decisions related to immigrants that are then passed on to other states.

In the years following the passage of these two pieces of legislation, there has been a considerable decrease in utilization rates of public benefits and increases in the rates of Mexican American and Mexican immigrant poverty. The impetus surrounding the Welfare Reform Act was that of encouraging the able-bodied to work and discouraging out-of-wedlock births (Fix and Passel, 2002). These concerns do not apply to the immigrant population however. Fix and Passel point out several aims of the legislation aimed specifically at immigration including: (1) an alteration of immigration flows resultant from restricted access to benefits, (2) an increased burden of responsibility upon sponsors rather than the government, and (3) a substantial amount of savings to the budget (2002). The outright goal of restricting immigrant access has been achieved, but at a potentially significant cost to those affected and the economy overall. Recent studies have shown that these restrictions have affected citizens as well as non-citizens. Thus, those who do have legitimate claim to participation have not done so due to confusing eligibility terms and fear of repercussions. Additionally, the claim that immigrants are drawn to states with more lenient policies has proven categorically false as we have observed continually increased settlement patterns in states that have not traditionally been immigrant receivers. In the face of looming recession, concerns over lack of safety net programs in such states could prove disastrous (Fix and Passel 2002).

The period following IRCA has been dominated by legislation aimed at curtailing the "problem" of immigration. First and foremost, it is very important to remember that it is the federal government that determines the classifications referring to immigrants and correspondingly the attitudes toward them. Legal immigrants are grouped into three categories: naturalized citizens, lawful permanent residents, and refugees/asylees (Alden-Dinan 2005). Undocumented thus refers to any immigrants who do not belong to one of the above-mentioned categories. As part of this classification eligibility for government assistance is determined. The classifications by which immigrants are referred to plays a key role not only in their eligibility for public assistance but also in the attitudes of the American public. Mexicans have the lowest rates of naturalization of any ethnic group in the United States (Durand, Massey, and Parrado, 1999), thus they stand the greatest chance of being negatively affected by such classifications. Federal laws and regulations are central to the well-being of American citizens. Recent acts such as the Welfare

Reform Act and Immigration Reform (1996) have been incredibly restrictive and have in many cases been evidenced to have little effect (at least in the sense they were intended) on rates of immigration. It has been posited that several changes could be enacted that would prove to be helpful to both the immigrant population and the nation overall. Given that the majority of immigrants who are low income are also members of the labor force, changes that would increase the minimum wage would be of great help to such families (Douglas-Hall and Koball 2004). Also, child care subsidies and programs that would increase English fluency would be beneficial in ensuring the long-term success of the children in these families. Finally, investments in education should prove beneficial to the overall population as we increasingly move toward a technologically-based global economy that requires the services of a highly skilled and educated population. These are members of society who do contribute to the tax base as well as the economy (Douglas-Hall and Koball 2004) and as such should be extended the privileges granted to the citizens of this country.

One of the most interesting outcomes of recent legislation is that it has not slowed the momentum of immigration, but rather gravely affected the stock of immigrants in a negative manner. Much in the way that the strictest of rules tend to have the opposite effect, these immigration laws have proven to be rather impotent in terms of slowing the flow of migration. These flows have gained a momentum all their own, and it seems that harsher policies have led to clandestine and malformed immigration attempts rather than legitimate and worthwhile ones. Thus, it appears that well-formed policy changes would have the greatest impact on this vital and growing segment of the population. Though briefly mentioned in this section, in the concluding chapter of this book I will provide full recommendations for policy change based not only on recent findings relative to policy, but also in light of the findings of this work.

2.7 Contributions to the Literature Base

It has become increasingly clear that Mexican American and Mexican immigrants are becoming more and more marginalized in this country as time passes. We have successfully enacted policies that restrict immigrant access to public benefits in some cases on an indefinite basis. It has also been determined that these policy changes have had significant negative effects on Mexican American citizens as well. The problem of restricted access is compounded by the fact that immigrants face a multitude of other barriers upon arrival including difficulties in the migration and assimilation process and lack of access to the traditional opportunity structure. Many studies have shown that immigrants with children who are citizens do not participate in safety net programs, and as such we are experiencing vast increases in the number of children who are uninsured and unable to participate in key programs that would benefit their well-being in the long-term. Additionally, those children in low income families are at a significant risk for poor performance in school (The Urban Institute, 2006).

Turning to the impacts of childhood poverty on immigrants, it is very clear that they are adversely impacted but for different reasons than other affected groups. An unbelievably large number of the children of immigrants are low-income (65% of recent immigrants), and even more distressing is the fact that 47% of those children are under the age of 6 (Douglas-Hall and Koball 2006). This indicates that they will be subject to the negative effects associated with early childhood poverty with much more frequency and at the early stages of development. Douglas-Hall and Koball point out that "the challenges in academic, physical, emotional, and social development usually associated with economic insecurity are likely to be exacerbated by language barriers, the process of migration and acculturation, and restrictions on access to safety net programs," (2006: 2). It is also very important to note that those children who do grow up in low income immigrant families will often be faced with the issue of low parental education, family instability relative to wages and general bureaucratic issues, and lowered access to early education programs (The Urban Institute, 2006).

Immigration rates show no signs of slowing in the coming decades. Much of what makes the immigration process for Mexicans so different from that of large scale European immigration in the early 1900s is that this wave has not been accompanied by the economic boom or "breathing space" which allowed Europeans to successfully assimilate into the mainstream (Massey 1995). Instead, the flow of immigration has become a continuous process that does not seem to be affected by policy changes. In fact, policies designed to curb immigration rates have had the opposite effect in that they have encouraged long-term rather than cyclical migration. Furthermore, immigrants have continued to enter the country during a time of economic scarcity and are increasingly finding themselves in poverty outcomes which prove more and more difficult to escape.

Much of the work on undocumented migration has shown that the rates are rising steadily and a majority of unauthorized migration originates in Mexico (Passel, 2006). This rise in undocumented migration is attributable to a number of factors including the changes in policy that have been discussed, changes to Mexican policy that encourages its citizens to work abroad and maintain dual citizenship, and the self-perpetuating nature of the migration process itself. It is not expected that future rates of migration will decrease, thus it becomes necessary not only to assess the impacts of issues such as poverty on migration but also how the American landscape will change in the coming years as a result of the change.

Mexican Americans and Mexican immigrants are in increasingly impoverished situations and this is the result of harsh immigration policy and a progressively skewed distribution of wealth and resources in the United States. This gap in earnings is likely attributable to a shift in the economy toward a more service and technology oriented society where there exists an abundance of low-wage and status jobs in the service sectors and only a modest amount of jobs in the high-skilled technology-based sector (Lichter and Crowley 2002). These two groups account for a sizeable proportion of the population and, moreover, are expected to grow through both immigration rates and increased fertility rates. In terms of the outcomes to be felt by this population we are faced with the question of long term success. In order for at risk populations to succeed, it is necessary that they procure quality education and achieve higher rates of completion of extra education. It is also necessary that the cycle of poverty not be perpetuated throughout successive generations. Given that this population is additionally burdened with very low levels of parental education and skill, we cannot expect that this sort of success will be realized. Countless studies have shown that low parental education translates into lowered chances of success in education and in turn less likelihood of completion of higher education. When this is combined with additional restrictions to government programs and lowered levels of participation for those who are eligible, it equates to a grim outlook for future generations of Mexican Americans and immigrants.

This book will provide a key contribution to the literature in its development of a variable for undocumented status that allows for an examination of the impacts of poverty upon this population. There exists in the literature several methods dedicated to the estimation of undocumented status. Work conducted by Bean, Browning, and Frisbie in the 1980s used a combination of several key variables such as young age, low education level, and others to create a proxy variable that would reliably predict an individual's undocumented status. This work proved to be an accurate indicator of such status when compared with residual methods for predicting the undocumented population. My work brings that research one step further by developing an updated proxy variable for undocumented status that allows me to ascertain the specific predisposing factors for poverty among the undocumented population. The information from previous studies has been renewed based on current findings and literature and will be used in an analysis of poverty at the four levels discussed in previous sections (extreme poverty, 100% poverty, low income, and relative poverty). In the coming chapters, a full discussion of the methodological and substantive issues involved in the formation of the proxy variable for undocumented status will be presented. In addition, a discussion of the undocumented population will be provided in a special section dedicated to the findings for this population relative to this study. The results of this study will be combined with previous findings in an effort to broaden our understanding of the nature of poverty for this population.

Also provided herein is a multi-level analysis of poverty. Thus, I will combine findings at the contextual level with individual level predictors of poverty. The group level variables are based on the Super-PUMA level of geography; these are geographic regions containing 400,000 or more persons based on census classifications. Key variables have been selected that should act as very important predictors of poverty. These group level analyses are provided in an effort to understand the role played by group contexts on the incidence of poverty. For example, the extent to which the percentage of poverty in a Super-PUMA will be analyzed with respect to the strength of that relationship upon poverty in the area as well as how it impacts poverty at the individual level. Other key variables provided at the group level include a full occupational distribution (includes the nine major classifications set forth by the Census Bureau), metropolitan status, and percentage of immigrants in the area. The *Data and Methods* chapter of this book will provide a full description and development of the contextual level data set that has been created.

The aforementioned literature has provided a vast array of information relative to the current situation of poverty for Mexican Americans and immigrants in this country, the policies that have gravely impacted immigrant populations, the history which has led up to the formation of such policy, as well as the rates with which these populations are affected. Much of the current research on immigration has been concentrated on determining the motivations to migration and estimating the undocumented population and their future impacts upon society. This book provides a key contribution in that it advances the work initiated by Bean et al. (1984) on the development of a proxy variable for undocumented status. Additionally, relatively little work has been done in the area of poverty using multi-level analysis. This is a very modern and sophisticated tool for statistical analysis, and the outputs to be obtained from this analysis will provide a great deal of information on the situation of poverty.

Chapter 3
Settlement and Geographic Redistribution Patterns

The following section describes the movement and settlement patterns of Hispanics from the 1990s onward. Special emphasis is placed on foreign-born individuals and maps are presented that detail the changing geographic distribution of this group from 1990 to 2006. Information is based on decennial census data for 1990 and 2000, while ACS data is used for 2006. The maps display that a significant change in movement patterns has been observed beginning in the 1990s with a greater concentration of immigrants settling in the South and Midwest.

3.1 Hispanic Settlement and Growth

Recent immigration patterns are shifting in relation to what has traditionally been observed. In the years prior to the Immigration Reform and Control Act of 1986, immigrants settled in metro gateway cities and remained geographically concentrated in relatively few destinations. As mentioned in Chapter 2, the period following IRCA has come to be known as the *New Era of Migration*, and the immigrant population shifted into a long-term, urbanized, and geographically dispersed population. In addition, the racial and ethnic composition of immigrants has changed dramatically in recent decades. During the great migration of the late 1800s and early 1900s the majority of immigrants to the United States were of European origin. In sharp contrast, the majority of immigrants entering from the 1970s onward were of Latin or Asian origin. In 1960, 75% of the foreign-born population was from Europe, whereas 80% of the foreign-born population in 2007 was of Latin American or Asian origin (Grieco 2010). By far, Hispanic immigrants comprise the greatest proportion of immigrants to the US. In fact, 2007 estimates indicate that 53.6% of the foreign-born population came from Latin America and within that group 64% were of Mexican origin (Grieco 2010). Much of the growth experienced in overall population by the United States is accounted for by Latinos. As a group, the Mexican population experienced a growth rate of approximately 53% between 1990 and 2000 (Saenz 2004). Today, Latinos account for one in eight persons in the US, but it is projected that by 2035 one in every five persons will be Latino, and one in every three persons for 2100 (Saenz 2004).

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Current trends indicate that though many immigrants are continuing to settle in urban areas, a growing number are relocating to rural areas or initially settling in the South and Midwest (Kandel and Cromartie 2004; Lichter and Johnson 2006). Hispanic immigrants have traditionally been concentrated in specific locations throughout the US, with Mexicans primarily settled in the Southwest and Chicago (Gouveia and Saenz 2000). In addition, the majority of Latinos have been concentrated in urban areas. However, during the 1990s rapid increases in the Hispanic population resulted in significant population growth in nonmetropolitan areas, especially in the South and Midwest (see Fig. 3.1) (Brown et al., 2003; Saenz and Torres 2003; Lichter and Johnson 2006). In fact, Hispanic population growth in non-metropolitan areas now represents the most rapidly growing segment of residents (Kandel and Cromartie 2004). The Midwest in particular has experienced tremendous growth in its Latino population. Recent studies have shown this trend and confirm that quite a few isolated counties in the Midwest had foreign-born populations that exceeded 5% for the first time (Lichter and Johnson 2006). Additionally, states in the South Census Region such as Georgia, Arkansas, and North Carolina experienced the highest rates of growth in the Latino population during 1990–1999 with values exceeding 100% in each case (Johnson-Webb 2002). Thus, states that have not traditionally been immigrant receivers are experiencing unprecedented growth in their Latino populations, and it is expected that these trends will continue into the foreseeable future.

The 1990s seems to have ushered in a new stage of immigrant settlement, especially among Hispanic immigrants. As of 1990, over 60% of Hispanics lived in the traditional Southwest states of Arizona, California, Colorado, New Mexico, and Texas (Kandel and Cromartie 2004). However, several authors have pointed out the changes in settlement trends, particularly among Hispanics. For example, as of 2000, approximately half of all nonmetropolitan Hispanics lived outside the traditional Southwestern states (Kandel and Cromartie 2004; Kandel and Parrado 2005). They accounted for little of the non-metropolitan population in 1990, but accounted for over 25% of this growth between 1990 and 2000 (Kandel and Cromartie 2004). As mentioned above, much of the recent growth in Latino populations has occurred in areas that were not established Hispanic communities. Furthermore, a great deal of these immigrants are recent arrivals with relatively low levels of education (Kandel and Cromartie 2004). A significant factor in the growth of Latino populations in previously unsettled areas is generated by the emergence of employment opportunities in meat and poultry processing, manufacturing, and low wage service work (Kandel and Cromartie 2004). Because the trends are still emerging, relatively few quantitative analyses are available. Thus, this section explores the settlement patterns of Hispanic immigrants in relation to restructuring of the US meat packing and other industries. These industries rely on immigrant labor characterized as low wage, low skill, and with little room for advancement, in order to maximize profitability. In addition, the importance of social networks becomes apparent as a highly useful recruiting tool and as a catalyst for increased immigration.

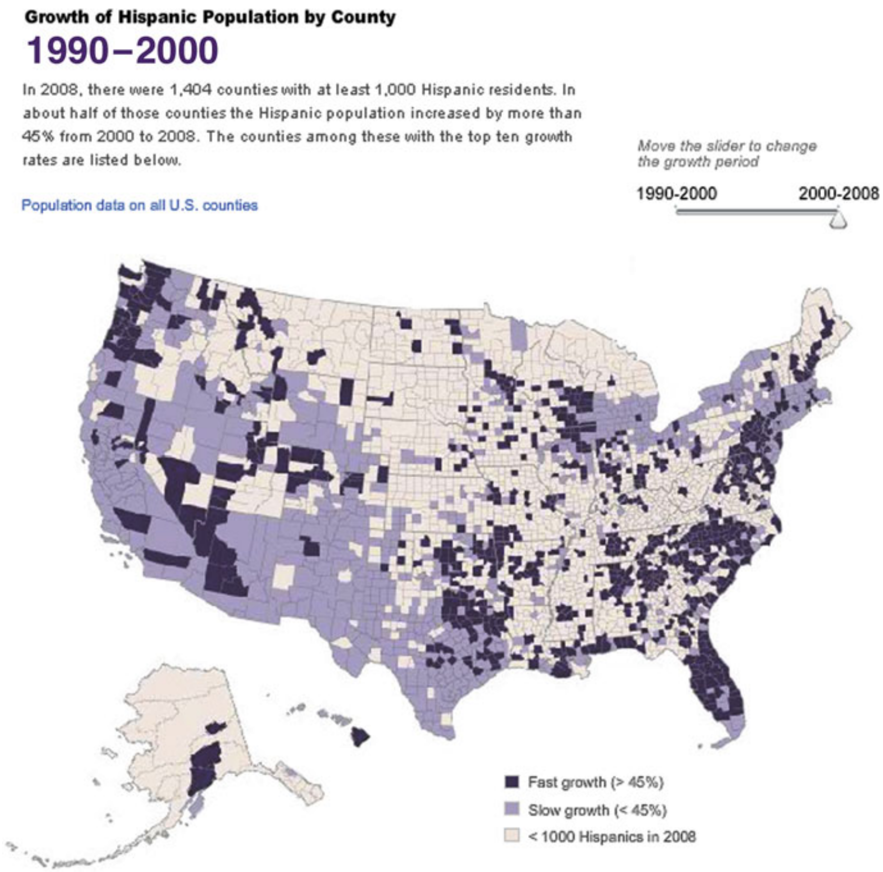

Fig. 3.1 Growth of hispanic population by county; Source: Pew Hispanic Center analysis of Decennial Census (for 1980 and 1990) and US Census Bureau county population estimates (vintage 2008 estimates for 2000 and 2008)

The theoretical basis for such arguments has been explored by several authors who report that service-related labor demands in combination with changes to US immigration policy, particularly the Immigration Reform and Control Act of 1986, have fueled the increased migration of Hispanic immigrants to new destinations (Johnson-Webb 2002; Kandel and Parrado 2005). I argue here that dual labor market theory may be applied to explain much of the initial movement of Hispanics into previously unsettled areas, while social capital theory, i.e. migrant networks, may be used to explain the continuation of migration streams into such areas. Dual labor market theory argues that, "international migration stems from the intrinsic labour demands of modern industrial societies" (Massey et al., 2005). Changes to the structure of certain industries have markedly altered the nature of employment in such jobs and as a result have provided the impetus for movement of Latinos into new locations. These changes were brought on by international competition and employers adjusted by doing such things as lowering wages and benefits and renegotiating or eliminating union contracts (Kandel and Parrado 2005). Fundamental changes to the structure of the industry include changes in American consumption patterns that require increased convenience, the concentration of production in relatively few large firms, relocation of processing plants to rural areas in an effort to reduce costs, and working conditions that are simultaneously physically demanding but poorly paid (Kandel and Parrado 2005). Hence, the need for an expanded labor force willing to accept low wages and poor working conditions is at the heart of the movement observed for this group. The secondary market is supplemented by the family members of those employed in manufacturing/service industries who fill positions in such areas as domestic care. This cycle of movement is then sustained by the utilization of migrant networks that employers readily tap into for recruitment purposes given the lack of job security and high turnover rates. In fact, a recent study indicated that word of mouth was the most prevalent recruitment tool for employers in such industries (Johnson-Webb 2002). Interestingly, employers cited a perceived work ethic, specific to Mexican immigrants, as the reason for the greater degree of desirability for such employees (Johnson-Webb 2002).

3.2 Data and Methods

Here, I consider the movement and geographic distribution of foreign-born recent immigrants using decennial census and ACS sample data obtained via the IPUMS extraction system. A series of maps are presented which display the spatial distribution of the Hispanic population over the period from 1990 to 2006. The analyses are based on sample data from 1990, 2000, and 2006 ACS data. Foreign-born persons have been defined as those who were not US citizens at birth. I also consider the behavior of recent immigrants by isolating those who immigrated during the 10 year period prior to the date of the census.[1] In order to fully understand the migration behaviors of this group, I have isolated those immigrants who identified Mexico as their place of birth.

The maps in this chapter were created using ArcGIS, a mapping software that has the ability to integrate the attributes associated with a certain level of geography (in this case the PUMA) with the boundary files for an area and display them in map format. A geographic information system (GIS) is used to manage geographic boundaries and attributes associated with certain locations (Longley 2001). For my purposes, multiple layers of information have been overlaid on US maps that identify the PUMA as the lowest level of geography. In order to maintain comparability across samples, the variable for consistent PUMA (CONSPUMA) was

[1] The recent immigrant variable is defined in a manner consistent with the work performed by Lichter and Johnson 2006.

utilized in the 1990 and 2000 5% sample and the 2006 ACS sample. This represents the most detailed geographic area that can consistently be indentified in samples from 1990 onward (Ruggles et al., 2008). The layers represented in the map are based on the foreign-born population, percent of recent immigrants, and percent of Mexican immigrants. A geographic representation of the data is provided for each of the above-mentioned years (1990, 2000, and 2006) so as to illustrate the changes in the distribution of Latinos over the past few decades. Spatial patterns occur as a result of cultural processes that have taken place and describing these patterns allows us to determine the factors that influence those patterns (Wong and Lee 2005). Spatial patterns may be observed in relation to areas (PUMAs), or polygons. These patterns can be categorized as clustered, dispersed, or random. Clustered patterns are indicated by a scale where darker shades indicate a greater degree of concentration, as illustrated for the foreign-born population (see Figs. 3.2, 3.3 and 3.4). Correspondingly, we can search for ways to deter patterns that result in undesirable changes.

3.3 Maps

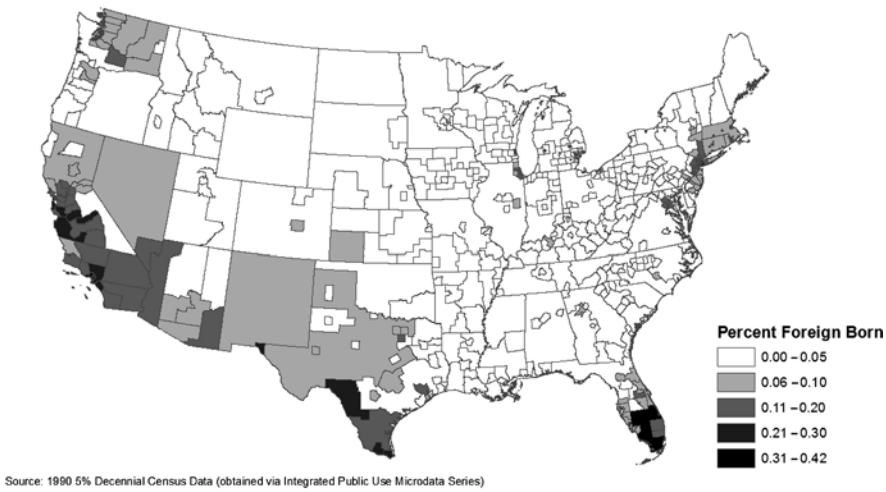

Fig. 3.2 Percent Foreign Born, 1990

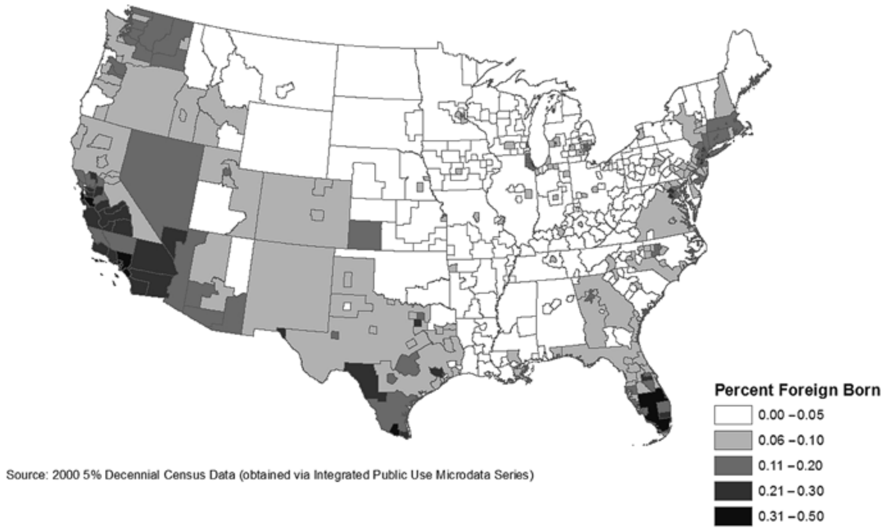

Fig. 3.3 Percent Foreign Born, 2000

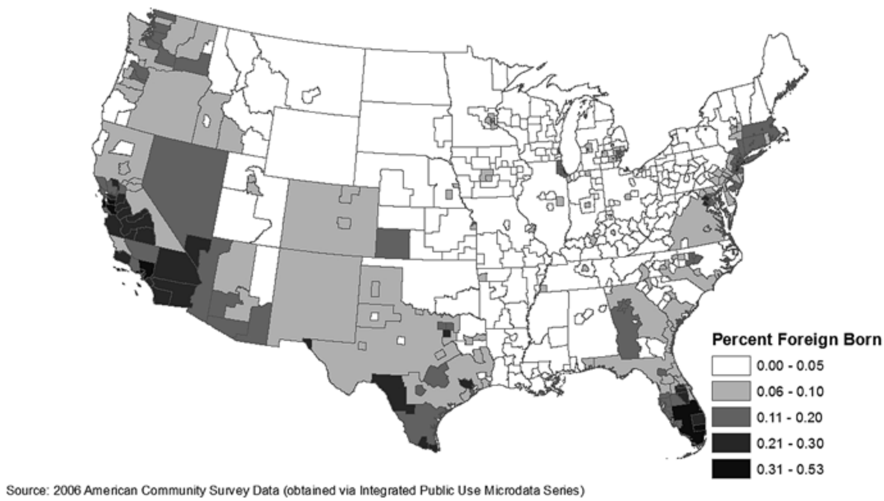

Fig. 3.4 Percent Foreign Born, 2006

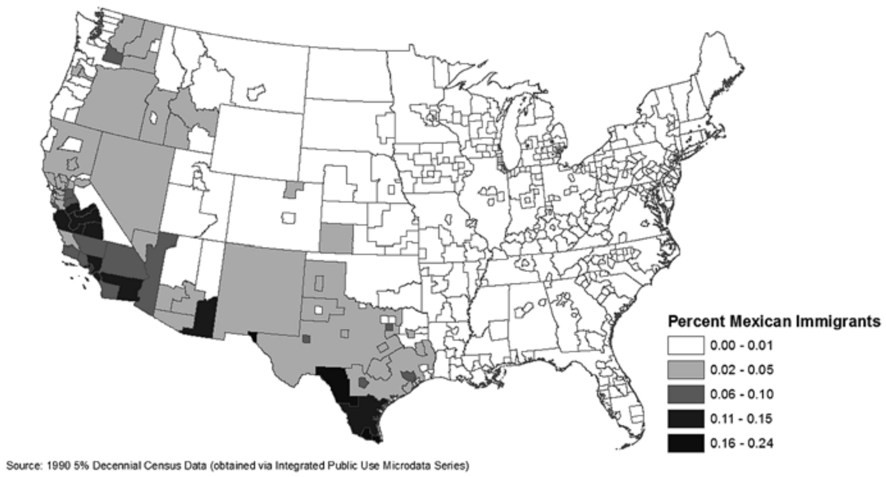

Fig. 3.5 Percent Mexican immigrants, 1990

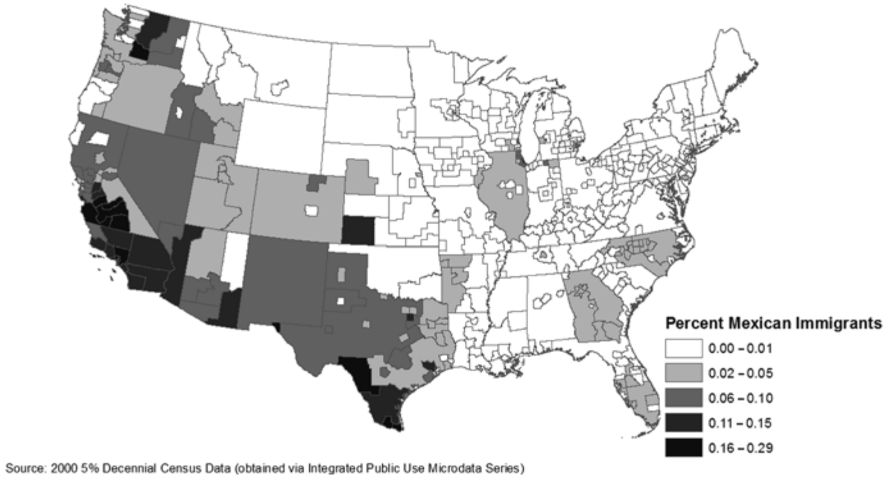

Fig. 3.6 Percent Mexican immigrants, 2000

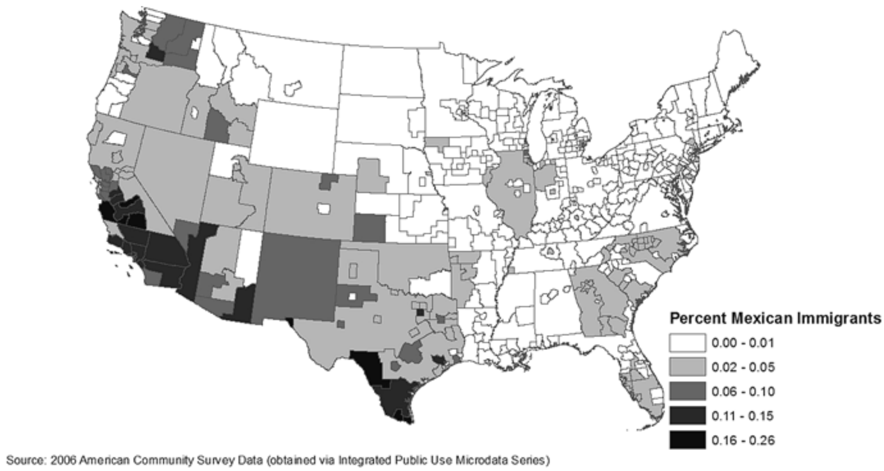

Fig. 3.7 Percent Mexican immigrants, 2006

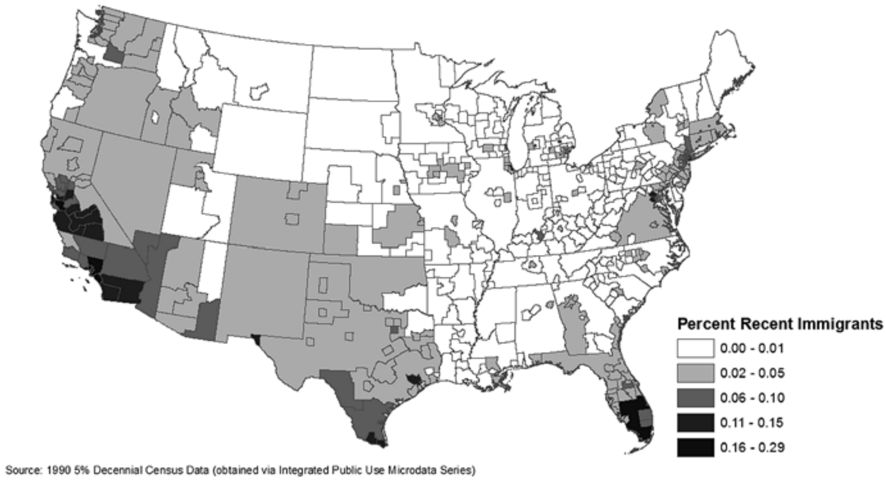

Fig. 3.8 Percent recent immigrants, 1990

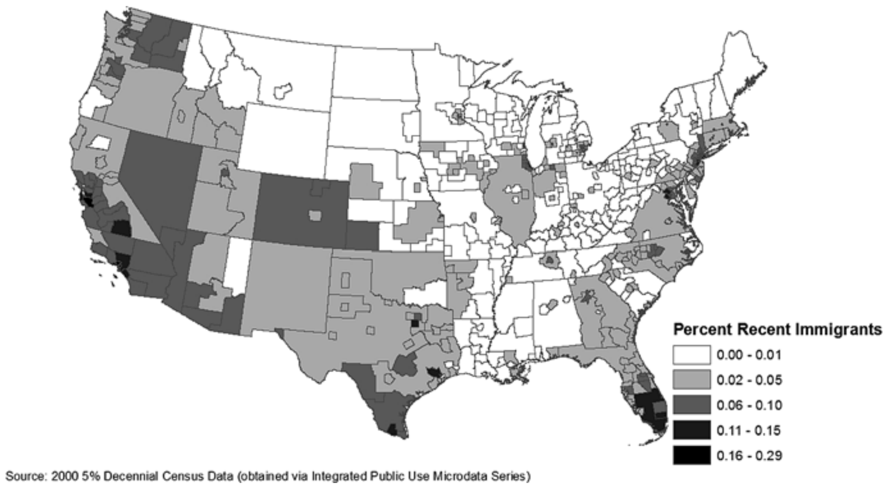

Fig. 3.9 Percent recent immigrants, 2000

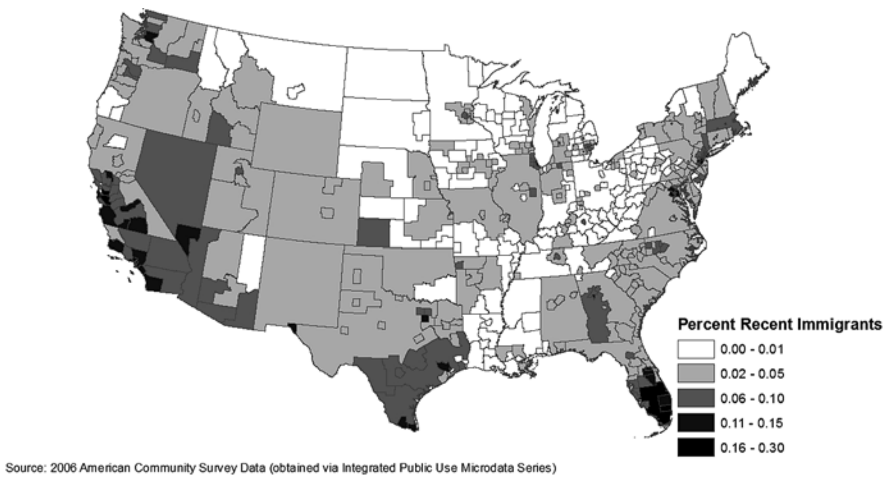

Fig. 3.10 Percent recent immigrants, 2006

3.4 Findings

The maps displayed above present visual evidence of the change in settlement patterns for the foreign-born, and more specifically, for the Latino and Mexican immigrant populations. Figures 3.2, 3.3, and 3.4 document the change observed for foreign-born individuals from 1990 to 2006. It is evident that more of the foreign-born population is taking up residence in areas that have not traditionally been considered gateway cities. These include rural areas in such states as Nebraska, Iowa, North Carolina, and Georgia. Many of the more densely populated areas contain meat packing or other manufacturing industries. This trend becomes even more evident when one focuses on the settlement patterns of Mexican immigrants. Figures 3.5, 3.6, and 3.7 depict the geographic distribution of this population over the years 1990–2006. Here, we can see that much more of the area in the rural Midwest and Southeast has experienced significant gains in their Mexican immigrant populations. Finally Figs. 3.8, 3.9, and 3.10 display the settlement patterns of recent immigrants, which are defined as those who arrived within the 10 years prior to the date of the census. As with the movement of the previously defined groups, it is observed that a great deal more of the initial settlement of immigrants is occurring in areas that have not previously been considered destinations for them.

Certainly, it is worthwhile to consider the driving force behind such dramatic shifts in the settlement patterns of Hispanic immigrants. Given that a great deal of emphasis in this work is placed on the importance of structural level forces, it is important to note that the changing structure of the labor market appears to account for a great deal of the movement by Hispanics (Gouveia and Saenz 2000). Specifically, expanded opportunities in the meat-packing industry and growth in low wage jobs have provided the impetus for the immigration of Latinos into new territory (Saenz 2004). The growth in this area is explained by the increased competition present in a global marketplace and accordingly, the need for low skilled and low wage workers. The usage of the variable “employment in a Mexican immigrant job” in the individual level analyses presented in Chapter 5 shows the predominance of this type of occupation among Mexican Americans and immigrants. Indeed, within the meatpacking industry, Latinos make up anywhere from 50 to 90% of any plant’s workforce (Gouveia and Saenz 2000). Additionally, the importance of social networks is also a highly important factor given that employers utilize this method of recruitment as an invaluable resource for the attainment of a continuous supply of workers with very little political power.

Because of the structure of this industry, which promotes dependence upon readily available, low skilled, and highly expendable workers, the potential for long term negative consequences is evident. Interestingly (though not surprisingly), the meatpacking industry itself has experienced vast increases in profitability, while wages for those employed in the industry have fallen to disproportionately low levels.

3.5 Implications

This rapid population growth and geographic redistribution is important to study given that the long-term well-being of Latinos and their receiving communities is at risk. It is expected that Latino populations will continue to increase and these individuals will continue to settle areas that offer employment opportunities. In areas such as the Midwest, where non-Latino population growth has slowed, the Latino population will likely come to monopolize the workforce in coming years. However, such areas are dominated by industries that require a continuous supply of poorly educated workers who are willing to labor under dangerous conditions and for low wages. These employment opportunities offer little room for advancement and increase the amount of inequality observed in this country. Additionally, the influx of low skill, low wage workers drives down wages in an area. This could potentially translate into even greater levels of poverty across the nation. Though the increased presence of Latino populations has had the effect of bolstering local economies, it is questionable as to whether Latinos as a group will experience any gains in social or economic status as a result. It is necessary to provide career ladders and greater job security in order to ensure that future generations and society as a whole prosper.

Further, immigrants are expected to continue geographically dispersing across the nation, which could result in greater levels of tension between native-born and foreign-born individuals in areas that have previously had little contact with minority group members. In addition, we may see that native-born populations will relocate from areas that are highly saturated with immigrants and increase rates of segregation. There is some evidence to suggest that this is a likely outcome and one that would only serve to decrease the rate of social inclusion among Hispanic immigrants. Next, receiving communities are ill-equipped to handle the demand for social, educational, and other services that are generated by a rapid influx of immigrants. The composition of these populations is much younger and requires a different set of social services than an older population. The infrastructure of such locations must be addressed and improved to account for populations that are characterized by a greater amount of foreign-born residents. Finally, number of years spent in the US has a tremendous impact on socioeconomic status, and given that great deals of the residents settling in new areas are recent arrivals, we can expect to observe poor outcomes in a great majority of cases.

On the positive side, some have argued that geographic disbursement may be a part of the solution in terms of combating poverty. Given that there are increased opportunities for work and solid social networks in place; Hispanic immigrants may be able to accumulate social capital and more effectively bargain for equitable arrangements. It is also argued that the arrival of young immigrants to an area may serve to invigorate local economies and organizations (Lichter and Johnson 2006).

Chapter 4
Data and Methods

This chapter describes the data and methods used to analyze rates of poverty at the individual and contextual levels for Mexican Americans and Mexican immigrants in the Southwestern United States. The individual-level data were extracted from the American Community Survey, 2006 using the IPUMS system provided by the Minnesota Population Center. The focus is on four dependent variables, namely, extreme poverty, 100% poverty, low income, and relative poverty status. These outcomes are examined relative to several principal independent variables including ethnicity, citizenship status, undocumented status (for Mexican immigrants) and type of occupation, among others. As the results are considered on the basis of a binary dependent variable (i.e. likelihood of reporting to any of the four outcomes of poverty), logistic regression is the proper method of analysis and is described in full detail. This is followed by descriptive tables containing the selected variables and their definitions.

Also included in this chapter is a discussion of the methodology surrounding the development of a proxy variable for undocumented status among Mexican immigrants. This variable is an extension of the work initiated by Bean et al. (1984), and is implemented in an effort to gain a fuller understanding of undocumented status on the likelihood of poverty.

The last sections of this chapter are devoted to discussion of the contextual level method employed. Data have been obtained from the 2000 decennial census and are used to represent various features of the Super-PUMAs (geographic areas containing 400,000 or more persons) located within each of the five Southwest states. Contextual level variables include a weighted percentage of poverty within the area, a weighted percentage of Hispanics and Hispanic/Latino immigrants, metropolitan status, and weighted variables for each of the major industries identified by the US Census Bureau. These predictors are used in conjunction with the individual level independent variables in a multi-level analysis. Such a method is the statistically correct way to examine the effects of contexts, i.e. Super-PUMA characteristics, on poverty. A description of the methodology involved is presented as is a description of the decennial census data employed at the contextual level.

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4.1 Individual Level Data

The data analyzed at the individual level are from the 2006 American Community Survey (ACS), as provided in the Integrated Public Use Microdata Series (IPUMS), Version 3.0, made available by the Minnesota Population Center (Ruggles et al., 2008). The American Community Survey is an updated survey that is now conducted in place of the decennial census long form. Whereas the decennial census was somewhat of a snapshot of the population taken once every 10 years, the ACS may be viewed as more of a video taken throughout the decade (Taeuber 2006). The ACS conducts a series of monthly surveys, which are then compiled on an annual basis. One of the key strengths of the ACS data is that it is based on continuous measurement. This has long been a goal of the census bureau, and with the implementation of the ACS, it began in 2000. The ACS was developed as an alternative method to the decennial long form, which provided detailed information on population and housing characteristics. The ACS also provides this detailed information, but it is conducted on a continual basis and is based on a sample rather than a count of the nation's population. Thus, given that it is conducted on an on-going basis it may be argued that it provides more accurate and time-sensitive estimates regarding population attributes (ACS 2006).

Full implementation of the ACS occurred in January 2005. This sampling scheme covered all 3,141 counties in the United States and those in Puerto Rico. The ACS data are collected by three methods: (1) monthly mail outs from the National Processing Center, (2) telephone non-response follow-ups, and (3) follow-up visits conducted by field representatives. Population and housing profiles were first available in 2006 for areas containing 65,000 or more persons, 3-year period estimates were made available in 2008 for areas containing 20,000 or more individuals, and in 2010, 5-year period estimates will be available down to the smallest level of geography contained in the census (ACS 2006). In the ACS sampling design, each housing unit is assigned a month for which it is eligible to receive a mail out survey (these interviews may be conducted in the eligible month or 2 months following). If after the eligible time period no response is received and a telephone number exists, the housing unit's information is then sent on to the computer assisted telephone interviewing (CATI) personnel who may conduct an interview 1 month following. A sub-sample of those who are not reached by telephone is then selected for computer assisted personal interviews (CAPI) in the third month (ACS 2006).

The ACS content includes 25 housing and 42 population questions, and is designed to maximize efficiency by maintaining consistency. As stated by the Census Bureau (2006), "the ACS is designed to produce detailed demographic, housing, social, and economic data every year. Because it accumulates data over time to obtain sufficient levels of reliability for small geographic areas, the Census Bureau must minimize content changes" (p. 52). Data on the age, sex, and race of the respondents are considered to be critical information and are thus collected initially. Data are also collected for each household member and contain questions pertaining to citizenship, place of origin, industry, and income among other items.

The data used for individual analyses in the next chapters are based on a nationally representative sample of the United States and were extracted from the Census

Bureau's 2006 ACS, 1% IPUMS sample, within which PUMAs are the lowest level of geography and contain at least 100,000 persons. As was stated previously, the data were extracted using the IPUMS on-line data extraction system. Here, data users are able to select sub-sets of samples and variables that are necessary for their work. The data are referred to as microdata because they provide information on persons and households rather than data in aggregated tabular form (Ruggles et al., 2008).

The 2006 ACS data are based on a 1 in 100 national sample of the population. As of 2006, information on group quarters is available, and the smallest identifiable unit of geography is the PUMA, as stated above. The data are weighted and data users must weight accordingly through the use of statistical analysis software to produce accurate estimates (see below for a discussion of weighting) (Ruggles et al., 2008).

Overall, the 2006 ACS sample contains information on approximately 1,344,000 households and 2,970,000 persons. These are the data from which samples were drawn for the analysis contained herein. Once extracted the sample was limited to cases in the Southwest region of the United States, which includes Arizona, California, Colorado, New Mexico and Texas. The sample for the Southwest region contains information on 277,091 households and covers 423 counties. The data on individuals were used to create the household sample given that the IPUMS system provides a variable entitled PERNUM. This particular variable refers to the position of the individual within the household unit (a value of 1 refers to the head of household). I have restricted the sample to head of household only (as well as basing the analysis on them); I can estimate a model which is representative of the proper number of households but which also provides individual level detail, such as occupation and place of origin.

I first estimate models (Model 1) for households headed by a person of Mexican ethnicity, who is married with spouse present, and has at least one child present in the household; the total sample size for the five SW states is 19,674 households (weighted value equal to 2,227,073). The rationale for restricting based on these qualifications is that I want to be sure and exclude any confounding effects that would appear based on the type of household. The overarching argument is that Mexican households are at a disadvantage despite the fact that they reside in married couple households (which tends to offer some protection in White and Black married households). Thus, this allows for an analysis that highlights the effects on poverty of variables such as occupational classification and citizenship status on this population independently.

I next estimate models (Model 2) for households configured in the same way as in Model 1 but which does a Mexican immigrant head; the total sample for the five SW states is 12,421 households (weighted value equal to 1,434,327). Also included in the analyses will be three separate models restricted to White, Black and Asian households. These models include the same dependent and independent variables as Models 1 and 2. They are presented for comparison and should accurately display the similarities/dissimilarities that exist between the different populations regarding the prediction of poverty.

Weighting within samples such as the American Community Survey is of significant issue and will now be discussed. In many instances, IPUMS provides data that are flat, or un-weighted. This indicates that each case in the sample is representative of one case in the population. In the case of weighted samples such as the ACS, it is necessary to assign an applicable weight given that certain persons are overrepresented in the sample and others are underrepresented (Ruggles et al., 2008). Further, the ACS must be weighted to provide reliable and statistically accurate estimates about the population (ACS 2003). The process of weighting itself reflects sample design, adjusts for the effects of non-response, and corrects survey under coverage (ACS 2003). Thus, data users must apply sample weights if they wish to obtain representative statistics of the general population (Ruggles et al., 2008; ACS 2003).

Thus, it is specified by IPUMS that data users weight the extracted data based upon the proper weighting scheme (2008). Data users are offered two weighting options: (1) person weight (PERWT), and (2) household weight (HHWT). Given that this analysis is based upon the head of household, HHWT (the variable used in the weighting calculation) is the applicable choice and gives the number of households in the general population represented by each household in the sample (Ruggles et al., 2008). This weighting scheme retains the original structure provided by the Census Bureau. I use the "svy" commands in STATA to weight each household given that I am using this data to provide nationally representative descriptions.

The ACS data are rich in demographic information and contain full descriptions of employment and migration behavior, among other variables. Below is a Table 4.1 containing the definitions of the dependent and independent variables chosen for analysis in the models. At level-1, I focus mainly on items that have been identified as important in predicting incidence of poverty among Mexican Americans and Mexican immigrants. Of paramount importance (in model 2) is the development of a proxy variable for undocumented status among Mexican immigrants. The following section describes the background and rationale for developing the variables presented as well its contents (see Chapters 5 and 6 for descriptive statistics and variable construction).

4.2 The Development of a Proxy for Undocumented Status

Perhaps one of the more important offerings to be made by this book is the development of a proxy variable for undocumented status. This work was originally developed by Bean et al. (1984) in an attempt to reveal the characteristics associated with undocumented immigrants. Using 1980 census data, they separated the Mexican origin population into four immigrant status groups. These groups included persons who were born in Mexico and who were not citizens in the 1980 census, Mexican-born persons who were deemed to be legal aliens, Mexican-born persons who reported they were naturalized citizens, and native-born persons who reported as Mexican origin (Bean et al., 1984). They are careful to note that

Table 4.1 Definitions of variables: individual level models

	Definition/Coding	Source
Dependent variables		
Extreme poverty	1 = household income at or below 50% of the federal poverty threshold	ACS 2006, constructed using POVERTY variable
100% poverty	1 = household income at or below 100% of the federal poverty threshold	ACS 2006, constructed using POVERTY variable
Low income	1 = household income at or below 200% of the federal poverty threshold	ACS 2006, constructed using POVERTY variable
Relative poverty	1 = household income at or below 50 percent of the state median income	ACS 2006, constructed using HHINCOME variable
Independent variables (Mexican American, Black, White, and Asian samples)		
Sex	1 = male, 0 = female	ACS 2006, based on SEX variable
Education	Educational attainment intervals, ranging from 0 (none) to 21 (Ph.D.)*	ACS 2006, EDUC99 variable
Number of children	Number of own children present in the household; 1–9+	ACS 2006, NCHILD variable
Immigrant	1 = birthplace outside contiguous U.S.	ACS 2006, constructed using BPL variable
Mexican immigrant job	1 = employment in specified job	ACS 2006, constructed using OCC1990
Employment status	1 = unemployed and/or not in the labor force	ACS 2006, constructed using EMPSTAT
Independent variables (Mexican Immigrant Population)		
Citizenship	1 = citizens, including naturalized	ACS 2006, CITZEN variable
Years spent in USA	0–87 (0 = less than 1 year)	ACS 2006, YRSUSA1
Undocumented	1 = undocumented migrant	ACS 2006, constructed using key variables *see next section for full description

* The education intervals were assigned values based on original assignments and median values. For example, those who were coded as 1^{st}–4^{th} grade level were assigned a value of 2.5 on the interval scale and those who had a 9^{th} grade education were assigned a value of 9. See Chapter V for a full description of variable construction.

their work does not provide an exact characterization of undocumented Mexican immigrants; however, their work did yield results that indicated that their first categorization (Mexican-born non-citizens) was more than likely comprised primarily of undocumented Mexican immigrants (Bean et al., 1984). These assertions have been confirmed by Warren and Passel (1987) who found that a majority of the persons in particular status groups were estimated to be undocumented individuals. This result was based on a residual method in which the undocumented population was estimated by subtracting naturalized citizens from the foreign-born population. It is important to note here that the express purpose of the work performed by Bean et al. (1984) was not intended for the creation of a variable to be used in the prediction of socioeconomic outcomes. In fact, they were much more interested in presenting a set of characteristics that typified undocumented individuals and could then be used in the estimation of the undocumented population.

The original work developed by the above-mentioned scholars sets forth a number of characteristics that are likely associated with undocumented status (what they refer to as Category 1). First and foremost, these individuals are clustered in the Mexican-born, non-citizen classification. Next, they observed a very high proportion of individuals in the younger ages (20–29) as well as high sex ratios in this age range in their Category 1. They also posited that undocumented immigrants were much less likely to reside in nuclear family scenarios and observed that often other adults were present in their households. Another very important observation is that of education level and English-language proficiency. They found that a significant delineation existed for those who reported to “No English” or “Speaks English Not Well” among the Category 1 individuals and those who were native-born Mexicans. Additionally, they found significant differences between the native-born Mexicans and foreign-born non-citizens (Category 1) relative to education level. Here they found that a majority of the Category 1 individuals reported to an 8th grade education level or less while very few of the Mexican Americans reported to this level of education. With respect to industry classification, their findings showed that a majority of the Category 1 individuals were concentrated in low status occupations (entry-level) such as construction, food service, and personal services (for females). Interestingly, their findings revealed that a majority of these individuals were concentrated in the manufacturing sector, which they reported as unexpected. Finally, income was used as an indicator of undocumented status as those who reported lower incomes were presumably in this category given their lower amounts of human capital (Bean et al. 1984). Their work has been reinforced by findings of Warren and Passel (1987) which indicate that about two-thirds of the individuals entering the United States post-1975 were undocumented. Taken together, these studies are incredibly helpful in understanding the characteristics of the undocumented population. Though their studies cannot be taken as irrefutable evidence, they have been shown to be as accurate as possible given the data constraints to be faced with such estimates.

