UNDERSTANDING NEIGHBORHOOD INFLUENCES ON THE

HISPANIC HEALTH PARADOX

By

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Understanding Neighborhood Influences on the Hispanic Health Paradox

Thesis directed by Professor Jason Boardman

ABSTRACT

In my dissertation research I dive deeper into the "Hispanic Health Paradox" – a pattern wherein Hispanic individuals often exhibit better health than other race/ethnic groups, even though they generally have lower socioeconomic standing. I examine the role Hispanic neighborhoods may play in the Hispanic Health Paradox by using electronic health records from over 150,000 adults in Denver, Colorado to document health differences between Hispanic and non-Hispanic groups. I find that Hispanic neighborhoods in Denver are associated with diverse health patterns, including higher rates of obesity but lower rates of depression. Hispanic neighborhoods also have lower rates of health inequality between Hispanic and non-Hispanic white residents compared to other types of neighborhoods. To understand these diverse findings and the literature more broadly, I propose a neighborhood health heterogeneity framework. I argue that multilevel intersectionality and cultural heterogeneity may be some of the mechanisms through which the same neighborhoods can produce diverse health outcomes for residents. I also test new statistical measures of Hispanic neighborhoods, and test the effects of measurement, geography, and spatial contiguity on my findings.

For my daughter, Harper

"Love life. Engage in it.

Give it all you've got.

Love it with a passion

because life truly does give back,

many times over,

what you put into it."

~ Maya Angelou

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Chapter 1: Introduction

The Hispanic Health Paradox (HHP) suggests that Hispanics[1] in the United States have better health than expected given their relatively low socioeconomic status (SES). Overall, Hispanics have lower rates of mortality than non-Hispanic Whites and African Americans (Markides and Eschbach 2011, Murphey et al. 2017), and generally have lower morbidity rates for chronic conditions such as hypertension, high cholesterol, and some cancers (Franzini, Ribble, and Keddie 2001, Murphey et al. 2017). However, the HHP is not an omnipresent pattern for all Hispanics. Nativity, country of origin, time spent in the United States, and gender all impact the presence and strength of this health advantage in ways that are thus far not completely clear (Balcazar et al. 2015, Camacho-Rivera et al. 2015, Hummer et al. 2000, Markides and Eschbach 2011). Furthermore, Hispanics have higher rates of diabetes and obesity, two of the most common and, in the case of diabetes, potentially fatal chronic conditions (CDC 2015a). When examining risk factors for cardiovascular disease, the leading cause of death in the United States, Hispanics display a mixed bag of risk factors: lower rates of hypertension and high cholesterol, and higher rates of obesity and diabetes compared to non-Hispanic whites. There is also speculation that the HHP will diminish or disappear for successive generations of Hispanics (varying by Hispanic subgroup), due to high rates of some chronic conditions, fewer new Hispanic migrants coming to the United States, and the negative effects of acculturation (Lariscy, Hummer, and Hayward 2015).

These mixed results on the HHP highlight the need to explicate the mechanisms that drive the paradox and Hispanic vulnerability to chronic illness. In addition to examining how

[1] For consistency, I will use the term "Hispanic" in this proposal to encompass those of Latino or Hispanic origin, and the terms "non-Hispanic White" or "NHW," and "non-Hispanic Black," "NHB," or African American.

Hispanic migrant selection into and out of the United States and data artifacts may be driving the HHP, researchers have identified a potentially protective association between living in Hispanic neighborhoods, or "barrios"[2] (for example, Aranda et al. 2011, Cagney et al. 2007, Eschbach et al. 2004, Keegan et al. 2010). Some research suggests that, unlike patterns documented in segregated African American communities, Hispanic neighborhoods may protect Hispanics from assimilating into health lifestyles typically associated with poverty.

In a review of how coethnic density impacts myriad health conditions for non-Hispanic Black (NHB) and Hispanic neighborhoods in the United States, Bécares and colleagues (2012) conclude that positive associations between coethnic density (i.e. segregation) and health are the most common among U.S. Hispanics. Although these neighborhood benefits may be more frequently documented among Hispanics compared to NHBs, their conclusion ignores wide variation in results from relevant studies. In fact, more studies have found mixed or negative associations between neighborhoods with high concentrations of Hispanic residents and health outcomes or behaviors. This heterogeneity is rarely mentioned in current research and, as a consequence, frameworks for understanding potential heterogeneity in these neighborhood associations have not been well developed.

In addition to theoretical shortcomings, research on the associations between Hispanic neighborhoods and health have methodological limitations. Bécares and colleagues (2012: e33) end their review by suggesting that the two major limitations of current research are "inadequate adjustment for area deprivation and limited statistical power across ethnic density measures and study samples." Measures used to define barrios or Hispanic neighborhoods have not been

[2] "barrio" means "neighborhood" in Spanish, and has taken on the meaning of dense Hispanic neighborhoods. I use Hispanic neighborhoods and barrios interchangeably throughout the dissertation.

compared to understand how sensitive results are different conceptualizations. In addition, small sample sizes are often insufficiently statistically powered to simultaneously assess how coethnic density may be mediated by other neighborhood characteristics, such as socioeconomic deprivation or inequality.

In this dissertation, I address these theoretical and methodological gaps in the literature on the association between Hispanic neighborhoods and health, with the goal of providing a broader understanding of neighborhood influences on the HHP. First, I review the literature on associations between coethnic density and health, and propose a theoretical framework that encompasses the heterogeneity that has been documented for Hispanics in the United States. I focus on how the role of culture has been applied in the current literature, and how this application has prevented theoretical models that encompass heterogeneous health outcomes within the same neighborhood. I then conduct a series of empirical analyses using a large sample of electronic health records (EHRs) from patients in Denver, Colorado, to examine the relationship between the Hispanic composition and a wide variety of health conditions. I conduct both ecological and multilevel analyses, examine prevalence and inequality of health conditions, compare different measures of Hispanic neighborhoods, and examine how results compare for specific population subgroups. To develop better understandings of Hispanic health broadly, in addition to ways in which neighborhood environments impact Hispanic health, I recommend that researchers engage reasons why complex patterns may exist within and between neighborhoods.

This dissertation has five chapters. In this chapter I provide background on the HHP, the state of the literature on coethnic density and health, and present a new framework for understanding heterogeneity in neighborhood associations with health conditions. I also present my primary research questions and introduce Denver, Colorado, as the research setting. In

Chapter 2 I provide a detailed description of the data, methods, and empirical analyses that I use in Chapters 3 and 4. In Chapter 3 I present ecological results that address the first research question. In Chapter 4 I present multilevel results that address the second research question. In Chapter 5 I provide a summary of findings, study limitations, and future directions for sociological theory and research.

BACKGROUND

Theories of the HHP

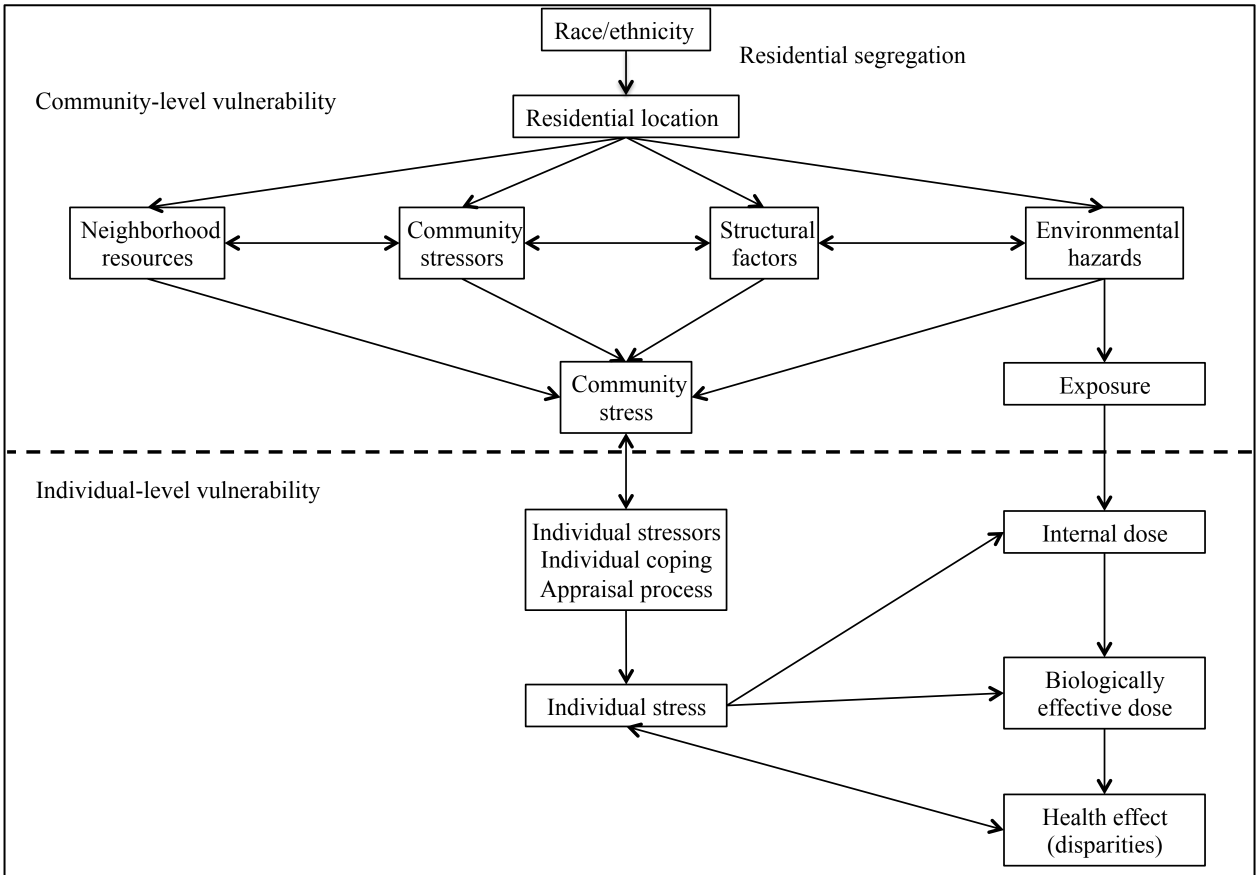
Researchers have identified three potential (and not mutually exclusive) contributors to the HHP and specifically to the healthy migrant advantage (HMA): data artifacts, migrant selection, and community-based protection (Palloni and Arias 2004). Data artifacts that could skew results on health surveys include misreporting of ethnicity, misreporting of age, and biased samples based on hesitancy of sick or fearful migrants to participate in health surveys. Migrant selection issues are twofold. First, the healthy migrant theory posits that healthier and/or more cognitively capable individuals are more likely to migrate to the U.S. in the first place. Second, the Salmon Bias Theory posits that unhealthy or sick migrants may return to their countries of origin, and are thus not included on health surveys (Palloni and Arias 2004). Research explicitly examining migration selection and data artifacts has found that HMA is attenuated, but not fully explained by selection and data artifacts (Riosmena, Wong, and Palloni 2013).

Another theory used to explain the HHP is that many Hispanics live in Hispanic neighborhoods in the United States, which provide an important social resource despite relatively low SES. The protective factors associated with Hispanic neighborhoods are hypothesized to be multifaceted, and explanations typically argue that they have richer social networks, greater social support, strong ethnic identities that prevent assimilation into the American "mainstream," and networks of communication that may produce access to resources such as employment (for example, see Aguilera and Massey 2003) or methods for accessing health care (Markides and Eschbach 2011, Palloni and Arias 2004, Riosmena et al. 2013). To understand how these mechanisms may play out, as well as their limitations, it is important to first provide an overarching review of neighborhoods and health research.

Segregation and Health

Research on the impacts of residential segregation and health has predominantly focused on how segregated neighborhood environments and concentrated poverty are associated with and perpetuate poor health outcomes (Williams and Collins 2001). Gee and Payne-Sturgis (2004) provide a "stress-exposure-disease" conceptual model for how residential segregation impacts health. Unlike other ecological models, it places race and residential segregation as central contributors to how neighborhood environments are created. Figure 1-1 shows the stress-exposure-disease model.

Figure 1-1. Stress-exposure-disease model for environmental health disparities



Source: Gee and Payne-Sturgis (2004)

The relationship between segregation and health has largely been examined in the context of segregated African American communities, rooted in the University of Chicago urban ethnography of the mid-twentieth century (Apter et al. 2009). Segregation impacts the health of residents through four primary avenues: neighborhood resources, community factors, structural factors, and environmental hazards. Although Gee and Payne-Sturgis (2004) acknowledge that segregation can simultaneously instigate resource investment and disinvestment, they focus in this model on how segregation can lead to a lack of investment in neighborhood resources, such as grocery stores with healthy and affordable food or safe places to be physically active (Williams and Collins 2001). Community stressors relate to physical and psychosocial characteristics such as crime, overcrowding, or social disorganization that may be exacerbated in high poverty areas with few neighborhood resources. Structural factors associated with segregation include concentrated poverty, which reduces access to a variety of different resources, such as reduced investment in quality grocery stores, parks, and other health-related resources, and is associated with increased crime (Sampson, Sharkey, and Raudenbush 2008). Structural factors also include policies that directly or indirectly perpetuate segregation, including housing discrimination (Massey and Denton 1993). In many cities across the United States, segregated African American communities are located in urban areas that have higher risk of exposure to environmental hazards, including proximity to industrial areas or near highly trafficked areas (Brown 1995).

Gee and Payne-Sturgis (2004:1646) conceptualize community-level stress as the concentration of lack of resources, structural disadvantages, and exposure to environmental hazards that prime a community for "ecological vulnerability." This community-level vulnerability can have negative consequences that manifest as individual-level stress (Acevedo-Garcia and Lochner 2003). The human body is designed to react to stressful situations through acute physical responses such as hormonal/chemical changes. While the body can recover from short bursts of stress, chronic stressors can take a toll on many physical systems (e.g. cardiovascular, metabolic, cognitive) through what is described as excessive allostatic load (allostasis is the body's action to return to homeostasis) (Seeman et al. 2004). Stressful social factors such as concentrated poverty, crime, and tragedy/loss. can create chronic physiological responses that begin to wear away at the body's resilience. This is important because individuals do not have to experience these stressors themselves (e.g. individual-level poverty) and can still be negatively impacted by them as a function of the neighborhood in which they live. Over time, a physical "weathering" can occur, in which physical systems age at faster rates for those who live in chronically stressful environments compared to those who do not (Cheadle and Goosby 2010, Geronimus et al. 2006, Seeman et al. 2004).

In addition to the effect of stress on physical systems, chronic stress from sociocultural and environmental factors can also affect behavior patterns (Ng and Jeffery 2003). Humans often turn to coping mechanisms to mitigate the physiological and mental effects of stress, and these coping mechanisms are strongly influenced by social norms. Coping mechanisms can be effective in reducing stress, but they can also have their own *independent* effect on health. For example, smoking is a common coping mechanism for stress, but has severe negative consequences in its own right (Steptoe et al. 1996).

Furthermore, the ways in which stress induced by neighborhood environments affects individuals and their coping mechanisms are influenced by the most proximate determinant of health – genetics. Studies have found that an individual's propensity to smoke or to become obese may be strongly influenced by genes, above and beyond social norms and circumstances (Boardman, Daw, and Freese 2013).

Thus, taken together, biosocial pathways through which place-based exposures instigated by segregation may impact health are complex and multifaceted. However, the relationship between segregation and health is so strong that Williams and Collins (2001) have described it as a "fundamental cause of racial disparities in health." They posit that segregation is essential in shaping the socioeconomic opportunities of African Americans. The socioeconomic differences created by segregation are in turn a fundamental source of health disparities (Williams and Collins 2001, Link and Phelan 1995). Although some research on African American segregation and health examines how segregated environments can promote community resilience and other positive social factors (Sonn and Fisher 1998), the dominant paradigm emphasizes increased psychosocial stress and negative health outcomes. This is notably different from the paradigm used to describe the relationship between Hispanic communities and health, which focus on the relationship between coethnic concentration and positive psychosocial processes. The paradigmatic differences are in part due to important distinctions between segregation in African American communities and Hispanic communities. Characteristics of African American segregation are distinct from segregation experienced by other race/ethnic groups in that they, a) have sustained high levels, making these communities "hypersegregated," b) were instituted by non-Hispanic whites rather than by African American preferences, and c) have not changed dramatically over time (Massey and Denton 1993). Hispanic residential composition is associated with more mobility into and out of Hispanic neighborhoods (Sharkey 2008), may be driven by preferences for particular social networks related to migration more so than African American segregation (Iceland 2004), and has shifted dramatically in congruence with changing immigration flows to newly emerging areas of the United States (Lichter et al. 2010). The association between Hispanic neighborhoods and Hispanic health may then be distinct from African Americans because of these diverse settlement patterns and the social context in which Hispanics live in the United States.

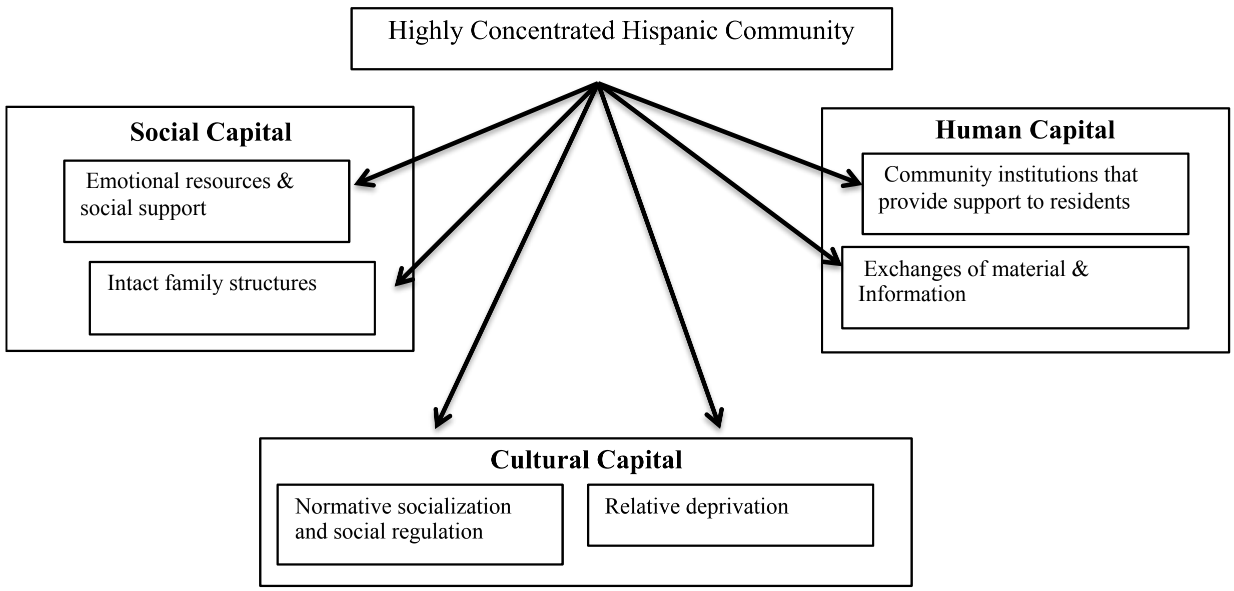
Hispanic Barrios and Health

Roughly half of all Hispanics are migrants (Flores 2017), and thus research on Hispanic neighborhoods and health involves understanding lives and social processes of both native and foreign-born Hispanics. Immigrant "enclaves" have long been studied in the context of immigrant adaptation processes (Wilson & Portes 1980) and among urban sociologists (Foote-Whyte 1943). These qualitative accounts provided in-depth insight into immigrant community networks and how migrants maintained ethnic identities in the early and mid-twentieth century. Studying immigrant enclaves can elucidate fundamental sociological phenomena; by examining the environments of societal newcomers, it reveals which social norms from the receiving society impact immigrants the most, which social norms from their countries of origin are the most important to maintain, and how this negotiation process unfolds. It also reveals mechanisms through which immigrants integrate or reject new social norms.

In the last two decades there has been a proliferation of quantitative studies examining the relationship between Hispanic neighborhoods and health. The emergence of the HHP and development of multilevel methods that allow neighborhood- and individual-level phenomena to be distinguished statistically have provided both theoretical and methodological incentives to examine Hispanic communities in more detail. Unlike the segregation and health literature for African Americans, the dominant paradigm for the Hispanic neighborhoods and health literature is that, although Hispanic neighborhoods often experience concentrated poverty similar to African American neighborhoods, community social processes in Hispanic neighborhoods *protect* residents from deleterious health conditions that are typically associated with low SES (Palloni and Arias 2004).

Social and cultural mechanisms have been used to explain why Hispanic neighborhoods are protective from poor health outcomes, and may be summarized using Pierre Bourdieu's framework of forms of capital. Bourdieu conceptualized of three types of capital: social, cultural, and human (Bourdieu 1990). In the context of Hispanic neighborhoods, social, cultural, and human capital resources may be levied to prevent Hispanics from developing chronic diseases (Aranda 2011). Social capital is broadly understood as benefits gained from social relationships (Lesser 2000). Social ties may be strong or weak, each with their own potential benefits in accessing resources and receiving support (Coleman 1988). Social capital may also manifest as social control (Portes 2000), preventing the uptake of unsanctioned actions or behaviors as determined by the community (Adler & Kwon 2002). In this framework, cultural capital is understood both as actual group norms and beliefs in addition to the *process* of creating group boundaries (Bourdieu 1990, Lamont & Lareau 1988, DiMaggio 1982), may also assist in creating barriers between "Hispanic" practices and from what may be viewed as "downward" or "bifurcated" assimilation to African American health patterns (Portes and Zhou 1993). Lastly, the production of human capital and resources generated from group knowledge may increase availability of health-related resources and access to affordable, quality care. Figure 1-2 summarizes the three forms of capital and how they relate to Hispanic neighborhoods.

Figure 1-2. Forms of social, cultural, and human capital in Hispanic communities



Descriptions

Social Capital	Cultural Capital	Human Capital
Hispanic residents' ability to obtain social support and close social ties within their community and building rich social networks. Increased social capital may help immigrants cope with challenging circumstances (e.g. low SES or health problems) and also may lead to better mental health.	The formation of social norms and customs specific to the Hispanic community. Normative contexts may shape immigrants conceptions of life in the U.S. (e.g. relative deprivation). Maintenance of cultural norms (e.g. speaking Spanish) may also protect from negative adaptation.	The ability to gain material resources and information from the community. Communities with more physical, economic, educational resources may increase an individual's likelihood for better socioeconomic position (which may also include better access to or knowledge of health resources).

Sources: Aranda et al. 2011, Blank and Torrecilha 1998, Eschbach et al. 2004, Moore and Vigil 1993, Patel et al. 2003, Rodriguez 1993, Vega et al. 2011, Vélez-Ibáñez1993

The problem with this paradigm is that it has not been substantiated by empirical evidence. In their examination of different mechanisms that may explain the HHP mortality advantage, Palloni and Arias (2004:388) make the following statement about the circumstances that would support the framework presented in Figure 1.2 (which they refer to as a cultural explanation):

> It follows that a successful accounting of the Hispanic mortality paradox using the cultural explanation must verify the joint occurrence of the following three regularities: (1) other things being equal, Hispanics who share advantageous

> mortality and health conditions must also share either beneficial behavioral-risk profiles and/or denser social networks and social, emotional, and material support than must individuals who do not display the advantage; (2) Hispanics who are not well-integrated into social networks and who receive less social support will experience higher exposure to health and mortality risks and will not share the advantage from which other members of the same ethnic group benefit; and (3) the mortality advantage should fade with increasing assimilation into the receiving country if the latter implies either the acquisition of a less-healthy behavioral profile or the abandonment of norms and behaviors that secure social support.

Underlying each of the "regularities" outlined by Palloni and Arias (2004) is an expectation of homogenous outcomes for those in similar social environments. For example, if Hispanic neighborhoods allowed U.S. and/or foreign-born Hispanics to form more social cohesion that protected from chronic stress compared to Hispanics living outside of Hispanic neighborhoods, health conditions related to chronic stress (i.e. hypertension, depression, obesity) would be consistently lower in Hispanic neighborhoods. However, what are the implications for understanding Hispanic neighborhood influences if these regularities are present for some individuals in a neighborhood but absent for others? Does it necessarily imply that Hispanic neighborhoods are not associated with health benefits? To understand the complexities of neighborhood environments and how they relate to Hispanic health, it is first instructive to examine the diversity of existing literature as a whole.

Table 1-1 provides a summary of quantitative studies that have examined associations between Hispanic neighborhoods and health in the United States. The 35 studies are organized into three broad categories. The first set of studies found positive associations between living in a Hispanic neighborhood and better health (n=13). The second set of studies found mixed results – a positive association for one or more subgroups in the analysis, and a negative or insignificant association for one or more other subgroups (n=13). The third set of studies found negative or insignificant associations between Hispanic neighborhoods and health (n=9). Thus, the majority of studies (n=22) have either found mixed, insignificant, or no association between Hispanic neighborhoods and health.

Generally, studies have found positive health associations for some cancers, asthma, frailty, depressive symptoms, and mortality (for example, Aranda et al. 2011, Cagney et al. 2007, Eschbach et al. 2004, Keegan et al. 2010, Mair 2010). However, in the case of mental health, mixed or negative associations have also been observed (Arévalo, Tucker, and Falcón 2015, Hong, Zhang, and Walton 2014). Mixed results have also been found for health behaviors, including smoking and binge drinking (Finch et al. 2000, Kimbro 2009), and for body mass index (BMI) (Do et al. 2007, Salinas et al. 2012).

Table 1.1: Summary of the literature on the relationship between "barrio" neighborhoods and adult health

Positive "barrio" association						
Citation	**Data source/s**	**Setting**	**Population**	**Health outcome/s**	**Neighborhood variables**	**Positive "barrio" association?**
Aranda et al. (2011)	Established Populations for Epidemiologic Studies of the Elderly (H-EPESE); 2000 Census	Texas, Colorado, New Mexico, Arizona, California	2,069 Mexican American adults ages 75 and older	Frailty	% Mexican American	Yes
Cagney, Browning, and Wallace (2007)	CCAHS, and the Chicago Metro Survey; 1990 Census	Chicago, IL	All adult residents, specifically exploring differences between foreign-born Latinos and US-born Latinos and other racial. groups.	Asthma/breathing problems	% foreign born, factor analysis for residential stability factor score, concentrated poverty	Yes
Dubowitz et al. (2008)	Primary data collection based on women participating in an intervention; 2000 Census	Boston and Springfield, MA	641 low-income, postpartum women	Daily consumption of fruit and vegetables	SES and segregation by race and nativity	Yes
Eschbach et al. (2004)	H-EPESE; 1990 census data	Texas, Colorado, New Mexico, Arizona, California	3,050 Mexican Americans (native or foreign born) 65 years or older	Mortality	% Mexican American	Yes
Keegan et al. (2010)	California Cancer Registry from 1988-2004; 2000 Census	California	Hispanic and non-Hispanic white women diagnosed with breast cancer in the cancer registry.	Prevalence of breast cancer	Principal components analysis of Hispanic, language, and foreign-born characteristics; neighborhood SES	Yes
Mair et al. (2010)	2000-2002 Multiethnic Study of Atherosclerosis (MESA); Census 2000	Baltimore, MD, Chicago, IL, Forsyth County, NC, Los Angeles, CA, New York, NY, Saint Paul, MN.	5,667 Adults	Depressive symptoms	% of residents with the same race/ethnicity	Yes
Ostir et al. (2003)	H-EPESE; 1990 census data	Texas, Colorado, New Mexico, Arizona, California	3,050 Mexican Americans (native or foreign born) 65 years or older	Depressive symptoms, chronic diseases and activities of daily living (ADL)	% Mexican American, SES	Yes
Patel et al. (2003)	H-EPESE; 1990 census data	Texas, Colorado, New Mexico, Arizona, California	3,050 Mexican Americans (native or foreign born) 65 years or older	Self-rated health, cigarette smoking	% Mexican American	Yes
Schupp, Press, and Gomez (2014)	California Cancer Registry (1995-2008); 2000 Census	California	35,427 Hispanic men diagnosed with prostate cancer	Mortality from prostate cancer	Principal components analysis of Hispanic, language, and foreign-born characteristics; neighborhood SES	Yes
Shaw et al. (2010)	2000 Infant birth and death data; 2000 Census	National	763,201 singleton births	Smoking during pregnancy	% Hispanic	Yes
Sheffield and Peek (2009)	H-EPESE; 1990 census data	Texas, Colorado, New Mexico, Arizona, California	3,050 Mexican Americans (native or foreign born) 65 years or older	Cognitive decline	% Mexican American; factor analysis for SES	Yes
Shell, Peek, and Schacht (2013)	2004 Texas City Stress and Health Study (TCSHS); 2000 Census	Texas City, Texas	1,238 U.S.-born and foreign-born Mexican Americans	Depressive symptoms	% Hispanic; socioeconomic disadvantage	Yes
Peak and Weeks (2002)	1990-1992 birth records; 1990 Census	San Diego, CA	34,609 births to U.S. and foreign-born Mexican women	Low birth weight	% Hispanic, % migrating to the US between 1980 and 1990, % monolingual Spanish speakers, % bilingual Spanish speakers, % Spanish speaking overall; principal components with all measures	Yes

Table 1.1 continued

Mixed findings for "barrio" association						
Citation	**Data source/s**	**Setting**	**Population**	**Health outcome/s**	**Neighborhood variables**	**Positive "barrio" association?**
Arévalo, Tucker, and Falcón (2015)	Boston Puerto Rican Health Study; 2000 Census	Boston and Puerto Rico	1,142 Puerto Rican adults 45-75 years old	Depressive symptoms	% Puerto Ricans	Mixed: yes, for men and for the second quartile of low acculturation; not for women or
Bécares (2014)	2002 Latino sample from the National Latino and Asian-American Study (NLAAS); 2000 Census	National	Latino subgroups: Puerto Rican, Mexican, Cuban, and "other" Latinos	Psychological distress	% of each Latino subgroup,% Latino, % Latin American immigrants, socioeconomic deprivation	Mixed: Yes, for Puerto Ricans; not for first generation Mexican Americans
Eschbach, Mahnken, and Goodwin (2005)	1988-1992 Surveillance, Epidemiology, and End Results program (SEER); 1990 Census	9 SEER states: Connecticut, Iowa, New Mexico, Utah, Hawaii, Detroit, Atlanta, San Francisco, Seattle	8,291 Hispanics living in SEER area with incidence of one of the types of cancers present in SEER study and with a census tract identification	Breast, colorectal, lung, non-in situ prostate, or cervical cancer diagnosis	% Hispanic	Mixed: yes for lung, breast and colorectal cancers; not for cervical or prostate cancer
Finch et al. (2000)	1992 Perinatal Substance Exposure Study in California, 1990 Census data	California	4,512 native born pregnant Latinas, 8,683 foreign born Latinas	Perinatal substance exposure (alcohol, tobacco, and other drugs)	SES, acculturation	Mixed: yes for substance use overall and alcohol use among foreign-born women; not for alcohol use among U.S.-born women
Franzini and Spears (2003)	1991 death certificates in Texas; 1990 Census	Texas	Roughly 50,000 adults who had died of heart disease; individual data was not separated by race/ethnicity	Death from heart disease	% Hispanic at census tract and county levels	Mixed: yes, at the census tract level, not at the county level
Inagami et al. (2006)	1999-2000 death records in New York City; 2000 Census	New York, NY	Ecological study of 160 zip codes	All cause mortality	% Hispanic	Mixed: yes, for men 25-64, not for men 65 and older or women
Jenny et al. (2001)	1995 to 1997 infant birth and death files; 1990 Census	Arizona, California, New Mexico, and Texas	> 1 million births to U.S. and foreign born Mexican American women	Infant mortality	% of all births in the county that were to Mexican American women	Mixed: Yes, for U.S. born Mexican American women; not for Mexican origin women
Kimbro (2009)	Los Angeles Families and Neighborhoods Study (LAFANS)	Los Angeles, CA	2,023 Latinos (75% Mexican origin)	Smoking and binge drinking	Factor analysis to identify majority Latino neighborhoods; neighborhood SES	Mixed: yes for binge drinking, not for smoking

Table 1.1 continued

Mixed findings for "barrio" association, continued						
Lee and Ferraro (2007)	Midlife Development in the US (MIDUS); 1995-1996 Survey of Minority Groups in Chicago and NYC; 1990 Census	Chicago, IL	Adults living in Chicago ages 25+	Physical health, including physical activity, pain, disability.	Isolation index, interaction index, median family income	Mixed: Yes for Mexican Americans and later generations; not for Puerto Ricans or first generation Mexican Americans
Osypuk et al. (2009)	MESA; Cross-Cultural Activity Participation Study; Census 2000	Baltimore, MD, Chicago, IL, Forsyth County, NC, Los Angeles, CA, New York, NY, Saint Paul, MN.	6,814 Hispanic and Chinese Men and Women aged 45-84 and free of clinical cardiovascular disease at baseline	Physical activity and diet	% foreign born Latin American	Mixed: Yes for eating foods with less fat; not for physical activity
Reyes-Ortiz et al. (2009)	NHANES III; 1990 Census	National	5,306 Mexican-Americans age 17-90	Consumption of particular foods and serum levels of micronutrients	% Mexican American	Mixed; consumptions of some foods increased with increased % Mexican American, others decreased; mixed findings for micronutrients
Salinas et al. (2012)	Behavioral Risk Factor Surveillance System; 2000 Census	Texas	Ecological analysis of Hispanics in Texas counties	Obesity - self reported weight and height	% Hispanic, SES	Mixed: Yes for counties that also had high educational attainment, otherwise no association.
Viruell-Fuentes et al. (2012)	2001–2003 CCAHS; 2000 Census	Chicago, IL	3,105 adults	hypertension prevalence, utilizing hypertension-related health care, treatment for hypertension;	Factor analysis of SES, racial/ethnic composition, age composition, family structure, proportion of owner-occupied housing, and residential stability	Mixed: yes, for hypertension prevalence; not for hypertension care and treatment

Table 1.1 continued

No positive "barrio" association						
Citation	**Data source/s**	**Setting**	**Population**	**Health outcome/s**	**Neighborhood variables**	**Positive "barrio" association?**
Booth et al. (2018)	2002-2003 Chicago Community Adult Health Study (CCAHS); 2000 Census	Chicago, IL	Adults in Chicago	Self-rated health	Latent profile analysis of racial/ethnic composition, SES, quality of services, quality of institutions, perceptions of safety, collective efficacy	No
Do et al. (2007)	National. Health and Nutrition Examination Survey (NHANES) III (1988-1994); 1990 Census	National	Adults in the United States	Body mass index (BMI)	Disadvantage, educational concentration at the extremes, Black segregation, Hispanic segregation	No
Hong, Zhang, and Walton (2014)	2002-2003 NLAAS, 2000 Census	National	2,095 Asian Americans and 2,554 Latinos	Self-rated mental health	% Hispanic/% Asian and neighborhood social cohesion	No
Li et al. (2017)	2006 and 2008 Southeastern Pennsylvania Household Health Survey; 2005-2009 ACS	Five Pennsylvania counties	1,563 Hispanic adults	Blood pressure and cholesterol levels	% Hispanic, % foreign born	No
Masi et al. (2007)	1991 birth records; 1990 Census	Illinois	15,929 births to Hispanic women	Preterm birth and birth weight	Combination of % Hispanic and % black	No
Park et al. (2008)	Primary data collection of Hispanics in New York City; 2000 Census	New York, NY	2,616 Hispanic adults	BMI	% Hispanic	No
Reyes-Ortiz et al. (2008)	SEER; 1990 and 2000 Census	13 SEER states; approximately 14% of US population covered by the SEER areas	20,818 Hispanic patients 21-90 living in SEER area with a diagnosis of non-in situ breast, cervical, and colorectal. carcinomas from 1988-2000	Tumor stage and size at time of diagnosis	% Hispanic	No
Rios, Aiken, and Zautra (2012)	2008 Arizona Health Survey, 2000 Census	Maricopa County, AZ	3,098 Hispanic and non-Hispanic adults	Self-rated health, psychological distress	% Hispanic, SES	No
Walton (2009)	2000 U.S. birth records; 2000 Census	National	616,750 Latino women living in urban areas	Low birth weight	% Hispanic	No

Some of the variation in findings could be due to existing quantitative analyses using a variety of city, state, and national data sources, including surveys and registries. Studies have also used different indicators for Hispanic neighborhoods (e.g., percent of Hispanic residents, percent of foreign-born residents, factor analyses and latent profile analyses to combine many measures). Additionally, it is difficult to assess the extent that Hispanic neighborhoods impact health broadly if studies only look at one health condition. Twenty of the 35 studies (57%) examine a single health outcome, and no studies to date have compared different indicators of Hispanic communities.

Many of the studies yielding mixed results find positive associations between Hispanic neighborhoods and health for one subgroup (e.g. by nativity or gender) but not another. For example, Lee and Ferraro (2007) found health benefits of living in Hispanic neighborhoods for second and third generation Mexican Americans, but not for first generation Mexican Americans or Puerto Ricans. Finch and colleagues (2000) found that less acculturated neighborhoods had lower rates of substance use (including tobacco) overall and lower rates of alcohol use for foreign-born pregnant Hispanic women, but higher rates of alcohol use among U.S.-born pregnant Hispanic women. Jenny and colleagues (2001) found positive associations for infant mortality among U.S.-born Mexican American women but not for foreign-born Mexican American women. Thus, factors such as acculturation, gender, and country of origin appear to moderate the existence and strength of associations between Hispanic neighborhoods and health.

A few studies have been able to explicitly test some of the social mechanisms from Figure 1.2. Cagney and colleagues (2016) found a nonlinear effect of perceived collective efficacy and an increase in Latino immigrant concentration, where initially an increase in Latino immigrants was associated with less perceived social efficacy, but once the concentration reached a certain threshold, perceived collective efficacy began to increase. Bécares (2014) found that experienced racism was lower for Mexican Americans and Puerto Ricans living in ethnically dense neighborhoods, and social cohesion was stronger for Puerto Ricans living in ethnically dense neighborhoods but not for Mexican Americans. Rios and colleagues (2012) found that self-reported neighborhood social cohesion and aggregated measures of neighborhood social cohesion both had mediating effects on the relationship between ethnic density and self-reported health. However, Hong and colleagues (2014) found that although ethnic density was associated with more social cohesion for Hispanics, social cohesion did not fully mediate the association between higher ethnic density and worse mental health.

Taken together, studies on the relationship between Hispanic neighborhoods and health do not meet the criteria laid out earlier by Palloni and Arias (2004). Denser social networks and increased social cohesion is not always associated with better health, and is not shared by all Hispanic subgroups. In some cases, there appear to be advantages for Hispanics who do not live in Hispanic neighborhoods, and thus not embedded in the same social spheres as those who live in Hispanic neighborhoods. However, because the existing paradigm for understanding Hispanic neighborhoods and health emphasizes *positive* sociocultural factors, the diversity of findings are rarely acknowledged or explicitly examined in the literature.

Neighborhood Health Heterogeneity Framework

One of the fundamental barriers to developing a new framework for understanding the relationship between Hispanic neighborhoods and health - one that encompasses the heterogeneity of existing findings - is the way culture (including understandings of social, cultural, and human capital) has been conceptualized and measured. Currently, the dominant understanding of culture in both the residential segregation literature (for NHBs and Hispanics) is as a static set of beliefs and practices that tie communities together (Harding and Hepburn 2014). In the context of segregation broadly, cultural frames are developed in reaction (and sometimes in opposition) to “mainstream” norms that are either unattainable or undesirable. In the context of segregated African American communities, this has most often been described as deviant subcultures, in which social and structural factors that isolate African Americans from participating in mainstream society give rise to alternative cultural practices that allow residents to create strong social bonds and participate in alternative economies (for example, Anderson 2000). In the context of Hispanic neighborhoods, this cultural framework has been used to describe efforts to prevent downward or bifurcated assimilation of Hispanic residents to the social circumstances of African Americans (Portes and Zhou 1993). Ethnic enclaves may contain more social cohesion, collective efficacy, and social control that benefits residents and, hypothetically, their health (as displayed in Figure 1-2).

These definitions of culture are reflected in how neighborhood social environments have been measured in the quantitative literature. In 1995, the Project on Human Development in Chicago Neighborhoods (PHDCN) developed and validated measures of neighborhood social capital that have been widely used by neighborhoods and health researchers (Sampson et al. 1997). Social capital was defined as “Ties or Networks, Collective Efficacy, Organizational Involvement, and Conduct Norms” (Sampson and Graif 2009). A few of the questions used to assess social capital on a Likert scale include: “This is a close-knit neighborhood,” “People in this neighborhood share the same values,” “There are adults in this neighborhood that children can look up to.” (Sampson and Graif 2009). The problem with these measures is that they do not provide residents an opportunity to define who they believe encompasses their neighborhood, who the people are that they share values with (or not), and likewise who the adults and children are who are modeling social norms. If residents feel like there are some people in their neighborhood with whom they share the same values, but others who have very different values, how does this get reflected in their answers on a Likert scale? There is no opportunity for respondents to clearly portray a heterogeneous sociocultural environment. For example, if a resident answered “This is a close-knit neighborhood” with the response “somewhat agree,” this could be interpreted as either a feeling that the resident feels like they live in a somewhat close-knit neighborhood or that there are some people they feel very closely tied to and others they do not. The implications for those two interpretations are significant as it relates to residents’ social environments.

However, there is reason to believe that heterogeneous sociocultural environments exist within and between neighborhoods. Understanding how cultural heterogeneity manifests may have implications for understanding the potential for heterogeneity in health within and between neighborhoods. Two theoretical frameworks are particularly useful in understanding neighborhood health heterogeneity. The first is David Harding’s concept of cultural heterogeneity (Harding 2007). His conceptualization of culture is based on developments in cultural sociology that conceive of culture as a “repertoire,” “toolkit,” or “schemas” with which information and expectations are processed and enacted (Swidler 1986, Dimaggio 1997). Using this definition, they challenge the idea of coherent neighborhood subcultures by proposing that cultural repertoires in disadvantaged neighborhoods are drastically more heterogeneous and complex than those in more advantaged neighborhoods. Individuals living in disadvantaged neighborhoods must negotiate more cultural models that are often not mutually coherent, representing both “mainstream” and “oppositional” ideals. The result of conflicting values and the availability of multiple cultural schemas is increased individual agency in selecting and switching between cultural schemas.

Table 1-2 is a replication of Harding and Hepburn's (2014) comparison of subcultures and cultural heterogeneity. Intersecting identities, including race/ethnicity, gender, nativity, and acculturation, at both the neighborhood and individual levels drives the variation inherent in cultural heterogeneity. Although they acknowledge the role of these identities, Nancy López (2013) has developed a more complete framework for understanding how identities intersect at multiple levels and their relationship to health, specifically.

Table 1-2. Harding and Hepburn's comparison of subculture and cultural heterogeneity theories of neighborhood culture and neighborhood effects

	Subculture	**Cultural Heterogeneity**
Cultural Concepts	Values (Ends)	Frames, Scripts, Narratives (Means)
Cultural Coherence	High	Low
Basis for Explanations of Behavior	Conformity to subculture	Availability and Deployment of Cultural Models (repertoire)
Social Networks and Culture	Tightly coupled (subculture as reference group)	Loosely coupled (multiple sources of cultural models)
Accounting for Variation	Different subcultures	Different Repertoires and Different Deployment
Role of Structural Positions & Material Circumstances	Subculture as response to blocked opportunities	Resonance, Social Support, Identities (Influencing availability, salience, and deployment of cultural models)
Individual Agency	Lower	Higher

Source: Harding and Hepburn (2014: Table 1)

López's "racialized-gendered social determinants of health" framework emphasizes the multilevel nature of racial and ethnic statuses and their interactions with gender and social class.

Intersectionality is essential to understand neighborhood cultural heterogeneity because intersecting social statuses play a role in organizing how social groups and norms develop and their implications for health. López (2013, 188) quotes Griffith (2012, 106) in describing the utility of this approach:

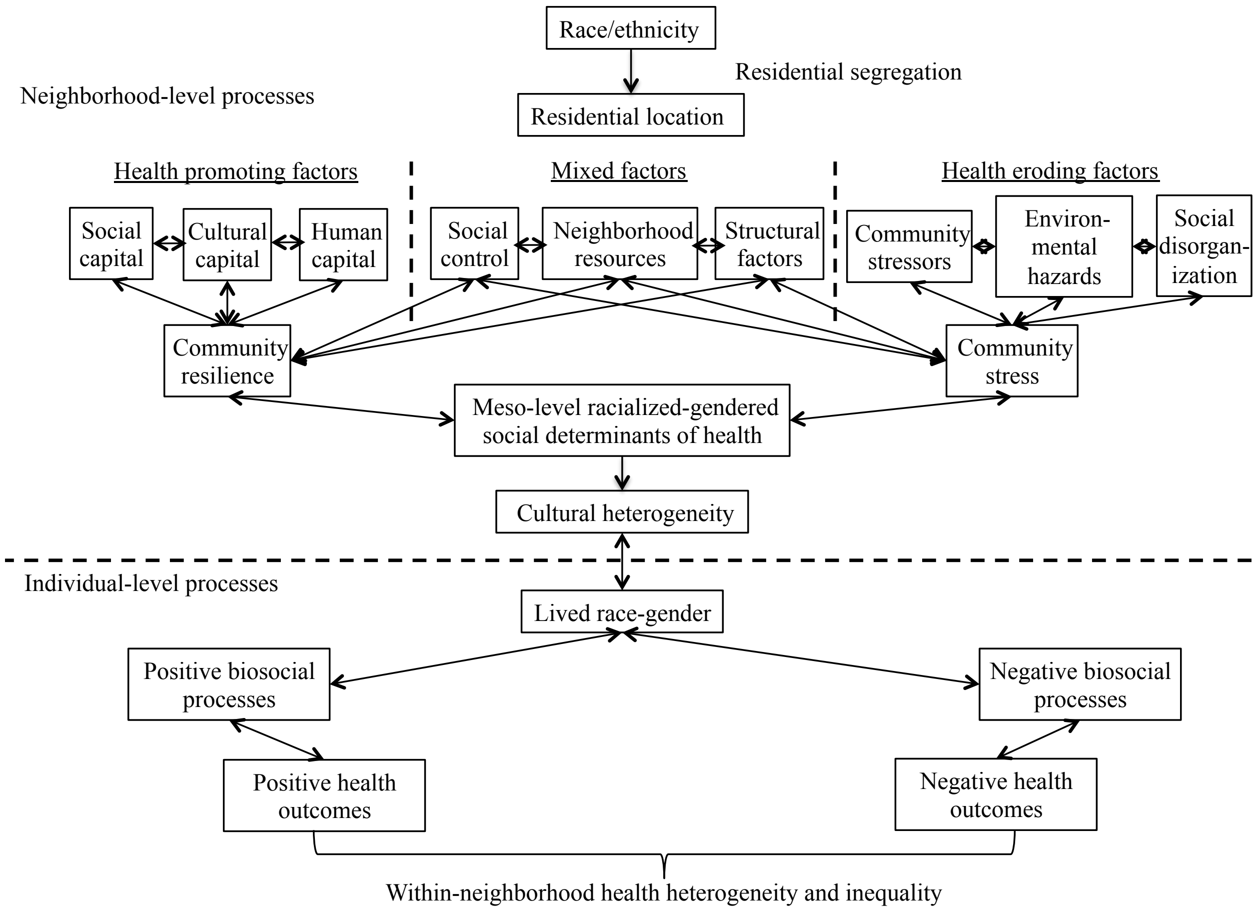
> The goal of an intersectional approach is to simultaneously examine the social and health effects of several key aspects of identity and contexts in ways that create new understandings of these factors and that are a more accurate reflection of the lived experiences of the populations of interest.

These primary social statuses often cannot be understood in isolation as they relate to health. At the neighborhood (meso) level, López argues that the meanings behind intersecting status are developed and perpetuated. This is compatible with Harding and Hepburn's (2014) cultural heterogeneity highlighted in Table 1.2, in which individuals balance "multiple sources of cultural models," and the "availability, salience, and deployment of cultural models." At the individual level, López describes a process of "lived race-gender" in which daily experiences of individuals reinforce or restructure the meanings behind their race/ethnic, gender, or migrant statuses. This understanding is compatible with Harding and Hepburn's description for how cultural variation manifests, through "different repertoires and different deployment."

This application of cultural heterogeneity and racialized-gendered social determinants of health does not refute the pathways developed using more static notions of culture. For example, a neighborhood health heterogeneity model would still support the premise that social cohesion may buffer individuals from the physiological impact of a stressful environment. What is different is that a neighborhood health heterogeneity framework allows processes of community resilience and community stress to exist within the same neighborhood because of the diverse groups and social processes that exist even in neighborhoods with high concentrations of a singe race/ethnic group.

In Figure 1-3 I present my conceptual model for understanding neighborhood health heterogeneity. It is based off of the Gee and Payne-Sturgis (2004) stress-exposure-disease model, but incorporates Harding and Hepburn's neighborhood-level cultural heterogeneity and López's meso-level racialized-gendered social determinants of health and individual-level lived race-gender. The model begins with the impact of race and ethnicity on residential location. The right side of the model represents health eroding factors. It is similar to the stress-exposure-disease model, but adds social disorganization as one of the neighborhood-level processes associated with community stress. The three processes in the middle—social control, neighborhood resources, and structural factors—can all contribute to both increased community stress or increased community resilience, depending on how they are deployed, received, and embodied by residents. On the left side of the figure are neighborhood-level processes presented in Figure 1-2 that are associated with community resilience, including social, cultural, and human capital.

Figure 1-3. Neighborhood health heterogeneity model



Community resilience and community stress can coexist because social environments can be interpreted differently by residents, based on racialized-gendered experiences (i.e. meso-level racialized-gendered social determinants of health). The different experiences brought about by intersecting social statuses lead to neighborhood cultural heterogeneity (i.e. the existence of multiple cultural repertoires or schemas that residents can or must employ). Each resident's own lived race-gender influences how these different cultural repertoires are embodied and perpetuated. The embodiment process has implications for whether the cultural repertoires have positive biosocial influences for individuals (i.e. stress reducing) or whether they have negative biosocial influences for individuals (i.e. stress exacerbating). When examining neighborhood health patterns, these complex processes can lead to both positive and negative health outcomes for the same neighborhood. Rather than concluding that neighborhoods are *either* good or bad for residents' health, they can indeed be both.

If neighborhood environments are seen as a contributor to the HHP, how does potential heterogeneity in neighborhood associations influence our understanding of the HHP more broadly? In fact, recent evidence suggests that the HHP may be more heterogeneous and vulnerable than originally anticipated decades ago (Lariscy et al. 2015). Neighborhood health heterogeneity may help explain incongruent health patterns for Hispanics compared to other race/ethnic groups and among Hispanic subgroups. Examining how different neighborhood environments (including different measurements of Hispanic neighborhood concentration) and individual-level factors such as acculturation and gender all modify health patterns for Hispanic residents is essential to developing more accurate frameworks and, importantly, relevant policy initiatives to improve health. If only dichotomous models exist that suggest neighborhood environments either lead to negative health patterns or positive ones, it creates problematic and ineffective opportunities for public health interventions. Although complex and nuanced frameworks such as the neighborhood health heterogeneity model may be challenging to quantify or explain, they may lead to more effective and targeted approaches to improve health by outreaching to specific groups within neighborhoods that may have otherwise not been identified.

Testing the neighborhood health heterogeneity model in its entirety necessitates either a detailed qualitative analysis or new quantitative measures that build on those developed in the PHDCN study. However, it is possible to use available data to examine the extent to which

Hispanic neighborhoods are associated with diverse health outcomes, and how prevalence and inequality in a variety of health conditions may vary by race/ethnicity, gender, and acculturation, as suggested by López (2013), and Harding and Hepburn (2014). To date, research on the influence of Hispanic neighborhoods and health has not examined a diverse set of health conditions within and between neighborhoods, and most studies lack the statistical power to test multiple neighborhood-level measures or examine specific subpopulations. I address these limitations in the literature using a large sample of EHRs from patients living in Denver, Colorado. In the next section, I describe the two research questions I examine in this dissertation to improve understanding of neighborhood influences on the HHP.

RESEARCH QUESTIONS

1. **What is the relationship between types of Denver neighborhoods, including barrios, and prevalence of common health conditions at the neighborhood-level? How are different types of neighborhoods associated with variation in prevalence of health conditions for Hispanic residents versus non-Hispanic white residents within neighborhoods?**

In Chapter 3 I use an ecological approach to examine how different types of neighborhoods are associated with type 2 diabetes, obesity, hypertension, diagnosed depression, and current smoking for patients living in Denver. Neighborhood types, in this context, refer to latent constructs of a number of composite neighborhood factors that, taken together, represent specific environments that may impact the health of residents. I selected variables that would specifically identify potential barrios in Denver. I use neighborhood measures that may be particularly relevant to the Hispanic population, including the proportion of Hispanic, foreign born, and non-citizen residents, and the residential stability of these groups within a given neighborhood. I combine these characteristics with neighborhood measures that have been more commonly used in the past and apply to all groups, including poverty and socioeconomic status, stability, and mobility.

In Chapter 3 I also examine how racial/ethnic health differences (which I refer to as health inequality) varies within neighborhoods and across neighborhood types. I compare differences in prevalence of the five health conditions for Hispanics and NHWs to understand how health equity is associated with different neighborhood environments, and the implications this has for Hispanic neighborhoods and health.

2. **a) Is there a Hispanic Health Paradox in prevalence of health conditions for Hispanics living in Denver, Colorado, compared to non-Hispanic whites and non-Hispanic blacks using EHR data from Denver, Colorado?**

   b) How is living in a Hispanic neighborhood associated with the likelihood of all patients and Hispanic patients having type 2 diabetes, obesity, hypertension, depression, or being a current smoker, taking into account the effects of socioeconomic status and inequality?

   c) How are racialized-gendered social statuses, including gender and acculturation, associated with the impact of living in a barrio neighborhood on health outcomes?

In Chapter 4 I take a multilevel approach to understanding the relationship between Hispanic neighborhoods and health. I use multilevel logistic regression to assess the association between living in a Hispanic neighborhood on individual-level odds of having each of the health conditions for all patients and Hispanic patients specifically.

In Chapter 4 I also compare *within-group* variations in health for Hispanic residents living in Denver. I use a sample of almost 50,000 Hispanic patients, making it possible to conduct analyses separately for Hispanics. I examine how living in Hispanic communities varies by gender, across the total population and the Hispanic population. Many previous studies on the relationship between Hispanic neighborhoods and health have had to make comparisons between Hispanic residents and residents from other race/ethnic groups because of sample size constraints, but those analyses assume homogeneity within groups. By focusing on how different types of neighborhoods are associated with Hispanic residents specifically, I can examine whether health differs for Hispanic patients living in particular types of neighborhoods. Furthermore, I compare health patterns between Hispanic patients who speak English as their primary language and Hispanic patients who speak Spanish as their primary language.

In both Chapter 3 and Chapter 4 I test how sensitive results are to the measure used to define Hispanic neighborhoods. If results are similar across measures, it suggests potentially more stable social processes within neighborhoods. If results are substantially different, it suggests that social processes may be more heterogeneous within neighborhoods.

In the next section, I describe the etiologies of each of the health conditions that I examine in the dissertation, how they vary by race and gender, and whether they have been examined in the literature on Hispanic neighborhoods and health.

ETIOLOGY OF FIVE HEALTH CONDITIONS

This study will examine the prevalence of five chronic health conditions: type 2 diabetes, obesity, high blood pressure (hypertension), diagnosed depression, and current smoking[3]. These

[3] Details on the definitions and construction of these variables are provided in Chapter 2.

five conditions were selected for two primary reasons. First, they represent a broad and varied set of health conditions, which together paint a picture of the health profile of a community. Second, they represent the “mixed bag” of national Hispanic health trends. Hispanics have lower prevalence rates of hypertension and smoking compared to non-Hispanic whites and blacks after accounting for socioeconomic status (Nwankwo et al. 2013). However, Hispanics have higher rates of diabetes and obesity compared to non-Hispanic Whites and comparable rates compared to non-Hispanic Blacks (Peek et al. 2007, Flegal et al. 2010). Each of the chronic conditions manifests in a physiologically different way, but they are also correlated to varying degrees.

Although I refer to these dependent variables as “health conditions” throughout the dissertation for simplicity, smoking is technically a health behavior. I include smoking for a few reasons. First, it helps to create a broad set of dependent variables that may be related to multifaceted neighborhood sociocultural processes to understand the extent to which a heterogeneous health framework is appropriate. Second, smoking has been strongly associated with neighborhood environments in past research (Finch 2001, Steptoe and Feldman 2001), but the relationship between Hispanic neighborhoods and smoking is complex (Finch et al. 2000, Kimbro 2009), as I will describe more below. Third, smoking has serious negative health implications, so results for smoking may elucidate opportunities for intervention. Finally, smoking was available in EHR data and thus provided an opportunity to examine it as both an independent and dependent variable.

These health conditions I selected are also precursors to the leading causes of death. Hypertension, obesity, diabetes and smoking are the primary risk factors for cardiovascular disease, which is the leading cause of death (Murphey et al. 2017). Diabetes is currently the seventh leading cause of death, and obesity is one of its primary precursors (Murphey et al.

2017). Depression is a common cause of disability in the United States, and has consequences for physical health and well-being more broadly (Pratt and Brody 2014). Thus, these health conditions are relevant both in their relationship to the HHP and in their significance as leading contributors to mortality, physical functioning, and well-being. I will now describe the etiology of each health condition and results from any studies that have examined the relationship between each health condition and Hispanic neighborhoods.

Diabetes

Diabetes mellitus ("diabetes") is a metabolic disorder resulting in buildup of glucose (sugars broken down from carbohydrates) in the bloodstream. This buildup is caused by the body's inability to produce enough insulin or effectively use the insulin that it has, and this prevents cells from adequately absorbing glucose from the blood. There are two main categories of diabetes: type 1 and type 2. Type 1 diabetes is an autoimmune disease (where the body is attacking itself) and is almost always caused by genetic susceptibility, although some environmental factors such as viruses or foods can trigger type 1 diabetes. This study will not examine prevalence of type 1 diabetes. Ninety to 95% of diabetes is Type 2 diabetes (CDC 2017a). Similar to type 1 diabetes, type 2 diabetes can be caused by genetic susceptibility. Genetics can affect susceptibility of developing type 2 diabetes in complex ways. For example, carriers of the TCF7L2 gene are more than twice as likely to develop type 2 diabetes than those who do not carry the gene variant. Genes can also influence susceptibility of risk factors for type 2 diabetes – particularly obesity – and thus have a more upstream but nontrivial effect on developing the disease.

Another common factor associated with type 2 diabetes is metabolic imbalance. Obese and physically inactive individuals are at much higher risk of developing type 2 diabetes. In obese individuals, muscle, fat, and liver cells stop responding normally to insulin and force the pancreas to produce excess insulin. As long as the pancreas can produce excess insulin, blood glucose levels will remain normal. However, risk factors such as obesity, hypertension, and high cholesterol impact the ability of the pancreas to produce enough insulin, and these factors combined result in type 2 diabetes. Thus, similar to high cholesterol, type 2 diabetes is often comorbid with other chronic conditions (CDC 2017a).

Diabetes is currently the seventh leading cause of death in the United States. Over time, increased levels of glucose in the blood begin to damage different organ and tissue systems in the body. This damage can cause stroke, cardiovascular disease, loss of limb function (and the need for amputation), loss of mobility, and diabetes has also been linked to increased risk of depression (CDC 2017a). Incidence of type 2 diabetes historically has begun in middle age, but the rise in obesity in the United States over the past three decades has been associated with earlier onset of type 2 diabetes, including childhood diabetes and prediabetes. The progression of diabetes varies drastically depending on age at diagnosis and adherence to medication and behavioral modification. There are a number of common oral and injection-based medications for type 2 diabetes. Behavioral modifications for type 2 diabetes include losing weight, exercising more, eating less sugar and fat, and controlling other comorbidities, particularly hypertension and high cholesterol (CDC 2017a). To date, no studies of which I am aware have examined the relationship between Hispanic neighborhoods and diabetes prevalence.

Obesity

Obesity is a diagnosis associated with having excess adipose (fatty) tissue. The buildup of excess adipose tissue can be the result of genetic, behavioral, social, and environmental factors. Although there is a genetic component to the predisposition of being obese, the World Health Organization has emphasized the behavioral, social, and environmental contributors as the primary drivers of the high prevalence of obesity worldwide (World Health Organization 2000). Behaviors such as low levels of physical activity, high alcohol consumption, and, relatedly, high caloric intake are associated with obesity. Extensive research has also been conducted on the social and environmental factors associated with obesity, including external stress, social isolation, poverty, and poor neighborhood conditions (Racette et al. 2003).

Obesity has some direct effects on poor health, such as limiting mobility, stressing joints and ligaments, and sleep problems. However, it is more often viewed as deleterious to health because of its more distal effects, increasing likelihood of developing other chronic conditions, cardiovascular disease, different types of cancers, stroke, and ultimately increased risk of mortality. Being obese increases the risk of developing other chronic conditions, particularly diabetes and high cholesterol, but also hypertension. Chronic obesity stresses many organs and tissues, and over time increases risk of acute illness (such as heart attack) and chronic illness (such as various cancers) (Racette et al. 2003).

Unlike the other chronic conditions in this study, obesity is primarily treated through intensive behavioral modification. Although some medications and medical procedures are available to reduce adiposity, these treatments are not widely used or accepted in the medical community. Instead, the most common treatments for obesity are losing weight through eating less fat and exercising more. Research has demonstrated that losing 5-10% of body weight can lead to meaningful health gains, and some treatment standards suggest that reducing weight by 5-10% for one year is considered to be a metric for a successful treatment trajectory. However, weight loss is extremely challenging for many obese individuals and depends on a multiplicity of factors, making long-term successful treatment trajectories difficult (Racette et al. 2003).

To date, one study has examined the relationship between Hispanic neighborhoods and obesity (Salinas et al. 2012) and two have examined BMI (Do et al. 2007, Park et al. 2008). Salinas and colleagues (2012) conducted an ecological study in Texas, examining the relationship between county-level obesity rates and the percent of Hispanic residents in the county. Their results supported a HHP (i.e. lower obesity rates for Hispanics) in counties that had a high concentration of Hispanics and high educational attainment, but otherwise they did not observe a significant association. In the two studies examining BMI, Park and colleagues (2008) found no association between the percent of foreign-born residents in the neighborhood and BMI, but increased linguistic isolation was associated with higher BMI for Hispanics. Using national data, Do and colleagues (2007) find that Hispanic neighborhoods are associated with higher BMI. Taken together, the existing studies suggest that there is a negative association between Hispanic neighborhoods and health for Hispanics, and that this relationship is influenced by social class of residents (Salinas 2012) and acculturation (Park 2008).

Hypertension

For blood to be adequately delivered to tissues and organs in the body, the pressure of the blood moving throughout the vascular system must stay within a particular threshold. Hypertension, or high blood pressure, exists when the blood pressure in the vascular system exceeds a normal limit. Hypertension is typically defined as having a systolic blood pressure at or above 140 mm Hg or diastolic blood pressure at or above 90 mm Hg. Systolic pressure is measured when the heart beats, and diastolic pressure is measured when the heart is not beating. Hypertension often develops slowly, beginning as intermittent hypertension or prehypertension (heightened levels of systolic and diastolic blood pressure that fall slightly short of the threshold for hypertension) and developing into "essential" or chronic hypertension. Intermittent hypertension or prehypertension can begin as early as age 10 and can persist for decades before developing into chronic hypertension. Over time, and when untreated, chronic hypertension starts to damage tissues and organs, including the heart, aorta, kidneys, nervous system, among others (CDC 2017b).

Hypertension can be both acute and chronic. When the system is under extreme stress, the activation of "fight or flight" hormones such as cortisol and adrenaline can raise blood pressure so that enough blood can reach essential organs in the case that fleeing or fighting becomes necessary. For example, acute hypertension is often observed among emergency room patients after an accident or gunshot wound. Acute hypertension can also manifest during other types of acute stress, such as the death of a family member or other traumas that have no apparent physical manifestation. In these cases, if the stressful circumstance subsides, so will the hypertensive state.

There is variability in the rate at which chronic hypertension develops, as it is influenced by many factors, including genetics, lifestyle (particularly smoking), environment, and chronic stress. For example, African Americans, on average, develop hypertension at earlier ages and experience a more severe progression of its consequences (Hayward et al. 2000). This "weathering" process reflects wear and tear on the body over the life course – from the in-utero environment, childhood conditions, and the continued stressors of poverty and disadvantage that extend into adulthood (Geronimus et al. 2006). Hispanics, on average, have lower rates of hypertension than non-Hispanic Whites and African Americans (CDC 2017b). However, as my research with Richard Rogers and Fernando Riosmena has shown, Hispanics are less likely to have their hypertension under control compared to NHWs (Bacon, Riosmena, and Rogers 2017).

Effective treatments for hypertension include medication and lifestyle modification. There are a number of drug treatment options for hypertension, often beginning with a diuretic. In many older adults, hypertension is comorbid with other chronic and acute conditions, and drug therapy is often tailored to account for multiple simultaneous conditions. Lifestyle changes to reduce blood pressure include eating less fat and sodium, exercising more or otherwise losing weight, quitting smoking, and reducing alcohol consumption. The efficacy of treatments depends on age at diagnosis, sex, genetic predisposition to hypertension, comorbidities, and environmental and social conditions that may contribute to high blood pressure or reduce its effects (NHLBI 2017).

To date, two studies have examined the relationship between Hispanic neighborhoods and blood pressure/hypertension. Viruell-Fuentes and colleagues (2012) found that Hispanics living in Hispanic neighborhoods had lower odds of hypertension compared to Hispanics living in other types of neighborhoods, but treatment and control of hypertension was worse among Hispanics living in Hispanic neighborhoods. Contrary to Viruell-Fuentes and colleagues, Li and colleagues (2017) used data from the 2006 and 2008 Southeastern Pennsylvania Household Health Survey and found that greater Hispanic and immigrant neighborhood concentration were associated with higher rates of hypertension.

Depression

Depression is a mood disorder that impacts how well an individual is able to carry out normal daily activities. It encompasses a variety of symptoms, which may include anxiety, sadness, extreme fatigue, increased risk of suicide, and psychosomatic symptoms such as achiness, headaches, and digestive problems. Major depression is the leading cause of disability in the United States. Depression is also highly comorbid with other health conditions, including cardiovascular disease, diabetes, and obesity, and studies have speculated that the causal pathways may be bidirectional (Pratt and Brody 2014).

Depression is one of the most commonly used indicators of poor mental health, and is usually assessed through one of a number of screening tools used by a healthcare provider. A patient must meet at least five of the criteria listed in the fifth edition of the Diagnostic and Statistical Manual of Mental Disorders (DSM-5), which include: "Depressed mood, marked diminished interest or pleasure, significant weight loss or weight gain, insomnia or hypersomnia, psychomotor agitation or retardation, fatigue or loss of energy, feelings of worthlessness or excessive guilt, diminished ability to concentrate, or recurrent thoughts of death or suicidal ideation" (Bienenfeld and Stinson 2014:1).

Between 2013-2016, prevalence of depression among adults 20 years and older in the United States was 8.1% (CDC 2018a). Similar to other health conditions, rates of depression vary by race/ethnicity, gender, geographic location, and are influenced by genetic, behavioral, and structural factors. NHB women and men have the highest rates of depression (9.2% overall), and Hispanics have slightly higher rates of depression than NHWs (8.2% compared to 7.9%, respectively), although this difference is driven by higher rates of depression among Hispanic men (6% compared to 5.5%) (CDC 2018a).

A large percentage of people with depressive symptoms go undiagnosed and untreated. Estimates from 2005-2008 National Health and Nutrition Examination Surveys suggest that roughly 37% of respondents who had depressive symptoms were not receiving treatment (Shim et al. 2011). Data from the Behavioral Risk Factor Surveillance System (BRFSS) suggest that as many as 45% of people with depressive symptoms are undiagnosed (Li et al. 2009).

In general, women are more than twice as likely as men to be diagnosed with depression (10.4% among women compared to 5.5% among men between 2013-2016) (CDC 2018a). Gender differences in depression are perhaps acknowledged more than gender differences in other chronic health conditions. For example, the National Institutes of Mental Health (NIMH) provides sex-specific resource guides for depression (something that is not done for other conditions like hypertension). Part of this is due to the relationship between depression and unique biological conditions that only affect women, such as postpartum depression or depressive symptoms associated with hormonal changes related to women's menstrual cycles.

Treatment for depression often includes behavioral and pharmacological strategies. Between 2009-2012, only 35% of adults with major depression reported receiving therapy (CDC 2018a). Hispanic patients were the least likely to have received therapy from a mental health professional regardless of the severity of depressive symptoms, compared to non-Hispanic whites and non-Hispanic blacks (CDC 2018a). Between 2011-2014, 7.8% of adults ages 20-39, 16.6% of adults ages 40-59, and 19.1% of adults ages 60 and over took antidepressant drugs in the past month. Despite the fact that non-Hispanic white patients have lower rates of diagnosed depression than non-Hispanic black and Hispanic adults, they were overwhelmingly more likely to have taken antidepressant medication in the past month (16.5% among non-Hispanic whites, 5.6 % among non-Hispanic blacks, and 5% among Hispanics) (CDC 2018a).

To date, a number of studies have examined the relationship between Hispanic neighborhoods and mental health, including depressive symptoms specifically (Arévalo, Tucker, and Falcón 2015, Bécares 2014, Hong, Zhang, and Walton 2014, Mair et al. 2010, Ostir et al. 2003, Rios, Aiken, and Zautra 2012, Shell, Peek, and Schacht 2013). Overall, studies have found positive, mixed, and negative associations between Hispanic neighborhoods and mental health. Three studies found only positive associations (Mair et al. 2010, Ostir et al. 2003, Shell, Peek, and Schacht 2013), two found mixed associations (Arévalo et al. 2015, Bécares 2014), and two found negative associations (Hong et al. 2014, Rios et al. 2012). Both studies that found negative associations also examined measures of social cohesion and found that it somewhat mediated the negative association between high concentrations of Hispanic residents and poor mental health (Hong et al. 2014, Rios et al. 2012). The studies that found mixed results found that Puerto Ricans benefited from living in neighborhoods with high concentrations of co-ethnics, but first generation Mexican Americans did not (Bécares 2014), and that less acculturated Puerto Rican men may experience more of a protective effect of living among co-ethnics compared to higher acculturated Puerto Rican men and all Puerto Rican women (Arévalo et al. 2015).

Smoking

Tobacco is most commonly consumed in the United States through smoking cigarettes. Unlike some of the other conditions examined in this study, smoking rates have declined substantially over the past several decades. As of 2016, 15.5% of adults were current cigarette smokers, which represents roughly 5% decline since 2005 (Jamal et al. 2018).

Cigarette smoking is the leading cause of death in the United States that is deemed preventable (CDC 2017c). As the Centers for Disease Control and Prevention states succinctly, “Cigarette smoking harms nearly every organ of the body, causes many diseases, and reduces the health of smokers in general" (CDC 2017c). Smoking causes lung cancer and is associated with increased risk of cardiovascular disease, stroke, abnormal fetal development in pregnant women, and many other health risks (CDC 2017c). Smoking cigarettes is strongly associated with poor mental health. More than 1/3 of adults with serious psychological distress were current smokers as of 2016, compared to 14.7% of adults without serious psychological distress (CDC 2018a).

As of 2016, smoking rates were higher among adult males (17.5%) than females (13.5%), and substantially higher among non-Hispanic American Indians/Alaskan Natives (31.8%) and individuals of mixed race (25.2%) than non-Hispanic whites (16.6%), non-Hispanic blacks (16.5%), Hispanics (10.7%), and Asians (9%) (CDC 2017c). Among Hispanics, acculturation is positively associated with cigarette smoking, with higher smoking rates associated with longer duration of stay in the United States and among U.S.-born Hispanics (Lorenzo-Blanco and Cortina 2013).

To date, three studies have examined the association between Hispanic neighborhoods and smoking/tobacco use, and two of them focus on perinatal exposure. Similar to mental health, results for smoking/tobacco use are mixed. Shaw and colleagues (2010) found that Hispanic neighborhoods were associated with lower odds of smoking during pregnancy for U.S.-born pregnant Hispanic women but not foreign-born pregnant Hispanic women. As mentioned earlier, Finch and colleagues (2000) found that pregnant Hispanic women in less acculturated neighborhoods had lower rates of tobacco use. Kimbro (2009) did not find a relationship between Hispanic neighborhoods and odds of smoking.

Taken together, existing research on the health conditions I use in this dissertation suggest diverse etiologies and heterogeneous associations between Hispanic neighborhoods and health. To date, no studies have examined diverse health conditions that may encompass a broader health profile of a community. Including diverse conditions prevents simplistic discussions of mechanisms that may tie neighborhood environments to residents' health. In the next section, I introduce the research setting before moving on to the data and methods in Chapter 2.

SETTING

This is the first study to examine the HHP and the relationship between Hispanic neighborhoods and health in Denver, Colorado. Similar to many American cities, Denver residents are unevenly distributed by race/ethnicity and socioeconomic status. Composition of NHW residents between Denver census tracts ranges from 26.6%-95.2%, composition of NHB residents ranges from 0.3%-54.8%, and concentration of Hispanic residents ranges from 3.1%-84.8%. Of the 144 census tracts in Denver, 34 census tracts (roughly 25%), are more than 50% Hispanic. About one quarter of these census tracts are more than 75% Hispanic. Thus, there is significant variation in residential composition of Hispanics, which provides the opportunity to compare neighborhoods with many Hispanic residents to those with fewer Hispanic residents.[4] Denver also has socioeconomic variation. Average full time employment rates at the census tract level range from 35.4%-87.4%, and median household income ranges substantially from $9,874-$160,694 between Denver census tracts (U.S. Census Bureau 2011).

[4] In Chapter 2 I provide a more detailed description of how neighborhoods are defined, different methods I use to define Hispanic neighborhoods, and how closely the patient population mirrors the residential population in Denver.

In Table 1-3 I show the comparison of Hispanic-white segregation and black-white segregation in the Denver metropolitan area compared to the ten metropolitan areas (also called metropolitan statistical areas, or MSAs) in the United States that had the most similar percentage of Hispanic residents in the 2005-2009 ACS. The dissimilarity index is a measure of residential segregation, and higher scores indicate more segregation. Compared to cities with a comparable percentage of Hispanic residents, Hispanic-white segregation in the Denver MSA was higher than in six of the ten other MSAs, comparable to two MSAs, and lower than two MSAs, making it one of the more segregated MSAs for Hispanic residents. Although these MSAs had different composition of black residents, black-white segregation was also greater in the Denver MSA than seven of the ten comparable MSAs as of 2009. Between 2000 and the 2005-2009 ACS estimates, segregation for Hispanic and black residents in Denver changed less than it did in most other comparable MSAs. Only one other MSA had a slight increase in Hispanic-white segregation, and only two other MSAs had stagnant or increased black-white segregation. Overall, these comparisons indicate that Denver is a moderately segregated MSA for both Hispanic and black residents compared to cities with similar Hispanic composition, and justifies its relevance as an important place to study the relationship between Hispanic neighborhoods and health (Frey 2010).

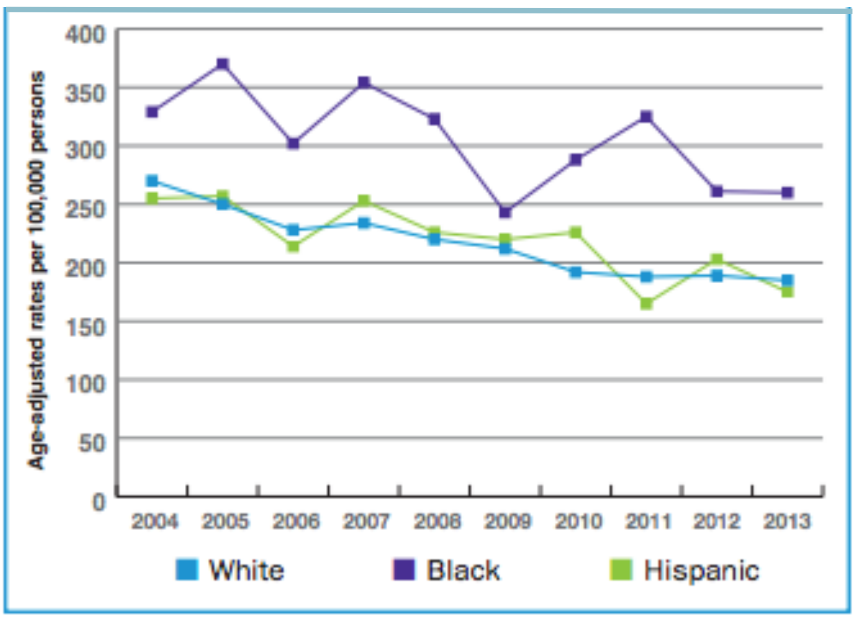
Table 1-3. Hispanic-white and black-white segregation in 2000 and 2005-9 in Denver metropolitan area compared to the ten U.S. metropolitan areas with the most comparable percentage of Hispanic residents in the 2005-9 American Community Survey

	Hispanic-White Dissimilarity index					**Black-White Dissimilarity index**			
	% Hispanic	2005-9	2000	Change		% Black	2005-9	2000	Change
Cape Coral-Fort Myers, FL	17.4	37	41	-4		7.5	62	69	-7
Sacramento--Arden-Arcade--Roseville, CA	19.3	40	40	0		7.1	56	58	-2
Chicago-Naperville-Joliet, IL-IN-WI	19.9	57	61	-4		17.4	78	81	-3
San Francisco-Oakland-Fremont, CA	20.7	50	50	0		8.3	64	66	-2
New York-Northern New Jersey-Long Island, NY-NJ-PA	21.8	63	66	-3		16.5	79	80	-1
Denver-Aurora, CO	**22.4**	**51**	**50**	1		**5.3**	**64**	**64**	**0**
Orlando-Kissimmee, FL	23.8	41	39	2		14.7	51	56	-4
San Jose-Sunnyvale-Santa Clara, CA	27.1	49	51	-2		2.4	45	42	4
Dallas-Fort Worth-Arlington, TX	27.9	51	52	-1		14.0	57	60	-2
Las Vegas-Paradise, NV	29.3	43	42	1		9.6	39	40	-2
Austin-Round Rock, TX	30.6	43	46	-3		7.2	52	52	0

Source: William H. Frey analysis of 2005-9 American Community Survey and 2000 US Census

Denver's health profile also makes it an appropriate research site for understanding the HHP. Similar to the nation as a whole, cardiovascular disease is the leading cause of death in Denver (Be Healthy Denver 2014). Figure 1-4 compares death rates from cardiovascular disease nationally to Denver overall as well as by race/ethnicity. NHB residents have the highest death rates from cardiovascular disease. NHW and Hispanic residents have comparable death rates from cardiovascular disease. Given lower SES among Hispanics comparable to NHWs in Denver, this suggests that the HHP may also manifest in Denver for the leading cause of death.

Figure 1-4. Age-adjusted death rates for cardiovascular disease by race/ethnicity for Denver, Colorado fro 2004-2013.



SOURCE: Vital Statistics, Health Statistics Section, Colorado Department of Public Health and Environment

In Table 1-4 I show prevalence rates of each health condition I examine in this dissertation for Denver compared to national rates from the Centers for Disease Control and Prevention's National Health and Nutrition Examination Survey (NHANES). I requested the Denver data from the Colorado Department of Public Health and Environment, which administers the Behavioral Risk Factor Surveillance System (BRFSS). Data were from the 2013 and 2015 combined BRFSS. The BRFSS is a health survey that relies on self-reported conditions, and therefore is likely an underestimate of actual prevalence. NHANES contains both self-report and clinical measures of each condition except for smoking. Overall, Denver had lower rates of diabetes, obesity, and hypertension compared to national rates, although it is unclear how much of this is due to underreporting. Denver had much higher rates of depression than NHANES, but this may also be due to differences in measurement.

Hispanics had higher rates of diabetes and obesity than NHWs and NHBs in Denver, although Hispanics had slightly lower rates of diabetes than NHBs nationally. Hispanics had comparable rates of hypertension to NHWs in Denver and nationally, and much lower rates than NHBs. Hispanics in Denver had the lowest rates of depression compared to other race/ethnic groups, but Hispanics nationally had slightly higher/comparable rates to NHWs. Hispanics in Denver had higher rates of smoking compared to NHWs and residents categorized as some other non-Hispanic race, but much lower smoking rates than NHBs. Hispanics nationally had lower smoking rates than all other groups except for non-Hispanic Asians. Taken together, Hispanics in Denver display mixed health patterns compared to other groups: higher rates of diabetes and obesity, similar or lower rates of hypertension, lower rates of depression, and slightly below average rates of smoking. Comparing Denver to the nation as a whole provides context and demonstrates that some national health patterns are similar to those in Denver (e.g., for hypertension, diabetes, and obesity), but others are distinct (e.g., for depression and smoking).

Table 1-4. Rates of type 2 diabetes, obesity, hypertension, depression, and smoking by race/ethnic groups in Denver, Colorado 2013-2015

	Hispanic		Non-Hispanic white		Non-Hispanic black		Non-Hispanic Asian or other race/ethnicity*		Total
	%	95% CI	%	95% CI	%	95% CI	%	95% CI	%
Diabetes									
Denver[a]	11.0	(8.2, 13.8)	3.9	(3, 4.7)	8.6	(5.4, 11.8)	6.4	(2.5, 10.3)	7.7
National[b]	16.4	(14.1-18.9)	9.3	(8.4,10.2)	17.7	(15.8-19.9)	16.0	(13.6-18.9)	11.5
Obesity									
Denver[a]	28.4	(23.7, 33)	13.3	(11.2, 15.5)	21.6	(15.8, 27.3)	15.7	(6.7, 24.7)	20.7
National[c]	47.0	(42.9, 51.1)	37.9	(34.4, 41.4)	46.8	(42.3, 51.3)	12.7	(10.5, 14.9)	39.8
Hypertension									
Denver[a]	24.9	(19.4, 30.4)	24.2	(20.9, 27.5)	41.9	(31.4, 52.5)	15.8	(4.9, 26.8)	28.2
National[d]	27.8	(25.1, 30.5)	27.8	(25.1, 30.5)	40.3	(36.4, 44.2)	25.0	(21.7, 28.3)	29.0
Depression									
Denver[a]	14.0	(11, 16.9)	18.8	(16.4, 21.2)	20.4	(13.5, 27.3)	21.2	(13.1, 29.3)	19.4
National[e]	8.2	(6.8, 9.6)	7.9	(6.9, 8.9)	9.2	(8.0, 10.4)	3.1	(2.1, 4.1)	8.1
Smoking									
Denver[a]	18.5	(14.9, 22.2)	15.9	(13.3, 18.4)	30.8	(22.7, 38.9)	17.5	(9.9, 25.2)	20.2
National[f]	14.5	(11.8–17.2)	17.8	(16.8–18.8)	20.2	(17.2–23.2)	14	(10.7–17.3)	17.5

Sources: a. BRFSS 2013 & 2015; b.CDC 2017a c. CDC 2017b; d. CDC 2017c; e. CDC 2017d; f. CDC 2017e;
* Non-Hispanic Asian for national statistics, Non-Hispanic other for Denver statistics

CONCLUSION

In this introductory chapter I addressed the state of current research on the HHP and the relationship between neighborhoods and health. I examine dominant frameworks that have been used to either suggest negative associations between residential segregation and health (particularly for African Americans) or positive associations between Hispanic neighborhoods and health. After reviewing the existing literature for Hispanics, I argue that empirical results of existing studies do not support *either* negative *or* positive associations between coethnic concentration and health, and warrant a framework that encompasses observed heterogeneity. I introduce a neighborhood health heterogeneity framework, which uses a dynamic understanding of culture and intersectional identities, to better explain results from existing studies. I also highlight the limitations of existing research, including a dearth of studies that examine multiple health conditions or test multiple measures of Hispanic neighborhoods. In the remainder of the dissertation, I will use EHR data from Denver, Colorado, to address these shortcomings and examine whether Hispanic neighborhoods are associated with heterogeneous health profiles for Denver residents. The next chapter provides details on the data sources and methods used to address these research questions, followed by the two empirical chapters and the conclusion.

Chapter 2: Data and Methods

In Chapter 2 I provide detailed descriptions of each of the data sources used to answer the research questions outlined in the previous chapter. I also describe data access, privacy, population coverage, and variable construction for the electronic health record (EHR) data, and explain the analytic strategy for each empirical chapter.

ELECTRONIC HEALTH RECORD DATA

For this dissertation project I used EHRs from the two largest health care providers in Denver County – Kaiser Permanente of Colorado (KPCO) and Denver Health (DH). Together, the data contain health records for over 150,000 adults, comprising roughly one third of the Denver adult population as of 2015. The dataset, henceforth referred to as the DHKP data, included patients who had at least one encounter at a DH or KPCO facility (e.g., outpatient clinic) in 2014 or 2015. Public health researchers in Denver have also used these data sources (Beck 2017, Davidson et al. 2018, Schroeder et al. 2012, Steiner 2009).

EHR data are stored at Denver Health using a virtual data warehouse (VDW) in which data tables from each health system are stored using a standard structure. This allows for common variables, such as demographic or diagnosis data, to be easily merged across sites and analyzed together. Data are stored in separate tables, including encounter data, demographic data, diagnosis codes, and pharmacy records. Table 2-1 provides the data tables and variables that I used for this dissertation.

Table 2-1. Virtual Data Warehouse (VDW) data tables and variables used in the analysis and their applications for the study

Data Table	Variables	Application
Census_Location	Person_ID Location_Start Location_End Geocode	To identify census tract and neighborhood of residence and proxies for duration at residence and in tract/neighborhood
Demographics	Person_ID Birth_Date Gender Primary_Language Needs_Interpreter Race1-Race5 Hispanic	To generate patient age, gender, race/ethnicity, and whether they are a primary Spanish speaker
Diagnosis	Person_ID Adate DX	To identify formal diagnoses related to diabetes, hypertension, pregnancy, depression, and comorbidities
Encounters	Person_ID Adate EncType Encounter_Subtype Department	To identify all patients with ambulatory visits at outpatient clinics in 2014/2015 for inclusion in study sample
Enrollment	Person_ID adate enr_end prim_pyr_cd reserve_ar_rollup ins_medicaid ins_commercial ins_privatepay ins_statesubsidized ins_selffunded ins_medicare ns_other plan_hmo plan_indemnity outside_utilization	To determine type of insurance used to make health care payments
Ever NDC	NDC Generic Brand	To link to pharmacy table for specific medication descriptions
Lab_Results	Person_ID Test_TYPE LOINC Result_c	To identify labs for diabetes and hypertension prevalence estimates
Pharmacy	Person_ID RXDate NDC	To identify patients taking medications for diabetes and hypertension in order to calculate prevalence estimates
Procedures	Person_ID Adate Px	Pregnancy-related procedures to identify pregnant women
Social_History	Person_ID Contact_Date Tobacco_used_years Smoking_quit_date ONC_Smoking_Status Tobacco_user	To calculate smoking status
Vital_Signs	Person_ID Measure_Date Ht Wt Diastolic Systolic	To identify patients with height and weight as inclusion criteria in study sample; to calculate obesity prevalence, to identify patients with hypertension who may not have been formally diagnosed

Data Access

I accessed and analyzed all EHR data at Denver Public Health through the secure DH network system. To access the data, I completed volunteer onboarding, which requires five hours of in-person and online training, and yearly compliance training. Once established in the DH system, I received an intern badge for access to the Denver Public Health building, a DH email, and a DH login to use a computer at Denver Public Health.

DH and KPCO have a data use agreement that allows them to share their EHR data. KPCO updates its data in VDW on a quarterly basis, and DH updates its data daily. The current data use agreement between the organizations stipulates that data can be used for public health surveillance, and representatives from DH and KPCO who oversaw my project determined that this dissertation project fits under the purview of an existing public health surveillance project called the Colorado Health Observation Regional Data Service (CHORDS). I conducted all data management in SAS, the approved program used by DH to conduct SQL queries of the VDW.

This dissertation project was part of the broader Colorado Health Observation Regional Data Service (CHORDS) public health surveillance project, which was designated by the Colorado Multiple Institutional Review Board (COMIRB) as not human subjects research (see Appendix Figure A2-1 for designation letter). This project was also designated by COMIRB as not human subjects research (see Appendix Figure A2-2 for designation letter).

Coverage

The DHKP EHR data were from patients who sought care, and were not necessarily representative of the entire Denver resident population. In Table 2-2 I examine the average percent coverage in census tracts of DHKP data for key demographic groups compared to the 2011-2015 5-year American Community Survey (ACS) estimates by race and gender. I only include tracts that have at least 10 residents of the particular race/ethnicity/gender group. For example, if a tract had fewer than 10 NHB women in the ACS, I did not include coverage for that tract because it would likely be either a very large or very small number and could skew the overall coverage results even though very few NHB women were in that tract.

The first two columns compare the composition of the DHKP data to the composition of adults in Denver, by race/ethnicity and gender. DHKP EHRs that I used in this study had a higher percentage of Hispanics than the ACS estimates for the total adult population in Denver, and this difference was due to a much higher percent of Hispanic women in DHKP EHRs. The percent of Hispanic men were similar between DHKP and the ACS estimates. The DHKP data also had a higher percentage of NHB patients than the percent in the Denver population as whole, and this was also because of a higher percentage of NHB women in DHKP. The DHKP data had fewer NHWs than the ACS estimates for Denver, and this was due primarily to fewer white men in the DHKP data. DHKP data also had fewer patients of other race/ethnicity compared to ACS estimates for Denver, and this was due to fewer women and men of other race/ethnicity in DHKP.

On average, DHKP EHR data covered 44% of Hispanic residents across 141 census tracts. As is true for all groups, there was a huge amount of variation by tract. For Hispanics, coverage ranged from 5% to 163%, with the latter indicating that there were more Hispanic patients in the DHKP dataset than were recorded living in the tract by the ACS. There are a few possible reasons why coverage would be greater than 100%. First, ACS 5-year population estimates may be inaccurate. They were averaged over a five-year period, and during which

Denver was growing quickly, likely undercounting the population. Additionally, ACS estimates often have large margins of error for census tracts and population subgroups because of limited sampling at those geographic/population levels. Second, data entry errors or cross-institution access may duplicate patients in the DHKP data. If patient data were incorrectly entered (i.e., a slightly different name or birth date was entered), a single patient may be represented as multiple patients. It is also possible that patients were seen in both DH and KPCO systems within the 2014/2015 period. Although unlikely to affect many patients, it would indicate a shift in health care coverage and could inflate aggregate DHKP data. For tracts with fewer residents of a particular race/gender subgroup, duplicates could substantially affect proportional coverage estimates.

DHKP coverage was better for Hispanic women (61% on average) compared to Hispanic men (34%), and both groups had the same standard deviation (68% of tracts fall within ±29% coverage of the respective estimates).

DHKP coverage was lower for non-Hispanic whites (NHWs) than for Hispanics and non-Hispanic blacks (NHBs). On average, DHKP covered 30% of NHW patients across all tracts. Because NHWs were the largest racial group in the city, the standard deviation was smaller overall (±14%). Coverage was better, on average, for NHW women (37%) than for NHW men (25%). This likely reflected the fact that NHW residents were more likely to have other types of health insurance such as Medicare, which permitted access to other healthcare providers.

DHKP coverage was higher for NHB residents. On average, the data covered 52% of the NHB population, with 63% coverage on average for NHB women and 40% coverage on average for NHB men. Similar to other race/gender groups, there was huge variation of proportional coverage, and the extremes (very low and very high coverage) were concentrated in tracts with few NHB residents (see Figures 2.12 and 2.14).

DHKP coverage was lowest for other race/ethnic groups (i.e., American Indian or Alaskan Native, Native Hawaiian or other Pacific Islander, Asian, mixed race, or other race). On average, DHKP covered just 18% of these other race/ethnic groups, and only 14% of men in this category.

The inter-quartile range (IQR) shows the range of the middle 50% of the distribution is an important indicator of variation in percent coverage because it is less sensitive than means, standard deviations, and ranges to the outlier tracts that have very high or very low coverage. The IQR for the total population was 12%, and the groups that deviated most from this are Hispanic women (IQR=34%), NHB men (IQR=27%) and NHB women (IQR=39%). Thus, although DHKP EHRs has high coverage for the abovementioned groups, there is wide variation in the percent of these residents who are covered across census tracts in Denver.

Table 2-2. Percent coverage of DHKP data for adults living in Denver, Colorado who have had any medical visit in 2014-2015 compared to ACS 2011-2015 5-year estimates

	Percent in DHKP	Percent in ACS	Average coverage across tracts	Std. Dev.	IQR	Min	Max	# of Tracts*
Total (N)	**151,027**	**473,270**	**32%**	**10%**	**12%**	**9%**	**109%**	**143**
Hispanic Total	**33%**	**23%**	**44%**	**18%**	**18%**	**5%**	**163%**	**141**
Hispanic Men	11%	12%	34%	29%	17%	3%	286%	141
Hispanic Women	21%	11%	61%	29%	34%	8%	194%	141
White Total	**45%**	**57%**	**30%**	**14%**	**13%**	**10%**	**124%**	**143**
White Men	19%	29%	25%	11%	10%	9%	107%	143
White Women	26%	28%	37%	22%	15%	10%	215%	143
Black Total	**13%**	**8%**	**52%**	**38%**	**27%**	**10%**	**257%**	**127**
Black Men	5%	4%	40%	27%	27%	7%	148%	122
Black Women	8%	4%	63%	39%	38%	3%	248%	120
Other Race Total	**5%**	**11%**	**18%**	**11%**	**11%**	**3%**	**70%**	**142**
Other Race Men	2%	6%	14%	10%	11%	1%	52%	140
Other Race Women	3%	6%	22%	16%	13%	3%	117%	142

*Tracts only included if there were greater than 10 residents of that race/gender reported by ACS in the tract

Figures 2-1 – 2-26 show how coverage varied for each race/gender subgroup across Denver census tracts, and the relationship between density of the subgroup and proportional coverage. For the coverage maps, blue census tracts represent places where DHKP coverage was 10% or less. Green shades represent between 11-99% coverage. Red census tracts represent places where DHKP coverage was greater than 100%.

Even among the least covered groups, the average overall coverage of DHKP patients for the Denver area was very relatively high. In general, coverage was positively related to population density, with higher coverage in places where there were more residents of a specific race/ethnicity or gender (this is represented in the density scatterplots [Figures 2-1-2-26]). Although patient selection was not random, one of the strengths of the DHKP data was its ability to cover a large number of residents of many race/gender groups. This and other strengths and limitations are discussed in the next section.

Figure 2-1. DHKP coverage of Denver census tracts for all patients ages 25-84 with a 2014/2015 outpatient visit compared to American Community Survey (ACS) 2011-2015 population estimates

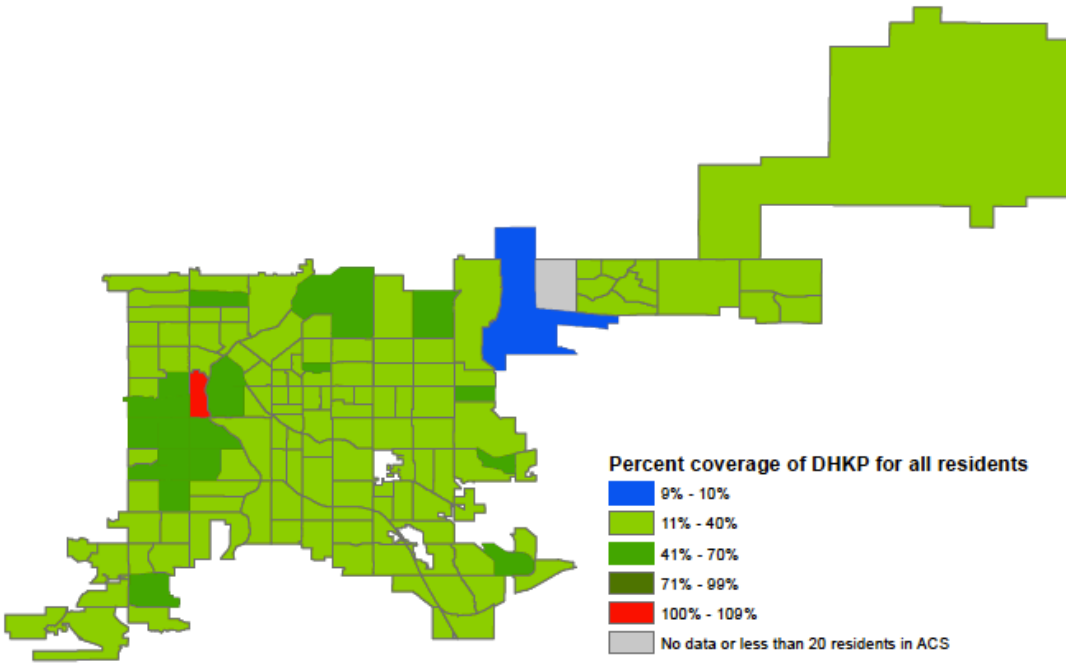


Figure 2.2 DHKP Coverage of All Denver Residents 25-84, 2014-2015

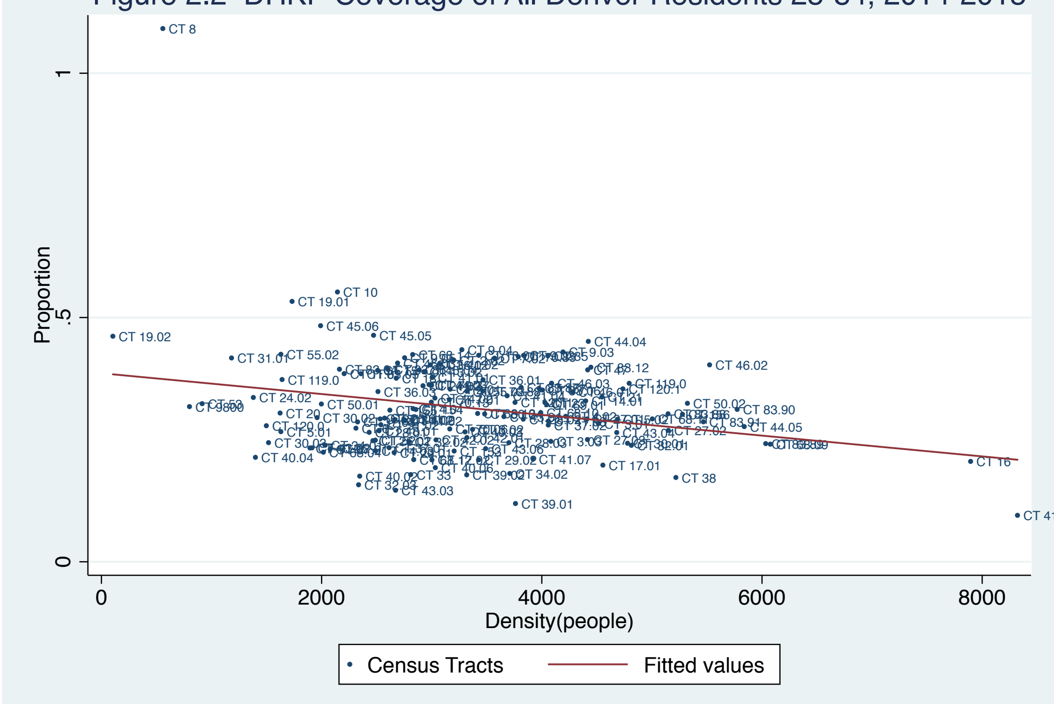


Figure 2-3. DHKP coverage of Denver census tracts for Hispanic patients ages 25-84 with a 2014/2015 outpatient visit compared to American Community Survey (ACS) 2011-2015 population estimates

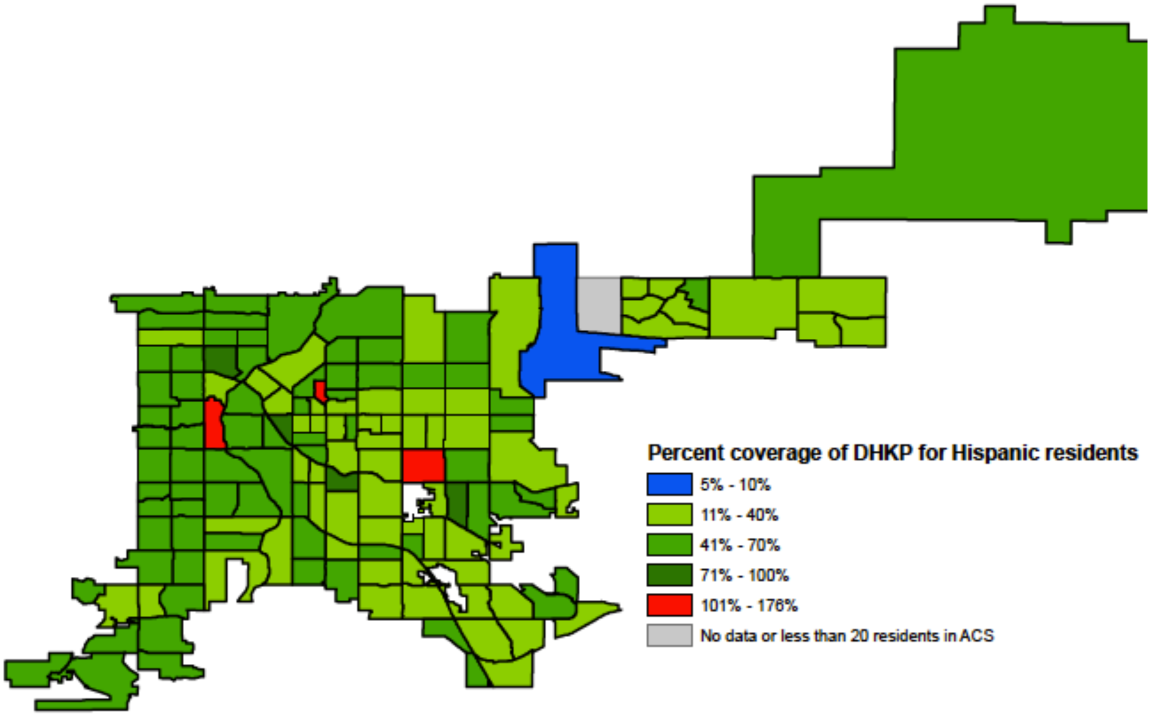


Figure 2.4 DHKP Coverage of All Hispanic Residents 25-84, 2014-2015

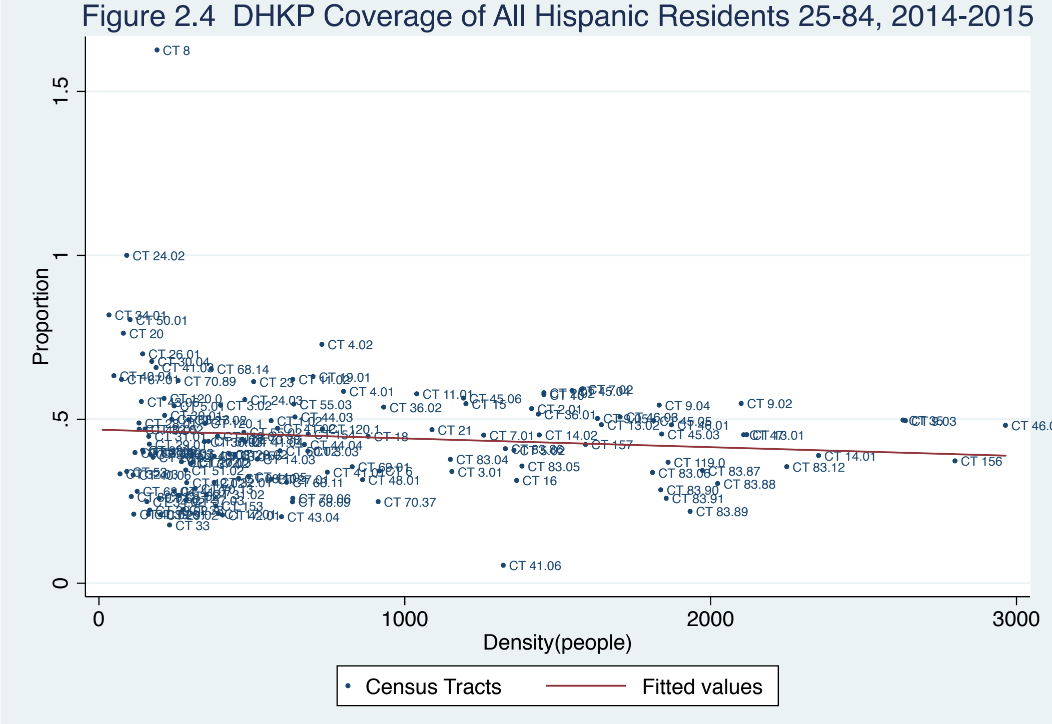
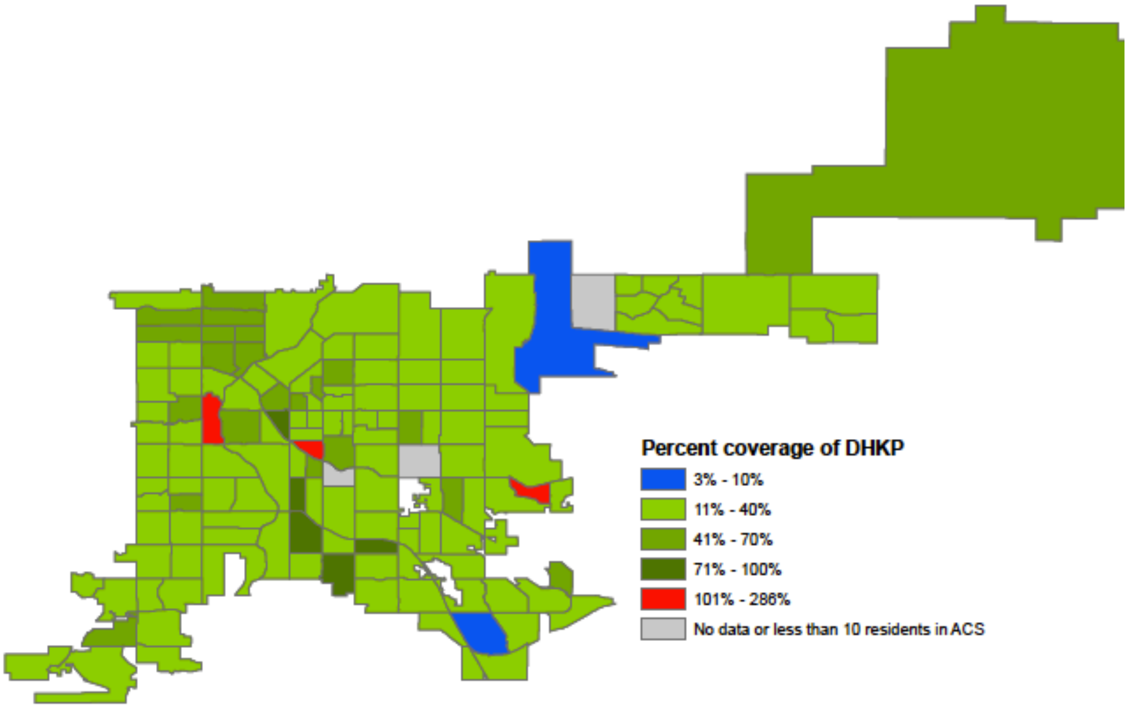


Figure 2-5. DHKP coverage of Denver census tracts for Hispanic men ages 25-84 with a 2014/2015 outpatient visit compared to American Community Survey (ACS) 2011-2015 population estimates



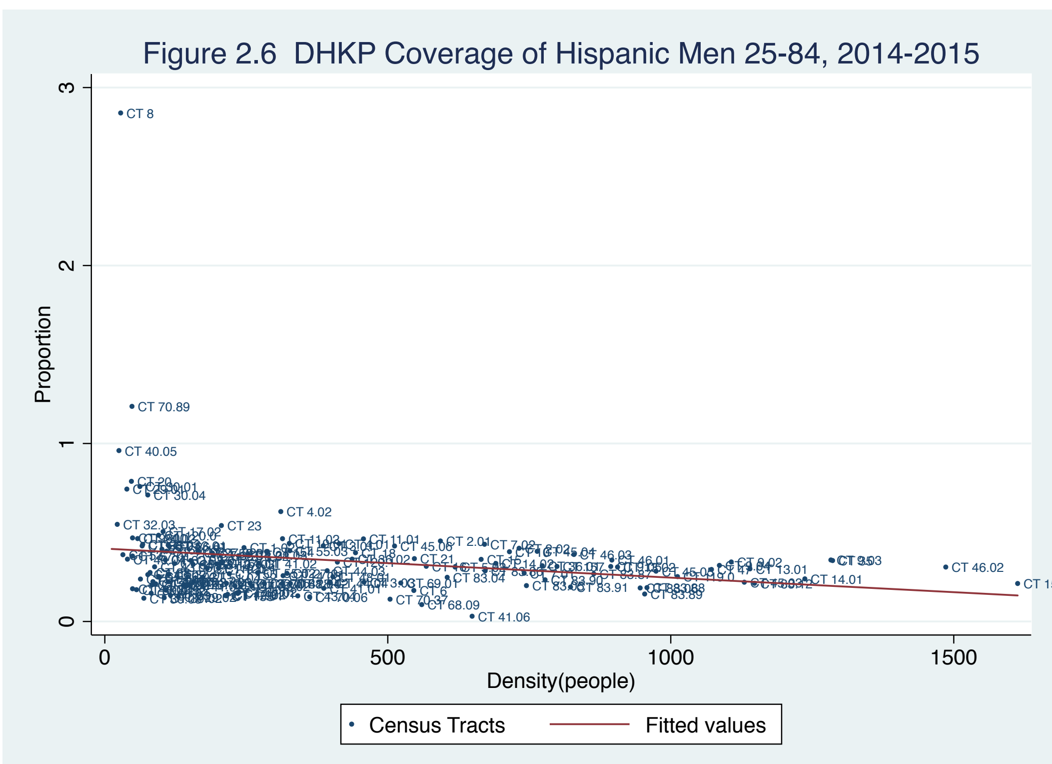
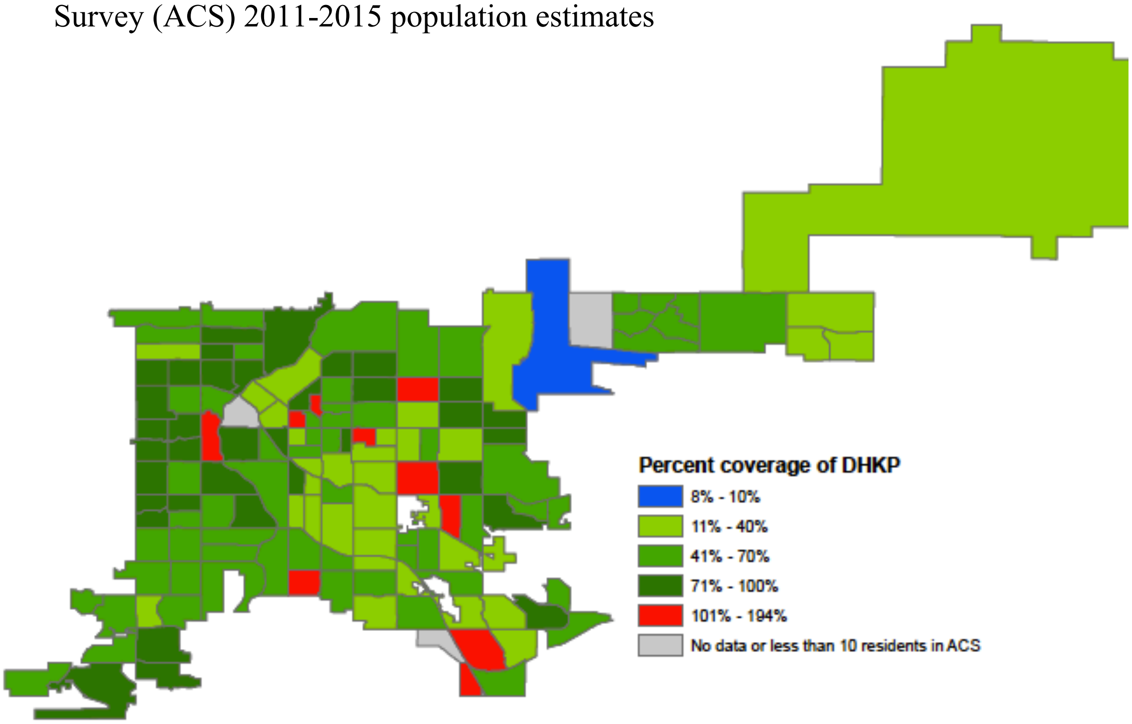


Figure 2-7. DHKP coverage of Denver census tracts for Hispanic women ages 25-84 with a 2014/2015 outpatient visit compared to American Community Survey (ACS) 2011-2015 population estimates



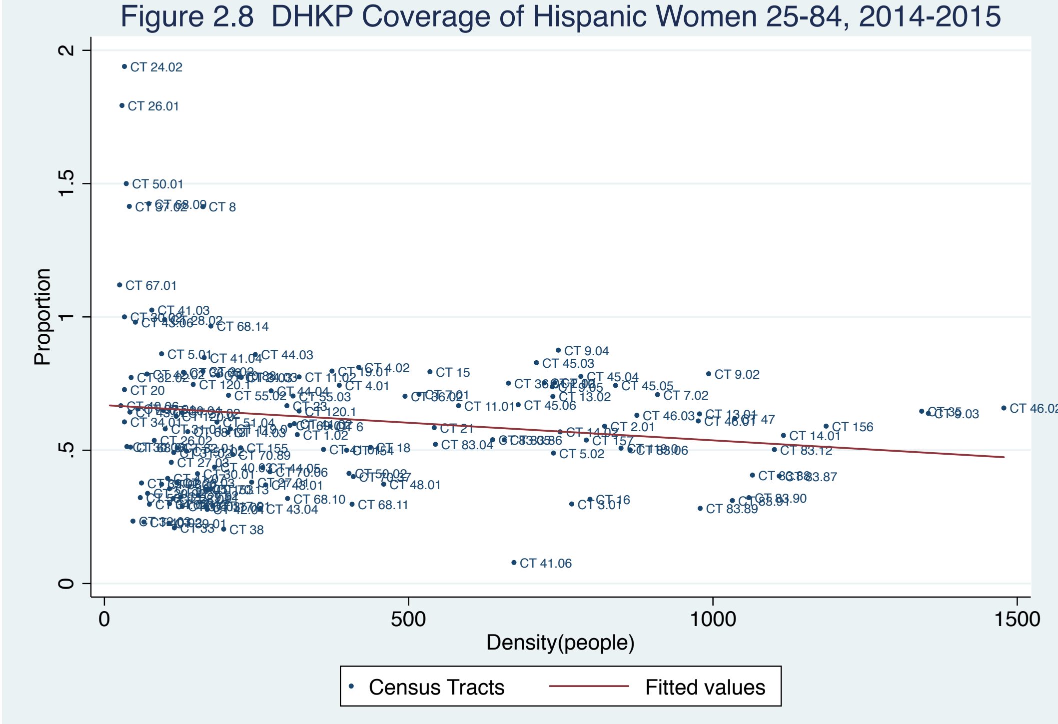
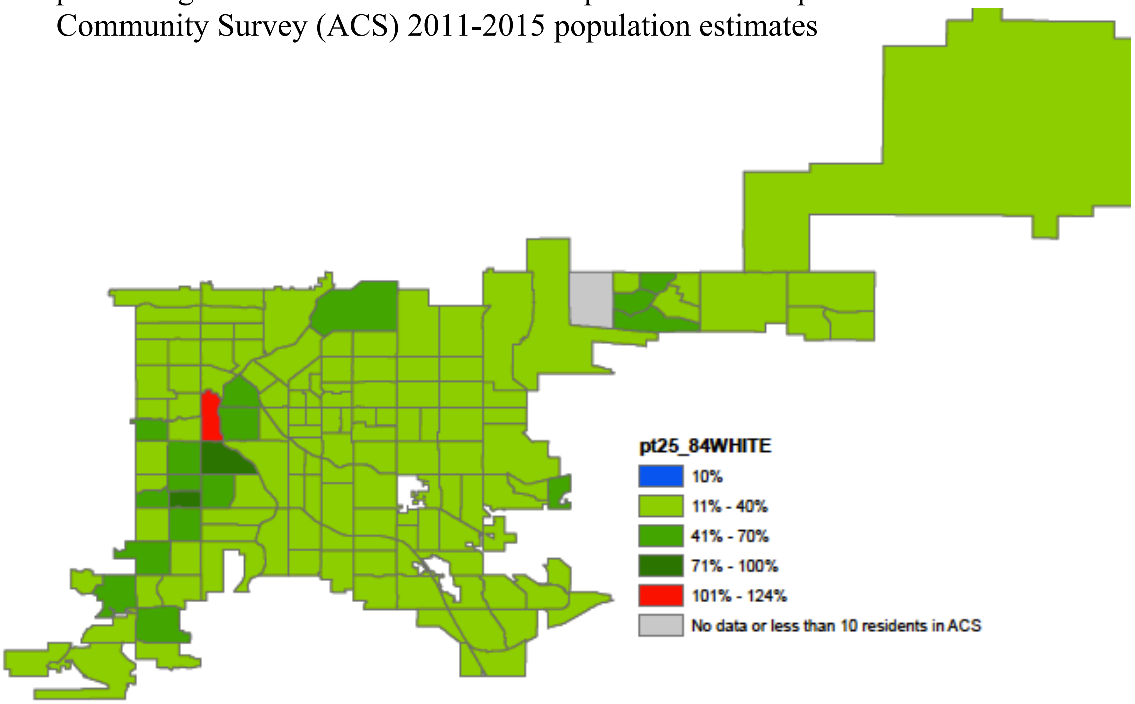


Figure 2.8 DHKP Coverage of Hispanic Women 25-84, 2014-2015

Figure 2-9. DHKP coverage of Denver census tracts for non-Hispanic white patients ages 25-84 with a 2014/2015 outpatient visit compared to American Community Survey (ACS) 2011-2015 population estimates



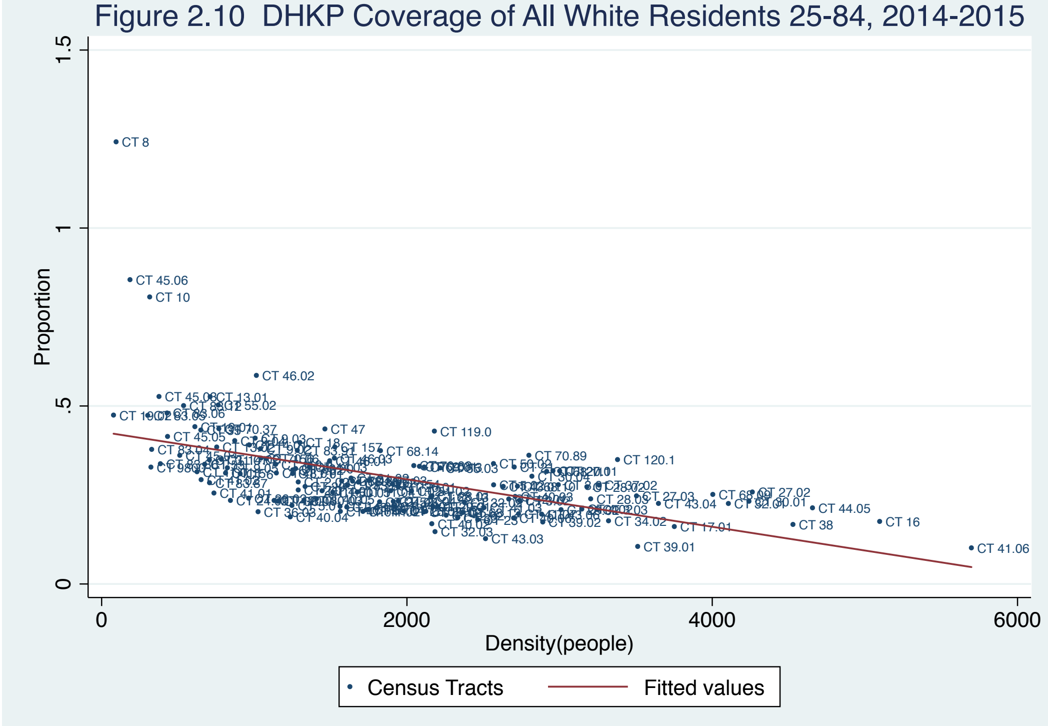


Figure 2.10 DHKP Coverage of All White Residents 25-84, 2014-2015

Figure 2-11. DHKP coverage of Denver census tracts for non-Hispanic white men ages 25-84 with a 2014/2015 outpatient visit compared to American Community Survey (ACS) 2011-2015 population estimates

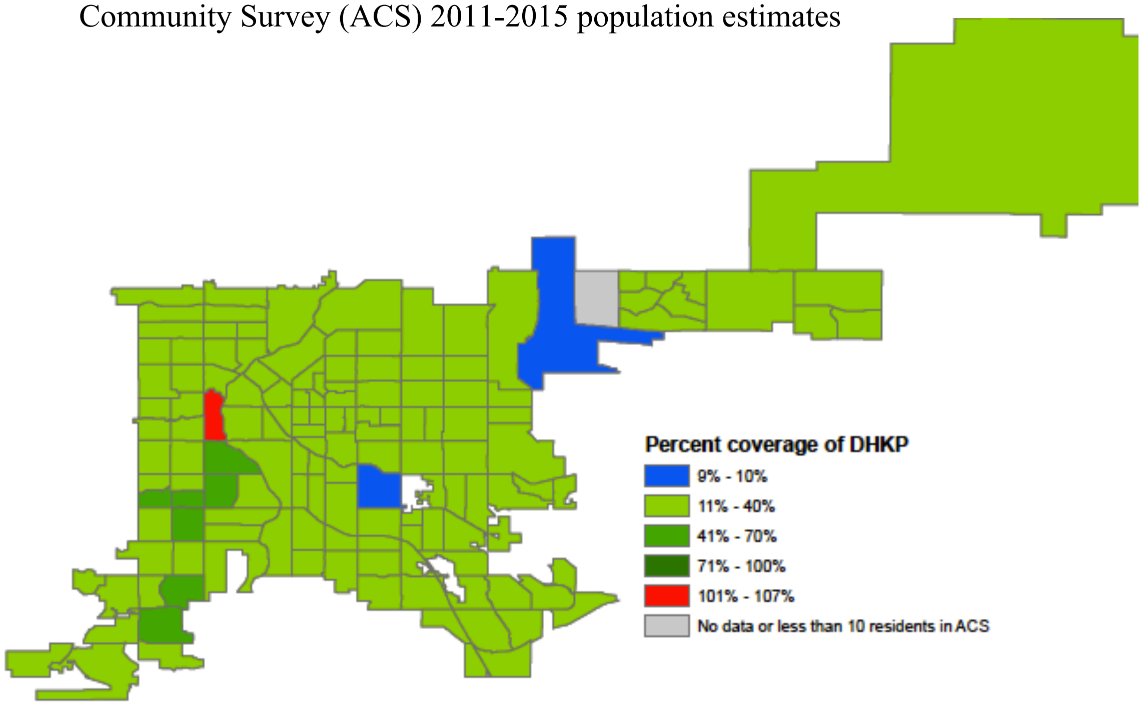


Figure 2.12 DHKP Coverage of White Men 25-84, 2014-2015

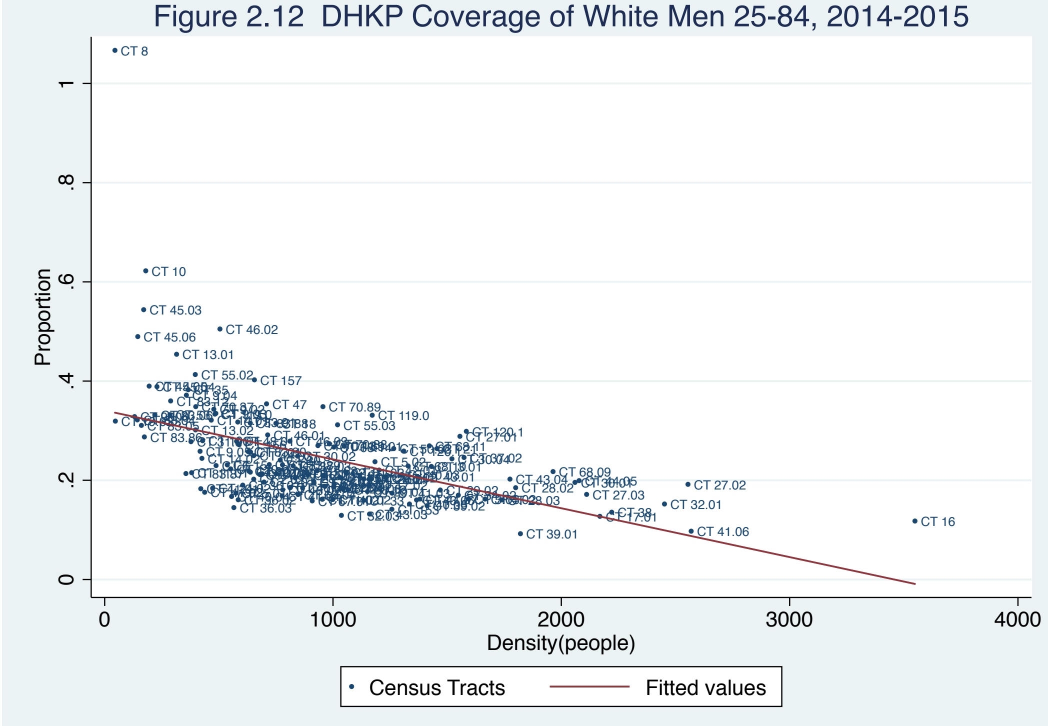


Figure 2-13. DHKP coverage of Denver census tracts for non-Hispanic white women ages 25-84 with a 2014/2015 outpatient visit compared to American Community Survey (ACS) 2011-2015 population estimates