My work uses Bean et al. (1984) research as the framework for the development of a more updated version of a proxy variable that allows for an estimation of poverty relative to the undocumented population present in the 2006 ACS data. Given that they were able to successfully identify a majority of the individuals in Category 1 as undocumented, I have used a similar (though more current) combination of variables to produce a proxy variable that may be used in the prediction of poverty. Many of their original indicators have been included and/or updated in this work (see Table 4.2). The sample is initially limited to individuals who reported Mexican as their ethnicity. For the development of the proxy I have first limited those I expect to be undocumented individuals to those who reported birthplace as Mexico (thus leaving only Mexican immigrants). Additionally, I have further restricted these individuals in my sample to non-citizens, or individuals who reported they had not achieved citizenship. Once these restrictions were put into place, I created a combination of variable that were anticipated to be predictors of undocumented status. First, the individuals were restricted to those between the ages of 20 and 29. This is based on the original findings noted above as well as previous research which indicates the increased propensity to migrate in early ages due to better health and greater mobility. Next, the group was restricted to those who reported "No English" or "Does Not Speak English Very Well". Again, this was based on the work of Bean et al. (1984) and the likelihood that undocumented immigrants would have lower levels of English-language proficiency.

The occupation classification has been amended in this work and includes the placement of an individual in a "Mexican immigrant job". Whereas in the original study an industrial distribution was presented, and it was observed that certain categories of immigrants had a greater propensity to fall in particular industries, here I have used a classification scheme that should contain an abundance of undocumented immigrants. This classification is based on the work of Douglas and Saenz (2008) who have created a listing of jobs they have deemed to be, "low-wage, dead-end, and dangerous where workers face tremendous levels of exploitation" (p. 24; see Appendix A). The very nature of such jobs lends itself toward a saturation of undocumented workers given their inability to avoid such circumstances. These

Table 4.2 Definition and construction of undocumented proxy variable

	Definition	Source
Undocumented (contains each of the below-mentioned variables)	1 = undocumented migrant status	ACS 2006
Age	1 = Young age, 20–29	ACS 2006, AGE variable
Birthplace	1 = Birthplace listed as Mexico	ACS 2006, BPL variable
English proficiency	1 = No English or does not speak very well	ACS 2006, NOSPEAK variable
Mexican job	1 = Employed in a Mexican immigrant job	ACS 2006, OCC1990 variable
Years spent in USA	1 = Less than 5 years in US	ACS 2006, YRSUSA1 variable
Education level	1 = Low education level, 0–8th grade education	ACS 2006, EDUC99 variable
Citizenship	1 = Non-citizen	ACS 2006, CITIZEN variable

classifications were based on criteria which specified that there be a ratio of 1.5 or higher (the ratio was calculated based on percentage of Mexican immigrant workers in a particular occupation relative to the percentage of all Mexican immigrant workers) and that a minimum number of workers be present in the industry (Douglas and Saenz 2008). Next, I restricted the group to individuals who reported year of arrival as 5 years or less. This decision was based on the finding that the majority of undocumented immigrants report to having been in the US for less than 5 years (Passel 2005). Finally, I restricted the group to those who reported an education level of 8th grade or less.

It is important to note that though every attempt has been made to create a reliable indicator for undocumented status, this work is certainly flawed in that it can only provide estimations based on previous research and in conjunction with the residual methods currently available. It is also a very restrictive and conservative measure which was chosen for reasons related specifically to this piece. Individuals may have been excluded and in that regard, valuable information may have been lost. Every attempt will be made to provide a proxy variable based in sound research methods.

Chapter 6 contains a review of the variables used to create the undocumented proxy as well as descriptive statistics and the results of logistic regressions for the Mexican immigrant population. In the following section a depiction of the methods used to obtain the results relative to each of the five populations mentioned in the opening remarks of this chapter is presented.

4.3 Individual Level Methodology

In the case of each of the four dependent variables (extreme poverty, 100% poverty, low income, and relative poverty status) the outcome will be binary. In other words, the dependent variable allows only two options. The negative result is typically signified by a zero and a positive result is signified by a one. Accordingly, a positive response to any of the three levels of poverty is coded as a one and a negative response is coded as a zero. The decision to use three binary variables in favor of one ordinal logistic regression which contains three ordered categories derives from the notion the separation of the categories allows for more of a distinction between categories. In other words, much of the distinction present in the three binary variables for absolute poverty would be lost if one were to combine these into one ordered variable. Thus, the usage of binary variables is the more statistically appropriate method in this sense. This methodology is reproduced for each of the four levels of poverty in five models: (1) Mexican American households, (2) Mexican Immigrant households, (3) White households, (4) Black households, and (5) Asian households.

Logistic regressions are employed in order to examine the probability of the specified event occurring. For example, what are the odds that a household will report to any level of poverty when one takes into account the effects of several independent variables? For the purposes of these analyses it is necessary to utilize logistic regression as it allows a model to be constructed in which the predicted probability is within the bounds of one and zero (Long and Freese 2003).

When conceptualizing the dependent variable of being or not being in poverty, I will do so within the context of a latent variable. That is, I will consider that there is an underlying propensity for reporting for being in poverty, and this propensity is unmeasured (see the discussion in Long and Freese 2003). Accordingly, some persons may be closer to the observed state than others, and the latent variable construct allows this to be considered. The observations made are the same as those made in linear regression with the key deviation that the dependent variable, in this case poverty, is unobserved. For example, let us assume that if persons are in poverty they will receive a score of one ($y = 1$) whereas if they are not in poverty they receive a score of zero ($y = 0$). I am estimating the models based on a number of independent variables including educational attainment, labor force participation, and number of children present. Not all Mexican Americans and Mexican immigrants in poverty ($y = 1$) are there with the same certainty. One household may be firmly entrenched in poverty whereas another may be very near to exiting poverty status. In both cases, we observe $y = 1$. The idea of a latent dependent (y^*) variable is that the underlying propensity for poverty generates the observed state. Thus, we cannot observe the propensity directly, however at some point a change in y^* results in a change in what we observe, or in this case whether the household is in poverty (Long and Freese 2003). The formula is provided below:

$$\Pr(y = 1|x) = \Pr(y^* > 0|x)$$

4.4 Individual Level Diagnostics

A number of diagnostics are employed in order to ensure the validity of the logistic regression models presented at the individual level. One of the first issues to be investigated is that of collinearity, or multi-collinearity. This particular issue arises when one or more of the independent variables is/are correlated with each other (Menard 1996). Perfect collinearity occurs when two of the independent variables maintain a perfect correlation with one another, thus making it impossible to obtain an estimate of the regression coefficients separately (Menard 1996). Collinearity is an issue that is found with a fair amount of frequency in regression models. Menard states:

> As collinearity increases among the independent variables, linear and logistic regression coefficients will be unbiased, and as efficient as they can be (given the relationships among the independent variables), but the standard errors for linear and logistic regression coefficients will tend to be large. (1996: 65)

It is possible to diagnose problems of collinearity in logistic regression through the use of the tolerance statistic available through the *vif* command in STATA. A tolerance value of 0.40 for any one independent variable indicates that 40% of its variance is independent of that of all the other independent variables in the equation. I will use a cut-off of 0.4 as my guide. That is, any tolerances of less than 0.4 will raise a "red flag" and cause me to examine the model and perhaps take certain steps to reduce the collinearity. Collinearity is easily detected but few strategies for removing its effects exist (Menard 1996). One option I will follow under the situation of strong collinearity will be to break the model into two separate models where the independent variables that may be correlated are broken apart and analyzed separately.

Once it has been determined that collinearity does not pose a threat within the logistic regression models it is necessary to check for non-normality of the error. It is assumed that the distribution of the error is not normal in logistic regression, but rather that it follows a binomial distribution that approximates a normal distribution in large samples (Menard 1996). It is possible to test for normality by calculating a standardized Pearson residual, which allows for the identification of cases for which the model fits poorly and/or exert a disproportionately large influence on the model parameters. This analysis of residuals and outliers is an important step in assessing the fit of a regression model (Long and Freese 2003). Long and Freese (2003) state the following, "Residuals are the difference between a model's predicted and observed outcome for each observation in the sample. Cases that fit poorly are known as outliers" (p. 123). If these outliers exert a large effect they are then referred to as influential. The command *predict rstd, rs* in STATA allows for the data user to produce a plot of residuals (Long and Freese 2003). This plot may then be inspected for problematic residuals and certain residuals may be identified as warranting further inspection. Additionally, through the use of the STATA command *sum rstd, detail* skewness and kurtosis values are estimated for the error term and may be used to determine whether non-normality is present in the model. These inspections may lead to the discovery of miscoded data or other misspecification issues with the model. The cases should not be discarded but rather inspected closely so as to determine the root cause of their influential exertion upon the model (Long and Freese 2003).

I also need to take into consideration the overall fit of the model. Model fit is the next step taken in order to ensure proper results relative to logistic regression analysis. It is possible to test for "model accuracy" through the use of a specification test which is obtained through the STATA command *linktest*. This is a simple approach to evaluating whether the model provides an adequate description of the data (Vittinghoff 2005). It involves fitting a second model, "using the estimated right-hand side (i.e., the linear predictor) from the previously fitted model as a predictor" (Vittinghoff 2005: 192). Vittinghoff (2005) states:

> We would expect that the Wald test for this predictor (labeled_hat) to be statistically significant if the original model provided a reasonable fit. The model fit by *linktest* also provides the square of this predictor (labeled _hatsq). The Wald test for inclusion of the latter variable is used to evaluate the hypothesis that the model is adequate; that is, the inclusion of the squared linear predictor should not improve the prediction is the original model was adequate. (pp. 192–193).

This test may call for rejection of the model and that an alternate binary model should be considered, or that important predictors have been omitted (Vittinghoff

2005). It does not however, indicate which of these two scenarios may have occurred or which model is preferable.

Other measures to test for model fit include Pseudo R^2 and McKelvey and Zavoina's R^2. Given that I am estimating my models in terms of an unmeasured latent dependent variable, McKelvey and Zavoina's R^2 is the more appropriate measure. It closely approximates the R^2 statistic produced in OLS regression by fitting the linear regression model based on the underlying measured latent variable (Long and Freese 2003). See *Individual Level Methodology* section for a full discussion of the latent variable premise. The Pseudo R^2 statistic ranges from 0 to 1, where a value of 0 is observed when the predictors are completely unrelated to the dependent variable. Hence these values may be used as one of the tools in the diagnosis of problems with model fit or adequacy.

Finally, it is necessary to report the Likelihood Ratio Chi-Square statistic, which is analogous to the F-test in linear regression and provides a measure of global fit of the model. In the case of this statistic larger values are better and indicate that the model is specified properly.

The last diagnostic measure to be taken in this protocol is that of an analysis of influential cases (or patterns). It is possible to test for influential cases through the use of ΔB_j, also known as *dBeta*, developed by D. Pregibon that is analogous to *Cook's D*. Once predicted, the user should evaluate any values that are seriously high, i.e. higher than 1. A graph may then be produced that signifies the existence of outliers. These outliers may then be removed from the model to determine their effect (this is signified by a significant change in inferences upon removal). It is very important to determine whether the outliers are data-errors and if there exclusion significantly impacts the model. If no appreciable change is detected comparing the model with the outliers with the model without the outliers, that is, if no differences in statistical inference are made, it may be determined that the model is satisfactory.

Each of these diagnostics is undertaken in an effort to ensure the highest level of accuracy within the individual level logistic regression results. It is important to note that diagnostics are more art than science (Menard 1996), and they merely point out the potential for error among the models. Hence, the values and cut points listed above are merely presented as "rules of thumb". It is the responsibility of the data user to thoroughly examine results and to provide the most accurate models possible.

4.5 Contextual Level Data

The data obtained for the contextual level data were collected from the Decennial Census 2000,[1] and are based on full counts of the population. The decennial

[1]The decennial census 2000 was the largest peacetime effort in the history of the United States. Information about the 115.9 million housing units and 281.4 million people across the United States are available in many formats and media including the internet and CD-ROM. More information may be obtained at http://www.census.gov

census provides 100% characteristics for several descriptors including race, sex, and Hispanic or Latino origin (Census 2000a). It also provides additional information (provided via the long-form) on 1 in 6 individuals in the population. These characteristics include marital status, educational attainment, labor force status, and many others.

The information used to create the contextual level data set was acquired via Summary File 1 and 3 (SF 1 & 3) using the American Fact Finder. SF 1 focuses primarily on age, sex, and race information and is based on 100% count data. These data are available through individual tables for each state (US Census Bureau 2001a), hence detailed tables were obtained and used as the basis for the statistics presented at the contextual level. SF 3 is the most comprehensive statistical data available on US residents (US Census Bureau 2002) and contains the information obtained from the long-form questionnaire. This summary file provides 484 population tables and 329 housing tables, all of which are released separately for each of the fifty states (US Census Bureau 2002). The file structure is organized hierarchically in the following manner: State, County, County Subdivision, Place (or Place Part), Census Tract, Block Group (US Census Bureau 2002; see Fig. 4.1). Given that the individual level data are based on sample data, it was necessary to aggregate the count information up to a higher level of geography so as to maintain privacy for individuals. As of 2006, the ACS provides population and housing profiles for areas that contain 65,000 or more people. Thus, county information is not yet available at the individual level. In order to allow for a fluid comparison and analysis at both levels it became necessary to utilize the PUMA, or public-use microdata area. The

Fig. 4.1 Census geography. Source: U.S. Census Bureau. Available at: http://www.census.gov/acs/www/guidance_for_data_users/geography/

variable PUMA identifies the geographic area within which a housing unit is located (Ruggles et al., 2008). PUMAs generally follow the boundaries of county groups or single counties, and if they exceed 200,000 persons they are divided into many areas of 100,000+ (Ruggles et al., 2008), thus each of the counties in the Southwest states is housed within PUMAs. It is further necessary to note that the PUMAs are state-dependent and identified based on the STATEFIP code provided in the ACS data.

Once a full delineation of the count data was obtained for each of the counties contained in the Southwest region, it was necessary to determine the geographic level of analysis from which to base the multi-level models. PUMAs allowed for a consistent measure from which comparisons could be drawn; however, in some cases, sufficient sample sizes did not exist (I decided to use a PUMA if it had at least 100 individual-level cases for my analyses). Thus, it became necessary to expand the analysis to the next highest level of geography because not all PUMAs had 100 or more cases for me to use.

Super-PUMAs are geographic areas containing 400,000+ persons and are the next level of geography available in the ACS data. They are unique from state to state, were not used before the year 2000, and do not cross state lines. State governments defined the boundaries for these geographical classifications, thus they should be meaningful for many data users (Ruggles et al., 2008). The geographical groupings are contiguous and often based on combinations of PUMAs. An original count of 126 Super-PUMAs was assembled for the five Southwest states. However, in many cases the boundaries separated large metropolitan areas, for example, Houston (Harris County was split into 7 Super-PUMAs). In these cases the Super-PUMAs were combined to create one massive Super-PUMA grouping. These groupings are referred to as SPUMAs. A second-level data set was constructed based on these data and contains information on 42 SPUMAs, which are based on all five Southwestern states (see Super-PUMA listings in Table 4.3 for detailed data on classifications). In some cases, the Super-PUMAs were collapsed even further (see contents column in Table 4.3 for combinations of PUMAs and Super-PUMAs) with regard to the requirement that each SPUMA contain at least 100 household heads for Model 1 and for Model 2. The combination of PUMAs and Super-PUMAs were made relative to geography and county-level characteristics. Hence, the most logical groupings were created based on where the PUMA was located according to the Super-PUMA boundaries provided by the Census Bureau (see Appendix B for detailed map/boundary files of the five Southwest states).

The independent variables that have been created at level-2 were constructed based on count data from the 2000 decennial census and are relative, county-weighted percentages for poverty, Mexican Americans, Hispanic immigrants, each of the nine major industries set forth by the US Census Bureau, and metropolitan status (see Table 4.4 for variable names and descriptions). The weighted values were derived by inputting count data for each county contained in any given SPUMA. Those values were then summed and each county was assigned a proportion of the entire SPUMA. Each proportion was multiplied by the county's value for the independent variables. For example, any given county was assigned a proportion which

Table 4.3 Final/combined Super-PUMA listing (SPUMAS)

SPUMA	State	Contents	Name
4150	AZ	4100, 4200	Flagstaff-Yuma-Mesa
4300	AZ	4301–4306	Phoenix
4400	AZ	4401–4402	Tucson
6015	CA	6010, 6020, 6030	N California
6045	CA	6040, 6050	Sonoma/Napa
6075	CA	6070, 6080, (6060, 6071, 6072 combined to form 6070)	Sacramento
6090	CA	6090	Merced
6100	CA	6100	Stockton-Lodi
6110	CA	6110	Modesto
6120	CA	6121–6122	Oakland/San Jose
6135	CA	6130, 6140, 6150, (6151–6153 combined to form 6150)	San Francisco-San Mateo-Berkeley
6160	CA	6161–6163	Santa Clara
6170	CA	6170	Salinas
6180	CA	6180	Fresno
6190	CA	6190	Visalia-Tulare-Porterville
6200	CA	6201–6203	San Bernardino
6210	CA	6210	Bakersfield
6220	CA	6220	Santa Barbara
6230	CA	6230	Ventura
6300	CA	6301–6307, 6401–6411	Los Angeles
6500	CA	6501–6505	Orange
6600	CA	6601–6603	Riverside/Imperial
6700	CA	6701–6705	San Diego
8150	CO	8100, 8104 (8101–8103 combined to form 8100)	Rural Colorado
8200	CO	8201–8205	Denver Area
35250	NM	35200, 35300	Santa Fe-Albuquerque
35450	NM	35100, 35400	Las Cruces-Taos
48015	TX	48010, 48020	Lubbock-Amarillo
48035	TX	48030, 48040	Sherman-Longview
48065	TX	48050, 48060, 48070	East Texas
48110	TX	48111–48113	Fort Worth
48115	TX	48080, 48090, 48100 (48101–104 combined to form 100)	Dallas-Denton-Collin
48125	TX	48120, 48130	Abilene-Odessa-Midland
48140	TX	48140	El Paso
48155	TX	48150, 48160	Central Texas
48170	TX	48170	N Houston Subrub (Conroe)
48185	TX	48180, 48190 (48181–48187 combined to form 48180)	Houston-Galveston
48225	TX	48200, 48210, 48220, (48221–221 combined to form 220)	Austin-Bastrop
48230	TX	48231–233	San Antonio
48240	TX	48240	Laredo
48255	TX	48250, 48260	McAllen-Corpus
48270	TX	48270	Brownsville-Harlingen

Table 4.4 Definitions of variables: contextual level models

	Definition/Coding	Source
Dependent variables		
Extreme poverty	1 = household income at or below 50% of the federal poverty threshold	ACS 2006, constructed using POVERTY variable
100% Poverty	1 = household income at or below 100% of the federal poverty threshold	ACS 2006, constructed using POVERTY variable
Low income	1 = household income at or below 200% of the federal poverty threshold	ACS 2006, constructed using POVERTY variable
Independent variables		
Poverty percentage	% value, 0.00 to 100.00	Census 2000: SF 3; Table QT-P34
Mexican ethnicity	% value, 0.00 to 100.00	Census 2000, SF 1; Table QT-P3
Immigrant population	% value, 0.00 to 100.00	Census 2000, SF 3; Table QT-P14
Agricultural industry	% value, 0.00 to 100.00	Census 2000, SF 3; Table QT-P29
F.I.R.E. industry	% value, 0.00 to 100.00	Census 2000, SF 3; Table QT-P29
Construction industry	% value, 0.00 to 100.00	Census 2000, SF 3; Table QT-P29
Transportation industry	% value, 0.00 to 100.00	Census 2000, SF 3; Table QT-P29
Information industry	% value, 0.00 to 100.00	Census 2000, SF 3; Table QT-P29
Professional industry	% value, 0.00 to 100.00	Census 2000, SF 3; Table QT-P29
Educational industry	% value, 0.00 to 100.00	Census 2000, SF 3; Table QT-P29
Service industry	% value, 0.00 to 100.00	Census 2000, SF 3; Table QT-P29
Public administration industry	% value, 0.00 to 100.00	Census 2000, SF 3; Table QT-P29
Metropolitan status	% value, 0.00 to 100.00	Census 2000, calculated based on MSA's
M1 measure	0.00 to 0.8889	Computed based on distribution of workers in each industry

was then multiplied by that county's poverty percentage. Finally, each of these values was summed to create a weighted poverty percentage for each SPUMA (and so on with the remainder of the independent variables). It is necessary to use this method, i.e. a relative method, rather than an absolute measure in light of the fact that the issue of interest is that of the relative percentage of poverty. If one were to use an absolute measure, the variation between counts would be lost.

4.6 Contextual Level Methodology

Sociologists are very familiar with the idea that group contexts play a significant role in behavior. I posit here that individual households are nested within SPUMAs (geographically based clusters of counties), and that the propensity for reporting to any level of poverty is affected not only by individual characteristics but also those of the context. A variety of models have been developed as a way to understand social processes at more than one level of analysis (DiPrete and Forristal 1994). These authors state the following:

> Multi-level models explain micro-level outcomes in two ways: (i) by showing that parameters of models specified at the micro level – where micro level covariates are used to explain micro level outcomes – are a function of context, and (ii) by showing that this micro-macro relationship can be expressed in terms of characteristics of the context, which take the form of macro level variables. (DiPrete and Forristal 1994: 333).

Statistical developments in the creation of multi-level models have advanced through a more sophisticated treatment of the error structure in the models (DiPrete and Forristal 1994). These new models specify the regression coefficients as random effects which allow for a more complex error structure and in turn an analysis of the within-context and between context variance for the micro-level outcome.

Multilevel models are used as a method of understanding the effect of contextual level characteristics, in this case characteristics of the SPUMA, on individual level outcomes. Figure 4.2 below presents a simple display of the possible relationships to be discovered between contexts and individuals (Anderton and Sellers 1989). In this model, line *b* represents the effects of individual level characteristics on individual outcomes ($o = bc$). Line B represents the effects of contextual characteristics on contextual outcomes ($O = BC$).

The more accurate assertion based on macro-effects in relation to their consistency with individual level models maintains the following conditions:

> (1) both models are appropriately specified in their linear format, and aggregating functions between individual and contextual measures are also linear (e.g., means, proportions); (2)

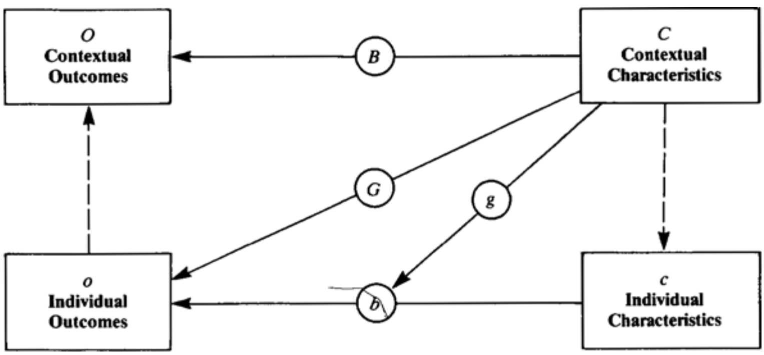

Fig. 4.2 Multilevel models. Source: Anderton and Sellers (1989)

> individuals are homogeneous in response to changes in the independent variables; and (3) individuals are grouped randomly or according to one of the included individual-level independent variables into contexts in such a fashion that no aggregation biases arise. (Anderton and Sellers 1989: 106)

Line G ($o = GC$) addresses the variations in individual-level outcomes based on contextual characteristics (Anderton and Sellers 1989). It is referred to as a conditional probability model which allows for the estimation of a conditional probability in the event of a given context (Anderton and Sellers 1989). For example, what is the likelihood that a household will report poverty status if they are located in an area that is heavily saturated in the agricultural industry? Here the data user should be careful in ensuring that the proper contexts have been specified. This is best accomplished by selecting contexts which maximize heterogeneity among homogeneity between contexts (Anderton and Sellers 1989). Additionally, it is important to note that though contexts may produce a change in outcome they are not thought to exert a direct causal influence. The combination of both contextual and individual effects is represented by lines b and G and is referred to as the contextual-effects model ($o = bc + GC$). In this particular model, we are able to observe the effects of contextual characteristics on individual outcomes (Anderton and Sellers 1989). Model misspecification should be an issue of importance as is collinearity. As stated in the diagnostics section, all individual models will be evaluated and issues of collinearity may be addressed through the usage of more broadly defined contexts, i.e. SPUMAs. Finally, lines b and g ($o = bc;\ b = g(C)$) represent the notion that an interaction effect may be observed as contextual effects, "alter individual-level relationships within contexts rather than directly affecting individual behavior" (Anderton and Sellers 1989: 109). This is a very helpful aspect of the multi-level model as it allows the data user to evaluate the effect of the context on the slope of the relationship between individual-level effects and their outcomes.

In the case of a binary outcome as exampled in this work the most effective method for such a case is the hierarchical generalized linear model (HGLM), also known as generalized linear mixed models, or generalized linear models with random effects (Raudenbush and Bryk 2002). Raudenbush and Bryk state the following, "[HGLMs] offer a coherent modeling framework for multilevel data with nonlinear structural models . . ." (2002: 292).

A number of issues are present in the usage of a standard individual level model in the case of a binary outcome, which requires the usage of an HGLM. These include the fact that: (1) there are no restrictions on the standard HLM model which allows for the ability to take on any value, rather than remaining within the constraints of 0 and 1 as necessitated by this analysis, (2) the outcome may only take on one of two values (0 or 1) and thus cannot be normally distributed, and (3) the level-1 random effect cannot have homogeneous variance (Raudenbush and Bryk 2002). This more appropriate framework specifies that the prediction of Y, in this case poverty status, be constrained to the bounds of 0 and 1. The HLM software allows for such constraints through the usage of their Bernoulli model.

The first step in the construction of a typical hierarchical generalized linear model involves the estimation of a one-way ANOVA. The one-way ANOVA allows the data user to examine the amount of variance present in the outcome variable at both the individual and contextual levels by generating the intra-class correlation for the model; and correspondingly, whether the model warrants the necessity of proceeding (Raudenbush and Bryk 2002). The intra-class correlation may be computed in terms of a latent variable accordingly:

> $\rho = \tau_{00}/(\tau_{00} + \pi^2/3)$; in which τ_{00} is the level-2 variance component and the level-1 variance component is the constant $\pi^2/3$. In order to estimate the variation between SPUMAs in poverty, it is necessary to estimate a model with no predictors at either of the two levels. (Raudenbush and Bryk 2002)

The level-1 structural model is

$$\eta_{ij} = n \log\left[\phi_{ij}/1 - \phi_{ij}\right] = \beta_{0j}$$

The level-2 structural model is

$$\beta_{0j} = \gamma_{00} + u_{0j}, u_{0j} \sim N(0, \tau_{00})$$

Here, γ_{00} is the average log-odds of poverty across SPUMAs, while τ_{00} is the variance between SPUMAs in SPUMA average log-odds of poverty (Raudenbush and Bryk 2002). In the level-1 model, n_{ij} is the predicted log-odds of success, or the logit.

The analysis of poverty at both the individual and contextual level allows for the data user to determine if a statistically significant amount of the variation in poverty occurs between contexts, i.e. SPUMAs, which would indicate that the context is a significant determinant of the outcome (DiPrete and Forristal 1994). Usually, it will be found that most of the variation occurs within households indicating that individual characteristics are much more potent in determining the outcome, but that a significant amount of the variation occurs at level-2. If there were not a significant amount of variation at level-2, then it would not be appropriate to estimate a multilevel model.

Having completed my discussion of the data and methods to be used in this book, I turn next to the results of my analysis. The following chapters explore individual level outcomes (Chapters 5 and 6) as well as the outcomes observed from the multilevel models (Chapter 7).

Chapter 5
Individual Level Results: Mexican Americans

This chapter presents the findings associated with the individual level outcomes for Mexican Americans. The next chapter will present similar results for Mexican immigrants. Several models have been developed; as noted, this chapter deals specifically with those estimated for the Mexican American population in the Southwest United States. Hypotheses are presented in reference to this population along with a discussion of the populations selected for comparison, namely, Blacks, Whites, and Asians. Summary statistics are presented for each population as are the details associated with variable construction, and operationalization, for the models. A series of diagnostics have been performed and are presented in reference to the logistic regressions performed for each of the above-mentioned populations. The chapter concludes with tables that represent the findings of the logistic regressions as well as a discussion of their implications.

5.1 Hypotheses, General and Specific

Chapter 2 detailed the relevant independent variables associated with poverty at any level, i.e. extreme poverty, 100% poverty, low income, or relative poverty. A model has been developed which should point out the salience of immigration status among other factors on the incidence of poverty. In this model (which includes only those who reported Mexican ethnicity, are married, and have at least one child present in the house), six variables have been selected including number of children, immigration status, employment in a "Mexican immigrant" job (Douglas and Saenz 2008), level of education, sex, and employment status. It is expected that positive relationships with poverty at any level will be observed for increased numbers of children, immigration status, and employment in an immigrant job. These hypothesized relationships are based on previous findings identified in the literature relative to this population. For example, Hispanics experience rates of poverty at nearly double those of their White counterparts (Mosisa 2003), and the overall wealth of Hispanic households is around one-tenth that of White households (Kochhar 2004). Additionally, immigrants have been shown to be significantly poorer than their native-born counterparts (Kochhar 2004). Increased numbers of children have

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also been shown to increase rates of poverty among households. The US Department of Labor reported in 2001 that families with children experience much higher rates of poverty than those without, at rates of 21.3 and 5.2% respectively (Mosisa 2003). Finally, employment in a Mexican immigrant job should significantly increase the likelihood of poverty as these jobs mainly because these are low-wage and low-status occupations (Douglas and Saenz 2008). Given that Hispanics are more often employed in such occupations it is expected that a significant positive relationship will be observed.

Negative relationships with poverty are expected for level of education, households headed by males, and employment status. Education has been identified as a key predictor of poverty status; for instance, those with college educations fare significantly better than those without. However, it is important to note that even those Hispanic households whose head is college educated experience a significant disparity relative to college educated White heads of households whose net worth is nearly three times higher ($161,613 versus $58,145) (Kochhar 2004). Hence, it is expected that education should vary negatively with poverty, but the insulation education offers other ethnic groups may not be observed with as much significance among Mexican Americans. Employment status has also been shown to lower the risk of poverty. In 2001, the majority of those in poverty did not participate in the labor force (about 59%) (US Department of Labor 2003). Thus, those who are employed and/or members of the labor force should experience some protection from poverty relative to those who are not employed. Finally, households headed by males experience poverty at rates lower than those headed by females (US Department of Labor 2003), and it is expected that the males in the sample will experience this same protection.

5.2 Operationalization and Construction of Variables

Four dependent variables based on the poverty categorizations introduced in preceding sections will be modeled in accordance with the model mentioned above (specifically, Model 1 refers to households whose head reports Mexican ethnicity, married with at least one child present). The dependent variables for each of the models will be labeled as follows: (1) extreme poverty, (2) 100% poverty, (3) low-income, and (4) relative poverty. These will be dummy variables, coded 1 if yes. It has been determined that the analysis of these particular populations should make very clear the relationship between immigrant status and incidence of poverty with no outside influences to confound the result.

The logistic regressions will include several independent variables of interest. The variables of interest for this particular study will be operationalized as follows in the first model: X1 is a dichotomous variable for sex where 1 represents male and 0 represents female. X2 is an interval level variable for years of education ranging from no school (0 years) to doctorate degree (21 years). This variable is based on the household head's highest level of educational attainment. It refers to the following levels: (0) no school, (2.5) 1st–4th grade, (6.5) 5–8th grade, (9) 9th grade, (10) 10th grade, (11) 11th grade, (12) 12th grade – no diploma, (12) high school diploma or GED, (14) some college, no degree, (14) associate degree, (16) bachelor's degree, (18) master's degree, (18) professional degree, and (21) doctorate degree. All persons for whom the variable did not apply to were excluded from the final sample. X3 is an interval level variable for number of children present in the household ranging from 1 to 9 or more (those with no children present were excluded from the sample). This variable counts the number of own children residing with the household head; it also includes step-children and adopted children. X4 is a dichotomous variable representing migration status with one being equal to those who are immigrants (indicated birthplace as Mexico) and 0 equal to all other responses. X5 is a dichotomous variable for "Mexican immigrant" job with 1 being equal to those who reported being employed in an occupation designated as such and 0 equal to all others. This variable was constructed based upon the work performed by Douglas and Saenz (2008) and represents those jobs that are low-wage and low-status as well as highly likely to be saturated with Mexican immigrants (see Appendix A). X6 is a dichotomous variable representing unemployment status where 1 represents individuals who are unemployed and/or not members of the labor force and 0 represents those who are employed or members of the labor force. This variable is based upon the employment status variable in the ACS which refers to the whether the respondent was a part of the labor force, working or seeking work. The constructed variable combines those who are unemployed and/or not in the labor force into one category, denoted by a value of 1.

5.3 Summary Statistics and Discussion: Mexican American Households

The following paragraph details the demographic characteristics of the extracted sample. Each of the variables was selected based on indications from prior research as well as their perceived level of relevance to incidence of poverty (in any form). The results are listed for Mexican households in the Southwestern United States (Arizona, California, Colorado, New Mexico, and Texas), in which the head is married with spouse present, of Mexican ethnicity, and with at least one child present. The total sample size for this population is 19,674. Here, each of the categories of poverty is detailed, as are the frequencies within each of the independent variables (see Table 5.1).

The table displayed presents the categories associated with the independent variables of interest and provides the rates of poverty within each of those categories. For instance, among those reporting a 5th–8th grade level of education, the rate of low income status was 64.74%. Overall, the rate of extreme poverty was 4.01, 17.21% of the sample fell into the 100% poverty threshold or below, and 49.58% fell into the low-income category. In comparison, the relative rate of poverty for Mexican Americans was 21.39%. Thus, we observe that as expected, the rate of relative poverty is somewhat higher than that for the standard poverty threshold. The most common response for education of the sample of Mexican households

Table 5.1 Poverty status for Mexican American households, 2006

Poverty status for Mexican American households by sex, level of education, number of children, immigration status, and employment, 2006

Characteristic	Total	Extreme poverty (%)	100% poverty (%)	Low income (%)	Relative poverty (%)
	19,674	4.01	17.21	49.58	21.39
Sex					
Male	14,070	3.48	15.64	47.5	21.15
Female	5,604	4.28	17.15	45.91	21.98
Education					
None	586	5.63	22.87	60.24	29.69
1st-4th	995	6.63	24.32	64.42	30.95
5th-8th	3,710	5.31	24.96	64.74	31.02
9th	1,370	5.04	24.53	65.91	32.12
10th	638	5.64	23.82	59.09	28.21
11th	708	5.51	22.18	59.46	28.95
12th/HS Grad/GED	5,720	3.53	14.84	47.26	21
Some College/Assoc.	4,056	1.68	7.27	28.43	10.8
Bachelor's	1,321	1.14	3.79	17.64	6.43
Master's/Prof	530	0.75	3.77	12.08	4.53
Doctorate	40	2.5	2.5	15	5
Number of children					
1	5,534	2.08	9.09	33.59	20.38
2	6,948	3.22	14.0	43.05	19.96
3	4,752	4.17	19.47	56.48	22.16
4	1,753	6.56	28.98	68.8	26.007
5	475	9.47	33.68	71.37	26.32
6	149	18.79	43.62	83.89	33.56
7+	63	7.94	38.1	82.54	12.7
Mexican immigrant					
Native-born	7,552	2.41	8.74	29.29	12.67
Immigrant	12,122	4.52	20.64	58.11	26.82
Employed in Mexican immigrant job					
Employed in	6,029	4.96	23.69	64.79	30.78
Not employed in	13,645	3.16	12.71	39.21	17.24
Unemployment status					
Employed	15,277	2.28	12.84	43.27	17.62
Unemployed	4,397	8.66	27.31	60.15	34.48

was that of 12th grade and/or a high school diploma or GED at a percentage of 29.07% (5,720 household heads); with those reporting some college and/or an associate's degree close behind at 20.6% (4,056 household heads). Additionally, the average level of education was a value of 10.60 (which is in the range of 10th–11th grade). The modal response for number of children present was two at a percentage of 35.32 (6,948 households), and among those households reporting 2 children the rates of poverty were 3.22, 14.06, 43.05, and 19.96 for extreme, 100%, low income, and relative poverty, respectively. Immigrants made up 63.06% (12,122) of the sample of Mexican households. The percentage of those who were employed in an occupation deemed to be a Mexican immigrant job, or low level job, was 31.99 (6,029 household heads). Finally, 21.21% of household heads reported to being unemployed and/or not in the labor force.

5.4 Summary Statistics and Discussion: White, Black, and Asian Households

Tables are also presented for each of the reference sets of households, i.e. Whites, Blacks and Asians. These are provided in an effort to display the differences and/or similarities observed between the populations. Tables 5.2, 5.3 and 5.4 contain descriptive information for White, Black, and Asian households and present each of their rates of poverty. The descriptive statistics are limited to the highest frequencies observed among the selected independent variables for purposes of comparison. Also, these samples are each restricted based on the same characteristics of those of the Mexican households, namely, married with spouse present, at least one child present in the household and report to the corresponding ethnicity (Hispanics are excluded from each of these samples).

Table 5.2 Poverty status for white households, 2006

Descriptive statistics for white households, 2006					
Characteristic	Total	Extreme poverty	100% poverty	Low income (%)	Relative poverty (%)
White (non-Hispanic)	39,689	0.89	2.78	10.92	4.52
Sex					
Male	28,373	0.78	2.45	10.00	4.00
Female	11,316	1.17	3.61	13.23	5.81
Education (modal response)					
Some College/Assoc.	12,977	0.91	2.67	12.16	4.51
Number of children (modal response)					
1 child (41.5%)	16,464	0.67	2.16	8.23	5.02
Immigrant status					
Native-born	36,400	0.80	2.55	10.60	4.24
Foreign-born	3,289	1.79	5.29	14.47	7.54
Mexican immigrant job					
Employed in	2,201	0.82	7.04	26.44	11.54
Not employed in	37,488	1.95	2.53	10.01	4.10
Employment status					
Employed	33,222	0.43	1.69	8.42	2.90
Unemployed	6,467	3.22	8.41	23.75	12.79

Table 5.3 Poverty status for black households, 2006

Descriptive statistics for black households, 2006					
Characteristic	Total	Extreme poverty (%)	100% poverty (%)	Low income (%)	Relative poverty (%)
Black (non-Hispanic)	3,121	1.89	6.25	22.27	9.48
Sex					
Male	2.141	1.35	5.56	20.50	8.69
Female	980	3.06	7.76	26.12	11.22
Education (modal response)					
Some College/Assoc. (39.2%)	1,222	2.05	5.65	20.95	8.51
Number of children (modal response)					
1 child (42.9%)	1,339	0.97	4.33	16.13	9.26
Immigrant status					
Native-born	2,709	1.81	5.50	20.60	8.53
Foreign-born	412	2.43	11.17	33.25	15.78
Mexican immigrant job					
Employed in	295	4.07	11.19	45.08	18.31
Not employed in	2,826	1.66	5.73	19.89	8.56
Employment status					
Employed	2,437	0.82	3.61	17.03	5.79
Unemployed	684	5.70	15.64	40.94	22.66

It was expected that both Whites and Asians would display poverty rates significantly lower than those of their Hispanic counterparts. For instance, White households experienced absolute poverty at rates of 0.89, 2.78, and 10.92%, and their rate of relative poverty was 4.52%. Additionally, Asian household's rates were 1.82, 5.35, and 17.32% for absolute poverty, and 8.5% for relative poverty. In comparison, Mexican households had significantly higher rates in each category at 4.01, 17.21, and 49.58% in absolute poverty, and 21.39% in relative poverty. It is interesting to note that the Mexican American households experienced poverty at rates approximately four times higher than Whites and more than three times higher than Asian households.

It was further expected that Blacks should experience similar rates of poverty to Hispanics. In the case of this data, the Black households are most similar to Mexican American households, though their rates are still somewhat lower at 1.89, 6.25, 22.27% in absolute poverty, and 9.48% in relative poverty. The preliminary findings support the assertion that both Whites and Asians display significantly lower rates of poverty in each of the three classifications. However, Blacks also maintain rates well below those of Mexican households. It is assumed that this protection is afforded given the restraints placed upon the sample populations, i.e. married couples with spouse present. Furthermore, the Black households' mean education

Table 5.4 Poverty status for Asian households, 2006

Descriptive statistics for asian households, 2006

Characteristic	Total	Extreme poverty (%)	100% poverty (%)	Low income (%)	Relative poverty (%)
Asian households	7,764	1.82	5.35	17.32	8.50
Sex					
Male	5,984	1.77	5.38	17.26	8.66
Female	1,780	1.97	5.22	17.53	7.98
Education (modal response)					
Bachelor's (32%)	2,496	0.96	2.44	9.62	4.29
Number of children (modal response)					
2 children (42.6%)	3,304	1.82	4.81	15.80	7.29
Immigrant status					
Native-born	913	1.10	2.30	8.32	3.83
Foreign-born	6,851	1.91	5.75	18.52	9.12
Mexican immigrant job					
Employed in	655	3.36	13.44	40.15	20.76
Not employed in	7,109	1.67	4.60	15.22	7.37
Employment status					
Employed	6,229	0.96	3.56	13.23	5.70
Unemployed	1,535	5.28	12.57	33.94	19.87

level is well above that of Mexican households at 14.00 (some college/associate's degree) versus 10.60 (a little more than 10th grade). Certainly this may play a role in the divergent rates of poverty for these two groups. Overall, these findings are striking given the reports found in the literature that Blacks maintain similar poverty rates. They also underscore the importance of Mexican ethnicity and type of occupation, i.e. employment in a "Mexican immigrant job" in determining poverty status. One can easily spot the discrepancies in rates when comparing those of Whites and Mexican Americans. Hence, the overall goal of this book is to point out that even after accounting for the protection afforded by having a spouse present, among other restrictions, the Mexican population remains significantly disadvantaged. The following paragraphs discuss the logistic regression equations estimated for each of the above-mentioned population and allow for a more in-depth analysis of this issue.

5.5 Logistic Regression Diagnostics

I have subjected each of my micro-models, i.e., those for Mexican Americans, for each of the four poverty outcomes, namely extreme poverty, 100% poverty, low income, and relative poverty to a series of diagnostics. The following discusses the findings associated with such diagnostics and confirms that the models are specified properly (for a full discussion of diagnostics see Chapter 4).

Model 1 depicts Mexican American households in extreme poverty. A series of diagnostics were performed including tests for collinearity, non-normality, and influential cases. After an investigation of each of these issues, none of the results indicated the need for re-specification of the model.

Model 2 represents Mexican American households in 100% poverty. The same series of diagnostics have been estimated for this model and indicate the following. No presence of collinearity is detected as each tolerance is well above 0.4; here, the lowest value is 0.74. Furthermore, no high zero-order correlations are evidenced. As for non-normality, the residuals were plotted and show no evidence of this. The skewness and kurtosis scores are also well within normal range and indicate no presence of problematic issues in this regard.

Model 3 represents Mexican American households in the low income classification (200% poverty). As performed above, the model has been checked for collinearity and none was detected. The lowest tolerance present in this model is 0.74. Non-normality is the next issue to be investigated through the evaluation of skewness and kurtosis and a plot of the residuals. The values obtained indicate no problems with non-normality. The final diagnostics are in reference to model adequacy, or fit and influential cases or patterns. Reasonable fit is indicated if by statistical significance for the z-test of the predictor, as is the case here.

Model 4 represents Mexican American households in relative poverty. The model was checked for collinearity and as above, none was detected (the lowest tolerance observed was 0.75). In addition, no high zero-order correlations were observed. With reference to non-normality, the residuals were plotted and there is no evidence of this issue. The skewness and kurtosis scores are within acceptable range and indicate no problem with non-normality. Model fit or adequacy is the last issue to be checked. Reasonable fit is indicated by a statistically significant z-test as is the case here.

5.6 Logistic Regression Results

As stated above, the importance of Mexican ethnicity is one of the underlying motivations for the analyses undertaken in this book. The following set of models are based specifically on the Mexican American population in the Southwestern United States, i.e. Arizona, California, Colorado, New Mexico, and Texas, and offer results relative to the odds of being in extreme poverty, 100% poverty, low income, and relative poverty. They have been analyzed for issues such as non-normality or significant departures from linearity and no such issues are evidenced. Odds ratios are presented, as are the standardized values so that the reader may be able to understand the effects of each of the independent variables relative to one another (see Table 5.5). In other words, one can use the semi-standardized coefficients across the X variables to assess how relatively important each of the independent variables is on the dependent variable. Logistic regression results are later presented on the comparison populations in Tables 5.6, 5.7, and 5.8.

5.7 Results: Mexican American Households

Table 5.5 reports some of the results from the logistic regressions for the sample based on Mexican headed households. Column 1 presents the results expressed as odds ratios and standardized values predicting extreme poverty; Column 2, 100% poverty level (poverty threshold); Column 3, low-income classification; and Column 4 represents relative poverty. The results in Column 1 (all findings for this model are significant at the 0.05 level with the exception of the variable for Mexican immigrant status, which is significant at the 0.1 level) indicate that other things being equal, the odds of being in extreme poverty are 29.9% lower for male heads than for female heads. For each additional level of education obtained, all else equal, the odds of being in extreme poverty are decreased by 4.5%. Additionally, a 40.2% increase in the odds of being in extreme poverty is experienced with each additional child. The odds of being in extreme poverty are 24.3% higher for immigrants than those who are native-born, and 40.0% higher for those employed in a Mexican immigrant job, all else equal. Finally, other things equal, the odds of being in extreme poverty are nearly 4 times higher (359.7%) for those who are unemployed and/or not members of the labor force. These findings are certainly supportive of the original hypotheses and indicate that employment status and number of children present exert a

Table 5.5 Logistic regression results: Mexican American households

Logistic regression results: Mexican American households, (presented in odds ratios and semi-standardized logit coefficients N = 19,674)

Model 1	Extreme poverty odds ratio b^{*L} *(x)*	100% poverty odds ratio b^{*L} *(x)*	Low income odds ratio b^{*L} *(x)*	Relative poverty odds ratio b^{*L} *(x)*
Sex	0.7014	0.9111*	0.9076	0.8908
	–0.1610	*–0.0423*	*–0.0440*	*–0.0525*
Education	0.9546	0.9470	0.9261	0.9500
	–0.1835	*–0.2151*	*–0.0551*	*–0.2026*
No. of children	1.4022	1.4413	1.5006	1.0172**
	0.3748	*0.4053*	*0.4499*	*0.0189*
Immigrant	1.2433*	1.7108	1.9344	1.7764
	0.1051	*0.2592*	*0.3185*	*0.2773*
Mexican immigrant job	1.4002	1.8168	2.1498	1.7856
	0.1570	*0.2785*	*0.3570*	*0.2704*
Unemployment	4.5969	3.1196	2.3848	2.7808
	0.6237	*0.8620*	*0.3554*	*0.4181*
Constant	–3.8874	–2.7041	–0.8435	–1.4495
McKelvey & Zavoina's R^2	0.179	0.189	0.239	0.129

All values significant at 0.05 or above
*Significant at 0.1
**Not Significant
Results are weighted and were obtained via "sv" using HHWT

heavy influence on the results; though the strength of employment status exerts the most significant influence, as indicated by the semi-standardized logit coefficient of 0.6237.

Column 2 (Model 1) represents the findings associated with the 100% poverty classification. All variables are significant at the 0.00 level with the exception of the variable for sex which is significant at the 0.1 level. Within this level of poverty, the odds of males being in poverty are 8.9% lower than for females, all else equal. Each additional level of education obtained coincides with a 5.3% decrease in the odds in being in 100% poverty, and each additional child results in a 44.1% increase in the odds of poverty, other things equal. Furthermore, the odds of being in poverty are about three-quarters (71.1%) higher for Mexican immigrants, and a little more than three-quarters (81.7%) higher for those employed in Mexican immigrant jobs than those who are not, all else equal. Finally, the odds of poverty are increased more than 2 times (212%) for those who are unemployed and/or not members of the labor force, other things equal. The relative strength of the variables may be assessed according to the $b^{*L}(x)$ values and indicates that unemployment status and number of children present exert the most significant influence (followed by employment in a Mexican immigrant job) on the 100% poverty outcome.

Column 3 (Model 1) represents the findings associated with the low-income classification. All variables were significant at the 0.05 level, performed as expected, and it is this model in particular that highlights the importance of employment in a Mexican immigrant job as a predictor of low income status. The odds of being low income were 9.2% lower for male heads than female heads, and were 93.4% higher for Mexican immigrants compared to non-immigrants, other things equal. For each additional level of education, all else equal, a 7.4% reduction in odds of low income status was experienced. For each additional child, all else equal, a 50.1 increase in odds of low income status was observed. Lastly, the odds of being in the low income classification were increased by over 100% (115) for those employed in a Mexican immigrant job and 138.5% for those who were unemployed and/or not members of the labor force, all else equal. As for the relative strength of these effects, this model indicates that education, number of children, employment in a Mexican immigrant job, immigration status, and unemployment all exerted a hefty influence on the low income classification outcome.

Column 4 (Model 1) displays the findings associated with relative poverty status. All variables were significant at the 0.01 level with the exception of the variable for number of children, which was not significant. For those in relative poverty, unemployment exerted the strongest influence, followed closely by immigrant status and employment in a Mexican immigrant job. The odds of being in relative poverty were 10.9% lower for males versus females, 77.6% higher for Mexican immigrants, 78.6% higher for those employed in a Mexican immigrant job, and nearly two times higher (178%) for those who were unemployed, all else equal. Additionally, and other things equal, the odds of being in relative poverty were decreased by 5% with each additional increase in level of education.