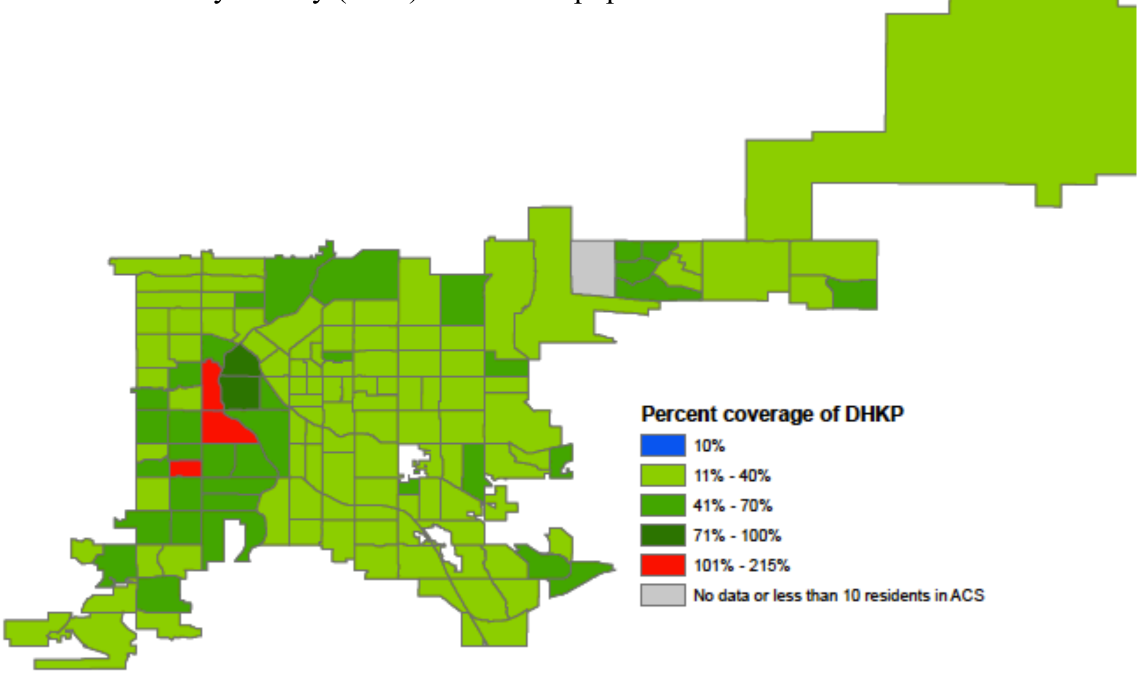


Figure 2.14 DHKP Coverage of White Women 25-84, 2014-2015

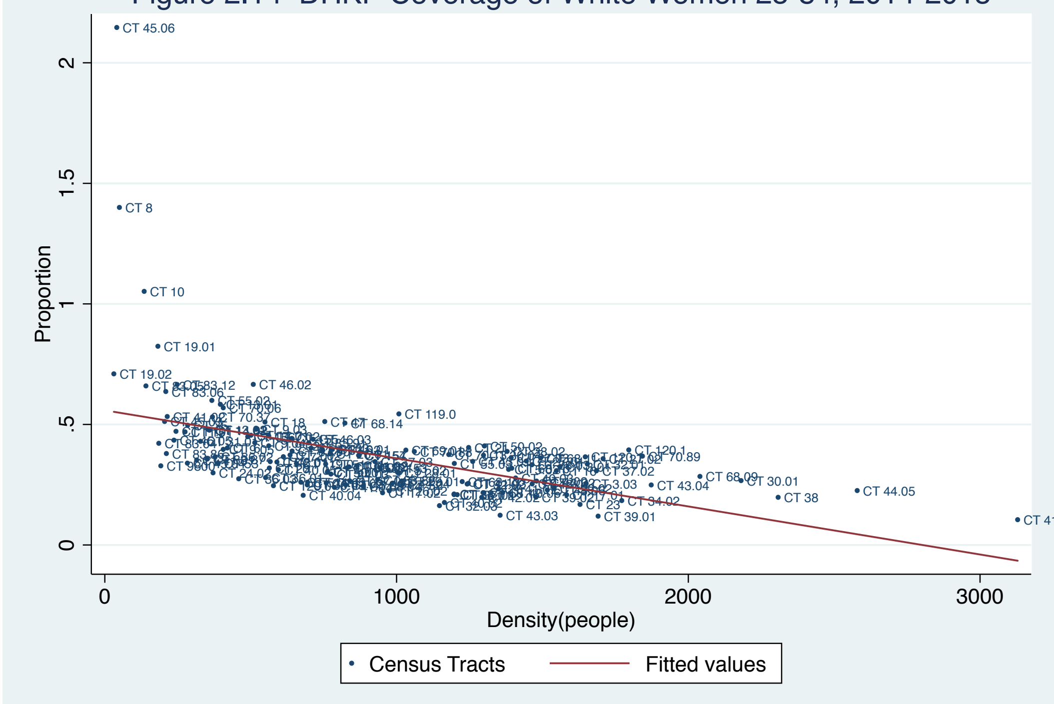
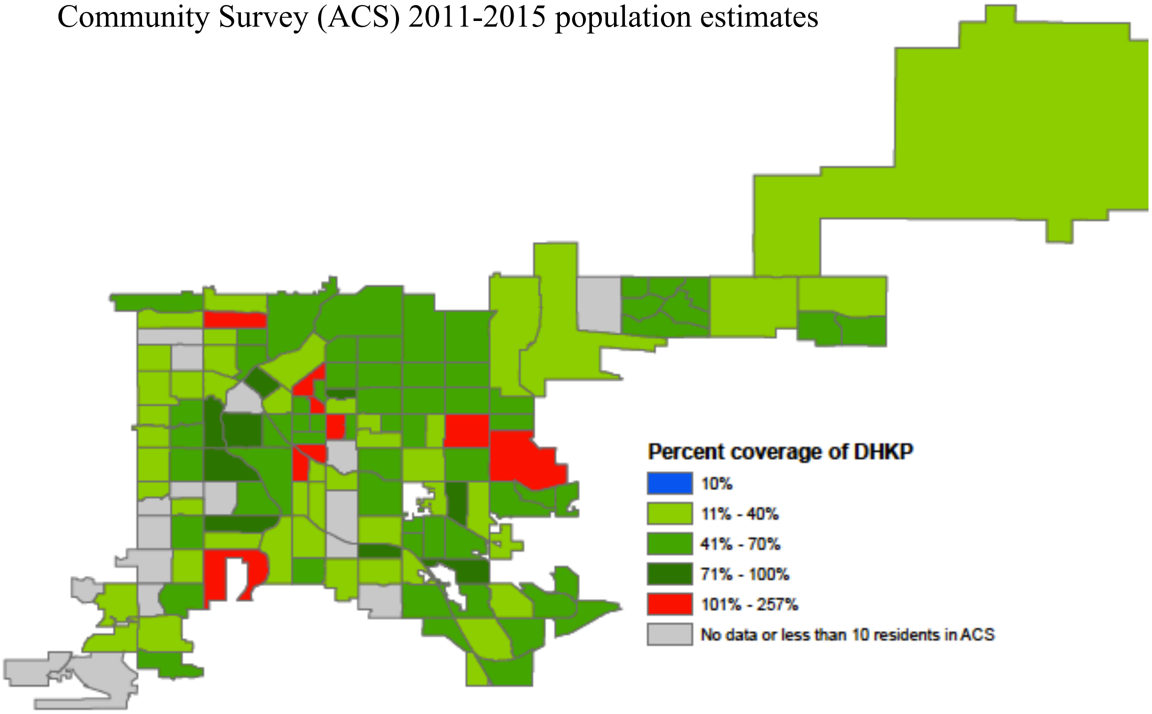


Figure 2-15. DHKP coverage of Denver census tracts for non-Hispanic black patients ages 25-84 with a 2014/2015 outpatient visit compared to American Community Survey (ACS) 2011-2015 population estimates



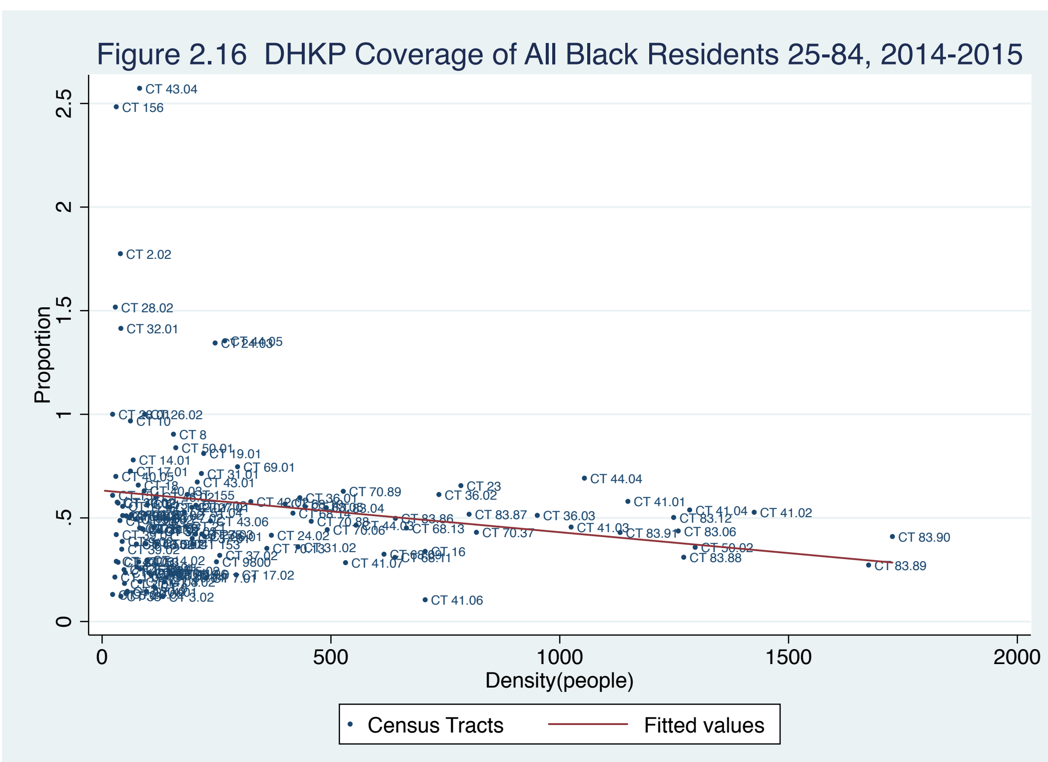
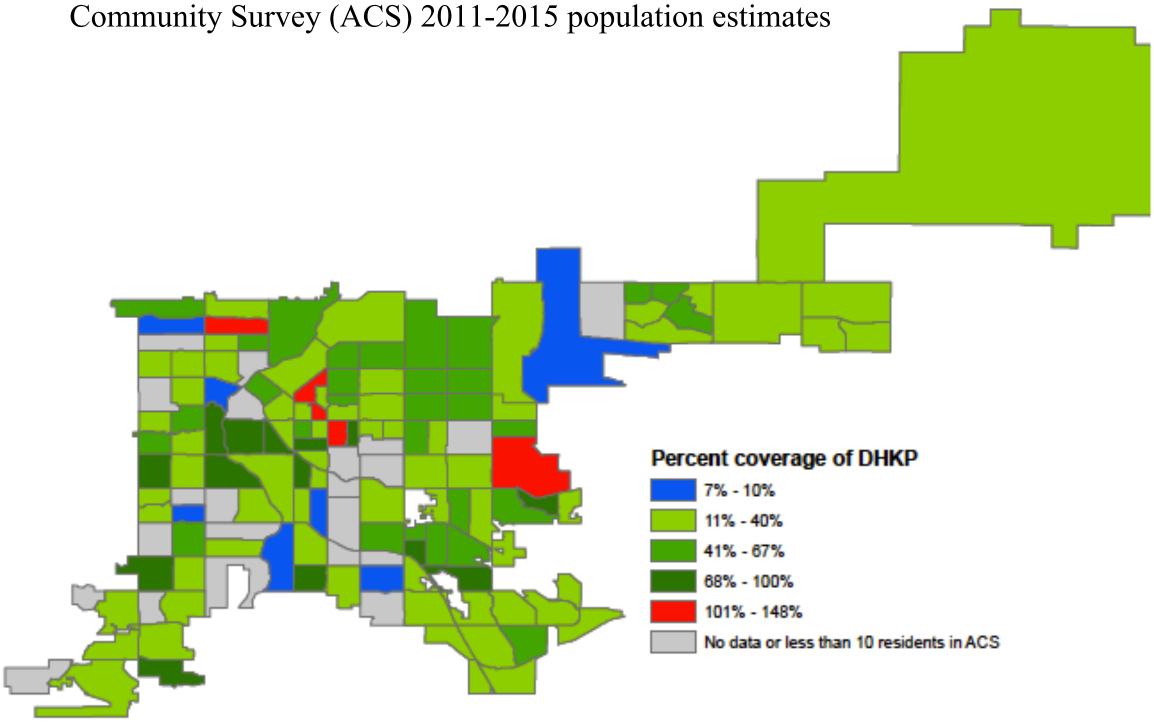


Figure 2.16 DHKP Coverage of All Black Residents 25-84, 2014-2015

Figure 2-17. DHKP coverage of Denver census tracts for non-Hispanic black men ages 25-84 with a 2014/2015 outpatient visit compared to American Community Survey (ACS) 2011-2015 population estimates



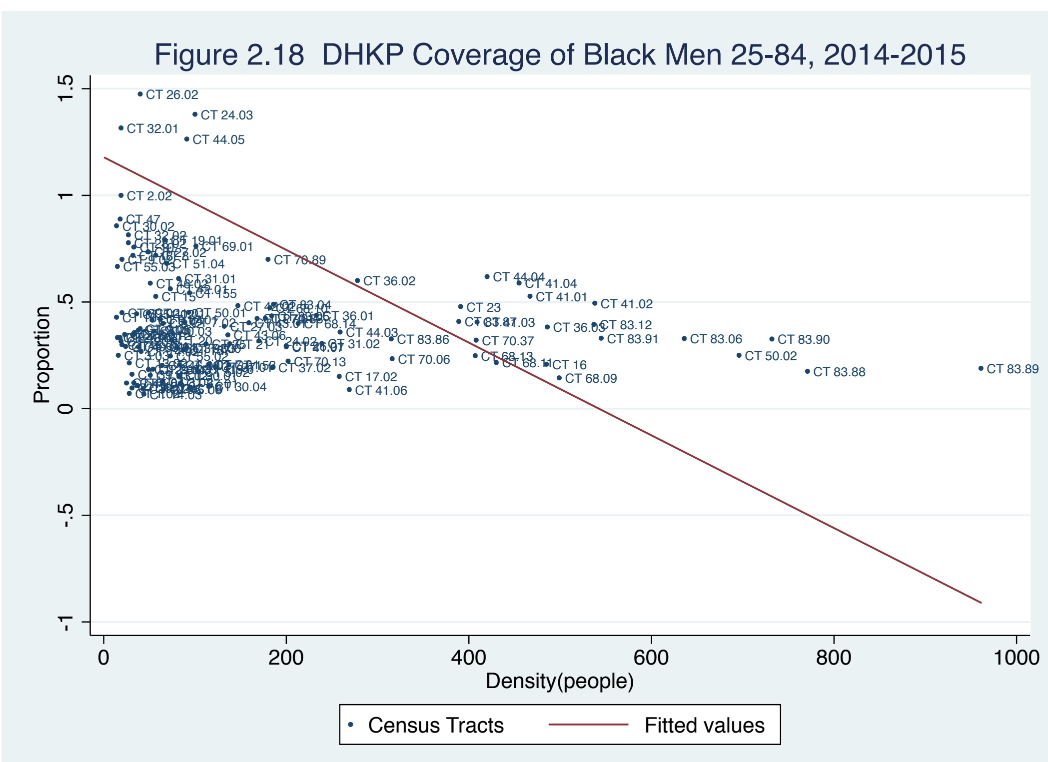
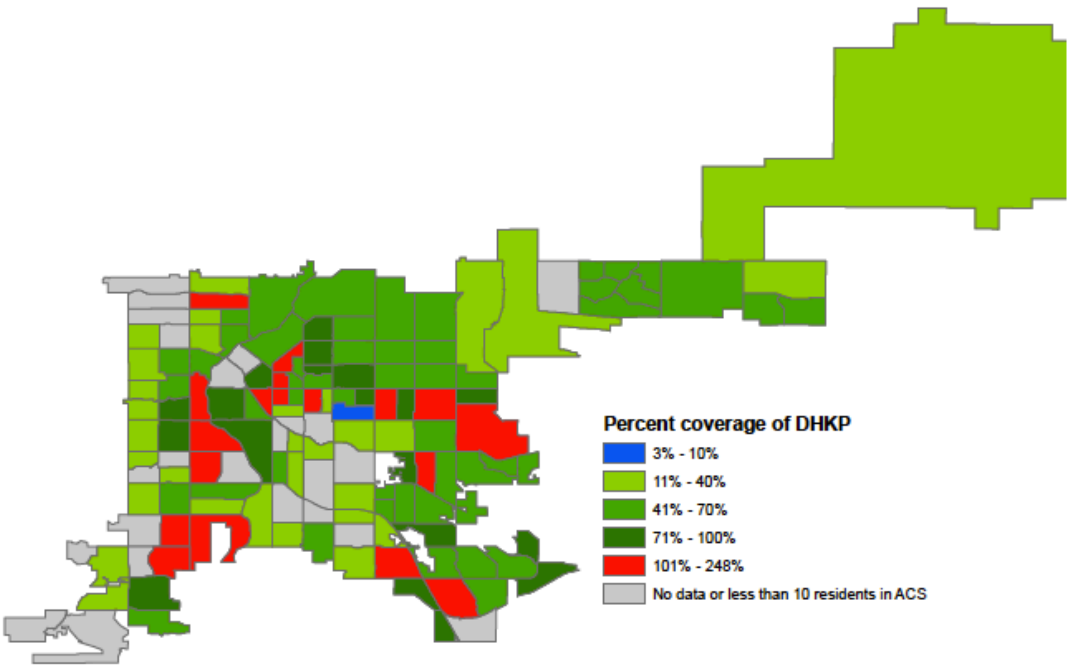


Figure 2-19. DHKP coverage of Denver census tracts for non-Hispanic black women ages 25-84 with a 2014/2015 outpatient visit compared to American Community Survey (ACS) 2011-2015 population estimates



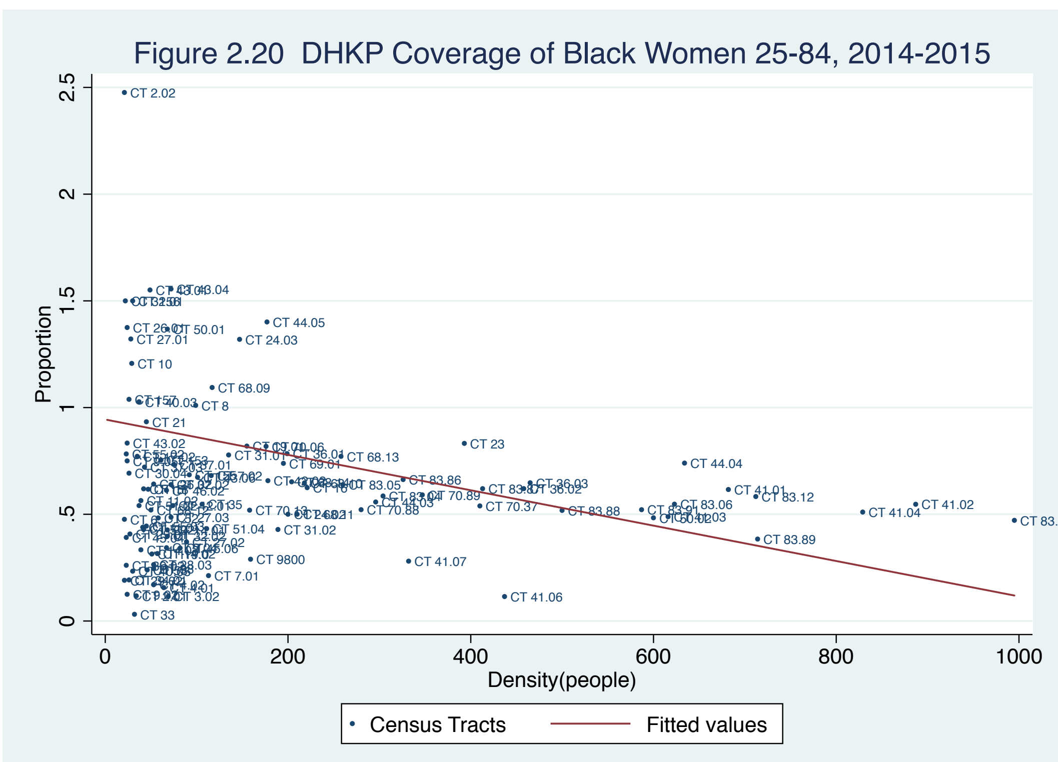


Figure 2.20 DHKP Coverage of Black Women 25-84, 2014-2015

Figure 2-21. DHKP coverage of Denver census tracts for non-Hispanic patients of some other race ages 25-84 with a 2014/2015 outpatient visit compared to American Community Survey (ACS) 2011-2015 population estimates

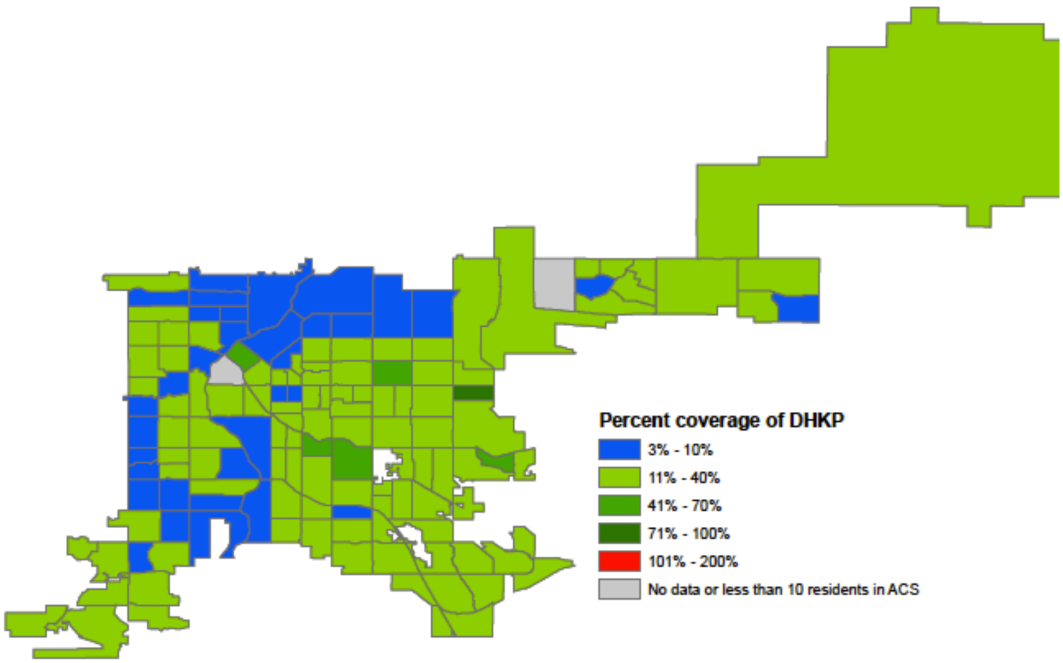


Figure 2.22 DHKP Coverage of All Other Race Residents 25-84, 2014-2015

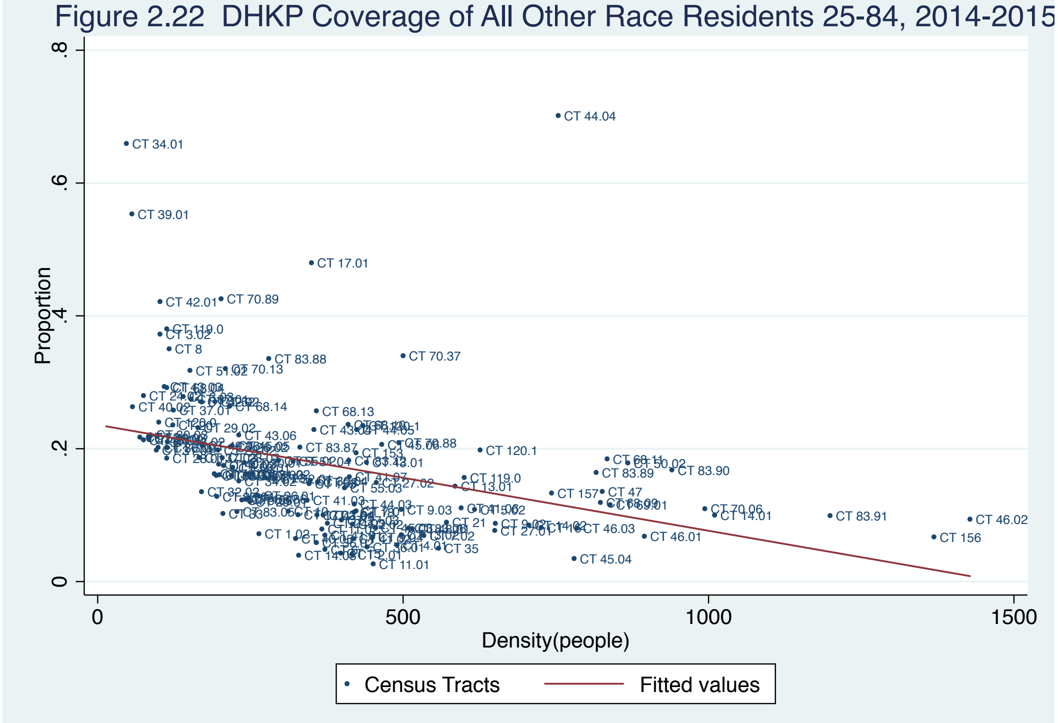
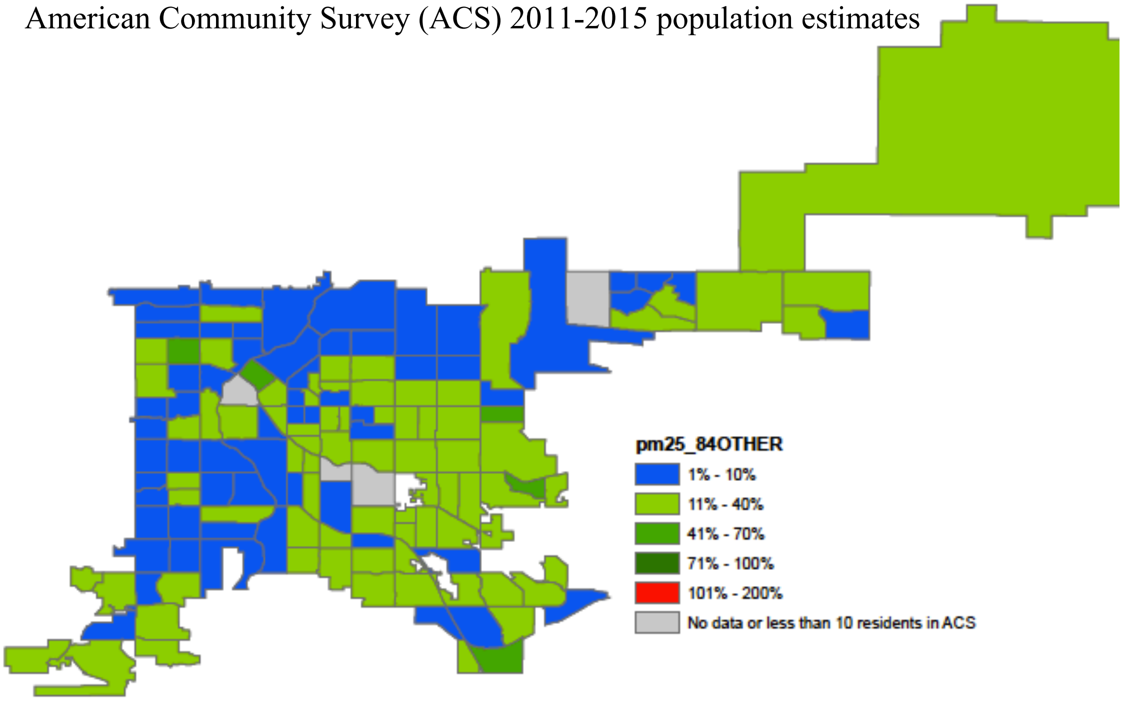


Figure 2-23. DHKP coverage of Denver census tracts for non-Hispanic men of some other race ages 25-84 with a 2014/2015 outpatient visit compared to American Community Survey (ACS) 2011-2015 population estimates



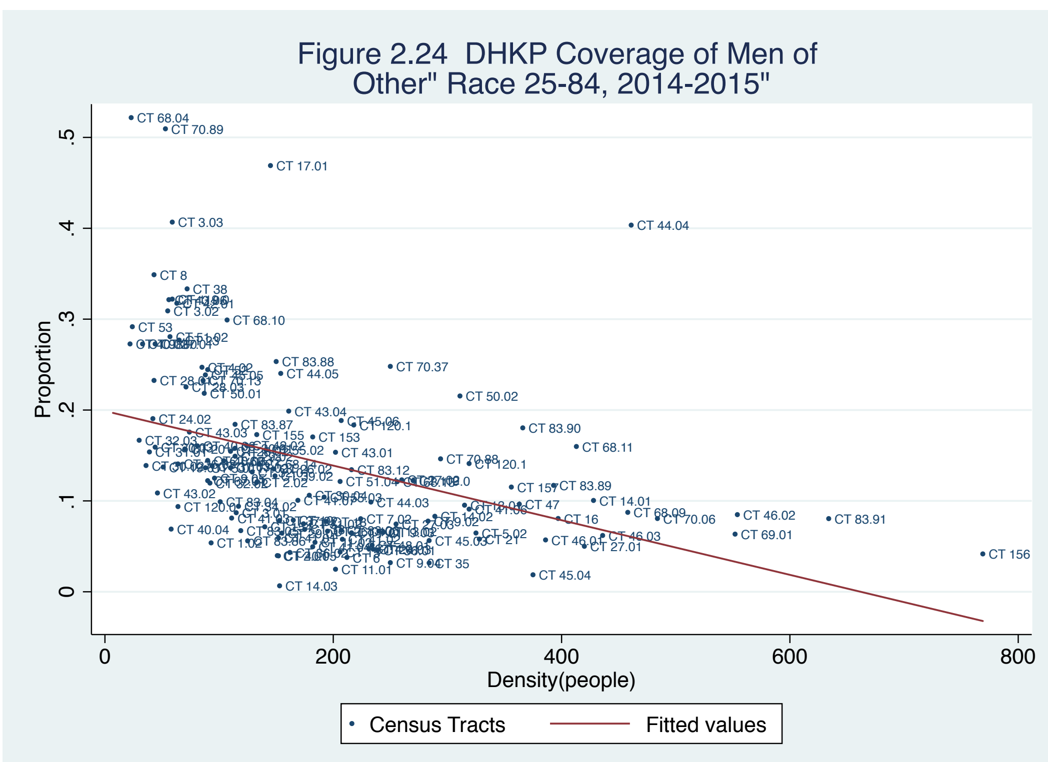


Figure 2-25. DHKP coverage of Denver census tracts for non-Hispanic women of some other race ages 25-84 with a 2014/2015 outpatient visit compared to American Community Survey (ACS) 2011-2015 population estimates

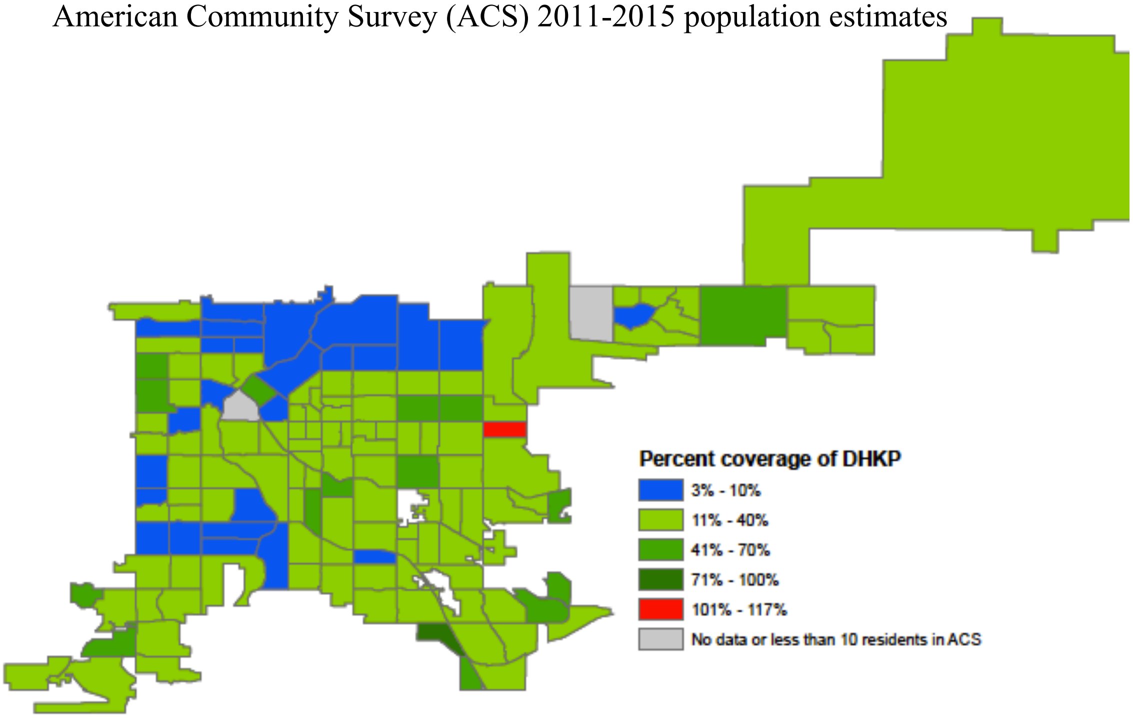
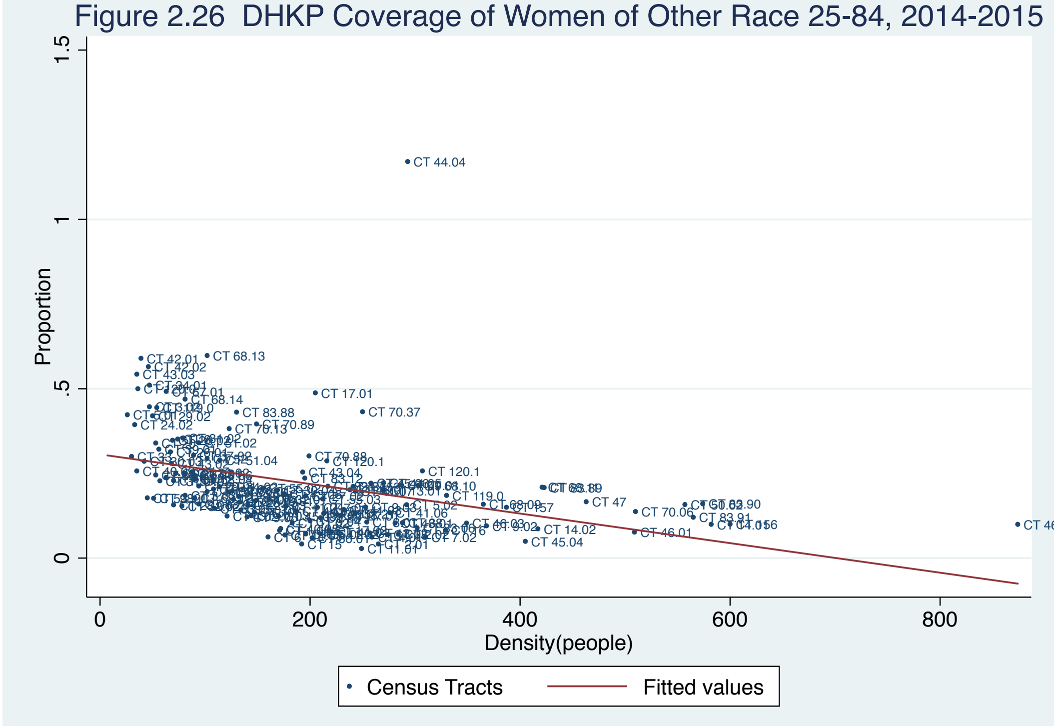


Figure 2.26 DHKP Coverage of Women of Other Race 25-84, 2014-2015



Data Strengths & Limitations

The DHKP data provide a valuable resource to answer my research questions, but also have limitations worth noting. Below are the primary strengths and limitations of the DHKP data.

Strengths:

- The EHRs used in this study contain health data for a large proportion of the Denver population, which provides statistical power for more nuanced and stratified analyses
- Data were available at the census tract level, allowing for neighborhood analyses that are not possible with some observational data
- The EHR data has clinical measures of chronic conditions, and does not rely on self-reported diagnosis, which can be particularly problematic for individuals who are not aware of having a chronic condition.

Limitations:

- Data from KPCO and DH represented a convenience sample of patients, not a representative sample of the Denver population. As described in more detail later in the proposal, each chapter includes analyses to examine the robustness of results.
- EHR data were not designed explicitly for use in population health research. DH and KPCO collected data in unique ways, and results must be examined for these organizations separately and together to identify whether these differences in data collection and variable expression may have impacted or biased the interpretation of results.
- Results cannot be generalized beyond patients in these health organizations in Denver, Colorado.

Despite these limitations, the opportunities presented by using EHR data to answer the research questions in this study outweighed the challenges in using the data and represent a growing area of population health research opportunities (Casey et al. 2016).

Study Cohort

Visits

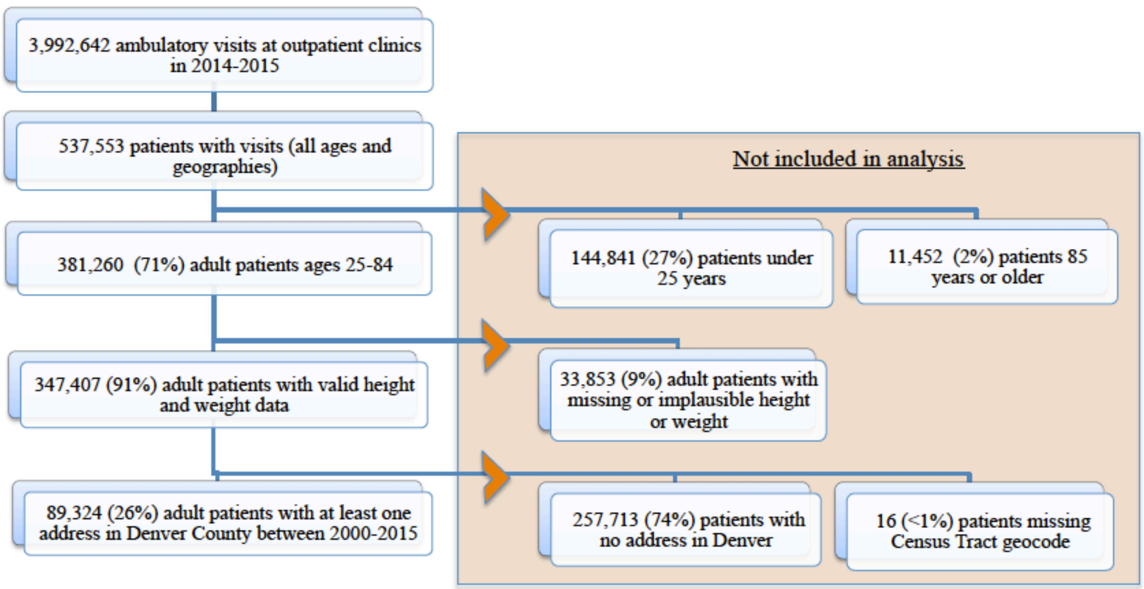
Patients from Denver Health (DH) and Kaiser Permanente of Colorado (KPCO) were included in the sample if they had an ambulatory visit at an outpatient clinic in 2014 or 2015. These two years were selected because they were the most recent years for which researchers at DH were confident that the data were comprehensive. Two years were selected to have a better chance of capturing a representative sample of the care-seeking population, as some patients are seen less often than every year. At the time of data management and analysis for this study, 2016 DH data were still being loaded into the virtual data warehouse (VDW) and evaluated for accuracy. Because Census data were used to define neighborhood characteristics, another strategy considered was to use 2010/2011 visit data so that it could line up with 2010 Census population counts, which would be more accurate than American Community Survey (ACS) estimates for the later dates. However, researchers from DH and KPCO believed that 2014 and 2015 patient data would be more accurate than 2010/2011 data, and this did appear to be the case. For example, in the KPCO 2010/2011 patient visit data, roughly 30% of the patients were missing height or weight data, whereas only roughly 9% of KPCO patients were missing height and weight data in the 2014/2015 patient visit data. This was in part due to the development of better data management systems for both organizations and requirements under the Affordable Care Act "Meaningful Use" criteria to collect more patient demographic data (for example, race/ethnicity) (Blumenthal and Tavenner 2010). Furthermore, using 2014/2015 data created an opportunity for study results to be more actionable; if more recent data were used, clearer implications would be inferred and dissemination of results may be more useful. This is particularly relevant for a study site like Denver because its population has grown and changed dramatically over the past five years. Denver was the 42nd fastest growing county between 2010-2015, with an increase in over 82,000 residents (13.8% growth) (U.S. Census Bureau 2016).

Although having a visit in 2014/2015 was required for inclusion in the dataset, once included, all of the patient's health records were reviewed to identify whether patients had specific health conditions. For Denver Health, EHR data date back to 2005. For KPCO, EHR data date back to 2000.

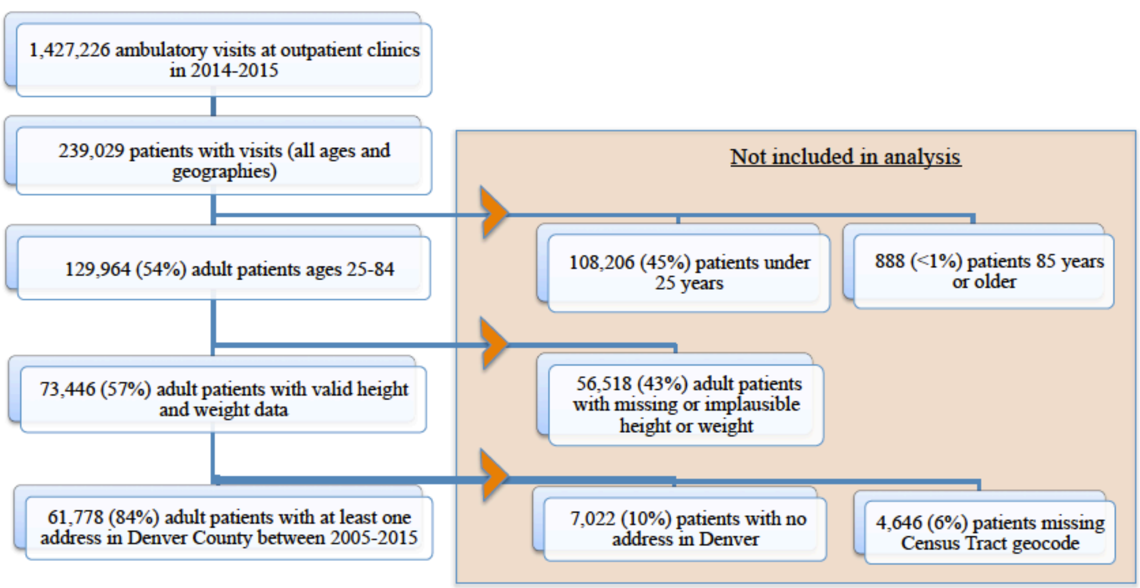
The dataset for analysis was limited to patients with an ambulatory visit at an outpatient clinic because their clinical measurements were less likely to be skewed by a severe physical event (e.g., extremely high blood pressure after a gunshot wound in the emergency room). Selecting patients with ambulatory visits for outpatient care required a two-step process. First, the patient encounter table was queried for any encounter type listed as 'AV' (ambulatory visit). There are a variety of encounter subtypes for ambulatory visits (e.g., same day surgeries, urgent care visits), so in addition to an 'AV' encounter type, a record must also have been an outpatient clinic 'OC' encounter subtype. Figure 2-27 summarizes the number of ambulatory visits at outpatient clinics for encounters in 2014/2015 by health care provider.

Figure 2-27. Cohort inclusion and exclusion criteria for Denver Health and Kaiser Permanente of Colorado 2014/2015 Patient Visits

Kaiser Permanente of Colorado 2014-2015 Patient Cohort



Denver Health 2014-2015 Patient Cohort



Age

Because the study focuses on neighborhood effects on cardiovascular disease (CVD) risk factors, only adults 25-84 were included in the analyses. Adults 18-25 were excluded because they were more likely to live with parents or in campus housing and less likely to have established their own residence. This may mean that they had less choice in selecting their place of residence or that they have only lived at that residence for a short period of time. Adults over the age of 84 were excluded from the analysis because of health selection at very old ages and small sample size. Patient age was calculated by subtracting the patient's birth date from the most recent visit date in 2014 or 2015 and dividing by 365.25. Figure 2.27 shows the number of adults excluded from the sample because of age, by health care provider.

Height and weight

Patients were only included in the sample if they had a recorded height or weight during any past visit. For patients with multiple height and weight measurements over time, the most recent records were retained. Although height and weight are standard measures taken at many types of visits, some ambulatory visits at outpatient clinics do not take height and weight measurements (e.g., dermatology or ophthalmology appointments). Height and weight data were used in most study analyses, combined to calculate either the dependent variable (obesity) or used as an independent variable (BMI) for other health outcomes. Therefore, patients with no height and weight, or whose weight was only recorded during a year when they were pregnant, were not included in the sample. Another reason why I excluded these patients was because of how they may impact prevalence estimates. In health surveys, all respondents are asked about whether they have had a specific condition, and those who replied "No" are in the denominator.

For EHRs, the denominator is comprised of all patients who had an encounter, but it is unclear whether they were tested for a specific condition. It is much more likely that patients were screened for common conditions (such as hypertension) if they had a height and weight in the system, because this indices that they were more likely to have had a routine encounter than, for example, an appointment with a specialist. This is supported in Table 2-3 by the fact that about three times as many patients were missing race/ethnicity data in addition to height or weight, compared to those who had height and weight data. The downside to this approach is that it is likely that younger and healthier patients would not have a height and weight in the system, would not be included in the denominator of prevalence estimates, and thus prevalence estimates may be inflated.

Table 2-3 describes height and weight exclusions for DH and KPCO by age, gender, and race. The age distribution of patients excluded because of missing height or weight data was similar between KPCO and DH, with a gradient of higher percent missing at the youngest ages and lower percent missing at the oldest ages. The gender distribution of percent missing was also similar across providers, with a higher percentage of male patients missing height or weight data compared to females. The majority (55%) of KPCO patients missing height or weight data were also missing racial/ethnic classification, compared to only 8% of DH patients. The majority (56%) of DH patients missing height or weight data were classified as non-Hispanic white. Compared to patients not reporting height and weight data, those missing data were younger, more likely to be male, and more likely to be NHW (particularly for DH) or missing race/ethnicity information.

Table 2-3. Patients with an encounter in 2014 or 2015 who have missing or implausible values for height and/or weight data compared to those without missing height or weight data by health care system and demographics

Panel A: Missing height and/or weight						
	Kaiser Permanemte of Colorado		Denver Health		Total	
	Column %	n	Column %	n	Column %	n
Total		1445		26637		28082
Age						
25-34	38%	553	47%	12590	47%	13143
35-44	21%	307	23%	6105	23%	6412
45-54	18%	265	15%	3887	15%	4152
55-64	16%	230	10%	2653	10%	2883
65-74	6%	82	4%	1051	4%	1133
75-84	1%	8	1%	351	1%	359
Gender						
Female	35%	502	40%	10646	40%	11148
Male	65%	943	60%	15991	60%	16934
Race						
Hispanic	9%	130	19%	5073	19%	5203
NH White	29%	419	56%	14977	55%	15396
NH Black	3%	38	13%	3402	12%	3440
Other	5%	70	0%	119	1%	189
Missing	55%	788	8%	2233	11%	3021
Panel B: Not missing height or weight						
	Column %	n	Column %	n	Column %	n
Total		89264		61778		151027
Age						
25-34	23%	20571	28%	17054	25%	37625
35-44	22%	19410	23%	14313	22%	33723
45-54	18%	15633	19%	11847	18%	27480
55-64	18%	15708	18%	10869	18%	26577
65-74	13%	11911	9%	5483	12%	17394
75-84	7%	6031	4%	2197	5%	8228
Gender						
Female	59%	52301	63%	39175	61%	91476
Male	41%	36963	37%	22587	39%	59550
Race						
Hispanic	21%	18423	50%	31171	33%	49594
NH White	57%	51299	27%	16818	45%	68117
NH Black	9%	8334	17%	10706	13%	19040
Other	5%	4906	4%	2625	5%	7531
Missing	7%	6302	1%	443	4%	6745

Records for height and weight spanned from 2000-2015 for KPCO and from 2005-2015 for DH. Even though height and weight data can be accessed for 10-15 years in the past, 97% of KPCO patients and 95% of DH patients living in Denver with an encounter during 2014/2015 who had a valid height and weight have had height and weight data collected in the past 2 years.

Records for height and weight that had implausible values were dropped from the analysis. Implausible values for height and weight were calculated using the same criteria that DH and KPCO used and consistent with criteria used elsewhere (Das et al. 2005, Perrin et al. 2010). Implausible values include a height greater than 96 inches or less than 48 inches or a weight greater than 700lbs or less than 75lbs. Overall, 90,371 of 511,224 patients (~18%) with an encounter in 2014 or 2015 had missing or implausible values for height or weight, or only had height/weight during pregnancy (these are broken down by health care provider in Figure 2.27, with the majority coming from DH). Among patients 25-84 years old living in Denver, 1,445 KPCO and 26,637 DH patients had missing or implausible values for height or weight.

Table 2-4 describes height and weight missingness by health care provider and neighborhood. KPCO had the highest percentage of patients with missing height/weight data from the Central Business District (4.9%) and Southmoor Park (3.2%) neighborhoods. DH had the highest percentage of patients with missing height/weight data from Chafee Park (5%) and Fort Logan (4.1%) neighborhoods.

Table 2-4. Patients with an encounter in 2014 or 2015 who have missing or implausible values for height and weight data by health care system and neighborhood

	Kaiser Permanente of Colorado		Denver Health		Total	
	% of total	n	% of total	n	% of total	n
Total		1445		26230		27675
Athmar Park	1.0%	14	0.0%	0	0.1%	14
Auraria	1.0%	14	1.6%	421	1.6%	435
Baker	0.8%	12	0.1%	21	0.1%	33
Barnum	0.8%	11	1.5%	396	1.5%	407
Barnum West	1.3%	19	1.1%	284	1.1%	303
Bear Valley	0.6%	9	0.8%	200	0.8%	209
Belcaro	2.0%	29	1.0%	264	1.1%	293
Berkeley	1.2%	18	0.4%	102	0.4%	120
CBD	4.9%	71	1.1%	276	1.3%	347
Capitol Hill	0.5%	7	0.9%	226	0.8%	233
Chaffee Park	2.8%	40	5.0%	1315	4.9%	1355
Cheesman Park	1.7%	24	0.5%	123	0.5%	147
Cherry Creek	0.7%	10	2.3%	593	2.2%	603
City Park	0.8%	11	0.8%	199	0.8%	210
City Park West	0.6%	8	0.6%	159	0.6%	167
Civic Center	0.4%	6	1.3%	334	1.2%	340
Clayton	0.5%	7	0.8%	205	0.8%	212
Cole	0.4%	6	0.7%	174	0.7%	180
College View / South Platt	2.8%	41	0.8%	216	0.9%	257
Congress Park	0.5%	7	1.0%	273	1.0%	280
Cory - Merrill	1.1%	16	2.0%	516	1.9%	532
Country Club	0.1%	2	0.4%	96	0.4%	98
DIA	1.2%	18	0.4%	96	0.4%	114
East Colfax	0.8%	12	0.1%	31	0.2%	43
Elyria Swansea	3.6%	52	1.9%	505	2.0%	557
Five Points	1.2%	18	1.0%	265	1.0%	283
Fort Logan	2.0%	29	4.1%	1085	4.0%	1114
Gateway / Green Valley	0.6%	9	1.1%	279	1.0%	288
Globeville	0.6%	8	2.9%	756	2.8%	764
Goldsmith	1.6%	23	0.9%	223	0.9%	246
Hale	2.5%	36	1.0%	255	1.1%	291
Hampden	2.3%	33	1.3%	333	1.3%	366
Hampden South	1.8%	26	2.1%	539	2.0%	565
Harvey Park	1.5%	22	1.3%	345	1.3%	367
Harvey Park South	1.8%	26	1.5%	391	1.5%	417
Highland	1.8%	26	1.2%	304	1.2%	330
Hilltop	0.8%	11	1.7%	435	1.6%	446

Table 2-4 continued

	Kaiser Permanente of Colorado		Denver Health		Total	
	% of total	n	% of total	n	% of total	n
Indian Creek	0.7%	10	0.7%	178	0.7%	188
Jefferson Park	0.2%	3	0.3%	81	0.3%	84
Kennedy	0.6%	8	0.6%	160	0.6%	168
Lincoln Park	1.4%	20	0.6%	170	0.7%	190
Lowry Field	1.7%	25	2.5%	657	2.5%	682
Mar Lee	2.1%	31	1.0%	266	1.1%	297
Marston	2.1%	31	2.3%	596	2.3%	627
Montbello	1.0%	14	1.1%	283	1.1%	297
Montclair	1.7%	24	7.8%	2041	7.5%	2065
North Capitol Hill	1.8%	26	0.8%	215	0.9%	241
North Park Hill	1.0%	15	2.0%	536	2.0%	551
Northeast Park Hill	0.1%	1	1.4%	379	1.4%	380
Overland	1.0%	15	1.4%	364	1.4%	379
Platt Park	0.4%	6	0.4%	107	0.4%	113
Regis	0.6%	9	0.8%	206	0.8%	215
Rosedale	0.9%	13	0.4%	117	0.5%	130
Ruby Hill	0.7%	10	0.3%	82	0.3%	92
Skyland	1.3%	19	1.4%	358	1.4%	377
Sloan Lake	1.8%	26	0.6%	145	0.6%	171
South Park Hill	0.8%	12	1.0%	265	1.0%	277
Southmoor Park	3.2%	46	0.8%	205	0.9%	251
Speer	2.7%	39	0.3%	88	0.5%	127
Stapleton	0.1%	2	2.9%	757	2.7%	759
Sun Valley	1.7%	24	1.4%	364	1.4%	388
Sunnyside	1.0%	15	1.2%	314	1.2%	329
Union Station	1.5%	21	1.6%	415	1.6%	436
University	0.6%	8	0.9%	227	0.8%	235
University Hills	1.4%	20	0.9%	238	0.9%	258
University Park	0.8%	12	0.7%	177	0.7%	189
Valverde	1.9%	27	0.7%	180	0.7%	207
Villa Park	1.3%	19	0.8%	214	0.8%	233
Virginia Village	0.9%	13	1.8%	476	1.8%	489
Washington Park	1.0%	15	1.8%	481	1.8%	496
Washington Park West	1.6%	23	0.8%	208	0.8%	231
Washington Virginia Vale	0.3%	5	1.0%	274	1.0%	279
Wellshire	1.2%	18	1.9%	493	1.8%	511
West Colfax	2.0%	29	0.2%	53	0.3%	82
West Highland	1.0%	15	1.9%	510	1.9%	525
Westwood	1.2%	17	1.0%	253	1.0%	270
Whittier	1.9%	28	2.4%	618	2.3%	646
Windsor	0.0%	0	0.9%	244	0.9%	244

Table 2-5 describes missing height and weight data by healthcare provider and by the department the patient visited for the 2014/2015 encounter. The majority of patients missing height and weight data were also missing information about the department they visited during their 2014/2015 visit (52% overall). This indicates that there was likely sparse data available for these patients or their record was a data entry error, and supports their exclusion from the sample. For DH, other department visits that had high missingness for height and weight were community health (6%), obstetrics/gynecology (6%), and orthopedics (5%). For KPCO, department visits that had high missingness include primary care (30%), dermatology (11%), and optometry (11%). Primary care patients should have a height and weight recorded, so the 439 KPCO patients who were excluded may bias the sample by removing a group of low utilizer or healthy individuals. However, they would only represent about 0.5% of the total KPCO sample.

Table 2-5. Patients with an encounter in 2014 or 2015 who have missing or implausible values for height and weight data by department and health care system in Denver, Colorado

	DH		KPCO		Total	
Department	n	%	n	%	n	%
Allergy	57	0.21	3	0.21	60	0.21
Audiology	238	0.89	9	0.62	247	0.88
Chemical and alcohol dependency	365	1.37	0	0	365	1.30
Community health	1604	6.02	0	0	1604	5.71
Dental	1099	4.13	0	0	1099	3.91
Dermatology	346	1.3	157	10.87	503	1.79
Dialysis	2	0.01	0	0	2	0.01
Endocrinology	84	0.32	0	0	84	0.30
Otolaryngology	234	0.88	22	1.52	256	0.91
Emergency Room	27	0.1	0	0	27	0.10
Family practice	76	0.29	54	3.74	130	0.46
Gerontology/Geriatrics	33	0.12	0	0	33	0.12
Gastro-Intestinal	185	0.69	7	0.48	192	0.68
Hepatology	13	0.05	0	0	13	0.05
Internal medicine	7	0.03	50	3.46	57	0.20
Infectious disease	179	0.67	1	0.07	180	0.64
Infusion center	50	0.19	0	0	50	0.18
Laboratory	58	0.22	0	0	58	0.21
Mental health	1106	4.15	68	4.71	1174	4.18
Nephrology	30	0.11	0	0	30	0.11
Neurology	282	1.06	5	0.35	287	1.02
Nutrition	8	0.03	0	0	8	0.03
Obstetrics/Gynecology	1531	5.75	28	1.94	1559	5.55
Occupational therapy	0	0	3	0.21	3	0.01
Oncology	50	0.19	0	0	50	0.18
Ophthalmology	1119	4.2	11	0.76	1130	4.02
Optometry	0	0	156	10.8	156	0.56
Orthopedics	1350	5.07	24	1.66	1374	4.89
Palliative	12	0.05	0	0	12	0.04
Primary care	783	2.94	439	30.38	1222	4.35
Pedicatrics	24	0.09	0	0	24	0.09
Plastic Surgery	16	0.06	0	0	16	0.06
Physical therapy	91	0.34	13	0.9	104	0.37
Puminary medicine	41	0.15	3	0.21	44	0.16
Radiology	425	1.6	0	0	425	1.51
Rheumatology	55	0.21	0	0	55	0.20
Speech Therapy	8	0.03	0	0	8	0.03
General Surgery	713	2.68	7	0.48	720	2.56
Unknown/Other	14332	53.8	375	25.96	14707	52.37
Urology	4	0.02	10	0.69	14	0.05
Total	26637		1445		28082	100.00

Geography

I included patients in the sample if they had at least one address in Denver for any encounter in available EHR data. I identified Denver addresses by using the FIPS codes associated with each encounter record that began with the geographic identifier for Denver County: '08031'. There were a number of specific addresses that I screened and removed from the analysis. Because I did not have direct access to patient addresses, this screening process was completed by a researcher at DH. Addresses that represented nursing homes, prisons, or homeless shelters were identified and flagged, and then I removed the addresses from the data[1]. Of the 295,161 total addresses (including multiple addresses for some patients), 3,100 (1%) were flagged at one of the address types mentioned above. Additionally, some homeless patients in the DH system were given a FIPS code of '08031' without a census tract identifier, so I excluded patients without a census tract identifier after the county identifier from the analysis. In Figure 2-27 I described the number of patients missing geocodes as well as those with and without an address in Denver County for each healthcare provider. KPCO had a much higher percent of patients without a home address geocoded to Denver (74%) compared to DH (10%) because KPCO serves residents across Colorado compared to DH, which primarily serves residents of Denver County. Overall, 84% of DH patients and 26% of KPCO patients with valid height/weight measurements had a residence address in Denver the time of their visit and retrospectively.