5.8 Discussion

Overall, the results of each of the four models confirmed my expectations with respect to the effects of various indicators on the incidence of poverty. Across the various levels of poverty, we see that many of the variables performed in a similar manner. For example, unemployment status exerted a very strong and significant influence on each of the poverty outcomes. In each of the models, immigrant status was significant and with each succession in level of poverty the odds were increased. Certainly, one of the main goals of this work was to highlight the importance on immigrant status on the risk of poverty and such findings serve to reinforce the notion that Mexican immigrants in particular are at a disadvantage with respect to poverty status.

Males were less likely to be in poverty in each of the four scenarios, and level of education slightly decreased the odds of poverty across models. With respect to low income status in particular, it is noteworthy that employment in a Mexican immigrant job, Mexican immigrant status, and unemployment status exerted similar influence on the dependent variable. Additionally, level of education and gender exerted relatively small effects. This certainly highlights the effects of labor market effects on the incidence of poverty for this population. Such findings confirm the effects of labor-related variables and furthermore, serve to support my initial assertions that Mexican Americans are at a considerable disadvantage even while controlling for family structure,[1] i.e. these models only considered married couple households with spouse present.

5.9 Results: White, Black, and Asian Households

Certainly it is necessary to gauge the effects of the same variables on various populations in order to gain a better understanding of the differences across racial groups. Let us now evaluate the models for the comparison populations (Tables 5.6, 5.7, and 5.8). Each of their logistic regression results are presented below in the same format as that presented for Mexican American households and with the same restrictions in place. I first present the model results for White households, and then for Blacks, and then for Asian households. Again, the findings are as expected and support the hypotheses.

I briefly discuss here the implications associated with the findings for the comparison populations. As stated above, the summary statistics revealed that there is a vast discrepancy between poverty outcomes for White and Mexican households. The more shocking observation is that Black households are significantly better off

[1] The presence of no additional earners in the household could conceivably be used as an argument as to why the poverty rates among Mexican Americans remain high despite maintaining full-time employment. However, upon inspection of the sample data, it was found that fully 64% of the households had 2 wage earners present. This serves to further confirm the importance of wage inequality for this population.

Table 5.6 Logistic regression results: White households

Logistic regression results: White households, (presented in odds ratios and semi-standardized logit coefficients N = 39,689)

Model 1	Extreme poverty odds ratio b^{*L} *(x)*	100% poverty odds ratio b^{*L} *(x)*	Low income odds ratio b^{*L} *(x)*	Relative poverty odds ratio b^{*L} *(x)*
Sex	0.6909	0.8463	0.9655**	0.9262**
	–0.1691	*–0.0763*	*–0.0161*	*–0.0581*
Education	0.8880	0.8290	0.7688	0.8168
	–0.2860	*–0.4513*	*–0.6328*	*–0.1535*
No. of children	1.4737	1.4934	1.6297	1.0567**
	0.2839	*0.3650*	*0.4445*	*0.0418*
Immigrant	2.3149	2.3035	1.5459	2.0582
	0.2414	*0.2400*	*0.1253*	*0.5474*
Mexican immigrant job	1.6076	2.1373	2.2663	2.2799
	0.1107	*0.1771*	*0.1908*	*0.6250*
Unemployment	7.7771	5.6006	3.4474	4.7152
	0.7649	*0.6425*	*0.4615*	*1.1760*
Constant	–4.0743	–2.1383	0.3508	–0.7544
McKelvey & Zavoina's R^2	0.206	0.201	0.218	0.183

All values significant at 0.05 or above
*Significant at 0.1
**Not significant
Results are weighted and were obtained via "sv" using HHWT

in terms of poverty than are Mexican Americans, and experience rates of poverty more than half that of their Mexican counterparts (22.27 versus 49.58% for low income). The findings for White households underscore the importance of education, number of children, and especially unemployment status for the household head. In the case of extreme poverty, the odds are increased by nearly 7 times for those who are unemployed. The effects of education are rather pronounced across each one of the poverty outcomes as is immigrant status (though unemployment does exert the greatest influence in each model).

The findings for Black households point to number of children present and (most heavily) unemployment status as the most significant predictors of poverty status in each of the poverty outcomes. Interestingly, in the case of low income, number of children actually surpasses unemployment status in its amount of influence on the outcome. Though Blacks and Latinos are often compared in the literature due to their comparable rates of poverty; this seems a noteworthy point of divergence. Family structure does indeed seem to have more of an effect for the Black population than is observed within the Mexican American sample. Finally, employment in a Mexican immigrant job plays a larger role for the Black population than it did among the Whites the sample. As pointed out for Mexican Americans, this also suggests that an unequal wage structure and opportunity system has measurable effects for these two populations.

Table 5.7 Logistic regression results: Black households

Logistic regression results: Black households, (presented in odds ratios and semi-standardized logit coefficients N = 3,121)

Model 1	Extreme poverty odds ratio b^{*L} *(x)*	100% poverty odds ratio b^{*L} *(x)*	Low income odds ratio b^{*L} *(x)*	Relative poverty odds ratio b^{*L} *(x)*
Sex	1.6929**	0.9999**	1.2603	0.9978**
	0.2479	*–0.0001*	*0.1089*	*–0.0010*
Education	0.9431	0.8871	0.7991	0.8690
	–0.1369	*–0.2801*	*–0.5242*	*–0.321*
No. of children	1.5074	1.4890	1.7409	1.1213**
	0.4166	*0.4042*	*0.5628*	*0.1163*
Immigrant	1.6519	2.9465	2.6523	3.0365
	0.1683	*0.3624*	*0.3272*	*0.3725*
Mexican immigrant job	1.7709	1.7277	3.1149	1.7957
	0.1674	*0.1601*	*0.3327*	*0.1714*
Unemployment	9.2637	5.8144	3.9515	4.9307
	1.5171	*0.7069*	*0.5518*	*0.6407*
Constant	–5.9389	–2.6781	–0.1779	–1.2564
McKelvey & Zavoina's R^2	0.238	0.205	0.265	0.188

All values significant at 0.05 or above
*Significant at 0.1
**Not significant
Results are weighted and were obtained via "sv" using HHWT

Level of education, number of children present, and unemployment status are the most significant predictors of poverty for Asian households. In fact, the influence of education becomes stronger as the level of poverty moves from extreme to low income. In terms of comparisons, Whites and Asians have strikingly similar outcomes, i.e. they are both strongly affected by unemployment, education, and number of children. Neither of these populations' poverty rates were highly influenced by employment in a Mexican immigrant job, as was observed for Mexican Americans and Black households. Thus, I posit here that my findings are consistent with prior research and reveal that White and Asian populations behave in similar fashion with respect to poverty. On the other hand the Mexican American and Black populations seem to be much more heavily influenced by the effects of labor-related variables and more specifically decreased wage potential and opportunity structure. Additionally, Mexican Americans are impacted by immigration status (this trend was not as apparent among Black households). This puts Mexican Americans at an additional disadvantage as rates of immigration continue and earnings potential and social capital will likely not increase for this group as a result. Past research has shown that though rates of poverty among these two groups (Blacks and Mexican Americans) has converged to an extent, the Black population has made significantly larger gains as they have become more entrenched in American society, while

Table 5.8 Logistic regression results: Asian households

Logistic regression results: Asian households, (presented in odds ratios and semi-standardized logit coefficients N = 7,764)

Model 1	Extreme poverty odds ratio b^{*L} *(x)*	100% poverty odds ratio b^{*L} *(x)*	Low income odds ratio b^{*L} *(x)*	Relative poverty odds ratio b^{*L} *(x)*
Sex	0.7465**	0.6408	0.7952	0.6610
	–0.1252	*–0.1906*	*–0.0981*	*–0.1773*
Education	0.9547	0.8963	0.8573	0.8826
	–0.1597	*–0.3770*	*–0.5302*	*–0.4304*
No. of children	1.4181	1.5865	1.5688	1.0187**
	0.3189	*0.4214*	*0.4111*	*0.0169*
Immigrant	1.5014**	2.0624	2.1134	2.3319
	0.1299	*0.2314*	*0.2392*	*0.2705*
Mexican immigrant job	1.2858**	2.1514	2.4624	2.3413
	0.0705	*0.2149*	*0.2528*	*0.2386*
Unemployment	5.2940	3.3915	3.1035	3.5100
	1.2976	*0.4857*	*0.4504*	*0.4993*
Constant	–4.5947	–2.7527	–0.9671	–1.3058
McKelvey & Zavoina's R^2	0.170	0.182	0.225	0.184

All values significant at 0.05 or above
*Significant at 0.1
**Not significant
Results are weighted are were obtained via "sv" using HHWT

Mexican Americans will continue to deal with the issue of recent immigration and its associated risks.

In an effort to underscore the effects of various indicators on Mexican immigrants, the following chapter, Chapter 6, presents the results of similar models estimated for the Mexican immigrant population alone, along with companion analyses for White, Black, and Asian immigrant households. In this chapter a variable for undocumented status will be introduced and should shed a great deal of light on the implications involved with poverty outcomes for the Mexican immigrant population. This is clearly a group that experiences significant burden with respect to the ability for earnings potential and socio-economic status, and the following chapter explores that relationship in-depth.

Chapter 6
Individual Level Results: Mexican Immigrants

A great deal of the literature on poverty focuses on the impacts of various independent variables on poverty for specific race and ethnic groups, particularly Blacks and Hispanics. It has been my intention in this book to emphasize that while these groups may experience similar levels of poverty, their predictors differ. Indeed we saw this in the previous chapter. Immigrants in particular face the most severe of problems relative to this issue. Mexican immigrants are much apt to be in married couple households and be members of the workforce, yet they experience the highest poverty rates of any group in the nation. The insulation of marriage and full-time workforce participation does not seem to apply to this population. Hence, the analyses in this chapter are offered as a means to better understand these differences. Additionally, focus is placed upon the undocumented population through the use of a proxy independent variable, in an attempt to ascertain whether and the extent to which undocumented status impacts the likelihood of poverty.

This chapter presents results of a number of hypothesis tests for the Mexican immigrant population with respect to key predictors as well as undocumented status. Also presented is a discussion of the operationalization and construction of the dependent and independent variables and a description of the rationale used in creating the undocumented proxy variable. Summary statistics are presented for the immigrant population as are the diagnostics that have been performed for each model. In certain cases, the models have been separated so as to appreciate the effects of the predictors separately; thus a discussion of these alterations is presented as well. Additionally, results and summary statistics are presented for White, Black, and Asian immigrants for purposes of comparison. Finally, the logistic regression results are presented along with a discussion of the findings.

6.1 Hypotheses, General and Specific

In this second series of models presented at the individual level, further restrictions are implemented given that only those households headed by immigrants are analyzed. Hence, I am analyzing the impacts of key independent variables

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on those who report Mexican ethnicity, are married with spouse present, have at least one child present in the household, and reported their birthplace as Mexico. Following the reviews of literature in Chapter 2 and elsewhere, I have selected for this model, eight independent variables, including sex, level of education, number of children present, citizenship status, employment in a Mexican immigrant job, unemployment status, number of years spent in the USA, and a proxy variable for undocumented status (see section below for construction and measurement of variables).

As for the expected relationships, many of the same associations are expected for the Mexican immigrants as was the case for the Mexican American population. For example, positive relationships are expected for number of children present, employment in a Mexican immigrant job, and unemployment status. These relationships are predicted based on prior research, largely indicating that additional children place an extra strain on the household, which translates into greater chances for poverty at any level. Those employed in Mexican immigrant jobs are also more apt to be in poverty as these are occupations which have been deemed to be low-wage and low-skill with little to no opportunity for advancement. Also, workforce participation has been shown to exert a significant influence on likelihood of reporting to poverty. Thus, those who are unemployed and/or not members of the labor force are expected to be at a significantly increased chance of reporting to any of the three levels of poverty.

The model for Mexican immigrants also contains a proxy variable for undocumented status. This variable was constructed based on prior research of Bean et al. (1984) and combines into one binary variable those who responded in the affirmative to a series of census questions meant to indirectly reflect undocumented status. It is expected that a strong positive relationship will be observed between undocumented status and the log odds of poverty given that undocumented migrants have been shown to experience significantly higher levels of poverty and difficulties in securing employment and/or education, among many other things.

Negative relationships are expected for the following variables: sex, i.e. male, level of education, citizenship status, and number of years spent in the USA. Much of the literature on poverty indicates that males are less likely to be in poverty than females. Hence, the same relationship is expected for the Mexican immigrant population. Also, as education increases, the likelihood of reporting to any level of poverty should decrease. This is based on findings which indicate that greater levels of education do offer some protection from the risk of poverty. Citizenship status should vary negatively with poverty outcomes, as also should number of years spent in the USA. This is based on research which posits that citizens are afforded the same protections and benefits as natives, and thus they are at less risk of being in poverty. Furthermore, the number of years spent in the USA should act as a barometer for the level of assimilation which has again been shown to lessen the risk of poverty.

6.2 Operationalization and Construction of Variables

As just noted, eight independent variables were selected for analysis with respect to the logistic regression equations to be estimated for the Mexican immigrant population. These include many of the variables used in the analysis of Mexican Americans with the key additions of number of years spent in the USA and undocumented status, as well as the replacement of immigration status with citizenship status. The four dependent variables remain the same, namely, dummy variables reflecting extreme poverty (measured as 50% of the federal poverty threshold), 100% poverty, low income (measured as 200% of the federal poverty threshold), and relative poverty (measured as 50% of the median income for each state). These are dichotomous variables coded 1, if yes.

The independent variables selected should provide key insights into the predictors associated with poverty outcomes for the Mexican immigrant population in the Southwestern United States. The first independent variable (X1) is sex. This is a dichotomous variable for sex where a value of 1 represents males and 0 represents females. X2 is an interval level variable for years of education ranging from no school, with a value of 0, to doctoral degree at a value of 21. This variable is operationalized in the same manner as for the Mexican American population and contains the following categories: (0) no school, (2.5) 1st–4th grade, (6.5) 5–8th grade, (9) 9th grade, (10) 10th grade, (11) 11th grade, (12) 12th grade – no diploma, (12) high school diploma or GED, (14) some college, no degree, (14) associate degree, (16) bachelor's degree, (18) master's degree, (18) professional degree, and (21) doctorate degree. X3 is an interval level variable for number of children present in the household ranging from 1 to 9 or more (those with no children present were excluded from the sample). It is operationalized in the same manner as in the models for Mexican Americans. This variable counts the number of own children residing with the household head; it includes step-children and adopted children. X4 is a dichotomous variable for citizenship status. It is based on the CITIZEN variable in the ACS 2006 which reports the respondent's citizenship status and distinguishes between naturalized and non-citizens. A value of 1 represents those who are citizens, both natives and naturalized, and a value of 0 represents those who are non-citizens. X5 is a dichotomous variable for "Mexican immigrant" job with 1 representing those employed in a Mexican immigrant occupation, as designated by Douglas and Saenz (2008), and 0 equal to all others. This variable is operationalized as described in Chapter 4. X6 is a dichotomous variable representing unemployment status where 1 represents individuals who are unemployed and/or not members of the labor force and 0 represents those who are employed or members of the labor force. This variable is based upon the employment status variable in the ACS which refers to the whether the respondent was a part of the labor force, working or seeking work. The constructed variable combines those who are unemployed and/or not in the labor force into one category, denoted by a value of 1. X7 is a continuous variable for number of years spent in the USA. It is based upon the variable YRSUSA1 in the

2006 ACS and reports the number of years a respondent has spent in the US The values range from 0 to 87. Lastly, X8 is a dichotomous variable for undocumented status. This variable was constructed based on a series of affirmative responses to the following census questionnaire items: (1) those who reported their birthplace as outside the United States, (2) those who reported to be in the young age category, i.e. ages 15–29, (3) those who did not speak English very well or did not speak English at all, (4) those who reported employment in a Mexican immigrant job, (5) those who have been in the US for 5 years or less, (6) those who reported an education level of less than 9th grade, (7) those who reported Mexican ethnicity, and (8) those who reported that they were not citizens. Thus, those who answered "yes" to all of the above census questions were combined to create a group of individuals who are more than likely undocumented Mexican immigrants. This variable was developed based on the work of Bean et al. (1984) and is provided as a proxy measure for undocumented status. It is expected that the measurement will not be definitive but will be an approximation of whether the respondent is an undocumented immigrant to the US.

In addition, it is important to note that this is a very conservative measure of the undocumented population. The original findings of Bean et al. (1984) indicated that about two-thirds of the 1.1 million undocumented individuals were accounted for with this method in 1984. Current estimates (2006) indicate that there are approximately 11.5–12 million undocumented migrants in the US this equates to about 3.6% of the total US population. Jeffrey Passel reports that 3.1 million children reside in households where the head of the family is unauthorized (about 1%) (2006).

My measure includes only about 0.4% of the sample. It is likely that this is due to the restrictions which have been placed on the population, i.e. married with spouse present and at least one child present in the household. Research has shown that many undocumented individuals do not reside in nuclear families and as such a great deal of persons may be excluded in this work. Also, and very importantly, I have required my definition of an undocumented Mexican person to include being an immigrant, being young (aged 15–29), having little or no English language ability, being in a Mexican immigrant job, being in the US for 5 years or less, having less than a 9th grade education, and not being a citizen. Certainly this is a very restrictive definition; there are likely many undocumented Mexican immigrants in the US whose identification does not include all of these specifications. My definition thus is a very conservative one. Were I to loosen the requirements, say extending the age range to 39, for example, I would be able to place more persons in the "undocumented" category. Perhaps in later research beyond this, I will want to experiment with a less restrictive definition.

6.3 Summary Statistics and Discussion: Mexican Immigrants

The following paragraphs detail the descriptive statistics of the Mexican immigrant population in the Southwest United States. This sample was restricted to household heads that were married with spouse present, had at least one child present, reported

Table 6.1 Poverty status for Mexican immigrant households

Poverty status for Mexican immigrant households by sex, level of education, number of children, citizenship status, employment status, number of years in US, and undocumented status, 2006

Characteristic	Total	Extreme poverty (%)	100% poverty (%)	Low income (%)	Relative poverty (%)
	12,122	4.52	20.64	58.11	26.82
Sex					
Male	9,260	4.22	19.69	58.09	2616
Female	2,862	5.49	23.72	58.18	28.97
Education					
None	541	5.73	23.48	61.00	29.57
1st–4th	933	6.11	24.54	64.63	30.55
5th–8th	3,376	5.18	25.24	65.76	31.07
9th	1160	4.83	24.48	67.67	32.67
10th	406	5.67	24.14	61.58	27.83
11th	398	6.03	22.86	61.81	29.15
12th/HS Grad/GED	3,207	4.18	18.33	56.78	25.72
Some College/Assoc.	1,437	2.37	12.46	40.15	16.91
Bachelor's	465	2.15	8.17	34.19	13.12
Master's/Prof	189	2.12	8.47	25.93	10.05
Doctorate	10	0.00	0.00	40.00	10.00
Number of children					
1	2,860	2.66	11.92	44.02	26.99
2	4,193	4.22	18.86	54.88	26.40
3	3,231	4.46	23.09	65.06	26.12
4	1,304	6.52	31.90	74.46	28.83
5	368	10.33	36.41	73.37	28.26
6	115	20.00	46.09	85.22	34.78
7+	51	9.80	41.18	84.31	15.69
Citizenship status					
Citizens (includes naturalized)	4,325	2.45	10.52	41.76	15.33
Non-citizen	7,797	5.67	26.25	67.18	33.19
Employed in Mexican immigrant job					
Employed in	5,077	4.85	24.86	67.50	30.78
Not employed in	7,045	4.29	17.60	51.34	17.24
Unemployment status					
Employed	9,407	2.96	17.17	55.15	23.01
Unemployed	2,715	9.94	32.67	68.36	40.00
Years in US					
0–5 years	726	11.57	40.91	79.75	51.52
6–10 years	1,579	7.41	32.43	74.98	42.18
11–15 years	1,567	5.74	27.31	70.33	35.10
16–20 years	2,348	4.51	21.47	64.65	27.09
21+ years	5,902	2.56	12.89	45.09	17.37
Undocumented status					
Documented	12,082	4.49	20.56	58.00	26.73
Undocumented	40	15.00	45.00	90.00	55.00

Mexican ethnicity, and listed their birthplace as Mexico. The final sample contains information on 12,122 households. The frequencies are presented with respect to each of the dependent variables, i.e. extreme poverty, 100% poverty, low income, and relative poverty as well as the independent variables (see Table 6.1). For example, approximately 60% of the Mexican immigrant sample fell into the low income classification while approximately 27% were considered to be in relative poverty. This is well above the rates of Mexican Americans at about 48 and 21%, respectively. Additionally, the modal response for level of education was that of 5th–8th grade at a rate of 27.85% (3,376 Households). Only about 0.4% of the sample fell into the undocumented classification (about 40 household heads). This is much less than the 648 individuals identified in the entire sample. However, the value represents those who were identified with all the restrictions in place, i.e. married with spouse present, at least one child present, and head of household and as mentioned above, this may exclude a great many of the undocumented individuals located in the sample.

It is very important to note the very high rates of poverty for Mexican immigrants in the Southwestern United States. Rates of 4.79, 21.71, and 59.94% were observed for the absolute categories of extreme poverty, 100% poverty, and low income, respectively. A rate of 26.82% was observed for the relative poverty classification. These rates are staggering and indicate the severity of poverty for the Mexican immigrant population. This is not a group of people who are unwilling to work as is evidenced by their rates of employment (only 21.26% reported to being unemployed). However, it is certainly arguable that their relatively low levels of education would have a great deal of influence on their ability to obtain anything other than low-wage, low-skill positions. This is supported by the observation that nearly half of the sample is employed in a Mexican immigrant job, in other words, jobs that are characterized as low status, low wage and so on. Thus, a very important question becomes what are the most important contributors to poverty outcomes for the Mexican immigrant population? Such questions are addressed in the following analyses of such indicators and their relative effects on the incidence of poverty at varying levels.

6.4 Summary Statistics and Discussion: White, Black, and Asian Immigrant Households

Tables are also presented for each of the reference sets of households, i.e. White, Black and Asian immigrants, and are provided to show the differences and similarities observed between the populations. Tables 6.2, 6.3, and 6.4 contain descriptive information on White, Black, and Asian immigrant households and present each of their rates of poverty at the three absolute levels along with the corresponding rates of relative poverty for these groups. The descriptive statistics are limited to the highest frequencies observed among the independent variables for purposes of comparison. Also, these samples are each restricted based on the same characteristics of those of the Mexican immigrant households, namely, married with spouse present, at least one child present in the household, immigrant status, and report

Table 6.2 Poverty status for white immigrant households

Descriptive statistics for white immigrant households, 2006

Characteristic	Total	Extreme poverty (%)	100% poverty (%)	Low income (%)	Relative poverty (%)
White (non-Hispanic)	3,289	1.79	5.29	14.47	7.54
Sex					
Male	2,473	1.94	5.58	14.84	7.89
Female	816	1.35	4.41	13.36	6.5
Education (modal response)					
Bachelor's (28.3%)	930	0.86	3.01	7.63	4.09
Number of children (modal response)					
2 children (42.0%)	1,381	2.03	4.56	12.74	5.94
Citizenship status					
Citizen (includes naturalized)	2,189	1.37	4.07	11.97	5.66
Non-citizen	1,100	2.64	7.73	19.45	11.29
Mexican immigrant job					
Employed in	208	1.92	9.13	33.65	13.94
Not employed in	3,081	1.79	5.03	13.18	7.11
Employment status					
Employed	2,731	1.03	3.37	11.28	5.2
Unemployed	558	5.56	14.70	30.11	19
No. Years in US					
21+ years (54.1%)	1,778	0.90	2.64	9.67	4.11
Undocumented status (n/a)					

to the corresponding races of White, Black or Asian (Hispanics are excluded from each of these samples).

It is apparent that Mexican immigrants experience poverty of any kind at higher rates than any other immigrant group in the United States. Their rates are more than double those of any of the comparison populations in any category of poverty. Furthermore, their average education level is lower than that of White, Black, or Asian immigrants, and they have significantly lower rates of citizenship than any group. Far fewer respondents were citizens in the Mexican immigrant population, while the majority within each of the other immigrant groups reported having citizenship. Finally, a great deal more of the Mexican immigrant population is employed in Mexican immigrant jobs. This is important to note given that these jobs are not necessarily restricted to Mexicans, but are more indicative of low-wage, and low-status occupations.

In terms of similarities, the modal response for number of children for each of the populations was (2). Additionally, in each of the groups, the modal response

Table 6.3 Poverty status for black immigrant households

Descriptive statistics for black immigrant households, 2006

Characteristic	Total	Extreme poverty (%)	100% poverty (%)	Low income (%)	Relative poverty (%)
Black (non-Hispanic)	412	2.43	11.17	33.25	15.78
Sex					
Male	311	2.25	11.58	34.08	16.4
Female	101	2.97	9.90	30.69	13.86
Education (modal response)					
Some College/Assoc (29.4%)	121	1.65	6.61	31.40	14.05
Number of children (modal response)					
2 children (43.2%)	178	0.56	8.43	26.97	14.04
Citizenship status					
Citizen (includes naturalized)	274	1.46	8.39	27.74	11.68
Non-citizen	138	4.35	16.67	44.20	23.91
Mexican immigrant job					
Employed in	43	4.65	18.60	72.09	30.23
Not employed in	369	2.17	10.30	28.73	14.09
Employment status					
Employed	348	1.15	8.33	29.89	12.64
Unemployed	64	9.38	26.56	51.56	32.81
No. Years in US					
21+ years (45.1%)	186	1.08	5.91	25.27	9.68
Undocumented status (n/a)					

for number of years in the United States was 21 or more years. This is a very interesting finding given that recent immigration is argued to be a prominent indicator of poverty status. Upon closer inspection of the statistics, it is observed that within this particular category (21+ years), the rates of poverty at each level are still astoundingly high. For example, the rate of low income is 45.09% for Mexican immigrants who have been in the US 21 or more years. This is very surprising if one considers the idea that increased time spent in the US generally correlates with an accumulation of social capital and accordingly decreased levels of poverty.

As with the native-born population, it was expected that Whites and Asians would experience poverty at rates significantly lower than Mexican immigrants. As illustrated here, the differences are tremendous and show a great deal of discrepancy on the basis of race. For example, the rate of low income was 14.47% for White immigrants and 18.52% for Asian immigrants. In comparison, Mexican immigrants had a rate of 58.11% in the low income classification. This is a rate nearly four times that observed for White immigrants and over three times that for Asian immigrants. Even Black immigrants fared better at a rate of 33.25% in

Table 6.4 Poverty status for Asian immigrant households

Descriptive statistics for Asian immigrant households, 2006

Characteristic	Total	Extreme poverty (%)	100% poverty (%)	Low income (%)	Relative poverty (%)
Asian households	6,851	1.91	5.75	18.52	9.12
Sex					
Male	5,333	1.88	5.85	18.49	9.34
Female	1,518	2.04	5.40	18.64	8.37
Education (modal response)					
Bachelor's (31.8%)	2,179	1.01	2.62	10.42	4.64
Number of children (modal response)					
2 children (42.8%)	2,939	1.94	5.10	16.77	7.69
Citizenship status					
Citizen (includes naturalized)	4,788	1.21	4.28	15.91	7.16
Non-citizen	2,063	3.54	9.16	24.58	13.67
Mexican immigrant job					
Employed in	624	3.21	13.46	40.38	20.99
Not employed in	6,227	1.78	4.98	16.33	7.93
Employment status					
Employed	5,491	1.02	3.90	14.17	6.14
Unemployed	1,360	5.51	13.24	36.10	21.18
No. years in US					
21+ years (48.0%)	3,286	1.31	3.77	14.18	6.70
Undocumented status (n/a)					

the low income classification. The modal response category for level of education among Mexican immigrants was 6.5, which corresponds to a 5th–8th grade level of education. Correspondingly, the modal response for White and Asian immigrants was 16 (Bachelor's degree), and 14 (Some college/Associate's degree) for Black immigrants. Hence the discrepancies in poverty rates among groups seem likely attributable to low educational attainment and skill among the Mexican immigrants, which translates into an inability to obtain employment at a living wage. Let us now continue on to the logistic regression results in order to gain a fuller understanding of the impacts of the individual level predictors on poverty outcomes for Mexican immigrants.

6.5 Logistic Regression Diagnostics

As was done in the previous chapter, a series of diagnostics have been performed for the logistic regression models that represent Mexican immigrants. The four models to be analyzed represent extreme poverty, 100% poverty, low-income, and relative poverty. Each of the models was diagnosed for major issues that might warrant model re-specification, and each set of diagnostics is discussed below.

The first of the models to be examined represents households headed by a Mexican immigrant in the Southwestern United States. Multi-collinearity is not a problem, nor is model fit. However, after undertaking a series of examinations, it was found that in order to best understand the effects of undocumented status, it was necessary to remove the variable for years spent in the USA, sex, and level of education (Model 1A). This was necessary given that these variables were used in the construction of the undocumented proxy variable. Once these three variables were removed, the tolerance values increased from 0.77 at their lowest to 0.94. Additionally, each of the predictors now maintains its significance. For Model 1B, the undocumented proxy variable was removed so that the effects of all the independent variables may be ascertained without concern over multi-collinearity.

Model 2 represents Mexican immigrants in 100% poverty. However, when the model was separated out into two models as discussed above the tolerance values for Model 2A (this model excludes the variables for sex and years spent in the USA) increased significantly from 0.78 to 0.90. The model was examined for issues of non-normality through the examination of a plot of residuals which indicated a normal distribution. Also, the skewness and kurtosis values were well within acceptable range. The model fit was examined and again statistically significant z-scores were observed. Finally, no influential covariate patterns were detected as none of the values of Pregibon's ΔB_j were above 1. Overall, it appears that this model displays no issues which would cause concern or warrant re-specification. However, given that one of the most important predictors in this analysis is undocumented status; I have again separated out the model into two: Model 2A which excludes sex and number of years spent in the USA, and Model 2B which excludes the proxy variable for undocumented status. This allows for a clearer analysis of the issues.

Model 3 represents Mexican immigrants in the low income classification, i.e. 200% poverty. Skewness and kurtosis values as well as a plot of the residuals allow for an evaluation of non-normality. In the case of Model 3, none is present given that the values observed are within normal range and a normal distribution is provided. The diagnostics for model fit indicate that the model is specified properly as is evidenced by the statistically significant z-tests. Finally, I have evaluated Pregibon's $\Delta B_{j,}$ and determined that there are no covariate patterns that exert an extreme influence on the model.

I have once again decided to separate Model 3 into two separate models. In Model 3A, the number of years spent in the USA was removed. Upon removal of this variable, the tolerance values increased from 0.78 at their lowest to 0.83. Furthermore, each of the independent variables maintains its significance once the model is specified as such. Model 3B does not contain the proxy variable for undocumented status. Again the tolerance values are acceptable and each of the independent variables maintains significance.

As with the previous models, the analyses have been separated in two for the relative poverty classification (50% of the state median income). Once separated, the tolerances were within acceptable range as were the skewness and kurtosis values.

The model fit, or adequacy, was examined and again statistically significant z-scores were observed. Lastly, no influential covariate patterns were detected as none of the values of Pregibon's ΔB_j were above 1. Overall, it appears that this model displays no issues which would cause concern or warrant re-specification. As above, given that one of the most important predictors in this analysis is undocumented status; I have chosen to separate out the model into two components: Model 2A which excludes sex and number of years spent in the USA, and Model 2B which excludes the proxy variable for undocumented status. This allows for a clearer analysis of the issues.

6.6 Logistic Regression Results

As was mentioned in the preceding section, each of the models for four levels of poverty has been separated out into two, to better understand the impacts of each of the independent variables. Thus, two models are presented for extreme poverty (Models 1A & 1B), 100% poverty (Models 2A & 2B), low income (Models 3A & 3B),[1] and relative poverty (Models 4A & 4B). Models 1A and 1B are presented first and refer to extreme poverty for Mexican immigrant households. A total of 12,122 household heads are included. In Model 1A, the removal of employment in a "Mexican immigrant" job, number of years spent in the US, sex, and level of education significantly improves the prediction of the model (see Table 6.5). Hence

Table 6.5 Logistic regression results: Mexican immigrant households in extreme poverty 1A

Logistic regression results: Mexican immigrant households in extreme poverty 1A. N = 12,122 (presented in odds ratios and semi-standardized logit coefficients)

Model 1A	Odds ratio b^{*L} *(x)*	*b*	t, p>0
Citizenship	0.4285 *−0.3971*	−0.8475	−6.50, 0.000
Unemployment	3.4778 *0.5100*	1.2464	11.90, 0.000
No. of children	1.3179 *0.3166*	0.2761	7.05, 0.000
Undocumented status	3.4607 *0.0822*	1.2415	2.60, 0.009
Constant		−3.9066	−4.27, 0.000

McKelvey & Zavoina's $R^2 = 0.152$
All values significant at 0.05 or below
Results are weighted and were obtained via "svy" using HHWT

[1]The top value in Column 2 refers to the odds ratio and the bottom value refers to the semi-standardized logit coefficient, that is, the logit coefficient multiplied by the standard deviation of the independent variable (see Long and Freese 2005, for more discussion).

Table 6.6 Logistic regression results: Mexican immigrant households in extreme poverty 1B

Logistic regression results: Mexican immigrant households in extreme poverty 1B. N = 12,122 (presented in odds ratios and semi-standardized logit coefficients)

Model 1B	Odds ratio b^{*L} *(x)*	*b*	t, p>0
Sex (Male = 1)	2.4163 *0.3794*	0.8822	6.15, 0.000
Education	0.9623 *−0.1541*	−0.0384	−2.92, 0.004
No. of children	1.3390 *0.3348*	0.2919	7.36, 0.000
Citizenship	0.7308 *−0.1469*	−0.3136	−2.23, 0.026
Mexican immigrant job	0.9878* *−0.0061*	−0.0123	−0.12, 0.908
Unemployment	5.3120 *0.6833*	1.6700	13.20, 0.000
Years spent in US	0.9400 *−0.6786*	−0.0618	−8.91, 0.000
Constant	−3.4566	−3.4566	−13.28, 0.000

McKelvey & Zavoina's $R^2 = 0.237$
All values significant at 0.05 or below
*Not significant
Results are weighted and were obtained via "svy" using HHWT

Model 1A contains the following independent variables: citizenship status, unemployment status, number of children present in the household, and undocumented status. Model 1B does not contain the variable for undocumented status and includes the above-mentioned variables in addition to sex, level of education, and years spent in the US (see Tables 6.5 and 6.6).

6.7 Results: Mexican Immigrant Households

Model 1A indicates that other things equal, citizens enjoy a 57.2% decrease in the odds of being in extreme poverty. It also indicates that those who are unemployed and those who were identified as undocumented immigrants are over two times more likely to report to extreme poverty, all else equal. Finally, each additional child results in 31.8% increase in the odds of being in extreme poverty, all else equal. These findings are as expected and the semi-standardized values indicate that the relative impacts of the unemployment and citizenship variables are quite important in the determination of extreme poverty status.

Model 1B (see Table 6.6) represents the findings for extreme poverty among Mexican immigrants and indicates the following. Females have 141.6% greater odds of being in extreme poverty, all else equal. For each additional level of education obtained, the odds of poverty are decreased by 3.8%, all else equal. For each additional child, the odds of extreme poverty are increased by 33.9%, other things equal. Citizens enjoyed 26.9% decrease in the odds of being in extreme poverty, all else equal. Each additional year in the US has resulted in a 6% decrease in the odds of extreme poverty, other things equal. Those who were unemployed and/or not in the labor force had more than 4 times higher odds of being in extreme poverty, other things equal. The findings associated with the variable for employment in a Mexican immigrant job were not significant. Additionally, the semi-standardized values indicate that the variables for sex, unemployment and years spent in the US have the greatest relative impacts on the extreme poverty outcome.

Models 2A and 2B (see Tables 6.7 and 6.8) represent the results obtained for the logistic regression equations estimated to predict 100% poverty. The results are presented in odds ratios, standardized values, and the coefficients. Model 2A represents the findings for Mexican immigrants with the inclusion of the proxy variable for undocumented status. Model 2B excludes the proxy for undocumented status and includes the following independent variables: sex, level of education, number of children present, citizenship status, employment in a Mexican immigrant job, unemployment status, and number of years spent in the USA.

The model above (2A) again supports the hypothesized relationships. Each of the relationships was significant. The key findings are as follows. For each additional level of education, a 2.3% decrease, and for each additional child a 39.4% increase in the odds of 100% poverty was observed, all else equal. Those respondents who reported citizenship had 63.4% lower odds of 100% poverty, other things equal. The odds of 100% poverty were about 54% higher for those employed in a "Mexican

Table 6.7 Logistic regression results: Mexican immigrants in 100% poverty 2A

Logistic regression results: Mexican immigrant households in 100% poverty 2A.
N = 12,122 (presented in odds ratios and semi-standardized logit coefficients)

Model 2A	Odds ratio b^{*L} *(x)*	*b*	t, p>0
Education	0.9767 *−0.0946*	−0.0236	−3.47, 0.001
No. of children	1.3939 *0.3809*	0.3321	14.67, 0.000
Citizenship	0.3663 *−0.4706*	−1.0044	−14.91, 0.000
Mexican immigrant job	1.5423 *0.2144*	0.4333	7.55, 0.000
Unemployment	2.8741 *0.4320*	1.0558	16.81, 0.000
Undocumented status	2.1469 *0.0506*	0.7640	2.12, 0.034
Constant	−2.1198		

McKelvey & Zavoina's $R^2 = 0.161$
All values significant at 0.05 or below
Results are weighted and were obtained via "svy" using HHWT

Table 6.8 Logistic regression results: Mexican immigrants in 100% poverty 2B

Logistic regression results: Mexican immigrant households in 100% poverty 2B.
N = 12,122 (presented in odds ratios and semi-standardized logit coefficients)

Model 2B	Odds ratio $b^{*L}(x)$	b	t, p>0
Sex	1.4525	0.3733	4.94, 0.000
	0.1605		
Education	0.9568	−0.0441	−6.22, 0.000
	−0.1770		
No. of children	1.4119	0.3449	14.83, 0.000
	0.3956		
Citizenship	0.5792	−0.5461	−7.52, 0.000
	−0.2559		
Mexican immigrant job	1.4004	0.3367	5.80, 0.000
	0.1666		
Unemployment	3.5063	1.2546	16.97, 0.000
	0.5133		
Years in USA	0.9483	−0.0531	−15.63, 0.000
	−0.5822		
Constant	−1.4039		

McKelvey & Zavoina's $R^2 = 0.228$
All values significant at 0.05 or below
Results are weighted and were obtained via "svy" using HHWT

immigrant" job. Finally, the odds of 100% poverty were nearly two times higher for those who were unemployed and 114.7% higher for those who were listed as undocumented, other things equal. Furthermore, the strength of citizenship, unemployment, number of children and employment in a Mexican immigrant job were very significant in the determination of the 100% poverty outcome for Mexican immigrants.

Model 2B (Table 6.8) presents the findings associated with the findings for the 100% poverty classification for Mexican immigrants without the inclusion of the proxy variable for undocumented status. Each of the relationships was significant at at least the 0.05 level. A positive relationship was observed for females and 100% poverty. The results of this model indicate that females experience 45.2% higher odds of being in 100% poverty, all else equal. This relationship confirms prior expectations and supports the idea that houses headed by a female are at a greater disadvantage with respect to poverty status.

The remainder of the variables also behaved as expected and evidenced the following. For each additional level of education a 4.3% decrease, and for each additional child a 41.2% increase in the odds of 100% poverty was observed, other things equal. Citizens experienced a 42.1% decrease in the odds of 100% poverty, and those employed in a "Mexican immigrant" job experienced a 40% increase in the odds of poverty. Each additional year spent in the US resulted in a 5.2% decrease in the odds of poverty, other things equal. Finally, those who were unemployed were more than two and a half times more likely to be in poverty than those who were not, all else equal. The strength of unemployment on poverty status was quite large as was the effect of additional children. However, the variable that exerted the most significant impact on poverty status was number of years spent in the USA. This is quite important for the findings of this book, and serves to support the notion that the recency of immigration plays a very important role in the determination of poverty.

Model 3A (see Table 6.9) reports the findings for Mexican immigrants in the low-income classification. This model includes the proxy variable for undocumented status. The variables performed as expected with the exception of the independent variable for sex (but see my earlier discussion of this variable). For each additional level of education, the odds of low-income classification were decreased by 3.3%, and for each additional child the odds of low-income classification were increased by 44.9%, other things equal. The odds of low-income classification were decreased by 60.3% for citizens, increased by 80.7% for those employed in a "Mexican immigrant" job, and were almost 140% higher for those who were unemployed and/or not members of the labor force, other things equal. Most importantly, the odds of low-income classification were increased by more than four times for those who were identified as undocumented.

Model 3B (Table 6.10) reports the findings for Mexican immigrants in the low-income classification and excludes undocumented status in favor of number of years spent in the USA. Here, all the variables are significant at the 0.05 level or below and once again with the exception of the variable for sex, performed as expected.

Table 6.9 Logistic regression results: Mexican immigrants in low income 3A

Logistic regression results: Mexican immigrant households in low income 3A.
N = 12,122 (presented in odds ratios and semi-standardized logit coefficients)

Model 3A	Odds ratio b^{*L} *(x)*	*b*	t, p>0
Sex	1.3137 *0.1173*	0.2729	4.58, 0.000
Education	0.9675 *−0.1327*	−0.0331	−5.57, 0.000
No. of children	1.4487 *0.4251*	0.3706	15.87, 0.000
Citizenship	0.3972 *−0.4327*	−0.9234	−19.12, 0.000
Mexican immigrant job	1.8066 *0.2927*	0.5915	11.87, 0.000
Unemployment	2.3922 *0.3569*	0.8722	13.21, 0.000
Undocumented	4.2786 *0.0963*	1.4536	2.41, 0.016
Constant	−0.4680		

McKelvey & Zavoina's $R^2 = 0.165$
All values significant at 0.05 or below
Results are weighted and were obtained via "svy" using HHWT

Table 6.10 Logistic regression results: Mexican immigrants in low income 3B

Logistic regression results: Mexican immigrant households in low income 3B. N = 12,122 (presented in odds ratios and semi-standardized logit coefficients)

Model 3B	Odds ratio b^{*L} *(x)*	*b*	t, p>0
Sex	1.4863 *0.1704*	0.3963	6.42, 0.000
Education	0.9455 *−0.2247*	−0.0560	−8.96, 0.000
No. of children	1.4331 *0.4127*	0.3598	15.28, 0.000
Citizenship	0.6384 *−0.2103*	−0.4489	−8.17, 0.000
Mexican immigrant job	1.6161 *0.2375*	0.4800	9.46, 0.000
Unemployment	2.7069 *0.4074*	0.9958	14.35, 0.000
Years in USA	0.9479 *−0.5876*	−0.0536	−19.82, 0.000
Constant	0.6385		

McKelvey & Zavoina's $R^2 = 0.243$
All values significant at 0.05 or below
Results are weighted and were obtained via "svy" using HHWT

Each additional year of education obtained resulted in a 5.4% decrease in the odds of low-income, all else equal. For each additional child, the odds of low-income were increased by 43.3%, other things equal. Those employed in a "Mexican immigrant" job had 61.6% higher odds of being low-income, and those who were citizens had 36.2% lower odds of low-income, all else equal. Additionally, those who were unemployed were nearly 2 times more likely to be low-income, and each additional year in the US resulted in a 5.2% decrease in the odds of low-income classification, other things equal. As was observed in Model 2B, the strength of number of years in the US was quite hefty in relation to the effects of the other independent variables.

Model 4A (Table 6.11) displays the findings for Mexican immigrants in relative poverty. This model includes the proxy variable for undocumented status. In this case, the independent variables performed as expected. Males were 24.1% less likely to report relative poverty status, all else equal. For each additional level of education, the odds of relative poverty were decreased by 1.5%, other things equal. The odds of relative poverty were also decreased by 62.9% for citizens, increased by 47% for those employed in a "Mexican immigrant" job, and were nearly two times higher (181%) for those who were unemployed and/or not members of the labor force, other things equal. Finally, the odds of relative poverty were increased by 95% for those who were identified as undocumented.

Model 4B (Table 6.12) reports the results from the analyses performed without the undocumented variable and with years spent in the US in its place. In the case

Table 6.11 Logistic regression results: Mexican immigrant households in relative poverty 4A

Logistic regression results: Mexican immigrant households in relative poverty 4A.
N = 12,122 (presented in odds ratios and semi-standardized logit coefficients)

Model 3A	Odds ratio b^{*L} *(x)*	*b*	t, p>0
Sex	0.7586 *0.1188*	−0.2763	−4.39, 0.000
Education	0.9851 *−0.0603*	−0.0150	−2.46, 0.014
Citizenship	0.3711 *−0.4646*	−0.9914	−16.93, 0.000
Mexican immigrant job	1.4706 *0.1908*	0.3856	7.35, 0.000
Unemployment	2.8110 *0.4229*	1.0336	16.29, 0.000
Undocumented	1.9564* *0.0444*	0.6711	1.83, 0.067
Constant	−0.46072		

McKelvey & Zavoina's $R^2 = 0.119$
All values significant at 0.05 below
*Significant at the .10 level
Results are weighted and were obtained via "svy" using HHWT

Table 6.12 Logistic regression results: Mexican immigrants in relative poverty 4B

Logistic regression results: Mexican immigrant households in relative poverty 4B.
N = 12,122 (presented in odds ratios and semi-standardized logit coefficients)

Model 3B	Odds ratio b^{*L} *(x)*	*b*	t, p>0
Sex	1.5618 *0.1917*	0.4459	6.55, 0.000
Education	0.9629 *−0.1517*	−0.0378	−5.93, 0.000
Citizenship	0.6071 *−0.2338*	−0.4989	−7.84, 0.000
Mexican immigrant job	1.3299 *0.1411*	0.2852	5.36, 0.000
Unemployment	3.1717 *0.4723*	1.1543	17.14, 0.000
Years in USA	0.9484 *−0.5818*	−0.0530	−17.78, 0.000
Constant	0.6385		

McKelvey & Zavoina's $R^2 = 0.243$
All values significant at 0.05 or below
Results are weighted and were obtained via "svy" using HHWT

of Model 4A, the following results were observed. Unemployment status and number of years spent in the United States exerted the most influence on the model relative to the rest of the independent variables with $b^{*L}(x)$ values of 0.4717 and –0.5818, respectively. The odds of relative poverty were increased by 56.2% for males and 33% for those employed in a Mexican immigrant job, other things equal. Additionally, the odds of relative poverty were increased by more than two times (217%) for those who were unemployed, all else equal. The odds of relative poverty status were decreased by 3.7% with each increase in level of education, 39.3% for citizens, and 5.2% for each additional year spent in the US, all else equal.

6.8 Discussion

Overall, the results of these analyses confirmed expectations with respect the hypotheses presented. In terms of the most influential variables, number of years spent in the US and unemployment status exerted the strongest effects for each level of poverty. Within the 100% poverty designation, citizenship and employment in a Mexican immigrant job were quite substantial in terms of their effects. These findings point to several prominent factors in the determination of poverty, namely variables that represent labor market effects (unemployment) and accumulation of social capital (as measured by number of years spent in the US). These analyses highlight the importance of participation in the labor force along and the fact that recent immigrants display an inability to attain a minimum standard of living. The following analyses investigate the effects of identical variables on the White, Black, and Asian immigrant populations in an effort to determine if similar relationships exist for these groups.

6.9 Results: White, Black, and Asian Immigrant Households

The final tables presented are those of the comparison populations' logistic regression results (Tables 6.13, 6.14, and 6.15). The analyses are run without the use of the undocumented variable as there was not a sufficient amount of individuals who fell into this category in any of the comparison populations (see Tables 6.2, 6.3, and 6.4 for details). Hence the logistic regression results are presented with the following 7 variables in place: sex, level of education, number of children present, citizenship status, employment in a Mexican immigrant job, unemployment status, and number of years spent in the USA. These models are comparable to Models 1B, 2B, and 3B for Mexican immigrants.

6.10 Discussion

The tables presented for the comparison populations reveal some striking findings. For instance, number of years spent in the USA exerts a very large influence for White and Asian immigrants for each level of poverty. Within the relative poverty

Table 6.13 Logistic regression results: White immigrant households

Logistic regression results: White immigrant households. N = 3,289 (presented in odds ratios and semi-standardized logit coefficients)

Model 1	Extreme poverty odds rastio b^{*L} (x)	100 % poverty odds ratio b^{*L} (x)	Low income odds ratio b^{*L} (x)	Relative poverty odds ratio b^{*L} (x)
Sex	3.7178	3.4114	2.1944	2.6624
	0.5813	*0.5433*	*0.3479*	*0.4335*
Education	0.9568*	0.8885	0.8281	0.8702
	−0.1386	*−0.3713*	*−0.5924*	*−0.4365*
No. of children	1.4823	1.5769	1.6345	1.2198
	0.3825	*0.4426*	*0.4775*	*0.1931*
Citizen	1.3073*	1.2893*	0.8492*	0.9529
	0.1271	*0.1204*	*−0.0775*	*−0.0229*
Mexican immigrant job	0.5192*	1.0545*	2.0120	1.3970
	−0.1668	*0.0135*	*0.1780*	*0.0851*
Unemployment	5.3755	5.4376	3.9561	4.6557
	0.6393	*0.6436*	*0.5227*	*0.5846*
No. years in USA	0.9278	0.9308	0.9575	0.9382
	−1.1009	*−1.0549*	*−0.6390*	*−0.9383*
Constant	−4.3182	−2.2423	0.0929	−0.7009
McKelvey & Zavoina's R^2	0.295	0.341	0.301	0.328

All values significant at 0.05 or below
*Not Significant
Results are weighted and were obtained via "svy" using HHWT

classification, this variable exerted the most influence by far. In fact, each additional year in the US resulted in a 6, 4, and 5% decrease in odds for Whites, Blacks, and Asians, respectively. This seems to suggest that these groups do a better job of decreasing their odds of poverty as a result of more time in the US and accordingly an accumulation of the skills and tools necessary to avoid poverty. Additionally, the relative importance of unemployment is seen for each of the comparison populations. In fact, among those who were unemployed and/or not members of the labor force, a 443 and 323% increase in the odds of 100% poverty was observed for White and Asian immigrants, respectively. In the case of extreme poverty among blacks, those who were unemployed and/or not members of the labor force experienced much greater odds than those who were not. It is obvious that workforce participation is a key component of poverty determination for the White, Black, and Asian immigrant populations. However, as noted above, this is not the most pronounced indicator of poverty status as was the case with the Mexican immigrant population. Citizenship was not a key determinant of poverty for any of these populations, nor was employment in a Mexican immigrant job. In fact, employment in a Mexican immigrant job had strikingly little effect on the determination of poverty for the comparison groups. The finding that citizenship did not have much of an effect was similar to the Mexican immigrant population and conceivably points to

Table 6.14 Logistic regression results: Black immigrant households

Logistic regression results: Black immigrant households. N= 412 (presented in odds ratios and semi-standardized logit coefficients)

Model 1	Extreme poverty odds ratio $b^{*L}(x)$	100% poverty odds ratio $b^{*L}(x)$	Low income odds ratio $b^{*L}(x)$	Relative poverty odds ratio $b^{*L}(x)$
Sex	10.8075	3.4180	1.9345	2.6701
	1.0277	*0.5307*	*0.2849*	*0.4240*
Education	0.9914*	0.9409*	0.8461	0.9583
	−0.0275	*−0.1931*	*−0.5297*	*−0.1349*
No. of children	2.2545	1.4655	1.6835	1.1958
	0.8318	*0.3910*	*0.5329*	*0.1830*
Citizen	0.6154*	0.7666*	0.6757*	0.6842
	−0.2299	*−0.1258*	−0.1856	*−0.1797*
Mexican immigrant job	1.4287*	0.7386*	2.6422	1.3592
	0.1077	*−0.0915*	*0.2933*	*0.0927*
Unemployment	22.7688	4.9990	2.7247	3.1071
	1.1559	*0.5952*	*0.3707*	*0.4193*
No. years in USA	0.9901*	0.9494	0.9692	0.9564
	−0.1088	*−0.5710*	*−0.3443*	*−0.4906*
Constant	−8.3433	−2.1741	0.7118	−1.2963
McKelvey & Zavoina's R^2	0.364	0.260	0.352	0.190

All values significant at 0.05 or below
*Not significant
Results are weighted and were obtained via "svy" using HHWT

the importance of time spent in the US rather and its resultant social gains rather than the importance of citizenship itself. Finally, education played a key role in the determination of low income status for each of the comparison populations. This was in direct opposition to the findings for Mexican immigrants and is perhaps indicative of an increased ability to acquire education for these groups.