In Table 2-6 I show demographic characteristics of those with an address in Denver during the 2014/2015 encounter, an address in Denver prior to the 2014/2015 encounter but not

[1] This does not necessarily mean that I removed the patient from the data. If he/she had another valid Denver address then I kept them in the dataset.

during the 2014/2015 encounter, and no address in Denver. As expected, a much higher percent of DH patients had an address in Denver either during 2014/2015 or before 2014/2015. When comparing those with a Denver address during 2014/2015 to those with a Denver address sometime before 2014/2015, current Denver residents were slightly older, with a higher proportion of Hispanic patients and a lower proportion of non-Hispanic white patients, and a similar gender distribution. Patients who had no Denver address during any encounter were older and more likely to be non-Hispanic white than those living in Denver at any point.

Table 2-6. Patients with an encounter in 2014 or 2015 by health care provider and type of address

Panel A: Kaiser Permanente of Colorado						
	Address in Denver during 2014/2015 encounter		Address in Denver, not during 2014/2015 encounter		No address in Denver during 2014/2015 encounter	
	Row %	n	Row %	n	Row %	n
Total		67177		22147		258083
Age						
25-34	22%	14875	26%	5705	13%	34538
35-44	19%	12996	29%	6427	16%	42293
45-54	17%	11397	19%	4252	21%	53114
55-64	19%	12715	14%	2999	23%	59708
65-74	15%	9936	9%	1986	18%	45610
75-84	8%	5258	4%	778	9%	22820
Gender						
Female	58%	39038	60%	13297	57%	146475
Male	42%	28139	40%	8850	43%	111608
Race						
Hispanic	20%	13179	21%	4565	12%	31233
NH White	58%	38712	58%	12840	72%	185532
NH Black	10%	6496	9%	1915	3%	6891
Other	6%	3816	7%	1468	6%	15535
Missing	7%	4974	6%	1359	7%	18892
Panel B: Denver Health						
	Row %	n	Row %	n	Row %	n
Total		55298		6480		11668
Age						
25-34	27%	15202	29%	1860	28%	3229
35-44	23%	12928	21%	1389	24%	2779
45-54	19%	10661	18%	1186	24%	2746
55-64	18%	9692	18%	1179	18%	2127
65-74	9%	4887	9%	596	5%	558
75-84	3%	1928	4%	270	2%	229
Gender						
Female	63%	34711	69%	4476	53%	6166
Male	37%	20586	31%	2004	47%	5502
Race						
Hispanic	48%	26756	48%	3128	21%	2420
NH White	29%	16252	27%	1749	55%	6394
NH Black	17%	9432	20%	1307	17%	1996
Other	<1%	252	0%	31	1%	83
Missing	5%	2606	4%	265	7%	775
Panel C: Total						
	Row %	n	Row %	n	Row %	n
Total		122475		28627		269751
Age						
25-34	25%	30077	26%	7565	14%	37767
35-44	21%	25924	27%	7816	17%	45072
45-54	18%	22058	19%	5438	21%	55860
55-64	18%	22407	15%	4178	23%	61835
65-74	12%	14823	9%	2582	17%	46168
75-84	6%	7186	4%	1048	9%	23049
Gender						
Female	60%	73749	62%	17773	57%	152641
Male	40%	48725	38%	10854	43%	117110
Race						
Hispanic	33%	39935	27%	7693	12%	33653
NH White	45%	54964	51%	14589	71%	191926
NH Black	13%	15928	11%	3222	3%	8887
Other	3%	4068	5%	1499	6%	15618
Missing	6%	7580	6%	1624	7%	19667

Pregnancy

Pregnant women can potentially bias the calculation of prevalence of chronic conditions because of acute risk of these conditions during pregnancy that may not reflect chronic risk. This is true for the primary health outcomes in this study, particularly diabetes, hypertension, and obesity. Many women who develop gestational diabetes, preeclampsia, or become "obese" during pregnancy do not continue to have these conditions after pregnancy. Therefore, it is important to remove observations from vital signs, diagnoses, lab results, and pharmacy records associated with diabetes, hypertension, and obesity for pregnant women, during the time they were pregnant. Because 10-15 years of health records were used to assess prevalence of chronic conditions, it was problematic for me to exclude any woman who was pregnant during that time period. This would create a biased sample that would have many fewer women of childbearing age than the general population. Instead, for each health outcome, I removed diagnosis, lab, vital, and pharmacy records (if applicable) if they were associated with women who were known to be pregnant in a given year.

I identified pregnant women by using diagnosis and procedure codes related to pregnancy, obtained from the list currently used by KPCO that I also applied to diagnosis and procedure codes for DH EHRs. Removing pregnancy records in this way was a technique that DH and KPCO researchers told me about, but to my knowledge has not been formally documented in peer-reviewed studies. Tables 2-7 and 2-8 display the diagnosis and procedure codes to identify pregnant women. Because there is no single diagnosis code that represents all pregnancies, if a woman had any of several diagnoses or procedures associated with pregnancy in a given year, I considered her to be pregnant during that year. Then, I merged the indicator for pregnancy to the diagnosis, lab, vital, or pharmacy tables and if a woman had a record in any of those tables during the year or years she was pregnant, I removed those records. If a woman had a record in any of those tables that was associated with a year when she was not pregnant, I retained those records. This allowed women who had been pregnant at any point in the retrospective EHR to remain in the sample denominator and I removed records potentially biased by pregnancy-related disease only during those pregnant years.

Table 2-7. ICD9 diagnosis and procedure codes used to identify pregnancy for women patients in Denver Health and Kaiser Permanente of Colorado

Diagnosis code	Description	Diagnosis code	Description	Diagnosis code	Description	Diagnosis code	Description
631	Other abnormal product of conception	646.3	habitual aborter	652.2	breech presentation	656.9	unspecified fetal/placental problem
633	Ectopic pregnancy	646.4	peripheral neuritis in pregnancy	652.3	transverse or oblique presentation of fetus	657	polyhydramnios
633	Abdominal pregnancy	646.5	asympt bacteriuria in pregnancy	652.5	high head at term	658	other amniotic cavity problem
633.1	Tubal pregnancy	646.6	gu tract infect in pregnancy	652.6	multiple gestation with malpresentation	658	oligohydramnios
633.2	Ovarian pregnancy	646.7	liver disorder in pregnancy	652.7	prolapsed arm	658.1	premature ruptured membranes
633.8	Other ectopic pregnancy	646.8	other pregnancy complication	652.8	other malposition	658.2	unspecified prolonged ruptured membrane
640	hemorrhage in early pregnancy	646.9	unspecified pregnancy complication	652.9	unspecified malposition	658.3	delayed delivery after artificial rupture of membranes.
640	threatened abortion	647	infective disease in pregnancy	653	disproportion	658.4	infection in amniotic cavity
640.8	other hemorrhage in early pregnancy	647	syphilis in pregnancy	653.3	outlet contract pelvis	658.8	other amniotic cavity problem
640.9	unspecified hemorrhage in early pregnancy	647.1	gonorrhea in pregnancy	653.4	fetopelvic disproportion	658.9	unspecified amniotic cavity problem
641	antepartem hemorrhage & placenta previa	647.2	other venereal disease in pregnancy	653.5	unspecified fetal disproportion	659	other indications for care or intervention related to labor and delivery not elsewhere classified
641	placenta previa without hemorrhage	647.3	tuberculosis in pregnancy	653.7	other fetal abnormality causing disproportion	659	failed mechanical induction of labor
641.1	hemorrage from placent previa	647.6	other viral disease in pregnancy	654	abnormal pelvic organ in pregnancy	659.1	unspecified failed induction of labor
641.2	premature separation placenta	647.9	unspecified infection in pregnancy	654	congenital abnormal uterus in pregnancy	659.3	septicemia during labor
641.8	other antepartum hemorrhage	648	other current condition in pregnancy	654.1	uterine tumor in pregnancy	659.4	grand multiparity
641.9	unspecified antepartum hemorrhage	648	diabetes mellitus in pregnancy	654.2	unspecified previous c-section	659.5	elderly primigravida
642	hypertension complication in pregnancy	648.1	thyroid dysfunction in pregnancy	654.3	retroverted and incarcerated gravid uterus	659.7	abnormal fetal heart rate
642	essential hypertension complication in pregnancy	648.2	anemia in pregnancy	654.4	other abnormalities in shape or position of gravid uterus and of neighboring structures	659.8	other specified indications for care or intervention related to labor and delivery
642.1	renal hypertenion of pregnancy	648.3	drug dependence in pregnancy	654.5	cervix incompetance in pregnancy	659.9	unspecified indications for care or intervention related to labor and
642.2	other old hypertension in pregnancy	648.4	mental disorders in pregnancy	654.6	other congenital or acquired abnormality of cervix complicating	669.5	forceps or vacuum extractor delivery without mention of indication

Table 2-7. Continued

642.3	transient hypertension pregnancy	648.5	congenital cardiovascular disease in pregnancy	654.7	abnormal vagina in pregnancy	669.6	forceps or vacuum extractor delivery without mention of indication
642.4	mild/unspecified pre-eclampsia	648.6	cardiovascular dis nec in pregnancy	654.8	abnormal vulva in pregnancy	669.7	forceps or vacuum extractor delivery without mention of indication
642.5	severe pre-eclampsia	648.7	bone disorder in pregnancy	654.9	other and unspecified abnormality of organs and soft tissues of pelvis	760	maternal condition affecting fetus/newborn
642.6	eclampsia	648.8	abnormal glucose tolerance in pregnancy	655	fetal abnormality affecting mother	760.6	surgical operation on mother affecting newborn
642.7	toxemia with old hypertension	648.9	other current condition of pregnancy	655	central nervous system malformation in fetus affecting management of	760.7	noxious substance affecting newborn
642.9	unspecified hypertension complication of pregnancy	649	complication related to pregnancy	655.1	fetal chromosomal abnormality	761	maternal complication affecting newborn
643	excess vomiting in pregnancy	649	tobacco use complication in pregnancy	655.2	family hereditary disease affecting fetus	762	complication of placenta/cord affecting newborn
643	mild hyperemesis gravidarum	649.1	obesity complication in pregnancy	655.3	suspected damage to fetus from viral disease in the mother affecting	V22	normal pregnancy
643.1	hyperemesis gravidarum with metabolic disorder	649.2	bariatric surgery status complicating pregnancy, childbirth, or the	655.4	suspected damage to fetus from other disease in the mother affecting	V23	supervision of high-risk pregnancy
643.8	Other vomiting complication pregnancy	649.3	coagulation defects complicating pregnancy, childbirth, or the	655.5	suspected damage to fetus from drugs affecting management of mother	V23.4	supervision of high-risk pregnancy with other poor obstetric history
643.9	Unspecified vomiting pregnancy	649.4	epilepsy complication in pregnancy	655.6	radiation causing fetal damage	V23.8	other suprvision of high-risk pregnancy
644	early/threatened labor	649.5	spotting complication in pregnancy	655.8	other fetal abnormality	V27	outcome of delivery
644	threaten premature labor	649.6	uterine size date discrepancy	655.9	unspecified fetal abnormality	V28	antenatal screening
644.1	other threatened labor	649.7	cerivcal shortening in pregnancy	656	other fetal problem affecting mother	V28.8	other antenatal screening
644.2	early onset of delivery	651	multiple gestation	656	fetal-maternal hemorrhage	V30.0	single newborn, born in hospital
645	prolonged pregnancy	651	twin pregnancy	656.1	rhesus isoimmunization	V31.0	twin, born in hospital
645.01	prolonged pregnancy, with delivery	651.1	triplet pregnancy	656.2	isoimmunization from other and unspecified blood-group incompatibility affecting management of mother	V32.0	twin, born in hospital, mate stillborn
645.22	prolonged pregnancy, delivered, antepartum condition	651.3	twins w fetal loss	656.3	fetal distress	V33.0	twin, born in hospital
646	other complication of pregnancy	651.9	unspecified multiple gestation	656.5	poor fetal growth	V34.0	other multiple, born in hospital
646	papyraceous fetus	652	malposition of fetus	656.6	excessive fetal growth	V35.0	other multiple, born in hospital
646.1	edema in pregnancy	652	unstable lie of fetus	656.7	other placental conditions	V36.0	other multiple, born in hospital
646.2	unspecified renal disease in pregnancy	652.1	breech or other malpresentation successfully converted to cephalic presentation	656.8	other fetal/placental problem	V37.0	other multiple, born in hospital
						V39.0	unspecified, born in hospital

Table 2-8. ICD9 procedure codes used to identify pregnant women in Denver Health and Kaiser Permanente of Colorado

Procedure Code	Description	Procedure Code	Description
0500F	initial prenatal care	73.5	other procedures inducing or assisting delivery
0501F	prenatal flow sheet	73.51	manual rotation of fetal head
0502F	subsequent prenatal care	73.59	other manually assisted delivery
36460	transfusion, intrauterine, fetal	73.6	episiotomy
59000	amniocentesis	73.8	operations on fetus to facilitate delivery
59001	amniocentesis; therapeutic amniotic fluid reduction	73.9	other procedures inducing or assisting delivery
59012	cordocentesis	73.91	external version assisting delivery
59015	chorionic villus sampling	73.92	replacement of prolapsed umbilical cord
59020	fetal contraction stress test	73.93	incision of cervix to assist delivery
59025	fetal contraction non-stress test	73.94	pubiotomy to assist delivery
59030	fetal scalp blood sampling	73.99	other operations assisting delivery
59050	fetal monitoring during labor by consulting physician	74	classical cesarean section
59051	fetal monitoring during labor by consulting physician	74.1	low cervical cesarean section
59070	transabdominal amnioinfusion, including ultrasound	74.2	extraperitoneal cesarean section
59072	fetal umbilical cord occlusion, including ultrasound	74.4	cesarean section of other specified type
59074	fetal fluid drainage	74.9	cesarean section and removal of fetus
59076	fetal shunt placement, including ultrasound guidance	74.99	other cesarean section of unspecified type
59320	cerclage of cervix, during pregnancy; vaginal	75.3	other intrauterine operations on fetus and amnion
59325	cerclage of cervix, during pregnancy; abdominal	75.32	fetal ekg (scalp)
59400	routine ob care incl antepartum car, vaginal delivery	75.33	fetal blood sampling and biopsy
59409	vaginal delivery only	75.34	other fetal monitoring
59410	vaginal delivery including postpartum care	75.35	other diagnostic procedures on fetus and amnion
59425	antepartum care only; 4-6 visits	75.36	correction of fetal defect
59426	antepartum care only; 7 or more visits	75.38	fetal pulse oximetry
59510	routine obstetric care including antepartum care, cesarean delivery	75.4	manual removal of retained placenta
59514	cesarean delivery only	75.7	manual exploration of uterine cavity, postpartum
59515	cesarean delivery, including postpartum care	75.94	immediate postpartum manual replacement of inverterted uterus
59610	obstetric care including antepartum care, vaginal delivery, postpartum	76801	ultrasound, pregnant uterus, first trimester, transvaginal
59612	vaginal delivery only after previous c-section	76802	ultrasound, pregnant uterus, first trimester, transvaginal
59614	vaginal delivery after previous c-section, including postpartum care	76805	ultrasound, pregnant uterus, after first trimester
59618	obstetric care including antepartum care, cesearian delivery, postpartum care	76810	ultrasound, pregnant uterus, after the first trimester
59620	cesarean delivery only after previous c-section	76811	ultrasound, pregnant uterus, plus detailed fetal anatomic ultrasound
59622	cesarean delivery after previous c-sect, including postpartum care	76812	ultrasound, pregnant uterus, after the first trimester
59866	multifetal pregnancy reduction	76813	ultrasound, pregnant uterus, first trimester, fetal
59897	unlisted fetal invasive procedure, including ultrasound	76814	ultrasound, pregnant uterus, first trimester, fetal
72	forceps, vacuum, and breech delivery	76815	ultrasound, pregnant uterus, limited
72.1	low forceps operation with episiotomy	76816	ultrasound, pregnant uterus, follow-up or repeat
72.2	forceps, vacuum, and breech delivery	76817	ultrasound, pregnant uterus, transvaginal
72.21	mid forceps operation with episiotomy	76818	fetal biophysical profile
72.3	forceps, vacuum, and breech delivery	76819	fetal biophysical profile; without non-stress test
72.31	high forceps operation with episiotomy	76820	doppler velocimetry, fetal; umbilical artery

Table 2-8 continued			
72.4	forceps rotation of fetal head	76821	doppler velocimetry, fetal; middle cerebral artery
72.5	forceps, vacuum, and breech delivery	76825	echocardiography, fetal
72.51	partial breech extraction with forceps to aftercoming head	76826	echocardiography, fetal, follow-up or repeat
72.52	other partial breech extraction	76827	doppler echocardiography, fetal
72.53	total breech extraction with forceps to aftercoming head	76828	doppler echocardiography, fetal, follow up or repeat
72.54	other total breech extraction	76946	ultrasonic guidance for amniocentesis
72.6	forceps application to aftercoming head	87.71	x-ray of gravid uterus
72.7	forceps, vacuum, and breech delivery	88.78	diagnostic ultrasound of gravid uterus
72.71	vacuum extraction with episiotomy	99500	home visit prenatal
72.79	other vacuum extraction	S2400	repair, congenital diaphragmatic hernia in the fetus
72.8	other specified instrumental delivery	S2401	repair, urinary tract obstruction in the fetus
72.9	unspecified instrumental delivery	S2402	repair, congenital cystic adenomatoid malformation
73	other procedures inducing or assisting delivery	S2403	repair, extralobar pulmonary sequestration in the fetus, procedure performed in utero
73	other procedures inducing or assisting delivery	S2404	repair, myelomeningocele in the fetus, procedure performed in utero
73.01	induction of labor by artificial rupture of membrane	S2405	repair of sacrococcygeal teratoma in the fetus
73.1	other surgical induction of labor	S2409	repair, congenital malformation of fetus, procedure performed in utero
73.2	other procedures inducing or assisting delivery	S2411	fetoscopic laser therapy for treatment of twin-to-twin transfusion syndrome
73.22	internal and combined version with extraction	S3625	maternal serum triple marker screen including alpha-fetoprotein (afp), estriol, and human chorionic gonadotropin (hcg)
73.3	failed forceps	S3626	maternal serum quadruple marker screen
73.4	medical induction of labor		

In Tables 2-9 and 2-10 I display the distribution of pregnant records and women, respectively, who had ever been pregnant in the data across key demographic variables and by neighborhood. Pregnant records are distinct from women who have ever been pregnant because women may have been pregnant multiple times or the pregnancy might have spanned two calendar years, in which case data from both years were excluded from the analyses. The number of pregnant records generally increased between 2000-2015, indicating better electronic data collection in later years (there were no data available for DH from 2000-2005). The age distribution of pregnant records and pregnant women demonstrate that KPCO had a higher proportion of women pregnant from 35-44 years old, whereas DH had a higher proportion of women pregnant during 25-34 years old. KPCO had a higher proportion of non-Hispanic white women who were pregnant, whereas about 70% of pregnant women from DH were Hispanic.

Using a year indicator for pregnancy had its limitations. For example, it is possible that a woman had a pregnancy-related diagnosis or procedure code from December 2012 that relates to a diagnosis or procedure from early on in pregnancy. In this case, all of this woman's 2012 data would be excluded from the analysis, even though she was not pregnant for the majority of the year. Similar to other exclusions such as height and weight, excluding pregnancy records was more likely to remove low-utilizers (including healthy individuals) from the data completely, since they may not have any other records in the data. Nonetheless, this process makes the most sense given that there is no diagnosis or procedure code uniformly given to pregnant women at the same point during their pregnancy. Instead, pregnancy indicators could come from any point (e.g. a procedure code for a cesarean section delivery or a procedure code for a first trimester ultrasound). Future analyses could design a method to sift through all of the diagnosis and procedure codes and attempt to distinguish the specific month when the woman became pregnant based on the time and type of diagnosis or procedure she received, but it was beyond the scope of this project.

Table 2-9. Pregnancy records by health care provider and demographic characteristics

	Kaiser Permanente of Colorado		Denver Health		Total	
	% of total	n	% of total	n	% of total	n
Total		25391		24006		49397
Year						
2000	2.5	637	NA	NA	1.3	637
2001	2.8	704	NA	NA	1.4	704
2002	2.9	742	NA	NA	1.5	742
2003	3.2	815	NA	NA	1.6	815
2004	4.0	1016	NA	NA	2.1	1016
2005	4.5	1149	8.4	2013	6.4	3162
2006	5.3	1345	9.0	2149	7.1	3494
2007	5.9	1492	9.6	2307	7.7	3799
2008	6.3	1600	10.3	2464	8.2	4064
2009	6.7	1701	10.2	2455	8.4	4156
2010	7.4	1865	10.0	2389	8.6	4254
2011	8.0	2032	8.8	2108	8.4	4140
2012	9.2	2337	9.0	2155	9.1	4492
2013	10.4	2650	8.8	2102	9.6	4752
2014	11.1	2822	8.6	2075	9.9	4897
2015	9.8	2484	7.5	1789	8.7	4273
Age						
25-34	43.0	10907	62.2	14932	52.3	25839
35-44	47.9	12161	33.0	7917	40.6	20078
45-54	8.8	2235	4.6	1092	6.7	3327
55-60	0.4	88	0.3	65	0.3	153
Race						
Hispanic	25.3	6432	75.5	17584	48.6	24016
NH White	55.1	13979	8.9	2083	32.5	16062
NH Black	10.6	2691	15.1	3528	12.6	6219
Other	7.1	1802	3.4	800	5.3	2602
Missing	1.9	487	0.1	11	1.0	498

Note: These numbers represent records. Individuals and pregnancies may appear more than once in records

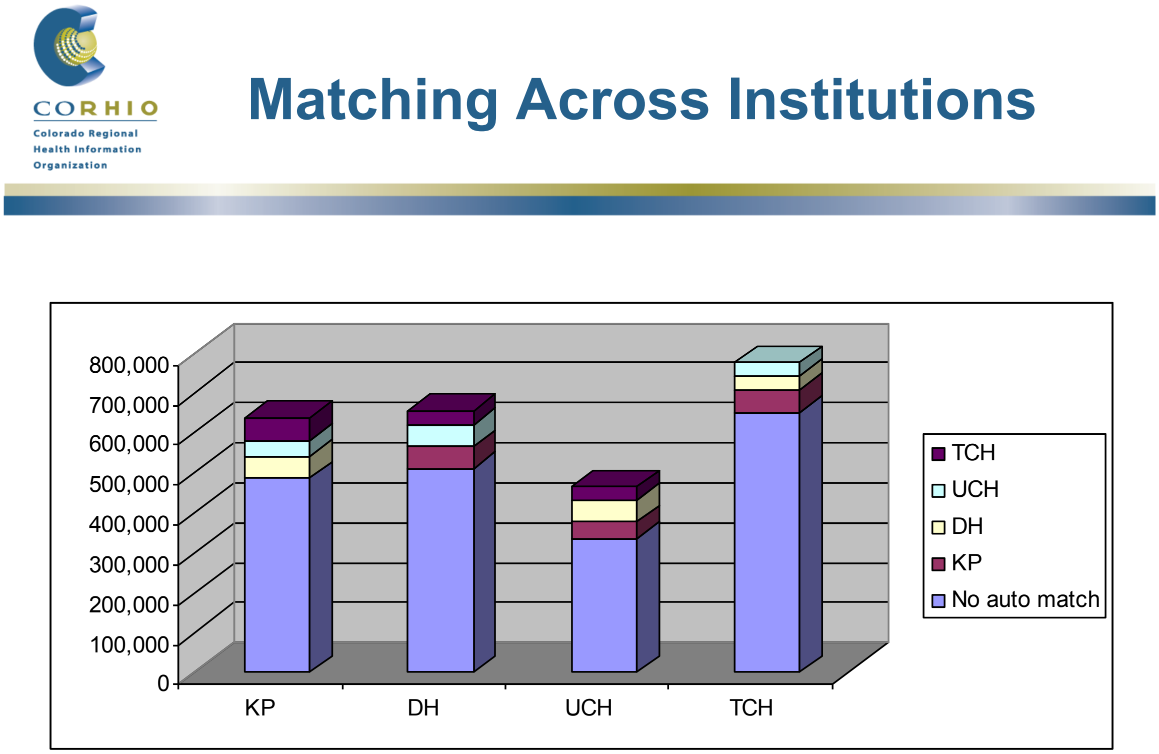
Table 2-10. Women ever pregnant in electronic health records by health care provider and demographic characteristics

	Kaiser Permanente of Colorado		Denver Health		Total	
	% of total	n	% of total	n	% of total	n
Total		11320		10920		22240
Age						
25-34	43.8	4958	57.9	6317	50.7	11275
35-44	45.2	5119	34.9	3815	40.2	8934
45-54	10.3	1169	6.7	727	8.5	1896
55-60	0.7	74	0.6	61	0.6	135
Race						
Hispanic	25.4	2872	73.4	7732	47.7	10604
NH White	54.9	6217	11.0	1159	33.2	7376
NH Black	10.2	1149	15.1	1592	12.3	2741
Other	7.4	832	4.1	428	5.7	1260
Missing	2.2	250	0.1	9	1.2	259

Duplicates

Although KPCO and DH for the most part serve complementary populations, a patient may have been seen in both KPCO and DH systems in 2014 and 2015, resulting in duplicate data in the denominator. Previous DH and KPCO duplicate analyses revealed a small overlap (see Figure 2-28). Additionally, researchers at the University of Colorado Anschutz Medical Campus received an informatics grant from the National Institutes of Health to identify probabilistic duplicates in the data. Duplicate identification process will not be completed before the conclusion of this dissertation, so for the time being no efforts have been undertaken to identify potential duplicates. I provide a more in-depth description of the potential problems with duplicate patient data in Chapter 5.

Figure 2-28. Estimates of duplicate patients across health systems, including Denver Health (DH) and Kaiser Permanente of Colorado (KP)



NEIGHBORHOOD DATASETS

American Community Survey

I combined DHKP EHR data with two data sources to generate neighborhood-level indicators. I used the publicly-available 2011-2015 5-year American Community Survey (ACS) for social/demographic neighborhood-level data. The ACS is executed by the U.S. Census Bureau, but is distinct from the decennial census in that it is based on sample estimates rather than population counts. The benefit of using the ACS is that it provides more frequent estimates and it asks more detailed questions than the decennial census. The biggest drawback is that estimates often have large margins of error at small geographic levels or for some population subgroups. As mentioned in the "study cohort" section, using the 2010 decennial census would have provided more accurate neighborhood-level social and demographic estimates, but if it were matched with DHKP EHRs from the same year it would come at the expense of EHR quality, since the 2010/2011 EHRs had more sparsely collected race/ethnicity (and potentially other) data. Furthermore, since Denver County has grown immensely between 2010 and 2015 (U.S. Census Bureau 2016), any policy or public health implications from 2010 results may not be as relevant in 2018 compared to results from 2014/2015.

Although ACS generated 1-, 3-, and 5-year estimates for counties, it only provided 5-year estimates for census tracts. Five-year estimates were comprised of multiple 1-year estimates and data represented an average across the entire 5-year span rather than a specific year. Many studies conducting neighborhood-level analyses have used single variables from the ACS without reporting margins of error or speculating about the reliability of the estimates. Spielman and Singleton (2015) suggest a few approaches to addressing uncertainly in ACS estimates. The method most appropriate for this dissertation was combining multiple ACS measures into a single measure. Combining multiple measures increases the likelihood that certain characteristics are valid descriptors of places. For example, if four measures of socioeconomic status (SES) were used to characterize neighborhoods, and a specific neighborhood had low SES on all four indicators, even if there were large margins of error it would be more likely that this neighborhood actually had lower SES than if a single indicator was used. In Chapters 3 and 4, I compare results from the composite indicators I created to single-variable indicators for some analyses in order to understand how sensitive results might have been to the type of indicator. In these cases, I discussed the uncertainty around the single-variable indicators. I address specific uses of ACS data in the analysis section of this chapter.

500 Cities Project

The DHKP EHRs and the ACS provide a variety of health, demographic, and social characteristics of neighborhoods, but have limited health behavior and healthcare access/utilization data. DHKP data includes well-populated information about patients' smoking status, but does not include other health behavior information for many patients. Health insurance information was not stored in the VDW; although often stored in the EHR, patient's billing/payments history was not a goal of those systems. Some categories of payment are difficult to map onto specific types of insurance. The ACS contains indicators of health insurance status (e.g., whether or not residents have insurance and some categories of insurance type) but does not have data about how individuals accessed and utilized health care.

To address these data shortfalls, I included neighborhood-level data from the 2013-2014 500 Cities Project. The 500 Cities Project was a Centers for Disease Control and Prevention (CDC) and Robert Wood Johnson Foundation (RWJF) project to provide census-tract-level estimates on health behaviors, conditions, and utilization for the 500 largest cities in the United States (and at least one city per state) (Scally et al. 2017). The project used data from the Behavioral Risk Factor Surveillance System (BRFSS), which is sampled at the county level for all counties in the United States. Researchers then conducted small area estimation (SAE) to generate reliable estimates at the census-tract-level (Zhang et al. 2015). I discuss specific variables I used from the 500 Cities Project later in the section describing neighborhood-level independent variables and in the section describing the analyses.

The three data sources I used in this study are complementary and, when combined, offer rich health, social, and behavioral data for Denver County. Although EHR data were not representative of the Denver population, they provided detailed clinical data that incorporated diagnoses, lab results, and treatment data. This combination of health information provides more internally valid prevalence estimates than health surveys that rely on patient self-reports, at the expense of some external validity (discussed in detail in Chapter 5). Nonetheless, EHR data I used in this analysis covered roughly 30% of the Denver adult population and has been used for population health surveillance by healthcare providers in the area (Beck 2017, Davidson et al. 2018, Schroeder et al. 2012, Steiner 2009), and are generally becoming more common in population health research (Casey et al. 2016).

ACS data provide in-depth social and demographic information about individuals and households that were more timely and too expensive to collect in EHRs and had not been collected in BRFSS. The ACS provided estimates at the census-tract level, although the sampling strategy often produced large margins of error for many measures. To reduce error in estimates, this study combined multiple social/demographic measures into a single independent variable using a latent class approach (described in detail below), as recommended by Spielman and Singleton (2016).

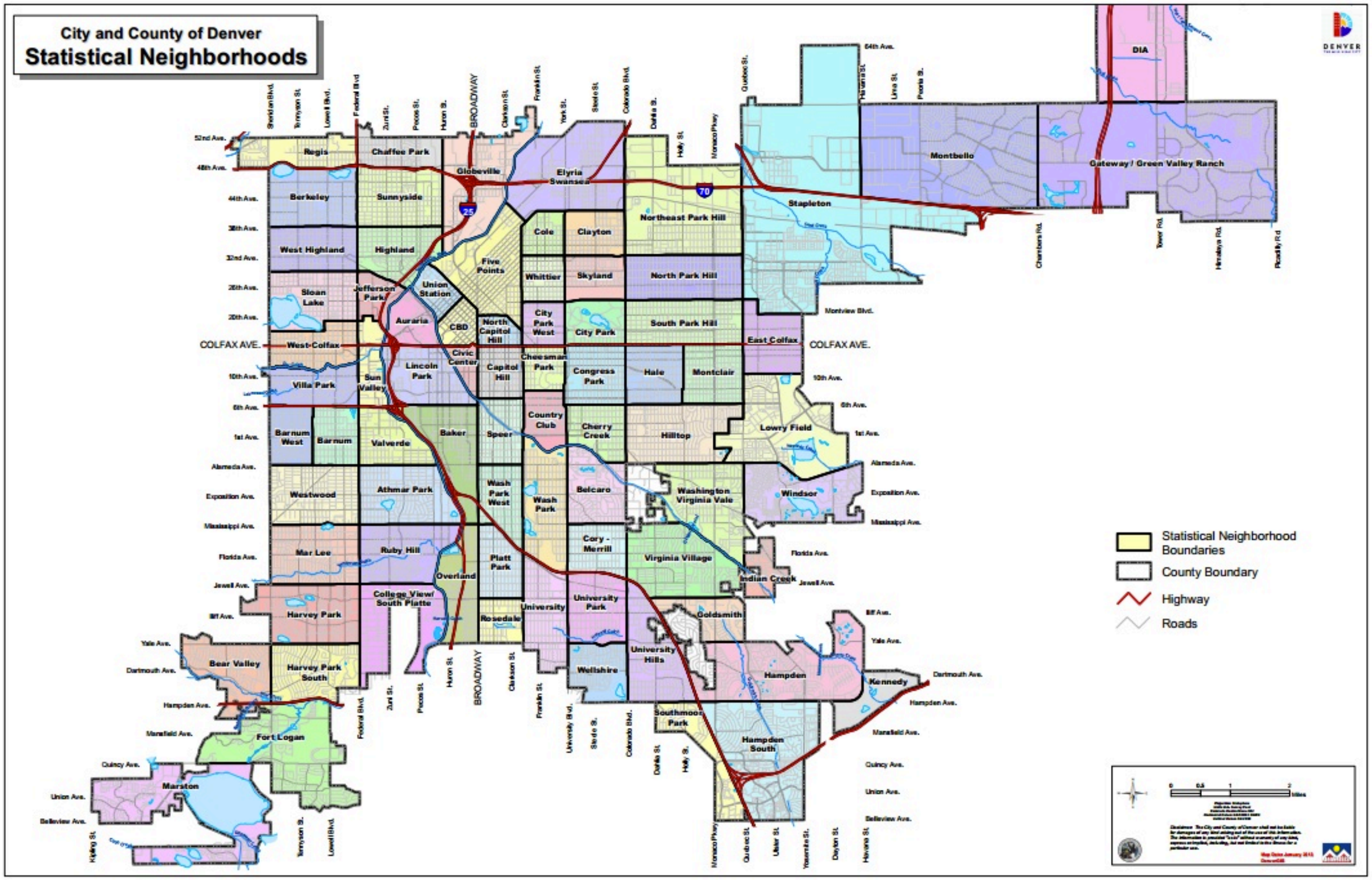
Data from the 500 Cities Project provided a unique source of health behavior and health access/utilization data that were not available in other sources. Because of “meaningful use” mandates from the Affordable Care Act (ACA) (Blumenthal & Tavenner 2010), EHRs have collected more comprehensive data on tobacco use, but other health behaviors such as alcohol consumption and physical activity were sparsely collected or not collected at all. 500 Cities Project also provided aggregate information about health screenings and insurance.

DEFINING "NEIGHBORHOODS"

I use two definitions of neighborhoods in this dissertation: census tracts and socially defined neighborhoods.[2] Denver has 78 socially defined neighborhoods encompassing the 144 census tracts. These socially defined neighborhoods were established qualitatively by residents over decades and administratively by the city, and represent clusters of census tracts. I used census tracts for the aggregate analysis in Chapter 3 because it was important to have the additional units for statistical power. I used both census tracts and socially defined neighborhoods for the Chapter 4 analysis, and compared results for each geographic definition. It was important to include both geographies in the Chapter 4 analysis to see how the population size of the neighborhood impacted results. The City and County of Denver provides a shapefile of these neighborhoods to the public, so it is possible to overlay census tract and block groups from the Census with meaningful neighborhood boundaries. It is also possible to aggregate census tracts to the neighborhood level. Figure 2-29 provides a map of the Denver neighborhoods and the census tracts are represented by grey outlines.

[2] The City of Denver refers to these socially defined neighborhoods as statistical neighborhoods.

Figure 2-29. City and County of Denver statistical neighborhoods with delineated census tracts



DEPENDENT VARIABLES

All health conditions I used as dependent variables were created using the DHKP EHR data. I used the same five health conditions in Chapter 3 and Chapter 4 analyses: type 2 diabetes, obesity, hypertension, depression, and current smoking. In Chapter 3 I used aggregated neighborhood-level rates of each health condition, and in Chapter 4 I examined individual-level odds of having each health condition. Because EHRs provide rich clinical data for patients, I used multiple sources of data (e.g., diagnosis codes and lab results) whenever possible.

Diabetes

The first dependent variable was ever having type 2 diabetes for patients in the study sample. There were two primary components to identifying type 2 diabetes prevalence in the DHKP EHRs. The first component was detecting diabetes using diagnosis codes from healthcare professionals, lab tests, and pharmacy records. The second component was classifying type 2 versus type 1 diabetes.

I identified patients with any form of diabetes using criteria established by the SUPREME-DM DataLink Project (Nichols et al. 2012). In Table 2-11 I display this study's inclusion criteria for diabetes. Patients were diagnosed with diabetes if they had two or more diagnoses or elevated lab results on separate occasions spanning all visits prior to 2016, or one diabetes-related medication prescription . The only modification that I applied to the SUPREME-DM criteria was an inclusion of diagnoses to align with Klompas and colleagues (2013) criteria for distinguishing between type 1 and 2 diagnoses.

Table 2-11. Criteria for identifying diabetes among patients in the DHKP electronic health records

Criterion		Value
*Diagnosis code for Type 1 or Type 2 diabetes during an ambulatory visit		≥ 2 diagnoses (diagnosis codes: 250.x)
	OR	
*Lab: elevated hemoglobin A1c		≥ 2 elevated lab results at ≥ 6.5 mg/dL
	OR	
*Lab: elevated random/plasma glucose		≥2 elevated lab results at ≥200 mg/dL
	OR	
*Lab: elevated fasting glucose		≥2 elevated lab results at ≥126 mg/dL
	OR	
*Combination of HA1c, random/plasma glucose, & fasting glucose		≥2 any elevated lab results
	OR	
Prescription for any anti-diabetic medication		≥1 prescription
	OR	
Combination of one diagnosis and one prescription		≥2 diagnoses and prescriptions
*Diagnoses and lab tests must be on separate occasions and span all patient visit records prior to 2016; Sources: Nichols et al. 2012, Klompas et al. 2013		

In Figure 2-30 I show the diabetes inclusion criteria and the process to distinguish between type 1 and type 2 diabetes. First, I divided patients into groups based on how many diabetes diagnoses they had throughout their history in the DH or KPCO health system. I sorted diagnosis codes chronologically within individuals and deleted any duplicate diagnoses on the same date. I evaluated patients with at least one diagnosis for whether they had type 1 or type 2 diabetes diagnosis codes, or some combination of both. A diagnosis code of 250.00 is a general diabetes diagnosis, and if a patient had two 250.00 codes I assumed that they had type 2 diabetes, since 95% of diabetes cases are type 2. If a patient had a diagnosis code of 250.0x where x was an odd number, I assigned them with a type 1 diagnosis. If a patient had a diagnosis code of

250.0x where x was an even number, I assigned them a type 2 diagnosis. At this point, I merged data with diagnosis records for pregnant women and removed all diagnoses that happened during the same year as pregnancy.

If a patient had 2 or more diabetes diagnoses that I had categorized as type 1 or type 2, then I considered that patient to have type 1 or type 2 diabetes, respectively, per the Nichols and colleagues (2012) criteria. However, many patients had both type 1 and type 2 diagnosis codes for diabetes, which is likely due to misclassification errors. If a patient had at least 2 diagnoses and either 50% of the diagnoses were for type 2 diabetes or there were the same number of type 1 and type 2 diagnoses, then I considered the patient to have type 2 diabetes, per the Klompas and colleagues (2013) criteria. Per the same criteria, if more than 50% of a patient's diagnoses were for type 1 diabetes, then I merged those patients' data with pharmacy records to confirm that they were taking type 1 diabetes medication (explained in more detail later). If patients only had 1 diabetes diagnosis for either type of diabetes, or no diabetes diagnoses at all, I merged their records with laboratory data to see if they had any positive lab tests for diabetes.

I used three lab tests to assess whether patients had diabetes: hemoglobin A1c, random/plasma glucose, and fasting glucose. In Table 2-12 I list the codes used to identify each type of diabetes-related lab test and the lab criteria for diagnosis. The lab tables in the EHRs contained two fields to identify the type of lab test: a "test_type" field, which is a text field, and a Logical Observation Identifiers Names and Codes (LOINC) field. LOINCs are standardized codes for types of lab tests so they translate across health systems, whereas the way test types are recorded vary both within and between health systems. Using both criteria to identify lab tests provided the best chance of getting all of the diabetes-related lab results.

Table 2-12. Identification criteria of lab tests for diabetes and threshold for diabetes diagnosis

Measure	Test Type	Logical Observation Identifiers Names and Codes (LOINCs)	Result
Hemoglobin A1c	a1c	4637-5, 74246-0, 4548-4, 17855-8, 4549-2, 17856-6, 62388-4, 17856-6, 17875-9, 59261-8	≥6.5%
Random/plasma glucose	glu_ran	999.131509, 14743-9, 2345-7, 2339-0, 14749-6	≥200 mg/dL
Fasting glucose	glu_f	1558-6, 17865-7, 14771-0, 2.69.2439	≥126 mg/dL

To identify labs for hemoglobin A1c, I queried any test type entry that was similar to "A1c" (I assessed this in SAS using code that searches for similar rather than exact entries, so for example "a1c" and "A1c" would both turn up). I checked all entry types for accuracy. Because multiple LOINCs refer to A1c tests, I queried each of these in addition to the test type. If a patient had more than one A1c lab, then I sorted the lab records chronologically within each patient and deleted duplicate labs for the same date. Similar to diagnoses, I removed any lab records associated with pregnant women during the year/s they were pregnant. Then I used the "results" field to assess whether the average blood sugar a1c level was higher than 6.5 percent. If so, I flagged the lab as positive for diabetes.

I repeated the same process of combining test types and LOINCs for random/plasma glucose and fasting glucose. For random/plasma glucose labs, I flagged any result greater than or equal to 200 milligrams per deciliter (mg/dL) as positive for diabetes, and flagged any fasting glucose of greater than or equal to 126 mg/dL as positive for diabetes. If a patient had multiple labs for different tests on the same day and at least one of the tests was positive (i.e., either an A1c and/or a fasting glucose test), I flagged the patient as having only one positive test for diabetes.

I then combined positive lab tests with records for patients who had no diabetes diagnoses or one diabetes diagnosis. As Figure 2-30 shows, if a patient had one diabetes diagnosis and one or more positive labs for diabetes, I considered them to have diabetes. If a patient had no diabetes diagnosis but two or more positive lab diagnoses, I considered them to have diabetes. However, if a patient had no diabetes diagnoses and one or no high labs for diabetes, I considered them to have diabetes.

To further validate whether these patients were diabetic, I merged pharmacy records for every patient in the group mentioned above (with the exception of those with one diagnosis and two or more positive labs) to their lab and diagnosis records. I created relevant pharmacy records by combining the table of national drug codes (NDCs) specific to diabetes with the patient prescription tables for DH and KPCO. I obtained the diabetes-specific NDC table from colleagues at KPCO who had created it for ongoing diabetes analyses. The NDC table was necessary because it included the specific NDC codes in addition to descriptions of each drug's generic and brand name, whereas the patient prescription tables included the NDC codes and prescription dates, but not the drug names. Because multiple NDC codes exist for the same drug depending on dosage, it was easier to identify drugs using generic and brand names than NDC codes. Based on recommendations from colleagues at KPCO, I removed acetone tests from the table that could be related to diabetes because they could also be related to other illnesses. Similar to lab and diagnosis tables, I excluded pharmacy records associated with pregnant women during the year/s of their pregnancies.

The method developed by Klompas and colleagues (2013) for distinguishing between type 1and type 2 diabetes requires a plurality of type 1 diagnoses combined with pharmacy records to determine whether a patient has type 1 diabetes. Thus, for patients with only one diabetes diagnosis or no diabetes diagnoses, I considered the type of diabetes to be unknown. I merged patients with a plurality of type 1 diagnoses to pharmacy records. If these patients had a prescription for glucagon, a drug that is used more commonly in patients with type 1 diabetes, I considered them to have type 1 diabetes. Otherwise, I considered patients with a plurality of type 1 diagnoses to have type 2 diabetes.

For patients with one or no diabetes diagnoses who had one or no positive lab results for diabetes, if they had a prescription for any diabetes related drug I considered them to have diabetes of an unknown type. I considered patients with no diabetes diagnoses who had two or more positive lab results and no prescription to have undiagnosed diabetes.

To create the binary outcome of whether (1) or not (0) patients had type 2 diabetes, patients with unknown type 1 or type 2 diabetes were assumed to have type 2 diabetes and were coded as a 1. Patients with definitive type 2 diagnoses were also coded as a 1. Similarly, undiagnosed patients were coded as a 1. Patients with definitive type 1 diabetes and patients who were considered not to have diabetes were coded as a 0. Table 2-13 shows diabetes rates by demographic characteristics.

Figure 2-30. Diabetes diagnosis criteria for Kaiser and Denver Health adult patients living in Denver during 2014-2015 outpatient visits (DH N=61,778, KP N=89,324)

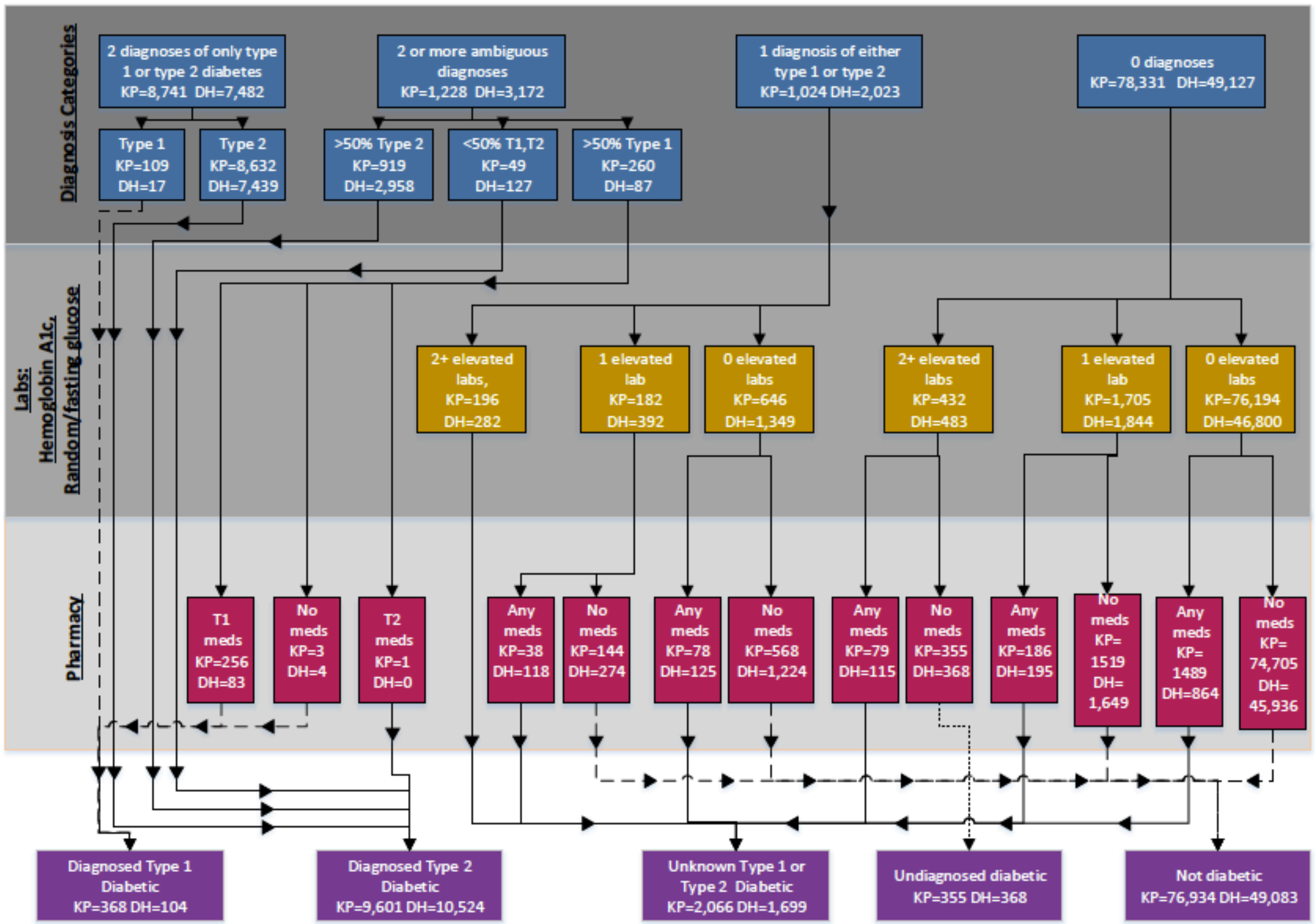


Table 2-13. Characteristics of patients with and without type 2 diabetes for adults ages 25-84 with visits in 2014-2015 and living in Denver, Colorado

	Have type 2 diabetes			Do not have type 2 diabetes			Total	
	N/mean	Column %/ SD	Row %	N/mean	Column %/ SD	Row %	Total N	Column %/ SD
Overall prevalence	24,604		16.29	126,423		83.71	151,027	
Denver Health	12,591	51.17	20.39	49,172	38.89	79.61	61763	40.90
Kaiser Permanente of Colorado	12,013	48.83	13.46	77,251	61.11	86.54	89264	59.10
Female	14,257	57.95	15.59	77,219	61.08	84.41	91476	60.57
Male	10,347	42.05	17.38	49,203	38.92	82.62	59550	39.43
Average age	58.05	13.57		45.88	14.82		47.86	15.30
Age categories:								
25-34 years	1,441	5.86	3.83	36,184	28.62	96.17	37625	24.91
35-44 years	2,924	11.88	8.67	30,799	24.36	91.33	33723	22.33
45-54 years	4,869	19.79	17.72	22,611	17.89	82.28	27480	18.20
55-64 years	6,895	28.02	25.94	19,682	15.57	74.06	26577	17.60
65-74 years	5,583	22.69	32.10	11,811	9.34	67.90	17394	11.52
75-84 years	2,892	11.75	35.15	5,336	4.22	64.85	8228	5.45
Hispanic - Total	11,624	47.24	23.44	37,970	30.03	76.56	49594	32.84
Hispanic - primary English speaker	7,012	28.50	22.99	23,491	18.58	77.01	30503	20.20
Hispanic - primary Spanish speaker	4,612	18.74	24.16	14,479	11.45	75.84	19091	12.64
NH White	7,179	29.18	10.54	60,938	48.20	89.46	68117	45.10
NH Black	4,170	16.95	21.90	14,870	11.76	78.10	19040	12.61
Other	1,129	4.59	14.99	6,402	5.06	85.01	7531	4.99
Missing	502	2.04	7.44	6,243	4.94	92.56	6745	4.47

Hypertension

I used a similar process to what was established for diabetes to calculate patients who ever had hypertension in the DHKP data, using criteria based on a validation study by Peng and colleagues (2016). Figure 2-31 shows the hypertension diagnosis criteria. If patients had two or more diagnoses for hypertension on different dates, then I considered them as having hypertension. If patients had one or no hypertension diagnoses, then I merged them with the vital signs and/or pharmacy tables to examine systolic and diastolic blood pressure readings and prescriptions for blood pressure lowering medication.

I defined high blood pressure according to the National Heart Lung and Blood Institute (NHLBI) guidelines as a systolic blood pressure reading of greater than or equal to 140 mm Hg or a diastolic blood pressure reading of greater than or equal to 90 mm Hg (NHLBI 2015). If patients had one hypertension diagnosis and two elevated blood pressure readings on different dates then I considered them as having hypertension. Otherwise, I merged patients to the pharmacy table to evaluate whether they received blood pressure lowering medication. Table 2-14 shows the diagnosis codes I used to assess hypertension.

Table 2-14. Diagnosis codes used to identify hypertension in DHKP patients

Diagnosis codes	362.11, 401, 402.00, 402.01,402.10, 402.11, 402.90, 402.91, 403.00, 403.01, 403.10, 403.11, 403.90, 403.91, 404.00, 404.01, 404.02, 404.03, 404.10, 404.11, 404.12, 404.13, 404.90, 404.91, 404.92, 404.93, 405.01, 405.09, 405.11, 405.19, 405.91, 405.99, 437.2

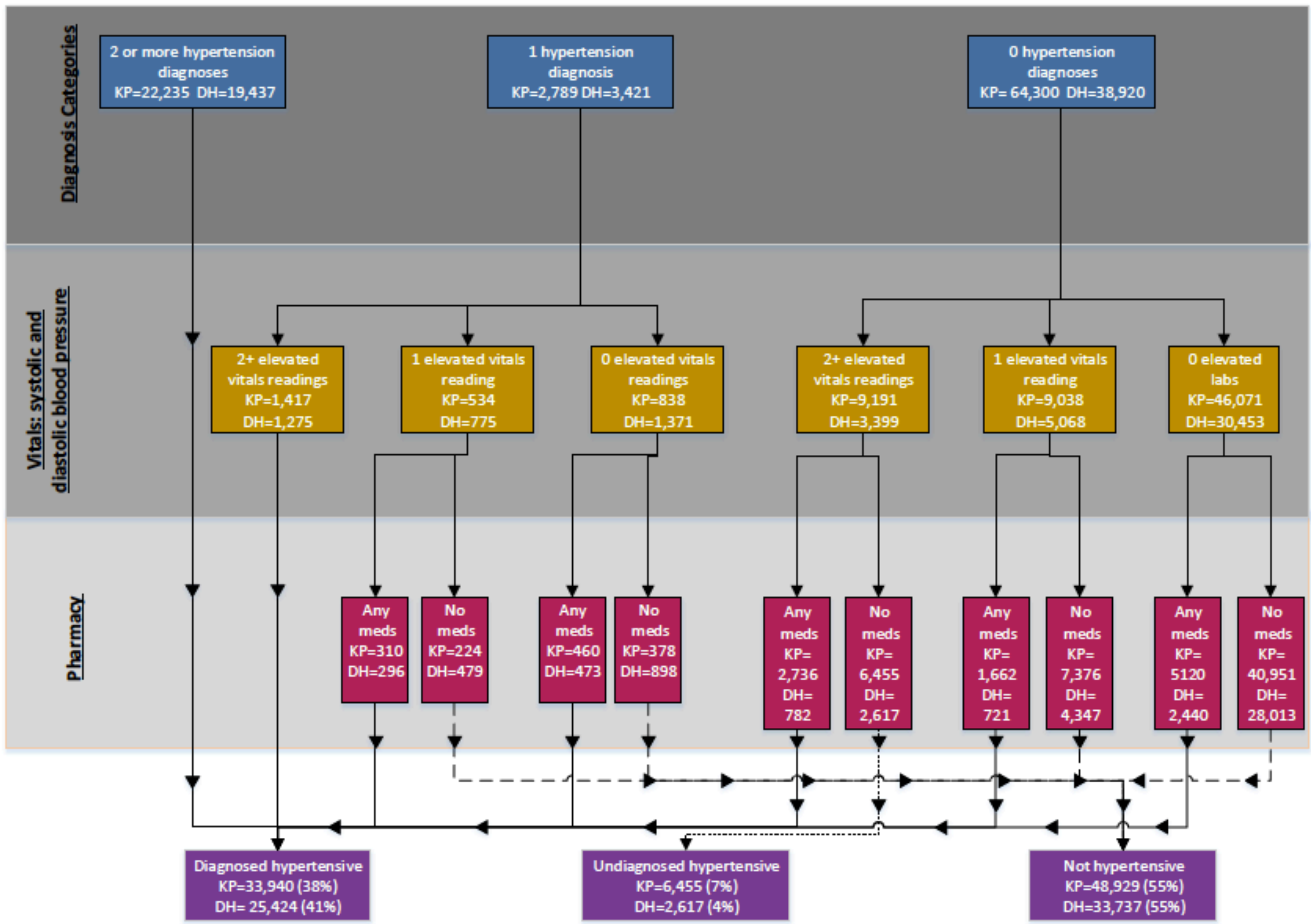
Similar to the diabetes prescription table, I obtained a prescription table for hypertension from colleagues at KPCO and verified it for accuracy. Once again, I combined the NDC table with pharmacy records, removed records for pregnant women, and flagged any remaining patients that had prescriptions for blood pressure lowering medications.

If patients had one hypertension diagnosis, one or no elevated blood pressure readings, and any hypertension medication, I coded them as ever having had hypertension (1). Otherwise, I considered patients with only one hypertension diagnosis and no prescription as not having hypertension (0). It is possible in these scenarios that some patients were given the diagnosis code for hypertension as a way to flag prehypertension, so lack of high blood pressure readings or a prescription indicates that the patient likely did not have hypertension. If patients had no diagnoses for hypertension but had any prescription for hypertension, I considered them as having hypertension. If patients had no diagnosis for hypertension, two or more high blood pressure readings, and no prescription, I considered them as having undiagnosed hypertension. I coded patients matching the hypertension or undiagnosed hypertension criteria as ever hypertensive (1), and those without adequate diagnosis, vitals, or prescription criteria to warrant diagnosis as not hypertensive (0). Table 2-15 shows hypertension rates by demographic characteristics.

Table 2-15. Characteristics of patients with and without hypertension for adults ages 25-84 with visits in 2014-2015 and living in Denver, Colorado

	Have hypertension			Do not have hypertension			Total	
	N/mean	Column %/ SD	Row %	N/mean	Column %/ SD	Row %	Total N	Column %/ SD
Overall prevalence	59,334		39.29	91,693		60.71	151,027	
Denver Health	25,420	42.84	41.16	36,343	39.64	58.84	61763	40.90
Kaiser Permanente of Colorado	33,914	57.16	37.99	55,350	60.36	62.01	89264	59.10
Female	33,344	56.20	36.45	58,132	63.40	63.55	91476	60.57
Male	25,990	43.80	43.64	33,560	36.60	56.36	59550	39.43
Average age	57.62	14.06		41.55	12.50		47.86	15.30
Age categories:								
25-34 years	4,206	7.09	11.18	33,419	36.45	88.82	37625	24.91
35-44 years	7,369	12.42	21.85	26,354	28.74	78.15	33723	22.33
45-54 years	11,570	19.50	42.10	15,910	17.35	57.90	27480	18.20
55-64 years	15,998	26.96	60.19	10,579	11.54	39.81	26577	17.60
65-74 years	12,938	21.81	74.38	4,456	4.86	25.62	17394	11.52
75-84 years	7,253	12.22	88.15	975	1.06	11.85	8228	5.45
Hispanic - Total	19,821	33.41	39.97	29,773	32.47	60.03	49594	32.84
Hispanic - primary English speaker	12,952	21.83	42.46	17,551	19.14	57.54	30503	20.20
Hispanic - primary Spanish speaker	6,869	11.58	35.98	12,222	13.33	64.02	19091	12.64
NH White	25,088	42.28	36.83	43,029	46.93	63.17	68117	45.10
NH Black	10,205	17.20	53.60	8,835	9.64	46.40	19040	12.61
Other	2,710	4.57	35.98	4,821	5.26	64.02	7531	4.99
Missing	1,510	2.54	22.39	5,235	5.71	77.61	6745	4.47

Figure 2-31. Hypertension diagnosis criteria for Kaiser and Denver Health adult patients living in Denver during 2014-2015 outpatient visits (DH N=61,778, KP N=89,324)



Obesity

I calculated obesity using height and weight data from the vital signs table. Because I used height and weight to select the eligible sample of patients, all patients had height and weight data. If patients had multiple records for height or weight, the most recent records were used to calculate body mass index (BMI) and obesity. It was common for patients to have a weight associated with a given date but not a height (because height is not taken as frequently at the doctor's office as weight); so in these adult and non-growing cases, I combined the most recently recorded height with the most recently recorded weight, even if they were on separate dates.

All height data were recorded in inches and weight data were recorded in pounds. To calculate BMI, I used the standard formula:

$$Equation\ 2.1 \qquad BMI = \frac{weight\ (lb)}{Height\ (in)^2}\ X\ 703$$

I considered any patient with a BMI greater than or equal to 30 as having obesity. Similar to diabetes and hypertension, I created a dichotomous variable for those who ever had obesity (1) and never had obesity (0). Table 2-16 shows obesity rates by demographic characteristics.

Table 2-16. Characteristics of patients with and without obesity for adults ages 25-84 with visits in 2014-2015 and living in Denver, Colorado

	Have obesity			Do not have obesity			Total	
	N/mean	Column %/ SD	Row %	N/mean	Column %/ SD	Row %	Total N	Column %/ SD
Overall prevalence	49,813		33.38	99,421		66.62	149,234	
Denver Health	22,196	44.56	37.01	37,774	37.99	62.99	59970	40.19
Kaiser Permanente of Colorado	27,617	55.44	30.94	61,647	62.01	69.06	89264	59.81
Female	31,396	63.03	35.01	58,287	58.63	64.99	89683	60.10
Male	18,417	36.97	30.93	41,133	41.37	69.07	59550	39.90
Average age	48.77	14.33		47.69	15.73		47.86	15.30
Age categories:								
25-34 years	9,865	19.80	27.12	26,511	26.67	72.88	36376	24.38
35-44 years	11,353	22.79	34.17	21,874	22.00	65.83	33227	22.27
45-54 years	10,686	21.45	38.95	16,751	16.85	61.05	27437	18.39
55-64 years	9,955	19.98	37.46	16,617	16.71	62.54	26572	17.81
65-74 years	5,883	11.81	33.82	11,511	11.58	66.18	17394	11.66
75-84 years	2,071	4.16	25.17	6,157	6.19	74.83	8228	5.51
Hispanic - Total	20,492	41.14	42.35	27,894	28.06	57.65	48386	32.42
Hispanic - primary English speaker	13,278	26.66	44.28	16,707	16.80	55.72	29985	20.09
Hispanic - primary Spanish speaker	7,214	14.48	39.20	11,187	11.25	60.80	18401	12.33
NH White	18,102	36.34	26.66	49,805	50.10	73.34	67907	45.50
NH Black	7,801	15.66	41.62	10,944	11.01	58.38	18745	12.56
Other	1,597	3.21	21.43	5,854	5.89	78.57	7451	4.99
Missing	1,821	3.66	27.00	4,924	4.95	73.00	6745	4.52

Depression

I identified patients with depression in EHR data using formal ICD-9 diagnosis codes. Providers screened or evaluated patients for depression during visits with their providers and if they were considered depressed or required depression medication a formal diagnosis was made using 5 diagnosis (ICD9) codes: 296.3, 296.5, 300.4, 309, and 311. I obtained the list of diagnosis codes from colleagues at KPCO and verified it. Compared to diabetes, hypertension, and obesity, depression may be the dependent variable most subject to selection bias due to limited access to care because it relies solely on diagnosis codes. The other health conditions combine lab, pharmacy, and/or vitals data so that individuals who are not formally diagnosed may still be captured in the prevalence estimates. Furthermore, the stigma associated with depression may also impact the way patients respond to mental health evaluations. Thus, depression estimates likely reflect underestimates, particularly in higher poverty areas where residents have less access to care and potentially more risk for developing mental health conditions (Wadsworth and Achenbach 2005). Table 2-17 shows depression rates by demographic characteristics.