These findings are quite interesting in that they underscore the importance of particular determinants as well as demonstrate noteworthy departures from equations estimated for the Mexican immigrant population. For Mexican immigrants, employment in a Mexican immigrant job, unemployment status, citizenship status, numbers of years spent in the USA and undocumented status all were significant in the determination of poverty outcomes. These findings were as expected and point out that there are major differences in the outcomes for Mexican immigrants relative to other populations. Whereas education played a key role in predicting poverty for Whites, Blacks, and Asians, it had very little effect on the Mexican immigrant population. Additionally, although unemployment did have a strong effect on the prediction of poverty for Mexican immigrants, it was nowhere near as salient for them as for the comparison groups. This seems to indicate that other immigrant groups could very well have more of a pro-active stance relative to poverty outcomes, while Mexican

Table 6.15 Logistic regression results: Asian immigrant households

Logistic regression results: Asian immigrant households. N = 6,851 (presented in odds ratios and semi-standardized logit coefficients)

Model 1	Extreme poverty odds ratio b^{*L} *(x)*	100 % poverty odds ratio b^{*L} *(x)*	Low income odds ratio b^{*L} *(x)*	Relative poverty odds ratio b^{*L} *(x)*
Sex	1.5422*	1.9301	1.4170	1.7784
	0.1835	*0.2785*	*0.1476*	*0.2438*
Education	0.9478	0.8819	0.8471	0.8733
	−0.1910	*−0.4475*	*−0.5910*	*−0.4825*
No. of children	1.4370	1.6111	1.6023	1.0444**
	0.3330	*0.4381*	*0.4331*	*0.0400*
Citizen	0.5777	0.7982*	0.8877**	0.8286*
	−0.2575	*−0.1058*	*−0.0559*	*−0.0882*
Mexican immigrant job	1.0571**	1.9911	2.3126	2.2345
	0.0162	*0.2004*	*0.2440*	*0.2340*
Unemployment	5.0512	3.2273	3.2359	3.6383
	0.6458	*0.4672*	*0.4682*	*0.5150*
No. years spent in USA	0.9511	0.9308	0.9473	0.9456
	−0.5297	*−0.7574*	*−0.5715*	*−0.5905*
Constant	−3.6489	−1.5537	0.4029	−0.2483
McKelvey & Zavoina's R^2	0.236	0.261	0.273	0.252

All values significant at 0.05 or below
*Significant at 0.1
**Non significant
Results are weighted and were obtained via "svy" using HHWT

immigrants are subject to poverty by way of predictors that are unmanageable, i.e. occupational type, for example.

The findings observed for this population certainly necessitate further investigation and are quite startling overall. It has most definitely become clear that Mexican immigrants do experience poverty at higher rates than their counterparts; moreover, the independent variables predicting poverty for this population are not always the same as those for other populations. Furthermore, the proxy variable for undocumented status proved to be quite salient for the Mexican immigrant population and adds a great deal to the analysis. The next chapter will expand the analysis of Mexican American and Mexican immigrant poverty by examining the effects of both individual and contextual level predictors on the three absolute poverty outcomes.

Chapter 7
Multilevel Analysis and Results

This chapter presents and discusses the results of multilevel logit regression equations examining the effects on poverty of the individual characteristics of Mexican Americans and Mexican immigrants in addition to the contextual level characteristics of SPUMAs in the Southwestern United States. These populations have emerged as ones that necessitate a multitude of analyses given their expected growth rates and levels of poverty in the coming decades. The preceding chapters examined the effects of individual level characteristics on the log odds of three different types of poverty, and offered quite a bit of insight into the nature of the disadvantages faced by both populations, i.e., Mexican Americans and Mexican immigrants. However, little has been done to examine the impact of contextual level characteristics with respect to these groups. Given the fact that Mexican Americans and Mexican immigrants maintain high rates of employment and more often reside in dual-parent households, it becomes essential to examine other influences than personal characteristics, which may be imparting significant impacts on poverty.

Multi-level models, in particular hierarchical generalized models (HGLM), are used to determine the extent of these effects on the likelihood of poverty for each of the three outcomes, namely extreme poverty, 100% poverty, and low income. Summary statistics are provided in reference to each of the 42 SPUMAs, which have been identified in the region of interest (for a full discussion of the construction of the SPUMAs see Chapter 3), as are the hypothesized relationships. I have also provided a section on the construction and operationalization of the level-2 independent variables. Finally, the results of the HGLM's are presented along with a discussion of the findings and associated implications. I expect that both individual characteristics and macro-level, i.e. SPUMA, characteristics, will play a role in the prediction of each of the three poverty outcomes.

7.1 Hypotheses, General and Specific

As was discussed in Chapter 4, little research has been focused specifically on the analysis of the Mexican American and Mexican immigrant population through the use of multi-level models. This book seeks to fill that void by examining the impacts

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of individual and contextual level characteristics on three different poverty outcomes. The dependent variables remain the same and are extreme poverty, 100% poverty, and low income. A number of essential individual level variables have been identified and include such predictors as immigration status (for the Mexican American population), level of education, unemployment status, and employment in a Mexican immigrant job. The most influential variables were chosen relative to their effects as evidenced in the logistic regressions performed in Chapter 5. For the Mexican immigrant population, key independent variables were also selected in reference to their impacts and include citizenship status, unemployment status, undocumented status, number of children present in the household, and number of years spent in the US (as shown in Chapter 7).

It is expected that macro, or contextual level, characteristics will also play a key role effecting poverty. SPUMAs have been selected as the geographic unit within which the individuals/households are nested. It is further expected that the likelihood of poverty will be associated with the characteristics of these SPUMAs. An underlying assumption is that the SPUMAs are different one from another and will thus provide a reliable base from which to draw conclusions.

At the contextual level, a number of variables were developed, and the most influential of which have been included in several multilevel models. Based on previous research some of the most influential predictors include the percentage of poverty in the area, the percentage of the labor force in each of the nine major industries present in the area, and the percentage of Mexican Americans and Hispanic immigrants present in the area. It is expected that the larger the presence of Mexican Americans and Mexican immigrants in an area, the higher the rate of poverty. This is based on prior research, which has shown that these two populations tend to be concentrated in areas of high poverty, and are more often employed in low-wage occupations and have lower levels of education. The percentage of poverty in the SPUMA will also be used as a predictor and it is expected that the higher the area poverty, the higher the probability of any poverty outcome.

Occupational classification has also been identified as a key predictor at the contextual level. Several macro-level independent variables were chosen for analysis based on their predictive success in preliminary analyses and include the following: the percentage of service occupations located in an area, the percentage of agricultural occupations, and the percentage of professional occupations in an area. It is expected that a greater presence of service-based occupations will coincide positively with poverty as these are low-skill, low-wage positions that rarely offer benefits. The same relationship is expected for agricultural occupations as these are also characterized by low-wages and seasonality, and it has been shown in prior research that greater concentrations of agricultural employment coincides with a greater concentration of poverty (Slack et al., 2009; Albrecht et al., 2000). Finally, a negative relationship is expected for professional occupations, i.e. the higher the percentage of professional occupations in an area, the lower the probability of poverty. This is based on the assumption that professional occupations provide an overall context for higher levels of skill and training and offer high wages in return, thus lessening the risk of poverty to the overall population.

7.2 Operationalization and Construction of Variables

The most influential independent variables in the logistic regressions performed in Chapters 5 and 6 have been selected for use in the multilevel models. As already noted the dependent variables to be used are extreme poverty (EXTPOV), 100% poverty (POV100), and low income (LOWINC); all of which are dichotomous variables. Two sets of models have been prepared; one for each population (Mexican Americans and Mexican immigrants). The data for Mexican Americans are restricted to household heads, married with spouse present, with at least one child present in the household, and reporting Mexican ethnicity. The Mexican American sample population contains information on 19,674 households.

The independent variables selected for analysis at level-1 for Mexican Americans are number of children present in the household (NCHILD). This is an interval level variable ranging from 1 to 9 or more (those with no children were excluded from the sample). Unemployment status (UNEMPLOY) was selected as another key predictor at level-1 and is measured as a dichotomous variable where 1 equals not employed and/or not a member of the labor force and 0 equals employed. Finally, immigration status (MEXIMM) reports whether or not the respondent indicated he/she was born in Mexico, where 1 equals yes and 0 equals no.

At the contextual level (level-2), a number of variables were selected based on their performance in preliminary HGLM analyses. The first of these variables is the relative, weighted percentage of poverty in an SPUMA (WTPOV). This variable was constructed using Summary File 3 data from the Decennial Census of 2000. The values were obtained by assigning a proportion (of the total SPUMA population) to each county within the SPUMA. The percentage of poverty for the corresponding county was then multiplied by its relative proportion. Each of these values was then summed for all the counties located in an SPUMA to obtain a weighted percentage of poverty for the entire SPUMA. Thus a poverty percentage is assigned to each of the 42 SPUMAs located in the level-2 data set, with values ranging from 7.5 to 35.9%. Each of the variables constructed at level-2 were created based on the above-mentioned method. Hence, county percentages were obtained for each of the level-2 variables for the counties in a SPUMA, multiplied by the proportion of the SPUMA population located in the county, and finally all county-based values were summed to obtain a weighted percentage for each independent variable.

The weighted percentage of those employed in service occupations has also been included in the HGLM analysis for Mexican Americans (WTSERV). This variable was constructed in the manner detailed above and ranges from 9.4 to 17.7% for the 42 SPUMAs. The final occupational variable selected was the percentage of those employed in professional occupations. Again, this is a weighted percentage and the values range from 5.22 to 16.31.

The last of the level-2 variables used in the analysis of Mexican Americans was the percentage of Hispanic immigrants located in the SPUMA (WTIMM). This variable was constructed using data from the Decennial Census 2000, Summary File 3. Data were available for Hispanic rather than Mexican Immigrants only. Despite this shortcoming in the data, I expect this variable should still act satisfactorily because the proportion of Mexican immigrants in the counties of the 42 SPUMAs is very high compared to that of other Hispanic immigrants. This variable was constructed in the manner described above for the occupations and the percentage of those in poverty, i.e. a weighted percentage of Hispanic immigrants was calculated for each of the 42 SPUMAs.

The data set for Mexican immigrants contains information on 12,122 household heads and is restricted to those with at least one child present, those who were married with spouse present, those who reported Mexican ethnicity, and those who listed their birthplace as Mexico. Each of the individual level variables mentioned above was also used in the analysis of Mexican immigrants in the Southwest, in addition to a proxy variable for undocumented status, number of years spent in the USA, and citizenship status. These variables proved to be quite influential in the logistic regressions (reported earlier) and were chosen accordingly. The variable for undocumented status (UNDOC) is a dichotomous variable where a value of 1 represents those who are more than likely undocumented Mexican immigrants and a value of 0 represents those who are not. It is based on a series of affirmative responses to questions in the ACS data that were identified as related to undocumented status by work initiated by Bean et al. in 1984. This variable is not a failsafe predictor of undocumented status, but the work of Bean and his colleagues showed that this method allowed for a relatively accurate measure of undocumented status in a majority of cases. The variable for number of years spent in the USA is an interval level variable ranging from 0 to 87. It was constructed using the YRSUSA1 variable located in the ACS 2006 data. The final variable used at the individual level for Mexican immigrants is citizenship status. This is a dichotomous variable where a value of one represents those who are citizens, both natives and naturalized, and a value of 0 represents those who are non-citizens.

The variables selected at level-2 for Mexican immigrants are operationalized in the same manner as those for the Mexican American population. They include the weighted percentage of poverty in the SPUMA, the percentage of the population employed in service, professional, and agricultural occupations, and the percentage of Hispanic immigrants.

7.3 Summary Statistics and Discussion

The information obtained at the individual level for the Mexican American population in the Southwest came from the American Community Survey, 2006. This is a nationally representative sample of the US population. The data obtained at the contextual level are derived from the Decennial Census 2000 and are based on actual counts of the population. These data provide 100% characteristics for race, sex, and Hispanic or Latino origin. Additionally, they provide information on marital status, educational attainment, labor force participation, and others for one in six individuals in the population via the long-form. The data described below (Table 7.1) provide information on 19,674 Mexican Americans nested within 42 SPUMAs. My primary

Table 7.1 Multilevel descriptive statistics for Mexican Americans

Level-1 descriptive statistics					
Variable name	N	Mean	sd	Minimum	Maximum
EXTPOV	19,674	0.04	0.19	0.0	1.0
POV100	19,674	0.16	0.37	0.0	1.0
LOWINC	19,674	0.47	0.50	0.0	1.0
NCHILD	19,674	2.26	1.12	1.0	9.0
UNEMPLOY	19,674	0.22	0.42	0.0	1.0
MEXIMM	19,674	0.62	0.49	0.0	1.0
EDUC	19,674	10.68	4.08	0.0	21.0
Level-2 descriptive statistics					
Variable name	J	Mean	sd	Minimum	Maximum
WTPOV	42	15.51	5.91	7.50	35.90
WTSERV	42	13.15	1.6	9.40	17.70
WTPROF	42	9.27	3.04	5.22	16.31
WTIMM	42	10.92	5.93	3.32	28.74

interest lies in the likelihood of poverty at any level, i.e. extreme poverty, 100% poverty, or low income; each of which are modeled separately.

The results in the table describe seven level-1 variables, namely, extreme poverty (EXTPOV), 100% poverty (POV100), low income (LOWINC), number of children present in the household (NCHILD), unemployment status (UNEMPLOY), immigration status (MEXIMM), and level of education (EDUC). The findings indicate that approximately 4% of Mexican Americans were in extreme poverty, 16% in 100% poverty, and 47% in low income. The population had an average of 2.26 children per household, about 22% were unemployed, 62% were Mexican immigrants, 31% were employed in a Mexican immigrant job, and the average level of education attained was 10.68 years.

The data in the table also describe four SPUMA level variables, namely, a weighted average poverty score (WTPOV), a weighted percentage of service occupations concentrated in the area (WTSERV), a weighted percentage of those employed in professional occupations (WTPROF), and a weighted percentage of Hispanic immigrants present. Across the 42 SPUMAs, there was an average of 15.51% in poverty, 13.15% employed in service occupations, 9.27% employed in professional occupations, and 10.92% Hispanic immigrants.

Table 7.2 presents the descriptive data for the Mexican immigrant population in the Southwest. Here the individual level data were also obtained from the ACS 2006 and the contextual level data from the Decennial Census of 2000. The data in the table describe nine individual level variables, namely, extreme poverty, 100% poverty, low income, number of children present in the household, unemployment status, a proxy variable for undocumented status, citizenship status, and number of years spent in the USA. The findings indicate that 4.52% of Mexican immigrants

Table 7.2 Multilevel descriptive statistics for Mexican immigrants

Level-1 descriptive statistics

Variable name	N	Mean	sd	Minimum	Maximum
EXTPOV	12,122	0.045	0.21	0.0	1.0
POV100	12,122	0.21	0.40	0.0	1.0
LOWINC	12,122	0.58	0.49	0.0	1.0
NCHILD	12,122	2.40	1.15	1.0	9.0
UNEMPLOY	12,122	0.22	0.42	0.0	1.0
UNDOC	12,122	0.3	0.06	0.0	1.0
CIT	12,122	0.36	0.48	0.0	1.0
YRSUSA1	12,122	21.14	11.05	0.0	87.0

Level-2 descriptive statistics

Variable name	J	Mean	sd	Minimum	Maximum
WTPOV	42	15.51	5.91	7.50	35.90
WTSERV	42	13.15	1.6	9.40	17.70
WTPROF	42	9.27	3.04	5.22	16.31
WTIMM	42	10.92	5.93	3.32	28.74
WTAG	42	3.90	3.56	0.30	15.04

were in extreme poverty, about 21% in 100% poverty, and 58% were low income. The Mexican immigrant population had an average of 2.4 children per household, 22% were unemployed, 0.3% was undocumented, 36% of the household heads were citizens, and the population averaged 21.14 years in the USA.

The data also describe five level-2 (SPUMA) variables, namely, the weighted percentage of poverty for the SPUMA (WTPOV), the percentage of those employed in agriculture (WTAG), professional (WTPROF), and service (WTSERV) occupations, and the percentage of Hispanic immigrants in the SPUMA (WTIMM).

7.4 Hierarchical Generalized Linear Model Results

Traditionally, models using data at more than one level involved either aggregating up to the level of the context, or disaggregating down to the level of the individual. In the case of aggregation, the data user would assign the characteristics of individuals to the contexts in the form of mean values. The main problem with this is that frequently a lot of the within group variation is discarded before the analysis has even begun. In the case of disaggregation, the context (SPUMA) characteristics would be assigned to the individuals. However, in this scenario all individuals located in the same geographic unit would be assigned the same value, hence the assumption of independence would be lost (Poston 2007).

In order to avoid these issues I have employed a more appropriate statistical method for modeling binary multilevel outcomes, namely hierarchical generalized linear models (HGLM). This procedure is used to model the effects of both micro and macro level predictors on, in turn, each of the three binary outcomes of poverty, simultaneously and without losing any of the within and between group variation. Thus I am able to assess (through the usage of a multilevel model) the extent of the effects of individual level characteristics, such as education level and immigration status, as well as the extent of the effects of contextual characteristics of SPUMAs, such as concentration of poverty in the area or industrial diversification (through the use of M1), on the probability of poverty. Additionally, HGLM is the appropriate model given that it allows for the estimation of a binary outcome (see Chapter 3 for discussion of a latent dependent variable construct) in a situation where the random effects are not normally distributed. In other words, I am able to constrain my outcome to a value between one and zero. Hence, the HLM software utilized for analyses allows for a nonlinear application appropriate for binary outcomes, and which is a direct application of the generalized linear model to hierarchical data (Raudenbush and Bryk 2002). This is referred to as a Bernoulli model.

Through the use of HLGM, I am essentially able to perform a regression of regressions (Poston 2000). In this case the outcome variable is one of three dichotomous dependent variables: extreme poverty, 100% poverty, and low income. First, regressions are performed at the lowest level for each of the SPUMAs, i.e., at level-1, in order to predict a level-1 outcome as a function of the other level-1 characteristics. These equations are performed separately for the various level-2 units and are referred to as within-region equations. The intercepts and coefficients produced are then used as the dependent variables in a set of equations across the regions, or SPUMAs, and are referred to as the level-2 equations (Poston and Duan 2000). Here, the level-2 units are the unit of analysis, and the other level-2 characteristics are the independent variables. These equations are referred to as the between-region models.

The data being analyzed in this book are from a nationally representative sample of the United States population (ACS 2006) and contains information on 19,674 Mexican American households, and on 12,122 Mexican immigrant households, nested within 42 SPUMAs in the Southwestern United States. My primary interest lies in the probability that the household will report to extreme poverty, 100% poverty, or low income status (EXTPOV = 1 if yes, EXTPOV = 0 if no; POV100 = 1 if yes, POV100 = 0 if no; LOWINC = 1 if yes, LOWINC = 0 if no). It is hypothesized that level of education, number of children present in the household, unemployment status, and immigration status will be associated with the likelihood of poverty for Mexican Americans. It is also hypothesized that the number of children present, unemployment status, undocumented status, number of years spent in the USA, and citizenship status will be associated with poverty outcomes for the Mexican immigrant population. Each level-1 record corresponds to a household head, with a single binary outcome for each; hence the model type is Bernoulli (Raudenbush et al., 2004). A number of models have been specified based on several combinations of the level-1 and level-2 variables. The formula below denotes the specifications of the level-1 and level-2 structural models for one of these models (Mexican Americans).

The level-1 structural model is as follows:

$$\eta_{ij} = \log[\varphi_{ij}/1-\varphi_{ij}] = \beta_{0j} + \beta_{1j}(\mathrm{NCHILD})_{ij} + \beta_{2j}(\mathrm{UNEMPLOY})_{ij} + \beta_{3j}(\mathrm{MEXIMM})_{ij}$$

The level-2 structural model is as follows:

$$\beta_0 = \gamma_{00}+\gamma_{01}{}^*(\mathrm{WTPOV}) + \gamma_{02}{}^*(\mathrm{WTSERV}) + u_{0j}$$

$$\beta_1 = \gamma_{10}+\gamma_{11}{}^*(\mathrm{WTPOV}) + \gamma_{12}{}^*(\mathrm{WTSERV}) + u_{1j}$$

$$\beta_2 = \gamma_{20}+\gamma_{21}{}^*(\mathrm{WTPOV}) + \gamma_{22}{}^*(\mathrm{WTSERV}) + u_{2j}$$

$$\beta_3 = \gamma_{30}+\gamma_{31}{}^*(\mathrm{WTPOV}) + \gamma_{32}{}^*(\mathrm{WTSERV}) + u_{3j}$$

In the level-1 model, n_{ij} is the predicted log-odds of success, or the logit of being in poverty. This value may be converted to an odds ratio by taking the exponentiated (η_{ij}). It is predicted (in this case) based on the household head's number of children (NCHILD), their unemployment status (UNEMPLOY), and whether or not they are a Mexican immigrant (MEXIMM). In the level-2 model, each of the level-1 coefficients, i.e. the intercept and the three logistic regression coefficients are predicted by the percentage of poverty (WTPOV) and the percentage of employment in a service occupation (WTSERV) of the SPUMA. The level-2 equations are then substituted into the level-1 equation and solved (Poston 2000).

The following paragraphs will detail the models and results associated with each of the HGLM analyses performed for Mexican Americans and Mexican immigrants in the Southwest United States (see Appendix C for additional multilevel models not discussed in the text). The results presented are done so based on the *Population-Average Model*. This type of model has been chosen because, "[they] give answers to population-average questions…The population-average results can be deduced as one characteristic of the distribution of the unit-specific results" (Raudenbush and Bryk 2002). Thus, given that I am interested in how the risk of poverty differs between those who are and who are not Mexican immigrants across SPUMAs, for example, a population-average estimate is needed.

As a first step in HGLM analyses, the data user performs a one-way ANOVA with random effects. This is very useful as a preliminary step in the analysis because "it provides important information about the outcome variability at each of the levels of the hierarchy" (du Toit and du Toit 2001: 72). This value is referred to as the intra-class correlation and may be calculated in the following manner:

$\rho = \tau_{00}/(\tau_{00} + \pi^2/3)$; in which τ_{00} is the level-2 variance component and the level-1 variance component is the constant $\pi^2/3$. In this case the τ_{00} value is 0.238 and results in an intra-class correlation of 0.068. This may interpreted to mean that about 6.8% of the variance in extreme poverty among Mexican Americans occurs at the contextual level. Hence, I am justified in pursuing further analysis at the contextual level for this population. This level-2 variance, i.e., $\tau_{00} = .238$, is significantly different from zero; hence there is variation in extreme poverty at level-2, i.e., among the 42 SPUMAs, justifying my conduct of a multi-level analysis of extreme poverty.

7.5 Results: Mexican Americans

Table 7.3 reports the results of the tests of the multilevel model for Mexican Americans in extreme poverty. This is the first of six models (see Fig. 7.1 for a depiction of how the models are organized) presented for this population and includes variables for number of children present, unemployment status, level of education, and immigration status at the individual level; as well as the percentage of persons in poverty and percentage of those employed in service

Table 7.3 HGLM equation: Mexican Americans (Model 1A)

HGLM Equation: Mexican Americans (Model 1A).
Effects with Robust Standard Errors, of Individual and SPMA Characteristics on the Likelihood of Extreme Poverty
19,674 Household Heads of Mexican Americans in 42 SPUMAs, 2006

Fixed effect	Coefficient	Odds ratio	Standard error	T-ratio
Intercept γ_{00}	−3.624	0.028	0.049	−74.065***
WTPOV γ_{01}	0.059	1.061	0.006	9.984***
WTSERV γ_{02}	−0.160	0.852	0.035	−4.617***
For NCHILD slope,				
Intercept γ_{10}	0.373	1.452	0.022	17.158***
WTPOV γ_{11}	0.005	1.005	0.003	1.836
WTSERV γ_{12}	0.013	1.013	0.016	0.809
For UNEMPLOY slope,				
Intercept γ_{20}	1.363	3.906	0.053	25.731***
WTPOV γ_{21}	−0.029	0.972	0.008	−3.571***
WTSERV γ_{22}	0.014	1.014	0.042	0.340**
For MEXIMM slope,				
Intercept γ_{30}	0.526	1.692	0.094	5.584***
WTPOV γ_{31}	−0.003	0.997	0.009	−0.292
WTSERV γ_{32}	0.121	1.128	0.053	2.277**
For EDUC slope,				
Intercept γ_{40}	−0.060	0.942	0.008	−7.865***
WTPOV γ_{41}	−0.001	0.999	0.001	−1.079
WTSERV γ_{42}	−0.003	0.997	0.005	−0.564

**p<.05, **p<.01. Source American community survey 2006 and decennial census 2000

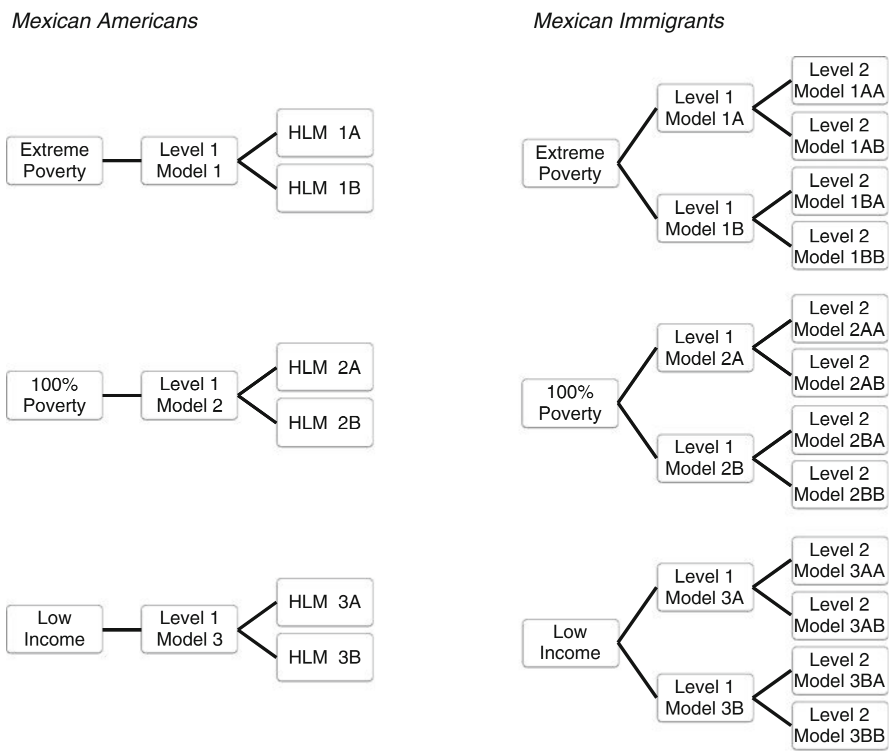

Fig. 7.1 Multilevel model organization

occupations at the contextual level. The following provides interpretations for each of the $\gamma_{\chi\chi}$ (gamma) coefficients, which may be interpreted in the same manner as logit coefficients in a logistic regression and converted into odds ratios by exponentiation.

The γ_{00} coefficient is the intercept and is the grand mean of the expected log-odds of extreme poverty. The values have been exponentiated and thus may be presented as predicted probabilities. Given that the level-1 and level-2 independent variables have been centered around their means, this value refers to individuals with average scores on the four individual level variables, and living in SPUMAs with mean scores on the two contextual level variables. The predicted probability of being in extreme poverty is 0.027, or 2.7%, for those who have an average number of children, are not unemployed and not Mexican immigrants, and is highly significant. This interpretation of the intercept is for general descriptive purposes. Now I will describe the results of the logit coefficients at level-1 and level-2.

The γ_{01} coefficient may be interpreted as the direct effect of percentage in poverty (measured at the contextual level) on the mean extreme poverty rate of the SPUMAs. It was hypothesized that this level-2 variable should have a positive relationship with extreme poverty and this is evidenced (it is significant at the 0.05 level). This means that the percentage of those in poverty in the SPUMA has a significant and positive effect on the average expected log odds of extreme poverty, and that the higher the percentage in poverty, the greater the likelihood of extreme poverty. The odds ratio is 1.061, meaning that for each 1% increase in poverty among the SPUMAs, other things equal, the odds of being in extreme poverty are multiplied by 1.061 times, that is, they increase by 6%. The γ_{02} coefficient is –0.160 $t = -4.617$. This is the direct effect of the percentage of those employed in a service occupation. It was hypothesized that this would have a positive effect on extreme poverty; however, the relationship here is negative and significant; which indicates that for every percentage increase in those employed in service occupations, the odds of being extreme poverty are multiplied by 0.85, that is, they decline by 15%.

The γ_{10} coefficient may be read as the direct effect of the household head's number of children on the probability of being in extreme poverty. A positive relationship was expected and is evidence below (significant at the 0.05 level). Hence, the results indicate that, other things equal, for each additional child, the odds of being in extreme poverty are multiplied by 1.45 times. The γ_{11} coefficient represents the cross-level interaction between WTPOV level-2 variable and the slope of number of children on extreme poverty. This is not statistically significant; if it were significant, it would suggest that, other things equal, for every increase in 1% of poverty in a SPUMA, the slope of number of children on poverty is increased by 0.005. The γ_{12} coefficient represents the cross-level interaction between WTSERV level-2 variable and the slope of number of children on extreme poverty. As was the previous coefficient, the effect is not significant.

The γ_{20} coefficient is 1.363 $t = 25.731$. This is the main effect of the household head's unemployment status on extreme poverty. A positive relationship was hypothesized and the results below indicate a very strong positive relationship. Those who are unemployed are nearly four times more likely to be in extreme poverty all else equal. The γ_{21} coefficient is –0.029 $t = -3.571$. This is the cross-level interaction involving the percentage in poverty in the SPUMA on the slope of the relationship between unemployment status and extreme poverty. The value is significant and indicates that for every increase in 1% of poverty, the slope of unemployment status is decreased by 0.03, other things equal. In other words, a higher percentage in poverty lessens the magnitude of the slope of unemployment on extreme poverty. The γ_{22} coefficient is 0.014 $t = 0.340$. This is the cross-level interaction between the percentage employed in service occupations on the slope of unemployment and extreme poverty, but its effect is not significant.

The γ_{30} coefficient is 0.526 $t = 5.584$. This is the direct effect of Mexican immigrant status on the probability of extreme poverty. A positive relationship was hypothesized and the results confirm that expectation. Thus, the odds of being in extreme poverty are multiplied by 1.69 for Mexican immigrants versus US born Mexicans, all else equal, that is, the odds increase by 69%. The γ_{31} coefficient is –0.003 $t = -0.292$. This is the cross-level interaction involving the WTPOV level-2 variable on the slope of immigration status on extreme poverty; however the effect is not significant. The γ_{32} coefficient is 0.121 $t = 2.277$. This is the cross-level interaction involving the WTSERV level-2 variable on the slope of immigration status and extreme poverty. This is a significant effect and indicates that for each increase of 1% for those employed in a service occupation in an SPUMA, other things equal, the slope of immigration status on extreme poverty is increased by 0.121. Or, the magnitude of the slope of immigration tends to be higher in SPUMAs with higher concentrations of those employed in service occupations.

The γ_{40} coefficient is –0.060 t = –7.865. This is the direct effect of level of education on extreme poverty among Mexican Americans in the Southwest. It was hypothesized that greater levels of education would coincide with lower levels of poverty and this relationship was confirmed. Thus, the odds of being in extreme poverty are decreased by around 6% with each increase of 1 year in level of education, all else equal. The γ_{41} coefficient is –0.001 t = –1.079. This represents the cross level interaction between WTPOV level-2 variable on the slope of education on extreme poverty. The results were not significant. Finally, the γ_{42} coefficient is –0.003 t = –0.564. This is the cross-level interaction involving percentage of employed in service occupations on the association between education and extreme poverty. The effect is not significant.

7.6 Discussion of Findings: Mexican Americans and Extreme Poverty

The results of the preceding analyses revealed some interesting findings. For example, it was observed that the effect of unemployment status at the individual level was lessened by an increased concentration of poverty in the area. In other words, the higher the contextual poverty rate; the lesser the unemployment relationship with poverty at the individual level. In considering the explanation for such a finding, one might argue that in areas where the rate of poverty is high, employment status has little to do with the determination of poverty given the depressed economic conditions and its influence on the entire community. Past research has effectively demonstrated the effect of place on poverty status in such as areas as the Texas Borderland, and this finding is in direct support of such assertions. Additionally, the importance of immigration status on extreme poverty was magnified by higher concentrations of employment in service occupations. As to the reasons for such a finding, it is helpful to consider the idea that in areas where there is a large concentration of service-related occupations, immigration status at the individual level adds to the incidence of poverty. It makes sense that these variables would coincide as immigrants are more often employed in low-wage, low-skill jobs – something that is characteristic of the service industry – thus we observe something of a multiplicative effect.

The next series of tables presents the remainder of the findings for Mexican Americans in the Southwest. Only the tables are presented in the interest of brevity; I do not go through each table and interpret all the coefficients. Tables have been

Table 7.4 HGLM equation: Mexican Americans (Model 1B)

HGLM Equation: Mexican Americans (Model 1B).
Effects with Robust Standard Errors, of Individual and SPUMA Characteristics on the Likelihood of Extreme Poverty
19,674 Household Heads of Mexican Americans in 42 SPUMAs, 2006

Fixed effect	Coefficient	Odds ratio	Standard error	T-ratio
Intercept γ_{00}	−3.588	0.027655	0.054	−66.582***
WTPOV γ_{01}	0.060	1.061333	0.011	5.522***
WTIMM γ_{02}	−0.015	0.984997	0.010	−1.519
For NCHILD slope,				
Intercept γ_{10}	0.370	1.447882	0.024	15.615***
WTPOV γ_{11}	0.007	1.007257	0.003	2.103**
WTIMM γ_{12}	−0.003	0.996815	0.003	−0.982
For UNEMPLOY slope,				
Intercept γ_{20}	1.373	3.948256	0.051	26.988***
WTPOV γ_{21}	−0.017	0.982656	0.009	−1.918**
WTIMM γ_{22}	−0.012	0.988298	0.005	−2.021**
For MEXIMM slope,				
Intercept γ_{30}	0.508	1.662081	0.086	5.927***
WTPOV γ_{31}	0.014	1.014470	0.010	1.388
WTIMM γ_{32}	−0.014	0.985728	0.010	−1.505
For EDUC slope,				
Intercept γ_{40}	−0.058	0.943765	0.007	−7.720***
WTPOV γ_{41}	−0.004	0.996351	0.001	−2.879***
WTIMM γ_{42}	0.003	1.003181	0.001	3.636

**p<.05, ***p<.01. Source American community survey 2006 and decennial census 2000

prepared for several different combinations of individual and contextual level variables for each of the three outcomes, i.e. extreme poverty, 100% poverty, and low-income. As mentioned above, the most influential variables were included in the multilevel analysis. Table 7.4 presents the remainder of the findings for extreme poverty among Mexican Americans. As evidenced below, the individual level predictors remain the same while the percentage of those employed in service occupations has been omitted in favor of the percentage of Hispanic immigrants located in the SPUMA (WTIMM).

Tables 7.5 and 7.6 report the findings with respect to Mexican Americans in 100% poverty. The individual level predictors selected for both models include number of children present in the household, unemployment status, level of education, and immigration status. The contextual level predictors include percentage in poverty, percentage employed in service occupations for Model 2A, and percentage in poverty and percentage of Hispanic immigrants present for Model 2B. A one-way ANOVA was first performed, and the results indicated that 3.68% of the variance in 100% poverty occurs at the contextual level. This

Table 7.5 HGLM equation: Mexican Americans (Model 2A)

HGLM Equation: Mexican Americans (Model 2A).
Effects with Robust Standard Errors, of Individual and SPUMA Characteristics on the Likelihood of 100% Poverty
19,674 Household Heads of Mexican Americans in 42 SPUMAs, 2006

Fixed effect	Coefficient	Odds ratio	Standard error	T-ratio
Intercept γ_{00}	−1.923	0.146	0.042	−45.405***
WTPOV γ_{01}	0.053	1.055	0.005	11.031***
WTSERV γ_{02}	−0.045	0.956	0.025	−1.778
For NCHILD slope,				
Intercept γ_{10}	0.399	1.490	0.017	23.187***
WTPOV γ_{11}	0.003	1.003	0.002	1.224
WTSERV γ_{12}	−0.015	0.985	0.013	−1.112
For UNEMPLOY slope,				
Intercept γ_{20}	0.982	2.670	0.050	19.769***
WTPOV γ_{21}	−0.019	0.981	0.006	−2.982***
WTSERV γ_{22}	−0.004	0.996	0.027	−0.164
For MEXIMM slope,				
Intercept γ_{30}	0.859	2.362	0.053	16.137***
WTPOV $\boldsymbol{\gamma_{31}}$	−0.023	0.977	0.012	−1.970**
WTSERV γ_{32}	0.037	1.038	0.043	0.854
For EDUC slope,				
Intercept γ_{40}	−0.066	0.936	0.005	−12.329***
WTPOV γ_{41}	−0.002	0.998	0.001	−2.921***
WTSERV γ_{42}	0.005	1.005	0.003	1.419

**p<.05, ***p<.01. Source American community survey 2006 and decennial census 2000

$\tau_{00} = 0.126$ value is significantly different from zero and indicates there is enough variation in 100% poverty at level-2, among the 42 SPUMAs to warrant my undertaking a multi-level analysis.

Tables 7.7 and 7.8 present the results of the HGLM analyses performed for Mexican Americans in the low income classification. The same four individual variables of education level, number of children present, immigration status, and unemployment status have been used. At the contextual level, Model 3A contains information on the two contextual level variables of percentage in poverty (WTPOV) and percentage employed in professional occupations (WTPROF). Model 3B contains information on the percentage of those in poverty (WTPOV) along with the percentage of Hispanic immigrants in the area (WTIMM). Also, a one-way ANOVA as been performed for this dependent variable and indicates that about 2.7% of the variance in low income occurs at the contextual level. This τ_{00} $=0.091$ value is significantly different from zero; there is a significant amount of variation in low income at level-2 warranting further analysis.

Table 7.6 HGLM equation: Mexican Americans (Model 2B)

HGLM Equation: Mexican Americans (Model 2B).
Effects with Robust Standard Errors, of Individual and SPUMA Characteristics on the Likelihood of 100% Poverty
19,674 Household Heads of Mexican Americans in 42 SPUMAs, 2006

Fixed effect	Coefficient	Odds ratio	Standard error	T-ratio
Intercept γ_{00}	−1.920	0.147	0.043	−44.370***
WTPOV γ_{01}	−0.058	1.060	0.007	8.309***
WTIMM γ_{02}	−0.012	0.988	0.007	−1.599
For NCHILD slope,				
Intercept γ_{10}	0.401	1.494	0.019	20.522***
WTPOV γ_{11}	0.004	1.004	0.003	1.152
WTIMM γ_{12}	−0.003	0.997	0.004	−0.583
For UNEMPLOY slope,				
Intercept γ_{20}	1.010	2.746	0.044	23.137***
WTPOV γ_{21}	−0.009	0.991	0.007	−1.246
WTIMM γ_{22}	−0.016	0.984	0.006	−2.515***
For MEXIMM slope,				
Intercept γ_{30}	0.851	2.341	0.053	16.129***
WTPOV γ_{31}	−0.027	0.974	0.011	−2.351**
WTIMM γ_{32}	0.007	1.007	0.012	0.554
For EDUC slope,				
Intercept γ_{40}	−0.068	0.934	0.005	−12.462***
WTPOV γ_{41}	−0.002	0.998	0.001	−2.613***
WTIMM γ_{42}	0.001	1.001	0.001	1.051

**p<.05, ***p<.01. Source American community survey 2006 and decennial census 2000

7.7 Discussion: Mexican Americans and 100% Poverty and Low Income

In summary, the results in these tables indicate that for Mexican Americans in 100% poverty and low income, the findings were generally as expected. For example, a greater concentration of those in poverty resulted in a positive, direct effect at the contextual level in all four sets of models. For those in 100% poverty, a greater concentration of those in poverty in the SPUMA resulted in a lessening of the relationship between unemployment status and level of education. Hence, it seems that higher concentrations of poverty lowered the extent to which unemployment and level of education predicted poverty. As mentioned previously, this could be explained by the argument that higher concentrations of poverty in an area have a generally depressing effect on the incidence of poverty and little additional effects are observed at the individual level by such factors as unemployment and level of education. This is a striking finding, and as before, it illustrates the importance of the context on the situation of poverty.

Table 7.7 HGLM equation: Mexican Americans (Model 3A)

HGLM Equation: Mexican Americans (Model 3A).
Effects with Robust Standard Errors, of Individual and SPUMA Characteristics on the Likelihood of Low Income
19,674 Household Heads of Mexican Americans in 42 SPUMAs, 2006

Fixed effect	Coefficient	Odds ratio	Standard error	T-ratio
Intercept γ_{00}	−0.112	0.894	0.044	−2.572***
WTPOV γ_{01}	0.020	1.020	0.008	2.431**
WTPROF γ_{02}	−0.060	0.942	0.018	−3.390***
For NCHILD slope,				
Intercept γ_{10}	0.459	1.583	0.018	25.194***
WTPOV γ_{11}	0.004	1.004	0.003	1.178
WTPROF γ_{12}	−0.014	0.986	0.007	−1.899
For UNEMPLOY slope,				
Intercept γ_{20}	0.777	2.175	0.045	17.236***
WTPOV γ_{21}	−0.023	0.977	0.009	−2.645***
WTPROF γ_{22}	−0.079	0.924	0.019	−4.103***
For MEXIMM slope,				
Intercept γ_{30}	1.004	2.730	0.047	21.549***
WTPOV γ_{31}	−0.016	0.984	0.010	−1.671
WTPROF γ_{32}	0.021	1.021	0.022	0.926
For EDUC slope,				
Intercept γ_{40}	−0.009	0.906	0.006	−15.395***
WTPOV γ_{41}	−0.003	0.997	0.001	−2.191**
WTPROF γ_{42}	−0.003	0.997	0.002	−1.141

**p<.05, ***p<.01. Source American community survey 2006 and decennial census 2000

It was also observed that a greater concentration of Hispanic immigrants in the SPUMA lessened the effect of unemployment for Mexican Americans in 100% poverty. Among those in low income, the percentage of persons employed in professional occupations in the SPUMA had a negative, direct effect. This was as hypothesized and statistically significant. In addition, greater concentrations of those employed in professional occupations resulted in a lessening of the relationship between unemployment and low income. Finally, and most interestingly, it was observed that a greater concentration of Hispanic immigrants resulted in a negative, direct effect on low income status. In other words, a higher concentration of immigrants resulted in a lower likelihood of low income status. This was opposite to the hypothesized relationship. Additionally, greater concentrations of immigrants in the SPUMA led to a lessening of the relationship between unemployment and number of children present on low income status. I posit here that this may be due to the fact that immigration may act as an indirect measure of economic development and as such may be seen as a positive factor. For instance, the argument could potentially be made that immigrants are drawn to areas where job opportunities are better; hence

Table 7.8 HGLM equation: Mexican Americans (Model 3B)

HGLM Equation: Mexican Americans (Model 3B).
Effects with Robust Standard Errors, of Individual and SPUMA Characteristics on the Likelihood of Low Income
19,674 Household Heads of Mexican Americans in 42 SPUMAs, 2006

Fixed effect	Coefficient	Odds ratio	Standard error	T-ratio
Intercept γ_{00}	−0.112	0.894	0.045	−2.484***
WTPOV γ_{01}	0.055	1.056	0.007	7.856***
WTIMM γ_{02}	−0.023	0.977	0.007	−3.056***
For NCHILD slope,				
Intercept γ_{10}	0.474	1.607	0.017	27.693***
WTPOV γ_{11}	0.015	1.015	0.003	5.210***
WTIMM γ_{12}	−0.011	0.989	0.003	−3.697***
For UNEMPLOY slope,				
Intercept γ_{20}	0.804	2.234	0.044	18.363***
WTPOV γ_{21}	0.027	1.027	0.009	3.128***
WTIMM γ_{22}	−0.039	0.962	0.007	−5.698***
For MEXIMM slope,				
Intercept γ_{30}	1.022	2.779	0.044	23.213***
WTPOV γ_{31}	−0.022	0.978	0.009	−2.239**
WTIMM γ_{32}	−0.001	0.999	0.010	−0.065
For EDUC slope,				
Intercept γ_{40}	−0.099	0.905	0.006	−16.304***
WTPOV γ_{41}	−0.002	0.998	0.001	−1.746
WTIMM γ_{42}	−0.000	0.999	0.001	−0.044

**p<.05, ***p<.01. Source American community survey 2006 and decennial census 2000

some protection is afforded at the level of the context. The protection offered may also be due in part to the fact that immigrants are able to offer each other valuable resources via social networking. These ideas will be discussed in detail in Chapter 8.

7.8 Results: Mexican Immigrants

The next series of tables are presented in reference to Mexican immigrants in extreme poverty, 100% poverty, and low income. As performed above, a set of interpretations are presented for those in extreme poverty, and tables are presented for the remainder of the analyses. In the case of Mexican immigrants, a total of 12 tables are presented in comparison to the six presented for Mexican Americans (see Fig. 3.10 for the layout of models presented in this book). This is due to the fact that the proxy variable for undocumented status is best analyzed without the influence of highly related variables such as citizenship status or years spent in the USA. For this reason the individual level predictors are separated into two models: one which

Table 7.9 HGLM equation: Mexican Immigrants (Model 1AA)

HGLM Equation: Mexican Immigrants (Model 1AA).
Effects with Robust Standard Errors, of Individual and SPUMA Characteristics on the Likelihood of Extreme Poverty
12,122 Household Heads of Mexican Immigrants in 42 SPUMAs, 2006

Fixed effect	Coefficient	Odds ratio	Standard error	T-ratio
Intercept γ_{00}	−3.203	0.041	0.060	−52.995***
WTPOV γ_{01}	0.069	1.072	0.010	7.138***
WTSERV γ_{02}	−0.091	0.913	0.040	−2.273***
For NCHILD slope,				
Intercept γ_{10}	0.332	1.394	0.022	15.068***
WTPOV γ_{11}	0.006	1.006	0.003	2.038**
WTSERV γ_{12}	0.014	1.014	0.017	0.827
For UNEMPLOY slope,				
Intercept γ_{20}	1.334	3.795	0.051	26.198***
WTPOV γ_{21}	−0.027	0.974	0.011	−2.530***
WTSERV γ_{22}	0.045	1.046	0.042	1.074
For UNDOC slope,				
Intercept γ_{30}	1.812	6.125	0.278	6.516***
WTPOV γ_{31}	−0.040	0.961	0.029	−1.374
WTSERV γ_{32}	0.302	1.352	0.216	1.393

**p<.05, ***p<.01. Source American community survey 2006 and decennial census 2000

includes number of children, unemployment status, and undocumented status; and another which includes number of years spent in the USA, unemployment status, and citizenship status. The variables utilized at the contextual level include the percentage of persons in poverty (WTPOV), the percentage of Hispanic immigrants in the area (WTIMM), the percentage of persons employed in service (WTSERV), professional (WTPROF), and agricultural occupations (WTAG).

Table 7.9 presents the findings associated with Mexican immigrants in extreme poverty. These findings are based on a sample of 12,122 Mexican immigrant households nested in 42 SPUMAs. I first estimated a one-way ANOVA; the results indicate that about 8.7% of the variance in extreme poverty occurs at the contextual level. The $\tau_{00} = 0.314$ value and is significantly different from zero. Thus I am justified in estimating the multi-level models presented below. This model contains the following individual level predictors: number of children present in the household, unemployment status, and undocumented status. It also contains information on two macro-level predictors: percentage of those in poverty and percentage of those employed in service occupations.

The γ_{00} coefficient is –3.203 t = –52.995. This is the grand mean of the log odds of the probability of being in extreme poverty. Thus the probability of being in extreme poverty for individuals who are not undocumented, have an average number of children, and are employed from an SPUMA with zero proportion of persons in poverty or employed in a service occupation is 0.041; though this interpretation is for general descriptive purposes. The results of the logits at level-1 and level-2 are described below.