Table 2-17. Characteristics of patients with and without depression for adults ages 25-84 with visits in 2014-2015 and living in Denver, Colorado

	Have depression			Do not have depression			Total	
	N/mean	Column %/ SD	Row %	N/mean	Column %/ SD	Row %	Total N	Column %/ SD
Overall prevalence	32,248		21.35	118,779		78.65	151,027	
Denver Health	17,163	53.22	27.79	44,600	37.55	72.21	61763	40.90
Kaiser Permanente of Colorado	15,085	46.78	16.90	74,179	62.45	83.10	89264	59.10
Female	23,166	71.84	25.32	68,310	57.51	74.68	91476	60.57
Male	9,082	28.16	15.25	50,468	42.49	84.75	59550	39.43
Average age	50.88	15.08		47.05	15.26		47.86	15.30
Age categories:								
25-34 years	5,753	17.84	15.29	31,872	26.83	84.71	37625	24.91
35-44 years	6,339	19.66	18.80	27,384	23.05	81.20	33723	22.33
45-54 years	6,452	20.01	23.48	21,028	17.70	76.52	27480	18.20
55-64 years	7,104	22.03	26.73	19,473	16.39	73.27	26577	17.60
65-74 years	4,404	13.66	25.32	12,990	10.94	74.68	17394	11.52
75-84 years	2,196	6.81	26.69	6,032	5.08	73.31	8228	5.45
Hispanic - Total	11,981	37.15	24.16	37,613	31.67	75.84	49594	32.84
Hispanic - primary English speaker	8,129	25.21	26.65	22,374	18.84	73.35	30503	20.20
Hispanic - primary Spanish speaker	3,852	11.94	20.18	15,239	12.83	79.82	19091	12.64
NH White	14,532	45.06	21.33	53,585	45.11	78.67	68117	45.10
NH Black	3,994	12.39	20.98	15,046	12.67	79.02	19040	12.61
Other	1,155	3.58	15.34	6,376	5.37	84.66	7531	4.99
Missing	586	1.82	8.69	6,159	5.19	91.31	6745	4.47

Current smoking

Smoking status was collected in a slightly different way in the DH and KPCO EHR systems. For DH, smoking status was calculated using a variable called ONC_Smoking_Status, with the following categories: (1) current every day smoker, (2) current some day smoker, (3) former smoker, (4) never smoker, (5) smoker, current status unknown, (6) unknown if ever smoked. I created a dichotomous variable for current smoking by combining categories 1 and 2 into a single current smoker category (1), and all other categories were combined into a not current smoker category (0). For each patient, I used the most recent smoking record to determine current smoking status, so if a patient was coded as being a current smoker in 2010 but a former smoker in 2013, I categorized them as a former smoker.

For KPCO, the variable Tobacco_Smoking_Use recorded the smoking status of patients. Unlike ONC_smoking_status, the KPCO variable was not mutually exclusive. The categories are as follows: (E) Current Everyday, (S) Current Some Days, (H) Heavy Smoker, (L) Light Smoker, (N) Never, (P) Passive, (Q) Former, (U) Unknown, (Y) Never Assessed, and (X) Smoker - Current Status Unknown. To create the current smoker variable, I coded categories E, S, H, L, and P as current smoker (1), and categories N, Q, U, Y, and X as not current smoker (0). Table 2-18 shows depression rates by demographic characteristics.

Table 2-18. Characteristics of patients who did and did not smoke cigarettes for adults ages 25-84 with visits in 2014-2015 and living in Denver, Colorado

	Current smoker			Not current smoker			Total	
	N/mean	Column %/ SD	Row %	N/mean	Column %/ SD	Row %	Total N	Column %/ SD
Overall prevalence	24,642		16.32	126,385		83.68	151,027	
Denver Health	13,879	56.32	22.47	47,884	37.89	77.53	61763	40.90
Kaiser Permanente of Colorado	10,763	43.68	12.06	78,501	62.11	87.94	89264	59.10
Female	13,050	52.96	14.27	78,426	62.05	85.73	91476	60.57
Male	11,592	47.04	19.47	47,958	37.95	80.53	59550	39.43
Average age	46.83	13.83		48.07	15.56		47.86	15.30
Age categories:								
25-34 years	6,102	24.76	16.22	31,523	24.94	83.78	37625	24.91
35-44 years	5,141	20.86	15.24	28,582	22.62	84.76	33723	22.33
45-54 years	5,491	22.28	19.98	21,989	17.40	80.02	27480	18.20
55-64 years	5,209	21.14	19.60	21,368	16.91	80.40	26577	17.60
65-74 years	2,135	8.66	12.27	15,259	12.07	87.73	17394	11.52
75-84 years	564	2.29	6.85	7,664	6.06	93.15	8228	5.45
Hispanic - Total	7,927	32.17	15.98	41,667	32.97	84.02	49594	32.84
Hispanic - primary English speaker	6,402	25.98	20.99	24,101	19.07	79.01	30503	20.20
Hispanic - primary Spanish speaker	1,525	6.19	7.99	17,566	13.90	92.01	19091	12.64
NH White	10,005	40.60	14.69	58,112	45.98	85.31	68117	45.10
NH Black	4,767	19.35	25.04	14,273	11.29	74.96	19040	12.61
Other	865	3.51	11.49	6,666	5.27	88.51	7531	4.99
Missing	1,078	4.37	15.98	5,667	4.48	84.02	6745	4.47

INDIVIDUAL-LEVEL INDEPENDENT VARIABLES

EHR Data Independent Variables

I used independent variables at the individual and neighborhood levels, and created them from the DHKP EHR data, the American Community Survey, and the 500 Cities Project/BRFSS. In Table 2-21 I present descriptive information for age, race, acculturation, gender, comorbidities, encounters, and payment types table by health system.

Age

I described my process for creating patient age earlier in the sample selection section. I also created four age variables for the analyses – continuous age between 25-84, 10-year age categories (6 categories altogether), and mean-centered age.

Race/Ethnicity

The most common way patient race and ethnicity were captured in EHRs was through a standard screening process during a doctor's visit. In general, providers and staff are trained not to classify patient race or ethnicity, and to ask patients to classify themselves. In some cases, patient race or ethnicity may have also been recorded in other administrative data for DH or KPCO. In cases where race/ethnicity were categorized in multiple places, the race/ethnic status was verified and, if different, patients were coded as having multiple race/ethnic statuses.

I used five race/ethnicity groups in the analyses: Hispanic, non-Hispanic white, non-Hispanic black, other race, and missing race. Missing race was included as a race category because I determined that data were not missing at random. Patients with missing race were more likely to be younger and healthier, and thus I included them as their own race/ethnic category in analyses.

I used two variables from the demographics table in the VDW to create the race/ethnicity variable in the DHKP dataset. I used the “Hispanic” variable to capture Hispanic ethnicity. Values included “Y” for Hispanic patients, “N” for non-Hispanic patients, and “U” for unknown ethnicity. If a patient had a “Y” for the “Hispanic” variable, I categorized them as Hispanic, regardless of their race. I used the “Race1” variable to create all race categories if the “Hispanic” variable was “N” or “U” (not Hispanic or unknown). If the “race1” value was “WH” then I considered the patient to be non-Hispanic white. If the “race1” value was “BA” then I considered the patient to be non-Hispanic black. If the “race1” value was “HP”, “MU”, “IN”, “AS” or “OT” (Native Hawaiian or Other Pacific Islander, American Indian/Alaska Native, Asian, more than one race, or other race, respectively) then I considered the patient’s race to be “other race.” Finally, if race1 was “UN” (unknown) then I considered the patient’s race to be missing, unless their primary language was Spanish, in which case I coded them as Hispanic.

Gender

I used the “gender” variable from the demographics table to create numeric male and female categories. If gender= ‘M’ then the patient’s gender was considered to be male, if gender= ‘F’ then gender was considered to be female.

Smoking status

I also used smoking status (described above in the dependent variable category) as an independent variable in some analyses.

Spanish speakers/acculturation

I measured acculturation by examining language preference among Hispanic patients. I used two variables to gauge whether Hispanic patients were primary Spanish speakers. First, if the value for the "primary_language" variable was "spa" (Spanish) then the patient was considered to be a primary Spanish speaker. Because there was some missingness in the "primary_language" variable, I evaluated another variable – "needs_interpreter" for those Hispanic patients missing the "primary_language" variable. If the value for the "needs_interpreter" variable was "Y" (yes) then those Hispanic patients were assumed to be native Spanish speakers.

Comorbidities

I used two common comorbidity measurement tools by Charlson and colleagues (1987) and Elixhauser and colleagues (1998) to create a single scale of health conditions using EHR data. The original scale contains some of the variables that I used as either dependent or independent variables in this study, such as hypertension, diabetes, obesity, and tobacco use. I removed these items from the scale to decrease the potential for colinearity when the comorbidity scale and any of these health conditions were used in the same analysis. Table 14 contains the conditions included in the comorbidity index as well as their ICD-9 diagnosis codes. I included twenty-one conditions in the comorbidity index. Conditions include cardiac arrhythmia, congestive heart failure, valvular disease, pulmonary circulation disorders, peripheral vascular disorders, paralysis, other neurological disorders, chronic pulmonary disease, hypothyroidism, renal failure, liver disease, peptic ulcer disease excluding bleeding, AIDS/HIV, lymphoma, metastatic cancer, solid tumor without metastasis, rheumatoid arthritis/collagen, coagulopathy, fluid/electrolyte disorders, blood loss anemia, and deficiency anemia. Table 2-19 contains the conditions and associated ICD-9 codes for each of the conditions I used in the comorbidity measure.

I calculated an additive scale of the total number of comorbidities for each patient. Because the distribution of comorbidities is a non-normal Poisson distribution, with no comorbidities as the most common response, I created the following ordinal variable with fairly even distribution: 0 comorbidities, 1 comorbidity, 2 comorbidities, 3+ comorbidities.

Table 2-19. Conditions included in comorbidity index and related ICD-9 diagnosis codes	
Condition	**Diagnosis codes**
Cardiac arrhythmia	426.0, 426.10, 426.12, 426.13, 426.7, 426.9, 427.0, 427.1, 427.2, 427.3, 427.4, 427.6, 427.8, 427.9, 785.0, 996.01, 996.04, V45.0, V53.3
Congestive heart failure	398.91, 402.01, 402.11, 402.91, 404.01, 404.03, 404.11, 404.13, 404.91, 404.93, 425.4, 425.5, 425.6, 425.7, 425.8, 425.9, 428
Valvular disease	093.2, 394, 395, 396, 397, 424, 746.3, 746.4, 746.5, 746.6, V42.2, V43.3
Pulmonary circulation disorders	415.0, 415.1, 416, 417.0, 417.8, 417.9
Peripheral vascular disorders	093.0, 437.3, 440, 441, 443.1, 443.2, 443.8, 443.9, 447.1, 557.9, 557.1, V43.4
Paralysis	334.1, 342, 343, 344.0, 344.1, 344.2, 344.3, 344.4, 344.5344.6, 344.9
Other neurological disorders	333.92, 331.9, 332.0, 332.1, 333.4, 333.5, 334, 335, 336.2, 340, 341, 345, 348.1, 348.3, 780.3, 784.3
Chronic pulmonary disease	416.8, 416.9, 490, 491, 492, 493, 494, 495, 496500, 501, 502, 503, 504, 505, 506.4, 508.1, 508.8
Hypothyroidism	240.9, 243, 244, 246.1, 246.8
Renal failure	403.01, 403.11, 403.91, 404.02, 404.03, 404.12, 404.13, 404.92, 404.93, 585, 586, 588.0, V56,
Liver disease	070.22, 070.23, 070.32, 070.33, 070.44, 070.54, 070.6, 070.9, 570, 571, 456.0, 456.1, 456.2, 572.2, 572.3, 572.4, 572.8, 573.3, 573.4, 573.8, 573.9, V42.7
Peptic ulcer disease excluding bleeding	531.7, 531.9, 532.7, 532.9, 533.7, 533.9, 534.7, 534.9
AIDS/HIV	042, 043, 044
Lymphoma	200, 201, 202, 203.0, 238.6
Metastatic cancer	196, 197, 198, 199
Solid tumor without metastasis	140, 141, 142, 143, 144, 145, 146, 147, 148, 149, 150, 151, 152, 153, 154, 155, 156, 157, 158, 159, 160, 161, 162, 163, 164, 165, 166, 167, 168, 169, 170, 171, 172, 174, 175, 176, 177, 178, 179, 180, 181, 182, 183, 184, 185, 186, 187, 188, 189, 190, 191, 192, 193, 194, 195
Rheumatoid Arthritis/collagen	446, 701.0, 710.0, 710.1, 710.2, 710.3, 710.4, 710.8, 710.9, 711.2, 714, 719.3, 720, 725, 728.5, 728.89, 729.30
Coagulopathy	286, 287.1, 287.3, 287.4, 287.5
Fluid and Electrolyte Disorders	253.6, 276
Blood Loss Anemia	280
Deficiency Anemia	280.1, 280.8, 280.9, 281

Total number of encounters

I included the total number of patient encounters as both a proxy for utilization of health services and a measure of overall health. Since frequent encounters could indicate either that patients have good access to care (e.g., utilizing preventive care and getting routine screenings) or that the patient is in poor health (e.g., requiring frequent follow-up for an illness or chronic condition). I assessed the number of encounters retrospectively for the patient's whole EHR history. Similar to comorbidities, the number of patient encounters has a Poisson distribution, with the largest number of patients having one encounter. Thus, I created a categorical variable that distributed encounters into quartiles: less than 22, 22-52, 53-114, and greater than 114 visits.

Payment types

I used the most recent available payment information to assess type of insurance for each patient. Type of insurance is an imperfect proxy for patient SES, and is important to include particularly because other indicators of SES, such as education level or income, are not currently available in the DHKP EHRs. KPCO payment types are organized into specific variables with yes/no values. The DH system stores payment information in a different way. They assign each payment type with a payer plan code. There are hundreds of codes to reflect each type of payer. DH researchers created a crosswalk to link payer plan codes to the primary payer codes available in the VDW. Primary payer codes were associated with categories of payers (reserve_ar_rollup). I created the following payment categories: Private insurance, Medicaid, Medicare, self-pay, other insurance, other type of payment, and missing payment information. Not surprisingly, I show in Table 2-21 that 97% of KPCO patients had private insurance. The largest payment category for DH was Medicaid. Table 2-20 shows each of the payment categories I created and the types of payment codes that fit into each category for DH and KPCO.

Table 2-20. Construction of the 'Payment Type' variable

Payment Type Category	**DH category (values from reserve_ar_roundup variable)**	**KPCO category (variable name)**
Private insurance or HMO	Commercial plan (commercial), Denver Health Medical Plan (DHMP N01, DHMP POS, Elevate Capitate, Elevate FFS)	HMO plan (plan_hmo), Point of service plan (plan_pos), preferred provider organization plan (plan_ppo)
Medicaid	Medicaid categories (Medicaid, DH medicaid choi, Medicaid Inactiv)	Medicaid insurance (ins_medicaid)
Medicare	Medicare categories (medicare, DHMP medicare)	Medicare insurance (ins_medicare)
Self pay or Denver Health Financial Assistance Plan (DFAP)	Denver Health Financial Assistance Plan (DFAP), self pay (Self Pay)	Self pay (ins_selffunded)
Other public insurance (state sponsored)	Colorado Indigent Care Program (CICP, CICP pending), CHP+ (CHP plus, DHMP CHP +), Colorado Access/behavioral health organization (Colo Access BHO)	State subsidized (ins_statesubsidized)
Other payment type		Other insurance (ins_other)
Missing payment information	Missing payment information	Missing payment information

Table 2-21. Descriptive characteristics used as independent variables by health system for adult patients ages 25-84 with an encounter in 2014/2015 in Denver, Colorado

	Denver Health			Kaiser Permanente of Colorado			Total	
	N/Mean	Column %/SD	Row %	N/Mean	Column %/SD	Row %	N/Mean	Column %/SD
Total	61,763			89,264			151,027	
Average age	46.08	14.51		49.10	15.71		47.86	15.3
Age categories: 25-34	17,054	28%	45%	20,571	23%	55%	37,625	25%
35-44	14,313	23%	42%	19,410	22%	58%	33,723	22%
45-54	11,847	19%	43%	15,633	18%	57%	27,480	18%
55-64	10,869	18%	41%	15,708	18%	59%	26,577	18%
65-74	5,483	9%	32%	11,911	13%	68%	17,394	12%
75-84	2,197	4%	27%	6,031	7%	73%	8,228	5%
Race: Hispanic Total	31,171	50%	63%	18,423	21%	37%	49,594	33%
Spanish speaking	14,987	24%	49%	15,516	17%	51%	30,503	20%
English speaking	16,184	26%	85%	2,907	3%	15%	19,091	13%
Non-Hispanic white	16,818	27%	25%	51,299	57%	75%	68,117	45%
Non-Hispanic black	10,706	17%	56%	8,334	9%	44%	19,040	13%
Non-Hispanic other	2,625	4%	35%	4,906	5%	65%	7,531	5%
Non-Hispanic missing	443	1%	7%	6,302	7%	93%	6,745	4%
Female	39,175	63%	43%	52,301	59%	57%	91,476	61%
Male	22,587	37%	38%	36,963	41%	62%	59,550	39%
Comorbidities: 0 conditions	29,726	48%	43%	38,627	43%	57%	68,353	45%
1 condition	14,384	23%	38%	23,917	27%	62%	38,301	25%
2 conditions	7,156	12%	39%	11,129	12%	61%	18,285	12%
3+ conditions	10,497	17%	40%	15,591	17%	60%	26,088	17%
Visits: Less than 22 visits	23,491	38%	64%	13,141	15%	36%	36,632	24%
22-52 (Q2)	19,243	31%	50%	19,011	21%	50%	38,254	25%
53-114 (Q3)	13,886	22%	36%	24,255	27%	64%	38,141	25%
115+ (Q4)	5,143	8%	14%	32,857	37%	86%	38,000	25%
Insurance type: Private insurace	6,144	10%	7%	86,361	97%	93%	92,505	61%
Medicaid	20,732	34%	100%	-	0%	0%	20,732	14%
Medicare	5,694	9%	98%	91	0%	2%	5,785	4%
Self pay	8,888	14%	100%	-	0%	0%	8,888	6%
Other insurance	3,713	6%	100%	-	0%	0%	3,713	2%
Other type of payment	2,072	3%	42%	2,812	3%	58%	4,884	3%
Missing payment information	14,520	24%	100%	-	0%	0%	14,520	10%

Neighborhood Data Independent Variables

ACS variables

As discussed earlier in the chapter, ACS variables measured at the census tract or neighborhood level often have large margins of error due to limited sampling. For this reason, I created composite ACS measures for each of the analyses.

Table 2-22. Description of variables from the American Community Survey included in the latent profile analysis	
Measure type	**Description**
Barrio measures	Percent of residents who are Hispanic/Latino
	Percent of residents who are not citizens
	Percent of residents who are foreign-born Hispanic/Latino
	Percent of Hispanic residents who have moved within Denver County in past year
	Percent of foreign born naturalized citizens who are in the same house as 1 year ago
	Percent of foreign born residents who are in the same house as 1 year ago
	Percent of non-citizens who are in the same house as 1 year ago
Poverty & SES	Percent of residents living under federal poverty level
	Percent without a car available
	Percent ages 16+ that are civilians in the labor force and unemployed
	Percent of occupied housing units that are renter occupied
	Percent of homes that are considered to be overcrowded (>1.5 people per room)
	Percent of population with less than a high school education
	Percent of houses that have at least one negative physical or financial condition related to housing
Stability/mobility	Percent who have moved in the past year
	Percent homeowners who moved into unit within past 5 years
	Percent renters who moved into unit within past 5 years
Distance to work	Percent of male commuters who commute to work in less than 10 minutes
	Percent of female commuters who commute to work in less than 10 minutes
	Percent of male commuters who commute to work within 10-29 minutes
	Percent of female commuters who commute to work within 10-29 minutes
	Percent of male commuters who commute to work in 30 minutes or more
	Percent of female commuters who commute to work in 30 minutes or more

Latent class variables

I used variables from the ACS to create latent classes for the analyses in Chapter 3, and to compare to another measure of barrios in Chapter 4. Table 2-21 shows the variables used in the latent profile analysis (LPA). The variables fall into four categories that all relate to defining "barrio" neighborhoods. The barrio measures include the percent of Hispanic, foreign-born, and non-citizen residents in each census tract and available housing characteristics for these groups. Poverty and SES variables include poverty, car availability, unemployment, renter occupied units, overcrowding, education, and negative physical or financial conditions of homes. Stability and mobility characteristics include the overall percent of residents who had moved in the past year as well as homeowners and renters who had moved. Finally, I included distance to work variables to gauge how far residents travel from their home to their work, which may indicate whether they are spending the majority of their time close to their homes or in other places. This is relevant to understanding neighborhood "exposure," in the sense that residents who work within 10 minutes of their home may be exposed to a similar environment for longer than those who work far away from their home. Additionally, those who live far from their work may do so because they want to or have to live in a specific neighborhood, so understanding variation in travel time to work may suggest different decision making processes for residents.

As I indicate in Table 2-22, all variables were measured as a percent (i.e., the percent of residents in a census tract/neighborhood who are Hispanic/Latino). I tested other ACS variables for inclusion in the latent classes, but only variables with significant variation across classes were included in the final analysis (described in more detail in the Analyses section).

Barrio rank

For the Chapter 4 analysis, I created a measure assessing the extent to which a neighborhood might constitute a "barrio" beyond solely looking at the percent of Hispanic residents. For the barrio rank measure, I equally weighted the importance of having immigrant and Hispanic residents in the neighborhood. This barrio rank consisted of three variables: percent of residents who were Hispanic/Latino, percent foreign-born, and percent non-citizens. I ranked each of these variables across the 142 census tracts used in the analysis, and then summed the three ranks to include a final "barrio" score for each tract. I then broke the scores into quartiles, with the first quartile representing neighborhoods with the highest barrio rank and the fourth quartile representing neighborhoods with the lowest barrio rank.

In Figure 2-32 I show a scatterplot comparison between the barrio rank and the percent of Hispanic residents in a tract. Although the two measures were highly correlated (r = 0.92), there were some differences. In the figure, I circled two particular tracts (for demonstrative purposes, I called them A and B). Tract A and B have the same percent of Hispanic residents, but very different compositions of foreign-born and non-citizen residents. For this reason, they are on the same horizontal axis for percent Hispanic but have different barrio ranks. To date, no research has examined a composite measure of barrios that incorporates both the immigrant composition and the Hispanic composition, and compared this to solely examining the Hispanic composition. This is important because these compositional differences could impact the social and cultural environments of neighborhoods. As I describe in more detail in Chapters 1, 4, and 5, immigrant social context may be distinct from the social context of U.S.-born Hispanic residents in ways that could have protective or deleterious health consequences.

Figure 2-32. Comparison between the percent Hispanic and the barrio rank for 142 census tracts in Denver, Colorado.

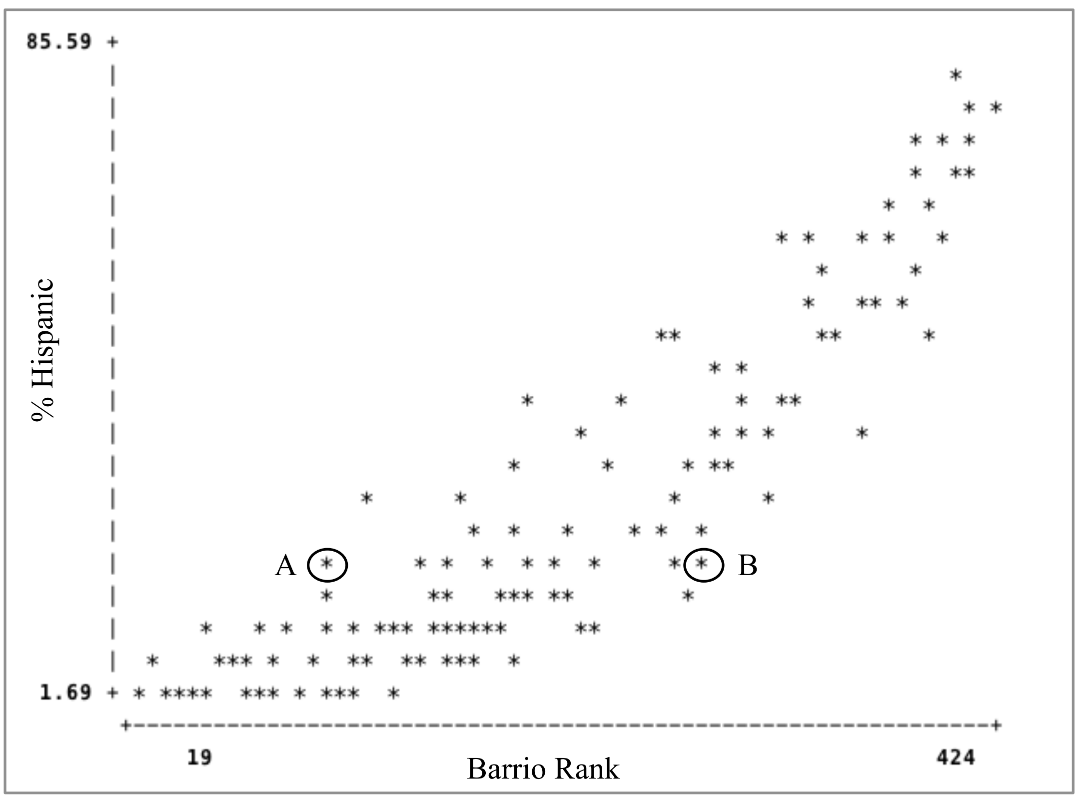


Table 2-23 shows the top 30 ranked tracts with the highest percent Hispanic and the highest barrio rank, and the neighborhood of each tract.

Table 2-23. Comparison of the rank of neighborhoods by percent Hispanic and barrio characteristics

	Hispanic Rank		Barrio Rank	
Order	Tract	Neighborhood	Tract	Neighborhood
1	8031004503	Westwood	8031003500	Elyria Swansea
2	8031004505	Westwood	8031004505	Westwood
3	8031003500	Elyria Swansea	8031004503	Westwood
4	8031001000	Valverde	8031015600	College View/South Platte
5	8031000903	Barnum	8031004602	Mar Lee
6	8031004504	Westwood	8031001402	Ruby Hill
7	8031015600	College View/South Platte	8031008305	Montbello
8	8031001301	Athmar Park	8031001000	Valverde
9	8031004602	Mar Lee	8031000902	Barnum West
10	8031000905	Villa Park	8031001302	Athmar Park
11	8031001302	Athmar Park	8031000903	Barnum
12	8031000904	Villa Park	8031008386	Montbello
13	8031004506	Westwood	8031008304	Montbello
14	8031000902	Barnum West	8031004506	Westwood
15	8031001401	Ruby Hill	8031000905	Villa Park
16	8031008386	Montbello	8031004504	Westwood
17	8031008305	Montbello	8031001301	Athmar Park
18	8031004601	Mar Lee	8031001401	Ruby Hill
19	8031008304	Montbello	8031008387	Montbello
20	8031001101	Sunnyside	8031000904	Villa Park
21	8031001402	Ruby Hill	8031008306	Montbello
22	8031001500	Globeville	8031000702	West Colfax
23	8031004700	Harvey Park	8031001500	Globeville
24	8031004603	Harvey Park	8031004601	Mar Lee
25	8031000201	Chaffee Park	8031008312	Montbello
26	8031008306	Montbello	8031008391	Gateway / Green Valley Ranch
27	8031008387	Montbello	8031001101	Sunnyside
28	8031008312	Montbello	8031008388	Gateway / Green Valley Ranch
29	8031003601	Cole	8031008390	Gateway / Green Valley Ranch
30	8031000702	West Colfax	8031000600	Jefferson Park

Townsend index of deprivation

The socioeconomic status of neighborhoods was assessed using the Townsend index of deprivation. The Townsend index is a common measure used in neighborhoods and health research (e.g., Krieger et al. 2002, Stafford and Marmot 2003), and traditionally includes the following variables: percent of residents with no car ownership, percent of residents who are unemployed, percent of residents who rent, and percent of residents who live in overcrowded houses. The ACS 2011-2015 contained all variables in the same format as the original Townsend index except for car ownership. In place of car ownership, the percent of residents who had *access* to a car was used instead. A standardized Z score was calculated for each measure in the index, and then the standardized scores were summed to create the index. Similar to the barrio rank, quartiles were created for the Townsend index, with the first quartile indicating neighborhoods with the most deprivation and the fourth quartile indicating neighborhoods with the lowest deprivation.

Krieger and colleagues (2002) conducted an extensive analysis on area-based measures for use in neighborhoods and health research. In addition to recommending the Townsend index, they also recommended a measure of socioeconomic position (SEP index). The SEP index includes measures of poverty, education, income, and a measure of expensive homes using median home values. The Kennedy neighborhood in Denver was missing median home values in the 2011-2015 ACS. Because the Townsend index could be calculated using data available for all neighborhoods, it was selected over the SEP index.

Gini coefficient

The gini coefficient (also called the Gini Index) is a measure of income inequality. It complements the Townsend index as a measure of SES (particularly because the Townsend index does not include income as one of its variables) and also provides information about income inequality *within* neighborhoods. The gini coefficient is calculated by the Census Bureau and is provided as part of the publicly available ACS data. It is calculated by using the difference between the observed income distribution in a census tract (called the Lorenz curve) and a scenario of equal income distribution. The larger the difference between equal income distribution and the observed income distribution, the larger the gini coefficient. Therefore, on the gini scale of 0 to 1, a value of 0 would represent equal income distribution (or no difference between the observed income distribution and a scenario of equal distribution) and a value of 1 would indicate complete inequality, in which one group would have all of the income in a neighborhood and another group would have no income at all (Census Bureau 2016).

500 Cities Project

I used three measures from the 500 Cities Project data for the Chapter 3 analysis.

Binge drinking

I used an aggregated census-tract-level measure for binge drinking to assess health behaviors of a community, in conjunction with the aggregated smoking measure from the DHKP EHRs. The BRFSS classifies binge drinking as five or more drinks on one occasion for men and four drinks on one occasion for women. The aggregated measure reflects the percent of adult residents ages 18 or older who report binge drinking in the past 30 days.

No health insurance

I also used a measure of the percent of adult residents ages 18-64 without health insurance from the 500 Cities Project data. I included respondents in the numerator if they reported not having healthcare coverage at the time of the 2015 BRFSS interview. Similar to binge drinking, I aggregated the percent of residents without healthcare coverage to the census tract level.

Doctor visits

The final measure that I used from the 500 Cities Project reflects access to health care. Although having health insurance increases the odds of using healthcare services, the two are not perfectly correlated. Health centers and systems (like DH) exist to provide access to populations that are uninsured or underinsured, so it is possible to have access to care without having health insurance. Because getting health insurance can be difficult for undocumented populations in particular, using an insurance variable to assess healthcare access alone would leave out this group even if they were accessing care. Thus, in addition to the insurance coverage variable, I also included an indicator of access. The BRFSS asks respondents whether they had been to the doctor for a routine visit in the past year. The aggregated variable is the percent of adult residents 18 years or older who have gone to the doctor for a routine visit.

ANALYSES

Empirical Analyses for Chapter 3

In Chapter 3 I conduct an ecological analysis of health conditions across neighborhoods. The dependent variables were the percent of residents with diabetes, obesity, hypertension, diagnosed depression, and current smoking. The primary independent variable was the type of neighborhood, defined by the LPA analysis.

Latent profile analysis

As mentioned earlier, I created the primary independent variable – neighborhood classes –using latent profile analysis (LPA), or Gaussian Finite Mixture Modeling. LPA (a version of latent class analysis using continuous variables) is an increasingly common approach for defining neighborhood "types" or classes because it can incorporate a variety of neighborhood characteristics without relying on equal weighting or simple scales (Weden et al. 2011). In this study, I combined social/demographic variables from the ACS (as shown in Table 2-22) to form four categories that define the latent construct of a Hispanic barrio. LPA also provides more nuance to the barrio effects literature, in which researchers often use a single variable – percent Hispanic – to define barrios. Relying solely on percent Hispanic is particularly problematic when using ACS data that have high margins of error at the census tract level.

I selected a four-class LPA solution that represented four neighborhood types across 142 census tracts in Denver. I selected the four-class solution based on theoretical and model fit. I selected initial variables to include in the LPA based on factors that may be related to barrio neighborhoods. Once I ran the initial LPA, I examined the average of each ACS variable that I included in the model across the best class solution. For example, I examined the average percent of foreign-born residents in each tract across all classes produced by the LPA. If the average percent foreign-born was outside the 95% confidence interval of the overall mean in at least half of the classes, then I kept that variable in the LPA because it demonstrated substantial variation from the mean. This was an iterative process, wherein I removed variables that did not demonstrate variation across classes, re-ran the LPA with the new, refined set of variables, and then examined the mean of each variable across the new classes. In the final four-class solution, one variable – women who travel more than 30 minutes to work - was kept in the model for theoretical reasons even though there was not substantial variation across the classes. All of the other work related variables showed variation across classes, so I decided to keep this variable in as well.

Another tool that I used to assess model fit of the LPA was the Bayesian Information Criteria (BIC) values. Table 2-24 shows the BIC values for 1-10 class solutions and the number of census tracts that would be in each class using the final set of ACS variables. Higher (less negative) values represented better model fit. The four-class solution has the higher BIC value (-16133.93). It also has fairly even distribution of tracts across each class, which is important for statistical power and for the neighborhood types to succinctly represent a city. Figure 2.33 shows the same BIC values plotted, and provides another visual representation of why the four-class solution was superior in model fit to the other class options.

Table 2-24. Model fit and Census tract distribution for latent profile analysis class solutions

Class solution	BIC	Census tract distribution
1	-16343.04	143
2	-16232.01	108, 35
3	-16271.25	49, 63, 31
4	-16133.93	44, 30, 36, 33
5	-16522.29	29, 29, 23, 23, 39
6	-16546.44	29, 30, 18, 27, 5, 34
7	-16642.77	29, 30, 18, 22, 7, 21, 16
8	-16695.1	30, 19, 16, 21, 7, 11, 23, 16
9	-16769.57	16, 19, 14, 18, 6, 11, 26, 16, 17
10	-16842.53	17, 19, 15, 20, 6, 11, 25, 16, 3, 11

Figure 2-33. Model fit for latent profile analysis class solutions

Regression analyses

I used the dependent variables in two ways; in the first set of analyses I used ordinary least squares (OLS) regression to understand the associations in prevalence of each condition across classes of neighborhoods for the total population of patients in EHRs. I presented all models in a nested (additive) fashion, which I describe in detail in Chapter 3.

In the second set of analyses I examined the extent of inequality in prevalence rates for each health condition between Hispanics and NHWs within each neighborhood. The dependent variables were the natural logs of the relative odds of Hispanics compared to NHWs. I calculated these values by first transforming the proportion of Hispanic residents with a health condition into the odds of having that condition. For example:

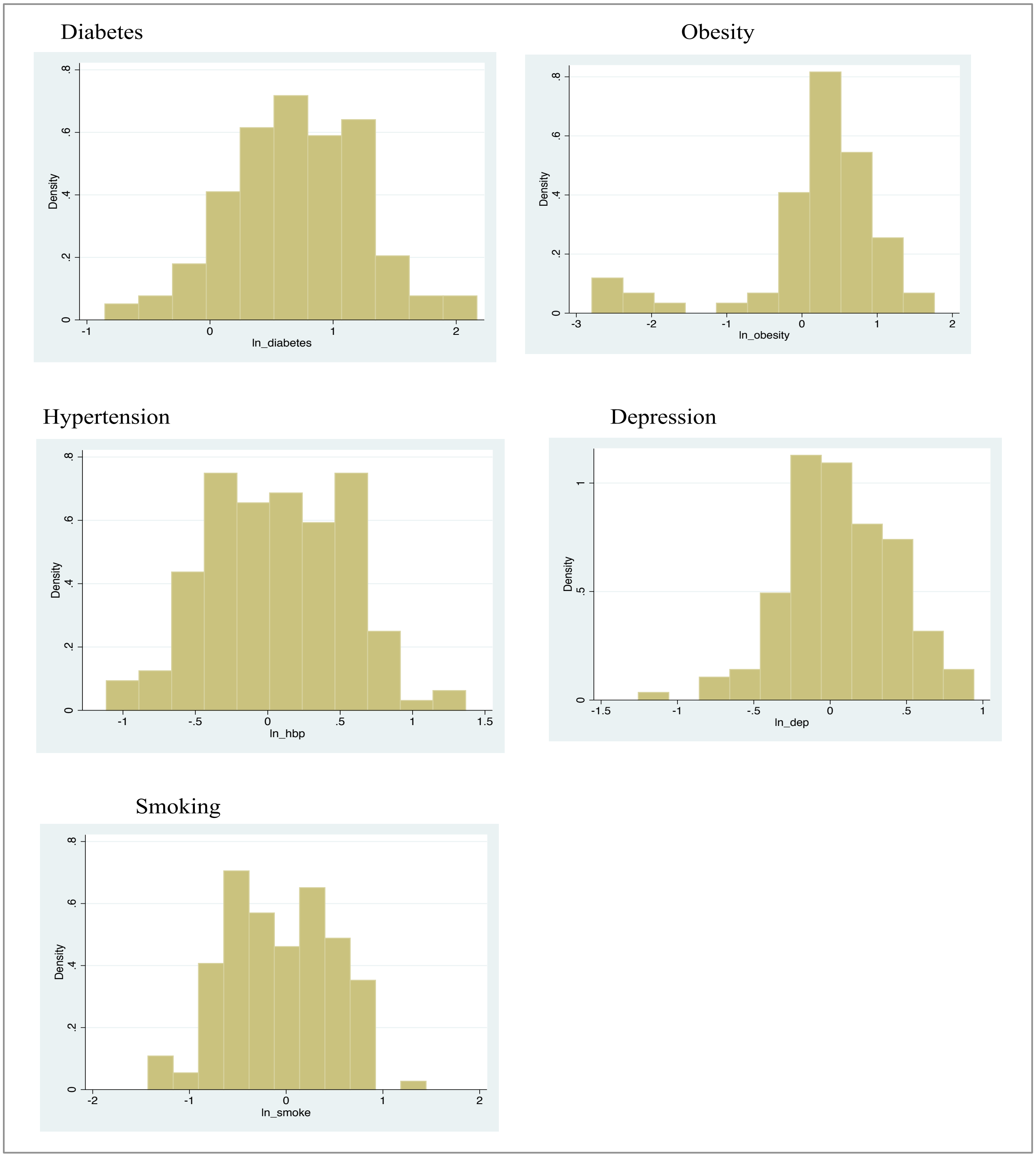
Equation 2.2 $$Odds_{Diabetes_{Hispanic}} = \frac{Proportion_{Diabetes}}{1-Proportion_{Diabetes}}$$

I used the same process to calculate the odds for NHWs. I calculated the relative odds by dividing odds of Hispanics by the odds of NHWs for each condition. Finally, I took the natural log of the relative odds to normalize the distribution.

Equation 2.3 $$LogOdds_{Diabetes} = \ln\left(\frac{Odds_{Hispanic\ Diabetes}}{Odds_{NHW\ Diabetes}}\right)$$

In Figure 2-34 I show the distributions of the natural logs of the relative odds for each condition. All resemble normal distributions, which helps to justify using OLS linear regressions.

Figure 2-34. Distributions for the natural log of the relative odds of five health conditions for Hispanic compared to non-Hispanic white residents in Denver, Colorado.



Spatial Representations of Prevalence and Inequality

I created maps to visually depict the unadjusted vs. adjusted prevalence rates and inequality and to show overall variation of prevalence and inequality across neighborhoods in Denver. I created four maps for each dependent variable and each type of regression analysis (prevalence models and inequality models, 40 maps total). For each dependent variable, in the first prevalence map I showed the unadjusted prevalence of each health condition. In the second prevalence map I showed the adjusted estimates of prevalence after accounting for all independent variables. In the third prevalence map I showed the percent change between unadjusted and adjusted prevalence. In the fourth prevalence map I showed the proportional rate of change from the unadjusted to the adjusted models (i.e., the percent change as a proportion of the unadjusted prevalence rate). I created the same maps for the inequality models, showing changes in inequality rather than changes in prevalence of conditions, and I presented odds instead of percents. I depicted barrio census tracts in the maps by using lines crossing through the barrio neighborhoods.

Spatial models

Ecological analyses are particularly susceptible to issues of spatial dependence. Because census tracts are contiguous in a dense, urban area, it is likely that the health and social processes taking place in one census tract are not independent from the processes taking place in surrounding tracts. This relationship between primary units of analysis violates the independence assumption of iid (independent and identically distributed random variables), which is a fundamental statistical assumption. I ran diagnostics for all prevalence and inequality models to assess the extent of spatial dependence. I then conducted spatial regression for the models that demonstrated substantial spatial dependence. In Chapter 3 I present results from the diagnostic test and comparisons of spatial models to the OLS models.

I conducted Chapter 3 analyses using three statistical software packages. I extracted EHR data using SAS. I conducted the LPA analysis using the “Mclust” package in R, and the spatial analyses were conducted using the “spdep” package in R. I conducted the regression analyses in STATA.

Empirical Analyses for Chapter 4

In Chapter 4 I conduct a multilevel examination of an individual resident’s probability of having the same five health conditions that I examined in Chapter 3: type 2 diabetes, obesity, hypertension, diagnosed depression, and current smoking, while taking into account neighborhood-level factors. There are four main differences between the analyses in Chapters 3 and 4. First, in Chapter 4 I included individual-level and neighborhood-level factors, rather than solely using aggregated data as in Chapter 3. In this same vein, in Chapter 3 I examined spatial autocorrelation of contiguous spaces and in Chapter 4 I examined interdependence of residents living in the same neighborhood. Second, in Chapter 3 I used a composite measure of demographic and SES information to define neighborhood types (using the LPA), and in Chapter 4 I decomposed similar measures to examine independent associations between barrio characteristics (barrio rank), SES (Townsend index), and inequality (gini coefficient). Third, in Chapter 4 I examined the probability of having a health condition (using multilevel logistic regression) rather than the percent of residents with a condition (using OLS regression). Fourth, in Chapter 3 I define neighborhoods as census tracts and in Chapter 4 I define neighborhoods using Denver’s statistical neighborhood boundaries (as shown in Figure 2-29).

Regression Analyses

In Chapter 4 I used multilevel modeling methods (specifically, mixed logistic models) Multilevel models take into account individual (patient) and contextual (neighborhood) characteristics and allow for the decomposition of error variance into discrete components at both levels (Raudenbush and Bryk 2002, Gelman 2012, Snijders 2011).

Multilevel models account for clustering of individuals within particular contexts (e.g. families, neighborhoods, schools) by adjusting the standard errors for nonindependence. Additionally, they allow researchers to examine independent contributions of individual-level variables and contextual variables to overall variation in a given outcome using an intraclass correlation coefficient (ICC) (Dedrick et al. 2009, Peugh 2010). In Equation 3 I provide the formula for a multilevel logistic regression:

Equation 2.4 $$\log\left(\frac{P_{ij}}{1-P_{ij}}\right) = \beta_{00} + \beta_1 x_i + \beta_2 z_j \quad + \beta_3 x_i z_j + u_j$$

where $\log\left(\frac{P_{ij}}{1-P_{ij}}\right)$ represents log odds of having the chronic condition for individual *i* in neighborhood *j*. In addition to the fixed effects for individuals x_i and neighborhoods z_j, there is a an interaction effect for individuals and neighborhoods $x_i z_j$. The term u_j captures the neighborhood specific error for the *j*th neighborhood (Dedrick et al. 2009). The variance of this estimate can be used with fixed value of individual-level error variance $(\frac{\pi^2}{3})$ to calculate the ICC described above.

The outcomes for the analyses were binary indicators of whether or not the patient had each of the health conditions. Similar to Chapter 3, I used a nested, additive model building approach to assess how groups of independent variables affected each dependent variable and to compare baseline models, individual-level/level 1 (L1) models, and neighborhood-level/level 2 (L2) models. I did not include any independent variables in the baseline models so that I could calculate an interclass correlation coefficient (ICC) for neighborhood-level (L2) effects (described in more detail in Chapter 4). I ran the first set of analyses on the total population and then ran the same models for the Hispanic population alone (using primary language as an independent model). All models for Chapter 4 were run using the PROC GLIMMIX procedure in SAS.

Chapter 3: Ecological analysis of health prevalence and inequality in Hispanic neighborhoods in Denver, Colorado

In Chapter 3 I provide a descriptive ecological analysis of how different types of neighborhoods vary in prevalence of common health conditions and inequality in health conditions across neighborhoods for Hispanics compared to non-Hispanic whites. This analysis addresses the first research set of questions in my dissertation: **What is the relationship between types of Denver neighborhoods, including "barrios," and the prevalence of common health conditions at the neighborhood-level? How are different types of neighborhoods associated with variation in prevalence of health conditions for Hispanic residents versus non-Hispanic white residents within neighborhoods?**

As I described in detail in Chapter 1, the relationship between Hispanic neighborhoods and health is complex; many studies suggest that Hispanic neighborhoods may be associated with better health outcomes for Hispanics as observed in the Hispanic Health Paradox (for example, Aranda et al. 2011, Cagney et al. 2007, Eschbach et al. 2004, Eschbach et al. 2005, Keegan et al. 2010). Other research suggests that these neighborhoods, which often have low SES, may demonstrate a negative relationship between disadvantage and health (for example, Do et al. 2007, Hong et al. 2014). One of the limitations to many existing studies is that they examine a single health condition, making it difficult to understand the health of a community more broadly. By examining five highly prevalent and diverse health conditions, in this chapter I weigh in on the broader health profile of all Hispanic neighborhoods in Denver, Colorado.

Examining inequality in prevalence of each condition between Hispanics and NHWs provides a unique opportunity to understand *within-neighborhood* health disparities. To date, no studies have examined the extent to which Hispanic neighborhoods are more or less equitable places for Hispanic and NHW residents. This comparison may be particularly important in Denver, where the average Hispanic resident lived in a neighborhood that is almost 50% NHW (as discussed previously in Chapter 1). Because Hispanics and NHWs make up such a large portion of Denver residents, it is important to understand how the health of these groups relate to one another within and between neighborhoods.

In Chapter 3 I also add methodological rigor to the existing literature. In addition to presenting regression results for prevalence and inequality of health conditions, I examine the extent to which neighborhood-level factors impact changes in prevalence and inequality spatially, through a series of maps of Denver. A benefit of conducting an ecological analysis is the ability to test for the spatial dependence of contiguous census tracts for each health condition, which is rarely included in this research area. Finally, most studies have used a single measure – the percent of Hispanic residents in each census tract – to define Hispanic neighborhoods. In this study I created a more comprehensive measure using latent profile analysis (LPA), and compared this measure to using the percent of Hispanic residents in each tract. My goal in using these methodological techniques was to understand how robust any observed health advantage (or disadvantage) may be in Hispanic neighborhoods. I engage a broader discussion of the implications of the results in Chapter 5.

METHODS

Data

In this study I combine data from three sources to conduct an ecological analysis of how types of neighborhoods vary in prevalence and disparities of common health conditions (i.e. between- and within- neighborhood health disparities). Each of the health conditions that I used as dependent variables and some of the independent variables are from a unique dataset of EHRs from two of the largest healthcare providers in Denver, Colorado – Denver Health (DH) and Kaiser Permanente of Colorado (KPCO). DH is the largest healthcare provider for Denver's uninsured and medically underserved adults, and KPCO is an HMO and the largest private provider for Denver residents, together serving a complementary group of patients. When combined, the EHR database includes over 150,000 patients. I included patients if they had an ambulatory visit in an outpatient clinic (similar to a primary care visit) in 2014 or 2015, were between the ages of 25-84 at the time of their 2014/2015 visit, had a valid height and weight recorded for any visit in their retrospective EHR (dating back to 2000 for DH data and 2005 for KPCO data), and had an address in Denver in their retrospective EHR. I included EHRs for women who had been pregnant, but removed records associated with the year/s they were pregnant.

In this chapter I define neighborhoods as census tracts. There are 144 census tracts in Denver County. I did not include a small number of tracts in some analyses because they either had too few residents overall, or too few Hispanic residents to perform comparison analyses between Hispanics and NHWs. For each analysis I used a minimum of 140 tracts. I had retrospective address data from DH and KPCO, and coded patients as living in a specific neighborhood if they ever had a Denver address in the retrospective address records. If patients had geocodes in more than one Denver census tract, I assigned them to the tract where they had lived the most recently. Seventy-seven percent of all patients, 80% of Hispanics, and 75% of NHWs lived in Denver within two years of their 2014/2015 visit.

I combined EHRs with neighborhood social/demographic data from the 2011-2015 5-year American Community Survey (ACS) and 2013-2014 health behavior/health access data from the CDC/RWJF 500 Cities Project and Behavioral Risk Factor Surveillance System (BRFSS) (Scally et al. 2017). The 500 Cities Project conducted small area estimation (SAE) based on BRFSS data sampled at the county level to calculate census-tract-level estimates for a variety of health conditions, behaviors, and utilization measures (Zhang et al. 2015).

Measures

All variables in the analysis represent aggregated census-tract-level averages or percentages. Table 3-1 summarizes the variables I used in the analyses and their respective data source.

Table 3-1. Description of study variables and data sources

Dependent variables	**Description**	**Data source**
Percent with diabetes	Percent of residents in tract with diagnosis, laboratory result, or pharmacy records for type 2 diabetes	Electronic Health Records (EHRs)
Percent with obesity	Percent of residents in tract with height and weight from vital statustics indicating BMI>29	EHRs
Percent with hypertension	Percent of residents in tract with diagnosis, clinical measure, or pharmacy records for hypertension	EHRs
Percent with depression	Percent of residents in tract with diagnosis of depression	EHRs
Percent of current smokers	Percent of residents in tract who ever reported being a current smoker	EHRs
Independent variables	**Description**	**Data source**
Model 1: Latent classes	Latent profile analysis using 21 social/demographic variables; 4 classes of neighborhoods	American Community Survey (ACS)
Model 2: Average age	Average age of residents in tract based on birth date and visit date	EHRs
Model 2: Gender	Percent of residents in tract who are female	EHRs
Model 3: Binge drinking	Percent of residents who have had five or more drinks (men) or four or more drinks (women) on an occasion in the past 30 days	500 cities project
Model 3: Current smokers	Same as depenent variable above	EHRs
Model 4: Health insurance coverage	Percent of residents in tract who have health insurance	500 cities project
Model 4: Health care visits	Percent of residents in tract who have visited a doctor in the past year for a routine checkup	500 cities project

Dependent variables

I used five health conditions as dependent variables: percent of residents in each tract ever having type 2 diabetes, obesity, hypertension, depression, and current smokers. I selected these conditions because they represent a mixed bag of health for Hispanics. Some conditions are typically higher among the Hispanic population (e.g., diabetes and obesity), and others are similar or lower (e.g., hypertension and smoking) compared to NHWs. When examined as a whole, these health conditions paint a broad picture of the health of communities.[1]

Independent variables

The primary independent variable for each of the analyses is neighborhood class or "type." I created the neighborhood classes using latent profile analysis (LPA) (described in more detail in Chapter 2 and below). All analyses adjusted for the average age of residents in each tract and the percent of residents who were female, both of which were derived from EHRs and aggregated to the census tract level. I calculated patient age by subtracting the patient's birth date from the most recent visit date in 2014 or 2015 and dividing by 365.25. Age was grand mean-centered for all analyses (the grand mean, in this context, is the average age across all census tracts).

I used two measures of poor health behaviors in the analyses as potential mediators. I used the percent of smokers in each tract, based on EHRs, as an independent variable when it was not being modeled as the dependent variable. Another health behavior - the percent of residents in each tract who reported binge drinking in the past month – came from the 500 Cities Project data. Binge drinking was classified as five or more drinks on one occasion for men and four or more drinks on one occasion for women.

Lastly, I included two measures of healthcare access/utilization as potential mediators. The percent of residents in each tract without health insurance came from the 500 Cities Project data. No health insurance indicates no public or private health insurance. A measure of healthcare access – the percent of patients in each tract who had a routine doctor's visit in the past year - came from the 500 Cities Project.

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[1] Detailed descriptions of how I created the dependent and independent variables are provided in Chapter 2.

Analysis

I used social and demographic variables from the ACS to conduct the LPA and extract neighborhood classes. Since the goal of the LPA was to model an underlying latent construct of Hispanic neighborhoods, or barrios, I did not include information about racial composition of other groups. I included percent of Hispanic, foreign-born, and non-citizen residents, Spanish speaking households, measures of neighborhood stability, inequality, socioeconomic status (SES), and travel time to work (23 variables overall) in each of the 142 Denver census tracts. I describe each of these variables in Table 2-22 in Chapter 2. I selected a four-class solution based on model fit criteria and theoretical meaningfulness.

I analyzed the dependent variables in two ways; in the first set of analyses I used ordinary least squares (OLS) regression to predict the prevalence of each condition across neighborhood classes for all residents. I present models in a nested (additive) fashion, adding independent variables in a four-step process (note: Table 3-1 contains the model in which each independent variable appears). In Model 1 I present the baseline effects of living in a Class 2, Class 3, or Class 4 neighborhood relative to a Class 1 neighborhood. In Model 2 I adjust for basic demographic factors – age and gender. In Model 3 I add health behaviors – binge drinking and smoking. In Model 4 I add healthcare access/utilization variables –health insurance or a routine visit in the past year.

I use slightly different sets of independent variables in the analyses based on model fit, parsimony, and multicolinearity. For models predicting prevalence of diabetes, obesity, hypertension and depression among Hispanics, I include smoking as an independent variable in Model 3 in addition to binge drinking. For the model predicting current smokers, I omit smoking as an independent variable in Model 3. For all prevalence models, I include percent of residents in each tract with health insurance in Model 4, but do not include health insurance in the inequality analyses (described below).

In the second set of analyses I examine the extent of within-neighborhood inequality in prevalence rates for each health condition between Hispanics and NHWs. In each census tract and for each condition, I divided the tract-level odds of having a condition for Hispanics by the odds of having a condition for NHWs. This relative odds measure estimates the degree of health inequality between Hispanics and NHWs. I used the logged odds because they produce an approximately normally distributed continuous measure (described in more detail in Chapter 2). Similar to the first set of analyses, I included smoking as an independent variable in Model 3 for analyses predicting inequality in diabetes, obesity, hypertension, and depression. I include a measure of healthcare access – the percent of residents in the tract who had a routine doctor's visit in the past year – in Model 4, instead of the health insurance measure used for the prevalence analyses.

I examined spatial patterns in the data in two ways. First, I created four maps for each health condition and each analysis (prevalence and inequality) examining how adjusting for neighborhood-level covariates impacted predicted prevalence rates of each health condition and predicted odds of inequality between Hispanics and NHWs. These maps also show the overall variation in prevalence and inequality across Denver neighborhoods with and without adjusting for the independent variables. For the prevalence maps, Map 1 shows baseline prevalence rates. Map 2 shows predicted probabilities from the final prevalence models, adjusting for all covariates. Map 3 shows the difference between adjusted and unadjusted rates. Map 4 shows the percent change of the adjusted prevalence from the baseline prevalence (the change value calculated for the third map divided by the baseline prevalence). I created the same four maps for inequality, but present results for the first three maps in odds rather than in percents. I present all maps in the results section.

The second way that I examined spatial patterns was through formal tests of spatial dependence. I applied a contiguity weights matrix to the data, which tests the extent to which census tracts that are contiguous (next to each other) are similar (Cliff and Ord 1981). I first conducted descriptive diagnostic tests to examine whether the analysis of each dependent variable (for prevalence and inequality, 10 models total) had a high level of spatial dependence across tracts. For models indicating a statistically significant spatial dependence, I re-ran the final regression models using spatial regression. I tested each model using three spatial methods: spatial error, spatial lag, and a higher order model (called a SARAR model) that combines both spatial error and spatial lag. I compared the model fit across each of the three spatial models and presented the best fitting spatial model next to the regular, non-spatial regression model to compare results.

As another sensitivity analysis, I compared the LPA classes with a single measure of the percent of Hispanic residents living in each neighborhood. To mimic the 4-group structure of the classes, I broke the percent of Hispanic residents into quartiles.

I conduced all analyses using EHRs at Denver Public Health on a secure system. I conduced analyses using three statistical software packages. I extracted EHRs from the VDW using SAS. I conduced the LPA using the "Mclust" package in R, and conduced the spatial analyses using the "spdep" package in R. I conduced neighborhood-level regression analyses in STATA.

RESULTS

Descriptive Results

In Table 3-2 I show average ACS characteristics in the LPA analysis overall and across each class. The first class (Class 1) contained 30 tracts that I labeled as “barrio neighborhoods.” These neighborhoods, on average, had the highest percentages of Hispanic residents, non-citizens, and foreign-born Hispanics. Barrio neighborhoods also had the most stable Hispanic population. Foreign-born and non-citizen residents of barrio neighborhoods were more likely to be in the same house as they were the prior year compared to foreign-born and non-citizen residents in the other neighborhood classes. Barrio neighborhoods, on average, had the highest percentage of residents with only a high school education, the highest percentage of residents living in poverty, and the most residential crowding compared to the other neighborhood classes. However, some of the socioeconomic characteristics of barrios were comparable to other neighborhoods. Access to a car, unemployment, and the percent of residents who rented their homes were all comparable to the average across all tracts in Denver. Barrio neighborhoods had a comparable percent of residents who worked close to home (within 10 minutes), the lowest percentages of mid-range workers (10-30 minutes) and the highest percentage of men traveling more than 30 minutes to work. This indicated that a higher proportion of men living in barrio communities may have been spending large amounts of time commuting for work and exposed to different environmental contexts at work (to the extent that distance indicated a different context).

The second class (Class 2) contained 36 tracts that I labeled as “low SES neighborhoods.” Low SES neighborhoods had substantially fewer Hispanics, non-citizens, and foreign-born Hispanics than barrio neighborhoods. The Hispanic community living in low SES neighborhoods was also less residentially stable than Hispanics living in barrio neighborhoods (although more stable than Class 3 and Class 4 neighborhoods). Low SES neighborhoods had slightly better SES on average than barrio neighborhoods, but were still substantially more socioeconomically disadvantaged than Class 3 and Class 4 neighborhoods, with more than triple the rate of residents with only a high school education and higher rates of residents living in poverty. Low SES neighborhoods also had the highest unemployment rate, on average. Although the Hispanic population was less stable in low SES neighborhoods compared to barrio neighborhoods, these neighborhoods generally had average rates of stability for the population as a whole. The distribution of travel times to work for low SES neighborhoods were also comparable to the overall averages for Denver.

The third class (Class 3) contains 32 tracts that I labeled as "mid/high SES neighborhoods." As I show in Table 3-4, mid/high SES neighborhoods have younger residents, on average, compared to the other neighborhood classes. These neighborhoods may be broadly characterized as places where young, educated, residentially mobile professionals live. Mid/high SES neighborhoods had fewer Hispanic residents than barrio neighborhoods and low SES neighborhoods, and the Hispanic population that did live in mid/high SES neighborhoods is less residentially stable, on average, than Hispanic residents in barrio or low SES neighborhoods. This residential instability was also present overall for mid/high SES neighborhoods; they had a substantially higher percentage of renters, on average, compared to all other neighborhood classes. Most residents living in mid/high SES neighborhoods had more than a high school degree (in fact, average education in these neighborhoods was the same as in high SES neighborhoods). Poverty and unemployment was also less common in mid/high SES neighborhoods compared to barrio and low SES neighborhoods. On average, mid/high SES neighborhoods had the highest percentage of residents who work close to their homes.

The fourth class (Class 4) contains 44 tracts that I labeled as “high SES neighborhoods.” High SES neighborhoods had the fewest Hispanic residents and the Hispanic residents who did live in high SES neighborhoods were the least residentially stable compared to Hispanic residents in other neighborhood classes. High SES neighborhoods were the most socioeconomically advantaged, with the lowest percent of residents who rented their homes, lived in poverty, and did not have access to a car. Furthermore, the renters who did live in high SES neighborhoods had the lowest rates of moving in the past five years compared to renters in other neighborhood classes. On average, high SES neighborhoods had the lowest rates of men who work close to home (within 10 minutes) and the highest rates of women who traveled 10-30 minutes to work.

Although comparisons between barrio neighborhoods and the other three classes are all interesting and important, the most important comparisons were between barrio neighborhoods and low SES neighborhoods (Class 1 and Class 2). Differences between these two classes may be more indicative of the impact that Hispanic, foreign-born, and non-citizen concentration has on health, since both classes of neighborhoods had relatively low SES, but barrio neighborhoods had much higher concentrations of Hispanic, foreign-born, and non-citizen residents. If SES is the dominant social force influencing health patterns in neighborhoods, I would expect results from Class 1 and Class 2 to be similar. If other factors play a substantial role, I would expect results between Class 1 and Class 2 to be different.

Table 3-2. Characteristics of four neighborhood classes from the latent profile analysis (column percents)*

	Class 1: Barrios	Class 2: Low SES	Class 3: Mid/high SES	Class 4: High SES	Total
Number of tracts	30	36	32	44	142
Barrio characteristics					
Hispanic	68%	31%	13%	12%	29%
Non-citizen	23%	10%	6%	3%	10%
Foreign-born Hispanic	4.3%	2.2%	1.1%	0.8%	1.9%
Non-citizens in same house as one year ago	20%	8%	4%	3%	8%
Foreign-born in same house as one year ago	26%	13%	7%	6%	12%
Foreign-born citizens in same house as one year ago	5.6%	5.1%	3.2%	3.4%	4.3%
Hispanics who moved within Denver in past year	8%	7%	17%	8%	10%
Socioeconomic characteristics					
Only high school education	36%	17%	5%	5%	14%
Living in poverty	26%	22%	17%	8%	17%
No access to a car	4%	6%	6%	2%	4%
Unemployed	5%	6%	4%	3%	5%
Renters	48%	56%	69%	29%	49%
Living in a crowded house (>1.5 people/bedroom)	3%	1%	1%	0%	1%
Stability					
Moved within the past year	14%	21%	34%	18%	22%
Homeowners who have moved in the past 5 years	9%	10%	9%	17%	12%
Renters who have moved in the past 5 years	31%	36%	52%	20%	33%
Travel time to work					
Men travel less than 10 minutes to work	5%	5%	7%	4%	5%
Women travel less than 10 minutes to work	4%	4%	5%	5%	5%
Men travel 10-30 minutes to work	25%	28%	30%	30%	28%
Women travel 10 -30 minutes to work	23%	26%	27%	28%	26%
Men travel 30+ minutes to work	28%	20%	17%	18%	20%
Women travel 30+ minutes to work	15%	16%	15%	15%	15%

*Source: American Community Survey (ACS) 2011-2015 5-year estimates

In Table 3-3 I show the distribution of EHR patients across each of the four neighborhood classes and by healthcare provider and for Hispanics and NHWs separately. Overall, a higher percentage of patients came from KPCO than from DH. Similar to ACS data, Class 1 (the barrio neighborhoods) had the highest concentration of Hispanic patients from EHRs, and the large majority of those Hispanic patients (72%) were DH patients. As the average SES of neighborhood classes increases, a higher percentage of the patients are from KPCO, with 78% of patients living in high SES (Class 4) neighborhoods coming from KPCO. The opposite is true for DH, with the highest percentage of DH patients represented in barrio neighborhoods (Class 1).

The fact that patients are unevenly distributed by provider across each class is both expected and introduces potential issues of selection bias. It is likely that there are systematic differences in access to care, the way care is delivered, and the way patients are tracked in each system. Each of these factors could impact how health conditions are recorded for each patient. These same factors, such as access and utilization, are also related to the fact that KPCO patients are generally going to have more resources and higher SES than DH patients because KPCO requires membership and is typically health insurance provided through employers, whereas DH serves a much more diverse group of patients.

Table 3-3. Distribution of patients across each latent class by healthcare provider for the total, Hispanic, and non-Hispanic white (NHW) patient population in the Denver Health (DH) and Kaiser Permanente of Colorado (KPCO) Electronic Health Records for 2014/2015 visits

	Class 1: Barrios		Class 2: Low SES		Class 3: Mid/High SES		Class 4: High SES		Total	
	DH	KPCO	DH	KPCO	DH	KPCO	DH	KPCO	DH	KPCO
Population total	62%	38%	44%	56%	34%	66%	22%	78%	41%	59%
Hispanic total	72%	28%	59%	41%	53%	47%	39%	61%	63%	37%
NHW total	46%	54%	29%	71%	28%	72%	15%	85%	26%	74%

In Table 3-4 I show each of the covariates across the neighborhood classes for the total population, presenting average means, percentages and standard deviations across each neighborhood class. Barrio neighborhoods, on average, had the highest unadjusted rates of all health conditions, making them the least healthy neighborhoods overall before accounting for any covariates. Barrio neighborhoods were slightly younger than low SES and high SES neighborhoods (with mid/high SES neighborhoods being the youngest). Barrio neighborhoods also had a higher proportion of females, on average. Examining health behaviors revealed mixed results; barrio neighborhoods had the highest rates of smoking (shown in the dependent variable category) but the lowest rates of binge drinking. Not surprisingly, barrio neighborhoods had the highest rates of uninsured residents and the lowest rates of routine access to care, due likely in part to the high percentage of foreign-born and non-citizen residents.

Table 3-4. Average rates and standard deviations of health conditions, and demographic, health behavior, and health insurance independent variables across four latent classes for patients in Denver, Colorado

		Class 1: Barrios (n=30)		Class 2: Low SES (n=36)		Class 3: Mid/high SES (n=32)		Class 4: High SES (n=44)		Total (n=142)	
	Characteristics	Mean/ %	Sd	Mean/ %	Sd	Mean/ %	Sd	Mean/ %	Sd	Mean/ %	Sd
Dependent variables	Diabetes[1]	22.5	2.1	16.9	3.5	11.0	3.6	12.1	4.0	15.3	5.6
	Obesity[1]	42.4	3.1	34.8	6.8	26.1	6.3	26.1	6.9	31.8	8.9
	Hypertension[1]	41.8	2.9	39.8	4.3	34.0	4.9	39.5	6.7	38.8	5.7
	Depression[1]	23.6	2.4	21.7	3.5	20.2	3.0	19.5	2.2	21.1	3.2
	Smoking[1]	18.7	2.7	17.9	5.5	16.3	4.7	11.4	3.7	15.7	5.2
Model 2	Age[1]	47.1	1.1	47.5	2.4	45.6	2.4	51.3	3.2	48.2	3.3
	Female[1]	63.7	1.7	61.1	3.4	57.0	4.0	58.7	2.6	60.0	3.8
Model 3	Binge drinkers[2]	18.5	1.6	20.4	2.8	24.2	3.0	21.1	3.2	21.1	3.4
Model 4	No health insurance[2]	37.0	6.4	21.6	9.7	13.7	4.1	10.1	3.5	19.5	11.8
	Checkup in past year[2]	53.9	2.3	57.2	3.2	55.8	2.9	61.6	3.7	57.5	4.3

[1] Source: Aggregate electronic health records (EHRs) from Denver Health and Kaiser Permanente of Colorado
[2] Source: 500 Cities Project small area estimates of Behavioral Risk Factor Surveillance System (BRFSS)

In Table 3-5 I show the average prevalence of each health condition across each class and the process of transforming the odds of Hispanics and NHWs to the logged relative odds used as the dependent variable in the analyses of inequalities. Examining health conditions across each class revealed that barrio neighborhoods (Class 1) had the highest rates of diabetes and obesity among Hispanics and NHWs, and were on average the least healthy neighborhoods for NHW residents across all five health conditions. Results suggested a mixed bag for Hispanics. Barrio neighborhoods had the highest rates of diabetes among Hispanic residents (25% had diabetes compared to just 10% of Hispanics in high SES neighborhoods). Although rates of obesity were high for Hispanics in barrio neighborhoods (45%), they were only slightly higher than rates for Hispanics living in low SES neighborhoods (43%). Rates of hypertension, depression, and smoking among Hispanics living in barrio neighborhoods were comparable to rates for Hispanics living in other types of neighborhoods.

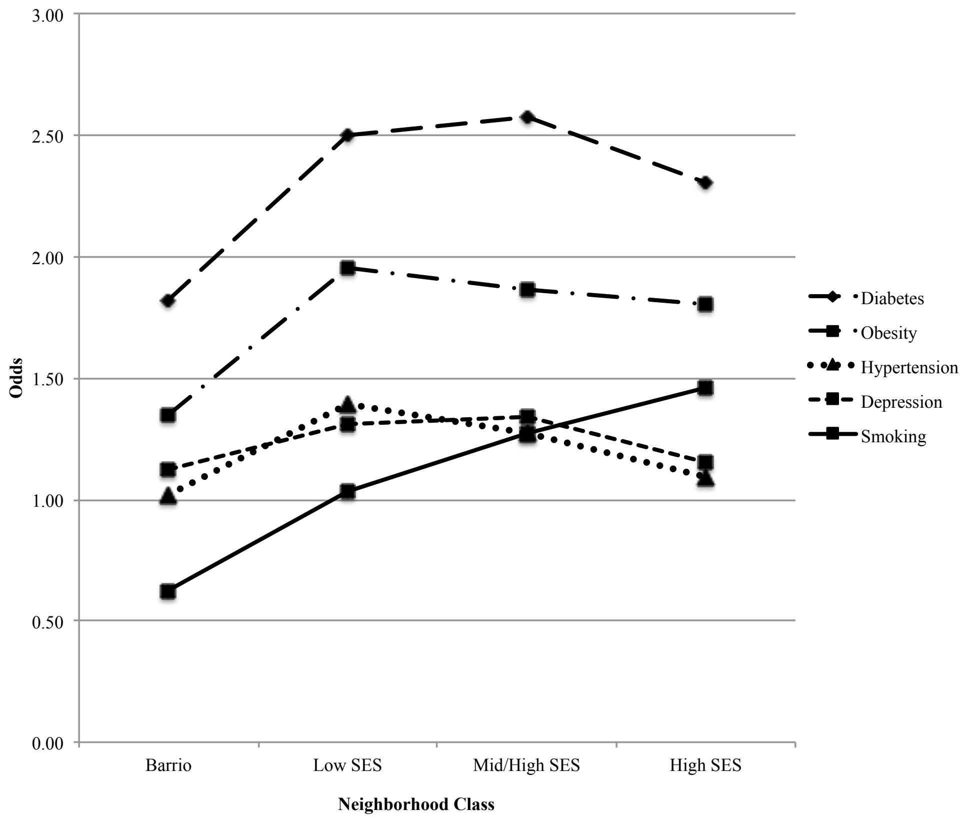
Comparing the odds of having diabetes for Hispanics relative to NHWs living in the same neighborhood reveals that, although Hispanics had higher odds of having diabetes, obesity, and depression on average across all neighborhood types, the unadjusted inequality was lowest within barrio neighborhoods (ORs=1.82, 1.35, 1.12 respectively). Hispanics, on average, had slightly higher/comparable rates of hypertension compared to NHWs across all neighborhood types, but these disparities were negligible within barrio neighborhoods (OR=1.02). For smoking, the disparities reversed from barrios compared to other neighborhood classes. Hispanics had much lower smoking rates on average compared to NHWs in barrio neighborhoods (OR=0.63) and higher rates in all other neighborhood types.

Figure 3-1 charts the change in relative odds across each neighborhood class. It presents the average relative odds values that are in Table 3-5. These baseline patterns reveal potential sources of residential selection processes for both Hispanics and NHWs. Under a "white-flight" hypothesis, where living in a neighborhood where the majority of residents are residents of color is undesirable for white residents, then the white residents who do live in these neighborhoods may be the least advantaged and least healthy. The opposite may be true for Hispanic residents, for whom the preference may be to live in neighborhoods with other Hispanic residents. Thus, those Hispanic residents who live in other (particularly low SES) neighborhoods may be less advantaged and less healthy than Hispanics living in barrio neighborhoods. These selection processes could explain why there was less baseline inequality in barrio neighborhoods compared to low SES neighborhoods. Regarding differences between barrio neighborhoods and higher SES neighborhoods (Classes 3 and 4), larger inequality suggests that Hispanic residents in higher SES neighborhoods may not reap the same positive benefits of the social and physical environments of more affluent neighborhoods, or that the Hispanic residents in those neighborhoods are not as advantaged as the NHW residents in ways that may impact their health. For example, if Hispanic residents face more discrimination in more affluent neighborhoods with fewer Hispanic residents, it is possible that they would have worse health than their NHW counterparts that are part of the racial majority in these neighborhoods.

Table 3-5. Prevalence of health conditions across four latent classes and transformations to the natural log of the relative odds of Hispanic to non-Hispanic White (NHW) prevalence

	Class 1: Barrios (n=30)		Class 2: Low SES (n=36)		Class 3: Mid/high SES (n=32)		Class 4: High SES (n=44)	
	Hispanic	NHW	Hispanic	NHW	Hispanic	NHW	Hispanic	NHW
Diabetes								
Average proportion with condition	0.25	0.17	0.22	0.11	0.17	0.09	0.18	0.10
Average odds for group	0.34	0.20	0.27	0.13	0.21	0.10	0.22	0.11
Average relative odds (Hispanic/NHW)	1.82		2.50		2.58		2.31	
Average natural log of the relative odds	0.55		0.78		0.82		0.73	
Obesity								
Average proportion with condition	0.45	0.39	0.43	0.30	0.34	0.23	0.34	0.23
Average odds for group	0.81	0.63	0.75	0.43	0.52	0.30	0.52	0.30
Average relative odds (Hispanic/NHW)	1.35		1.96		1.87		1.81	
Average natural log of the relative odds	0.25		0.58		0.54		0.54	
Hypertension								
Average proportion with condition	0.40	0.42	0.40	0.35	0.36	0.32	0.39	0.38
Average odds for group	0.68	0.73	0.67	0.55	0.57	0.48	0.63	0.62
Average relative odds (Hispanic/NHW)	1.02		1.40		1.27		1.09	
Average natural log of the relative odds	-0.06		0.21		0.17		0.03	
Depression								
Average proportion with condition	0.25	0.23	0.25	0.22	0.25	0.21	0.22	0.20
Average odds for group	0.33	0.30	0.34	0.27	0.33	0.26	0.28	0.25
Average relative odds (Hispanic/NHW)	1.12		1.31		1.34		1.15	
Average natural log of the relative odds	0.09		0.20		0.22		0.08	
Smoking								
Average proportion with condition	0.15	0.23	0.16	0.17	0.18	0.15	0.13	0.10
Average odds for group	0.18	0.31	0.20	0.21	0.22	0.18	0.14	0.11
Average relative odds (Hispanic/NHW)	0.63		1.03		1.27		1.46	
Average natural log of the relative odds	-0.52		-0.08		0.14		0.25	

Figure 3-1. Relative odds of prevalence of health conditions for Hispanic compared to non-Hispanic white adults



Prevalence Results

In Table 3-6 I present results from the OLS regression analyses predicting prevalence rates of each health condition. Note that the constant values for the base model (Model 1) are the same as the unadjusted prevalence of each health condition in barrio neighborhoods presented in Table 3-4. The coefficients for the other classes in Model 1 are deviations in baseline prevalence from the barrio neighborhoods (which can also be observed/verified in Table 3-4).

At baseline (Panel A, Model 1), barrio neighborhoods had the highest rates of diabetes. While accounting for the age structure and gender distribution of the neighborhoods (Panel A, Model 2) substantially lowered the differences (particularly between the mid/high SES "younger" neighborhoods and barrio neighborhoods), controlling for differences in health coverage reduced the differences between neighborhoods the most (Panel A, Model 4). Nonetheless, after accounting for demographic characteristics, health behaviors, and insurance, barrio neighborhoods still had the highest rates of diabetes.

Similar to diabetes, there were large disparities in obesity at baseline between barrio neighborhoods and each of the other classes (Panel B, Model 1). For example, the average rate of obesity in barrio neighborhoods was more than 16% higher than the average rate of obesity in high SES neighborhoods. The differences were still substantial and significant after accounting for demographic and health behavior differences (Panel B, Model 3), but after controlling for differences in health coverage (Panel B, Model 4), the differences in obesity were dramatically reduced and borderline significant.

Differences in neighborhood rates of hypertension showed a distinct pattern from rates of diabetes and obesity. At baseline (Panel C, Model 1), only mid/high SES neighborhoods had substantially lower rates of hypertension, and this difference was largely diminished after adjusting for age and gender differences (Panel C, Model 2). The differences between barrio neighborhoods and the other neighborhood classes were no longer significant after accounting for differences in health behaviors (Panel C, Model 3).

Differences in rates of diagnosed depression were not as substantial as differences in diabetes and obesity, but similarly, barrio neighborhoods had the highest baseline rates of depression compared to the other classes of neighborhoods (Panel D, Model 1). Differences in binge drinking and smoking partially accounted for neighborhood disparities (Panel D, Model 3), particularly for high SES neighborhoods compared to barrios. However, controlling for health coverage diminished neighborhood differences in rates of depression (Panel D, Model 4).

Smoking patterns across neighborhood types were distinct from the other health conditions. Although barrio neighborhoods had higher rates of smoking at baseline (Panel E, Model 1), the differences diminished after adjusting for demographics (Panel E, Model 2) and health behaviors (Panel E, Model 3), and were then reversed after accounting for health insurance differences (Panel E, Model 4). After accounting for health coverage, barrio neighborhoods had substantially lower rates of smoking compared to all other neighborhood types, including almost 5% lower rates than other low SES neighborhoods.

I evaluated model fit for each health condition using Bayesian information criteria (BIC) values. For diabetes, obesity, depression, and smoking, the final model (Model 4) represented the best fitting model. This indicates that adding all covariates did the best job at explaining differences in prevalence of the conditions. For hypertension, the health behavior model (Panel C, Model 3) represented the best fitting model, although the final model (Panel C, Model 4) was still superior to the first two models. This indicates that accounting for differences in health insurance did not substantially help in explaining differences in hypertension prevalence above and beyond examining the effects of neighborhood classes, demographics, and health behaviors.

Overall, prevalence findings suggest heterogeneous health patterns between barrio neighborhoods and other types of neighborhoods. Barrio neighborhoods had lower rates of smoking compared to other types of neighborhoods, there were no significant differences in rates of hypertension or depression after accounting for covariates, and barrio neighborhoods had higher rates of diabetes and obesity (although obesity results were borderline significant). First, this indicates that some health conditions may be more sensitive to the neighborhood characteristics included in the LPA classes (such as Hispanic, foreign-born, and non-citizen characteristics, and SES characteristics). Although differences in hypertension are significant at baseline, accounting for the age and gender composition of the neighborhoods diminishes the differences between barrio neighborhoods, low SES neighborhoods, and high SES neighborhoods. On the other hand, there are substantial differences in diabetes prevalence between barrio neighborhoods and each of the other classes, after accounting for neighborhood-level covariates. This suggests that the factors that make neighborhoods “barrios” may be more important for diabetes than for hypertension. However, I cannot draw any conclusions about how neighborhood differences reflect individual likelihood of having any of the health conditions without examining individual-level data.

Table 3-6. Neighborhood-level ordinary least squares coefficients for the prevalence of five health conditions across four classes of neighborhoods (n=142)

	Model 1: Base model		Model 2: Demographics		Model 3: Health behaviors		Model 4: Health coverage	
	β(%)	95% CI	β(%)	95% CI	β(%)	95% CI	β(%)	95% CI
Panel A: Diabetes								
Class 2 - low ses	-5.61 ***	-7.29,-3.92	-4.47 ***	-6.04,-2.90	-4.09 ***	-5.24,-2.94	-2.14 **	-3.72,-0.56
Class 3 - mid/high SES	-11.58 ***	-13.32,-9.85	-7.84 ***	-9.82,-5.87	-6.68 ***	-8.14,-5.22	-4.17 ***	-6.19,-2.15
Class 4 - high SES	-10.45 ***	-12.06,-8.83	-9.38 ***	-11.23,-7.54	-6.17 ***	-7.65,-4.69	-3.87 ***	-5.82,-1.92
Constant	22.54 ***	21.30,23.79	-7.94	-18.98,3.09	5.99	-8.36,20.33	-3.72	-18.63,11.20
BIC	770.4		745.74		661.48		654.57	
Panel B: Obesity								
Class 2 - low ses	-7.54 ***	-10.53,-4.56	-4.86 ***	-7.55,-2.17	-4.26 ***	-6.65,-1.86	-1.38	-4.75,1.98
Class 3 - mid/high SES	-16.28 ***	-19.34,-13.21	-9.15 ***	-12.54,-5.75	-7.57 ***	-10.60,-4.53	-3.87 +	-8.17,0.43
Class 4 - high SES	-16.25 ***	-19.11,-13.39	-11.40 ***	-14.56,-8.23	-7.26 ***	-10.35,-4.18	-3.88 +	-8.03,0.28
Constant	42.38 ***	40.18,44.59	-24.05 *	-42.99,-5.10	2.35	-27.51,32.20	-11.97	-43.68,19.74
BIC	932.69		899.23		869.66		868.77	
Panel C: Hypertension								
Class 2 - low ses	-1.97	-4.44,0.51	-1.05	-2.88,0.77	-0.57	-1.94,0.81	-1	-2.96,0.97
Class 3 - mid/high SES	-7.81 ***	-10.35,-5.27	-2.13 +	-4.43,0.16	-0.75	-2.49,0.99	-1.31	-3.82,1.20
Class 4 - high SES	-2.33 +	-4.70,0.04	-5.15 ***	-7.30,-3.01	-1.43	-3.19,0.34	-1.94	-4.36,0.49
Constant	41.81 ***	39.99,43.64	8.64	-4.19,21.47	28.08 **	10.98,45.19	30.24 **	11.72,48.76
BIC	879.03		788.52		711.47		716.03	
Panel D: Depression								
Class 2 - low ses	-1.95 **	-3.32,-0.57	-1.71 *	-3.12,-0.30	-1.57 **	-2.59,-0.55	0	-1.41,1.41
Class 3 - mid/high SES	-3.38 ***	-4.79,-1.97	-2.32 *	-4.10,-0.54	-1.52 *	-2.81,-0.23	0.5	-1.30,2.31
Class 4 - high SES	-4.10 ***	-5.41,-2.79	-4.27 ***	-5.93,-2.61	-1.74 **	-3.05,-0.43	0.11	-1.63,1.86
Constant	23.62 ***	22.60,24.63	16.38 **	6.43,26.33	15.38 *	2.68,28.09	7.55	-5.76,20.86
BIC	711.84		716.23		627.06		622.24	
Panel E: Current Smokers								
Class 2 - low ses	-0.76	-2.87,1.35	-0.22	-2.39,1.95	0.69	-1.27,2.65	4.81 ***	2.35,7.27
Class 3 - mid/high SES	-2.37 *	-4.54,-0.20	-1.61	-4.34,1.12	-0.08	-2.57,2.41	5.37 **	2.19,8.55
Class 4 - high SES	-7.22 ***	-9.24,-5.20	-5.28 ***	-7.84,-2.73	-2.14 +	-4.63,0.36	3.17 *	0.02,6.32
Constant	18.66 ***	17.10,20.21	7.39	-7.88,22.65	60.65 ***	38.47,82.82	30.38 *	6.51,54.24
BIC	834		837.95		809.17		790.73	

+ p≤.1; * p≤.05; ** p≤.01; *** p≤.001

In Tables 3-6a through 3-6e I show the individual effects of the independent variables for each of the health conditions presented in Table 3-6. Overall, having an older average age of residents was associated with higher rates of diabetes, depression, and particularly hypertension. Average age was not significantly associated with rates of obesity or smoking, after accounting for other covariates. Since obesity and smoking tend to affect younger people and are generally less associated with age, these findings make sense.

Having a higher percentage of female residents was associated with higher rates of all conditions except for smoking. Associations for smoking are likely largely driven by much lower rates of smoking among women (CDC 2018b), but it is interesting that having more women in the neighborhood overall was related to lower rates of smoking.

Higher neighborhood smoking rates was associated with higher rates of all conditions. This association could be a proxy for the how stressful neighborhood environments may be. More residents may smoke in stressful neighborhood environments as a coping mechanism. In turn, these stressful environmental conditions may also be related to higher rates of other health conditions. Higher rates of smoking could also be directly linked to worse health, but this cannot be verified by ecological data.

Higher rates of binge drinking were significantly associated with lower rates of diabetes, obesity, and smoking, but were mediated by accounting for those without health care coverage for all three conditions. However, binge drinking remained significantly associated with lower rates of hypertension. It is puzzling why rates of binge drinking were associated with generally better health (particularly since this association has only been found for moderate alcohol consumption (Castelnuovo et al. 2006)), and also puzzling why the percent of uninsured would account for the positive association between binge drinking and diabetes, obesity, and smoking. One common factor between binge drinking and not having health insurance is youth, but these associations are significant after accounting for average age of residents. It is possible that using a different form of the age variable or disaggregating by age may help explain some differences, but those analyses were beyond the scope of this dissertation.

A higher percentage of uninsured residents was associated with higher rates of all health conditions except for hypertension. Again, this association could be due to the age profile of those who do not have insurance; younger adults and undocumented immigrants generally have lower rates of hypertension. However, the underlying association is solely speculative.

Table 3-6a. Neighborhood-level ordinary least squares coefficients for the prevalence of diabetes across four classes of neighborhoods (n=142)

	Model 1: Base model		Model 2: Demographics		Model 3: Health behaviors		Model 4: Health coverage	
	β(%)	95% CI	β(%)	95% CI	β(%)	95% CI	β(%)	95% CI
Class 1 - barrios (ref)								
Class 2 - low ses	-5.61 ***	-7.29,-3.92	-4.47 ***	-6.04,-2.90	-4.09 ***	-5.24,-2.94	-2.14 **	-3.72,-0.56
Class 3 - mid/high SES	-11.58 ***	-13.32,-9.85	-7.84 ***	-9.82,-5.87	-6.68 ***	-8.14,-5.22	-4.17 ***	-6.19,-2.15
Class 4 - high SES	-10.45 ***	-12.06,-8.83	-9.38 ***	-11.23,-7.54	-6.17 ***	-7.65,-4.69	-3.87 ***	-5.82,-1.92
Average Age (mean-centered)			0.33 **	0.13,0.54	0.21 +	-0.02,0.44	0.46 ***	0.20,0.72
% Female (Male ref)			0.48 ***	0.31,0.66	0.24 **	0.08,0.41	0.23 **	0.07,0.39
% current smokers					0.42 ***	0.32,0.52	0.35 ***	0.24,0.45
% of binge drinkers					-0.35 **	-0.58,-0.11	-0.05	-0.34,0.23
% without health insurance							0.17 ***	0.07,0.27
Constant	22.54 ***	21.30,23.79	-7.94	-18.98,3.09	5.99	-8.36,20.33	-3.72	-18.63,11.20
BIC	770.4	142	745.74	142	661.48	142	654.57	142

+ p≤.1; * p≤.05; ** p≤.01; *** p≤.001

Table 3-6b. Neighborhood-level ordinary least squares coefficients for the prevalence of obesity across four classes of neighborhoods (n=142)

	Model 1: Base model		Model 2: Demographics		Model 3: Health behaviors		Model 4: Health coverage	
	β(%)	95% CI	β(%)	95% CI	β(%)	95% CI	β(%)	95% CI
Class 1 - barrios (ref)								
Class 2 - low ses	-7.54 ***	-10.53,-4.56	-4.86 ***	-7.55,-2.17	-4.26 ***	-6.65,-1.86	-1.38	-4.75,1.98
Class 3 - mid/high SES	-16.28 ***	-19.34,-13.21	-9.15 ***	-12.54,-5.75	-7.57 ***	-10.60,-4.53	-3.87 +	-8.17,0.43
Class 4 - high SES	-16.25 ***	-19.11,-13.39	-11.40 ***	-14.56,-8.23	-7.26 ***	-10.35,-4.18	-3.88 +	-8.03,0.28
Average Age (mean-centered)			0.1	-0.26,0.46	-0.19	-0.67,0.28	0.18	-0.38,0.74
% Female (Male ref)			1.04 ***	0.75,1.34	0.67 ***	0.33,1.01	0.66 ***	0.32,1.00
% current smokers					0.45 ***	0.24,0.66	0.35 **	0.12,0.57
% of binge drinkers					-0.61 *	-1.10,-0.12	-0.17	-0.78,0.43
% without health insurance							0.25 *	0.04,0.47
Constant	42.38 ***	40.18,44.59	-24.05 *	-42.99,-5.10	2.35	-27.51,32.20	-11.97	-43.68,19.74
BIC	932.69	142	899.23	142	869.66	142	868.77	142

+ p≤.1; * p≤.05; ** p≤.01; *** p≤.001

Table 3-6c. Neighborhood-level ordinary least squares coefficients for the prevalence of hypertension across four classes of neighborhoods (n=142)

	Model 1: Base model		Model 2: Demographics		Model 3: Health behaviors		Model 4: Health coverage	
	β(%)	95% CI	β(%)	95% CI	β(%)	95% CI	β(%)	95% CI
Class 1 - barrios (ref)								
Class 2 - low ses	-1.97	-4.44,0.51	-1.05	-2.88,0.77	-0.57	-1.94,0.81	-1	-2.96,0.97
Class 3 - mid/high SES	-7.81 ***	-10.35,-5.27	-2.13 +	-4.43,0.16	-0.75	-2.49,0.99	-1.31	-3.82,1.20
Class 4 - high SES	-2.33 +	-4.70,0.04	-5.15 ***	-7.30,-3.01	-1.43	-3.19,0.34	-1.94	-4.36,0.49
Average Age (mean-centered)			1.35 ***	1.11,1.59	1.15 ***	0.88,1.42	1.10 ***	0.77,1.42
% Female (Male ref)			0.54 ***	0.34,0.74	0.24 *	0.04,0.43	0.24 *	0.04,0.44
% current smokers					0.45 ***	0.33,0.57	0.47 ***	0.34,0.60
% of binge drinkers					-0.47 **	-0.75,-0.18	-0.53 **	-0.88,-0.18
% without health insurance							-0.04	-0.16,0.09
Constant	41.81 ***	39.99,43.64	8.64	-4.19,21.47	28.08 **	10.98,45.19	30.24 **	11.72,48.76
BIC	879.03	142	788.52	142	711.47	142	716.03	142

+ p≤.1; * p≤.05; ** p≤.01; *** p≤.001

Table 3-6d. Neighborhood-level ordinary least squares coefficients for the prevalence of depression across four classes of neighborhoods (n=142)

	Model 1: Base model		Model 2: Demographics		Model 3: Health behaviors		Model 4: Health coverage	
	β(%)	95% CI	β(%)	95% CI	β(%)	95% CI	β(%)	95% CI
Class 1 - barrios (ref)								
Class 2 - low ses	-1.95 **	-3.32,-0.57	-1.71 *	-3.12,-0.30	-1.57 **	-2.59,-0.55	0	-1.41,1.41
Class 3 - mid/high SES	-3.38 ***	-4.79,-1.97	-2.32 *	-4.10,-0.54	-1.52 *	-2.81,-0.23	0.5	-1.30,2.31
Class 4 - high SES	-4.10 ***	-5.41,-2.79	-4.27 ***	-5.93,-2.61	-1.74 **	-3.05,-0.43	0.11	-1.63,1.86
Average Age (mean-centered)			0.18 +	-0.00,0.37	0.27 **	0.07,0.47	0.47 ***	0.23,0.71
% Female (Male ref)			0.12	-0.04,0.27	0.02	-0.13,0.16	0.01	-0.13,0.15
% current smokers					0.45 ***	0.36,0.54	0.40 ***	0.30,0.49
% of binge drinkers					-0.05	-0.26,0.16	0.19	-0.06,0.44
% without health insurance							0.14 **	0.05,0.23
Constant	23.62 ***	22.60,24.63	16.38 **	6.43,26.33	15.38 *	2.68,28.09	7.55	-5.76,20.86
BIC	711.84	142	716.23	142	627.06	142	622.24	142

+ p≤.1; * p≤.05; ** p≤.01; *** p≤.001

Table 3-6e. Neighborhood-level ordinary least squares coefficients for the prevalence of smoking across four classes of neighborhoods (n=142)

	Model 1: Base model		Model 2: Demographics		Model 3: Health behaviors		Model 4: Health coverage	
	β(%)	95% CI	β(%)	95% CI	β(%)	95% CI	β(%)	95% CI
Class 1 - barrios (ref)								
Class 2 - low ses	-0.76	-2.87,1.35	-0.22	-2.39,1.95	0.69	-1.27,2.65	4.81 ***	2.35,7.27
Class 3 - mid/high SES	-2.37 *	-4.54,-0.20	-1.61	-4.34,1.12	-0.08	-2.57,2.41	5.37 **	2.19,8.55
Class 4 - high SES	-7.22 ***	-9.24,-5.20	-5.28 ***	-7.84,-2.73	-2.14 +	-4.63,0.36	3.17 *	0.02,6.32
Average Age (mean-centered)			-0.26 +	-0.54,0.03	-0.99 ***	-1.34,-0.64	-0.3	-0.72,0.13
% Female (Male ref)			0.17	-0.07,0.41	-0.36 *	-0.63,-0.08	-0.32 *	-0.58,-0.07
% of binge drinkers					-1.09 ***	-1.44,-0.73	-0.29	-0.75,0.18
% without health insurance							0.37 ***	0.22,0.53
Constant	18.66 ***	17.10,20.21	7.39	-7.88,22.65	60.65 ***	38.47,82.82	30.38 *	6.51,54.24
BIC	834		837.95		809.17		790.73	

+ p≤.1; * p≤.05; ** p≤.01; *** p≤.001

Hispanic-NHW Inequality Results

In Table 3-7 I present results from the OLS regression analyses predicting inequality in health conditions for Hispanics compared to NHWs. The coefficients represent logged relative odds; negative coefficients represent less inequality compared to the referent, and positive coefficients represent more inequality compared to the referent. Note that the constant values for each Model 1 are the same as the natural log of the relative odds values for barrio neighborhoods (Class 1) presented in Table 3-5.

All neighborhood classes had higher average rates of diabetes among Hispanic than among NHW residents (Table 3-5). At baseline (Panel A, Model 1), the inequality in diabetes prevalence between Hispanic and NHW residents was the lowest in barrio and high SES neighborhoods, and higher in low SES and mid/high SES neighborhoods. Adjusting for demographics accounted for the differences in Hispanic/NHW disparities between barrios and mid/high SES neighborhoods, but exacerbated the differences in disparities between barrios and high SES neighborhoods (Panel A, Model 2). Health behaviors tempered the inequality differences across all neighborhoods (Panel A, Model 3), whereas health coverage slightly increased differences in the Hispanic/NHW disparities (Panel A, Model 4). After controlling for all covariates, the inequality between Hispanics/NHWs was the largest in high SES neighborhoods compared to barrios, and otherwise not statistically significant.

Compared to diabetes, disparities in obesity prevalence between Hispanics/NHWs were larger in all neighborhood classes compared to barrio neighborhoods. Although adjusting for all covariates tempered the differences in disparities somewhat, disparities in barrio neighborhoods remained the lowest (Panel B, Model 4).

For hypertension prevalence, there was more inequality in low SES and mid/high SES neighborhoods compared to barrio neighborhoods at baseline (Panel C, Model 1). Differences in inequality diminished after accounting for health behaviors (Panel C, Model 3), but returned for low SES neighborhoods compared to barrios after controlling for differences in healthcare access (Panel C, Model 4).

The differences in prevalence of depression between Hispanics/NHWs were not substantially or significantly different across neighborhood types, even after accounting for all covariates (Panel D, Model 4).

Although disparities in smoking prevalence were the largest among barrio neighborhoods (Table 3-5), average smoking rates were lower among Hispanics compared to NHWs in barrio neighborhoods, and higher among Hispanics compared to NHWs in other neighborhood classes (Panel E, Model 1). Although adjusting for demographic characteristics tempered the disparities (Panel E, Model 2), the disparities continued to be greater across all other neighborhood types after accounting for differences in binge drinking (Panel E, Model 3) and health insurance (Panel E, Model 4).

Overall, results from the final models (Model 4) for inequality suggest that barrio neighborhoods are generally more equitable health environments for Hispanics and NHWs compared to other neighborhoods. Accounting for covariates does reduce the differences between neighborhoods for each health condition, and differences remain the starkest for rates of smoking and obesity. Comparisons between barrio neighborhoods and low SES neighborhoods suggest that low SES neighborhoods are less equitable health environments for Hispanics and NHWs, indicating that something about the characteristics of barrio neighborhoods is associated with either better health among Hispanics, worse health among NHWs, or both.

Tables 3-7a through 3-7e show the individual effects of the independent variables for each of the health conditions presented in Table 3-7. Generally, having a higher average age in the tract was associated with increased inequality of diabetes, obesity, and hypertension, for Hispanics compared to NHWs, but not for smoking or depression. It is possible that the higher average age reflected a higher percentage of old Hispanic residents, who may have worse health compared to younger Hispanic adults, therefore widening the gap between Hispanics and NHWs.

A higher percentage of female residents was associated with more inequality in diabetes and obesity, but not hypertension, depression, or smoking. It is unclear why the percentage of female residents would be associated with greater inequality for some health conditions but not others, particularly because the split in positive/negative associations with inequality do not map onto the individual-level gender differences in presented later in Chapter 4. However, I did not test gender differences in health across race/ethnic groups, and future analyses could compare these differences to further understand the role gender composition may play in within-neighborhood health inequality between Hispanics and NHWs.

Higher rates of smoking were associated with greater inequality for all health conditions except for depression. Although the directionality is unclear, there may be a link between the generally low rates of smoking in barrio neighborhoods and the low rates of inequality. They could both be associated with an underlying omitted variable, or lower rates of smoking among Hispanics could indicate less stress for Hispanics (and thus better health) but more stress (and thus worse health) among NHWs, which would effectively lower the inequality between the groups in barrio neighborhoods. Factors other than stress could also be at work, including omitted social and environmental influences.

Higher rates of binge drinking were associated with increased inequality across all health conditions except depression. Furthermore, the effect sizes for binge drinking were the larger than the effect sizes for other covariates (except the classes) for each health condition except depression. It is unclear why this health behavior may have a stronger association with inequality than age, gender, smoking, or healthcare access. It could be that higher rates of binge drinking are associated with less social control. Or stated in the other direction, it could be that neighborhoods with more social control and tighter social networks are more likely to discourage binge drinking. Future analyses could examine binge drinking as an outcome, and better understand what neighborhood factors are associated with higher rates of binge drinking.

Higher rates of healthcare access (defined as the percent of residents with a checkup in the past year) were not strongly associated with any of the health conditions. Healthcare access was only statistically significantly associated with lower rates of depression. This association was likely due to the way depression was measured; neighborhoods that had more residents seeking care also had increased chances that those residents would be diagnosed with depression in a healthcare setting. It is unlikely that there is a direct relationship between healthcare access and depressive symptoms.

Table 3-7. Neighborhood-level ordinary least squares coefficients for the natural log of the relative odds of five health conditions for Hispanic compared to non-Hispanic white patients across neighborhood classes (n=142)

	Model 1: Base model		Model 2: Demographics		Model 3: Health behaviors		Model 4: Health coverage	
	β	95% CI	β	95% CI	β	95% CI	β	95% CI
Class 1 - Barrios (ref)								
Panel A: Diabetes								
Class 2 - Low SES	0.23 +	-0.01,0.47	0.21 +	-0.03,0.46	0.13	-0.09,0.35	0.19	-0.07,0.46
Class 3 - Mid/high SES	0.27 *	0.02,0.51	0.1	-0.20,0.41	0.02	-0.26,0.31	0.1	-0.23,0.44
Class 4 - High SES	0.18	-0.05,0.41	0.32 *	0.03,0.60	0.25 +	-0.04,0.53	0.32 +	-0.02,0.66
Constant	0.55 ***	0.37,0.73	1.37	-0.34,3.08	-4.51 **	-7.27,-1.75	-3.55 +	-7.11,0.01
BIC	213.26		214.29		192.19		196.37	
Panel B: Obesity								
Class 2 - Low SES	0.32 ***	0.15,0.50	0.30 **	0.12,0.49	0.25 **	0.08,0.42	0.28 **	0.08,0.49
Class 3 - Mid/high SES	0.29 **	0.11,0.47	0.23 +	-0.00,0.46	0.18	-0.04,0.40	0.23 +	-0.04,0.49
Class 4 - High SES	0.28 **	0.11,0.45	0.25 *	0.04,0.47	0.22 +	-0.01,0.44	0.26 +	-0.00,0.52
Constant	0.25 ***	0.12,0.38	0.78	-0.52,2.08	-3.01 **	-5.18,-0.85	-2.48 +	-5.27,0.30
BIC	128.52		137.74		124.1		128.67	
Panel C: Hypertension								
Class 2 - Low SES	0.27 *	0.06,0.47	0.18 +	-0.02,0.38	0.11	-0.07,0.28	0.19 +	-0.02,0.40
Class 3 - Mid/high SES	0.23 *	0.02,0.44	-0.1	-0.35,0.15	-0.18	-0.40,0.05	-0.07	-0.34,0.20
Class 4 - High SES	0.09	-0.10,0.28	0.08	-0.15,0.32	0.02	-0.21,0.24	0.11	-0.15,0.38
Constant	-0.06	-0.21,0.09	2.37 **	0.98,3.76	-2.88 *	-5.09,-0.67	-1.64	-4.47,1.19
BIC	169.34		157.9		129.91		132.87	
Panel D: Depression								
Class 2 - Low SES	0.11	-0.06,0.28	0.05	-0.13,0.22	0.04	-0.14,0.21	0.15	-0.05,0.36
Class 3 - Mid/high SES	0.12	-0.05,0.30	-0.08	-0.30,0.14	-0.09	-0.31,0.14	0.07	-0.19,0.34
Class 4 - High SES	-0.02	-0.18,0.15	-0.07	-0.28,0.13	-0.05	-0.28,0.17	0.1	-0.17,0.36
Constant	0.09	-0.03,0.22	1.76 **	0.53,2.98	0.69	-1.50,2.88	2.56 +	-0.22,5.35
BIC	121.03		121.74		128.11		128.37	
Panel E: Current Smokers								
Class 2 - Low SES	0.44 ***	0.21,0.67	0.37 **	0.14,0.61	0.32 **	0.08,0.55	0.39 **	0.12,0.66
Class 3 - Mid/high SES	0.66 ***	0.42,0.89	0.43 **	0.13,0.73	0.34 *	0.04,0.63	0.44 *	0.09,0.79
Class 4 - High SES	0.77 ***	0.55,0.99	0.71 ***	0.43,0.99	0.51 ***	0.22,0.81	0.62 ***	0.26,0.97
Constant	-0.52 ***	-0.69,-0.35	1.29	-0.39,2.96	-2.05	-4.70,0.59	-1.05	-4.27,2.17
BIC	206.46		210.29		205.07		208.81	

+ p≤.1; * p≤.05; ** p≤.01; *** p≤.001

Table 3-7a. Neighborhood-level ordinary least squares coefficients for the natural log of the relative odds of diabetes for Hispanic compared to non-Hispanic white patients across neighborhood classes (n=142)

	Model 1: Base model		Model 2: Demographics		Model 3: Health behaviors		Model 4: Health checkup	
	β	95% CI	β	95% CI	β	95% CI	β	95% CI
Class 1 - Barrios (ref)								
Class 2 - Low SES	0.23 +	-0.01,0.47	0.21 +	-0.03,0.46	0.13	-0.09,0.35	0.19	-0.07,0.46
Class 3 - Mid/high SES	0.27 *	0.02,0.51	0.1	-0.20,0.41	0.02	-0.26,0.31	0.1	-0.23,0.44
Class 4 - High SES	0.18	-0.05,0.41	0.32 *	0.03,0.60	0.25 +	-0.04,0.53	0.32 +	-0.02,0.66
Average Age (mean-centered)			-0.05 **	-0.08,-0.01	0.04 +	-0.00,0.09	0.05 *	0.00,0.11
% Female (Male ref)			-0.01	-0.04,0.01	0.03 *	0.00,0.06	0.03 *	0.00,0.07
% current smokers					0.05 ***	0.03,0.07	0.05 ***	0.03,0.07
% of binge drinkers					0.11 ***	0.07,0.16	0.11 ***	0.06,0.15
% with a checkup in past year							-0.02	-0.06,0.02
Constant	0.55 ***	0.37,0.73	1.37	-0.34,3.08	-4.51 **	-7.27,-1.75	-3.55 +	-7.11,0.01
BIC	213.26		214.29		192.19		196.37	

+ p≤.1; * p≤.05; ** p≤.01; *** p≤.001

Table 3-7b. Neighborhood-level ordinary least squares coefficients for the natural log of the relative odds of obesity for Hispanic compared to non-Hispanic white patients across neighborhood classes (n=142)

	Model 1: Base model		Model 2: Demographics		Model 3: Health behaviors		Model 4: Health checkup	
	β	95% CI	β	95% CI	β	95% CI	β	95% CI
Class 1 - Barrios (ref)								
Class 2 - Low SES	0.32 ***	0.15,0.50	0.30 **	0.12,0.49	0.25 **	0.08,0.42	0.28 **	0.08,0.49
Class 3 - Mid/high SES	0.29 **	0.11,0.47	0.23 +	-0.00,0.46	0.18	-0.04,0.40	0.23 +	-0.04,0.49
Class 4 - High SES	0.28 **	0.11,0.45	0.25 *	0.04,0.47	0.22 +	-0.01,0.44	0.26 +	-0.00,0.52
Average Age (mean-centered)			0	-0.03,0.02	0.05 **	0.02,0.09	0.06 **	0.02,0.10
% Female (Male ref)			-0.01	-0.03,0.01	0.02 +	-0.00,0.05	0.02 +	-0.00,0.05
% current smokers					0.03 ***	0.02,0.05	0.03 ***	0.02,0.05
% of binge drinkers					0.07 ***	0.04,0.11	0.07 ***	0.03,0.11
% with a checkup in past year							-0.01	-0.04,0.02
Constant	0.25 ***	0.12,0.38	0.78	-0.52,2.08	-3.01 **	-5.18,-0.85	-2.48 +	-5.27,0.30
BIC	128.52		137.74		124.1		128.67	

+ p≤.1; * p≤.05; ** p≤.01; *** p≤.001

Table 3-7c. Neighborhood-level ordinary least squares coefficients for the natural log of the relative odds of hypertension for Hispanic compared to non-Hispanic white patients across neighborhood classes (n=142)

	Model 1: Base model		Model 2: Demographics		Model 3: Health behaviors		Model 4: Health checkup	
	β	95% CI	β	95% CI	β	95% CI	β	95% CI
Class 1 - Barrios (ref)								
Class 2 - Low SES	0.27 *	0.06,0.47	0.18 +	-0.02,0.38	0.11	-0.07,0.28	0.19 +	-0.02,0.40
Class 3 - Mid/high SES	0.23 *	0.02,0.44	-0.1	-0.35,0.15	-0.18	-0.40,0.05	-0.07	-0.34,0.20
Class 4 - High SES	0.09	-0.10,0.28	0.08	-0.15,0.32	0.02	-0.21,0.24	0.11	-0.15,0.38
Average Age (mean-centered)			-0.05 ***	-0.07,-0.02	0.03 +	-0.00,0.07	0.05 *	0.01,0.09
% Female (Male ref)			-0.04 ***	-0.06,-0.02	0	-0.02,0.03	0	-0.02,0.03
% current smokers					0.04 ***	0.03,0.06	0.04 ***	0.02,0.05
% of binge drinkers					0.10 ***	0.06,0.14	0.09 ***	0.06,0.13
% with a checkup in past year							-0.02	-0.05,0.01
Constant	-0.06	-0.21,0.09	2.37 **	0.98,3.76	-2.88 *	-5.09,-0.67	-1.64	-4.47,1.19
BIC	169.34		157.9		129.91		132.87	

+ p≤.1; * p≤.05; ** p≤.01; *** p≤.001

Table 3-7d. Neighborhood-level ordinary least squares coefficients for the natural log of the relative odds of depression for Hispanic compared to non-Hispanic white patients across neighborhood classes (n=142)

	Model 1: Base model		Model 2: Demographics		Model 3: Health behaviors		Model 4: Health checkup	
	β	95% CI	β	95% CI	β	95% CI	β	95% CI
Class 1 - Barrios (ref)								
Class 2 - Low SES	0.11	-0.06,0.28	0.05	-0.13,0.22	0.04	-0.14,0.21	0.15	-0.05,0.36
Class 3 - Mid/high SES	0.12	-0.05,0.30	-0.08	-0.30,0.14	-0.09	-0.31,0.14	0.07	-0.19,0.34
Class 4 - High SES	-0.02	-0.18,0.15	-0.07	-0.28,0.13	-0.05	-0.28,0.17	0.1	-0.17,0.36
Average Age (mean-centered)			-0.02	-0.04,0.00	0	-0.04,0.03	0.02	-0.02,0.06
% Female (Male ref)			-0.03 **	-0.05,-0.01	-0.02	-0.04,0.01	-0.02	-0.04,0.01
% current smokers					0.01 +	-0.00,0.03	0.01	-0.01,0.02
% of binge drinkers					0.02	-0.02,0.06	0.01	-0.03,0.05
% with a checkup in past year							-0.03 *	-0.06,-0.00
Constant	0.09	-0.03,0.22	1.76 **	0.53,2.98	0.69	-1.50,2.88	2.56 +	-0.22,5.35
BIC	121.03		121.74		128.11		128.37	

+ p≤.1; * p≤.05; ** p≤.01; *** p≤.001

Table 3-7e. Neighborhood-level ordinary least squares coefficients for the natural log of the relative odds of smoking for Hispanic compared to non-Hispanic white patients across neighborhood classes (n=142)

	Model 1: Base model		Model 2: Demographics		Model 3: Health behaviors		Model 4: Health checkup	
	β	95% CI	β	95% CI	β	95% CI	β	95% CI
Class 1 - Barrios (ref)								
Class 2 - Low SES	0.44 ***	0.21,0.67	0.37 **	0.14,0.61	0.32 **	0.08,0.55	0.39 **	0.12,0.66
Class 3 - Mid/high SES	0.66 ***	0.42,0.89	0.43 **	0.13,0.73	0.34 *	0.04,0.63	0.44 *	0.09,0.79
Class 4 - High SES	0.77 ***	0.55,0.99	0.71 ***	0.43,0.99	0.51 ***	0.22,0.81	0.62 ***	0.26,0.97
Average Age (mean-centered)			-0.02	-0.05,0.01	0.02	-0.02,0.07	0.04	-0.01,0.10
% Female (Male ref)			-0.03 *	-0.05,-0.00	0	-0.03,0.04	0.01	-0.03,0.04
% binge drinkers					0.07 **	0.03,0.11	0.07 **	0.02,0.11
% with a checkup in past year							-0.02	-0.06,0.02
Constant	-0.52 ***	-0.69,-0.35	1.29	-0.39,2.96	-2.05	-4.70,0.59	-1.05	-4.27,2.17
BIC	206.46		210.29		205.07		208.81	

+ p≤.1; * p≤.05; ** p≤.01; *** p≤.001

Spatial Representations of Prevalence and Inequality

Figures 3-2 - 3-11 show four maps for each health condition based on the prevalence and inequality analyses. For the prevalence maps, Map 1 (top left) shows baseline prevalence rates, Map 2 (top right) shows prevalence rates after adjusting for all covariates (predicted rates from Table 3-6: Model 4). Map 3 (bottom left) shows the overall change in prevalence between Map 1 and Map 2. Map 4 shows the percent change of the adjusted prevalence from the baseline prevalence. Barrio neighborhoods (Class 1) are demarcated by diagonal black lines running through tracts.

Figure 3-2 shows the prevalence maps for diabetes. Overall, there were large variations in rates of diabetes across neighborhoods, ranging from 6%-27%.[2] Adjusting for covariates had diverse impacts on predicted prevalence rates. For some neighborhoods, adjusting for covariates lowered predicted rates by as much as 7.5%, and for other neighborhoods adjusting for covariates increased predicted rates by as much as 7.5%. Although there was not a dramatic shift in unadjusted and adjusted rates of prevalence for barrio neighborhoods (i.e. barrio neighborhoods generally have high rates of diabetes before and after adjusting for covariates), examining change from unadjusted to adjusted models (Maps 3-4) reveals more about the effect of demographics, health behaviors, and health insurance on diabetes rates for barrios. Because barrios were generally disadvantaged with regard to SES and health care access/utilization, adjusting for these covariates lowered diabetes rates in about half of barrio neighborhoods, and only one neighborhood would have had an estimated increase in diabetes greater than 2.3% after adjusting for covariates (Map 3).

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[2] As a reminder, these rates reflect the *patient population* from the EHRs and are not necessarily representative of the total residential population. Rates are likely higher among the patient population than they would be among the general residential population.

Figure 3-3 shows the prevalence maps for obesity. There were also large variations in obesity rates across Denver neighborhoods, with unadjusted rates ranging from 15.6% - 48%. The impact of neighborhood-level covariates dramatically changed estimated rates of obesity in some neighborhoods, lowering the estimated prevalence by as much as 19.2% in some neighborhoods, and increasing the estimated prevalence by as much as 10.7% in other neighborhoods. Similar to diabetes prevalence rates, obesity prevalence rates remained high in barrio neighborhoods at baseline (Map 1) and after adjusting for covariates (Map 2). Adjusting for neighborhood demographic, behavioral, and healthcare factors had mixed impacts on obesity rates in barrio neighborhoods. Some barrio neighborhoods showed lower predicted obesity rates (green or yellow tracts in Map 3), whereas others showed higher predicted obesity rates (tracts orange or red tracts in Map 3) after covariate adjustment.

Figure 3-4 shows the prevalence maps for hypertension. There was also a lot of variation in baseline and predicted prevalence rates of hypertension across neighborhoods, ranging from as low as 25% to as high as 69%. Overall, the relative percent changes in prevalence from baseline was less dramatic for hypertension (ranging from 8% lower to 7% higher) than they were for diabetes and obesity, suggesting that the select covariates were more influential in explaining variation in obesity and diabetes than in hypertension. For many of barrio neighborhoods, particularly those in West Denver, adjusting for neighborhood demographic, behavioral, and healthcare factors increased predicted rates of hypertension. However, adjusting for neighborhood demographic, behavioral, and healthcare factors decreased prevalence of hypertension for barrio neighborhoods in Northeast Denver and had little overall effect on barrio neighborhoods in North Denver.

Figure 3-5 shows the prevalence maps for depression. Again, there was extensive variation in unadjusted and adjusted prevalence rates of depression, ranging from 13%-32% across neighborhoods. Similar to hypertension, however, the covariates did not have as large of an impact on predicted prevalence of depression compared to diabetes and obesity. Adjusting for covariates lowered predicted prevalence of depression by as much as 5% in some neighborhoods and increased predicted prevalence by as much as 6% in others. Similar to the other health conditions, adjusting for neighborhood demographic, behavioral, and healthcare factors had mixed effects on rates of depression. Overall, adjusted rates suggest that depression rates were some of the highest in barrio neighborhoods compared to other neighborhoods in Denver, despite the fact that accounting for covariates decreased the predicted rates of depression by an estimated 9-17% in some barrio neighborhoods in North and West Denver.

Figure 3-6 shows the prevalence maps for smoking rates. Prevalence rates for smoking ranged from as low as 5% to as high as 28%. Predicted prevalence rates were moderately sensitive to covariates, with covariates lowering the predicted smoking rates by as much as 9% and increasing the predicted smoking rates by as much as 8%. Adjusting for neighborhood demographic, behavioral, and healthcare factors had both positive and negative effects on smoking rates across barrio neighborhoods (similar to the other health conditions). Even contiguous tracts showed varied or contradictory responses to covariate adjustment. For example, some of the barrio neighborhoods in North Denver had 5-9% lower predicted smoking rates after adjusting for covariates, but another contiguous North Denver neighborhood had 2-4% higher predicted smoking rates after adjusting for the same covariates.

Overall, findings from the prevalence maps showed extensive neighborhood differences for all health conditions, and suggested wide variation in the effect of neighborhood demographic, behavioral, and healthcare factors across barrio neighborhoods. Hypertension showed the least amount of change from unadjusted to adjusted prevalence rates, but also showed mixed effects of covariate adjustment. Examining unadjusted and adjusted prevalence rates reiterate findings from the regression analyses that barrio communities have some of the highest rates of all health conditions compared to other classes of neighborhoods in Denver.

Figures 3-7 through 3-11 show inequality maps based on results from Table 3-7. Figure 3-7 shows the inequality maps for diabetes. Overall, adjusting for neighborhood demographic, behavioral, and healthcare factors slightly increased diabetes inequality in many barrio neighborhoods. Nonetheless, even after a slight increase in diabetes inequality, adjusted odds of Hispanic prevalence compared to NHW prevalence of diabetes were still lower in barrio neighborhoods than in many other neighborhoods across Denver. Furthermore, no barrio communities had the highest levels of inequality (indicated in red for Maps 1 and 2) or the biggest increases in inequality (indicated in red for Maps 3 and 4) after adjusting for covariates.

Figure 3-8 shows the inequality maps for obesity. Although overall patterns were similar for inequality in obesity and diabetes, there was slightly more variation in the effect of covariates on the adjusted odds of inequality in obesity across barrio neighborhoods. As shown particularly in Map 4, the percent change in odds from baseline decreased 4-34% in almost half of the barrio neighborhoods, whereas about one quarter of barrio neighborhoods increased a 22-62% increase in odds after adjusting for covariates. Nonetheless, barrio neighborhoods still had some of the lowest levels of inequality in obesity compared to other Denver neighborhoods.

Figure 3-9 shows the inequality maps for hypertension. Similar to the prevalence results, hypertension inequality was less sensitive to neighborhood demographic, behavioral, and healthcare factors than diabetes and obesity inequality. Although only two barrio neighborhoods had high predicted levels of inequality from the adjusted models (indicated in orange in Map 2), many barrio neighborhoods experienced the largest increases in inequality from unadjusted to adjusted models (indicated in orange and red in Maps 3 and 4). This increase was specific to individual tracts, and not represented in clusters of barrio neighborhoods.

Figure 3-10 shows the inequality maps for depression. Unlike diabetes, obesity, and hypertension, depression inequality in about half of barrio neighborhoods decreased after adjusting for neighborhood demographic, behavioral, and healthcare factors. This was not true for all barrio neighborhoods; some experienced slight increases in inequality and a few experienced the highest increases in inequality from unadjusted to adjusted models. Similar to diabetes, obesity, and hypertension, overall unadjusted and adjusted levels of inequality in depression were lower in most barrio neighborhoods than in other neighborhoods across Denver.

Figure 3-11 shows the inequality maps for smoking. Patterns match those shown for inequality in other health conditions; generally results suggest lower overall inequality in smoking in both unadjusted and adjusted models. However, variation exists within barrio neighborhoods in the effect that adjusting for neighborhood demographic, behavioral, and healthcare factors has on smoking inequality.