The γ_{01} coefficient is 0.069 $t = 7.138$. This is the direct effect of the macro-level variable, percentage of persons in poverty (WTPOV). In this case, the higher the percentage of persons in poverty, the higher the SPUMA's expected log odds of extreme poverty; or, for every 1% increase in poverty, the SPUMA's average odds of extreme poverty are multiplied by 1.07 times; that is they increase by 7%. The γ_{02} coefficient is –0.091 $t = -2.273$. This is the main effect of the macro-level variable of percentage of persons employed in service occupations on the mean extreme poverty rate of the SPUMAs. I expected that this variable would be related positively with extreme poverty; however a negative relationship is observed. This indicates that the higher the percentage of persons employed in service occupations, the lower the SPUMA's expected log odds of extreme poverty. In other words, for every 1% increase in persons employed in service occupations in an SPUMA, the average odds of extreme poverty are multiplied by 0.913 times; that is they decline by around 9%.

The γ_{10} coefficient is 0.332 $t = 15.068$. This is the direct effect of the number of children present on the likelihood of extreme poverty. The effect is positive and highly significant (as hypothesized). Thus, this indicates that for each additional child, the odds of being in extreme poverty are multiplied by 1.394 times, all else equal. That is, for each additional child present, the odds of extreme poverty are increased by 39%. The γ_{11} coefficient is 0.006 $t = 2.038$. This is the cross-level interaction involving the WTPOV level-2 variable on the slope of number of children on extreme poverty. The effect is positive and significant and indicates that for every percentage increase of individuals in poverty in the SPUMA, the slope of number of children on extreme poverty is increased by 0.006. The γ_{12} coefficient is 0.014 $t = 0.827$. This is the cross-level interaction involving percentage employed in service occupations on the slope of number of children on extreme poverty. The effect is not significant.

The γ_{20} coefficient is 1.334 $t = 26.198$. This is the direct effect of unemployment status on the probability of extreme poverty. A positive relationship was hypothesized and is observed herein (this variable is highly significant). This indicates that those who are unemployed are about 3.8 times more likely to be in extreme poverty than those who are employed, all else equal. The γ_{21} coefficient is –0.027 $t = -2.530$. This is the cross-level interaction involving the percentage of persons in poverty in an SPUMA on the association between unemployment status and extreme poverty. The findings are significant and suggest that for every increase in percentage of those in poverty in the SPUMA, other things equal, the slope of unemployment on extreme poverty is decreased by 0.027. Thus, a higher percentage of those in poverty lessen the magnitude of the slope of unemployment on extreme poverty. The γ_{22} coefficient is 0.045 $t = 1.074$. This is the cross-level interaction involving the macro-level variable of percentage of persons employed in service occupations (WTSERV) on the slope of unemployment on extreme poverty. The effect is not significant.

The γ_{30} coefficient is 1.812 $t = 6.516$. This is the main effect of the household head's undocumented status on the probability of being in extreme poverty. A positive effect was hypothesized and is evidenced below. Hence, for those who are undocumented the odds of being in extreme poverty are multiplied by 6.12. This is highly significant and very important to the findings for this analysis as they indicate that undocumented status has quite an impact on poverty status at both the individual and contextual level. The γ_{31} coefficient is –0.040 $t = –1.374$. This is the cross-level interaction involving the percentage in poverty on the level-1 coefficient of undocumented on extreme poverty status. The effect is not significant. The γ_{32} coefficient is 0.302 $t = 1.393$. This is the cross-level interaction involving the macro-level variable of percentage of those employed in service occupations on the slope of undocumented status on extreme poverty. The effect also is not significant.

The remainder of the findings for Mexican immigrants is presented in table format and shown below. A total of 12 tables are presented relative to the Mexican immigrant population in the Southwest United States and are based on a sample population of 12,122 household heads collected from the American Community Survey, 2006. These household heads are nested within 42 SPUMAs. The tables are presented first with the undocumented variable in place and then with the undocumented variable omitted in favor of number of years spent in the USA and citizenship status (see Fig. 3.3 for organization of Models). Table 7.10 is presented

Table 7.10 HGLM equation: Mexican Immigrants (Model 1AB)

HGLM Equation: Mexican Immigrants (Model 1AB).
Effects with Robust Standard Errors, of Individual and SPUMA Characteristics on the Likelihood of Extreme Poverty
12,122 Household Heads of Mexican Immigrants in 42 SPUMAs, 2006

Fixed effect	Coefficient	Odds ratio	Standard error	T-ratio
Intercept γ_{00}	−3.199	0.041	0.059	−54.255***
WTPOV γ_{01}	0.093	1.098	0.013	7.003***
WTIMM γ_{02}	−0.043	0.958	0.011	−3.606***
For NCHILD slope,				
Intercept γ_{10}	0.330	1.391	0.027	12.216***
WTPOV γ_{11}	0.007	1.007	0.003	2.042**
WTIMM γ_{12}	−0.001	0.999	0.003	−0.401
For UNEMPLOY slope,				
Intercept γ_{20}	1.359	3.891	0.066	20.715***
WTPOV γ_{21}	−0.014	0.986	0.013	−1.067
WTIMM γ_{22}	−0.016	0.984	0.010	−1.662
For UNDOC slope,				
Intercept γ_{30}	1.669	5.305	0.344	4.847***
WTPOV γ_{31}	−0.109	0.897	0.029	−3.735***
WTIMM γ_{32}	0.098	1.103	0.047	2.094***

**p<.05, ***p<.01. Source American community survey 2006 and decennial census 2000

Table 7.11 HGLM Equation: Mexican Immigrants (Model 1BA)

HGLM Equation: Mexican Immigrants (Model 1BA).
Effects with Robust Standard Errors, of Individual and SPUMA Characteristics on the Likelihood of Extreme Poverty
12,122 Household Heads of Mexican Immigrants in 42 SPUMAs, 2006

Fixed effect	Coefficient	Odds ratio	Standard error	T-ratio
Intercept γ_{00}	−3.183	0.041	0.055	−57.759***
WTPOV γ_{01}	0.059	1.061	0.008	7.061***
WTSERV γ_{02}	−0.080	0.923	0.037	−2.158***
For YRUSA1 slope,				
Intercept γ_{10}	−0.026	0.975	0.003	−8.300***
WTPOV γ_{11}	−0.002	0.998	0.000	−5.998***
WTSERV γ_{12}	0.001	1.001	0.002	0.481
For UNEMPLOY slope,				
Intercept γ_{20}	1.336	3.804	0.050	26.941***
WTPOV γ_{21}	−0.023	0.977	0.010	−2.332**
WTSERV γ_{22}	0.049	1.051	0.037	1.345
For CIT slope,				
Intercept γ_{30}	−0.420	0.657	0.086	−4.876***
WTPOV γ_{31}	−0.021	0.979	0.010	−2.135**
WTSERV γ_{32}	−0.012	0.987	0.060	−0.210

**p<.05, ***p<.01. Source American community survey 2006 and decennial census 2000

below and contains information on the macro-level predictors of percentage in poverty and percentage of Hispanic immigrants. Tables 7.11 and 7.12 contain the same macro-level predictors; however the variables for undocumented status and number of children have been removed in favor of number years spent in the USA and citizenship status.

7.9 Discussion: Mexican Immigrants and Extreme Poverty

In summary, the results in these tables indicate that among Mexican immigrants in extreme poverty the direct effect of greater concentrations of those in poverty in the SPUMA was positive and significant in each case. Additionally, this macro-level variable amplified the effect of number of children present and lessened the relationship of unemployment, citizenship, years spent in the USA, and undocumented status on extreme poverty. As was mentioned previously with Mexican American population, it is plausible that high concentrations of poverty in an area allow for little additional effects on the determination of poverty given that poverty itself is so widespread. Following that logic, it is reasonable to assert that the effect of number of children is amplified by a greater concentration of poverty on the basis that this would further strain the individual in terms of the ability to effectively avoid

Table 7.12 HGLM Equation: Mexican Immigrants (Model 1BB)

HGLM Equation: Mexican Immigrants (Model 1BB).
Effects with Robust Standard Errors, of Individual and SPUMA Characteristics on the Likelihood of Extreme Poverty
12,122 Household Heads of Mexican Immigrants in 42 SPUMAs, 2006

Fixed effect	Coefficient	Odds ratio	Standard error	T-ratio
Intercept γ_{00}	−3.212	0.040	0.055	−58.445***
WTPOV γ_{01}	0.088	1.091	0.012	6.931***
WTIMM γ_{02}	−0.051	0.950	0.011	−4.506***
For YRUSA1 slope,				
Intercept γ_{10}	−0.030	0.970	0.004	−7.482***
WTPOV γ_{11}	−0.001	0.999	0.001	−1.443
WTIMM γ_{12}	−0.002	0.998	0.001	−2.923***
For UNEMPLOY slope,				
Intercept γ_{20}	1.352	3.864	0.062	21.660***
WTPOV γ_{21}	−0.015	0.985	0.012	−1.197
WTIMM γ_{22}	−0.011	0.989	0.009	−1.117
For CIT slope,				
Intercept γ_{30}	−0.413	0.662	0.099	−4.160***
WTPOV γ_{31}	−0.032	0.969	0.019	−1.694
WTIMM γ_{32}	0.013	1.013	0.018	0.711

***p<.01. Source American community survey 2006 and decennial census 2000

poverty. The percentage of those employed in service occupations displayed a negative, direct effect on extreme poverty, contrary to what was hypothesized. Finally, a greater concentration of Hispanic immigrants in the SPUMA resulted in a negative direct effect on extreme poverty. This was also contrary to hypothesis and as mentioned above may be due to the idea that immigration is related to higher levels of economic development. A greater concentration of immigrants also resulted in a magnification of the relationship between undocumented status and extreme poverty and a lessening of the relationship between number of years spent in the USA and extreme poverty.

Tables 7.13 and 7.14 contain information on the following micro-level predictors for those in 100% poverty: number of children present, unemployment status, and undocumented status. Table 7.13 presents findings relative to the two macro-level predictors of percentage of those in poverty as well as percentage of those employed in service occupations. Table 7.14 presents findings for the two macro-level predictors of percentage of those in poverty in conjunction with the percentage of Hispanic immigrants in the SPUMA. Table 7.15 presents findings for the macro-level predictors of percentage in poverty and percentage employed in professional occupations (the variable for professional occupation was chosen in favor of service given that no significance was detected), while the micro-level predictors have been amended to include number of years spent in the USA, unemployment status, and citizenship

Table 7.13 HGLM equation: Mexican Immigrants (Model 2AA)

HGLM Equation: Mexican Immigrants (Model 2AA).
Effects with Robust Standard Errors, of Individual and SPUMA Characteristics on the Likelihood of 100% Poverty
12,122 Household Heads of Mexican Immigrants in 42 SPUMAs, 2006

Fixed effect	Coefficient	Odds ratio	Standard error	T-ratio
Intercept γ_{00}	−1.398	0.247	0.047	−29.718***
WTPOV γ_{01}	0.055	1.057	0.007	7.934***
WTSERV γ_{02}	−0.028	0.972	0.031	−0.926
For NCHILD slope,				
Intercept γ_{10}	0.382	1.466	0.016	23.450***
WTPOV γ_{11}	0.003	1.003	0.002	1.174
WTSERV γ_{12}	−0.013	0.987	0.013	−0.966
For UNEMPLOY slope,				
Intercept γ_{20}	0.927	2.527	0.050	18.482***
WTPOV γ_{21}	−0.017	0.983	0.007	−2.514**
WTSERV γ_{22}	0.017	1.018	0.031	0.572
For UNDOC slope,				
Intercept γ_{30}	1.471	4.352	0.289	5.089***
WTPOV γ_{31}	−0.022	0.979	0.048	−0.429
WTSERV γ_{32}	0.221	1.247	0.154	1.432

**p<.05, ***p<.01. Source American community survey 2006 and decennial census 2000

status. Table 7.16 contains the same micro-level predictors and the macro-level predictors of percentage in poverty and percentage of Hispanic immigrants. A one-way ANOVA has been performed and indicates that about 4.7% of the variance in 100% poverty occurs at the contextual level. This $\tau_{00} = 0.164$ value is significantly different from zero and indicates there is enough variation in 100% poverty at level-2, among the 42 SPUMAs to warrant further analysis.

In summary, the results in these tables indicate that as evidenced above, greater concentrations of those in poverty in the SPUMA resulted in a positive, direct effect on 100% poverty as hypothesized. This macro-level variable also lessened the relationship between unemployment and 100% poverty. Also, a greater concentration of Hispanic immigrants in the SPUMA resulted in a negative, direct effect on 100% poverty as shown above.

Tables 7.17, 7.18, 7.19 and 7.20 present the findings relative to the Mexican immigrant population in low income. Four tables are presented and the first two (Tables 7.17 and 7.18) describe the micro-level predictors of number of children present, unemployment status, and undocumented status. This is in accordance with each of the models performed above. These two tables also contain information on the macro-level predictors of percentage of persons employed in either agricultural or professional occupations, the percentage in poverty, and the percentage of Hispanic immigrants in the area. These macro-level predictors were chosen

Table 7.14 HGLM equation: Mexican Immigrants (Model 2AB)

HGLM Equation: Mexican Immigrants (Model 2AB).
Effects with Robust Standard Errors, of Individual and SPUMA Characteristics on the Likelihood of 100% Poverty
12,122 Household Heads of Mexican Immigrants in 42 SPUMAs, 2006

Fixed effect	Coefficient	Odds ratio	Standard error	T-ratio
Intercept γ_{00}	−1.388	0.249	0.045	−31.145***
WTPOV γ_{01}	0.072	1.074	0.008	8.849***
WTIMM γ_{02}	−0.030	0.971	0.008	−3.813***
For NCHILD slope,				
Intercept γ_{10}	0.384	1.468	0.023	16.179***
WTPOV γ_{11}	0.004	1.004	0.004	0.979
WTIMM γ_{12}	−0.003	0.997	0.004	−0.750
For UNEMPLOY slope,				
Intercept γ_{20}	0.959	2.609	0.053	17.994***
WTPOV γ_{21}	−0.008	0.992	0.008	−1.047
WTIMM γ_{22}	0.013	0.987	0.007	−1.836**
For UNDOC slope,				
Intercept γ_{30}	1.681	5.373	0.375	4.487***
WTPOV γ_{31}	0.041	1.042	0.074	0.555
WTIMM γ_{32}	−0.084	0.919	0.062	−1.358

**p<.05, ***p<.01. Source American community survey 2006 and decennial census 2000

based on level of significance observed in preliminary analyses, and thus a departure from previous analyses is taken by way of omission of percentage employed in service occupations for those employed in agriculture and professional occupations. Tables 7.19 and 7.20 present the findings relative to three micro-level predictors of number of years spent in the USA, unemployment status and citizenship status. These models contain the same macro-level predictors mentioned above. Additionally, a one-way ANOVA has been performed for this population and indicates that about 4.3% of the variance in low income status occurs at the contextual level. This level-2 variance, i.e., $\tau_{00} = 0.147$, is significantly different from zero; hence there is variation in low income at level-2, i.e., among the 42 SPUMAs, justifying my conduct of a multi-level analysis of low income.

In summary, the results in these tables indicate that a greater concentration of poverty in the SPUMA coincided with a positive, direct effect on low income status. For those immigrants in low income, it also magnified the relationship between number of children present, number of years spent in the USA, and unemployment on low income status. This macro-level variable lessened the relationship between undocumented and low income status. A greater concentration of immigrants in the SPUMA resulted in a negative, direct effect on low income status. This variable lessened the relationship between numbers of children present, years spent in the USA,

Table 7.15 HGLM equation: Mexican Immigrants (Model 2BA)

HGLM Equation: Mexican Immigrants (Model 2BA).
Effects with Robust Standard Errors, of Individual and SPUMA Characteristics on the Likelihood of 100% Poverty
12,122 Household Heads of Mexican Immigrants in 42 SPUMAs, 2006

Fixed effect	Coefficient	Odds ratio	Standard error	T-ratio
Intercept γ_{00}	−1.441	0.237	0.051	−28.093***
WTPOV γ_{01}	0.041	1.042	0.011	3.784***
WTPROF γ_{02}	−0.032	0.968	0.019	−1.665
For YRUSA1 slope,				
Intercept γ_{10}	−0.039	0.962	0.003	−12.775***
WTPOV γ_{11}	−0.001	0.999	0.001	−1.225
WTPROF γ_{12}	−0.003	0.997	0.002	−1.867**
For UNEMPLOY slope,				
Intercept γ_{20}	0.947	2.578	0.044	21.431***
WTPOV γ_{21}	−0.022	0.978	0.008	−2.941***
WTPROF γ_{22}	−0.022	0.978	0.022	−1.000
For CIT slope,				
Intercept γ_{30}	−0.653	0.520	0.060	−10.945***
WTPOV γ_{31}	−0.027	0.973	0.011	−2.370**
WTPROF γ_{32}	−0.001	0.999	0.029	−0.037

*p<.1, **p<.05, ***p.<0.1. Source American community survey 2006 and decennial census 2000

citizenship status, and unemployment status with low income status; and magnified the relationship between undocumented status and low income status. This is essentially the exact opposite of the relationship observed for the WTPOV variable; hence, suggesting a greater concentration of those in poverty exacerbates the situation of poverty for the individual while a greater concentration of immigrants offers relief from poverty in some sense. This is perhaps attributable to the availability of social networks. A greater concentration of those employed in professional occupations (WTPROF) in the SPUMA displayed a negative, direct effect on low income status as hypothesized. This variable also lessened the relationship between unemployment and years spent in the USA on low income status. The macro-level variable for those employed in agricultural occupations (WTAG) in the SPUMA lessened the relationship between undocumented status and low income.

7.10 Discussion: Mexican Immigrants

In summation of the findings for Mexican immigrants, it is important to note that greater concentrations of professional occupations resulted in the hypothesized relationships. For example, the direct effect of percentage employed in professional occupations was negative and highly significant among those in low income

Table 7.16 HGLM equation: Mexican Immigrants (Model 2BB)

HGLM Equation: Mexican Immigrants (Model 2BB).
Effects with Robust Standard Errors, of Individual and SPUMA Characteristics on the Likelihood of 100% Poverty
12,122 Household Heads of Mexican Immigrants in 42 SPUMAs, 2006

Fixed effect	Coefficient	Odds ratio	Standard error	T-ratio
Intercept γ_{00}	−1.440	0.237	0.048	−30.089***
WTPOV γ_{01}	0.073	1.075	0.008	8.604***
WTIMM γ_{2}	−0.034	0.966	0.009	−4.022***
For YRUSA1 slope,				
Intercept γ_{10}	−0.040	0.961	0.003	−12.353***
WTPOV γ_{11}	0.001	1.001	0.001	1.062
WTIMM γ_{12}	−0.001	0.999	0.001	−1.437
For UNEMPLOY slope,				
Intercept γ_{20}	0.952	2.590	0.049	19.443***
WTPOV γ_{21}	−0.011	0.989	0.008	−1.398
WTIMM γ_{22}	−0.007	0.993	0.007	−1.049
For CIT slope,				
Intercept γ_{30}	−0.667	0.513	0.069	−9.370***
WTPOV γ_{31}	−0.022	0.978	0.011	−1.951**
WTIMM γ_{32}	−0.007	0.993	0.009	−0.819

*p<.1, **p<.05, ***p.<0.1. Source American community survey 2006 and decennial census 2000

(see Table 7.17). However, the effect of employment in service and agricultural occupations performed in directions opposite to what I had hypothesized. For example, a greater concentration of agricultural occupations resulted in a lowered association between undocumented status and low income status (see Table 7.17). It would seem that greater concentrations of agricultural employment would magnify the effect of undocumented status, but this not the case. This may be due to the fact that the agricultural economy is much more equipped to deal with the undocumented population given that they are able to work on a temporary and unregulated basis. Furthermore, the direct effect of percentage employed in service occupations was negative for Mexican immigrants in extreme poverty (see Table 7.16). It is possible that this is due to the fact that employment of any nature lessens the effects of poverty. Other noteworthy findings were that the percentage of those in poverty in the area heightened the magnitude of number of children present on extreme poverty, greater concentrations of immigrants lessened the association between unemployment and extreme poverty, the percentage employed in service occupations heightens the association between unemployment and extreme poverty, and greater concentrations in poverty result in a lessening of the association between number of years spent in the USA and extreme poverty.

Table 7.17 HGLM equation: Mexican Immigrants (Model 3AA)

HGLM Equation: Mexican Immigrants (Model 3AA).
Effects with Robust Standard Errors, of Individual and SPUMA Characteristics on the Likelihood of Low Income
12,122 Household Heads of Mexican Immigrants in 42 SPUMAs, 2006

Fixed effect	Coefficient	Odds ratio	Standard error	T-ratio
Intercept γ_{00}	0.461	1.586	0.055	8.388***
WTAG γ_{01}	0.005	1.005	0.023	0.216
WTPROF γ_{02}	−0.083	0.920	0.024	−3.497***
For NCHILD slope,				
Intercept γ_{10}	0.435	1.545	0.018	24.197***
WTAG γ_{11}	0.001	1.001	0.006	0.107
WTPROF γ_{12}	−0.011	0.989	0.008	−1.405
For UNEMPLOY slope,				
Intercept γ_{20}	0.671	1.956	0.051	13.128***
WTAG γ_{21}	−0.024	0.977	0.017	−1.375
WTPROF γ_{22}	−0.057	0.944	0.021	−2.801**
For UNDOC slope,				
Intercept γ_{30}	2.101	8.178	0.298	7.127***
WTAG γ_{31}	−0.278	0.757	0.074	−3.782***
WTPROF γ_{32}	−0.038	0.962	0.107	−0.358

**p<.05, ***p<.01. Source American community survey 2006 and decennial census 2000

With regard to the prediction of 100% poverty, greater concentrations of those employed in service occupations resulted in a magnification of the association between undocumented status and 100% poverty. The percentage in poverty decreased the effect of unemployment on 100% poverty, a greater percentage of Hispanic immigrants lessened the effect of unemployment, and greater concentrations of those employed in professional occupations lessened the slope of unemployment on 100% poverty. Unexpectedly, the direct effect of percentage of Hispanic immigrants on 100% poverty was negative. In other words, the odds of being in 100% poverty were multiplied by 0.97 times with each increase in percentage of immigrants, other things equal.

Overall, the substantive findings observed in relation to both sample populations were highly significant and revealed a good deal of relevant information. For the most part, the hypothesized relationships were confirmed. However, several of the relationships for type of occupation performed unexpectedly. The multilevel analyses were informative and offer much in the way of discovery. At the individual level, the hypothesized relationships were confirmed unanimously. And most importantly, the findings for Mexican immigrants indicate that undocumented status along with citizenship status play a very important role in the determination of poverty at any level. At the macro-level, it was also observed that many of the hypothesized relationships were confirmed as well. In some cases, a lack of significance was present,

Table 7.18 HGLM equation: Mexican Immigrants (Model 3AB)

HGLM Equation: Mexican Immigrants (Model 3AB).
Effects with Robust Standard Errors, of Individual and SPUMA Characteristics on the Likelihood of Low Income
12,122 Household Heads of Mexican Immigrants in 42 SPUMAs, 2006

Fixed effect	Coefficient	Odds ratio	Standard error	T-ratio
Intercept γ_{00}	0.477	1.611	0.047	10.299***
WTPOV γ_{01}	0.069	1.072	0.008	8.257***
WTIMM γ_{02}	−0.042	0.958	0.008	−5.574***
For NCHILD slope,				
Intercept γ_{10}	0.451	1.571	0.022	20.200***
WTPOV γ_{11}	0.013	1.013	0.004	3.817***
WTIMM γ_{12}	−0.009	0.991	0.003	−2.955**
For UNEMPLOY slope,				
Intercept γ_{20}	0.729	2.072	0.056	12.942***
WTPOV γ_{21}	0.025	1.025	0.010	2.640***
WTIMM γ_{22}	−0.027	0.973	0.010	−2.711***
For UNDOC slope,				
Intercept γ_{30}	1.744	5.718	0.281	6.202***
WTPOV γ_{31}	−0.191	0.826	0.062	−3.100***
WTIMM γ_{32}	0.099	1.104	0.045	2.193**

**p<.05, ***p<.01. Source American community survey 2006 and decennial census 2000

Table 7.19 HGLM equation: Mexican Immigrants (Model 3BA)

HGLM Equation: Mexican Immigrants (Model 3BA).
Effects with Robust Standard Errors, of Individual and SPUMA Characteristics on the Likelihood of Low Income
12,122 Household Heads of Mexican Immigrants in 42 SPUMAs, 2006

Fixed effect	Coefficient	Odds ratio	Standard error	T-ratio
Intercept γ_{00}	0.457	1.580	0.055	8.244***
WTAG γ_{01}	0.006	1.006	0.023	0.247
WTPROF γ_{02}	−0.081	0.922	0.024	−3.414***
For YRUSA1 slope,				
Intercept γ_{10}	−0.293	0.746	0.018	−16.724***
WTAG γ_{11}	−0.009	0.991	0.006	−1.402
WTPROF γ_{12}	−0.028	0.973	0.009	−2.978***
For UNEMPLOY slope,				
Intercept γ_{20}	0.609	1.839	0.047	12.965***
WTAG γ_{21}	−0.021	0.979	0.016	−1.320
WTPROF γ_{22}	−0.041	0.960	0.020	−2.005**
For CIT slope,				
Intercept γ_{30}	−0.690	0.502	0.048	−14.422***
WTAG γ_{31}	0.011	1.011	0.016	0.677
WTPROF γ_{32}	0.019	1.019	0.022	0.892

*p<.1, **p<.05, ***p<.01. Source American community survey 2006 and decennial census 2000

Table 7.20 HGLM equation: Mexican Immigrants (Model 3BB)

HGLM Equation: Mexican Immigrants (Model 3BB).
Effects with Robust Standard Errors, of Individual and SPUMA Characteristics on the Likelihood of Low Income
12,122 Household Heads of Mexican Immigrants in 42 SPUMAs, 2006

Fixed effect	Coefficient	Odds ratio	Standard error	T-ratio
Intercept γ_{00}	0.468	1.596	0.046	10.097***
WTPOV γ_{01}	0.068	1.070	0.009	7.983***
WTIMM γ_{02}	−0.040	0.960	0.008	−5.260***
For YRUSA1 slope,				
Intercept γ_{10}	−0.286	0.751	0.019	−14.872***
WTPOV γ_{11}	0.012	1.012	0.005	2.557***
WTIMM γ_{12}	−0.011	0.989	0.004	−2.969***
For UNEMPLOY slope,				
Intercept γ_{20}	0.659	1.933	0.051	12.812***
WTPOV γ_{21}	0.017	1.017	0.010	1.718
WTIMM γ_{22}	−0.022	0.978	0.008	−2.706***
For CIT slope,				
Intercept γ_{30}	−0.676	0.508	0.056	−12.151***
WTPOV γ_{31}	−0.007	0.993	0.009	−0.754
WTIMM γ_{32}	−0.015	0.985	0.007	−2.086**

**p<.05, ***p<.01. Source American community survey 2006 and decennial census 2000

and it is possible that this was due to the fact that the SPUMAs did not contain enough variation for a significant impact to be observed, i.e. the rate of employment in service occupations ranged from about 9% to about 17%, for example. However, the results did reveal several significant macro-level effects. Additionally, the results confirm that the cross-level interactions observed are well worth investigating.

Chapter 8
Implications and Policy Suggestions

8.1 Implications and Discussion

As mentioned above, the associations with poverty of a number of the variables employed at both the individual and contextual levels call for further investigation. At the individual level, some of the most salient predictors were immigration status (for Mexican Americans), unemployment status, number of children present, number of years spent in the USA (For Mexican immigrants), employment in a Mexican immigrant job, and undocumented status (for Mexican immigrants). The descriptive statistics revealed that both the Mexican American and Mexican immigrant populations are significantly disadvantaged relative to other ethnic groups. In some cases they displayed poverty rates nearly four times higher than those of the comparison populations. The importance of this finding lies in the fact that protections were in place to ensure that family structure would not interfere in the prediction of poverty. As such, other factors are much more significant in the prediction of poverty for Mexican Americans and Mexican immigrants. The predictors related to immigration played a significant role in the prediction of poverty and serve to underscore its importance in the determination of any poverty outcome. In addition, employment in a Mexican immigrant job was a significant predictor of poverty status for both populations and serves to highlight the importance of type of occupation rather than actual employment status per se for these groups. As a result, we clearly see the effects of wage inequality on the Mexican American and Mexican immigrant populations.

The descriptive results revealed that both populations maintain employment in a majority of cases (78% for Mexican Americans and 78% for Mexican immigrants). Hence, we are called upon to examine both the extent of employment in "Mexican immigrant jobs" and the effects of this trend. In the samples for Mexican Americans, it was observed that 31% were employed in a "Mexican immigrant job", while 42% of Mexican immigrants were employed in these types of occupations. As was shown in Chapter 3, increasing numbers of Mexican Americans and immigrants are initially settling or relocating to areas such as the Midwest and Southeast that provide employment in meat packing and other manufacturing-type positions. It is expected

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that as this trend continues, it will result in a number of negative outcomes including an inability on the part of receiving areas to provide the infrastructure necessary to deal with large foreign-born populations, increasing numbers of those in poverty even while maintaining full-time employment, a lack of education and training for the children of immigrants who relocate to gain employment in such areas, and increased tensions in areas that have not previously been exposed to large, foreign-born populations. Previous studies have shown that though these individuals are prompted toward relocation in these areas, once there they are faced with a lack of access to resources and hostility from the local population (Crowley et al. 2006).

Among the Mexican immigrants, citizenship status, number of years spent in the USA, and undocumented status all played central roles in the prediction of poverty. Both citizenship status and number of years spent in the USA served to lessen the likelihood of poverty at any level and as such suggest that assimilation does indeed play a part in the prediction of poverty status. However, previous research shows that Mexican immigrants have the lowest rates of naturalization; as immigration rates continue to climb this problem may well be magnified. Further, the effect of undocumented status was significant and positive and revealed that those who were more than likely undocumented immigrants were at a significantly greater risk of poverty than those who were not. This relationship was as expected and future studies should explore this relationship as well as expand the population of study.

Given that a number of restrictions were placed on the proxy variable for undocumented status it is likely that many undocumented individuals were not identified as such in my analyses. The restrictions I imposed were necessary in this case; however in future studies the controls for marital status and age and some of the other classifying variables among others could be lifted in an effort to better identify this population.

At the contextual level, one of the more interesting findings was that percentage of Hispanic immigrants in the SPUMA had the opposite effect in relation to that hypothesized. I have reflected at length on these findings. I suspect that it is likely that percentage of immigrants is more of an indicator of economic activity in an area, thus the greater the concentration of immigrants, the higher the availability of jobs. It is likely that immigrants are drawn to areas where work is plentiful and as such their concentrations act as a barometer for economic development. Additionally, it may be argued that greater concentrations of immigrants in an area offer a protective effect by way of social networking. However, as mentioned above the effects of greater concentrations of immigrants in an area may result in negative outcomes in areas where the population is unaccustomed to dealing with large, foreign-born populations. In addition, the type of work that is increasingly available to immigrants, both long-term and recent, has been shown to be high-risk, low-wage, and without room for advancement. Hence, the likelihood of greater attainment of social capital is questionable.

Another impressive finding at the contextual level centered on the relationship between greater concentrations of poverty in an area and a corresponding decrease in the magnitude of effect for such variables as unemployment and education. It is arguable that in areas where poverty rates are concentrated, individual level variables have little to do with the determination of poverty. This is possibly caused by the overall influence of poverty and its negative effects on the entire community. Certainly, we may consider areas such as the Texas Borderland in an examination of this issue. In that particular location, there is a high concentration of Mexican immigrants and very high rates of poverty. Given this finding, it is reasonable that policy suggestions that focus on the individual as the root source of poverty will have little effect. These analyses suggest that structural level solutions to poverty are the most viable option to combating such high levels across the country.

8.2 Policy Suggestions

In light of the findings discussed above, I now address some issues of policy that could well afford some positive change for these populations as well as many others. Many of the adult members of the Mexican American and Mexican immigrant populations are employed and reside in dual-parent households, yet they experience poverty at rates much higher than any other group. Thus, the widely held belief that those who are poor deserve to be poor simply does not apply to these populations. A number of policy changes could be enacted which would greatly benefit society as a whole.

In the short-term, beneficial changes would include increases to the minimum wage as well as a relaxation of policies that restrict immigrant access to government benefits. Additionally, an increase in wages manufacturing and service industries that are saturated with foreign-born workers would do a great deal to ease the burden of poverty for current employees as well as future generations. Child care subsidies and health care are also an effective way to improve the economic situation of Mexican Americans and Mexican immigrants in the short-term. Increases in minimum wage, health care, and childcare subsidies would work to reward those families that are low-income, but that remain employed, as is the case with these two populations. Additionally, it has been determined that recent immigrants are contributing members of society; thus the restrictive policies aimed at them have had negative effects on immigrants and citizens alike. Thus, eligibility terms should be clearly explained and individual states of the US should act in an informed and responsible manner with respect to their citizens. Expansion of the federal Earned Income Tax Credit and the TANF (temporary assistance for needy families) programs would also go a long way in terms of moving immigrants toward economic security.

Researchers have suggested that recent policy changes have not had the desired effect of halting the immigration process. To the contrary, highly restrictive policies have led to a situation where the stock of immigration has been significantly impacted in a negative way. In other words, we have successfully barred access to our country for immigrants who have contributions to make in favor of illegal immigrants who in effect, have nothing to lose. In addition, rates of immigration have not slowed and do not appear to be slowing down anywhere in the near future. Rather than focus policy efforts on halting immigration, it would be more beneficial to accept that immigration is a self-perpetuating process and work to improve the stock of immigrants.

In the long term, it would behoove policy makers to direct their efforts toward improving the situation for those immigrants who are already here and encouraging more highly trained and skilled workers to enter the country. Immigrants are increasingly moving to new destinations and entering the labor force and education system with voracity. Thus, immigration policy could best be focused on the education and training of the children of recent immigrants. Given that local economies are receiving economic benefits as a direct result of increased immigration, it would be most beneficial to apply those increased benefits to the expansion of school systems and training programs. These policy changes could include investments in more English as a Second Language (ESL) programs, early education programs such as Head Start, and bi-lingual education. A major gap in the education and skill levels of those in the upper and lower levels of society is becoming more and more apparent and it is expected that this gap will widen in coming years. The children of immigrants are at a further disadvantage as the limited English language proficiency of their parents often translates into poor performance in school. Further, recent studies on immigration have shown that immigrants are not adapting as well economically as they have in past decades. In fact, George Borjas (1999) has written that, "the most recent immigrant waves will probably suffer a substantial economic disadvantage for decades to come" (p. 4). Increasingly, immigrants are being pushed out of areas where there is saturation in the job market, unemployment is high, and anti-immigrant sentiment has grown (Crowley et al. 2006). Thus, they are moving toward areas where there is a demand for low-wage labor. However, the result is that these groups are increasingly vulnerable and without access to the safety nets and provisions afforded other groups. It is imperative that low levels of parental education not be transferred onto their children and that these children be given every opportunity to successfully assimilate and become beneficial members of society. Thus, programs geared toward the enrichment of second and third generation immigrants would serve to improve not only the situation of immigrants but also that of natives. In other words, improvements to the education system would disseminate onto the general public.

Chapter 9
Conclusion

The main goals of this book were to assess and review the situation of the incidence of poverty for Mexican Americans and Mexican immigrants in the Southwest United States. Logistic regression equations were estimated predicting the likelihood of being in poverty for these two groups, and independent variables were used at both the individual and contextual levels. These two populations are of particular interest for a number of reasons. These include the fact that Mexican Americans and immigrants do not seem to enjoy the protection from poverty normally afforded via employment and marital status, i.e. married with spouse present, and they are the largest and most quickly growing ethnic group in the US population. Additionally, they maintain rates of poverty well above those of other ethnic groups when controls for marital status and other relevant variables are in place.

In this final chapter, I provide a brief review of the results of my analyses in the form of a summary of the most influential findings and the necessity for future research. A literature review was offered in Chapter 2 as a means to understand the predictors associated with poverty as well as the historical background of these two populations. It also provided a review of the current poverty threshold and a discussion of relevant policy issues. As such, the analyses in this book allowed for an expansion of the standard poverty threshold and a consideration of a relative measure of poverty in an effort to more fully appreciate the extent of poverty in this nation.

The current measure of poverty, or the federal poverty threshold, has been deemed by most poverty scholars to be inadequate in a number of respects (see the report of the National Academy of Science 1995). The current measure utilizes an absolute measure of poverty while the NAS reports that a relative measure would be much more appropriate given the economic differences by region and changes in the standards of living in recent decades. The current measure is based on the original plan developed in 1965, which was the least expensive of the four food plans offered by the Department of Agriculture and multiplies the economy food plan by three (NAS 1995). It was determined during this time by staff economist Mollie Orshansky that a family in poverty would need to spend one third of its income on food in order to survive. It has subsequently been found that this measure does not adequately provide for a sound diet. It has even been conceded by

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the US government that the measure is only intended as a statistical yardstick and does not properly measure poverty status in a number of respects. However, it is currently the only official measure available through which the analysis of poverty outcomes may be determined, and as such was used as the measure for absolute poverty in this book. As mentioned above, I expanded the notion of poverty to account for more of the population that is negatively affected by stagnant wages and decreased opportunities for employment in positions that offer room for advancement. The three absolute measures of poverty are described below as is the relative measure.

The ACS 2006 data which are utilized assign each household a value for poverty ranging from 1 to 500. Hence, values of 1–50 were used to measure *extreme poverty*; values of 1–100 to measure 100% *poverty*; and values of 1–200 to measure low *income*. These were the three dependent variables used for analysis in each of the two sample populations, i.e. Mexican Americans and Mexican immigrants. Additionally, and as a result of the recommendations made by the National Academy of Science and others I also included a relative measure of poverty in the individual level analyses. This measure was created by determining the state median income and then multiplying that value by 50%. For instance, in California the median household income in 2006 was $56,645. Thus, individuals who lived in California and made $28,322 or less were identified as being in relative poverty. Individual level analyses were performed for both sample populations on the basis of this binary dependent variable as well.

A number of individual level predictors were identified as relevant for predicting any of the outcomes of poverty. Hence, once several restrictions were in place[1] a number of independent variables were used in the equations. These independent variables included sex, level of education, number of children present, immigration status, employment in a Mexican immigrant job, and unemployment status for Mexican Americans. For the Mexican immigrants, the independent variables included sex, level of education, number of children present, citizenship status, employment in a Mexican immigrant job, unemployment status, number of years spent in the USA, and undocumented status. Of particular importance was the proxy variable endeavoring to measure undocumented status. This variable (though conservative in its estimation) was highly significant in the logistic regression equations and served to underscore the importance of undocumented status in the prediction of poverty.

At the contextual level, the macro-level predictors included the percentage of those in poverty in the SPUMA, the percentage of Mexicans and Hispanic immigrants in the area, percentages of those employed in the nine major occupational classifications, metropolitan status of the SPUMA, and an index of industrial

[1] Mexican Americans were restricted to those married with spouse present, reported Mexican ethnicity, and at least one child present in the household. Mexican immigrants were restricted to those who reported Mexican ethnicity, were married with spouse present, reported birthplace as Mexico, and had at least one child present in the household.

diversification (M1). Each of these variables was selected based on prior research performed at the aggregate level.

The literature with respect to multilevel analyses of poverty among Mexican Americans and Mexican immigrants is limited. Thus, many of the findings observed at the contextual level were as expected with respect to this prior literature, but several were unexpected (see *Implications and Discussion* section for more information).

The major research question posed at both levels of analysis was the following: What are the most important predictors of poverty status among Mexican Americans and Mexican immigrants? Previous research indicates that even though these two populations are more often in married couple households and maintain high rates of employment, they are more often subject to outcomes of poverty. Further, Mexican immigrants find themselves in even more problematic situations than Mexican Americans with 100% poverty rates at nearly two times those of their native counterparts (25.3% compared with 14%). In addition, the rates may be understated given that the children of immigrants are not included in their numbers but rather for natives (CIS 2001). Thus, it was of great importance to ascertain the effects of both the individual and contextual level variables in the determination of poverty for these populations.

The significance of studying poverty for Mexican Americans and Mexican immigrants derives from the observation that exposure to poverty leads to a host of additional negative impacts. These include restricted access to quality education, lack of access to healthcare, an inability to secure adequate and/or safe housing, low levels of parental education which lead to poor educational attainment among the children of immigrants, and restricted access to government benefits. It has also been pointed out by the Center for Immigration Studies (2001) that increases in the numbers of those in poverty may eventually lead to a general inability to offer aid to those in need overall. The long-term effects of poverty are also of great interest as recent studies have shown that Mexican Americans and Mexican immigrants remain in poverty for longer periods of time and are unable to attain the levels of economic achievement of other groups even in light of considerable assimilation time. This is a segment of the population, which is rapidly growing and as such cannot afford to be unaddressed in this regard.

Many would argue that poverty is a relatively short-term or episodic experience, yet recent studies suggest that Mexican Americans and Mexican immigrants lag far behind other ethnic groups (CIS 2001). This issue is compounded by undocumented immigration as these individuals are faced with even greater barriers to economic and social success than their documented counterparts. Given the expectation of growth for the Mexican American and Mexican immigrant population (a 436% growth rate was observed for the number of documented migrants from Mexico between 1970 and 2000) through immigration as well as fertility, as well as their increased participation in the labor force and education systems, it becomes imperative that studies assess and highlight the most relevant predictors of poverty for these groups. Hence, the independent variables of immigration status, citizenship status and undocumented status among others were highly salient in this work.

Another issue to be explored in the determination of poverty is the extent to which policy affects such populations. Two major pieces of policy legislation have had considerable impacts on the immigrant population. These were the Immigration Reform Act and the Personal Responsibility and Work Reconciliation Act (PWORA) of 1996. It is no secret that these acts were aimed specifically at curtailing the “problem” of immigration and as such have resulted in a strong anti-immigrant stance in this country. The Immigration Reform Act was designed to drastically reduce the level of illegal immigration through stricter border controls, harsher employer sanctions, and increased penalties for smuggling (Fragomen 1997). The PRWORA, or Welfare Reform Act, had the most significant impacts on the immigrant population. This act specifically created new restrictions targeted at immigrants and has now created a situation in which immigrants are banned (in some cases permanently) from receiving such government benefits as supplemental security income and food stamps. This is in spite of the fact that a majority of immigrants are full-time members of the labor force. Additionally, this act shifted much of the responsibility in determining eligibility for benefits to the states. This becomes quite important in the decision-making process for traditionally immigrant-receiving states such as Texas and California given that their decisions have far-reaching impacts relative to the other states in future terms.

It has been posited that these two pieces of legislation have resulted not only in significantly negative impacts for the immigrant population, but also for the economy overall (Fix and Passel 2002). Recent studies suggest that two these pieces of legislation have had far-reaching impacts on citizens and non-citizens alike. For instance, confusing eligibility terms and fear of repercussions have led to the decreased participation of all members of the population. It has also been argued that in the face of looming recession, lack of safety net programs could prove disastrous for the general population (Fix and Passel 2002). Given that federal laws are central to the well being of American citizens, it becomes necessary to enact policies that protect all contributing members of society.

Suggestions for policy changes were offered in the previous chapter and were made in light of the special circumstances surrounding the determination of poverty for Mexican Americans and Mexican immigrants. As discussed previously, these are unique populations in that their predictors of poverty are not the same as those for other ethnic groups. Therefore, it is necessary to discuss the findings observed for these populations at both the individual and contextual level.

9.1 Future Research Directions

In this work it has been suggested that a number of issues need further exploration. It would be of great interest to conduct studies that highlight the importance of undocumented status in the determination of poverty as well as develop a more encompassing measure of undocumented status itself. Given the nature of this work, it was necessary to restrict the classification of undocumented immigrants to those who were head of households, were married with spouse present, and had at least one child present. Research on the undocumented population has shown that more often than not, undocumented immigrants do not reside in nuclear families. In fact, Passel has estimated that undocumented household heads make up less than one third of the undocumented population. Hence, future studies should focus on a more broadly identified undocumented population, so that poverty outcomes for this group could be predicted with more certainty.

Another issue that requires further exploration is the development of a relative measure of poverty. Relative poverty measures are helpful because they reveal how much of a gap exists between the poor and all Americans (Lichter and Crowley 2002). Ultimately they provide a measure of the amount of inequality in an area. The literature review in Chapter 2 discussed the idea that the current measure of poverty is gravely lacking in its assessment of poverty and as such the study of poverty should involve a more accurate indicator. As was shown, the conception of a relative measure is rather simple and can easily be calculated at a variety of geographic levels. Future work could involve an increase in level of geographic precision such as a county or city measure, which would provide a more accurate indicator of cost of living by location.

A natural extension of this work would be the expansion of the analyses to include the entire United States. Increasingly, both Mexican Americans and Mexican immigrants are initially settling or relocating in areas that have been previously unaffected. As such, the effects of poverty described herein are likely going to be felt in more and more areas of the country. The Mexican American and immigrant population is increasing by way of natural increase and immigration. Thus, future studies should concentrate on the nationwide effects of such changes in population structure.

Finally, several of the macro-level predictors of poverty either lacked significance or did not behave in the manner expected. One of the first steps in addressing these issues would be expanding the analysis of poverty at the contextual level to the entire nation. In addition, I would like to narrow the level of geography to below the SPUMA, so to capture more so the between group variation which may have been problematic in this study which utilized the SPUMA as the regional unit of analysis. Were I to go to the county level, or multi-county level, I would need a broader base from which to draw my level-1 units. The cumulative American Community Survey for 2010 could well be a natural extension of this research.

The Mexican American and Mexican immigrant population constitute the largest ethnic groups in the US society. Their rates are growing and it is expected that their labor force participation and participation in the education system will increase exponentially. Such changes must be met with well-informed policy decisions as discussed above. Unique circumstances surround these populations and a strong anti-immigrant sentiment is detectable at levels much higher than in the past. Given the gaps in parental education and skill of recent immigrants, we must assess the situation with an eye to the future. Recent shifts in the economy toward a more service-based economy have led to a proliferation of low-wage low-skills jobs and a widening of the distance between the upper and lower classes. Every effort must be made to narrow this gap if the United States is to continue to act as a competitor in the global market place. Thus, well-formed attempts at analyzing poverty with respect to these groups are key to the improvement of their overall situation.

One of the major contributions of this book lies in the analysis of immigration related variables in the prediction of poverty.I have observed that the Mexican American and Mexican immigrant population are indeed at a distinct economic disadvantage, and it is through the advancement of scholarly work such as that in this book that we may begin to resolve such issues.

Appendix A

List of Occupations Comprising "Mexican Immigrants Jobs by Sex"

Men

Code	Occupation
402	Cooks
403	Food Preparation Workers
411	Waiters and Waitresses
413	Dining Room & Cafeteria Attendants, Bartender Helpers, & Miscellaneous Food Preparation & Serving Related Workers
414	Dishwashers
422	Janitors and Building Cleaners
425	Grounds Miscellaneous Workers
605	Miscellaneous Agricultural Workers, Including Animal Breeders
622	Brick masons, Block masons, and Stonemasons
623	Carpenters
624	Carpet, Floor, and Tile Installers and Finishers
626	Construction Laborers
633	Drywall Installers, Ceiling Tile Installers and Tapers
642	Painters, Construction and Maintenance
651	Roofers
775	Miscellaneous Assemblers and Fabricators
781	Butchers and Other Meat, Poultry, and Fish Processing Workers
814	Welding, Soldering, and Brazing Workers
822	Other Metal Workers and Plastic Workers, Incl. Milling, Planing, and Machine Tool Operators
832	Sewing Machine Operators
880	Packing and Filing Machine Operators and Tenders
896	Other Production Workers, Including Semiconductor Processors & Cooling & Freezing Equipment Operators
960	Industrial Truck and Tractor Operators

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961	Cleaners of Vehicles and Equipment
964	Hand Packers and Packagers

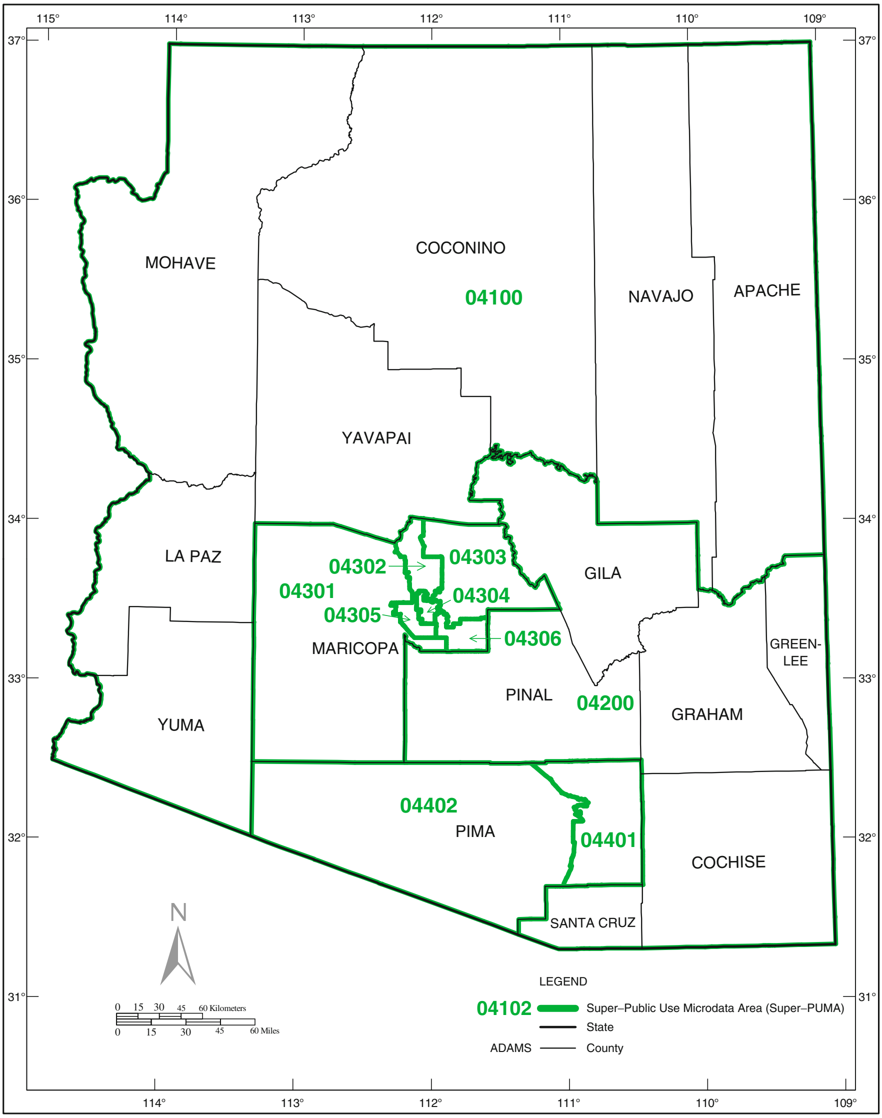
Women

Code	Occupation
402	Cooks
403	Food Preparation Workers
413	Dining Room & Cafeteria Attendants, Bartender Helpers, & Miscellaneous Food Preparation & Serving Related Workers
422	Janitors and Building Cleaners
423	Maids and Housekeeping Cleaners
460	Chefs and Head Cooks
461	Personal and Home Care Aides
561	Shipping, Receiving, and Traffic Clerks
604	Agriculture Products Graders and Sorters
605	Miscellaneous Agricultural Workers, Including Animal Breeders
770	First-Line Supervisors/Managers of Production and Operating Workers
772	Electrical, Electronics and Electromechanical Assemblers
775	Miscellaneous Assemblers and Fabricators
781	Butchers and Other Meat, Poultry, and Fish Processing Workers
822	Other Metal Workers and Plastic Workers, Including Milling, Planing, and Machine Tool Operators
830	Laundry and Dry-Cleaning Workers
831	Pressers, Textile, Garment and Related Materials
832	Sewing Machine Operators
874	Inspectors, Testers, Sorters, Samplers, and Weighters
880	Packing and Filing Machine Operators and Tenders
896	Other Production Workers, Including Semiconductor Processors & Cooling & Freezing Equipment Operators
962	Hand Laborers and Freight, Stock and Material Movers
964	Hand Packers and Packagers

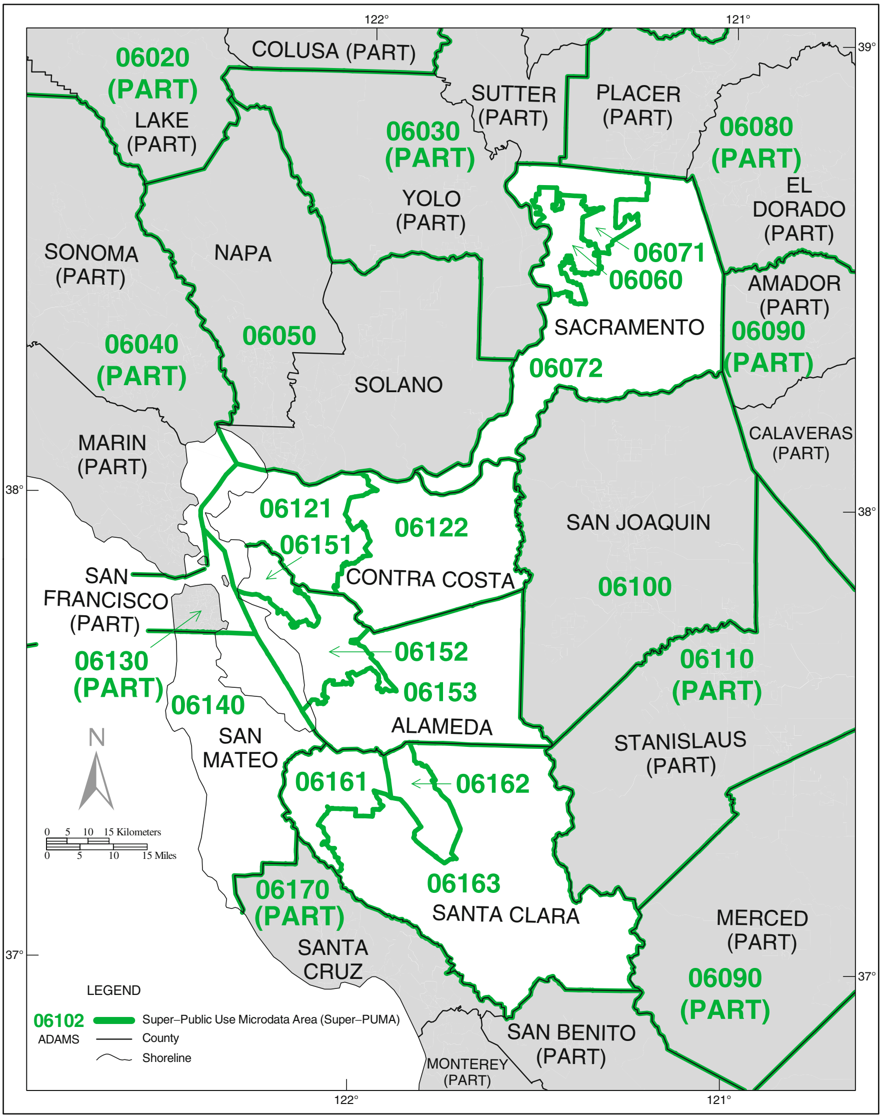
Appendix B

Maps and Boundary Files of the Southwest United States

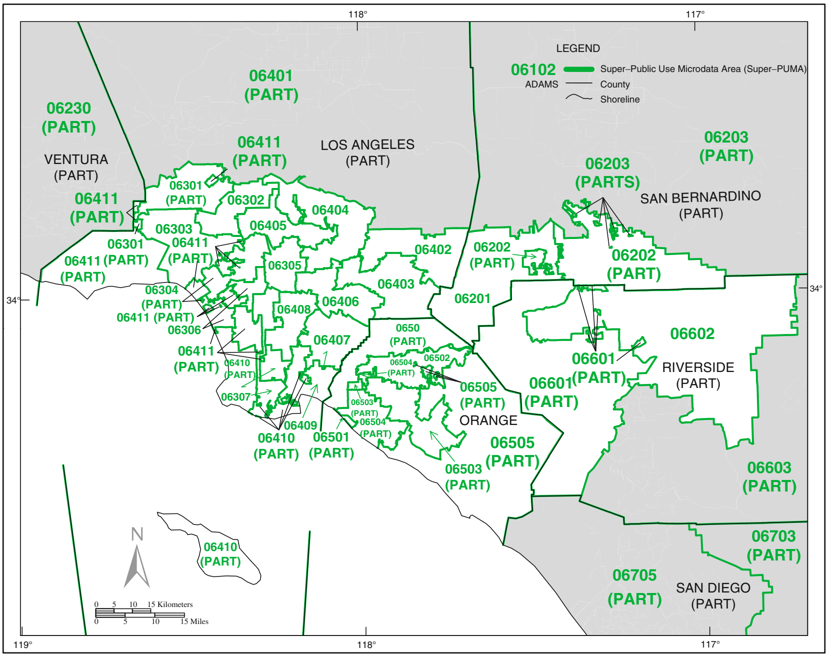
ARIZONA – Census 2000 Super–Public Use Microdata Areas (Super–PUMAs)



CALIFORNIA (Inset A) – Census 2000 Super–Public Use Microdata Areas (Super–PUMAs)



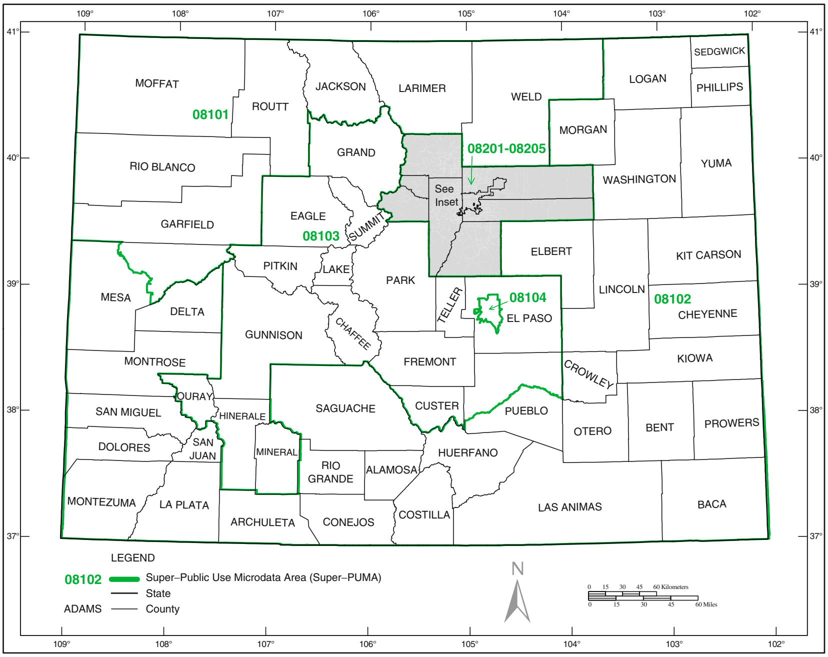
CALIFORNIA (Inset B) – Census 2000 Super–Public Use Microdata Areas (Super–PUMAs)



Public Use Microdata Sample (PUMS) files
U.S. Census Bureau, Census 2000

California 3

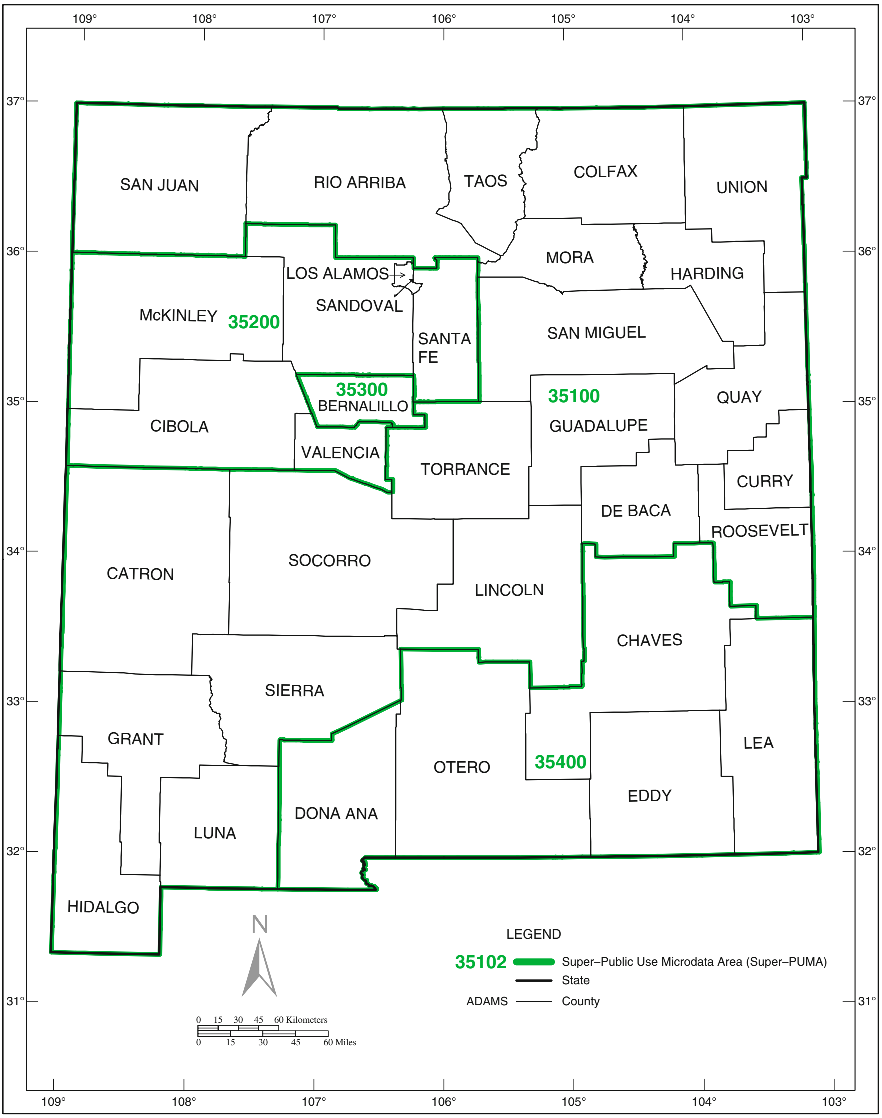
COLORADO – Census 2000 Super–Public Use Microdata Areas (Super–PUMAs)



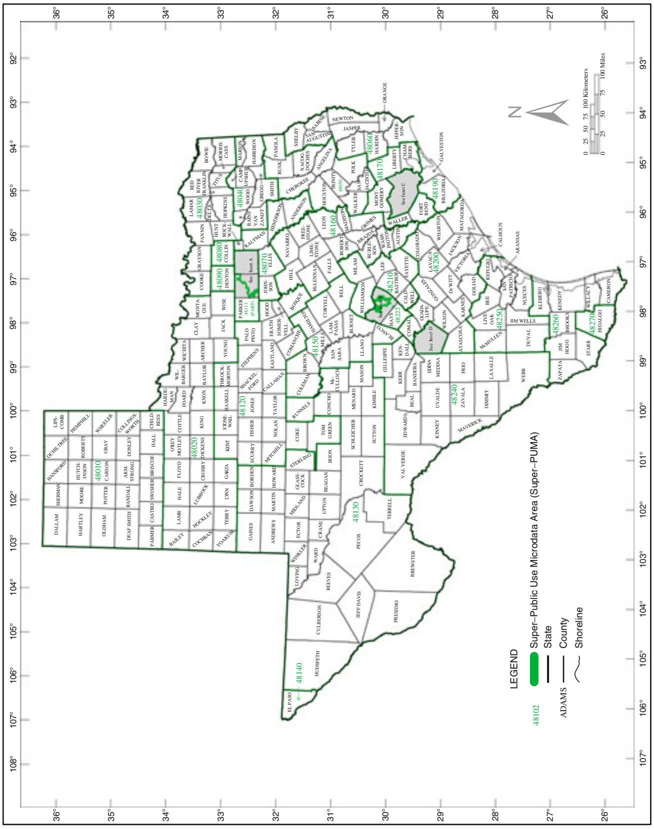
Public Use Microdata Sample (PUMS) files
U.S. Census Bureau, Census 2000

Colorado 1

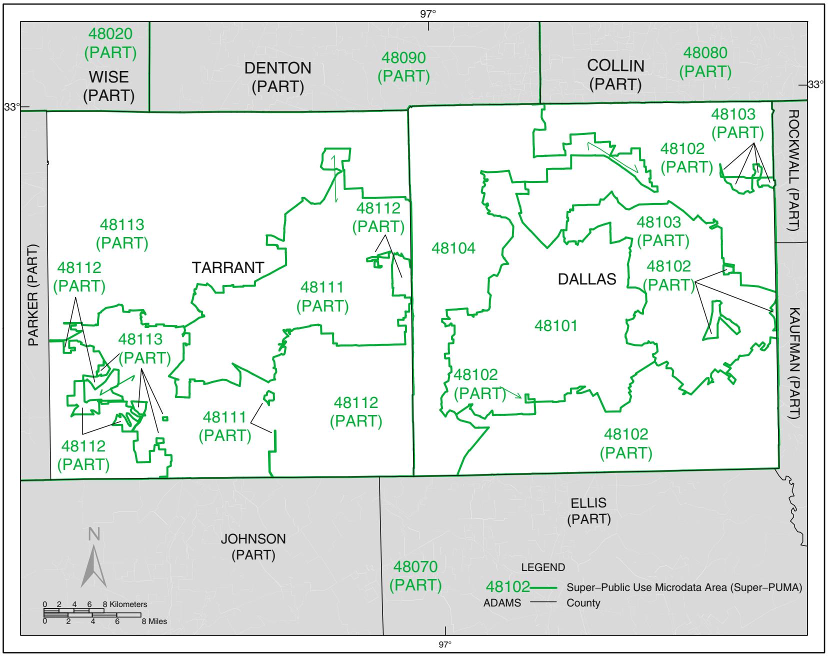
NEW MEXICO – Census 2000 Super–Public Use Microdata Areas (Super–PUMAs)



TEXAS – Census 2000 Super–Public Use Microdata Areas (Super–PUMAs)



TEXAS (Inset A) – Census 2000 Super–Public Use Microdata Areas (Super–PUMAs)

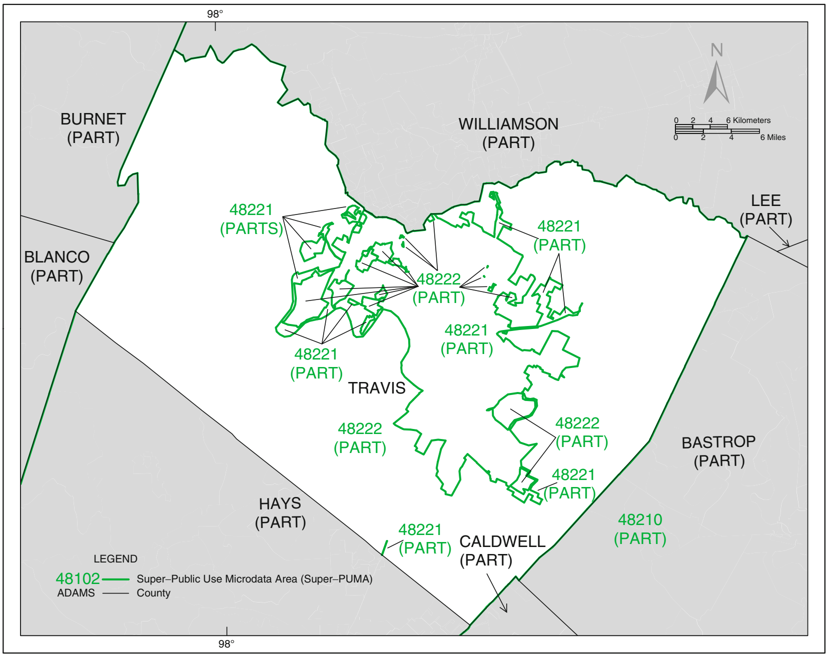


2 Texas

Public Use Microdata Sample (PUMS) files

U.S. Census Bureau, Census 2000

TEXAS (Inset B) – Census 2000 Super–Public Use Microdata Areas (Super–PUMAs)

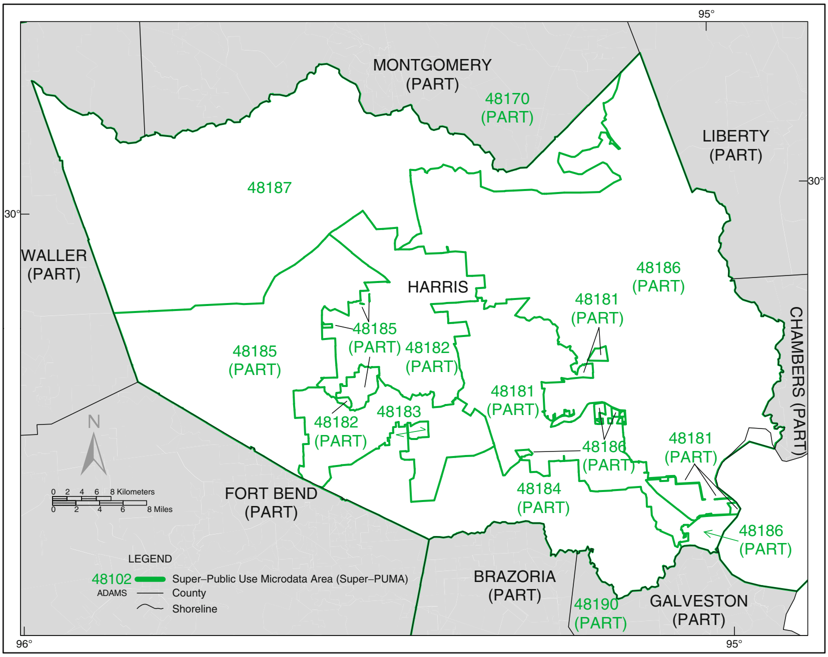


Public Use Microdata Sample (PUMS) files

U.S. Census Bureau, Census 2000

Texas 3

TEXAS (Inset C) – Census 2000 Super–Public Use Microdata Areas (Super–PUMAs)



4 Texas

Public Use Microdata Sample (PUMS) files
U.S. Census Bureau, Census 2000

Appendix C

HGLM Results

HGLM Results: Mexican Americans in Extreme Poverty

Mexican Americans in extreme poverty (modeled based on WTPOV & WTAG), 19,674 household heads nested in 42 SPUMAs

Fixed effect		Coefficient	Standard error	T-ratio	Approx. d.f.	P-value
For INTRCPT1, B0						
INTRCPT2,	G00	–3.58476	0.059029	–60.729	39	0.000
WTPOV,	G01	0.053884	0.009442	5.707	39	0.000
WTAG,	G02	–0.00771	0.012709	–0.607	39	0.547
For NCHILD, slope, B1						
INTRCPT2,	G10	0.376576	0.024905	15.12	39	0.000
WTPOV,	G11	0.004449	0.003173	1.402	39	0.169
WTAG,	G12	0.003566	0.006082	0.586	39	0.561
For UNEMPLOY slope, B2						
INTRCPT2,	G20	1.444318	0.05056	28.566	39	0.000
WTPOV,	G21	–0.02472	0.007099	–3.482	39	0.002
WTAG,	G22	0.024426	0.011122	2.196	39	0.034
For MEXIMM slope, B3						
INTRCPT2,	G30	0.706234	0.08239	8.572	39	0.000
WTPOV,	G31	0.00621	0.009827	0.632	39	0.531
WTAG,	G32	–0.01185	0.018993	–0.624	39	0.536

Odds ratios

Fixed effect		Coefficient	Odds ratio	Confidence interval
For INTRCPT1, B0				
INTRCPT2,	G00	–3.58476	0.027743	(0.025,0.031)
WTPOV,	G01	0.053884	1.055362	(1.035,1.076)
WTAG,	G02	–0.00771	0.992318	(0.967,1.018)
For NCHILD slope, B1				
INTRCPT2,	G10	0.376576	1.457286	(1.386,1.532)
WTPOV,	G11	0.004449	1.004459	(0.998,1.011)
WTAG,	G12	0.003566	1.003572	(0.991,1.016)
For UNEMPLOY slope, B2				
INTRCPT2,	G20	1.444318	4.238959	(3.827,4.695)
WTPOV,	G21	–0.02472	0.975585	(0.962,0.990)
WTAG,	G22	0.024426	1.024726	(1.002,1.048)
For MEXIMM slope, B3				
INTRCPT2,	G30	0.706234	2.026346	(1.716,2.393)
WTPOV,	G31	0.00621	1.00623	(0.986,1.026)
WTAG,	G32	–0.01185	0.988218	(0.951,1.027)

Mexican Americans in extreme poverty (modeled based on WTPOV & WTFIRE), 19,674 household heads nested in 42 SPUMAs

Fixed effect		Coefficient	Standard error	T-ratio	Approx. d.f.	P-value
For	INTRCPT1,	B0				
INTRCPT2,	G00	–3.57896	0.05855	–61.127	39	0.000
WTPOV,	G01	0.044296	0.01211	3.658	39	0.001
WTFIRE,	G02	–0.05297	0.041482	–1.277	39	0.209
For	NCHILD	slope,	B1			
INTRCPT2,	G10	0.376884	0.023938	15.744	39	0.000
WTPOV,	G11	0.001587	0.00417	0.381	39	0.705
WTFIRE,	G12	–0.02195	0.013292	–1.651	39	0.106
For	UNEMPLOY	slope,	B2			
INTRCPT2,	G20	1.439994	0.049313	29.201	39	0.000
WTPOV,	G21	–0.02615	0.01009	–2.591	39	0.014
WTFIRE,	G22	–0.02944	0.049486	–0.595	39	0.555
For	MEXIMM	slope,	B3			
INTRCPT2,	G30	0.688758	0.084393	8.161	39	0.000
WTPOV,	G31	0.017667	0.012059	1.465	39	0.151
WTFIRE,	G32	0.091989	0.042994	2.14	39	0.038

Odds ratios

Fixed effect		Coefficient	Odds ratio	Confidence interval
For	INTRCPT1,	B0		
INTRCPT2,	G00	–3.57896	0.027905	(0.025,0.031)
WTPOV,	G01	0.044296	1.045292	(1.020,1.071)
WTFIRE,	G02	–0.05297	0.948406	(0.872,1.031)
For	NCHILD	slope,	B1	
INTRCPT2,	G10	0.376884	1.457735	(1.389,1.530)
WTPOV,	G11	0.001587	1.001588	(0.993,1.010)
WTFIRE,	G12	–0.02195	0.97829	(0.952,1.005)
For	UNEMPLOY	slope,	B2	
INTRCPT2,	G20	1.439994	4.22067	(3.821,4.663)
WTPOV,	G21	–0.02615	0.974191	(0.955,0.994)
WTFIRE,	G22	–0.02944	0.970994	(0.879,1.073)
For	MEXIMM	slope,	B3	
INTRCPT2,	G30	0.688758	1.991242	(1.679,2.361)
WTPOV,	G31	0.017667	1.017824	(0.993,1.043)
WTFIRE,	G32	0.091989	1.096353	(1.005,1.196)

Mexican Americans in extreme poverty (modeled based on WTPOV & WTCONS), 19,674 household heads nested in 42 SPUMAs

Fixed effect		Coefficient	Standard error	T-ratio	Approx. d.f.	P-value
For	INTRCPT1,	B0				
INTRCPT2,	G00	–3.61585	0.055302	–65.384	39	0.000
WTPOV,	G01	0.062665	0.006682	9.377	39	0.000
WTCONS,	G02	0.050159	0.013897	3.609	39	0.001
For	NCHILD	slope,	B1			
INTRCPT2,	G10	0.367506	0.022993	15.983	39	0.000
WTPOV,	G11	0.006522	0.002561	2.547	39	0.015
WTCONS,	G12	0.006533	0.006552	0.997	39	0.325
For	UNEMPLOY	slope,	B2			
INTRCPT2,	G20	1.441558	0.056746	25.404	39	0.000
WTPOV,	G21	–0.02284	0.007809	–2.924	39	0.006
WTCONS,	G22	–0.00438	0.017961	–0.244	39	0.809
For	MEXIMM	slope,	B3			
INTRCPT2,	G30	0.735981	0.079156	9.298	39	0.000
WTPOV,	G31	0.00374	0.009707	0.385	39	0.702
WTCONS,	G32	–0.0142	0.022607	–0.628	39	0.533

Odds ratios

Fixed effect		Coefficient	Odds ratio	Confidence interval
For	INTRCPT1,	B0		
INTRCPT2,	G00	–3.61585	0.026894	(0.024,0.030)
WTPOV,	G01	0.062665	1.06467	(1.050,1.079)
WTCONS,	G02	0.050159	1.051438	(1.022,1.081)
For	NCHILD	slope,	B1	
INTRCPT2,	G10	0.367506	1.444129	(1.379,1.513)
WTPOV,	G11	0.006522	1.006544	(1.001,1.012)
WTCONS,	G12	0.006533	1.006555	(0.993,1.020)
For	UNEMPLOY	slope,	B2	
INTRCPT2,	G20	1.441558	4.227276	(3.769,4.741)
WTPOV,	G21	–0.02284	0.977423	(0.962,0.993)
WTCONS,	G22	–0.00438	0.995625	(0.960,1.032)
For	MEXIMM	slope,	B3	
INTRCPT2,	G30	0.735981	2.087529	(1.779,2.449)
WTPOV,	G31	0.00374	1.003747	(0.984,1.024)
WTCONS,	G32	–0.0142	0.985905	(0.942,1.032)

Mexican Americans in extreme poverty (modeled based on WTPOV & WTMETRO), 19,674 household heads nested in 42 SPUMAs

Fixed effect		Coefficient	Standard error	T-ratio	Approx. d.f.	P-value
For	INTRCPT1,	B0				
INTRCPT2,	G00	–3.58174	0.057993	–61.762	39	0.000
WTPOV,	G01	0.05037	0.009996	5.039	39	0.000
WTMETRO,	G02	–0.00235	0.002089	–1.126	39	0.267
For	NCHILD	slope,	B1			
INTRCPT2,	G10	0.372884	0.023158	16.102	39	0.000
WTPOV,	G11	0.004658	0.002832	1.645	39	0.108
WTMETRO,	G12	0.000181	0.001013	0.179	39	0.859
For	UNEMPLOY	slope,	B2			
INTRCPT2,	G20	1.438953	0.050099	28.722	39	0.000
WTPOV,	G21	–0.0221	0.007261	–3.043	39	0.005
WTMETRO,	G22	–0.00304	0.001939	–1.566	39	0.125
For	MEXIMM	slope,	B3			
INTRCPT2,	G30	0.711953	0.078283	9.095	39	0.000
WTPOV,	G31	0.004321	0.011165	0.387	39	0.700
WTMETRO,	G32	–0.00343	0.003054	–1.123	39	0.269

Odds ratios

Fixed effect		Coefficient	Odds ratio	Confidence interval
For	INTRCPT1,	B0		
INTRCPT2,	G00	–3.58174	0.027827	(0.025,0.031)
WTPOV,	G01	0.05037	1.05166	(1.031,1.073)
WTMETRO,	G02	–0.00235	0.997651	(0.993,1.002)
For	NCHILD	slope,	B1	
INTRCPT2,	G10	0.372884	1.451916	(1.386,1.521)
WTPOV,	G11	0.004658	1.004668	(0.999,1.010)
WTMETRO,	G12	0.000181	1.000181	(0.998,1.002)
For	UNEMPLOY	slope,	B2	
INTRCPT2,	G20	1.438953	4.216279	(3.810,4.665)
WTPOV,	G21	–0.0221	0.978145	(0.964,0.993)
WTMETRO,	G22	–0.00304	0.996968	(0.993,1.001)
For	MEXIMM	slope,	B3	
INTRCPT2,	G30	0.711953	2.037967	(1.740,2.387)
WTPOV,	G31	0.004321	1.004331	(0.982,1.027)
WTMETRO,	G32	–0.00343	0.996576	(0.990,1.003)

Mexican Americans in extreme poverty (modeled based on WTPOV & M1), 19,674 household heads nested in 42 SPUMAs

Fixed effect		Coefficient	Standard error	T-ratio	Approx. d.f.	P-value
For	INTRCPT1,	B0				
INTRCPT2,	G00	–3.6129	0.056287	–64.187	39	0.000
WTPOV,	G01	0.05534	0.006995	7.911	39	0.000
M1,	G02	–8.85152	2.341807	–3.78	39	0.001
For	NCHILD	slope,	B1			
INTRCPT2,	G10	0.362993	0.022153	16.386	39	0.000
WTPOV,	G11	0.005697	0.002552	2.232	39	0.031
M1,	G12	–1.98373	1.03973	–1.908	39	0.063
For	UNEMPLOY	slope,	B2			
INTRCPT2,	G20	1.43747	0.055379	25.957	39	0.000
WTPOV,	G21	–0.0221	0.007648	–2.89	39	0.007
M1,	G22	–0.48037	3.078445	–0.156	39	0.877
For	MEXIMM	slope,	B3			
INTRCPT2,	G30	0.741275	0.080281	9.233	39	0.000
WTPOV,	G31	0.006084	0.010203	0.596	39	0.554
M1,	G32	4.300343	3.610902	1.191	39	0.241

Odds ratios

Fixed effect		Coefficient	Odds ratio	Confidence interval
For	INTRCPT1,	B0		
INTRCPT2,	G00	–3.6129	0.026973	(0.024,0.030)
WTPOV,	G01	0.05534	1.0569	(1.042,1.072)
M1,	G02	–8.85152	0.000143	(0.000,0.016)
For	NCHILD	slope,	B1	
INTRCPT2,	G10	0.362993	1.437626	(1.375,1.503)
WTPOV,	G11	0.005697	1.005713	(1.001,1.011)
M1,	G12	–1.98373	0.137556	(0.017,1.124)
For	UNEMPLOY	slope,	B2	
INTRCPT2,	G20	1.43747	4.210032	(3.764,4.708)
WTPOV,	G21	–0.0221	0.978141	(0.963,0.993)
M1,	G22	–0.48037	0.618558	(0.001,310.472)
For	MEXIMM	slope,	B3	
INTRCPT2,	G30	0.741275	2.09861	(1.784,2.468)
WTPOV,	G31	0.006084	1.006103	(0.986,1.027)
M1,	G32	4.300343	73.72505	(0.050,108484.739)

Mexican Americans in extreme poverty (modeled based on WTPOV & WTMEX), 19,674 household heads nested in 42 SPUMAs

Fixed effect		Coefficient	Standard error	T-ratio	Approx. d.f.	P-value
For	INTRCPT1,	B0				
INTRCPT2,	G00	–3.58332	0.057026	–62.836	39	0.000
WTPOV,	G01	0.070556	0.0182	3.877	39	0.001
WTMEX,	G02	–0.00799	0.006816	–1.173	39	0.248
For	NCHILD	slope,	B1			
INTRCPT2,	G10	0.372278	0.02202	16.906	39	0.000
WTPOV,	G11	0.011641	0.005526	2.107	39	0.041
WTMEX,	G12	–0.00288	0.002096	–1.371	39	0.178
For	UNEMPLOY	slope,	B2			
INTRCPT2,	G20	1.434994	0.053992	26.578	39	0.000
WTPOV,	G21	–0.01924	0.014742	–1.305	39	0.200
WTMEX,	G22	–0.0011	0.005134	–0.214	39	0.832
For	MEXIMM	slope,	B3			
INTRCPT2,	G30	0.715384	0.082255	8.697	39	0.000
WTPOV,	G31	0.017598	0.020372	0.864	39	0.393
WTMEX,	G32	–0.00552	0.007795	–0.709	39	0.483

Odds ratios

Fixed	Effect	Coefficient	Odds ratio	Confidence interval
For	INTRCPT1,	B0		
INTRCPT2,	G00	–3.58332	0.027783	(0.025,0.031)
WTPOV,	G01	0.070556	1.073105	(1.034,1.113)
WTMEX,	G02	–0.00799	0.992039	(0.978,1.006)
For	NCHILD	slope,	B1	
INTRCPT2,	G10	0.372278	1.451037	(1.388,1.517)
WTPOV,	G11	0.011641	1.011709	(1.000,1.023)
WTMEX,	G12	–0.00288	0.997129	(0.993,1.001)
For	UNEMPLOY	slope,	B2	
INTRCPT2,	G20	1.434994	4.199621	(3.766,4.684)
WTPOV,	G21	–0.01924	0.980949	(0.952,1.011)
WTMEX,	G22	–0.0011	0.998902	(0.989,1.009)
For	MEXIMM	slope,	B3	
INTRCPT2,	G30	0.715384	2.044972	(1.732,2.415)
WTPOV,	G31	0.017598	1.017754	(0.977,1.061)
WTMEX,	G32	–0.00552	0.994492	(0.979,1.010)

HGLM Results: Mexican Americans in 100 Poverty

Mexican Americans in 100% poverty (modeled based on WTPOV & WTAG), 19,674 household heads nested in 42 SPUMAs

Fixed effect		Coefficient	Standard error	T-ratio	Approx. d.f.	P-value
For	INTRCPT1,	B0				
INTRCPT2,	G00	–1.82912	0.042626	–42.911	39	0.000
WTPOV,	G01	0.043424	0.005555	7.817	39	0.000
WTAG,	G02	0.013717	0.010938	1.254	39	0.218
For	MEXJOB	slope,	B1			
INTRCPT2,	G10	0.388636	0.046572	8.345	39	0.000
WTPOV,	G11	0.022473	0.005208	4.315	39	0.000
WTAG,	G12	0.006769	0.016039	0.422	39	0.675
For	MEXIMM	slope,	B2			
INTRCPT2,	G20	0.720434	0.058566	12.301	39	0.000
WTPOV,	G21	–0.01824	0.012672	–1.439	39	0.158
WTAG,	G22	–0.01269	0.017473	–0.726	39	0.472
For	EDUC	slope,	B3			
INTRCPT2,	G30	–0.12227	0.007811	–15.654	39	0.000
WTPOV,	G31	–0.00185	0.001014	–1.828	39	0.075
WTAG,	G32	–0.00022	0.002513	–0.088	39	0.931

Odds ratios

Fixed effect		Coefficient	Odds ratio	Confidence interval
For	INTRCPT1,	B0		
INTRCPT2,	G00	–1.82912	0.160556	(0.147,0.175)
WTPOV,	G01	0.043424	1.044381	(1.033,1.056)
WTAG,	G02	0.013717	1.013811	(0.992,1.036)
For	MEXJOB	slope,	B1	
INTRCPT2,	G10	0.388636	1.474968	(1.343,1.620)
WTPOV,	G11	0.022473	1.022728	(1.012,1.034)
WTAG,	G12	0.006769	1.006792	(0.975,1.040)
For	MEXIMM	slope,	B2	
INTRCPT2,	G20	0.720434	2.055325	(1.826,2.313)
WTPOV,	G21	–0.01824	0.981926	(0.957,1.007)
WTAG,	G22	–0.01269	0.987388	(0.953,1.023)
For	EDUC	slope,	B3	
INTRCPT2,	G30	–0.12227	0.884911	(0.871,0.899)
WTPOV,	G31	–0.00185	0.998148	(0.996,1.000)
WTAG,	G32	–0.00022	0.99978	(0.995,1.005)

Mexican Americans in 100% poverty (modeled based on WTPOV & WTFIRE), 19,674 household heads nested in 42 SPUMAs

Fixed effect		Coefficient	Standard error	T-ratio	Approx. d.f.	P-value
For	INTRCPT1,	B0				
INTRCPT2,	G00	–1.82737	0.042874	–42.622	39	0.000
WTPOV,	G01	0.041112	0.007115	5.779	39	0.000
WTFIRE,	G02	–0.03175	0.034601	–0.917	39	0.365
For	MEXJOB	slope,	B1			
INTRCPT2,	G10	0.384917	0.041102	9.365	39	0.000
WTPOV,	G11	0.021813	0.00602	3.623	39	0.001
WTFIRE,	G12	–0.01143	0.028237	–0.405	39	0.687
For	MEXIMM	slope,	B2			
INTRCPT2,	G20	0.70935	0.058283	12.171	39	0.000
WTPOV,	G21	–0.00526	0.012498	–0.421	39	0.676
WTFIRE,	G22	0.090156	0.038934	2.316	39	0.026
For	EDUC	slope,	B3			
INTRCPT2,	G30	–0.1213	0.007429	–16.328	39	0.000
WTPOV,	G31	–0.00226	0.00142	–1.587	39	0.120
WTFIRE,	G32	–0.00198	0.005736	–0.345	39	0.731

Odds ratios

Fixed effect		Coefficient	Odds ratio	Confidence interval
For	INTRCPT1,	B0		
INTRCPT2,	G00	–1.82737	0.160836	(0.147,0.175)
WTPOV,	G01	0.041112	1.041969	(1.027,1.057)
WTFIRE,	G02	–0.03175	0.968752	(0.903,1.039)
For	MEXJOB	slope,	B1	
INTRCPT2,	G10	0.384917	1.469493	(1.352,1.597)
WTPOV,	G11	0.021813	1.022052	(1.010,1.035)
WTFIRE,	G12	–0.01143	0.988631	(0.934,1.047)
For	MEXIMM	slope,	B2	
INTRCPT2,	G20	0.70935	2.03267	(1.807,2.287)
WTPOV,	G21	–0.00526	0.994753	(0.970,1.020)
WTFIRE,	G22	0.090156	1.094345	(1.012,1.184)
For	EDUC	slope,	B3	
INTRCPT2,	G30	–0.1213	0.885771	(0.873,0.899)
WTPOV,	G31	–0.00226	0.997748	(0.995,1.001)
WTFIRE,	G32	–0.00198	0.998021	(0.987,1.010)

Mexican Americans in 100% poverty (modeled based on WTPOV & WTCONS), 19,674 household heads nested in 42 SPUMAs

Fixed effect		Coefficient	Standard error	T-ratio	Approx. d.f.	P-value
For	INTRCPT1,	B0				
INTRCPT2,	G00	–1.83456	0.041872	–43.813	39	0.000
WTPOV,	G01	0.050204	0.005103	9.837	39	0.000
WTCONS,	G02	0.018952	0.012104	1.566	39	0.125
For	MEXJOB	slope,	B1			
INTRCPT2,	G10	0.382008	0.038923	9.814	39	0.000
WTPOV,	G11	0.022856	0.004913	4.652	39	0.000
WTCONS,	G12	–0.00498	0.014466	–0.344	39	0.732
For	MEXIMM	slope,	B2			
INTRCPT2,	G20	0.720839	0.059737	12.067	39	0.000
WTPOV,	G21	–0.01898	0.011712	–1.621	39	0.113
WTCONS,	G22	0.008693	0.020383	0.426	39	0.672
For	EDUC	slope,	B3			
INTRCPT2,	G30	–0.12331	0.006958	–17.721	39	0.000
WTPOV,	G31	–0.00144	0.000765	–1.877	39	0.068
WTCONS,	G32	0.002736	0.002626	1.042	39	0.304

Odds ratios

Fixed effect		Coefficient	Odds ratio	Confidence interval
For	INTRCPT1,	B0		
INTRCPT2,	G00	–1.83456	0.159684	(0.147,0.174)
WTPOV,	G01	0.050204	1.051485	(1.041,1.062)
WTCONS,	G02	0.018952	1.019133	(0.995,1.044)
For	MEXJOB	slope,	B1	
INTRCPT2,	G10	0.382008	1.465223	(1.354,1.585)
WTPOV,	G11	0.022856	1.02312	(1.013,1.033)
WTCONS,	G12	–0.00498	0.995034	(0.966,1.025)
For	MEXIMM	slope,	B2	
INTRCPT2,	G20	0.720839	2.056157	(1.822,2.320)
WTPOV,	G21	–0.01898	0.981197	(0.958,1.005)
WTCONS,	G22	0.008693	1.00873	(0.968,1.051)
For	EDUC	slope,	B3	
INTRCPT2,	G30	–0.12331	0.883992	(0.872,0.897)
WTPOV,	G31	–0.00144	0.998565	(0.997,1.000)
WTCONS,	G32	0.002736	1.00274	(0.997,1.008)

Mexican Americans in 100% poverty (modeled based on WTPOV & WTINFO), 19,674 household heads nested in 42 SPUMAs

Fixed effect		Coefficient	Standard error	T-ratio	Approx. d.f.	P-value
For	INTRCPT1,	B0				
INTRCPT2,	G00	–1.82842	0.04291	–42.611	39	0.000
WTPOV,	G01	0.04348	0.006613	6.575	39	0.000
WTINFO,	G02	–0.02823	0.044113	–0.64	39	0.526
For	MEXJOB	slope,	B1			
INTRCPT2,	G10	0.378314	0.043784	8.64	39	0.000
WTPOV,	G11	0.02497	0.0055	4.54	39	0.000
WTINFO,	G12	0.011104	0.026551	0.418	39	0.678
For	MEXIMM	slope,	B2			
INTRCPT2,	G20	0.721644	0.060752	11.879	39	0.000
WTPOV,	G21	–0.01624	0.013168	–1.233	39	0.225
WTINFO,	G22	0.038561	0.045123	0.855	39	0.398
For	EDUC	slope,	B3			
INTRCPT2,	G30	–0.12171	0.007389	–16.472	39	0.000
WTPOV,	G31	–0.0021	0.001263	–1.666	39	0.103
WTINFO,	G32	–0.00252	0.007029	–0.358	39	0.722

Odds ratio

Fixed effect		Coefficient	Odds ratio	Confidence interval
For	INTRCPT1,	B0		
INTRCPT2,	G00	–1.82842	0.160668	(0.147,0.175)
WTPOV,	G01	0.04348	1.044439	(1.031,1.058)
WTINFO,	G02	–0.02823	0.972167	(0.889,1.063)
For	MEXJOB	slope,	B1	
INTRCPT2,	G10	0.378314	1.459821	(1.336,1.595)
WTPOV,	G11	0.02497	1.025284	(1.014,1.037)
WTINFO,	G12	0.011104	1.011166	(0.958,1.067)
For	MEXIMM	slope,	B2	
INTRCPT2,	G20	0.721644	2.057813	(1.820,2.326)
WTPOV,	G21	–0.01624	0.983892	(0.958,1.010)
WTINFO,	G22	0.038561	1.039314	(0.949,1.138)
For	EDUC	slope,	B3	
INTRCPT2,	G30	–0.12171	0.885408	(0.872,0.899)
WTPOV,	G31	–0.0021	0.997898	(0.995,1.000)
WTINFO,	G32	–0.00252	0.997487	(0.983,1.012)

Mexican Americans in 100% poverty (modeled based on WTPOV & WTMETRO), 19,674 household heads nested in 42 SPUMAs

Fixed effect		Coefficient	Standard error	T-ratio	Approx. d.f.	P-value
For	INTRCPT1,	B0				
INTRCPT2,	G00	–1.8304	0.042349	–43.222	39	0.000
WTPOV,	G01	0.043853	0.005384	8.144	39	0.000
WTMETRO,	G02	–0.00309	0.001521	–2.029	39	0.049
For	MEXJOB	slope,	B1			
INTRCPT2,	G10	0.382821	0.036561	10.471	39	0.000
WTPOV,	G11	0.023556	0.005164	4.561	39	0.000
WTMETRO,	G12	–0.00036	0.00181	–0.196	39	0.846
For	MEXIMM	slope,	B2			
INTRCPT2,	G20	0.725306	0.060446	11.999	39	0.000
WTPOV,	G21	–0.01736	0.010719	–1.619	39	0.113
WTMETRO,	G22	0.004741	0.002556	1.855	39	0.071
For	EDUC	slope,	B3			
INTRCPT2,	G30	–0.12243	0.007216	–16.965	39	0.000
WTPOV,	G31	–0.00184	0.001021	–1.798	39	0.079
WTMETRO,	G32	0.000064	0.000297	0.215	39	0.831

Odds ratios

Fixed effect		Coefficient	Odds ratio	Confidence interval
For	INTRCPT1,	B0		
INTRCPT2,	G00	–1.8304	0.160349	(0.147,0.175)
WTPOV,	G01	0.043853	1.044829	(1.034,1.056)
WTMETRO,	G02	–0.00309	0.996918	(0.994,1.000)
For	MEXJOB	slope,	B1	
INTRCPT2,	G10	0.382821	1.466415	(1.362,1.579)
WTPOV,	G11	0.023556	1.023835	(1.013,1.035)
WTMETRO,	G12	–0.00036	0.999645	(0.996,1.003)
For	MEXIMM	slope,	B2	
INTRCPT2,	G20	0.725306	2.065363	(1.828,2.334)
WTPOV,	G21	–0.01736	0.982795	(0.962,1.004)
WTMETRO,	G22	0.004741	1.004752	(1.000,1.010)
For	EDUC	slope,	B3	
INTRCPT2,	G30	–0.12243	0.884769	(0.872,0.898)
WTPOV,	G31	–0.00184	0.998165	(0.996,1.000)
WTMETRO,	G32	0.000064	1.000064	(0.999,1.001)

Mexican Americans in 100% poverty (modeled based on WTPOV & M1), 19,674 household heads nested in 42 SPUMAs

Fixed effect		Coefficient	Standard error	T-ratio	Approx. d.f.	P-value
For	INTRCPT1,	B0				
INTRCPT2,	G00	–1.83361	0.042136	–43.517	39	0.000
WTPOV,	G01	0.047343	0.005212	9.084	39	0.000
M1,	G02	–3.53734	2.410418	–1.468	39	0.150
For	MEXJOB	slope,	B1			
INTRCPT2,	G10	0.382487	0.037718	10.141	39	0.000
WTPOV,	G11	0.023606	0.005095	4.633	39	0.000
M1,	G12	1.202088	2.418813	0.497	39	0.622
For	MEXIMM	slope,	B2			
INTRCPT2,	G20	0.723213	0.060173	12.019	39	0.000
WTPOV,	G21	–0.02035	0.01117	–1.822	39	0.076
M1,	G22	–0.97759	3.953771	–0.247	39	0.806
For	EDUC	slope,	B3			
INTRCPT2,	G30	–0.12276	0.007092	–17.309	39	0.000
WTPOV,	G31	–0.00186	0.000918	–2.029	39	0.049
M1,	G32	–0.47714	0.557926	–0.855	39	0.398

Odds ratios

Fixed effect		Coefficient	Odds ratio	Confidence interval
For	INTRCPT1,	B0		
INTRCPT2,	G00	–1.83361	0.159835	(0.147,0.174)
WTPOV,	G01	0.047343	1.048482	(1.038,1.060)
M1,	G02	–3.53734	0.029091	(0.000,3.788)
For	MEXJOB	slope,	B1	
INTRCPT2,	G10	0.382487	1.465925	(1.358,1.582)
WTPOV,	G11	0.023606	1.023887	(1.013,1.034)
M1,	G12	1.202088	3.327057	(0.025,440.580)
For	MEXIMM	slope,	B2	
INTRCPT2,	G20	0.723213	2.061045	(1.825,2.327)
WTPOV,	G21	–0.02035	0.979853	(0.958,1.002)
M1,	G22	–0.97759	0.376216	(0.000,1106.576)
For	EDUC	slope,	B3	
INTRCPT2,	G30	–0.12276	0.884475	(0.872,0.897)
WTPOV,	G31	–0.00186	0.99814	(0.996,1.000)
M1,	G32	–0.47714	0.620558	(0.201,1.915)

Mexican Americans in 100% poverty (modeled based on WTPOV & WTMEX), 19,674 household heads nested in 42 SPUMAs

Fixed effect		Coefficient	Standard error	T-ratio	Approx. d.f.	P-value
For	INTRCPT1,	B0				
INTRCPT2,	G00	–1.82751	0.040814	–44.776	39	0.000
WTPOV,	G01	0.070356	0.010181	6.911	39	0.000
WTMEX,	G02	–0.01097	0.004477	–2.45	39	0.019
For	MEXJOB	slope,	B1			
INTRCPT2,	G10	0.369452	0.039043	9.463	39	0.000
WTPOV,	G11	0.003576	0.012688	0.282	39	0.780
WTMEX,	G12	0.009203	0.00463	1.988	39	0.054
For	MEXIMM	slope,	B2			
INTRCPT2,	G20	0.732359	0.059679	12.272	39	0.000
WTPOV,	G21	–0.01312	0.019367	–0.678	39	0.502
WTMEX,	G22	–0.00341	0.008355	–0.408	39	0.685
For	EDUC	slope,	B3			
INTRCPT2,	G30	–0.12145	0.007367	–16.484	39	0.000
WTPOV,	G31	–0.00039	0.002409	–0.162	39	0.872
WTMEX,	G32	–0.00065	0.000844	–0.77	39	0.446