Figure 3-2. Baseline prevalence of diabetes compared to estimated adjusted prevalence, overall estimated change, and relative change to baseline for census tracts in Denver, Colorado for patients with a 2014/2015 visit

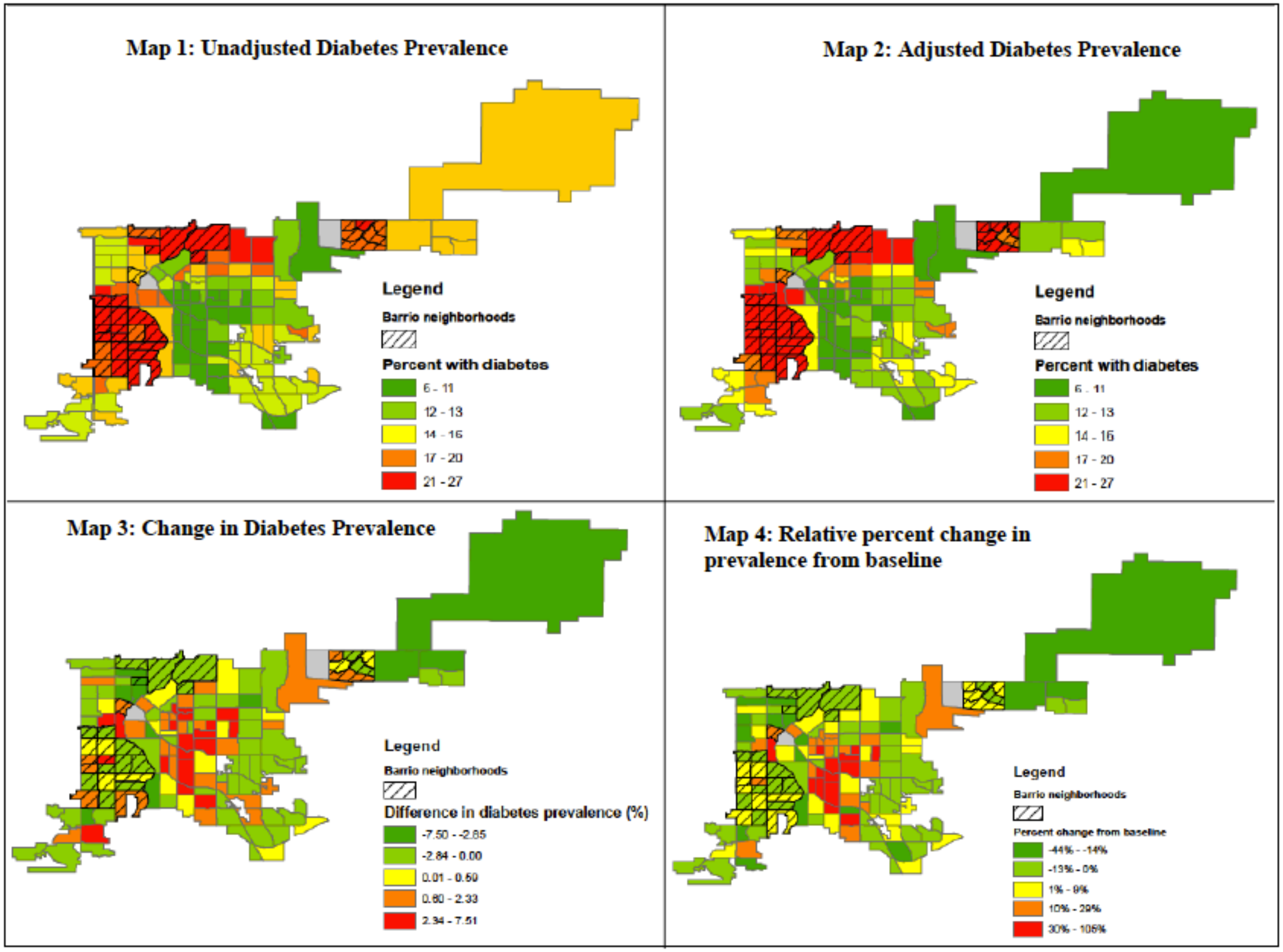


Figure 3-3. Baseline prevalence of obesity compared to estimated adjusted prevalence, overall estimated change, and relative change to baseline for census tracts in Denver, Colorado for patients with a 2014/2015

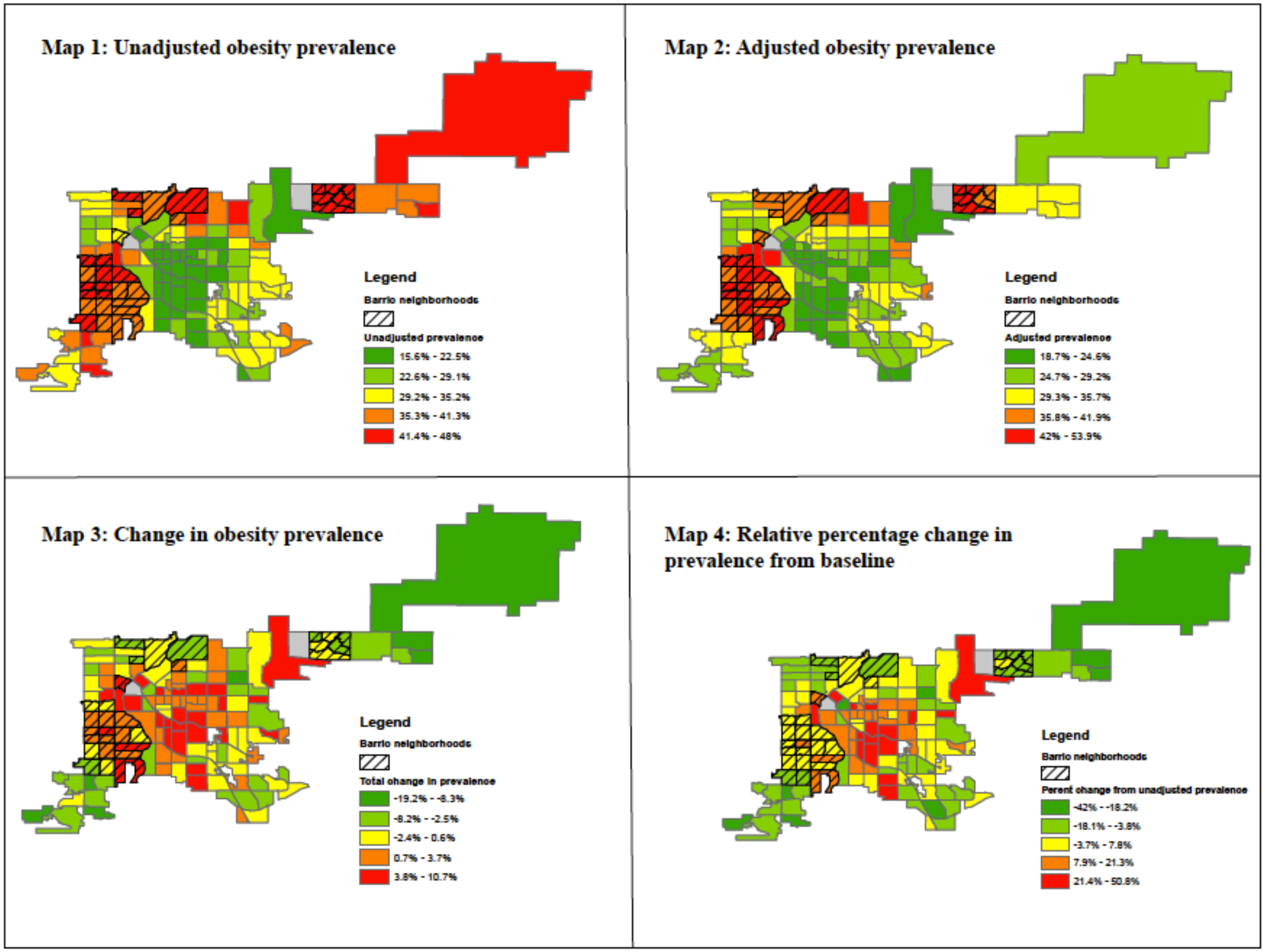


Figure 3-4. Baseline prevalence of hypertension compared to estimated adjusted prevalence, overall estimated change, and relative change to baseline for census tracts in Denver, Colorado for patients with a 2014/2015 visit

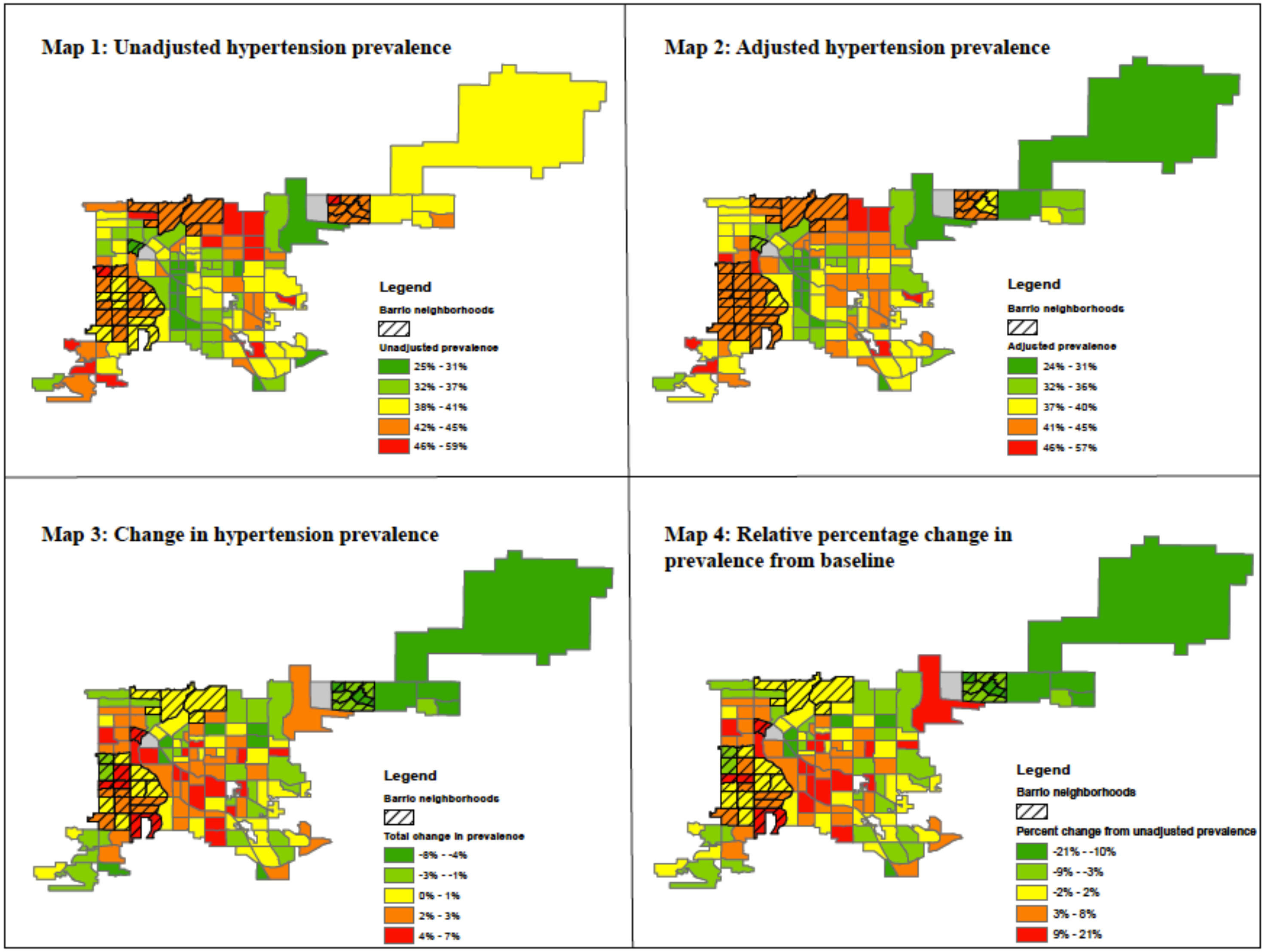


Figure 3-5. Baseline prevalence of depression compared to estimated adjusted prevalence, overall estimated change, and relative change to baseline for census tracts in Denver, Colorado for patients with a 2014/2015 visit

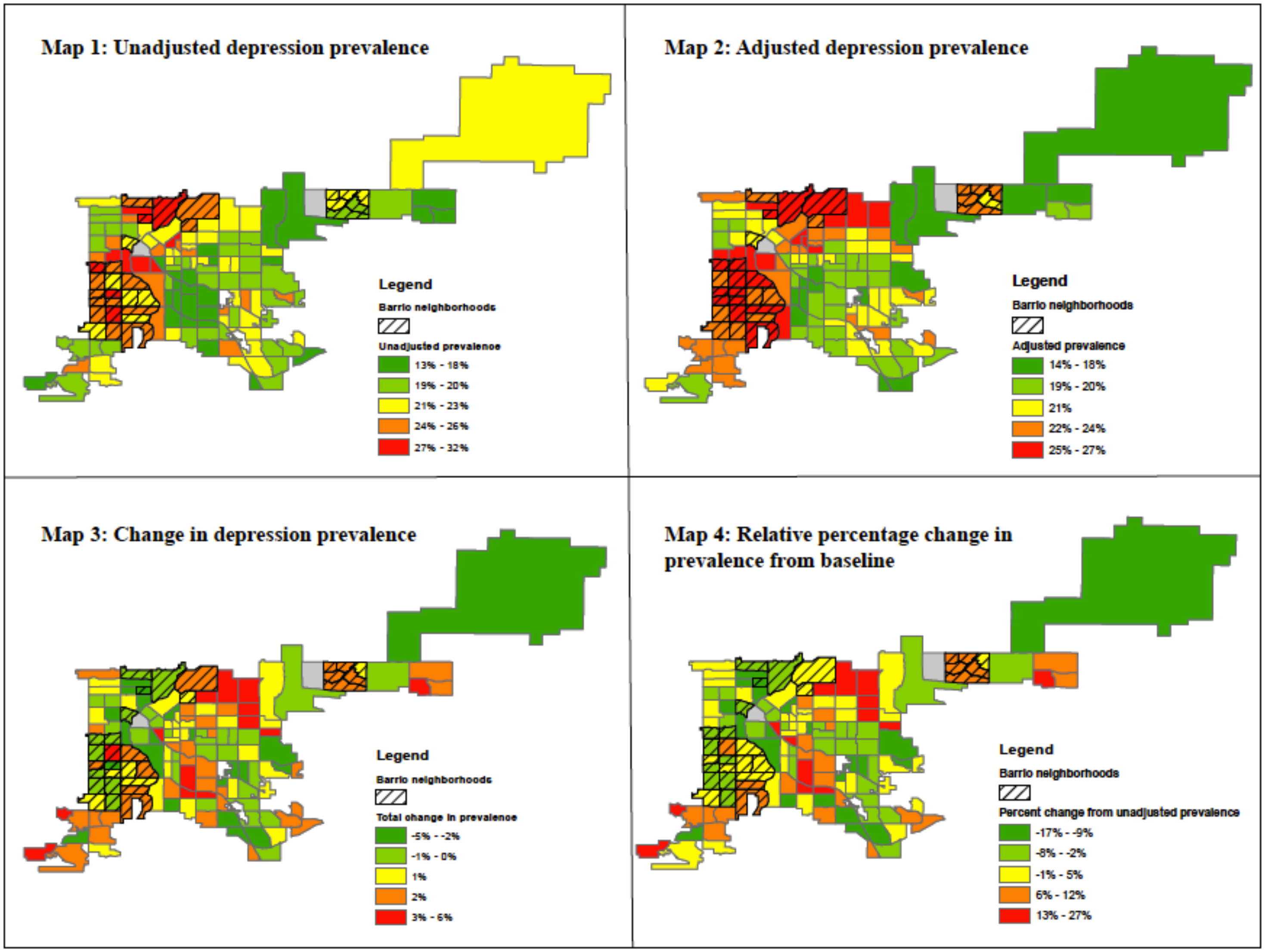


Figure 3-6. Baseline prevalence of current smoking compared to estimated adjusted prevalence, overall estimated change, and relative change to baseline for census tracts in Denver, Colorado for patients with a 2014/2015 visit

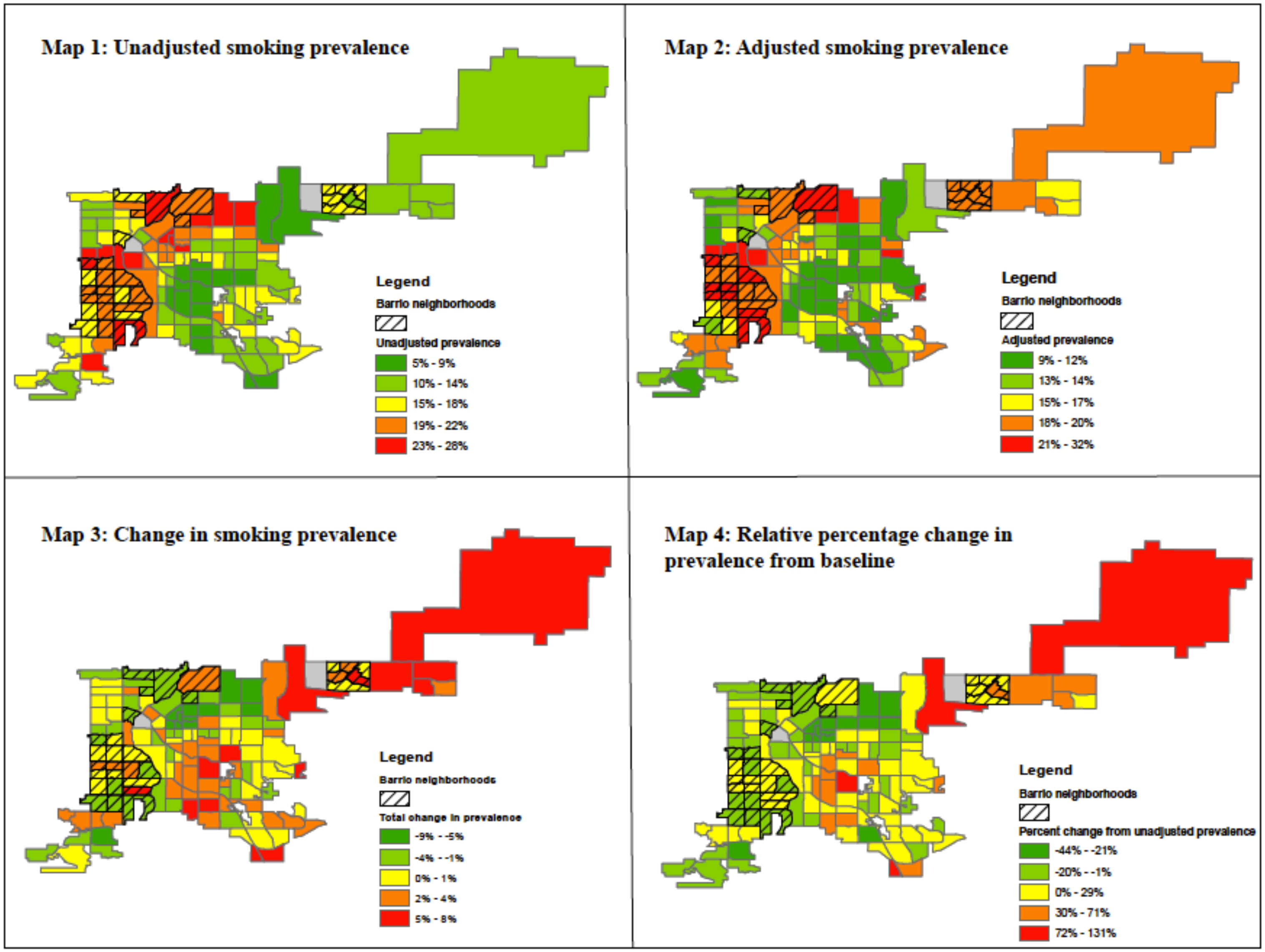


Figure 3-7. Baseline relative odds of diabetes between Hispanics and non-Hispanic whites compared to estimated adjusted odds, overall estimated change in odds, and relative percent change to baseline for census tracts in Denver, Colorado for patients with a 2014/2015 visit

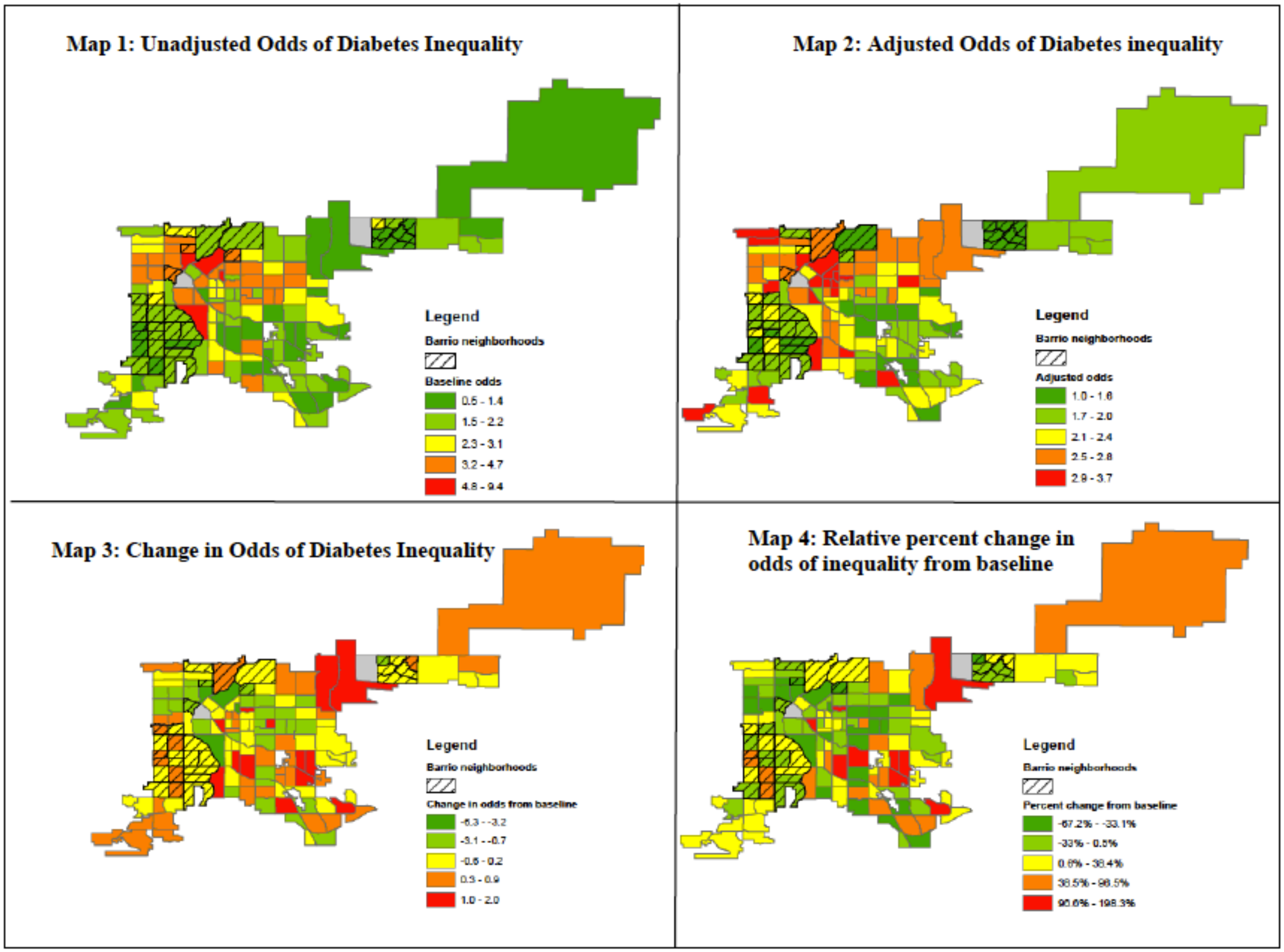


Figure 3-8. Baseline relative odds of obesity between Hispanics and non-Hispanic whites compared to estimated adjusted odds, overall estimated change in odds, and relative percent change to baseline for census tracts in Denver, Colorado for patients with a 2014/2015 visit

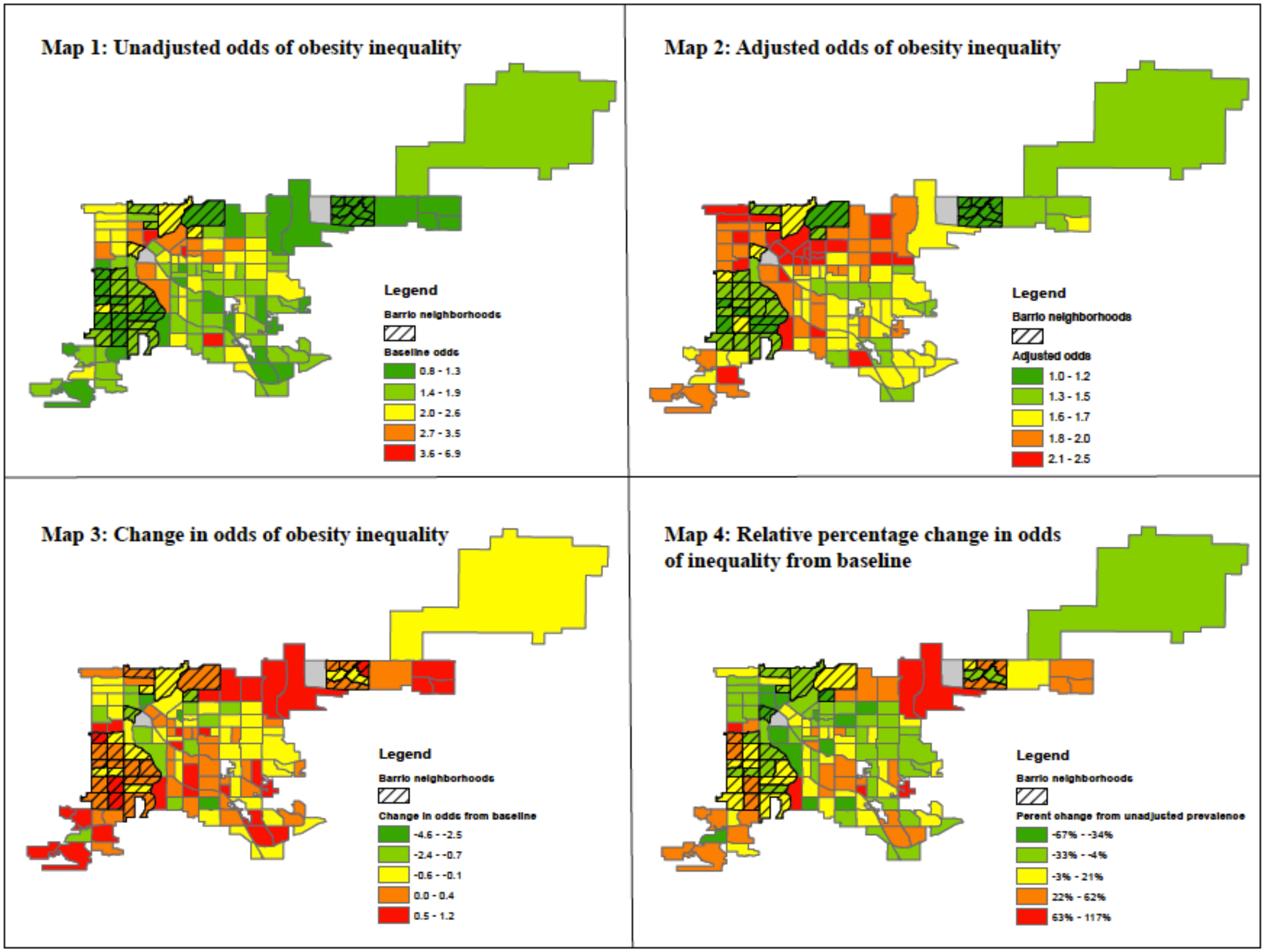


Figure 3-9. Baseline relative odds of hypertension between Hispanics and non-Hispanic whites compared to estimated adjusted odds, overall estimated change in odds, and relative percent change to baseline for census tracts in Denver, Colorado for patients with a 2014/2015 visit

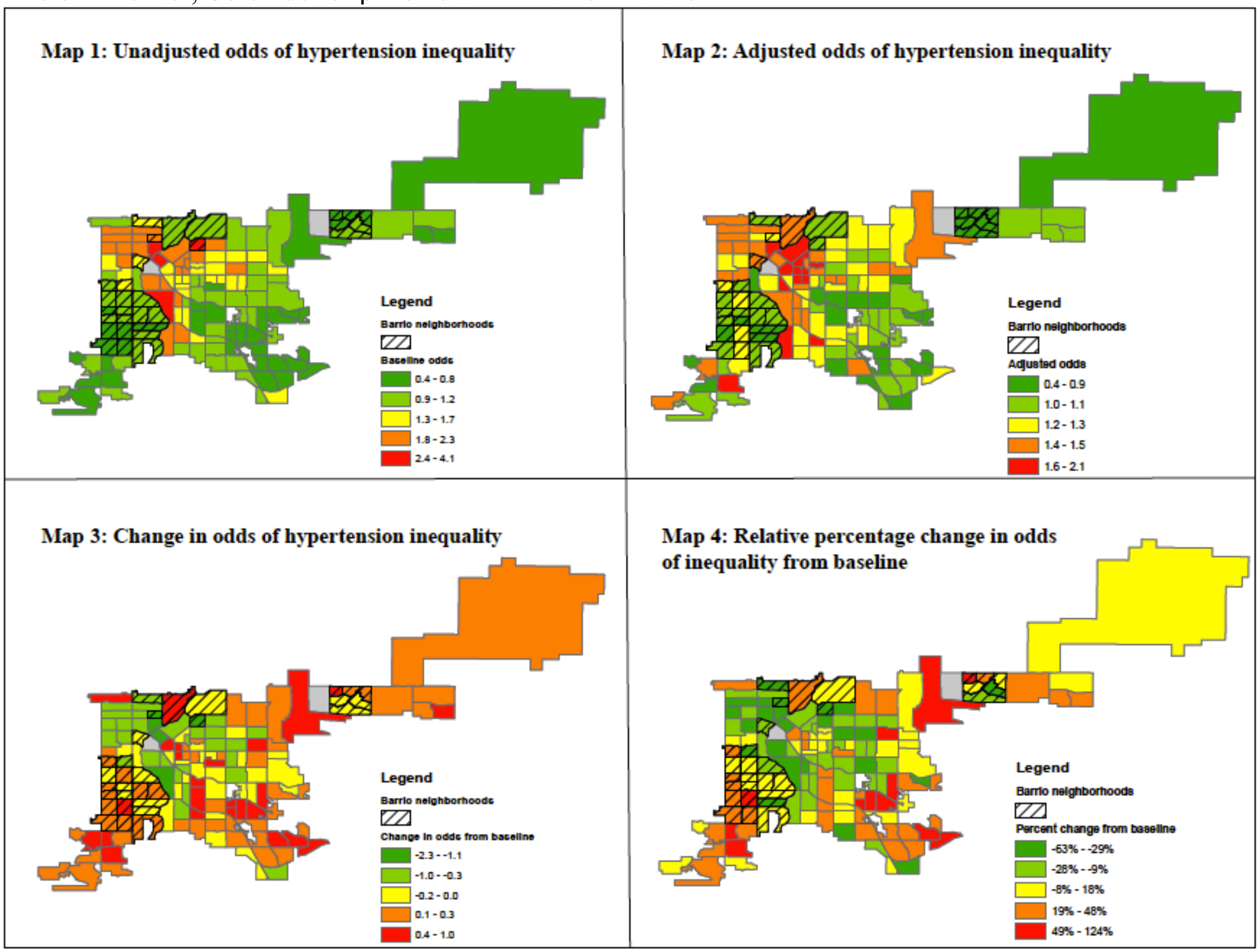


Figure 3-10. Baseline relative odds of depression between Hispanics and non-Hispanic whites compared to estimated adjusted odds, overall estimated change in odds, and relative percent change to baseline for census tracts in Denver, Colorado for patients with a 2014/2015 visit

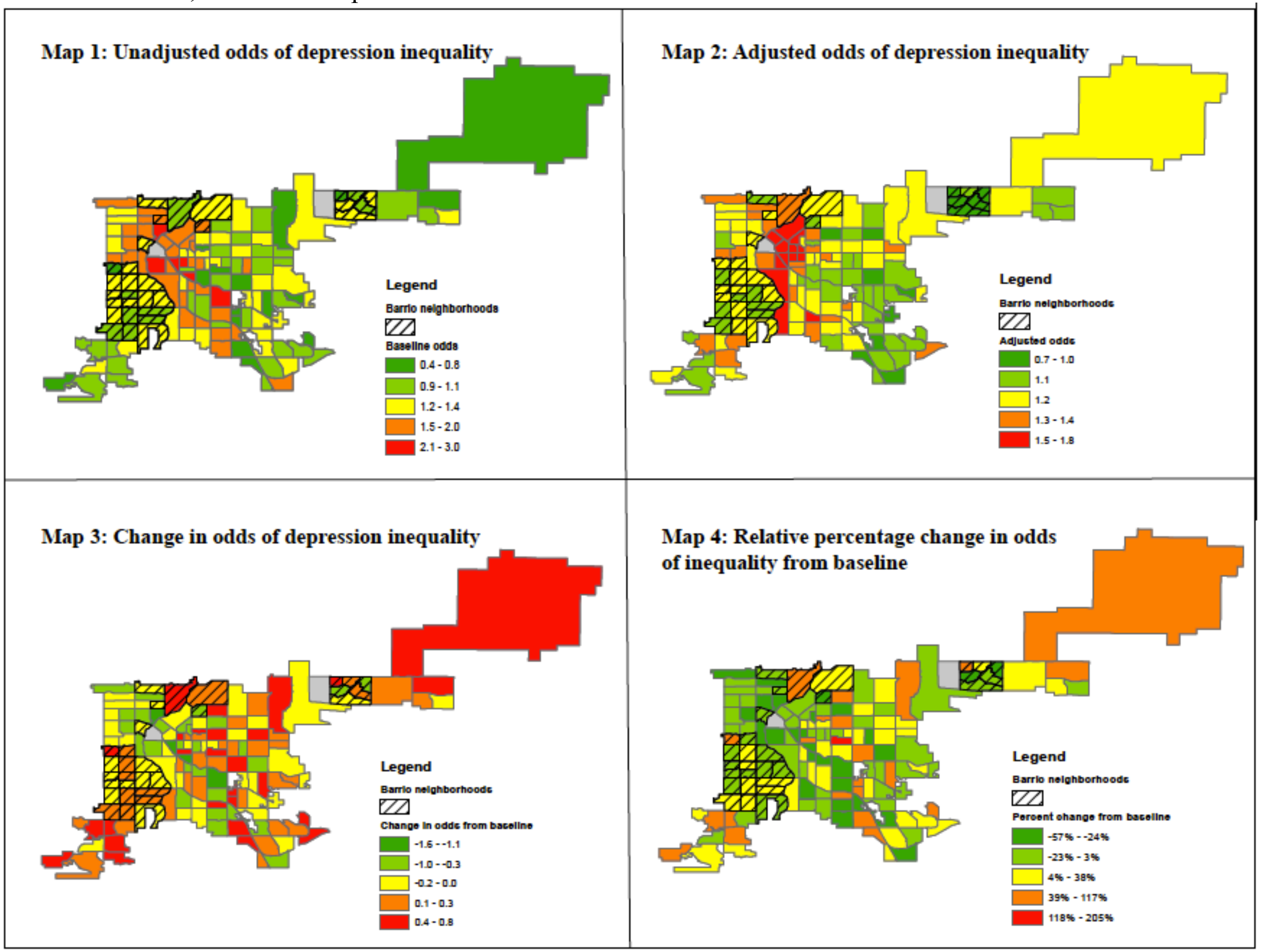
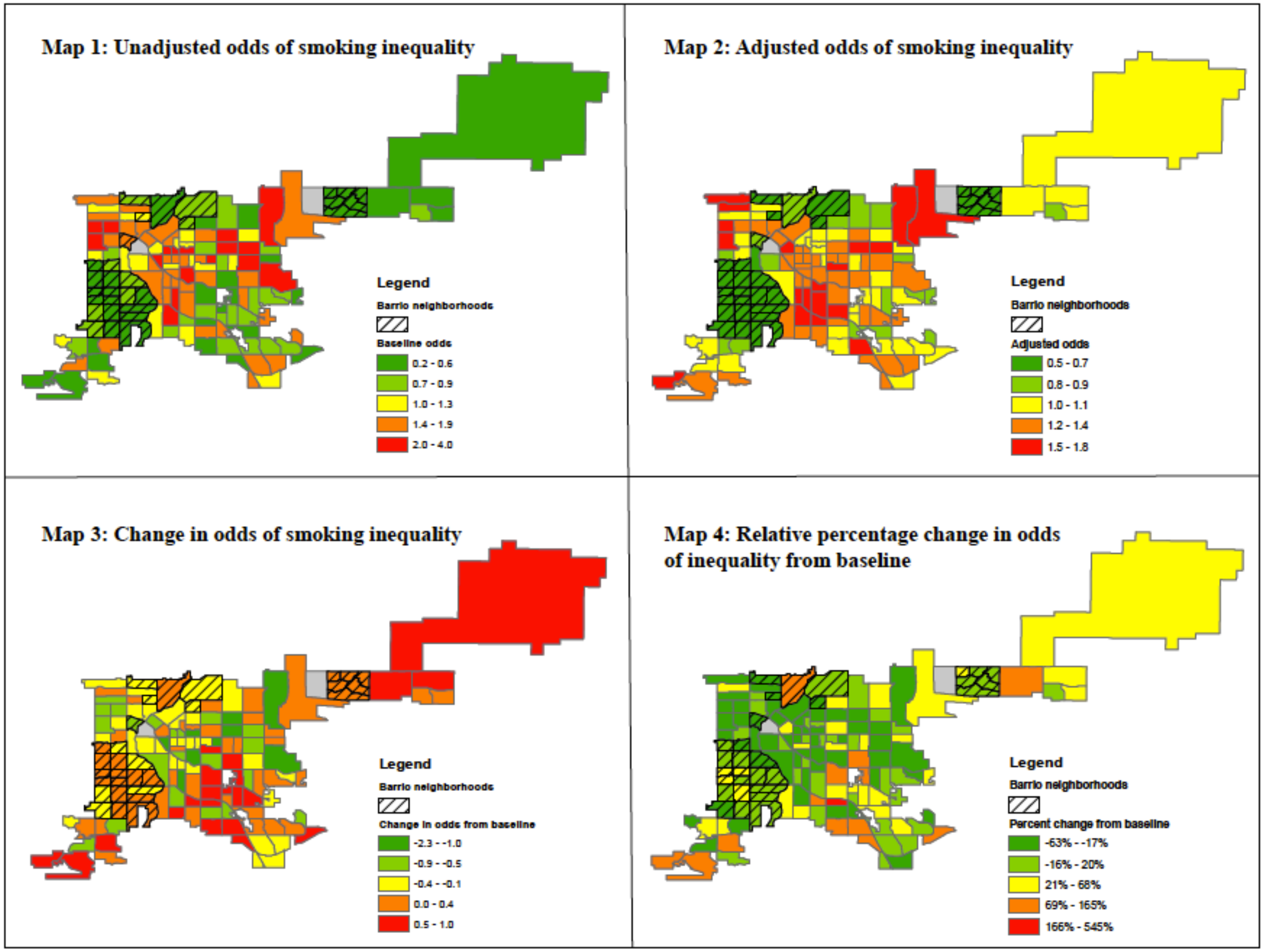


Figure 3-11. Baseline relative odds of smoking between Hispanics and non-Hispanic whites compared to estimated adjusted odds, overall estimated change in odds, and relative percent change to baseline for census tracts in Denver, Colorado for patients with a 2014/2015 visit



Robustness and Sensitivity Analyses

Spatial analyses

Ecological analyses are particularly susceptible to issues of spatial dependence. Because census tracts are contiguous in a dense, urban area, it is likely that the health and social processes taking place in one census tract are not independent from the processes taking place in surrounding tracts. This relationship between primary units of analysis violates the independence assumption of iid (independent and identically distributed variables) (Anselin and Griffith 1988). In Table 3-8 I present values of the global Moran's I as a diagnostic test for spatial dependence for each of the regression analyses (10 models total) .[3] The global Moran's I tests for spatial autocorrelation across all census tracts, meaning that they produce a single value of spatial dependence for all 142 census tracts. The value for global Moran's I is on a scale of -1 to 1, and is an observed value that is compared to an expected value to gauge statistical significance. The p values are presented for each global Moran's I test (Anselin and Griffith 1988, Bivand et al. 2011, Cliff and Ord 1981).

[3] I also conducted other diagnostic tests, including examining Geary's C and measures of heteroskedasticity in error terms, and results confirmed what was demonstrated using the global Moran's I.

Table 3-8. Global Moran's I statistical test for spatial dependence for prevalence and inequality regression analyses by health condition

Measure	Global Moran's I	
	Value	p value
Diabetes		
Prevalence	**0.14**	0.005
Inequality	0.08	0.092
Obesity		
Prevalence	**0.16**	0.001
Inequality	**0.10**	0.043
Hypertension		
Prevalence	**0.15**	0.003
Inequality	**0.16**	0.001
Depression		
Prevalence	-0.02	0.878
Inequality	-0.03	0.611
Smoking		
Prevalence	**0.13**	0.007
Inequality	**0.17**	0.001

Using the global Moran's I as the primary diagnostic for spatial dependence, seven of the ten models revealed spatial dependence that could affect accuracy of results (highlighted in bold in Table 3-8). Only diabetes inequality and depression models did not indicate high enough values for the global Moran's I to justify examining spatial models.

In Tables 3-9 through 3-15 I present the comparisons between the final OLS models in Table 3-6 or Table 3-7 and the results from best fitting spatial model. I tested spatial error, lag, and SARAR (error and lag) models for each spatially dependent outcome, and selected the best fitting spatial model based on Akaike information criteria (AICs). Although the effect sizes are slightly different for each OLS model compared to the spatial model, the overall results, including statistical significance, do not change.

Table 3-9. OLS regression compared to spatial lag/error (SARAR) model for diabetes prevalence (n=142)

	Model 4: Final OLS model	SARAR model
	β(%)	β(%)
Class 1 - barrios (ref)		
Class 2 - low ses	-2.14**	-2.15**
Class 3 - mid/high SES	-4.17***	-3.8***
Class 4 - high SES	-3.87***	-3.49***
Average mean-centered age	0.46***	0.43***
% female	0.23**	0.2**
% current smokers	0.35***	0.36***
% of binge drinkers	-0.05	-0.06
% without insurance	0.17***	0.16***
Constant	-3.72	-4.35
AIC	629.96	615.9
Lambda		0.15***

+ p≤.1; * p≤.05; ** p≤.01; *** p≤.001

Table 3-10. OLS regression compared to spatial lag model for obesity prevalence (n=142)

	Model 4: Final OLS model	Lag model
	β(%)	β(%)
Class 1 - barrios (ref)		
Class 2 - low ses	-1.38	-1.38
Class 3 - mid/high SES	-3.87	-3.52
Class 4 - high SES	-3.88	-3.35
Average mean-centered age	0.18	0.13
% female	0.66***	0.57***
% current smokers	0.35**	0.38***
% of binge drinkers	-0.17	-0.19
% without insurance	0.25*	0.22*
Constant	-11.97	-13.96
AIC	844.17	833.83
Wald statistic		13.34***

* p≤.05; ** p≤.01; *** p≤.001

Table 3-11. OLS regression compared to spatial error/lag (SARAR) model for obesity inequality (n=141)

	Model 4: Final OLS model	SARAR model
	β	β
Class 1 - barrios (ref)		
Class 2 - low ses	0.28**	0.25**
Class 3 - mid/high SES	0.23	0.19
Class 4 - high SES	0.26	0.23
Average mean-centered age	0.06**	0.06**
% female	0.02	0.02*
% current smokers	0.03***	0.03***
% of binge drinkers	0.07***	0.07***
% with annual checkup	-0.01	-0.01
Constant	-2.48	-2.80*
AIC	104.07	101.8
Lambda		-0.48**

* p≤.05; ** p≤.01; *** p≤.001

Table 3-12. OLS regression compared to spatial lag model for hypertension prevalence (n=142)

	Model 4: Final OLS model	Lag model
	β(%)	β(%)
Class 1 - barrios (ref)		
Class 2 - low ses	-1	-1.14
Class 3 - mid/high SES	-1.31	-1.09
Class 4 - high SES	-1.94	-1.88
Average mean-centered age	1.1***	1.08***
% female	0.24*	0.20*
% current smokers	0.47***	0.49***
% of binge drinkers	-0.53**	-0.50**
% with annual checkup	-0.04	-0.05
Constant	30.24**	21.99*
AIC	691.42	679.18
Wald statistic		17.1***

* p≤.05; ** p≤.01; *** p≤.001

Table 3-13. OLS regression compared to spatial error/lag (SARAR) model for hypertension inequality (n=142)

	Model 4: Final OLS model	SARAR model
	β	β
Class 1 - barrios (ref)		
Class 2 - low ses	0.19	0.14
Class 3 - mid/high SES	-0.07	-0.09
Class 4 - high SES	0.11	0.09
Average mean-centered age	0.05*	0.02
% female	0	0.01
% current smokers	0.04***	0.02***
% of binge drinkers	0.09***	0.06***
% with annual checkup	-0.02	-0.01
Constant	-1.64	-1.56
AIC	108.26	71.5
Lambda		-0.59***

* p≤.05; ** p≤.01; *** p≤.001

Table 3-14. OLS regression compared to spatial lag model for smoking prevalence (n=142)

	Model 4: Final OLS model	Lag model
	β(%)	β(%)
Class 1 - barrios (ref)		
Class 2 - low ses	4.81***	4.32***
Class 3 - mid/high SES	5.37**	4.96***
Class 4 - high SES	3.17*	3.20**
Average mean-centered age	-0.3	-0.39
% female	-0.32*	-0.33**
% of binge drinkers	-0.29	-0.41
% with annual checkup	0.37***	0.33
Constant	30.38*	30.8***
AIC	769.08	763.78
Wald statistic		7.38**

* p≤.05; ** p≤.01; *** p≤.001

Table 3-15. OLS regression compared to spatial error (SARAR) model for smoking inequality (n=142)

	Model 4: Final OLS model	Error model
	β	β
Class 1 - barrios (ref)		
Class 2 - low ses	0.39**	0.41**
Class 3 - mid/high SES	0.44*	0.45*
Class 4 - high SES	0.62***	0.71**
Average mean-centered age	0.04	0.02
% female	0.01	0.01
% of binge drinkers	0.07**	0.05**
% with annual checkup	-0.02	-0.01
Constant	-1.05	-2.00
AIC	187.16	177.82
Lambda		0.42***

* p≤.05; ** p≤.01; *** p≤.001

Characterizations of "barrio" neighborhoods

As a sensitivity analysis and a primary contribution to the field of Hispanic neighborhoods and health, I compared results from the analyses using the LPA classes with quartiles of the percent of Hispanic residents in each census tract, and present results in Table 3-16. Classes 1-3 and Quartiles 1-3 had similar average percent of Hispanic residents in the tracts. Class 4 neighborhoods had, on average, almost twice as many Hispanic residents compared to the neighborhoods with the fewest Hispanic residents. With the exception of Class 1 neighborhoods, the LPA classes had more tract-level variation in the percent of Hispanic residents than the quartiles that only used percent Hispanic. Because tracts in the LPA classes were unevenly distributed into quarters, there were fewer tracts in Class 1 than Quartile 1, and more tracts in Class 4 than Quartile 4.

Table 3-16. Comparison of descriptive statistics for neighborhood classes and quartile distribution of percent of Hispanic residents in census tracts in Denver, Colorado (N=142)*

Class/Quartile	Average % Hispanic	Standard deviation	Number of tracts
Quartile 1	65.4	10.4	35
Class 1	67.8	9.1	30
Quartile 2	31.2	8.5	36
Class 2	31.5	14.2	36
Quartile 3	13.8	2.9	35
Class 3	13.3	8.5	32
Quartile 4	6.1	2.0	36
Class 4	11.9	7.1	44
Total	29.0	23.8	142

*Source: American Community Survey (ACS) 2011-2015 5-year sample

In Table 3-17 I compare the final OLS regression models (Model 4) in Table 3-6 with results from using quartiles of percent Hispanic instead of LPA classes. The overall patterns were similar for each health condition except for smoking, but the effect sizes and, in some cases, statistical significance varied between the LPA classes and quartiles of percent Hispanic.

Barrio neighborhoods (Class 1) and the neighborhoods with the most Hispanic residents (Quartile 1) had the highest rates of diabetes after accounting for all covariates (Panel A). However, the differences were more pronounced across quartiles, with tracts in Quartile 4 having, on average, 6.51% lower prevalence of diabetes, compared to the 3.87% difference between Class 1 and Class 4 neighborhoods. However, the differences between Class 1 and Classes 2 and 3 were similar to the differences between Quartile 1 and Quartiles 2 and 3 for diabetes prevalence.

Differences in obesity prevalence were also larger between quartiles than between classes, and dramatically so (Panel B). Differences were about twice as large between Quartile 1 and Quartiles 2 and 3 than they were between Class 1 and Classes 2 and 3. There was more than three times the difference in obesity prevalence between Quartile 1 and Quartile 4 (12.12%) compared to Class 1 and Class 4 (3.88%). Additionally, the differences between quartiles were statistically significant at the alpha=0.05 level, whereas differences between classes were significant at the alpha=0.1 level (except for differences between Class 1 and Class 2, which were not statistically significant).

Differences in hypertension prevalence across classes and quartiles were similar for Classes 1-3 (Panel C). However, the difference in hypertension prevalence between Class 1 and Class 4 was not statistically significant, and the difference between Quartile 1 and Quartile 4 suggests that the neighborhoods with the lowest proportion of Hispanic residents had roughly 4% lower rates of hypertension, on average, compared to the neighborhoods with the highest proportion of Hispanic residents, and results were statistically significant.

Depression results were similar for classes and quartiles (Panel D).

Smoking results represent the only results in which the effects between classes and quartiles did not all work in the same direction (Panel E). Unlike the other health conditions, the effect sizes between classes were larger than the effect sizes between quartiles. The differences in average smoking rates between Class 1 and Classes 2 and 3 were about twice as large as the differences in average smoking rates between Quartile 1 and Quartiles 2 and 3. Additionally, quartile differences were borderline or not statistically significant. Differences between classes were statistically significant at the alpha=0.05 level or lower. Class 4 neighborhoods had, on average, 3.17% higher smoking rates than Class 1 neighborhoods, whereas Quartile 4 neighborhoods had lower smoking rates, on average, than Quartile 1 neighborhoods.

Table 3-17. Neighborhood-level ordinary least squares coefficients for prevalence of five health conditions compared to quartiles of percent of Hispanic residents across neighborhood classes (n=142)

	LPA classes, Model 4		Percent Hispanic quartiles	
	β(%)	95% CI	β(%)	95% CI
Class 1 - Barrios (ref)				
Panel A: Diabetes				
Class 2 - low ses/Hispanic quartile 2	-2.14 **	-3.72,-0.56	-2.4***	-3.74,-1.07
Class 3 - mid/high SES/Hispanic quartile 3	-4.17 ***	-6.19,-2.15	-4.35***	-6.06,-2.64
Class 4 - high SES/Hispanic quartile 4	-3.87 ***	-5.82,-1.92	-6.51***	-8.33,-4.70
Constant	-3.72	-18.63,11.20	5.57	-8.05,19.19
BIC	654.57		623.19	
Panel B: Obesity				
Class 2 - low ses/Hispanic quartile 2	-1.38	-4.75,1.98	-2.66*	-5.28,-0.03
Class 3 - mid/high SES/Hispanic quartile 3	-3.87 +	-8.17,0.43	-7.49***	-10.86,-4.11
Class 4 - high SES/Hispanic quartile 4	-3.88 +	-8.03,0.28	-12.12***	-15.71,-8.54
Constant	-11.97	-43.68,19.74	15.92	-10.93,42.78
BIC	868.77		816.03	
Panel C: Hypertension				
Class 2 - low ses/Hispanic quartile 2	-1	-2.96,0.97	-0.89	-2.64,0.87
Class 3 - mid/high SES/Hispanic quartile 3	-1.31	-3.82,1.20	-1.77	-4.02,0.49
Class 4 - high SES/Hispanic quartile 4	-1.94	-4.36,0.49	-3.95***	-6.34,-1.55
Constant	30.24 **	11.72,48.76	41.37***	23.45,59.28
BIC	716.03		701.14	
Panel D: Depression				
Class 2 - low ses/Hispanic quartile 2	0	-1.41,1.41	-0.1	-1.42,1.22
Class 3 - mid/high SES/Hispanic quartile 3	0.5	-1.30,2.31	0.3	-1.39,2.00
Class 4 - high SES/Hispanic quartile 4	0.11	-1.63,1.86	-0.5	-2.30,1.30
Constant	7.55	-5.76,20.86	12.36+	-1.12,25.84
BIC	622.24		620.39	
Panel E: Current Smokers				
Class 2 - low ses/Hispanic quartile 2	4.81 ***	2.35,7.27	2.09+	-0.27,4.44
Class 3 - mid/high SES/Hispanic quartile 3	5.37 **	2.19,8.55	2.5	-0.53,5.54
Class 4 - high SES/Hispanic quartile 4	3.17 *	0.02,6.32	-1.27	-4.52,1.98
Constant	30.38 *	6.51,54.24	54.65***	32.14,77.16
BIC	790.73		784.6	

Table 3-18 compares differences in inequality across each of the health conditions for classes and quartiles. Similar to the comparisons between classes and quartiles in the prevalence models, the comparisons in the inequality models generally reflected the same broad patterns, but the effect sizes and statistical significance varied across some health conditions. One of the differences between prevalence and inequality models is that, for the prevalence models, the percent Hispanic quartiles had better model fit for all health conditions (lower BIC values in Table 3-17). For the inequality models, the classes had better model fit for all health conditions except for obesity.

For diabetes inequality, there was more inequality between high SES neighborhoods (class 4) and barrio neighborhoods (class 1) than between the lowest percent Hispanic neighborhoods (quartile 4) and the highest percent Hispanic neighborhoods (quartile 1), but otherwise results were similar.

There was more inequality between percent Hispanic quartiles than between classes. The effect sizes were slightly larger and all quartile differences were significant at the alpha=0.01 level or smaller, whereas the differences between class 1 and class 3 and 4 were borderline significant at the alpha=0.1 level.

Results for hypertension and depression inequality were similar for classes and quartiles.

Results for smoking inequality show greater inequality between classes, particularly high SES neighborhoods (class 4) and barrio neighborhoods (class 1), than between quartiles.

Overall, it could be that measures used to characterize Hispanic neighborhoods were similar for hypertension and depression because these two conditions were generally less influenced by neighborhood-level measures throughout the analysis than the other health conditions. The takeaway from these sensitivity analyses is that the measure selected to define

Hispanic neighborhoods *does matter*. This issue will be discussed more at the end of the chapter and in Chapter 5.

Table 3-18. Neighborhood-level ordinary least squares coefficients for inequality of health conditions comparing results from neighborhood classes compared to quartiles of percent of Hispanic residents in census tracts in Denver, Colorado (n=142)

	LPA classes, Model 4		Percent Hispanic quartiles	
	β	95% CI	β	95% CI
Class 1 - Barrios (ref)				
Panel A: Diabetes				
Class 2 - low ses/Hispanic quartile 2	0.19	-0.07,0.46	0.19	-0.06,0.45
Class 3 - mid/high SES/Hispanic quartile 3	0.1	-0.23,0.44	0.06	-0.27,0.38
Class 4 - high SES/Hispanic quartile 4	0.32 +	-0.02,0.66	0.15	-0.21,0.51
Constant	-3.55 +	-7.11,0.01	-4.88*	-8.63,-1.13
BIC	196.37		197.77	
Panel B: Obesity				
Class 2 - low ses/Hispanic quartile 2	0.28 **	0.08,0.49	0.34***	0.14,0.53
Class 3 - mid/high SES/Hispanic quartile 3	0.23 +	-0.04,0.49	0.34**	0.09,0.58
Class 4 - high SES/Hispanic quartile 4	0.26 +	-0.00,0.52	0.37**	0.09,0.64
Constant	-2.48 +	-5.27,0.30	-2.42+	-5.30,0.45
BIC	128.67		124.35	
Panel C: Hypertension				
Class 2 - low ses/Hispanic quartile 2	0.19 +	-0.02,0.40	0.16	-0.04,0.36
Class 3 - mid/high SES/Hispanic quartile 3	-0.07	-0.34,0.20	0.01	-0.25,0.27
Class 4 - high SES/Hispanic quartile 4	0.11	-0.15,0.38	0.19	-0.10,0.47
Constant	-1.64	-4.47,1.19	-3.1*	-6.10,-0.11
BIC	132.87		135.61	
Panel D: Depression				
Class 2 - low ses/Hispanic quartile 2	0.15	-0.05,0.36	0.08	-0.11,0.28
Class 3 - mid/high SES/Hispanic quartile 3	0.07	-0.19,0.34	0.05	-0.20,0.30
Class 4 - high SES/Hispanic quartile 4	0.1	-0.17,0.36	0.16	-0.12,0.44
Constant	2.56 +	-0.22,5.35	1.78	-1.15,4.70
BIC	128.37		129.06	
Panel E: Current Smokers				
Class 2 - low ses/Hispanic quartile 2	0.39 **	0.12,0.66	0.27+	-0.00,0.54
Class 3 - mid/high SES/Hispanic quartile 3	0.44 *	0.09,0.79	0.41*	0.06,0.76
Class 4 - high SES/Hispanic quartile 4	0.62 ***	0.26,0.97	0.33+	-0.05,0.71
Constant	-1.05	-4.27,2.17	-1.4	-4.76,1.96
BIC	208.81		215.27	

+ p≤.1; * p≤.05; ** p≤.01; *** p≤.001

CONCLUSION

In this chapter I examined patterns of prevalence and inequality of pervasive health conditions for barrio neighborhoods – classified as having the highest percentage of Hispanic, foreign-born, non-citizen residents, high poverty, and high stability – compared to other types of neighborhoods in Denver (low SES, mid/high SES, and high SES). I conduced the analyses at an ecological level to understand neighborhood contexts as a whole, and to provide a broader understanding of Hispanic communities before examining individual-level differences in Chapter 4.

Results suggest that complex health patterns exist within and between Hispanic neighborhoods, and support the neighborhood health heterogeneity framework. Evidence that Hispanic neighborhoods provide protective health environments for residents is supported by lower overall prevalence rates for smoking compared to other types of neighborhoods with fewer Hispanics and more socioeconomic resources. Results for depression also provide some weak evidence of a potential protective effect of Hispanic neighborhoods. Because Hispanic neighborhoods are the most socioeconomically disadvantaged, it would be expected that depression rates would be higher in these communities. However, there were no statistically significant differences in depression after accounting for neighborhood-level demographic, health behavior, and health care differences.

Examining results for prevalence of diabetes, obesity, and hypertension tell a different story. Prevalence rates for these conditions were higher (and substantially so in the cases of obesity and diabetes) in Hispanic neighborhoods compared to other types of neighborhoods.

Even after accounting for neighborhood-level covariates, rates of diabetes were on average 2-4% higher in Hispanic neighborhoods compared to other types of neighborhoods.

This is the first study that explicitly examined how neighborhood-level inequality varied across types of neighborhoods. Examining patterns of inequality adds additional nuance to the health patterns and experiences of residents in Hispanic neighborhoods. Whereas prevalence results were mixed, barrio neighborhoods consistently had less health inequality compared to other types of neighborhoods. Thus, even though overall health may not be better in barrio communities, they may be more equitable places to live. This equity, however, appears to be because of worse health among NHWs, not better health among Hispanics. If Hispanic neighborhoods are culturally heterogeneous, it is possible that this cultural heterogeneity is more apparent within racial/ethnic groups than between them. For example, it could be that there are larger differences by gender, class, or other characteristics than between race/ethnic groups in Hispanic neighborhoods. The issue of inequality requires more in-depth examination in future research.

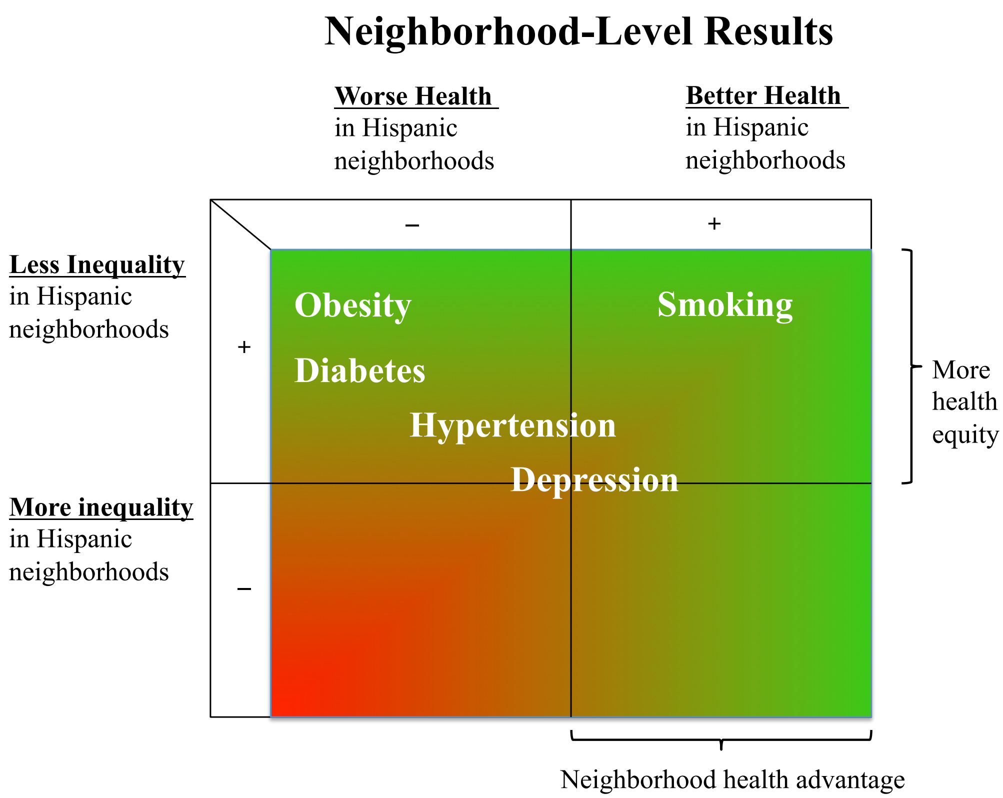
In Table 3-19 I provide a summary of the final results for prevalence and inequality models across each neighborhood class. The prevalence percentages may be thought of as between-neighborhood differences in prevalence, whereas the inequality coefficients may be thought of as within-neighborhood differences in inequality. All values are relative to barrio neighborhoods. In Figure 3-12 I provide a visual overview of prevalence and inequality across all five health conditions.

Table 3-19. Comparison of final models for between-neighborhood differences in prevalence and within-neighborhood differences in inequality across neighborhood classes

Barrio (referent)	Class 2 - Low SES	Class 3 - Mid/high SES	Class 4 - High SES
Diabetes			
Between neighborhoods (prevalence)	-2.14 **	-4.17 ***	-3.87 ***
Within neighborhoods (inequality)	0.23 +	0.27 *	0.18
Obesity			
Between neighborhoods (prevalence)	-1.38	-3.87 +	-3.88 +
Within neighborhoods (inequality)	0.32 ***	0.29 **	0.28 **
Hypertension			
Between neighborhoods (prevalence)	-1.00	-1.31	-1.94
Within neighborhoods (inequality)	0.27 *	0.23 *	0.09
Depression			
Between neighborhoods (prevalence)	0	0.5	0.11
Within neighborhoods (inequality)	0.11	0.12	-0.02
Smoking			
Between neighborhoods (prevalence)	4.81 ***	5.37 **	3.17 *
Within neighborhoods (inequality)	0.44 ***	0.66 ***	0.77 ***

+ p≤.1; * p≤.05; ** p≤.01; *** p≤.001

Figure 3-12. Summary of neighborhood-level results for prevalence and inequality of five health conditions



Both categories of results pose sociologically interesting questions. In the first category (the box on the left), health conditions are worse in barrio neighborhoods but have less inequality between Hispanics and NHWs. NHWs who can afford to live in higher SES neighborhoods have on average even lower relative odds of diabetes and obesity compared to Hispanics that can afford to live in those same neighborhoods. This could indicate that the social/environmental/physical benefits of higher SES neighborhoods disproportionately affect NHWs in ways that produce lower rates of diabetes or obesity. It also suggests that the relationship between community-level SES and health may be stronger for NHWs than for Hispanics, which supports a similar argument that has been made at the individual-level

(Beltrán-Sánchez et al. 2016) and is at the very root of the HHP. Neighborhood selection also likely plays a key role in these patterns. Greater opportunities for residential mobility among NHWs may produce a stronger positive gradient in some health conditions as neighborhood types become more socioeconomically advantaged. Similarly, Hispanic residents who have resources and could opt to live in more affluent places may opt to stay in more Hispanic neighborhoods because of some social benefits. Patterns of smoking and depression may support this latter hypothesis. To the extent that smoking may be interpreted as an externalizing behavior to help individuals cope with stress, it is noteworthy that both depression and smoking are lower in barrio neighborhoods and there is less inequality in these conditions. The potentially positive impact that the neighborhood social environment may have on smoking and depression does not appear to extend to lower rates of diabetes, obesity, or hypertension. I will provide more nuance to these hypotheses in Chapter 4 through examining how neighborhoods impact individual-level differences in health conditions, and how these patters vary by language preference (acculturation) and gender.