Odds ratios

Fixed effect		Coefficient	Odds ratio	Confidence interval
For	INTRCPT1,	B0		
INTRCPT2,	G00	–1.82751	0.160813	(0.148,0.175)
WTPOV,	G01	0.070356	1.07289	(1.051,1.095)
WTMEX,	G02	–0.01097	0.989089	(0.980,0.998)
For	MEXJOB	slope,	B1	
INTRCPT2,	G10	0.369452	1.446941	(1.337,1.566)
WTPOV,	G11	0.003576	1.003582	(0.978,1.030)
WTMEX,	G12	0.009203	1.009245	(1.000,1.019)
For	MEXIMM	slope,	B2	
INTRCPT2,	G20	0.732359	2.079982	(1.844,2.346)
WTPOV,	G21	–0.01312	0.986964	(0.949,1.026)
WTMEX,	G22	–0.00341	0.996597	(0.980,1.014)
For	EDUC	slope,	B3	
INTRCPT2,	G30	–0.12145	0.88564	(0.873,0.899)
WTPOV,	G31	–0.00039	0.99961	(0.995,1.004)
WTMEX,	G32	–0.00065	0.999351	(0.998,1.001)

HGLM Results: Mexican Americans in Low Income

Mexican Americans in low income (modeled based on WTPOV & WTMEX), 19,674 household heads nested in 42 SPUMAs

Fixed effect		Coefficient	Standard error	T-ratio	Approx. d.f.	P-value
For	INTRCPT1,	B0				
INTRCPT2,	G00	–0.11785	0.041626	–2.831	39	0.008
WTPOV,	G01	0.067255	0.009264	7.26	39	0.000
WTMEX,	G02	–0.01374	0.004032	–3.407	39	0.002
For	MEXJOB	slope,	B1			
INTRCPT2,	G10	0.590416	0.04867	12.131	19662	0.000
WTPOV,	G11	–0.00463	0.014107	–0.328	19662	0.742
WTMEX,	G12	0.007409	0.005309	1.396	19662	0.163
For	MEXIMM	slope,	B2			
INTRCPT2,	G20	0.901016	0.046119	19.537	19662	0.000
WTPOV,	G21	0.007023	0.016499	0.426	19662	0.670
WTMEX,	G22	–0.01006	0.006731	–1.494	19662	0.135
For	EDUC	slope,	B3			
INTRCPT2,	G30	–0.13744	0.008029	–17.119	19662	0.000
WTPOV,	G31	0.001409	0.002464	0.572	19662	0.567
WTMEX,	G32	–0.00184	0.00095	–1.932	19662	0.053

Odds ratios

Fixed effect		Coefficient	Odds ratio	Confidence interval
For	INTRCPT1,	B0		
INTRCPT2,	G00	–0.11785	0.888828	(0.817,0.967)
WTPOV,	G01	0.067255	1.069568	(1.050,1.090)
WTMEX,	G02	–0.01374	0.986358	(0.978,0.994)
For	MEXJOB	slope,	B1	
INTRCPT2,	G10	0.590416	1.804738	(1.641,1.985)
WTPOV,	G11	–0.00463	0.99538	(0.968,1.023)
WTMEX,	G12	0.007409	1.007437	(0.997,1.018)
For	MEXIMM	slope,	B2	
INTRCPT2,	G20	0.901016	2.462104	(2.249,2.695)
WTPOV,	G21	0.007023	1.007048	(0.975,1.040)
WTMEX,	G22	–0.01006	0.989995	(0.977,1.003)
For	EDUC	slope,	B3	
INTRCPT2,	G30	–0.13744	0.871586	(0.858,0.885)
WTPOV,	G31	0.001409	1.00141	(0.997,1.006)
WTMEX,	G32	–0.00184	0.998166	(0.996,1.000)

Mexican Americans in low income (modeled based on WTPOV & WTAG), 19,674 household heads nested in 42 SPUMAs

Fixed effect		Coefficient	Standard error	T-ratio	Approx. d.f.	P-value
For	INTRCPT1,	B0				
INTRCPT2,	G00	–0.11877	0.043286	–2.744	39	0.010
WTPOV,	G01	0.032002	0.006372	5.023	39	0.000
WTAG,	G02	0.027117	0.011593	2.339	39	0.025
For	MEXJOB	slope,	B1			
INTRCPT2,	G10	0.615085	0.041776	14.723	19662	0.000
WTPOV,	G11	0.008662	0.008349	1.037	19662	0.300
WTAG,	G12	0.008878	0.012136	0.732	19662	0.464
For	MEXIMM	slope,	B2			
INTRCPT2,	G20	0.858248	0.047045	18.243	19662	0.000
WTPOV,	G21	–0.01272	0.009673	–1.314	19662	0.189
WTAG,	G22	–0.01427	0.018053	–0.79	19662	0.429
For	EDUC	slope,	B3			
INTRCPT2,	G30	–0.14185	0.007152	–19.834	19662	0.000
WTPOV,	G31	–0.00282	0.001461	–1.928	19662	0.053
WTAG,	G32	0.000278	0.002854	0.098	19662	0.923

Odds ratios

Fixed effect		Coefficient	Odds ratio	Confidence interval
For	INTRCPT1,	B0		
INTRCPT2,	G00	–0.11877	0.888014	(0.814,0.969)
WTPOV,	G01	0.032002	1.03252	(1.019,1.046)
WTAG,	G02	0.027117	1.027488	(1.004,1.052)
For	MEXJOB	slope,	B1	
INTRCPT2,	G10	0.615085	1.849814	(1.704,2.008)
WTPOV,	G11	0.008662	1.0087	(0.992,1.025)
WTAG,	G12	0.008878	1.008917	(0.985,1.033)
For	MEXIMM	slope,	B2	
INTRCPT2,	G20	0.858248	2.359025	(2.151,2.587)
WTPOV,	G21	–0.01272	0.987365	(0.969,1.006)
WTAG,	G22	–0.01427	0.985832	(0.952,1.021)
For	EDUC	slope,	B3	
INTRCPT2,	G30	–0.14185	0.867754	(0.856,0.880)
WTPOV,	G31	–0.00282	0.997187	(0.994,1.000)
WTAG,	G32	0.000278	1.000279	(0.995,1.006)

Mexican Americans in low income (modeled based on WTPOV & WTFIRE), 19,674 household heads nested in 42 SPUMAs

Fixed effect		Coefficient	Standard error	T-ratio	Approx. d.f.	P-value
For	INTRCPT1,	B0				
INTRCPT2,	G00	–0.11959	0.04475	–2.672	39	0.011
WTPOV,	G01	0.031633	0.00825	3.835	39	0.001
WTFIRE,	G02	–0.04018	0.037332	–1.076	39	0.289
For	MEXJOB	slope,	B1			
INTRCPT2,	G10	0.605254	0.049521	12.222	19662	0.000
WTPOV,	G11	0.009806	0.01098	0.893	19662	0.372
WTFIRE,	G12	–0.00638	0.03449	–0.185	19662	0.853
For	MEXIMM	slope,	B2			
INTRCPT2,	G20	0.840858	0.044034	19.096	19662	0.000
WTPOV,	G21	–0.00147	0.00874	–0.169	19662	0.866
WTFIRE,	G22	0.078467	0.029501	2.66	19662	0.008
For	EDUC	slope,	B3			
INTRCPT2,	G30	–0.14029	0.008537	–16.433	19662	0.000
WTPOV,	G31	–0.00338	0.001645	–2.054	19662	0.040
WTFIRE,	G32	–0.00331	0.005673	–0.584	19662	0.559

Odds ratios

Fixed effect		Coefficient	Odds ratio	Confidence interval
For	INTRCPT1,	B0		
INTRCPT2,	G00	–0.11959	0.887289	(0.811,0.971)
WTPOV,	G01	0.031633	1.032139	(1.015,1.049)
WTFIRE,	G02	–0.04018	0.960614	(0.891,1.036)
For	MEXJOB	slope,	B1	
INTRCPT2,	G10	0.605254	1.831718	(1.662,2.018)
WTPOV,	G11	0.009806	1.009855	(0.988,1.032)
WTFIRE,	G12	–0.00638	0.993636	(0.929,1.063)
For	MEXIMM	slope,	B2	
INTRCPT2,	G20	0.840858	2.318356	(2.127,2.527)
WTPOV,	G21	–0.00147	0.998527	(0.982,1.016)
WTFIRE,	G22	0.078467	1.081628	(1.021,1.146)
For	EDUC	slope,	B3	
INTRCPT2,	G30	–0.14029	0.869111	(0.855,0.884)
WTPOV,	G31	–0.00338	0.996627	(0.993,1.000)
WTFIRE,	G32	–0.00331	0.996694	(0.986,1.008)

Mexican Americans in low income (modeled based on WTPOV & WTCONS) 19,674 household heads nested in 42 SPUMAs

Fixed	Effect	Coefficient	Standard error	T-ratio	Approx. d.f.	P-value
For	INTRCPT1	B0				
INTRCPT2,	G00	–0.12283	0.044843	–2.739	39	0.010
WTPOV,	G01	0.041876	0.0058	7.22	39	0.000
WTCONS,	G02	0.015749	0.013883	1.134	39	0.264
For	MEXJOB	slope	B1			
INTRCPT2,	G10	0.604866	0.046747	12.939	19662	0.000
WTPOV,	G11	0.009797	0.007628	1.284	19662	0.199
WTCONS,	G12	–0.00291	0.013718	–0.212	19662	0.832
For	MEXIMM	slope	B2			
INTRCPT2,	G20	0.8651	0.046927	18.435	19662	0.000
WTPOV,	G21	–0.01382	0.009111	–1.517	19662	0.129
WTCONS,	G22	0.010759	0.01483	0.726	19662	0.468
For	EDUC	slope	B3			
INTRCPT2,	G30	–0.14355	0.007929	–18.103	19662	0.000
WTPOV,	G31	–0.00234	0.001214	–1.928	19662	0.053
WTCONS,	G32	0.002157	0.002295	0.94	19662	0.348

Odds ratios

Fixed	Effect	Coefficient	Odds ratio	Confidence interval
For	INTRCPT1	B0		
INTRCPT2,	G00	–0.12283	0.884418	(0.808,0.968)
WTPOV,	G01	0.041876	1.042765	(1.031,1.055)
WTCONS,	G02	0.015749	1.015873	(0.988,1.045)
For	MEXJOB	slope	B1	
INTRCPT2,	G10	0.604866	1.831007	(1.671,2.007)
WTPOV,	G11	0.009797	1.009845	(0.995,1.025)
WTCONS,	G12	–0.00291	0.997093	(0.971,1.024)
For	MEXIMM	slope	B2	
INTRCPT2,	G20	0.8651	2.375244	(2.167,2.604)
WTPOV,	G21	–0.01382	0.986274	(0.969,1.004)
WTCONS,	G22	0.010759	1.010817	(0.982,1.041)
For	EDUC	slope	B3	
INTRCPT2,	G30	–0.14355	0.866281	(0.853,0.880)
WTPOV,	G31	–0.00234	0.997663	(0.995,1.000)
WTCONS,	G32	0.002157	1.002159	(0.998,1.007)

Mexican Americans in low income (modeled based on WTPOV & WTINFO), 19,674 household heads nested in 42 SPUMAs

Fixed effect		Coefficient	Standard error	T-ratio	Approx d.f.	P-value
For	INTRCPT1,	B0				
INTRCPT2,	G00	–0.11892	0.044459	–2.675	39	0.011
WTPOV,	G01	0.031043	0.006833	4.543	39	0.000
WTINFO,	G02	–0.06409	0.052608	–1.218	39	0.231
For	MEXJOB	slope,	B1			
INTRCPT2,	G10	0.624245	0.043855	14.234	19662	0.000
WTPOV,	G11	0.007025	0.006983	1.006	19662	0.315
WTINFO,	G12	–0.04128	0.030245	–1.365	19662	0.172
For	MEXIMM	slope,	B2			
INTRCPT2,	G20	0.860434	0.048273	17.825	19662	0.000
WTPOV,	G21	–0.01229	0.009682	–1.269	19662	0.205
WTINFO,	G22	0.033451	0.030247	1.106	19662	0.269
For	EDUC	slope,	B3			
INTRCPT2,	G30	–0.14241	0.007692	–18.513	19662	0.000
WTPOV,	G31	–0.00263	0.001546	–1.703	19662	0.088
WTINFO,	G32	0.001056	0.007449	0.142	19662	0.888

Odds ratios

Fixed effect		Coefficient	Odds ratio	Confidence interval
For	INTRCPT1,	B0		
INTRCPT2,	G00	–0.11892	0.887879	(0.812,0.971)
WTPOV,	G01	0.031043	1.03153	(1.017,1.046)
WTINFO,	G02	–0.06409	0.937923	(0.843,1.043)
For	MEXJOB	slope,	B1	
INTRCPT2,	G10	0.624245	1.866836	(1.713,2.034)
WTPOV,	G11	0.007025	1.00705	(0.993,1.021)
WTINFO,	G12	–0.04128	0.959561	(0.904,1.018)
For	MEXIMM	slope,	B2	
INTRCPT2,	G20	0.860434	2.364187	(2.151,2.599)
WTPOV,	G21	–0.01229	0.987787	(0.969,1.007)
WTINFO,	G22	0.033451	1.034017	(0.974,1.097)
For	EDUC	slope,	B3	
INTRCPT2,	G30	–0.14241	0.867269	(0.854,0.880)
WTPOV,	G31	–0.00263	0.99737	(0.994,1.000)
WTINFO,	G32	0.001056	1.001056	(0.987,1.016)

Mexican Americans in low income (modeled based on WTPOV & WTMETRO), 19,674 household heads nested in 42 SPUMAs

Fixed effect		Coefficient	Standard error	T-ratio	Approx. d.f.	P-value
For	INTRCPT1,	B0				
INTRCPT2,	G00	–0.12088	0.043176	–2.8	39	0.008
WTPOV,	G01	0.034098	0.006323	5.393	39	0.000
WTMETRO,	G02	–0.00431	0.001787	–2.413	39	0.021
For	MEXJOB	slope,	B1			
INTRCPT2,	G10	0.607199	0.04506	13.475	19662	0.000
WTPOV,	G11	0.009646	0.007503	1.286	19662	0.199
WTMETRO,	G12	–0.0007	0.002124	–0.33	19662	0.741
For	MEXIMM	slope,	B2			
INTRCPT2,	G20	0.854082	0.046043	18.55	19662	0.000
WTPOV,	G21	–0.0125	0.008257	–1.513	19662	0.130
WTMETRO,	G22	0.00422	0.00238	1.773	19662	0.076
For	EDUC	slope,	B3			
INTRCPT2,	G30	–0.14116	0.007883	–17.907	19662	0.000
WTPOV,	G31	–0.00279	0.001343	–2.078	19662	0.037
WTMETRO,	G32	–0.00012	0.000372	–0.326	19662	0.744

Odds ratios

Fixed effect		Coefficient	Odds ratio	Confidence interval
For	INTRCPT1,	B0		
INTRCPT2,	G00	–0.12088	0.88614	(0.812,0.967)
WTPOV,	G01	0.034098	1.034686	(1.022,1.048)
WTMETRO,	G02	–0.00431	0.995698	(0.992,0.999)
For	MEXJOB	slope,	B1	
INTRCPT2,	G10	0.607199	1.835284	(1.680,2.005)
WTPOV,	G11	0.009646	1.009692	(0.995,1.025)
WTMETRO,	G12	–0.0007	0.999299	(0.995,1.003)
For	MEXIMM	slope,	B2	
INTRCPT2,	G20	0.854082	2.349218	(2.146,2.571)
WTPOV,	G21	–0.0125	0.987581	(0.972,1.004)
WTMETRO,	G22	0.00422	1.004229	(1.000,1.009)
For	EDUC	slope,	B3	
INTRCPT2,	G30	–0.14116	0.868352	(0.855,0.882)
WTPOV,	G31	–0.00279	0.997213	(0.995,1.000)
WTMETRO,	G32	–0.00012	0.999879	(0.999,1.001)

Mexican Americans in low income (modeled based on WTPOV & M1), 19,674 household heads nested in 42 SPUMAs

Fixed effect		Coefficient	Standard error	T-ratio	Approx. d.f.	P-value
For	INTRCPT1,	B0				
INTRCPT2,	G00	–0.12229	0.045075	–2.713	39	0.010
WTPOV,	G01	0.039474	0.005809	6.795	39	0.000
M1,	G02	–2.4125	2.778572	–0.868	39	0.391
For	MEXJOB	slope,	B1			
INTRCPT2,	G10	0.604504	0.048315	12.512	19662	0.000
WTPOV,	G11	0.010186	0.007378	1.381	19662	0.168
M1,	G12	0.772188	2.740617	0.282	19662	0.778
For	MEXIMM	slope,	B2			
INTRCPT2,	G20	0.866661	0.048574	17.842	19662	0.000
WTPOV,	G21	–0.01545	0.008539	–1.81	19662	0.070
M1,	G22	–2.446	2.703701	–0.905	19662	0.366
For	EDUC	slope,	B3			
INTRCPT2,	G30	–0.14317	0.008359	–17.127	19662	0.000
WTPOV,	G31	–0.00267	0.001181	–2.262	19662	0.024
M1,	G32	–0.48447	0.457386	–1.059	19662	0.290

Odds ratios

Fixed effect		Coefficient	Odds ratio	Confidence interval
For	INTRCPT1,	B0		
INTRCPT2,	G00	–0.12229	0.884896	(0.808,0.969)
WTPOV,	G01	0.039474	1.040263	(1.028,1.053)
M1,	G02	–2.4125	0.089591	(0.000,24.538)
For	MEXJOB	slope,	B1	
INTRCPT2,	G10	0.604504	1.830344	(1.665,2.012)
WTPOV,	G11	0.010186	1.010238	(0.996,1.025)
M1,	G12	0.772188	2.164497	(0.010,465.820)
For	MEXIMM	slope,	B2	
INTRCPT2,	G20	0.866661	2.378954	(2.163,2.617)
WTPOV,	G21	–0.01545	0.984664	(0.968,1.001)
M1,	G22	–2.446	0.086639	(0.000,17.344)
For	EDUC	slope,	B3	
INTRCPT2,	G30	–0.14317	0.866603	(0.853,0.881)
WTPOV,	G31	–0.00267	0.997332	(0.995,1.000)
M1,	G32	–0.48447	0.616024	(0.251,1.510)

HGLM Results: Mexican Immigrants in Extreme Poverty (with Undocumented Proxy)

Mexican immigrants in extreme poverty (modeled based on WTPOV & WTMEX), 12,122 household heads nested in 42 SPUMAs

Fixed effect		Coefficient	Standard error	T-ratio	Approx. d.f.	P-value
For	INTRCPT1,	B0				
INTRCPT2,	G00	–3.21105	0.074935	–42.851	39	0.000
WTPOV,	G01	0.088281	0.022463	3.93	39	0.000
WTMEX,	G02	–0.01223	0.008153	–1.5	39	0.141
For	UNEMPLOY	slope,	B1			
INTRCPT2,	G10	1.341187	0.05797	23.136	12110	0.000
WTPOV,	G11	–0.0111	0.019758	–0.562	12110	0.574
WTMEX,	G12	–0.00806	0.007285	–1.106	12110	0.269
For	CIT	slope,	B2			
INTRCPT2,	G20	–0.74893	0.100445	–7.456	12110	0.000
WTPOV,	G21	–0.0633	0.030183	–2.097	12110	0.036
WTMEX,	G22	0.006674	0.011568	0.577	12110	0.564
For	UNDOC	slope,	B3			
INTRCPT2,	G30	0.987462	0.494926	1.995	12110	0.046
WTPOV,	G31	–0.37169	0.118273	–3.143	12110	0.002
WTMEX,	G32	0.158659	0.053716	2.954	12110	0.004

Odds ratios

Fixed effect		Coefficient	Odds ratio	Confidence interval
For	INTRCPT1,	B0		
INTRCPT2,	G00	–3.21105	0.040314	(0.035,0.047)
WTPOV,	G01	0.088281	1.092294	(1.044,1.143)
WTMEX,	G02	–0.01223	0.987842	(0.972,1.004)
For	UNEMPLOY	slope,	B1	
INTRCPT2,	G10	1.341187	3.823579	(3.413,4.284)
WTPOV,	G11	–0.0111	0.988958	(0.951,1.028)
WTMEX,	G12	–0.00806	0.991976	(0.978,1.006)
For	CIT	slope,	B2	
INTRCPT2,	G20	–0.74893	0.472874	(0.388,0.576)
WTPOV,	G21	–0.0633	0.938663	(0.885,0.996)
WTMEX,	G22	0.006674	1.006696	(0.984,1.030)
For	UNDOC	slope,	B3	
INTRCPT2,	G30	0.987462	2.684413	(1.018,7.082)
WTPOV,	G31	–0.37169	0.689569	(0.547,0.869)
WTMEX,	G32	0.158659	1.171939	(1.055,1.302)

Mexican immigrants in extreme poverty (modeled based on WTPOV & WTAG), 12,122 household heads nested in 42 SPUMAs

Fixed effect		Coefficient	Standard error	T-ratio	Approx. d.f.	P-value
For	INTRCPT1,	B0				
INTRCPT2,	G00	–3.21085	0.075746	–42.39	39	0.000
WTPOV,	G01	0.062499	0.013408	4.661	39	0.000
WTAG,	G02	–0.00736	0.017845	–0.412	39	0.682
For	UNEMPLOY	slope,	B1			
INTRCPT2,	G10	1.346781	0.063416	21.237	12110	0.000
WTPOV,	G11	–0.03215	0.012141	–2.648	12110	0.008
WTAG,	G12	0.019061	0.015825	1.204	12110	0.229
For	CIT	slope,	B2			
INTRCPT2,	G20	–0.70224	0.094834	–7.405	12110	0.000
WTPOV,	G21	–0.0519	0.012588	–4.123	12110	0.000
WTAG,	G22	0.026518	0.021754	1.219	12110	0.223
For	UNDOC	slope,	B3			
INTRCPT2,	G30	0.967869	0.639385	1.514	12110	0.130
WTPOV,	G31	0.0207	0.043693	0.474	12110	0.635
WTAG,	G32	–0.21821	0.145421	–1.501	12110	0.133

Odds ratios

Fixed effect		Coefficient	Odds ratio	Confidence interval
For	INTRCPT1,	B0		
INTRCPT2,	G00	–3.21085	0.040322	(0.035,0.047)
WTPOV,	G01	0.062499	1.064493	(1.036,1.094)
WTAG,	G02	–0.00736	0.992666	(0.958,1.029)
For	UNEMPLOY	slope,	B1	
INTRCPT2,	G10	1.346781	3.845028	(3.396,4.354)
WTPOV,	G11	–0.03215	0.968358	(0.946,0.992)
WTAG,	G12	0.019061	1.019243	(0.988,1.051)
For	CIT	slope,	B2	
INTRCPT2,	G20	–0.70224	0.495475	(0.411,0.597)
WTPOV,	G21	–0.0519	0.949425	(0.926,0.973)
WTAG,	G22	0.026518	1.026873	(0.984,1.072)
For	UNDOC	slope,	B3	
INTRCPT2,	G30	0.967869	2.632329	(0.752,9.217)
WTPOV,	G31	0.0207	1.020916	(0.937,1.112)
WTAG,	G32	–0.21821	0.803957	(0.605,1.069)

Mexican immigrants in extreme poverty (modeled based on WTPOV & WTFIRE), 12,122 household heads nested in 42 SPUMAs

Fixed effect		Coefficient	Standard error	T-ratio	Approx. d.f.	P-value
For	INTRCPT1,	B0				
INTRCPT2,	G00	–3.20061	0.076598	–41.785	39	0.000
WTPOV,	G01	0.05448	0.017384	3.134	39	0.004
WTFIRE,	G02	–0.03968	0.052344	–0.758	39	0.453
For	UNEMPLOY	slope,	B1			
INTRCPT2,	G10	1.308831	0.056406	23.204	12110	0.000
WTPOV,	G11	–0.02403	0.015035	–1.598	12110	0.110
WTFIRE,	G12	0.031314	0.040834	0.767	12110	0.443
For	CIT	slope,	B2			
INTRCPT2,	G20	–0.72548	0.089567	–8.1	12110	0.000
WTPOV,	G21	–0.05204	0.014135	–3.682	12110	0.000
WTFIRE,	G22	–0.02947	0.074408	–0.396	12110	0.692
For	UNDOC	slope,	B3			
INTRCPT2,	G30	1.160974	0.722731	1.606	12110	0.108
WTPOV,	G31	–0.0089	0.10746	–0.083	12110	0.934
WTFIRE,	G32	0.017081	0.383761	0.045	12110	0.965

Odds ratios

Fixed effect		Coefficient	Odds ratio	Confidence interval
For	INTRCPT1,	B0		
INTRCPT2,	G00	–3.20061	0.040738	(0.035,0.048)
WTPOV,	G01	0.05448	1.055991	(1.020,1.094)
WTFIRE,	G02	–0.03968	0.961093	(0.865,1.068)
For	UNEMPLOY	slope,	B1	
INTRCPT2,	G10	1.308831	3.701845	(3.314,4.135)
WTPOV,	G11	–0.02403	0.976257	(0.948,1.005)
WTFIRE,	G12	0.031314	1.03181	(0.952,1.118)
For	CIT	slope,	B2	
INTRCPT2,	G20	–0.72548	0.484091	(0.406,0.577)
WTPOV,	G21	–0.05204	0.949291	(0.923,0.976)
WTFIRE,	G22	–0.02947	0.970961	(0.839,1.123)
For	UNDOC	slope,	B3	
INTRCPT2,	G30	1.160974	3.193041	(0.774,13.165)
WTPOV,	G31	–0.0089	0.991138	(0.803,1.224)
WTFIRE,	G32	0.017081	1.017228	(0.479,2.158)

Mexican immigrants in extreme poverty (modeled based on WTPOV & WTCONS), 12,122 household heads nested in 42 SPUMAs

Fixed effect		Coefficient	Standard error	T-ratio	Approx. d.f.	P-value
For	INTRCPT1,	B0				
INTRCPT2,	G00	–3.22622	0.074404	–43.361	39	0.000
WTPOV,	G01	0.068657	0.010238	6.706	39	0.000
WTCONS,	G02	0.039606	0.018168	2.18	39	0.035
For	UNEMPLOY	slope,	B1			
INTRCPT2,	G10	1.326852	0.064182	20.673	12110	0.000
WTPOV,	G11	–0.02945	0.012352	–2.384	12110	0.017
WTCONS,	G12	–0.00618	0.021599	–0.286	12110	0.775
For	CIT	slope,	B2			
INTRCPT2,	G20	–0.75233	0.101014	–7.448	12110	0.000
WTPOV,	G21	–0.04427	0.010949	–4.043	12110	0.000
WTCONS,	G22	0.014382	0.026951	0.534	12110	0.593
For	UNDOC	slope,	B3			
INTRCPT2,	G30	1.124688	0.547944	2.053	12110	0.040
WTPOV,	G31	–0.00779	0.041036	–0.19	12110	0.850
WTCONS,	G32	0.049207	0.172309	0.286	12110	0.775

Odds ratios

Fixed effect		Coefficient	Odds ratio	Confidence interval
For	INTRCPT1,	B0		
INTRCPT2,	G00	–3.22622	0.039707	(0.034,0.046)
WTPOV,	G01	0.068657	1.071069	(1.049,1.093)
WTCONS,	G02	0.039606	1.040401	(1.003,1.079)
For	UNEMPLOY	slope,	B1	
INTRCPT2,	G10	1.326852	3.76916	(3.324,4.274)
WTPOV,	G11	–0.02945	0.970978	(0.948,0.995)
WTCONS,	G12	–0.00618	0.993836	(0.953,1.037)
For	CIT	slope,	B2	
INTRCPT2,	G20	–0.75233	0.471266	(0.387,0.574)
WTPOV,	G21	–0.04427	0.956701	(0.936,0.977)
WTCONS,	G22	0.014382	1.014486	(0.962,1.070)
For	UNDOC	slope,	B3	
INTRCPT2,	G30	1.124688	3.079257	(1.052,9.013)
WTPOV,	G31	–0.00779	0.992238	(0.916,1.075)
WTCONS,	G32	0.049207	1.050438	(0.749,1.472)

Mexican immigrants in extreme poverty (modeled based on WTPOV & WTINFO), 12,122 household heads nested in 42 SPUMAs

Fixed effect		Coefficient	Standard error	T-ratio	Approx. d.f.	P-value
For	INTRCPT1,	B0				
INTRCPT2,	G00	–3.20554	0.07627	–42.029	39	0.000
WTPOV,	G01	0.058183	0.015984	3.64	39	0.001
WTINFO,	G02	–0.02631	0.07118	–0.37	39	0.713
For	UNEMPLOY	slope,	B1			
INTRCPT2,	G10	1.354773	0.063349	21.386	12110	0.000
WTPOV,	G11	–0.03543	0.012277	–2.886	12110	0.004
WTINFO,	G12	–0.0665	0.036997	–1.797	12110	0.072
For	CIT	slope,	B2			
INTRCPT2,	G20	–0.66981	0.089586	–7.477	12110	0.000
WTPOV,	G21	–0.06037	0.011824	–5.106	12110	0.000
WTINFO,	G22	–0.14042	0.039102	–3.591	12110	0.001
For	UNDOC	slope,	B3			
INTRCPT2,	G30	0.912041	0.731085	1.248	12110	0.213
WTPOV,	G31	0.029266	0.063797	0.459	12110	0.646
WTINFO,	G32	0.411194	0.267958	1.535	12110	0.125

Odds ratios

Fixed effect		Coefficient	Odds ratio	Confidence interval
For	INTRCPT1,	B0		
INTRCPT2,	G00	–3.20554	0.040537	(0.035,0.047)
WTPOV,	G01	0.058183	1.059909	(1.026,1.095)
WTINFO,	G02	–0.02631	0.974031	(0.844,1.125)
For	UNEMPLOY	slope,	B1	
INTRCPT2,	G10	1.354773	3.875881	(3.423,4.388)
WTPOV,	G11	–0.03543	0.96519	(0.942,0.989)
WTINFO,	G12	–0.0665	0.935662	(0.870,1.006)
For	CIT	slope,	B2	
INTRCPT2,	G20	–0.66981	0.511804	(0.429,0.610)
WTPOV,	G21	–0.06037	0.941418	(0.920,0.963)
WTINFO,	G22	–0.14042	0.868991	(0.805,0.938)
For	UNDOC	slope,	B3	
INTRCPT2,	G30	0.912041	2.489397	(0.594,10.433)
WTPOV,	G31	0.029266	1.029698	(0.909,1.167)
WTINFO,	G32	0.411194	1.508618	(0.892,2.551)

Mexican immigrants in extreme poverty (modeled based on WTPOV & WTMETRO), 12,122 household heads nested in 42 SPUMAs

Fixed effect		Coefficient	Standard error	T-ratio	Approx. d.f.	P-value
For	INTRCPT1,	B0				
INTRCPT2,	G00	–3.16863	0.059229	–53.498	39	0.000
WTPOV,	G01	0.055787	0.012514	4.458	39	0.000
WTMETRO,	G02	–0.0047	0.002403	–1.955	39	0.057
For	UNEMPLOY	slope,	B1			
INTRCPT2,	G10	1.319823	0.050155	26.315	39	0.000
WTPOV,	G11	–0.03015	0.009979	–3.021	39	0.005
WTMETRO,	G12	–0.00508	0.002187	–2.321	39	0.026
For	CIT	slope,	B2			
INTRCPT2,	G20	–0.71182	0.084697	–8.404	39	0.000
WTPOV,	G21	–0.04602	0.010321	–4.459	39	0.000
WTMETRO,	G22	–0.00014	0.00411	–0.035	39	0.973
For	UNDOC	slope,	B3			
INTRCPT2,	G30	1.416191	0.407036	3.479	39	0.002
WTPOV,	G31	–0.02306	0.030985	–0.744	39	0.461
WTMETRO,	G32	–0.01048	0.023682	–0.442	39	0.660

Odds ratios

Fixed effect		Coefficient	Odds ratio	Confidence interval
For	INTRCPT1,	B0		
INTRCPT2,	G00	–3.16863	0.042061	(0.037,0.047)
WTPOV,	G01	0.055787	1.057373	(1.031,1.084)
WTMETRO,	G02	–0.0047	0.995313	(0.990,1.000)
For	UNEMPLOY	slope,	B1	
INTRCPT2,	G10	1.319823	3.74276	(3.382,4.142)
WTPOV,	G11	–0.03015	0.970303	(0.951,0.990)
WTMETRO,	G12	–0.00508	0.994937	(0.991,0.999)
For	CIT	slope,	B2	
INTRCPT2,	G20	–0.71182	0.490752	(0.414,0.582)
WTPOV,	G21	–0.04602	0.955023	(0.935,0.975)
WTMETRO,	G22	–0.00014	0.999857	(0.992,1.008)
For	UNDOC	slope,	B3	
INTRCPT2,	G30	1.416191	4.121391	(1.811,9.378)
WTPOV,	G31	–0.02306	0.977202	(0.918,1.040)
WTMETRO,	G32	–0.01048	0.989579	(0.943,1.038)

Mexican immigrants in extreme poverty (modeled based on WTPOV & M1), 12,122 household heads nested in 42 SPUMAs

Fixed effect		Coefficient	Standard error	T-ratio	Approx. d.f.	P-value
For	INTRCPT1,	B0				
INTRCPT2,	G00	–3.18582	0.059465	–53.575	39	0.000
WTPOV,	G01	0.062438	0.008143	7.668	39	0.000
M1,	G02	–7.71384	2.405629	–3.207	39	0.003
For	UNEMPLOY	slope,	B1			
INTRCPT2,	G10	1.320903	0.051599	25.6	39	0.000
WTPOV,	G11	–0.02758	0.010589	–2.605	39	0.013
M1,	G12	1.406313	2.850984	0.493	39	0.624
For	CIT	slope,	B2			
INTRCPT2,	G20	–0.7089	0.078793	–8.997	39	0.000
WTPOV,	G21	–0.04506	0.00875	–5.149	39	0.000
M1,	G22	–2.01388	3.152933	–0.639	39	0.526
For	UNDOC	slope,	B3			
INTRCPT2,	G30	1.326241	0.305469	4.342	39	0.000
WTPOV,	G31	–0.04499	0.033255	–1.353	39	0.184
M1,	G32	–5.69744	15.49414	–0.368	39	0.715

Odds ratios

Fixed effect		Coefficient	Odds ratio	Confidence interval
For	INTRCPT1,	B0		
INTRCPT2,	G00	–3.18582	0.041344	(0.037,0.047)
WTPOV,	G01	0.062438	1.064428	(1.047,1.082)
M1,	G02	–7.71384	0.000447	(0.000,0.058)
For	UNEMPLOY	slope,	B1	
INTRCPT2,	G10	1.320903	3.746803	(3.376,4.158)
WTPOV,	G11	–0.02758	0.972794	(0.952,0.994)
M1,	G12	1.406313	4.080883	(0.013,1293.751)
For	CIT	slope,	B2	
INTRCPT2,	G20	–0.7089	0.492187	(0.420,0.577)
WTPOV,	G21	–0.04506	0.955942	(0.939,0.973)
M1,	G22	–2.01388	0.133469	(0.000,77.870)
For	UNDOC	slope,	B3	
INTRCPT2,	G30	1.326241	3.766857	(2.032,6.982)
WTPOV,	G31	–0.04499	0.956012	(0.894,1.022)
M1,	G32	–5.69744	0.003355	(0.000,131296315234.993)

HGLM Results: Mexican Immigrants in Extreme Poverty (Without Undocumented Variable)

Mexican immigrants in extreme poverty (modeled based on WTPOV & WTMEX), 12,122 household heads nested in 42 SPUMAs

Fixed effect		Coefficient	Standard error	T-ratio	Approx. d.f.	P-value
For	INTRCPT1,	B0				
INTRCPT2,	G00	–3.21382	0.05778	–55.622	39	0.000
WTPOV,	G01	0.090167	0.01799	5.012	39	0.000
WTMEX,	G02	–0.01502	0.006564	–2.287	39	0.028
For	YRSUSA1	slope,	B1			
INTRCPT2,	G10	–0.0409	0.002986	–13.697	39	0.000
WTPOV,	G11	–0.00091	0.00085	–1.071	39	0.291
WTMEX,	G12	–0.0005	0.000344	–1.44	39	0.158
For	UNEMPLOY	slope,	B2			
INTRCPT2,	G20	1.584864	0.063139	25.101	39	0.000
WTPOV,	G21	–0.01616	0.020491	–0.789	39	0.435
WTMEX,	G22	–0.0084	0.008508	–0.987	39	0.330
For	MALE	slope,	B3			
INTRCPT2,	G30	0.57617	0.084528	6.816	39	0.000
WTPOV,	G31	–0.01863	0.020481	–0.91	39	0.369
WTMEX,	G32	–0.00624	0.008546	–0.73	39	0.469

Odds ratios

Fixed effect		Coefficient	Odds ratio	Confidence interval
For	INTRCPT1,	B0		
INTRCPT2,	G00	–3.21382	0.040203	(0.036,0.045)
WTPOV,	G01	0.090167	1.094356	(1.055,1.135)
WTMEX,	G02	–0.01502	0.985096	(0.972,0.998)
For	YRSUSA1	slope,	B1	
INTRCPT2,	G10	–0.0409	0.959926	(0.954,0.966)
WTPOV,	G11	–0.00091	0.99909	(0.997,1.001)
WTMEX,	G12	–0.0005	0.999505	(0.999,1.000)
For	UNEMPLOY	slope,	B2	
INTRCPT2,	G20	1.584864	4.878628	(4.294,5.542)
WTPOV,	G21	–0.01616	0.983969	(0.944,1.026)
WTMEX,	G22	–0.0084	0.99164	(0.975,1.009)
For	MALE	slope,	B3	
INTRCPT2,	G30	0.57617	1.779211	(1.500,2.110)
WTPOV,	G31	–0.01863	0.981542	(0.942,1.023)
WTMEX,	G32	–0.00624	0.993778	(0.977,1.011)

Mexican immigrants in extreme poverty (modeled based on WTPOV & WTCONS), 12,122 household heads nested in 42 SPUMAs

Fixed effect		Coefficient	Standard error	T-ratio	Approx. d.f.	P-value
For	INTRCPT1,	B0				
INTRCPT2,	G00	–3.21119	0.055177	–58.199	39	0.000
WTPOV,	G01	0.064153	0.007927	8.093	39	0.000
WTCONS,	G02	0.033204	0.013469	2.465	39	0.018
For	YRSUSA1	slope,	B1			
INTRCPT2,	G10	–0.03888	0.002786	–13.955	39	0.000
WTPOV,	G11	–0.00181	0.000264	–6.864	39	0.000
WTCONS,	G12	0.000135	0.000799	0.168	39	0.867
For	UNEMPLOY	slope,	B2			
INTRCPT2,	G20	1.551877	0.066122	23.47	39	0.000
WTPOV,	G21	–0.02954	0.014716	–2.007	39	0.051
WTCONS,	G22	0.019662	0.02	0.983	39	0.332
For	MALE	slope,	B3			
INTRCPT2,	G30	0.51009	0.081012	6.296	39	0.000
WTPOV,	G31	–0.02473	0.012706	–1.946	39	0.058
WTCONS,	G32	0.051324	0.023953	2.143	39	0.038

Odds ratios

Fixed effect		Coefficient	Odds ratio	Confidence interval
For	INTRCPT1,	B0		
INTRCPT2,	G00	–3.21119	0.040308	(0.036,0.045)
WTPOV,	G01	0.064153	1.066255	(1.049,1.083)
WTCONS,	G02	0.033204	1.033761	(1.006,1.062)
For	YRSUSA1	slope,	B1	
INTRCPT2,	G10	–0.03888	0.961869	(0.956,0.967)
WTPOV,	G11	–0.00181	0.998191	(0.998,0.999)
WTCONS,	G12	0.000135	1.000135	(0.999,1.002)
For	UNEMPLOY	slope,	B2	
INTRCPT2,	G20	1.551877	4.72032	(4.130,5.395)
WTPOV,	G21	–0.02954	0.970893	(0.942,1.000)
WTCONS,	G22	0.019662	1.019857	(0.979,1.062)
For	MALE	slope,	B3	
INTRCPT2,	G30	0.51009	1.665441	(1.414,1.962)
WTPOV,	G31	–0.02473	0.975571	(0.951,1.001)
WTCONS,	G32	0.051324	1.052664	(1.003,1.105)

Mexican immigrants in extreme poverty (modeled based on WTPOV & WTPROF & WTSERV), 12,122 household heads nested in 42 SPUMAs

Fixed effect		Coefficient	Standard error	T-ratio	Approx. d.f.	P-value
For	INTRCPT1,	B0				
INTRCPT2,	G00	–3.21108	0.055406	–57.956	38	0.000
WTPOV,	G01	0.050065	0.013537	3.698	38	0.001
WTPROF,	G02	–0.03063	0.021142	–1.449	38	0.155
WTSERV,	G03	–0.07278	0.034473	–2.111	38	0.041
For	YRSUSA1	slope,	B1			
INTRCPT2,	G10	–0.03981	0.002782	–14.306	38	0.000
WTPOV,	G11	–0.00258	0.000399	–6.478	38	0.000
WTPROF,	G12	–0.00212	0.001199	–1.765	38	0.085
WTSERV,	G13	0.001404	0.002405	0.584	38	0.563
For	UNEMPLOY	slope,	B2			
INTRCPT2,	G20	1.590016	0.066918	23.761	38	0.000
WTPOV,	G21	–0.05029	0.014107	–3.565	38	0.001
WTPROF,	G22	–0.06382	0.02856	–2.235	38	0.031
WTSERV,	G23	–0.01316	0.040941	–0.321	38	0.749
For	MALE	slope,	B3			
INTRCPT2,	G30	0.538131	0.079372	6.78	38	0.000
WTPOV,	G31	–0.03315	0.013774	–2.407	38	0.021
WTPROF,	G32	–0.02583	0.036058	–0.716	38	0.478
WTSERV,	G33	–0.13555	0.038791	–3.494	38	0.002

Odds ratios

Fixed effect		Coefficient	Odds ratio	Confidence interval
For	INTRCPT1,	B0		
INTRCPT2,	G00	–3.21108	0.040313	(0.036,0.045)
WTPOV,	G01	0.050065	1.05134	(1.023,1.081)
WTPROF,	G02	–0.03063	0.969831	(0.929,1.012)
WTSERV,	G03	–0.07278	0.929802	(0.867,0.997)
For	YRSUSA1	slope,	B1	
INTRCPT2,	G10	–0.03981	0.960976	(0.956,0.966)
WTPOV,	G11	–0.00258	0.997421	(0.997,0.998)
WTPROF,	G12	–0.00212	0.997886	(0.995,1.000)
WTSERV,	G13	0.001404	1.001405	(0.997,1.006)
For	UNEMPLOY	slope,	B2	
INTRCPT2,	G20	1.590016	4.903826	(4.283,5.614)
WTPOV,	G21	–0.05029	0.950957	(0.924,0.978)
WTPROF,	G22	–0.06382	0.938173	(0.886,0.994)
WTSERV,	G23	–0.01316	0.986929	(0.909,1.072)
For	MALE	slope,	B3	
INTRCPT2,	G30	0.538131	1.712803	(1.459,2.011)
WTPOV,	G31	–0.03315	0.96739	(0.941,0.995)
WTPROF,	G32	–0.02583	0.974498	(0.906,1.048)
WTSERV,	G33	–0.13555	0.873237	(0.807,0.944)

HGLM Results: Mexican Immigrants in 100% Poverty (with Undocumented Proxy)

Mexican immigrants in 100% poverty (modeled based on WTPOV & WTMEX), 12,122 household heads nested in 42 SPUMAs

Fixed effect		Coefficient	Standard error	T-ratio	Approx. d.f.	P-value
For	INTRCPT1,	B0				
INTRCPT2,	G00	–1.39416	0.045473	–30.659	39	0.000
WTPOV,	G01	0.080913	0.011201	7.224	39	0.000
WTMEX,	G02	–0.01295	0.004387	–2.953	39	0.006
For	NCHILD	slope,	B1			
INTRCPT2,	G10	0.383919	0.017797	21.572	39	0.000
WTPOV,	G11	0.006747	0.007421	0.909	39	0.369
WTMEX,	G12	–0.00225	0.003219	–0.697	39	0.490
For	UNEMPLOY	slope,	B2			
INTRCPT2,	G20	0.934591	0.051601	18.112	39	0.000
WTPOV,	G21	–0.00713	0.011987	–0.595	39	0.555
WTMEX,	G22	–0.00449	0.004618	–0.973	39	0.337
For	UNDOC	slope,	B3			
INTRCPT2,	G30	1.452752	0.30301	4.794	39	0.000
WTPOV,	G31	–0.01964	0.112644	–0.174	39	0.863
WTMEX,	G32	–0.00115	0.047588	–0.024	39	0.981

Odds ratios

Fixed effect		Coefficient	Odds ratio	Confidence interval
For	INTRCPT1,	B0		
INTRCPT2,	G00	–1.39416	0.248041	(0.226,0.272)
WTPOV,	G01	0.080913	1.084277	(1.060,1.109)
WTMEX,	G02	–0.01295	0.987131	(0.978,0.996)
For	NCHILD	slope,	B1	
INTRCPT2,	G10	0.383919	1.468027	(1.416,1.522)
WTPOV,	G11	0.006747	1.00677	(0.992,1.022)
WTMEX,	G12	–0.00225	0.997758	(0.991,1.004)
For	UNEMPLOY	slope,	B2	
INTRCPT2,	G20	0.934591	2.546171	(2.294,2.826)
WTPOV,	G21	–0.00713	0.992894	(0.969,1.017)
WTMEX,	G22	–0.00449	0.995516	(0.986,1.005)
For	UNDOC	slope,	B3	
INTRCPT2,	G30	1.452752	4.274864	(2.318,7.884)
WTPOV,	G31	–0.01964	0.980549	(0.781,1.231)
WTMEX,	G32	–0.00115	0.998848	(0.907,1.100)

Mexican immigrants in 100% poverty (modeled based on WTPOV & WTAG), 12,122 household heads nested in 42 SPUMAs

Fixed effect		Coefficient	Standard error	T-ratio	Approx. d.f.	P-value
For	INTRCPT1,	B0				
INTRCPT2,	G00	–1.39711	0.047594	–29.355	39	0.000
WTPOV,	G01	0.050799	0.008182	6.209	39	0.000
WTAG,	G02	0.010582	0.011949	0.886	39	0.382
For	NCHILD	slope,	B1			
INTRCPT2,	G10	0.381791	0.017912	21.314	39	0.000
WTPOV,	G11	0.002147	0.002406	0.893	39	0.378
WTAG,	G12	–0.00019	0.004252	–0.044	39	0.965
For	UNEMPLOY	slope,	B2			
INTRCPT2,	G20	0.955944	0.047065	20.311	39	0.000
WTPOV,	G21	–0.02376	0.005325	–4.462	39	0.000
WTAG,	G22	0.035602	0.012175	2.924	39	0.006
For	UNDOC	slope,	B3			
INTRCPT2,	G30	1.358927	0.30749	4.419	39	0.000
WTPOV,	G31	0.000219	0.044081	0.005	39	0.996
WTAG,	G32	–0.08463	0.081443	–1.039	39	0.306

Odds ratios

Fixed effect		Coefficient	Odds ratio	Confidence interval
For	INTRCPT1,	B0		
INTRCPT2,	G00	–1.39711	0.247311	(0.225,0.272)
WTPOV,	G01	0.050799	1.052112	(1.035,1.070)
WTAG,	G02	0.010582	1.010638	(0.987,1.035)
For	NCHILD	slope,	B1	
INTRCPT2,	G10	0.381791	1.464906	(1.413,1.519)
WTPOV,	G11	0.002147	1.00215	(0.997,1.007)
WTAG,	G12	–0.00019	0.999813	(0.991,1.008)
For	UNEMPLOY	slope,	B2	
INTRCPT2,	G20	0.955944	2.601125	(2.365,2.861)
WTPOV,	G21	–0.02376	0.97652	(0.966,0.987)
WTAG,	G22	0.035602	1.036243	(1.011,1.062)
For	UNDOC	slope,	B3	
INTRCPT2,	G30	1.358927	3.892015	(2.091,7.243)
WTPOV,	G31	0.000219	1.000219	(0.915,1.093)
WTAG,	G32	–0.08463	0.918855	(0.779,1.083)

Mexican immigrants in 100% poverty (modeled based on WTPOV & WTFIRE & WTCONS), 12,122 household heads nested in 42 SPUMAs

Fixed effect		Coefficient	Standard error	T-ratio	Approx. d.f.	P-value
For	INTRCPT1,	B0				
INTRCPT2,	G00	–1.40385	0.047436	–29.594	38	0.000
WTPOV,	G01	0.056984	0.009397	6.064	38	0.000
WTFIRE,	G02	0.015384	0.032373	0.475	38	0.637
WTCONS,	G03	0.002913	0.011705	0.249	38	0.805
For	NCHILD	slope,	B1			
INTRCPT2,	G10	0.385228	0.018618	20.692	38	0.000
WTPOV,	G11	0.001021	0.003107	0.329	38	0.744
WTFIRE,	G12	–0.0122	0.013792	–0.885	38	0.382
WTCONS,	G13	0.006074	0.006557	0.926	38	0.360
For	UNEMPLOY	slope,	B2			
INTRCPT2,	G20	0.975817	0.042344	23.045	38	0.000
WTPOV,	G21	–0.03702	0.007002	–5.287	38	0.000
WTFIRE,	G22	–0.09764	0.036801	–2.653	38	0.012
WTCONS,	G23	–0.01511	0.014689	–1.029	38	0.311
For	UNDOC	slope,	B3			
INTRCPT2,	G30	1.238307	0.34629	3.576	38	0.001
WTPOV,	G31	0.027658	0.070467	0.392	38	0.697
WTFIRE,	G32	0.247505	0.243813	1.015	38	0.317
WTCONS,	G33	–0.10318	0.107748	–0.958	38	0.345

Odds ratios

Fixed effect		Coefficient	Odds ratio	Confidence interval
For	INTRCPT1,	B0		
INTRCPT2,	G00	–1.40385	0.24565	(0.223,0.270)
WTPOV,	G01	0.056984	1.058639	(1.039,1.079)
WTFIRE,	G02	0.015384	1.015503	(0.951,1.084)
WTCONS,	G03	0.002913	1.002917	(0.979,1.027)
For	NCHILD	slope,	B1	
INTRCPT2,	G10	0.385228	1.469949	(1.416,1.526)
WTPOV,	G11	0.001021	1.001021	(0.995,1.007)
WTFIRE,	G12	–0.0122	0.987871	(0.961,1.016)
WTCONS,	G13	0.006074	1.006092	(0.993,1.020)
For	UNEMPLOY	slope,	B2	
INTRCPT2,	G20	0.975817	2.653334	(2.436,2.891)
WTPOV,	G21	–0.03702	0.963658	(0.950,0.977)
WTFIRE,	G22	–0.09764	0.906974	(0.842,0.977)
WTCONS,	G23	–0.01511	0.985003	(0.956,1.015)
For	UNDOC	slope,	B3	
INTRCPT2,	G30	1.238307	3.449768	(1.713,6.948)
WTPOV,	G31	0.027658	1.028044	(0.892,1.185)
WTFIRE,	G32	0.247505	1.280826	(0.782,2.097)
WTCONS,	G33	–0.10318	0.901965	(0.725,1.122)

Mexican immigrants in 100% poverty (modeled based on WTPOV & M1), 12,122 household heads nested in 42 SPUMAs

Fixed effect		Coefficient	Standard error	T-ratio	Approx. d.f.	P-value
For	INTRCPT1,	B0				
INTRCPT2,	G00	–1.3973	0.047591	–29.361	39	0.000
WTPOV,	G01	0.053786	0.006745	7.975	39	0.000
M1,	G02	–0.87623	2.18741	–0.401	39	0.691
For	NCHILD	slope,	B1			
INTRCPT2,	G10	0.379835	0.015515	24.482	39	0.000
WTPOV,	G11	0.002428	0.002438	0.996	39	0.326
M1,	G12	–0.87719	1.177328	–0.745	39	0.461
For	UNEMPLOY	slope,	B2			
INTRCPT2,	G20	0.928186	0.049678	18.684	39	0.000
WTPOV,	G21	–0.01659	0.005971	–2.779	39	0.009
M1,	G22	3.022447	2.428674	1.244	39	0.221
For	UNDOC	slope,	B3			
INTRCPT2,	G30	1.426904	0.307564	4.639	39	0.000
WTPOV,	G31	–0.01719	0.057225	–0.3	39	0.765
M1,	G32	16.33351	23.25188	0.702	39	0.486

Odds ratios

Fixed effect		Coefficient	Odds ratio	Confidence interval
For	INTRCPT1,	B0		
INTRCPT2,	G00	–1.3973	0.247263	(0.225,0.272)
WTPOV,	G01	0.053786	1.055259	(1.041,1.070)
M1,	G02	–0.87623	0.416349	(0.005,34.548)
For	NCHILD	slope,	B1	
INTRCPT2,	G10	0.379835	1.462044	(1.417,1.509)
WTPOV,	G11	0.002428	1.002431	(0.998,1.007)
M1,	G12	–0.87719	0.41595	(0.039,4.486)
For	UNEMPLOY	slope,	B2	
INTRCPT2,	G20	0.928186	2.529915	(2.288,2.797)
WTPOV,	G21	–0.01659	0.983543	(0.972,0.995)
M1,	G22	3.022447	20.54151	(0.152,2774.897)
For	UNDOC	slope,	B3	
INTRCPT2,	G30	1.426904	4.165781	(2.238,7.754)
WTPOV,	G31	–0.01719	0.982959	(0.876,1.103)
M1,	G32	16.33351	12403780	(0.000,3103.000)

HGLM Results: Mexican Immigrants in 100% Poverty (Without Undocumented Proxy)

Mexican immigrants in 100% poverty (modeled based on WTPOV & WTMEX), 12,122 household heads nested in 42 SPUMAs

Fixed effect		Coefficient	Standard error	T-ratio	Approx. d.f.	P-value
For	INTRCPT1,	B0				
INTRCPT2,	G00	–1.47391	0.048639	–30.303	39	0.000
WTPOV,	G01	0.086474	0.01231	7.024	39	0.000
WTMEX,	G02	–0.01485	0.004864	–3.054	39	0.005
For	NCHILD	slope,	B1			
INTRCPT2,	G10	0.381387	0.018725	20.367	39	0.000
WTPOV,	G11	0.004614	0.007314	0.631	39	0.532
WTMEX,	G12	–0.00348	0.003178	–1.096	39	0.280
For	YRSUSA1	slope,	B2			
INTRCPT2,	G20	–0.05237	0.002966	–17.653	39	0.000
WTPOV,	G21	0.000788	0.000964	0.818	39	0.419
WTMEX,	G22	–0.00019	0.000378	–0.5	39	0.619
For	UNEMPLOY	slope,	B3			
INTRCPT2,	G30	0.983698	0.044858	21.929	39	0.000
WTPOV,	G31	–0.00706	0.01166	–0.606	39	0.548
WTMEX,	G32	–0.00278	0.00522	–0.532	39	0.597

Odds ratios

Fixed effect		Coefficient	Odds ratio	Confidence interval
For	INTRCPT1,	B0		
INTRCPT2,	G00	–1.47391	0.229029	(0.208,0.253)
WTPOV,	G01	0.086474	1.090323	(1.064,1.118)
WTMEX,	G02	–0.01485	0.985258	(0.976,0.995)
For	NCHILD	slope,	B1	
INTRCPT2,	G10	0.381387	1.464313	(1.410,1.521)
WTPOV,	G11	0.004614	1.004624	(0.990,1.020)
WTMEX,	G12	–0.00348	0.996524	(0.990,1.003)
For	YRSUSA1	slope,	B2	
INTRCPT2,	G20	–0.05237	0.948983	(0.943,0.955)
WTPOV,	G21	0.000788	1.000789	(0.999,1.003)
WTMEX,	G22	–0.00019	0.999811	(0.999,1.001)
For	UNEMPLOY	slope,	B3	
INTRCPT2,	G30	0.983698	2.674326	(2.443,2.928)
WTPOV,	G31	–0.00706	0.992962	(0.970,1.017)
WTMEX,	G32	–0.00278	0.997226	(0.987,1.008)

HGLM Results: Mexican Immigrants in Low Income (with Undocumented Proxy)

Mexican immigrants in low income (modeled based on WTPOV & WTMEX), 12,122 household heads nested in 42 SPUMAs

Fixed effect		Coefficient	Standard error	T-ratio	Approx. d.f.	P-value
For	INTRCPT1,	B0				
INTRCPT2,	G00	0.467519	0.048421	9.655	39	0.000
WTPOV,	G01	0.086986	0.012104	7.186	39	0.000
WTMEX,	G02	–0.02064	0.004733	–4.36	39	0.000
For	NCHILD	slope,	B1			
INTRCPT2,	G10	0.447169	0.019562	22.859	39	0.000
WTPOV,	G11	0.016012	0.005445	2.94	39	0.006
WTMEX,	G12	–0.00393	0.002295	–1.712	39	0.094
For	UNEMPLOY	slope,	B2			
INTRCPT2,	G20	0.673219	0.056768	11.859	39	0.000
WTPOV,	G21	0.018575	0.015637	1.188	39	0.242
WTMEX,	G22	–0.0048	0.006397	–0.75	39	0.458
For	UNDOC	slope,	B3			
INTRCPT2,	G30	2.054639	0.273554	7.511	39	0.000
WTPOV,	G31	–0.22833	0.087113	–2.621	39	0.013
WTMEX,	G32	0.049384	0.030351	1.627	39	0.111

Odds ratios

Fixed effect		Coefficient	Odds ratio	Confidence interval
For	INTRCPT1,	B0		
INTRCPT2,	G00	0.467519	1.59603	(1.447,1.760)
WTPOV,	G01	0.086986	1.090881	(1.065,1.118)
WTMEX,	G02	–0.02064	0.979577	(0.970,0.989)
For	NCHILD	slope,	B1	
INTRCPT2,	G10	0.447169	1.563878	(1.503,1.627)
WTPOV,	G11	0.016012	1.01614	(1.005,1.027)
WTMEX,	G12	–0.00393	0.996079	(0.991,1.001)
For	UNEMPLOY	slope,	B2	
INTRCPT2,	G20	0.673219	1.960538	(1.748,2.199)
WTPOV,	G21	0.018575	1.018749	(0.987,1.051)
WTMEX,	G22	–0.0048	0.995217	(0.982,1.008)
For	UNDOC	slope,	B3	
INTRCPT2,	G30	2.054639	7.804022	(4.491,13.561)
WTPOV,	G31	–0.22833	0.795861	(0.667,0.949)
WTMEX,	G32	0.049384	1.050624	(0.988,1.117)

Mexican immigrants in low income (modeled based on WTPOV & WTAG), 12,122 household heads nested in 42 SPUMAs

Fixed effect		Coefficient	Standard error	T-ratio	Approx. d.f.	P-value
For	INTRCPT1,	B0				
INTRCPT2,	G00	0.45595	0.053407	8.537	39	0.000
WTPOV,	G01	0.039072	0.009414	4.151	39	0.000
WTAG,	G02	0.023142	0.016763	1.381	39	0.175
For	NCHILD	slope,	B1			
INTRCPT2,	G10	0.439663	0.018487	23.783	39	0.000
WTPOV,	G11	0.007665	0.002724	2.814	39	0.008
WTAG,	G12	0.002259	0.005141	0.439	39	0.662
For	UNEMPLOY	slope,	B2			
INTRCPT2,	G20	0.668221	0.058785	11.367	39	0.000
WTPOV,	G21	0.008757	0.009006	0.972	39	0.337
WTAG,	G22	0.003009	0.021862	0.138	39	0.892
For	UNDOC	slope,	B3			
INTRCPT2,	G30	1.956744	0.261264	7.49	39	0.000
WTPOV,	G31	–0.04595	0.030539	–1.505	39	0.140
WTAG,	G32	–0.23647	0.067292	–3.514	39	0.001

Odds ratios

Fixed effect		Coefficient	Odds ratio	Confidence interval
For	INTRCPT1,	B0		
INTRCPT2,	G00	0.45595	1.577671	(1.416,1.757)
WTPOV,	G01	0.039072	1.039845	(1.020,1.060)
WTAG,	G02	0.023142	1.023412	(0.989,1.059)
For	NCHILD	slope,	B1	
INTRCPT2,	G10	0.439663	1.552184	(1.495,1.611)
WTPOV,	G11	0.007665	1.007695	(1.002,1.013)
WTAG,	G12	0.002259	1.002261	(0.992,1.013)
For	UNEMPLOY	slope,	B2	
INTRCPT2,	G20	0.668221	1.950763	(1.732,2.197)
WTPOV,	G21	0.008757	1.008795	(0.991,1.027)
WTAG,	G22	0.003009	1.003014	(0.960,1.048)
For	UNDOC	slope,	B3	
INTRCPT2,	G30	1.956744	7.076252	(4.174,11.995)
WTPOV,	G31	–0.04595	0.955093	(0.898,1.016)
WTAG,	G32	–0.23647	0.789409	(0.689,0.904)

Mexican immigrants in low income (modeled based on WTPOV & WTFIRE), 12,122 household heads nested in 42 SPUMAs

Fixed effect		Coefficient	Standard error	T-ratio	Approx. d.f.	P-value
For	INTRCPT1,	B0				
INTRCPT2,	G00	0.45238	0.054001	8.377	39	0.000
WTPOV,	G01	0.043673	0.011235	3.887	39	0.001
WTFIRE,	G02	–0.00516	0.038985	–0.132	39	0.896
For	NCHILD	slope,	B1			
INTRCPT2,	G10	0.448246	0.018862	23.765	39	0.000
WTPOV,	G11	0.00536	0.003398	1.577	39	0.122
WTFIRE,	G12	–0.01419	0.010686	–1.328	39	0.192
For	UNEMPLOY	slope,	B2			
INTRCPT2,	G20	0.689365	0.056122	12.283	39	0.000
WTPOV,	G21	–0.00373	0.011703	–0.319	39	0.752
WTFIRE,	G22	–0.06594	0.039649	–1.663	39	0.104
For	UNDOC	slope,	B3			
INTRCPT2,	G30	1.765593	0.245887	7.18	39	0.000
WTPOV,	G31	0.006032	0.056714	0.106	39	0.916
WTFIRE,	G32	0.705633	0.149876	4.708	39	0.000

Odds ratios

Fixed effect		Coefficient	Odds ratio	Confidence interval
For	INTRCPT1,	B0		
INTRCPT2,	G00	0.45238	1.572049	(1.410,1.753)
WTPOV,	G01	0.043673	1.044641	(1.021,1.069)
WTFIRE,	G02	–0.00516	0.994854	(0.920,1.076)
For	NCHILD	slope,	B1	
INTRCPT2,	G10	0.448246	1.565563	(1.507,1.626)
WTPOV,	G11	0.00536	1.005375	(0.998,1.012)
WTFIRE,	G12	–0.01419	0.985909	(0.965,1.007)
For	UNEMPLOY	slope,	B2	
INTRCPT2,	G20	0.689365	1.99245	(1.779,2.232)
WTPOV,	G21	–0.00373	0.996279	(0.973,1.020)
WTFIRE,	G22	–0.06594	0.936185	(0.864,1.014)
For	UNDOC	slope,	B3	
INTRCPT2,	G30	1.765593	5.845035	(3.557,9.605)
WTPOV,	G31	0.006032	1.006051	(0.897,1.128)
WTFIRE,	G32	0.705633	2.025128	(1.496,2.741)

Mexican immigrants in low income (modeled based on WTPOV & WTCONS), 12,122 household heads nested in 42 SPUMAs

Fixed effect		Coefficient	Standard error	T-ratio	Approx. d.f.	P-value
For	INTRCPT1,	B0				
INTRCPT2,	G00	0.453876	0.053471	8.488	39	0.000
WTPOV,	G01	0.044979	0.008031	5.601	39	0.000
WTCONS,	G02	0.000081	0.013613	0.006	39	0.995
For	NCHILD	slope,	B1			
INTRCPT2,	G10	0.444722	0.017801	24.983	39	0.000
WTPOV,	G11	0.007833	0.002758	2.84	39	0.008
WTCONS,	G12	–0.00232	0.00501	–0.464	39	0.645
For	UNEMPLOY	slope,	B2			
INTRCPT2,	G20	0.651654	0.053863	12.098	39	0.000
WTPOV,	G21	0.015141	0.005566	2.72	39	0.010
WTCONS,	G22	0.03244	0.013512	2.401	39	0.021
For	UNDOC	slope,	B3			
INTRCPT2,	G30	2.324676	0.367081	6.333	39	0.000
WTPOV,	G31	–0.10428	0.039788	–2.621	39	0.013
WTCONS,	G32	0.351755	0.134936	2.607	39	0.013

Odds ratios

Fixed effect		Coefficient	Odds ratio	Confidence interval
For	INTRCPT1,	B0		
INTRCPT2,	G00	0.453876	1.574403	(1.413,1.754)
WTPOV,	G01	0.044979	1.046006	(1.029,1.063)
WTCONS,	G02	0.000081	1.000081	(0.973,1.028)
For	NCHILD	slope,	B1	
INTRCPT2,	G10	0.444722	1.560057	(1.505,1.617)
WTPOV,	G11	0.007833	1.007863	(1.002,1.013)
WTCONS,	G12	–0.00232	0.997679	(0.988,1.008)
For	UNEMPLOY	slope,	B2	
INTRCPT2,	G20	0.651654	1.918711	(1.721,2.139)
WTPOV,	G21	0.015141	1.015256	(1.004,1.027)
WTCONS,	G22	0.03244	1.032972	(1.005,1.062)
For	UNDOC	slope,	B3	
INTRCPT2,	G30	2.324676	10.22337	(4.870,21.460)
WTPOV,	G31	–0.10428	0.900976	(0.831,0.976)
WTCONS,	G32	0.351755	1.42156	(1.082,1.867)

Mexican immigrants in low income (modeled based on WTPOV & WTMETRO), 12,122 household heads nested in 42 SPUMAs

Fixed effect		Coefficient	Standard error	T-ratio	Approx. d.f.	P-value
For	INTRCPT1,	B0				
INTRCPT2,	G00	0.459702	0.053365	8.614	39	0.000
WTPOV,	G01	0.039326	0.008221	4.784	39	0.000
WTMETRO,	G02	–0.00459	0.002528	–1.815	39	0.077
For	NCHILD	slope,	B1			
INTRCPT2,	G10	0.439266	0.018677	23.519	39	0.000
WTPOV,	G11	0.007624	0.002315	3.293	39	0.002
WTMETRO,	G12	–0.0002	0.00108	–0.181	39	0.857
For	UNEMPLOY	slope,	B2			
INTRCPT2,	G20	0.698435	0.057657	12.114	39	0.000
WTPOV,	G21	0.002666	0.008722	0.306	39	0.761
WTMETRO,	G22	–0.00672	0.003513	–1.913	39	0.063
For	UNDOC	slope,	B3			
INTRCPT2,	G30	2.247883	0.236747	9.495	39	0.000
WTPOV,	G31	–0.11222	0.047281	–2.373	39	0.023
WTMETRO,	G32	–0.02073	0.012065	–1.718	39	0.093

Odds ratios

Fixed effect		Coefficient	Odds ratio	Confidence interval
For	INTRCPT1,	B0		
INTRCPT2,	G00	0.459702	1.583603	(1.422,1.764)
WTPOV,	G01	0.039326	1.04011	(1.023,1.058)
WTMETRO,	G02	–0.00459	0.995422	(0.990,1.001)
For	NCHILD	slope,	B1	
INTRCPT2,	G10	0.439266	1.551569	(1.494,1.611)
WTPOV,	G11	0.007624	1.007653	(1.003,1.012)
WTMETRO,	G12	–0.0002	0.999804	(0.998,1.002)
For	UNEMPLOY	slope,	B2	
INTRCPT2,	G20	0.698435	2.010604	(1.790,2.259)
WTPOV,	G21	0.002666	1.002669	(0.985,1.020)
WTMETRO,	G22	–0.00672	0.9933	(0.986,1.000)
For	UNDOC	slope,	B3	
INTRCPT2,	G30	2.247883	9.467671	(5.869,15.273)
WTPOV,	G31	–0.11222	0.893846	(0.812,0.983)
WTMETRO,	G32	–0.02073	0.97948	(0.956,1.004)

Mexican immigrants in low income (modeled based on WTPOV & M1), 12,122 household heads nested in 42 SPUMAs

Fixed effect		Coefficient	Standard error	T-ratio	Approx. d.f.	P-value
For	INTRCPT1,	B0				
INTRCPT2,	G00	0.454158	0.05347	8.494	39	0.000
WTPOV,	G01	0.045065	0.007878	5.72	39	0.000
M1,	G02	–0.29994	2.602927	–0.115	39	0.909
For	NCHILD	slope,	B1			
INTRCPT2,	G10	0.441208	0.017259	25.563	39	0.000
WTPOV,	G11	0.008404	0.00248	3.389	39	0.002
M1,	G12	–0.39805	0.777826	–0.512	39	0.611
For	UNEMPLOY	slope,	B2			
INTRCPT2,	G20	0.65118	0.052139	12.489	39	0.000
WTPOV,	G21	0.010686	0.004355	2.453	39	0.019
M1,	G22	–7.24174	1.864612	–3.884	39	0.001
For	UNDOC	slope,	B3			
INTRCPT2,	G30	2.390152	0.340259	7.025	39	0.000
WTPOV,	G31	–0.14856	0.042261	–3.515	39	0.001
M1,	G32	–61.1211	24.94331	–2.45	39	0.019

Odds ratios

Fixed effect		Coefficient	Odds ratio	Confidence interval
For	INTRCPT1,	B0		
INTRCPT2,	G00	0.454158	1.574846	(1.414,1.754)
WTPOV,	G01	0.045065	1.046095	(1.030,1.063)
M1,	G02	–0.29994	0.740863	(0.004,142.305)
For	NCHILD	slope,	B1	
INTRCPT2,	G10	0.441208	1.554584	(1.501,1.610)
WTPOV,	G11	0.008404	1.008439	(1.003,1.014)
M1,	G12	–0.39805	0.671631	(0.140,3.232)
For	UNEMPLOY	slope,	B2	
INTRCPT2,	G20	0.65118	1.917803	(1.726,2.131)
WTPOV,	G21	0.010686	1.010743	(1.002,1.020)
M1,	G22	–7.24174	0.000716	(0.000,0.031)
For	UNDOC	slope,	B3	
INTRCPT2,	G30	2.390152	10.91515	(5.489,21.704)
WTPOV,	G31	–0.14856	0.861949	(0.791,0.939)
M1,	G32	–61.1211	0	(0.000,0.000)

HGLM Results: Mexican Immigrants in Low Income (Without Undocumented Proxy)

Mexican immigrants in low income (modeled based on WTPOV & WTMEX), 12,122 household heads nested in 42 SPUMAs

Fixed effect		Coefficient	Standard error	T-ratio	Approx. d.f.	P-value
For	INTRCPT1,	B0				
INTRCPT2,	G00	0.469519	0.048811	9.619	39	0.000
WTPOV,	G01	0.0892	0.012477	7.149	39	0.000
WTMEX,	G02	–0.02093	0.00487	–4.297	39	0.000
For	YRSUSA1	slope,	B1			
INTRCPT2,	G10	–0.05212	0.002549	–20.446	39	0.000
WTPOV,	G11	0.000561	0.000766	0.732	39	0.468
WTMEX,	G12	0.000062	0.000287	0.217	39	0.830
For	MEXJOB	slope,	B2			
INTRCPT2,	G20	0.68033	0.046215	14.721	39	0.000
WTPOV,	G21	–0.01047	0.015673	–0.668	39	0.508
WTMEX,	G22	0.012222	0.005844	2.091	39	0.043
For	UNEMPLOY	slope,	B3			
INTRCPT2,	G30	0.844792	0.044105	19.154	39	0.000
WTPOV,	G31	0.011585	0.01608	0.72	39	0.475
WTMEX,	G32	–0.0024	0.006214	–0.385	39	0.702

Odds ratios

Fixed effect		Coefficient	Odds ratio	Confidence interval
For	INTRCPT1,	B0		
INTRCPT2,	G00	0.469519	1.599225	(1.449,1.765)
WTPOV,	G01	0.0892	1.093299	(1.066,1.121)
WTMEX,	G02	–0.02093	0.97929	(0.970,0.989)
For	YRSUSA1	slope,	B1	
INTRCPT2,	G10	–0.05212	0.949219	(0.944,0.954)
WTPOV,	G11	0.000561	1.000561	(0.999,1.002)
WTMEX,	G12	0.000062	1.000062	(0.999,1.001)
For	MEXJOB	slope,	B2	
INTRCPT2,	G20	0.68033	1.974528	(1.799,2.168)
WTPOV,	G21	–0.01047	0.989589	(0.959,1.021)
WTMEX,	G22	0.012222	1.012297	(1.000,1.024)
For	UNEMPLOY	slope,	B3	
INTRCPT2,	G30	0.844792	2.327493	(2.129,2.544)
WTPOV,	G31	0.011585	1.011652	(0.979,1.045)
WTMEX,	G32	–0.0024	0.997608	(0.985,1.010)

Mexican immigrants in low income (modeled based on WTPOV & WTAG), 12,122 household heads nested in 42 SPUMAs

Fixed effect		Coefficient	Standard error	T-ratio	Approx. d.f.	P-value
For	INTRCPT1,	B0				
INTRCPT2,	G00	0.460637	0.054605	8.436	39	0.000
WTPOV,	G01	0.040029	0.009619	4.162	39	0.000
WTAG,	G02	0.024105	0.017323	1.391	39	0.172
For	YRSUSA1	slope,	B1			
INTRCPT2,	G10	–0.05168	0.002641	–19.572	39	0.000
WTPOV,	G11	0.000622	0.000429	1.45	39	0.155
WTAG,	G12	0.000078	0.000858	0.09	39	0.929
For	MEXJOB	slope,	B2			
INTRCPT2,	G20	0.701334	0.047151	14.874	39	0.000
WTPOV,	G21	0.014339	0.01001	1.433	39	0.160
WTAG,	G22	0.000423	0.012485	0.034	39	0.973
For	UNEMPLOY	slope,	B3			
INTRCPT2,	G30	0.828312	0.055334	14.969	39	0.000
WTPOV,	G31	0.009673	0.008186	1.182	39	0.245
WTAG,	G32	–0.01051	0.018504	–0.568	39	0.573

Confidence Interval

Fixed effect		Coefficient	Ratio	Interval
For	INTRCPT1,	B0		
INTRCPT2,	G00	0.460637	1.585083	(1.420,1.770)
WTPOV,	G01	0.040029	1.040841	(1.021,1.061)
WTAG,	G02	0.024105	1.024398	(0.989,1.061)
For	YRSUSA1	slope,	B1	
INTRCPT2,	G10	–0.05168	0.949631	(0.945,0.955)
WTPOV,	G11	0.000622	1.000622	(1.000,1.001)
WTAG,	G12	0.000078	1.000078	(0.998,1.002)
For	MEXJOB	slope,	B2	
INTRCPT2,	G20	0.701334	2.016441	(1.833,2.218)
WTPOV,	G21	0.014339	1.014443	(0.994,1.035)
WTAG,	G22	0.000423	1.000423	(0.976,1.026)
For	UNEMPLOY	slope,	B3	
INTRCPT2,	G30	0.828312	2.289452	(2.047,2.560)
WTPOV,	G31	0.009673	1.00972	(0.993,1.027)
WTAG,	G32	–0.01051	0.989546	(0.953,1.027)

Mexican immigrants in low income (modeled based on WTPOV & WTFIRE), 12,122 household heads nested in 42 SPUMAs

Fixed effect		Coefficient	Standard error	T-ratio	Approx. d.f.	P-value
For	INTRCPT1,	B0				
INTRCPT2,	G00	0.457961	0.055001	8.326	39	0.000
WTPOV,	G01	0.044974	0.011576	3.885	39	0.001
WTFIRE,	G02	–0.0066	0.041196	–0.16	39	0.874
For	YRSUSA1	slope,	B1			
INTRCPT2,	G10	–0.05121	0.002436	–21.019	39	0.000
WTPOV,	G11	0.000348	0.000521	0.667	39	0.509
WTFIRE,	G12	–0.00183	0.002088	–0.874	39	0.388
For	MEXJOB	slope,	B2			
INTRCPT2,	G20	0.693147	0.051408	13.483	39	0.000
WTPOV,	G21	0.019949	0.011836	1.685	39	0.099
WTFIRE,	G22	0.026899	0.035282	0.762	39	0.450
For	UNEMPLOY	slope,	B3			
INTRCPT2,	G30	0.850265	0.053322	15.946	39	0.000
WTPOV,	G31	0.001793	0.012282	0.146	39	0.885
WTFIRE,	G32	–0.03094	0.040375	–0.766	39	0.448

Odds ratios

Fixed effect		Coefficient	Odds ratio	Confidence interval
For	INTRCPT1,	B0		
INTRCPT2,	G00	0.457961	1.580847	(1.415,1.767)
WTPOV,	G01	0.044974	1.046	(1.022,1.071)
WTFIRE,	G02	–0.0066	0.993417	(0.914,1.080)
For	YRSUSA1	slope,	B1	
INTRCPT2,	G10	–0.05121	0.950079	(0.945,0.955)
WTPOV,	G11	0.000348	1.000348	(0.999,1.001)
WTFIRE,	G12	–0.00183	0.998177	(0.994,1.002)
For	MEXJOB	slope,	B2	
INTRCPT2,	G20	0.693147	1.999999	(1.803,2.219)
WTPOV,	G21	0.019949	1.02015	(0.996,1.045)
WTFIRE,	G22	0.026899	1.027264	(0.957,1.103)
For	UNEMPLOY	slope,	B3	
INTRCPT2,	G30	0.850265	2.340268	(2.101,2.606)
WTPOV,	G31	0.001793	1.001794	(0.977,1.027)
WTFIRE,	G32	–0.03094	0.969532	(0.894,1.052)

Mexican immigrants in low income (modeled based on WTPOV & WTCONS), 12,122 household heads nested in 42 SPUMAs

Fixed effect		Coefficient	Standard error	T-ratio	Approx. d.f.	P-value
For	INTRCPT1,	B0				
INTRCPT2,	G00	0.45798	0.054571	8.392	39	0.000
WTPOV,	G01	0.046154	0.008261	5.587	39	0.000
WTCONS,	G02	0.000074	0.01409	0.005	39	0.996
For	YRSUSA1	slope,	B1			
INTRCPT2,	G10	–0.0515	0.002648	–19.45	39	0.000
WTPOV,	G11	0.000525	0.000384	1.366	39	0.180
WTCONS,	G12	–0.00081	0.000711	–1.133	39	0.265
For	MEXJOB	slope,	B2			
INTRCPT2,	G20	0.702285	0.048374	14.518	39	0.000
WTPOV,	G21	0.013016	0.008796	1.48	39	0.147
WTCONS,	G22	–0.00617	0.014465	–0.426	39	0.672
For	UNEMPLOY	slope,	B3			
INTRCPT2,	G30	0.825686	0.043613	18.932	39	0.000
WTPOV,	G31	0.013189	0.005664	2.329	39	0.025
WTCONS,	G32	0.031739	0.014548	2.182	39	0.035

Odds ratios

Fixed effect		Coefficient	Odds ratio	Confidence interval
For	INTRCPT1,	B0		
INTRCPT2,	G00	0.45798	1.580877	(1.416,1.765)
WTPOV,	G01	0.046154	1.047236	(1.030,1.065)
WTCONS,	G02	0.000074	1.000074	(0.972,1.029)
For	YRSUSA1	slope,	B1	
INTRCPT2,	G10	–0.0515	0.949807	(0.945,0.955)
WTPOV,	G11	0.000525	1.000525	(1.000,1.001)
WTCONS,	G12	–0.00081	0.999195	(0.998,1.001)
For	MEXJOB	slope,	B2	
INTRCPT2,	G20	0.702285	2.018359	(1.830,2.226)
WTPOV,	G21	0.013016	1.013101	(0.995,1.031)
WTCONS,	G22	–0.00617	0.993851	(0.965,1.023)
For	UNEMPLOY	slope,	B3	
INTRCPT2,	G30	0.825686	2.283447	(2.091,2.494)
WTPOV,	G31	0.013189	1.013276	(1.002,1.025)
WTCONS,	G32	0.031739	1.032248	(1.002,1.063)

Mexican immigrants in low income (modeled based on WTPOV & M1), 12,122 household heads nested in 42 SPUMAs

Fixed effect		Coefficient	Standard error	T-ratio	Approx. d.f.	P-value
For	INTRCPT1,	B0				
INTRCPT2,	G00	0.458398	0.054656	8.387	39	0.000
WTPOV,	G01	0.046211	0.008159	5.664	39	0.000
M1,	G02	–0.18281	2.643865	–0.069	39	0.946
For	YRSUSA1	slope,	B1			
INTRCPT2,	G10	–0.05165	0.002661	–19.41	39	0.000
WTPOV,	G11	0.000645	0.00037	1.745	39	0.088
M1,	G12	0.078047	0.116167	0.672	39	0.505
For	MEXJOB	slope,	B2			
INTRCPT2,	G20	0.703173	0.04873	14.43	39	0.000
WTPOV,	G21	0.013331	0.00837	1.593	39	0.119
M1,	G22	2.019582	2.555493	0.79	39	0.434
For	UNEMPLOY	slope,	B3			
INTRCPT2,	G30	0.828483	0.040572	20.42	39	0.000
WTPOV,	G31	0.009132	0.004401	2.075	39	0.044
M1,	G32	–6.9893	2.215809	–3.154	39	0.004

Odds ratios

Fixed effect		Coefficient	Odds ratio	Confidence interval
For	INTRCPT1,	B0		
INTRCPT2,	G00	0.458398	1.581538	(1.416,1.766)
WTPOV,	G01	0.046211	1.047296	(1.030,1.065)
M1,	G02	–0.18281	0.832926	(0.004,173.781)
For	YRSUSA1	slope,	B1	
INTRCPT2,	G10	–0.05165	0.949663	(0.945,0.955)
WTPOV,	G11	0.000645	1.000646	(1.000,1.001)
M1,	G12	0.078047	1.081174	(0.855,1.367)
For	MEXJOB	slope,	B2	
INTRCPT2,	G20	0.703173	2.020152	(1.831,2.229)
WTPOV,	G21	0.013331	1.013421	(0.996,1.031)
M1,	G22	2.019582	7.535178	(0.043,1315.113)
For	UNEMPLOY	slope,	B3	
INTRCPT2,	G30	0.828483	2.289842	(2.110,2.485)
WTPOV,	G31	0.009132	1.009174	(1.000,1.018)
M1,	G32	–6.9893	0.000922	(0.000,0.081)

References

ACS. 2003. *American Community Survey Operations Plan*, edited by U. C. Bureau. American Community Survey (ACS): Government Printing Office.

ACS. 2006a. *United States Census Bureau*, edited by U. C. Bureau. American Community Survey (ACS): Government Printing Office.

ACS. 2006b. *Design and Methodology*, edited by U. C. Bureau. American Community Survey (ACS): Government Printing Office.

Albrecht, Don E., Albrecht Carol Mulford, and Stan L. Albrecht. 2000. Poverty in Nonmetropolitan America: Impacts of Industrial, Employment, and Family Structure Variables. *Rural Sociology* 65 (1): 87–103.

Anderton, Douglas L., and Deborah E. Sellers. 1989. A Brief Review of Contextual-Effect Models and Measurement. *Historical Methods* 22 (3): 106–115.

Atkinson, Tony, Bea Cantillon, Eric Marlier, and Brian Nolan. 2002. *Social Indicators: The EU and Social Inclusion*. Oxford [u.a.]: Oxford University Press.

Atkinson, Anthony B., Eric Marlier, and Brian Nolan. 2004. Indicators and Targets for Social Inclusion in the European Union. *Journal of Common Market Studies* 42 (1): 47–75.

Bean, Frank D., Harley L. Browning, and Frisbie W. Parker. 1984. The Sociodemographic Characteristics of Mexican Immigrant Status Groups: Implications for Studying Undocumented Mexicans. *International Migration Review* 18 (3): 672–691.

Bean, Frank D., Edward E. Telles, and B. Lindsay Lowell. 1987. Undocumented Migration to the United States: Perceptions and Evidence. *Population and Development Review* 13 (4): 671–690.

Blank, Rebecca M. 2008. Presidential Address: How to Improve Poverty Measurement in the United States. *Journal of Policy Analysis & Management* 27 (2): 233–254.

Borjas, George J. 1999. *The Top Ten Symptoms of Immigration*. Washington, DC: Center for Immigration Studies.

Brown, David L., Louis E. Swanson, and Alan W. Barton. 2003. *Challenges for Rural America in the Twenty-First Century, Rural studies series*. University Park: Pennsylvania State University Press.

Burkhauser, Richard V. 2009. Deconstructing European Poverty Measures: What Relative and Absolute Scales Measure. *Journal of Policy Analysis and Management* 28 (4): 715–725.

Casterline, John B., ed. 1985. Community Effects on Fertility. In *The Collection and Analysis of Community Data*, edited by J. B. Casterline. Netherlands: International Statistical Institute.

Census Bureau, US. 2001a. *2000 Census of Population and Housing*. Washington, DC: US Census Bureau.

Census Bureau, US. 2001b. *Introduction to Census 2000 Data Products*, edited by U. S. C. Bureau, U. S. D. o. Commerce and E. a. S. Administration. Washington, DC: Government Printing Office.

Census Bureau, US. 2002. *2000 Census of Population and Housing*. Washington, DC: US Census Bureau.

Census Bureau, US. 2007. *Poverty Measurement Studies and Alternative Measures*. Washington, DC: US Census Bureau.

Census Bureau, US. 2008. *Median Household Income (In 2008 Inflation-Adjusted Dollars)*. US Census Bureau, American Community Survey 2008, Washington, DC.

Center for Immigration Studies, CIS. 2001. *Poverty and Income*. San Diego, CA: Center for Immigration Studies (CIS).

Citro, Constance F., and Robert T. Michael. 1995. Poverty Panel on, and Assistance Family. *Measuring poverty a new approach*. Washington, DC: National Academy Press. Available from http://www.netlibrary.com/urlapi.asp?action=summary&v=1&bookid=739

Congressional Budget Office, CBO. 2005. *Remittances: International Payments by Migrants*. In A Series on Immigration. Washington, DC: Congressional Budget Office.

Cotter, David A. 2002. Poor People in Poor Places: Local Opportunity Structures and Household Poverty. *Rural Sociology* 67 (4): 534–555.

Crowley, Martha, Daniel T. Lichter, and Qian Zhenchao. 2006. Beyond Gateway Cities: Economic Restructuring and Poverty Among Mexican Immigrant Families and Children. *Family Relations* 55 (3): 345–360.

Danziger, Sheldon H. 2007, Spring-Summer. Fighting Poverty Revisited: What did Researchers Know 40 Years Ago? What do We Know Today? *Focus* 25 (1): 3–11.

Danziger, Sheldon, and Peter Gottschalk, Foundation Russell Sage, and Bureau Population Reference. 2004. *Diverging Fortunes: Trends in Poverty and Inequality, The American People*. New York, NY; Washington, DC: Russell Sage Foundation; Population Reference Bureau.

DeNavas-Walt, Carmen, Bernadette D. Proctor, and Jessica C. Smith. 2009. Income, Poverty, and Health Insurance Coverage in the United States: 2008. In *Current Population Reports*. Washington, DC: US Census Bureau. pp. 60–238.

DiPrete, Thomas A., and Jerry D. Forristal. 1994. Multilevel Models: Methods and Substance. *Annual Review of Sociology* 20 (1): 331–357.

Dinan, Kinsey Alden. 2005a. Federal Policies Restrict Immigrant Children's Access to Key Public Benefits. In *Children in Low-Income Families Policy Brief*. New York, NY: National Center for Children in Poverty (NCCP).

Dinan, Kinsey Alden. 2005b. State Policies can Promote Immigrant Children's Economic Security. In *Children in Low-Income Families Policy Brief*. New York, NY: National Center for Children in Poverty (NCCP).

Donato, Katherine M. 1994. U.S. Policy and Mexican Migration to the United States, 1942–92. *Social Science Quarterly* 75 (4): 705–729.

Douglas, Karen M., and Rogelio Saenz. 2008. No Phone, No Vehicle, No English, and No Citizenship: The Vulnerability of Mexican Immigrants in the United States. In *Globalization and America: Race, Human Rights, and Inequality*, edited by A. J. Hattery, D. G. Embrick, E. Smith. Lanham, MD: Rowman and Littlefield.

Douglas-Hall, Ayana, and Heather Koball. 2004. *Children of Recent Immigrants: National and Regional Trends*. Washington, DC: National Center for Children in Poverty (NCCP).

Durand, Jorge, and Douglas S. Massey. 1999. The New Era of Mexican Migration to the United States. *Journal of American History* 86 (2): 518–536.

Entwisle, Barbara, and William M. Mason. 1985. Multilevel Effects of Socioeconomic Development and Family Planning Programs on Children Ever Born. *The American Journal of Sociology* 91 (3): 616–649.

Espenshade, Thomas J., and Katherine Hempstead. 1996. Contemporary American Attitudes Toward US Immigration. *International Migration Review* 30 (2): 535–570.

Fisher, Gordon M. 1997. *The Development and History of the US Poverty Thresholds – A Brief Overview*, edited by D. o. H. a. H. Services. Washington, DC: US Department of Health and Human Services.

Fix, Michael, and Jeffrey Passel. 2002. The Scope and Impact of Welfare Reform's Immigrant Provisions. In *Assessing the New Federalism*. Washington, DC: The Urban Institute.

Fontenot, Kayla, Joachim Singelmann, Tim Slack, Carlos Siordia, Dudley Poston, and Rogelio Saenz. 2010. Understanding Falling Poverty in the Poorest Places: An Examination of the Experience of the Texas Borderland and Lower Mississippi Delta, 1990–2000. *Journal of Poverty* 14 (2): 216–236.

Fragomen, Austin T. Jr. 1997. The Illegal Immigration Reform and Immigrant Responsibility Act of 1996: An Overview. *International Migration Review* 31 (2): 438–460.

Gibbs, Jack P., and Walter T. Martin. 1962. Urbanization, Technology, and the Division of Labor: International Patterns. *American Sociological Review* 27 (5): 667–677.

Gibbs, Jack P., and Dudley L. Poston. 1975. The Division of Labor: Conceptualization and Related Measures. *Social Forces* 53: 468–475.

Gouveia, Lourdes, and Rogelio Saenz. 2000. Global Forces and Latino Population Growth in the Midwest: A Regional and Subregional Analysis. *Great Plains Research* 10: 305–328.

Grieco, Elizabeth M. 2010. Race and Hispanic Origin of the Foreign-Born Population in the United States: 2007. In *American Community Survey Reports*. Washington, DC: US Census Bureau.

Holzer, Harry. 2009. Testimony on Income and Poverty in the United States: 2008. Paper read at Joint Economic Committee of the United States Congress, at Washington, DC.

Hoynes, Hilary W., Marianne E. Page, and Ann Huff Stevens. 2006. Poverty in America: Trends and Explanations. *The Journal of Economic Perspectives* 20 (1): 47–68.

Iceland, John H. 2000. Poverty Among Working Families: Findings from Experimental Poverty Measures. In *Current Population Reports*. Washington, DC: US Bureau of the Census.

Iceland, John. 2003. Why Poverty Remains High: The Role of Income Growth, Economic Inequality, and Changes in Family Structure, 1949–1999. *Demography* 40 (3): 499–519.

Iceland, John H. 2006. *Poverty in America: A Handbook*. Los Angeles, CA: University of California Press.

International Monetary Fund, IMF. 1993. *Balance of Payments Manual*, 5th Edition. Washington, DC: International Monetary Fund.

Johnson-Webb, Karen D. 2002. Employer Recruitment and Hispanic Labor Migration: North Carolina Urban Areas at the End of the Millennium. *The Professional Geographer* 54 (3): 406–421.

Kandel, William., and John Cromartie. 2004. *New Patterns of Hispanic Settlement in Rural America*, edited by U. S. D. o. Agriculture. Washington, DC: U.S. Department of Agriculture, Economic Research Service.

Kandel, William, and Emilio A. Parrado. 2005. Restructuring of the US Meat Processing Industry and New Hispanic Migrant Destinations. *Population and Development Review* 31 (3): 447–471.

Kochhar, Rakesh. 2004. *The Wealth of Hispanic Households: 1996 to 2002*. Washington, DC: Pew Hispanic Center.

Lichter, Daniel T., and Martha L. Crowley. 2002. Poverty in America: Beyond Welfare Reform. *Population Bulletin* 57 (2): 3.

Lichter, Daniel T., and Kenneth M. Johnson. 2006. Emerging Rural Settlement Patterns and the Geographic Redistribution of America's New Immigrants. *Rural Sociology* 71: 109–131.

Long, J. Scott, and Jeremy Freese. 2003. *Regression Models for Categorical Dependent Variables Using STATA*, Revised Edition. College Station, TX: STATA Press.

Longley, Paul. 2001. *Geographic Information Systems and Science*. Chichester; NY: Wiley.

Markides, Kyriakos S., and Jeannine Coreil. 1986. The Health of Hispanics in the Southwestern United States: An Epidemiologic Paradox. *Public Health Reports* 101 (3): 253–265.

Massey, Douglas S. 1981. Dimensions of the New Immigration to the United States and the Prospects for Assimilation. *Annual Review of Sociology* 7: 57–85.

Massey, Douglas S. 1995. The New Immigration and Ethnicity in the United States. *Population and Development Review* 21 (3): 631–652.

Massey, Douglas S., Joaquin Arango, Graeme Hugo, Ali Kouaouchi, Adela Pellegrino, and J. Edward Taylor. 2005. *Worlds in Motion: Understanding International Migration at the End of the Millennium, International Studies in Demography*. Oxford; NY: Clarendon Press.

Menard, Scott W. 1996. *Applied Logistic Regression Analysis,* Sage University Papers, 106. Beverly Hills, CA: Sage Publications.

Michael, Robert T., and Anthony B. Atkinson. 1997. Measuring Poverty: A New Approach. *Advancing the Consumer Interest* 9 (1): 18.

Mosisa, Abraham. 2003. *A Profile of the Working Poor, 2001*. Washington, DC: US Department of Labor.

National Academy of Science, NAS. 1995. *Measuring Poverty: A New Approach*. Washington, DC: National Academy of Science.

Notten, Geranda, and Chris de Neubourg. 2007. *Relative or Absolute Poverty in the US and EU? The Battle of the Rates*. The Netherlands: Maastricht Graduate School of Governance.

Orthner, Dennis K., Hinckley Jones-Sanpei, and Sabrina Williamson. 2004. The Resilience and Strengths of Low-Income Families. *Family Relations* 53 (2): 159–167.

Parisi, Domenico, Diane K. McLaughlin, Steven Michael Grice, Michael Taquino, and Duane A. Gill. 2003. TANF Participation Rates: Do Community Conditions Matter? *Rural Sociology* 68 (4): 491.

Passel, Jeffrey. 2005. *Estimates of the Size and Characteristics of the Undocumented Population*. Washington, DC: Pew Hispanic Center.

Passel, Jeffrey. 2006. *The Size and Characteristics of the Unauthorized Migrant Population in the US: Estimates Based on the March 2005 Current Population Survey*. Washington, DC: Pew Hispanic Center.

Poston, Dudley L. Jr., and Chengrong Charles Duan. 2000. Non-agricultural Employment in Beijing: A Multilevel Analysis. *Research in Community Sociology* 10: 1–27.

Poston, Dudley L., David Alvirez, and Marta Tienda. 1976. Earnings Differences Between Anglo and Mexican American Male Workers in 1960 and 1970: Changes in the Cost of Being Mexican American. *Social Science Quarterly* 57: 618–631.

Rank, Mark R., and Thomas A. Hirschl. 1999. The Economic Risk of Childhood in America: Estimating the Probability of Poverty Across the Formative Years. *Journal of Marriage and the Family* 61 (4): 1058–1067.

Raudenbush, Stephen W., and Anthony S. Bryk. 2002. *Hierarchical Linear Models: Applications and Data Analysis Methods, Advanced Quantitative Techniques in the Social Sciences*, Vol. 1. Thousand Oaks, CA: Sage Publications.

Raudenbush, Stephen W., Anthony S. Bryk, Yuk Fai Cheong, Richard Congdon, and Mathilda du Toit. 2004. *HLM6: Hierarchical Linear and Nonlinear Modeling*. Chicago, IL: Scientific Software International.

Reichert, Josh, and Douglas S. Massey. 1980. History and Trends in US Bound Migration from a Mexican Town. *The International Migration Review* 14 (4): 475–491.

Ruggles, Steven, Matthew Sobek, Trent Alexander, Catherine A. Fitch, Ronald Goeken, Patricia Kelly Hall, Miriam King, and Chad Ronnander. 2008. *Integrated Public Use Microdata Series: Version 3.0 [Machine-Readable Database]*. Minnesota Population Center [producer and distributor].

Rupasingha, Anil, and Stephan J. Goetz. 2007. Social and Political Forces as Determinants of Poverty: A Spatial Analysis. *The Journal of Socio-Economics* 36 (4): 650.

Saenz, R. 2004. *Latinos and the Changing Face of America*. In The American People Series. Washington, DC: Population Reference Bureau.

Saenz, Rogelio, and Cruz C. Torres. 2003. Latinos in Rural America. In *Challenges for Rural America in the Twenty-First Century*, edited by D. L. Brown, L. E. Swanson. University Park, TX: Pennsylvania State University Press.

Seccombe, Karen. 2000. Families in Poverty in the 1990s: Trends, Causes, Consequences, and Lessons Learned. *Journal of Marriage and the Family* 62 (4): 1094–1113.

Singelmann, Joachim. 1978. *From Agriculture to Services: The Transformation of Industrial Employment*, Sage Library of Social Research, V. 69. Beverly Hills, CA: Sage Publications.

Slack, Tim, Kayla Fontenot, Joachim Singelmann, Dudley L. Poston Jr., R. Saenz, and Carlos Siordia. 2009. Poverty in the Texas Borderland and Lower Mississippi Delta: A Comparative Analysis of Differences by Family Type. *Demographic Research* 20: 353–376.

Smeeding, Timothy. 2006. Poor People in Rich Nations: The United States in Comparative Perspective. *Journal of Economic Perspectives* 20 (1): 69–90.

Smeeding, Timothy M., Gary Burtless, and Lee Rainwater. 2000. *United States Poverty in a Cross-National Context*, Working Paper Series, Luxembourg Income Study, 244. [Walferdange].

Suro, Roberto, Jeffrey S. Passel, and Center Pew Hispanic. 2003. *The Rise of the Second Generation: Changing Patterns in Hispanic Patterns in Hispanic Population Growth.* Washington, D.C.: Pew Hispanic Center.

Suro, Roberto, Richard Fry, Rakesh Kochhar, and Jeffrey Passel. 2005. *Hispanics: A People in Motion*. Washington, DC: Pew Hispanic Center.

Taeuber, Cynthia Murray. 2006. *American Community Survey Data for Community Planning*. Victoria, British Columbia: Trafford Publishing.

The Urban Institute. 2006. *Children of Immigrants: Facts and Figures*. Washington, DC: The Urban Institute, Office of Public Affairs.

Toit, Mathildadu, and Stephen du Toit. 2001. Multilevel Modeling. In *Interactive LISREL: User's Guide*. Lincolnwood, IL: Scientific Software International, Inc.

Trejo, Stephen J. 1997. Why Do Mexican Americans Earn Low Wages? *Journal of Political Economy* 105 (6): 1235–1268.

UN. 1989. *Handbook on Social Indicators*, edited by D. o. I. E. a. S. Affairs New York, NY: United Nations (UN).

Vittinghoff, Eric. 2005. *Regression Methods in Biostatistics: Linear, Logistic, Survival, and Repeated Measures Models, Statistics for Biology and Health*. New York, NY: Springer.

Warren, Robert, and Jeffrey S. Passel. 1987. A Count of the Uncountable: Estimates of Undocumented Aliens Counted in the 1980 United States Census. *Demography* 24 (3): 375–393.

White, Michael J., Frank D. Bean, and Thomas J. Espenshade. 1990. The US 1986 Immigration Reform and Control Act and Undocumented Migration to the United States. *Population Research and Policy Review* 9: 93–116.

Wong, David W. S., and Jay Lee. 2005. *Statistical Analysis of Geographic Information with ArcView GIS and ArcGIS*. Hoboken, NJ: John Wiley & Sons, Inc.

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