The spatial representations of baseline and adjusted prevalence and inequality for each health condition reveal overall variation in health conditions across neighborhoods and how differences in neighborhood-level demographic characteristics, health behaviors, and healthcare access impact differences in prevalence and inequality. Overall, the maps reveal the same overarching heterogeneity in the effects of adjusting for covariates. Some barrio neighborhoods are more sensitive to adjusting for neighborhood demographic, behavioral, and healthcare factors, and the influence of these effects works to both narrow gaps in prevalence and inequality and exacerbate them, depending on neighborhood and health condition. The same neighborhoods that show an increase in inequality or prevalence between unadjusted and adjusted models for one health condition are not always the same neighborhoods that show an increase in prevalence or inequality for another health condition. This suggests that mechanisms influencing prevalence and inequality between Hispanic and NHW prevalence rates are sensitive to specific health conditions and unexplained neighborhood-level factors that may work in different ways for different barrio neighborhoods.

Robustness checks examining spatial dependence across census tracts revealed two primary findings. First, spatial dependence existed for most of the dependent variables in the prevalence and inequality analyses. Second, adjusting for spatial dependence had only small impacts on the effect size and statistical significance of the models. One of the benefits of conducting ecological analyses is that researchers can account for spatial dependence, but in this study this accounting did not substantially change the findings. In this case, the spatiality of the data was not explicitly examined. Future research could conduct local spatial tests to identify "hotspots" where contiguous census tracts are particularly related in their rates of certain health conditions or inequality.

Analyses testing how sensitive results were to the type of measure used to define "barrios" revealed that using quartiles of the percent of Hispanic residents in each census tract did produce different findings for some health conditions than the classes produced by the LPA. For prevalence models, the quartiles produced better model fit for all models, and larger differences between the most concentrated Hispanic neighborhoods and other quartiles for diabetes and obesity (and hypertension to a lesser extent) compared to differences across classes. For inequality models, the class analyses had better model fit (except for obesity) than the quartile analyses. The quartile analyses revealed greater inequality across quartiles for obesity but less inequality for smoking, compared to the classes. In Chapter 4 I compare another measure of barrio neighborhoods to the percent of Hispanics living in each tract and the LPA classes, and in Chapter 5 I address the measurement issue more broadly. For the purposes of the results in Chapter 3, there appears to be tradeoffs to using an LPA approach that incorporates many variables versus a simple approach using only the percent of Hispanic residents in the tract. The LPA classes may more accurately capture tract-level differences because they incorporate multiple measures, which make them less sensitive to large margins of error in ACS estimates. However, the LPA classes may overcomplicate particular neighborhood environments and make it difficult for other studies to replicate results, since the classes are sensitive to the specific geographic environment.

Limitations

This study is a descriptive ecological analysis. Thus, results reflect characteristics of neighborhoods and not individuals. In Chapter 4 I address this limitation by conducting individual-level analyses. In this study, I use census tracts as the unit of analyses, even though socially defined neighborhoods were also available. I did this because there are 144 census tracts in Denver (I used142 in this analysis), and 76 socially defined neighborhoods (75 with a large enough sample for analytical use). Because this was an ecological analysis, I had more statistical power using 142 tracts compared to 75 socially defined neighborhoods. In Chapter 4, I conduct multilevel analyses on both census tracts and socially defined neighborhoods to examine how changes in geographic boundaries impact results.

There are several limitations to the variables I chose for the LPA analysis. Because my goal was to construct classes around the latent variable of “barrios,” I did not include composition of other race/ethnic groups. Future analyses could also use an LPA approach to identify types of neighborhoods that included segregated NHB or NHW neighborhoods. This would be useful for a broader analysis of racial/ethnic health disparities, which was beyond the scope of this study. Additionally, I did not include measures that incorporated how neighborhoods change over time. Measures of neighborhood change and, specifically, gentrification, would have been interesting and important inclusions. To my knowledge, no studies have examined how gentrification has influenced the relationship between Hispanic neighborhoods and health, and this would be a promising area for future research. I address broader limitations of the data as well as areas for future research in Chapter 5.

Chapter 4: Multilevel analysis of racial/ethnic, gender, and acculturation differences in health in Hispanic neighborhoods in Denver, Colorado

In Chapter 4, I extend the inquiries made in Chapter 3 by conducting multilevel analysis to better understand how both individual- and neighborhood-level characteristics impact an individual's risk of having type 2 diabetes, obesity, hypertension, diagnosed depression, or being a current smoker. This addresses my second research question, which has four components. **First, is there a Hispanic Health Paradox in prevalence of health conditions for Hispanics living in Denver, Colorado, compared to non-Hispanic whites and non-Hispanic blacks using EHR data? Second, how does living in a "barrio" neighborhood influence the likelihood of all patients and Hispanic patients having each of the health conditions, above and beyond neighborhood-level socioeconomic status and inequality? Third, how does acculturation affect the impact of living in a barrio neighborhood on health outcomes? Fourth, how does gender shape the relationship between health conditions and living in a barrio neighborhood?**

In addition to understanding variation in health across place of residence, race/ethnicity, acculturation, and gender, I also conduct novel sensitivity analyses to understand how robust results are to changes in the geographic units used to characterize neighborhoods and the measures used to characterize barrios. I compare results for census tracts and socially defined neighborhoods. I also test a new barrio measure that ranks neighborhoods based on the percent of Hispanic, foreign-born, and non-citizen residents. I compare this new barrio rank to simply using the percent of Hispanic residents in each neighborhood and also compare it to the LPA classes created in Chapter 3. All analyses are conducted on the total population of patients as well as for

Hispanic patients specifically. Total population analyses are required to understand whether there is a Hispanic health advantage compared to NHWs. Hispanic-specific analyses are useful to understand the role of acculturation and gender within the Hispanic community. The Hispanic-specific analyses also include a cross-level interaction between a patient's gender and quartiles of the barrio rank measure to understand whether highly concentrated Hispanic neighborhoods have different impacts on health for Hispanic men and women. In Chapter 2 I provided an in-depth description of measures and methods. In the next section I provide an overview of data, measures, and analyses, and then present results from the primary analyses and sensitivity analyses. I conclude with a series of figures that summarize findings. Chapter 5 will provide an overall summary and implications for Chapter 3 and Chapter 4 findings.

METHODS

Data

For this study, I combined data from two sources to conduct a multilevel analysis of individual odds of having five health conditions: type 2 diabetes, obesity, hypertension, depression, and being a current smoker. Each of the health conditions used as dependent variables and some of the independent variables were from a unique dataset of EHRs from two of the largest healthcare providers in Denver, Colorado – Denver Health (DH) and Kaiser Permanente of Colorado (KPCO). DH is the largest healthcare provider for Denver's medically indigent and underserved adults, and KPCO is an HMO and the largest private provider for Denver residents, together serving a complementary group of patients. When combined, the EHR database included over 150,000 patients. I included patients if they had at least one ambulatory visit in an outpatient clinic (similar to a primary care visit) in 2014 or 2015, were between the ages of 25-84 at the time of their 2014/2015 visit, had a valid height and weight recorded for any visit in their retrospective EHR (dating back to 2000 for DH data and 2005 for KPCO data), and had an address in Denver in their retrospective EHR. I included EHRs for women who had been pregnant, but removed the records associated with the year/s they were pregnant.

I combined neighborhood-level data from the 2011-2015 ACS with EHRs to create a multilevel dataset of individual- and neighborhood-level characteristics. In this chapter, I used Denver's socially defined neighborhoods instead of census tracts (although I compare results using both). Socially defined neighborhoods are generally larger than census tracts. This study used 76 socially defined neighborhoods, comprising 142 census tracts (the map of the socially defined neighborhoods can be found in Figure 2-29 in Chapter 2).[1] Since many cities do not have socially defined neighborhoods, Denver provides an opportunity to compare results between socially defined neighborhoods and census tracts. The boundaries between census tracts and socially defined neighborhoods align (i.e. census tracts map cleanly within socially defined neighborhoods), so I could aggregate ACS data to create estimates for socially defined neighborhoods.

Measures[2]

Dependent variables

I used five health conditions as dependent variables: type 2 diabetes, obesity, hypertension, depression, and current smoking. These are the same health conditions that I evaluated in Chapter 3, but in Chapter 4 I analyzed all variables at the individual-level, and coded each as a binary outcome. If an individual had ever had the condition in his or her

[1] I omitted two neighborhoods from the total of 78 neighborhoods because of small sample size.
[2] I provided details of how each dependent and independent variable was defined and coded in Chapter 2.

retrospective EHR, I coded him/her as a 1 for that condition. If the patient did not have the condition or not enough data existed to confirm the diagnosis, I coded the patient as a 0 for that condition.

Independent variables: individual-level

In this study, I included independent variables at the individual and neighborhood level. The primary individual-level independent variable in the analyses that included all patients was race/ethnicity. The race/ethnicity variable contained six categories: Hispanic – primary English speaker, Hispanic – primary Spanish speaker, non-Hispanic white, non-Hispanic black, non-Hispanic other race/ethnicity, and missing race/ethnicity. For the analyses that only included Hispanics, the primary individual-level independent variable was the acculturation measure - whether or not the patient primarily spoke English or Spanish. I also included two demographic control variables– mean-centered patient age and patient gender (coded as whether the patient was female). I included two variables to assess patient health status: whether the patient was a current smoker and an ordinal variable representing quartiles of comorbid health conditions: 0, 1, 2, or 3 or more comorbid conditions. I also controlled for mean-centered body mass index (BMI) in the diabetes analyses. To assess access/utilization of health care services, I included an ordinal variable of the total number of patient visits, and broke the variable into a quartile distribution. I coded patients with less than 22 visits as 0 and used this as the reference category for the regression models. I coded patients with between 22-52 visits as a 1. I coded patients with between 53-114 visits as a 2. I coded patients with more than 114 visits as a 3. While the primary intention of the visits variable was to assess utilization of services, it may also be a proxy for patient health (for example, comorbid conditions and total encounters are correlated at r=0.59). Examples of a high number of visits being associated with more access/utilization would be patients getting preventive screenings. Examples of a high number of visits being associated with worse health would be patients with health conditions that require routine follow-up or patients who get sick often.

The other variable I used to assess access to care was the primary type of payment/insurance a patient used at his/her most recent visit. This variable is also the closest proxy available to assess patient socioeconomic status. The insurance categories were private (including HMO insurance from KPCO), Medicaid, Medicare, self pay, other type of insurance, other type of payment, and no insurance information.

Independent variables: neighborhood-level

The primary neighborhood-level variable was a rank of how much each neighborhood may be considered a "barrio" neighborhood. The barrio rank variable comprised three neighborhood-level characteristics from the ACS: the percent of Hispanic residents, the percent of foreign-born residents, and the percent of residents who are not citizens. I ranked each neighborhood by these three characteristics and then broke the neighborhoods into quartiles for analysis. The first quartile contains neighborhoods that most resemble barrios, and the fourth quartile contains neighborhoods that least resemble barrios. As detailed in Chapter 2, the barrio rank is highly correlated with the percent Hispanic in the tract, but there are differences between the two that warrant comparison. Particularly, in the barrio rank conceptualization, having a high concentration of foreign-born and non-citizen residents is equally important to the composition of Hispanic residents. This conceptualization aligns with characterizations of "ethnic enclaves" as places where newly arriving immigrants often settle. As discussed in Chapter 1, it is possible that the social processes that lead to protective or detrimental health outcomes may be different in areas with many foreign-born or non-citizen residents than places with many co-ethnics.

To understand how the barrio rank measure is mediated by socioeconomic status, I included two additional neighborhood-level measures. I used quartiles of the Townsend index to assess socioeconomic deprivation. The first quartile of deprivation contained neighborhoods with the most deprivation, and the fourth quartile contained neighborhoods with the least amount of deprivation. I used quartiles of the gini index to assess economic inequality. The first quartile of inequality contained neighborhoods with the most inequality and the fourth quartile of inequality contained neighborhoods with the least amount of inequality.

Analysis

I conducted multilevel models (specifically, mixed logistic models) to assess a patient's odds of ever having each health condition. Multilevel models take into account individual (patient) and contextual (neighborhood) characteristics and allow for the decomposition of error variance into discrete components at each specific level (Gelman et al. 2012, Raudenbush and Bryk 2002, Snijders 2011). Similar to Chapter 3, I used a nested, additive model building approach to assess how groups of independent variables affected each dependent variable and to compare baseline models, individual-level/level 1 (L1) models, and neighborhood-level/level 2 (L2) models. I did not include any independent variables in the baseline models so that I could calculate an interclass correlation coefficient (ICC) for neighborhood-level (L2) effects (described in more detail in Chapter 2).

I ran the first set of analyses on the total population and then ran the same models for the Hispanic population alone (using primary language as an independent model). In the "L1: race" model for the total population I included race as the only independent variable, and broke Hispanic into subcategories of those who spoke English and those who spoke Spanish as their primary language. In the Hispanic-only models, I included whether the patient spoke primarily

English or primarily Spanish in the first L1 model, instead of race. In the “L1: demographics” model I added gender and age to the previous model. In the “L1: health behaviors, comorbidities” model I added current smoking (for all dependent variables except smoking), the categorical variable for number of comorbid conditions, and average BMI for the diabetes models. In the “L1: visits, insurance” model I added the categorical variable for total number of encounters and the payment type. The “L2: barrio quartiles” is the first model with level 2 variables, and I added the quartiles of the barrio rank. In the “L2: deprivation quartiles” I added the Townsend index quartiles to the barrio quartiles and all of the L1 variables. In the “L2: inequality quartiles” I added quartiles of the gini coefficient. In the final model I added a cross-level interaction between a resident’s gender (L1) and the barrio quartiles (L2). Similar to Chapter 3, as a sensitivity analysis I compared the barrio rank measure to the percent Hispanic in each tract. All models for Chapter 4 were run using the PROC GLIMMIX procedure in SAS.

RESULTS

Descriptive Results

In Table 4-1 I present descriptive results of each dependent and independent variable by each race/ethnic group. Before accounting for any covariates, including age adjustment, both Hispanic subgroups had slightly higher rates of diabetes compared to NHBs, and more than double the rates of diabetes compared to NHWs. Primary Spanish speakers had lower rates of all conditions except diabetes, compared to primary English speakers and NHBs. Primary Spanish speakers also had comparable rates of hypertension and depression compared to NHWs, and the lowest rates of smoking overall. Thus, descriptive results revealed differences by acculturation for Hispanic patients, wherein primary English speakers had generally worse health profiles compared to primary Spanish speakers, with the exception of diabetes.

Interestingly, although barrio quartile 1 had the highest percentage of Hispanic residents in the ACS data, barrio quartile 2 had the highest percentage of Hispanic patients from the DHKP EHRs. This difference was driven by a higher percentage of primary English speaking patients who lived in barrio quartile 2. Primary Spanish speakers were evenly distributed across barrio quartiles 1 and 2. The highest percentage of Hispanic patients (both English and Spanish speaking) lived in neighborhoods with the most socioeconomic deprivation (i.e., deprivation index quartile 1). Primary English speaking Hispanic patients were fairly evenly distributed across neighborhoods based on income inequality, but the highest rates of primary Spanish speakers lived in the most economically unequal neighborhoods. Overall, descriptive results suggest variation in both health and neighborhood characteristics by race and ethnicity.

Table 4-1. Descriptive characteristics by race/ethnicity and acculturation for patients with an encounter in 2014/2015 in Denver, Colorado

	Hispanic - primary English speakers		Hispanic - primary Spanish speakers		Non-Hispanic white		Non-Hispanic black		Non-Hispanic other race/ethnicity		Missing race/ethnicity		Total	
	Column % or mean	(n) or (sd)	Column % or mean	(n) or (sd)	Column % or mean	(n) or (sd)	Column % or mean	(n) or (sd)	Column % or mean	(n) or (sd)	Column % or mean	(n) or (sd)	Column % or mean	(n) or (sd)
N		30503		19091		68117		19040		7531		6745		151027
Dependent variables														
Diabetes	23	(7013)	24	(4612)	11	(7180)	22	(4170)	15	(1129)	7	(502)	16	
Obesity	44	(13507)	39	(7484)	27	(18160)	42	(7924)	21	(1614)	27	(1821)	33	
Hypertension	42	(12952)	36	(6869)	37	(25087)	54	(10205)	36	(2710)	22	(1510)	39	
Depression	27	(8129)	20	(3853)	21	(14529)	21	(3995)	15	(1155)	9	(586)	21	
Smoking	21	(6403)	8	(1525)	15	(10006)	25	(4768)	11	(865)	16	(1078)	16	
Individual-level variables														
Average age	46.7	(15)	46.6	(14.1)	48.8	(15.9)	48.9	(14.8)	47.8	(15.3)	44.9	(14.3)	47.9	(15.3)
Age categories: 25-34	27	(8355)	22	(4135)	25	(17091)	22	(4124)	25	(1848)	31	(2071)	25	
35-44	22	(6601)	30	(5771)	21	(14127)	20	(3795)	24	(1829)	24	(1599)	22	
45-54	19	(5786)	21	(4001)	16	(11089)	21	(4038)	17	(1304)	19	(1260)	18	
55-64	18	(5451)	13	(2560)	18	(12200)	21	(4054)	17	(1267)	15	(1044)	18	
65-74	10	(2925)	9	(1756)	14	(9230)	11	(2047)	11	(848)	9	(585)	12	
75-84	5	(1385)	5	(867)	6	(4373)	5	(981)	6	(435)	3	(186)	5	
Female	64	(19385)	68	(12990)	59	(39951)	62	(11712)	62	(4655)	41	(2779)	61	
Comorbid conditions: 0	39	(11857)	56	(10737)	44	(30237)	40	(7544)	48	(3640)	64	(4342)	45	
1 condition	26	(8031)	23	(4442)	26	(17642)	25	(4825)	25	(1893)	22	(1468)	25	
2 conditions	14	(4334)	10	(1863)	12	(8229)	13	(2511)	12	(866)	7	(482)	12	
3+ conditions	21	(6281)	11	(2048)	18	(12016)	22	(4158)	15	(1132)	7	(453)	17	
Average BMI	30.2	(7.3)	29.3	(5.6)	27.4	(6.3)	29.8	(7.4)	26.4	(5.8)	27.6	(6)	28.5	(6.7)
Visits: less than 22	20	(5991)	34	(6525)	23	(15830)	25	(4735)	26	(1978)	47	(3169)	25	
22-52	26	(7922)	34	(6556)	22	(14890)	27	(5063)	27	(1998)	27	(1825)	25	
53-114	29	(8779)	25	(4738)	25	(16893)	25	(4836)	24	(1772)	17	(1124)	25	
115+	27	(8138)	8	(1564)	31	(21116)	24	(4600)	25	(1859)	11	(721)	25	
Insurance type: Private	53	(16115)	19	(3568)	78	(53036)	46	(8703)	65	(4904)	92	(6176)	61	
Medicaid	15	(4640)	19	(3601)	10	(6485)	22	(4280)	21	(1551)	3	(178)	14	
Medicare	3	(973)	6	(1224)	3	(2377)	5	(963)	3	(229)	0	(20)	4	
Self pay	2	(607)	40	(7682)	1	(341)	1	(137)	1	(95)	0	(26)	6	
Other insurance	2	(488)	7	(1350)	1	(960)	3	(560)	4	(317)	1	(35)	2	
Other type of payment	2	(711)	3	(590)	4	(2548)	3	(508)	4	(269)	4	(260)	3	
Missing insurance data	23	(6967)	6	(1077)	3	(2377)	20	(3886)	2	(166)	1	(50)	10	
Neighborhood-level variables														
Barrio quartile 1 (Highest barrio rank)	26	(8056)	40	(7592)	6	(4210)	7	(1371)	11	(813)	9	(598)	15	
Barrio quartile 2	36	(10850)	41	(7766)	18	(12050)	33	(6241)	25	(1910)	22	(1452)	27	
Barrio quartile 3	26	(7970)	16	(3121)	40	(27131)	46	(8673)	40	(2999)	37	(2523)	35	
Barrio quartile 4	12	(3624)	3	(611)	36	(24726)	14	(2755)	24	(1809)	32	(2172)	24	
Deprivation index quartile 1 (Highest deprivation)	33	(9990)	38	(7300)	21	(14454)	31	(5874)	32	(2384)	22	(1483)	27	
Deprivation index quartile 2	30	(9062)	33	(6205)	26	(17377)	29	(5485)	25	(1910)	27	(1793)	28	
Deprivation index quartile 3	24	(7190)	20	(3746)	29	(19829)	19	(3709)	23	(1727)	28	(1911)	25	
Deprivation index quartile 4	14	(4258)	10	(1842)	24	(16457)	21	(3972)	20	(1510)	23	(1558)	20	
Inequality quartile 1 (Highest income inequality)	26	(8013)	31	(5966)	19	(12711)	24	(4514)	25	(1891)	22	(1453)	23	
Inequality quartile 2	25	(7644)	24	(4513)	26	(17588)	24	(4610)	21	(1606)	27	(1792)	25	
Inequality quartile 3	24	(7202)	26	(4967)	22	(14924)	29	(5546)	26	(1976)	22	(1455)	24	
Inequality quartile 4	25	(7641)	19	(3644)	34	(22901)	23	(4368)	27	(2058)	30	(2045)	28	

Regression Results

Total population

Tables 4-2 through 4-6 show results for odds of having type-2 diabetes, obesity, hypertension, diagnosed depression, and being a current smoker for the entire patient population. I include log likelihood values to compare model fit across models. For each health condition, the best fitting model was the final model (L2: inequality quartiles), which indicates that accounting for economic inequality improved overall model fit (i.e., had the highest log likelihood values).

I present results from the multilevel logistic regressions for odds of having type-2 diabetes for the total patient population in Table 4-2. The baseline ICC for diabetes is 6%, meaning that 6% of the total variation in diabetes can be accounted for by neighborhood level (level 2) factors. As expected, the ICC value gets smaller after accounting for individual- and neighborhood-level characteristics.

Individuals in both Hispanic subgroups had higher odds of having type-2 diabetes compared to NHWs, and differences were larger among Hispanics who speak primarily Spanish. Diabetes differences were the largest after adjusting for demographics and controlling for health behaviors and comorbidities (OR=2.39, 3.48 respectively) (L1: health behaviors, comorbidities), and before accounting for differences in visits and health insurance (OR=2.19, 2.93 respectively) (L1: visits, insurance). Thus, there is no Hispanic health advantage in odds of having type-2 diabetes for this patient population. Adding gender to the models revealed that women had 9% lower odds of having diabetes at baseline. After adjusting for other covariates, the gender gap got substantially bigger, with women having 32% lower odds of having diabetes compared to men.

Comorbidities and the number of visits had large and independent effects on odds of having diabetes; the relationships worked in the expected ways, with more comorbid conditions and visits associated with higher odds of having diabetes. Because managing diabetes requires potentially more monitoring and medical interventions than, for example, obesity, it is not surprising that these effect sizes are large. Similarly, patients with all types of non-private health insurance had higher odds of having diabetes compared to those with private/HMO insurance (with the exception of those in the “other type of payment” category).

Level 2 results revealed no significant differences in odds of having diabetes between the top quartile of barrio ranked neighborhoods and the second quartile. However, odds of diabetes were between 20-34% lower for residents in the 3rd and 4th quartile barrio ranked neighborhoods (those with the fewest Hispanics, foreign-born, and non-citizens) (L2: Barrio quartiles). These differences in barrio quartiles were slightly attenuated after accounting for neighborhood-level differences in socioeconomic deprivation and economic inequality. Overall, results suggest that, in addition to no apparent diabetes health advantage for Hispanics, there was no positive barrio effect. Similar to ecological findings in Chapter 3, living in a barrio neighborhood may have a negative impact on odds of having diabetes. The utility of the multilevel analysis is that it reveals that the neighborhood disadvantage was above and beyond individual-level characteristics, particularly being Hispanic.

Table 4-2. Multilevel models predicting odds of having type-2 diabetes for adults 25-84 with an outpatient visit in 2014/2015 and examining influence of barrio neighborhoods, socioeconomic deprivation, and economic inequality at the neighborhood level (N=149,234)

	Baseline ICC	L1: Race		L1: demographics		L1: health behaviors, comorbidities		L1: visits, insurance		L2: Barrio quartiles		L2: Deprivation quartiles		L2: Inequality quartiles	
		OR	p value	OR	p value	OR	p value	OR	p value	OR	p value	OR	p value	OR	p value
Individual-level covariates															
Race (NH white, referent)															
Hispanic - English speaking		2.07	<.0001	2.62	<.0001	2.39	<.0001	2.19	<.0001	2.17	<.0001	2.17	<.0001	2.18	<.0001
Hispanic - Spanish speaking		2.12	<.0001	2.72	<.0001	3.48	<.0001	2.93	<.0001	2.88	<.0001	2.89	<.0001	2.89	<.0001
NH black		2.21	<.0001	2.41	<.0001	2.19	<.0001	2	<.0001	2	<.0001	2	<.0001	2	<.0001
NH Other race		1.40	<.0001	1.56	<.0001	1.99	<.0001	1.97	<.0001	1.96	<.0001	1.96	<.0001	1.96	<.0001
Missing race/ethnicity		0.66	<.0001	0.83	0.0003	1.02	0.7471	1.38	<.0001	1.38	<.0001	1.38	<.0001	1.38	<.0001
Average Age (mean centered)				1.06	<.0001	1.05	<.0001	1.05	<.0001	1.05	<.0001	1.05	<.0001	1.05	<.0001
Female				0.91	<.0001	0.78	<.0001	0.68	<.0001	0.68	<.0001	0.68	<.0001	0.68	<.0001
Current smoker						1.13	<.0001	1.1	<.0001	1.1	<.0001	1.1	<.0001	1.1	<.0001
Comorbidities (0 conditions, referent)															
1 comorbid condition						1.42	<.0001	1.12	<.0001	1.12	<.0001	1.12	<.0001	1.12	<.0001
2 comorbid conditions						2.05	<.0001	1.37	<.0001	1.37	<.0001	1.37	<.0001	1.37	<.0001
3+ comorbid conditions						3.16	<.0001	1.81	<.0001	1.81	<.0001	1.8	<.0001	1.8	<.0001
Average BMI (mean centered)						1.1	<.0001	1.1	<.0001	1.1	<.0001	1.1	<.0001	1.1	<.0001
Visits (Less than 22 visits, referent)															
22-52 (Q2)								1.89	<.0001	1.89	<.0001	1.89	<.0001	1.89	<.0001
53-114 (Q3)								2.81	<.0001	2.81	<.0001	2.81	<.0001	2.81	<.0001
115+ (Q4)								4.29	<.0001	4.3	<.0001	4.3	<.0001	4.3	<.0001
Insurance type (private insurace, referent)															
Medicaid								2.24	<.0001	2.24	<.0001	2.23	<.0001	2.23	<.0001
Medicare								2.39	<.0001	2.37	<.0001	2.36	<.0001	2.37	<.0001
Self pay								2.2	<.0001	2.2	<.0001	2.19	<.0001	2.19	<.0001
Other insurance								2.34	<.0001	2.33	<.0001	2.33	<.0001	2.33	<.0001
Other type of payment								1.02	0.799	1.02	0.812	1.01	0.819	1.02	0.809
Missing payment information								2.01	<.0001	2	<.0001	1.99	<.0001	1.99	<.0001
Neighborhood-level covariates															
Barrio Quartile 1 (Highest barrio rank, referent)															
Barrio Quartile 2										0.95	0.129	0.95	0.1501	0.98	0.458
Barrio Quartile 3										0.78	<.0001	0.8	<.0001	0.83	<.0001
Barrio Quartile 4 (Lowest barrio rank)										0.66	<.0001	0.67	<.0001	0.71	<.0001
Deprivation index Quartile 1 (highest deprivation, referent)															
Deprivation Quartile 2												0.96	0.1134	0.95	0.041
Deprivation Quartile 3												0.96	0.2127	0.95	0.053
Deprivation Quartile 4 (lowest deprivation)												0.92	0.0133	0.89	0.0005
Inequality Quartile 1 (highest inequality, referent)															
Inequality Quartile 2														0.94	0.031
Inequality Quartile 3														0.94	0.039
Inequality Quartile 4 (lowest inequality)														0.89	0.0007
Constant	0.17	0.12	<.0001	0.09	<.0001	0.05	<.0001	0.02	<.0001	0.03	<.0001	0.03	<.0001	0.03	<.0001
ICC	0.06	0.02		0.03		0.02		0.01		0.003		0.002		0.002	
log likelihood	738418.2	744294.1		782208.6		803002.9		816213.7		816350.5		816261.3		816377.5	

I present results from the multilevel logistic regressions for obesity for the total patient population in Table 4-3. The baseline ICC for obesity was 5%, and this was reduced to just 1.5% in the final L2 model. Results for obesity were similar to results for diabetes, but individual-level differences were generally smaller. Both Hispanic subgroups had higher odds of obesity compared to NHWs, though unlike diabetes, obesity differences were larger between Hispanics who spoke English and NHWs than for Hispanics who spoke Spanish and NHWs. Notably, the effect of age worked in opposite ways for diabetes and obesity; this will be explored more explicitly later in the chapter.

The gender differences in obesity were opposite to those seen in the diabetes models. For obesity, women had 17% higher odds than men after accounting for race/ethnic differences, and that gap shortened to 9% higher odds after adjusting for other covariates. Level 2 results were similar for obesity and diabetes. Living in a highly ranked barrio neighborhood increased odds of having obesity, above and beyond individual-level factors. There were no significant differences between barrio quartiles 1 and 2. Although accounting for economic inequality had a similar impact on the effect sizes of barrio quartiles, the only significant obesity differences by inequality were between quartiles 1 and 3, suggesting that lower economic inequality may have slightly reduced odds of having obesity.

Table 4-3. Multilevel models predicting odds of being obese for adults 25-84 with an outpatient visit in 2014/2015 and examining influence of barrio neighborhoods, socioeconomic deprivation, and economic inequality at the neighborhood level (N=149,234)

	Baseline ICC	L1: Race		L1: demographics		L1: health behaviors, comorbidities		L1: visits, insurance		L2: Barrio quartiles		L2: Deprivation quartiles		L2: Inequality quartiles	
		OR	p	OR	p	OR	p	OR	p	OR	p	OR	p	OR	p
Level 1 covariates															
Race (NH white, referent)															
Hispanic - English speaking		1.74	<.0001	1.76	<.0001	1.74	<.0001	1.68	<.0001	1.67	<.0001	1.67	<.0001	1.67	<.0001
Hispanic - Spanish speaking		1.29	<.0001	1.29	<.0001	1.33	<.0001	1.33	<.0001	1.33	<.0001	1.33	<.0001	1.33	<.0001
NH black		1.67	<.0001	1.66	<.0001	1.67	<.0001	1.61	<.0001	1.61	<.0001	1.61	<.0001	1.61	<.0001
NH Other race		0.68	<.0001	0.68	<.0001	0.68	<.0001	0.68	<.0001	0.68	<.0001	0.68	<.0001	0.68	<.0001
Missing race/ethnicity		0.97	0.26	1.02	0.5654	1.08	0.0121	1.13	<.0001	1.13	<.0001	1.13	<.0001	1.13	<.0001
Average Age (mean centered)				1.01	<.0001	1	0.0319	1	0.132	1	0.238	1	0.2446	1	0.254
Female				1.17	<.0001	1.12	<.0001	1.09	<.0001	1.09	<.0001	1.09	<.0001	1.09	<.0001
Current smoker						0.82	<.0001	0.8	<.0001	0.8	<.0001	0.8	<.0001	0.8	<.0001
Comorbidities (0 conditions, referent)															
1 comorbid condition						1.33	<.0001	1.28	<.0001	1.28	<.0001	1.28	<.0001	1.28	<.0001
2 comorbid conditions						1.49	<.0001	1.38	<.0001	1.38	<.0001	1.38	<.0001	1.38	<.0001
3+ comorbid conditions						1.54	<.0001	1.37	<.0001	1.37	<.0001	1.37	<.0001	1.37	<.0001
Visits (Less than 22 visits, referent)															
22-52 (Q2)								1.09	<.0001	1.09	<.0001	1.09	<.0001	1.09	<.0001
53-114 (Q3)								1.15	<.0001	1.15	<.0001	1.15	<.0001	1.15	<.0001
115+ (Q4)								1.26	<.0001	1.26	<.0001	1.26	<.0001	1.26	<.0001
Insurance type (private insurace, referent)															
Medicaid								1.17	<.0001	1.16	<.0001	1.16	<.0001	1.17	<.0001
Medicare								1.23	<.0001	1.23	<.0001	1.23	<.0001	1.23	<.0001
Self pay								1.03	0.299	1.03	0.322	1.03	0.3346	1.03	0.303
Other insurance								0.99	0.724	0.99	0.698	0.98	0.6914	0.99	0.694
Other type of payment								0.87	<.0001	0.87	<.0001	0.87	<.0001	0.87	<.0001
Missing payment information								1.23	<.0001	1.22	<.0001	1.22	<.0001	1.22	<.0001
Level 2 covariates															
Barrio Quartile 1 (Highest barrio rank, referent)															
Barrio Quartile 2										0.95	0.083	0.95	0.0932	1	0.913
Barrio Quartile 3										0.79	<.0001	0.8	<.0001	0.82	<.0001
Barrio Quartile 4 (Lowest barrio rank)										0.68	<.0001	0.69	<.0001	0.7	<.0001
Deprivation index Quartile 1 (highest deprivation, referent)															
Deprivation Quartile 2												0.99	0.6261	0.99	0.677
Deprivation Quartile 3												0.98	0.4535	0.97	0.321
Deprivation Quartile 4 (lowest deprivation)												0.98	0.4693	0.96	0.25
Inequality Quartile 1 (highest inequality, referent)															
Inequality Quartile 2														0.98	0.387
Inequality Quartile 3														0.91	0.002
Inequality Quartile 4 (lowest inequality)														0.98	0.448
Constant	0.44	0.37	<.0001	0.34	<.0001	0.29	<.0001	0.26	<.0001	0.33	<.0001	0.33	<.0001	0.34	<.0001
ICC	0.05	0.03		0.03		0.03		0.03		0.015		0.015		0.015	
log likelihood	654114.1	656631.8		657115.8		658578.6		658957.9		658939.2		658959.6		658999.9	

I present results from the multilevel logistic regressions for hypertension for the total patient population in Table 4-4. The ICC for hypertension was small – just 1%, indicating that most of the variation in odds of having hypertension were accounted for at the individual-level. In the first individual-level model (L1: Race), there was a Hispanic health advantage in hypertension for Hispanics who primarily spoke Spanish compared to NHWs. However, this advantage was reversed after accounting for differences in health behaviors and comorbidities (L1: health behaviors, comorbidities). Both English and Spanish speaking patients had 20-25% higher odds of hypertension compared to NHWs after accounting for individual and neighborhood-level characteristics. Although there was no Hispanic health advantage, there was a smaller difference in odds between Hispanics and NHWs than between NHBs and NHWs. Similar to diabetes and obesity, the gender differences in hypertension were large. For hypertension, women had 20% lower odds than men after accounting for race/ethnic differences, and that gap widened to 43% lower odds after adjusting for other covariates. Similar to the diabetes models, there were large differences in odds of having hypertension by number of comorbid conditions, total visits, and health insurance type. The relationships worked in the expected ways, with higher odds of having hypertension among those with more comorbid conditions, more visits, and non-private health insurance.

Finally, similar to diabetes and obesity, the level 2 models do not support a positive barrio effect on odds of having hypertension. Again, although there were no statistical differences between the first and second quartiles of barrio neighborhoods, there were lower odds of hypertension for residents in the least "barrio" neighborhoods compared to the most "barrio" neighborhoods. These differences were slightly attenuated by accounting for differences in deprivation, and more so by accounting for differences in economic inequality. In the final model (L2: Inequality quartiles) neighborhoods with less economic inequality had lower odds of hypertension compared to those with more economic inequality.

Table 4-4. Multilevel models predicting odds of having hypertension for adults 25-84 with an outpatient visit in 2014/2015 and examining influence of barrio neighborhoods, socioeconomic deprivation, and economic inequality at the neighborhood level (N=151,027)

	Baseline ICC	L1: Race		L1: demographics		L1: health behaviors, comorbidities		L1: visits, insurance		L2: Barrio quartiles		L2: Deprivation quartiles		L2: Inequality quartiles	
		OR	p	OR	p	OR	p	OR	p	OR	p	OR	p	OR	p
Level 1 covariates															
Race (NH white, referent)															
Hispanic - English speaking		1.15	<.0001	1.48	<.0001	1.39	<.0001	1.23	<.0001	1.21	<.0001	1.21	<.0001	1.21	<.0001
Hispanic - Spanish speaking		0.85	<.0001	1.02	0.375	1.3	<.0001	1.25	<.0001	1.23	<.0001	1.24	<.0001	1.24	<.0001
NH black		1.92	<.0001	2.28	<.0001	2.24	<.0001	2.05	<.0001	2.05	<.0001	2.05	<.0001	2.05	<.0001
NH Other race		0.94	0.01	1.01	0.645	1.09	0.0048	1.09	0.01	1.08	0.012	1.08	0.0133	1.08	0.013
Missing race/ethnicity		0.49	<.0001	0.55	<.0001	0.68	<.0001	0.94	0.111	0.94	0.097	0.94	0.0962	0.94	0.097
Average Age (mean centered)				1.09	<.0001	1.07	<.0001	1.07	<.0001	1.07	<.0001	1.07	<.0001	1.07	<.0001
Female				0.8	<.0001	0.7	<.0001	0.57	<.0001	0.57	<.0001	0.57	<.0001	0.57	<.0001
Current smoker						1.11	<.0001	1.1	<.0001	1.09	<.0001	1.09	<.0001	1.09	<.0001
Comorbidities (0 conditions, referent)															
1 comorbid condition						1.81	<.0001	1.39	<.0001	1.39	<.0001	1.39	<.0001	1.39	<.0001
2 comorbid conditions						3.09	<.0001	1.96	<.0001	1.96	<.0001	1.96	<.0001	1.96	<.0001
3+ comorbid conditions						8.14	<.0001	4.23	<.0001	4.22	<.0001	4.22	<.0001	4.21	<.0001
Visits (Less than 22 visits, referent)															
22-52 (Q2)								2.01	<.0001	2.01	<.0001	2.01	<.0001	2.01	<.0001
53-114 (Q3)								2.98	<.0001	2.98	<.0001	2.98	<.0001	2.98	<.0001
115+ (Q4)								5.32	<.0001	5.32	<.0001	5.33	<.0001	5.33	<.0001
Insurance type (private insurace, referent)															
Medicaid								2.05	<.0001	2.04	<.0001	2.04	<.0001	2.04	<.0001
Medicare								2.84	<.0001	2.82	<.0001	2.82	<.0001	2.82	<.0001
Self pay								1.59	<.0001	1.58	<.0001	1.58	<.0001	1.59	<.0001
Other insurance								2.26	<.0001	2.25	<.0001	2.25	<.0001	2.25	<.0001
Other type of payment								1.1	0.016	1.11	0.015	1.11	0.0149	1.11	0.015
Missing payment information								2.37	<.0001	2.35	<.0001	2.35	<.0001	2.35	<.0001
Level 2 covariates															
Barrio Quartile 1 (Highest barrio rank, referent)															
Barrio Quartile 2										1.01	0.87	1.01	0.7494	1.05	0.17
Barrio Quartile 3										0.88	<.0001	0.89	0.0017	0.93	0.054
Barrio Quartile 4 (Lowest barrio rank)										0.77	<.0001	0.79	<.0001	0.82	<.0001
Deprivation index Quartile 1 (highest deprivation, referent)															
Deprivation Quartile 2												1.01	0.8156	1	0.949
Deprivation Quartile 3												0.98	0.5372	0.97	0.25
Deprivation Quartile 4 (lowest deprivation)												0.94	0.0334	0.91	0.002
Inequality Quartile 1 (highest inequality, referent)															
Inequality Quartile 2														0.96	0.114
Inequality Quartile 3														0.91	0.002
Inequality Quartile 4 (lowest inequality)														0.92	0.007
Constant	0.63	0.60	<.0001	0.53	<.0001	0.29	<.0001	0.13	<.0001	0.15	<.0001	0.15	<.0001	0.16	<.0001
ICC	0.01	0.01		0.01		0.01		0.01		0.003		0.003		0.003	
log likelihood	646739.8	649620.5		711106.7		731877.5		744088.8		744245.5		744246.5		744298.6	

I present results from the multilevel logistic regressions for diagnosed depression for the total patient population in Table 4-5. Similar to hypertension models, the ICC for depression was only 1% and was reduced to 0.1% after accounting for neighborhood-level characteristics. In the first L1 model (L1: Race) Hispanics who primarily spoke English had higher odds of being diagnosed with depression compared to NHWs. However, Hispanics who primarily spoke Spanish had lower odds of being diagnosed than NHWs, suggesting a potentially negative impact of acculturation on mental health. Differences between groups appeared to diminish after accounting for demographic characteristics, health behaviors and comorbidities (L1: health behaviors, comorbidities). In this model, both Hispanic subgroups had higher odds of being diagnosed with depression. However, after accounting for number of visits and health insurance, both Hispanic subgroups had lower odds of being diagnosed with depression, indicating a Hispanic health advantage.

Women had much higher odds of being diagnosed with depression compared to men. After accounting for race/ethnic differences, women were almost twice as likely to be diagnosed with depression (OR=1.96). This difference was reduced to 41% higher odds after accounting for frequency of visits and health insurance, likely because women overall have more encounters with health professionals and are thus more likely to be diagnosed.

In the first level 2 model, it does not appear that barrio characteristics significantly impact odds of being diagnosed with depression. However, after accounting for differences in socioeconomic deprivation, differences in barrio quartiles 1-3 and 1-4 became statistically significant and indicated a negative association between barrio neighborhoods and odds of being diagnosed with depression (i.e. a potentially protective effect). Furthermore, accounting for economic inequality slightly increased the differences between barrio quartiles and produced statistically significant differences between the most “barrio” neighborhoods (quartile 1) and quartile 2. The depression models are the first in which the direction of the associations for the neighborhood-level variables work in different ways. As neighborhoods become less like barrios, the odds of diagnosed depression increase, whereas as neighborhoods become less disadvantaged and more equal, odds of diagnosed depression decrease. These findings support other studies that have found a potentially protective health effect in barrio neighborhoods above and beyond socioeconomic differences.

Table 4-5. Multilevel models predicting odds of having diagnosed depression for adults 25-84 with an outpatient visit in 2014/2015 and examining influence of barrio neighborhoods, socioeconomic deprivation, and economic inequality at the neighborhood level (N=151,027)

	Baseline ICC	L1: Race		L1: demographics		L1: health behaviors, comorbidities		L1: visits, insurance		L2: Barrio quartiles		L2: Deprivation quartiles		L2: Inequality quartiles	
		OR	p	OR	p	OR	p	OR	p	OR	p	OR	p	OR	p
Level 1 covariates															
Race (NH white, referent)															
Hispanic - English speaking		1.24	<.0001	1.26	<.0001	1.16	<.0001	0.84	<.0001	0.84	<.0001	0.84	<.0001	0.84	<.0001
Hispanic - Spanish speaking		0.85	<.0001	0.84	<.0001	1.06	0.0125	0.74	<.0001	0.74	<.0001	0.74	<.0001	0.74	<.0001
NH black		0.97	0.13	0.95	0.017	0.82	<.0001	0.58	<.0001	0.58	<.0001	0.58	<.0001	0.58	<.0001
NH Other race		0.66	<.0001	0.65	<.0001	0.68	<.0001	0.62	<.0001	0.62	<.0001	0.62	<.0001	0.62	<.0001
Missing race/ethnicity		0.35	<.0001	0.41	<.0001	0.49	<.0001	0.82	<.0001	0.82	<.0001	0.82	<.0001	0.82	<.0001
Average Age (mean centered)				1.02	<.0001	1	0.7453	0.99	<.0001	0.99	<.0001	0.99	<.0001	0.99	<.0001
Female				1.96	<.0001	1.94	<.0001	1.59	<.0001	1.59	<.0001	1.59	<.0001	1.59	<.0001
Current smoker						1.71	<.0001	1.6	<.0001	1.6	<.0001	1.6	<.0001	1.6	<.0001
Comorbidities (0 conditions, referent)															
1 comorbid condition						1.81	<.0001	1.24	<.0001	1.24	<.0001	1.24	<.0001	1.24	<.0001
2 comorbid conditions						2.92	<.0001	1.53	<.0001	1.53	<.0001	1.53	<.0001	1.53	<.0001
3+ comorbid conditions						5.44	<.0001	2.18	<.0001	2.19	<.0001	2.18	<.0001	2.18	<.0001
Visits (Less than 22 visits, referent)															
22-52 (Q2)								2.58	<.0001	2.58	<.0001	2.58	<.0001	2.58	<.0001
53-114 (Q3)								4.89	<.0001	4.89	<.0001	4.89	<.0001	4.9	<.0001
115+ (Q4)								11.5	<.0001	11.5	<.0001	11.5	<.0001	11.5	<.0001
Insurance type (private insurace, referent)															
Medicaid								4.26	<.0001	4.27	<.0001	4.26	<.0001	4.27	<.0001
Medicare								5.52	<.0001	5.53	<.0001	5.5	<.0001	5.51	<.0001
Self pay								2.93	<.0001	2.94	<.0001	2.93	<.0001	2.94	<.0001
Other insurance								4.06	<.0001	4.07	<.0001	4.06	<.0001	4.06	<.0001
Other type of payment								1.29	<.0001	1.29	<.0001	1.28	<.0001	1.29	<.0001
Missing payment information								4.99	<.0001	5	<.0001	4.98	<.0001	4.99	<.0001
Level 2 covariates															
Barrio Quartile 1 (Highest barrio rank, referent)															
Barrio Quartile 2										1.05	0.12	1.05	0.09	1.06	0.049
Barrio Quartile 3										1.05	0.118	1.07	0.0343	1.08	0.02
Barrio Quartile 4 (Lowest barrio rank)										1.06	0.07	1.09	0.0111	1.11	0.006
Deprivation index Quartile 1 (highest deprivation, referent)															
Deprivation Quartile 2												1	0.9995	1	0.89
Deprivation Quartile 3												0.97	0.2383	0.97	0.199
Deprivation Quartile 4 (lowest deprivation)												0.94	0.0304	0.93	0.013
Inequality Quartile 1 (highest inequality, referent)															
Inequality Quartile 2														1	0.903
Inequality Quartile 3														0.98	0.449
Inequality Quartile 4 (lowest inequality)														0.97	0.242
Constant	0.27	0.28	<.0001	0.17	<.0001	0.08	<.0001	0.02	<.0001	0.02	<.0001	0.02	<.0001	0.02	<.0001
ICC	0.01	0.01		0.01		0.00		0.00		0.001		0.001		0.001	
log likelihood	699150.4	702329.5		710147.6		728279.2		758558.9		758599.0		758581.2		758633.1	

I present results from the multilevel logistic regressions for odds of being a current smoker for the total patient population in Table 4-6. The baseline ICC for smoking is similar to diabetes and obesity at 5%. The ICC is reduced to 1.3% after accounting for individual- and neighborhood-level covariates. Similar to depression and hypertension, the first level 1 model (L1: Race) revealed opposite patterns for Hispanics who spoke primarily English and those who spoke primarily Spanish, compared to NHWs. Again, Spanish-speaking Hispanics had lower odds of smoking, and English-speaking Hispanics had higher odds of smoking, suggesting a negative acculturation effect. However, accounting for individual-level covariates has a distinct effect on odds of smoking compared to hypertension and depression. In the hypertension models, odds increased for English-speaking Hispanics as covariates were added. In the depression models, odds decreased below 1 for English-speaking Hispanics as covariates were added. For smoking, odds were unchanged after accounting for demographics, health behaviors, and comorbidities, but differences between English-speaking Hispanics and NHWs decreased after accounting for visits and insurance (L1: visits, insurance) so that in the final models English-speaking Hispanics were slightly less likely than NHWs to smoke. Unlike the hypertension models, in which odds of hypertension increased for Spanish-speaking Hispanics as covariates were added, odds of smoking relative to NHWs remained consistently low across models (67% lower odds in the final model). While visits and insurance variables decreased relative odds of smoking by 23% for English-speaking Hispanics, they only reduced relative odds of smoking by 6% for Spanish-speaking Hispanics. As I will highlight in Hispanic-only models and in the conclusion, these results support a broader understanding of intersectional, heterogeneous associations between certain characteristics (e.g. health insurance) and health conditions between Hispanic subgroups.

Gender differences in smoking support existing research that women are less likely to smoke than men (Smith et al. 2016). In this population, women had 32-24% lower odds of smoking compared to men, and the differences were not largely influenced by other covariates.

The association between barrio quartiles and smoking elucidate results from Chapter 3, in which ecological analyses suggested that highly concentrated Hispanic neighborhoods had lower rates of smoking. In the multilevel analysis, lower barrio quartiles had much lower odds of smoking compared to the highest ranked barrio neighborhoods. This indicates that compositional factors were likely driving the associations seen in the ecological analysis; it was the high percentage of Hispanics who spoke Spanish who were likely driving the low neighborhood-level smoking rates, not characteristics specific to barrio neighborhoods. After accounting for socioeconomic deprivation and economic inequality, differences between the first barrio quartile and the other quartiles were slightly attenuated (between 2-5%) and differences between the first and second barrio quartiles were no longer statistically significant.

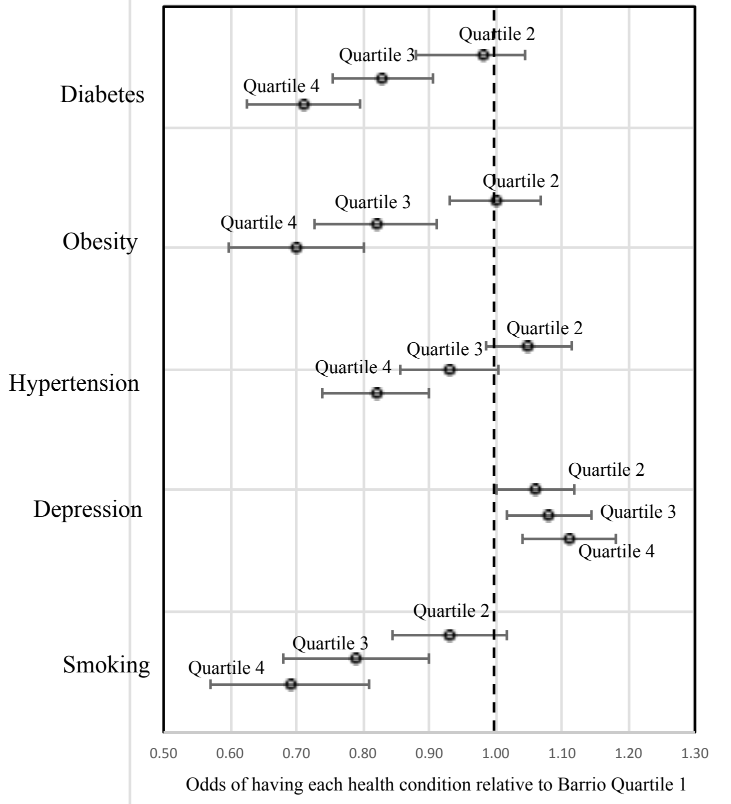
Table 4-6. Multilevel models predicting odds of smoking for adults 25-84 with an outpatient visit in 2014/2015 and examining influence of barrio neighborhoods, socioeconomic deprivation, and economic inequality at the neighborhood level (N=151,027)

	Baseline ICC	L1: Race		L1: demographics		L1: health behaviors, comorbidities		L1: visits, insurance		L2: Barrio quartiles		L2: Deprivation quartiles		L2: Inequality quartiles	
		OR	p	OR	p	OR	p	OR	p	OR	p	OR	p	OR	p
Level 1 covariates															
Race (NH white, referent)															
Hispanic - English speaking		1.19	<.0001	1.2	<.0001	1.19	<.0001	0.96	0.039	0.95	0.018	0.95	0.0199	0.95	0.019
Hispanic - Spanish speaking		0.37	<.0001	0.37	<.0001	0.39	<.0001	0.33	<.0001	0.33	<.0001	0.33	<.0001	0.33	<.0001
NH black		1.81	<.0001	1.84	<.0001	1.82	<.0001	1.32	<.0001	1.32	<.0001	1.31	<.0001	1.31	<.0001
NH Other race		0.72	<.0001	0.72	<.0001	0.73	<.0001	0.66	<.0001	0.66	<.0001	0.66	<.0001	0.66	<.0001
Missing race/ethnicity		1.07	0.05	0.97	0.4741	1.01	0.8215	1.11	0.004	1.11	0.005	1.11	0.0046	1.11	0.005
Average Age (mean centered)				0.99	<.0001	0.99	<.0001	0.99	<.0001	0.99	<.0001	0.99	<.0001	0.99	<.0001
Female				0.67	<.0001	0.66	<.0001	0.68	<.0001	0.68	<.0001	0.68	<.0001	0.68	<.0001
Comorbidities (0 conditions, referent)															
1 comorbid condition						1.11	<.0001	1.18	<.0001	1.18	<.0001	1.18	<.0001	1.18	<.0001
2 comorbid conditions						1.29	<.0001	1.42	<.0001	1.41	<.0001	1.41	<.0001	1.41	<.0001
3+ comorbid conditions						1.34	<.0001	1.51	<.0001	1.5	<.0001	1.50	<.0001	1.5	<.0001
Visits (Less than 22 visits, referent)															
22-52 (Q2)								0.88	<.0001	0.88	<.0001	0.88	<.0001	0.88	<.0001
53-114 (Q3)								0.79	<.0001	0.79	<.0001	0.79	<.0001	0.79	<.0001
115+ (Q4)								0.62	<.0001	0.62	<.0001	0.62	<.0001	0.62	<.0001
Insurance type (private insurace, referent)															
Medicaid								2.15	<.0001	2.15	<.0001	2.15	<.0001	2.15	<.0001
Medicare								2.18	<.0001	2.17	<.0001	2.17	<.0001	2.16	<.0001
Self pay								1.17	0.001	1.17	0.001	1.16	0.0016	1.16	0.002
Other insurance								1.38	<.0001	1.38	<.0001	1.37	<.0001	1.37	<.0001
Other type of payment								0.88	0.009	0.88	0.009	0.88	0.0092	0.88	0.009
Missing payment information								3.06	<.0001	3.05	<.0001	3.05	<.0001	3.04	<.0001
Level 2 covariates															
Barrio Quartile 1 (Highest barrio rank, referent)															
Barrio Quartile 2										0.91	0.013	0.92	0.0254	0.93	0.129
Barrio Quartile 3										0.74	<.0001	0.78	<.0001	0.79	<.0001
Barrio Quartile 4 (Lowest barrio rank)										0.64	<.0001	0.68	<.0001	0.69	<.0001
Deprivation index Quartile 1 (highest deprivation, referent)															
Deprivation Quartile 2												1.00	0.9509	1	0.989
Deprivation Quartile 3												0.96	0.2350	0.96	0.165
Deprivation Quartile 4 (lowest deprivation)												0.86	0.0001	0.86	<.0001
Inequality Quartile 1 (highest inequality, referent)															
Inequality Quartile 2														0.94	0.098
Inequality Quartile 3														0.96	0.321
Inequality Quartile 4 (lowest inequality)														0.99	0.857
Constant	0.18	0.17	<.0001	0.22	<.0001	0.20	<.0001	0.19	<.0001	0.24	<.0001	0.25	<.0001	0.25	<.0001
ICC	0.05	0.05		0.05		0.05		0.03		0.015		0.01		0.013	
log likelihood	735227.5	744366.7		745716.2		746446.3		756640.6		756684.6		756772.2		756810.7	

In Tables 4-7 through 4-11 I present results from the Hispanic-only models. Examining results for the total population revealed that there were differences within the Hispanic population and NHWs by acculturation. Thus, Tables 4-7 through 4-11 use primary language as the primary independent variable. The reference category in each model is Hispanics speaking English, and I present the relative odds for Hispanics speaking Spanish (i.e., the lowest levels of acculturation). These models also include a cross-level interaction between a patient's gender and the barrio quartiles to understand whether highly concentrated Hispanic neighborhoods have different impacts on health for Hispanic men and women. Because there was less total variation across neighborhoods for Hispanic residents than the total population, the ICC values in the Hispanic models were very small. Model fit was best for the final interaction models for each health condition.

I summarize results for the barrio quartile comparisons for the odds of having each health condition total population in Figure 4-1. The visual comparison shows the clear gradient of lower odds of having each health condition, except depression, among neighborhoods with a lower barrio rank. For depression, Figure 4-1 shows how the gradient is reversed, with higher odds of having depression among neighborhoods with a lower barrio rank.

Figure 4-1. Comparison of odds of having five health conditions in barrio quartiles relative to barrio quartile 1 for the total population



Hispanic population

I present results for odds of having diabetes among Hispanic patients in Table 4-7. Primary Spanish speakers had slightly higher odds of having diabetes compared to primary English speakers after adjusting for demographics, but the difference jumped 36% after accounting for differences in health behaviors, comorbid conditions, and average BMI. Differences were only slightly attenuated by number of visits, insurance, and level 2 characteristics. Gender differences for Hispanics largely mirror gender differences for the total population, in which Hispanic women had 44% lower odds of having diabetes after accounting for covariates.

The level 2 characteristics compared Hispanics living in the highest ranked barrio neighborhoods to Hispanics living in lower ranked barrio neighborhoods. As Table 4-1 shows, the largest proportion of primary English speakers lived in quartile 2 (36%) followed by equal distribution between first and third quartiles (26% in each), whereas the largest proportion of primary Spanish speakers lived in quartiles 1 and 2 (40% and 41% respectively). In the models that only include quartiles of barrio rank, there were no significant differences between quartile 1 and 2, but quartiles 3 and 4 have 23% and 35% lower odds of diabetes compared to quartile 1. This reflected patterns seen in the total population (Table 4-2), that even among Hispanics, barrio neighborhoods were not protective against diabetes. The strength of the associations between barrio quartiles was relatively unchanged after accounting for socioeconomic deprivation and economic inequality. Gender interactions were not significant, indicating that the effect of living in a barrio on diabetes was similar for Hispanic women and men.

Table 4-7. Multilevel models predicting odds of having type-2 diabetes for Hispanic adults 25-84 with an outpatient visit in 2014/2015 and examining influence of barrio neighborhoods, socioeconomic deprivation, and economic inequality at the neighborhood level (N=49,594)

	Baseline ICC	L1: Race		L1: demographics		L1: health behaviors, comorbidities		L1: visits, insurance		L2: barrio quartiles		L2: deprivation quartiles		L2: inequality quartiles		Interactions: gender*barrio	
		OR	p	OR	p	OR	p	OR	p	OR	p	OR	p	OR	p	OR	p
Level 1 covariates																	
Spanish speaking (English, referent)		1.07	<.0001	1.06	0.0224	1.42	<.0001	1.40	<.0001	1.38	<.0001	1.38	<.0001	1.38	<.0001	1.38	<.0001
Average Age (mean centered)				1.06	<.0001	1.06	<.0001	1.06	<.0001	1.06	<.0001	1.06	<.0001	1.06	<.0001	1.06	<.0001
Female				0.96	0.0577	0.81	<.0001	0.66	<.0001	0.66	<.0001	0.66	<.0001	0.66	<.0001	0.62	<.0001
Current smoker						1.04	0.28	1.04	0.23	1.04	0.26	1.04	0.27	1.04	0.27	1.04	0.27
Comorbidities (0 conditions, referent)																	
1 comorbid condition						1.36	<.0001	1.05	0.14	1.05	0.15	1.05	0.14	1.05	0.14	1.05	0.14
2 comorbid conditions						1.89	<.0001	1.22	<.0001	1.22	<.0001	1.22	<.0001	1.22	<.0001	1.22	<.0001
3+ comorbid conditions						2.98	<.0001	1.58	<.0001	1.58	<.0001	1.58	<.0001	1.58	<.0001	1.58	<.0001
Average BMI (mean centered)						1.09	<.0001	1.09	<.0001	1.09	<.0001	1.09	<.0001	1.09	<.0001	1.09	<.0001
Visits (Less than 22 visits, referent)																	
22-52 (Q2)								2.09	<.0001	2.09	<.0001	2.09	<.0001	2.09	<.0001	2.10	<.0001
53-114 (Q3)								3.27	<.0001	3.28	<.0001	3.28	<.0001	3.28	<.0001	3.29	<.0001
115+ (Q4)								5.09	<.0001	5.12	<.0001	5.12	<.0001	5.12	<.0001	5.13	<.0001
Insurance type (private insurace, referent)																	
Medicaid								1.88	<.0001	1.87	<.0001	1.86	<.0001	1.86	<.0001	1.86	<.0001
Medicare								1.86	<.0001	1.84	<.0001	1.84	<.0001	1.84	<.0001	1.84	<.0001
Self pay								2.05	<.0001	2.04	<.0001	2.03	<.0001	2.03	<.0001	2.04	<.0001
Other insurance								1.89	<.0001	1.87	<.0001	1.87	<.0001	1.87	<.0001	1.87	<.0001
Other type of payment								1.11	0.30	1.11	0.30	1.11	0.30	1.11	0.30	1.11	0.30
Missing payment information								1.79	<.0001	1.77	<.0001	1.77	<.0001	1.77	<.0001	1.77	<.0001
Level 2 covariates																	
Barrio Quartile 1 (Highest barrio rank, referent)																	
Barrio Quartile 2										0.95	0.11	0.95	0.13	0.96	0.26	0.90	0.05
Barrio Quartile 3										0.77	<.0001	0.78	<.0001	0.78	<.0001	0.74	<.0001
Barrio Quartile 4 (Lowest barrio rank)										0.65	<.0001	0.67	<.0001	0.67	<.0001	0.63	<.0001
Deprivation index Quartile 1 (highest deprivation, referent)																	
Deprivation Quartile 2												0.97	0.34	0.97	0.33	0.97	0.34
Deprivation Quartile 3												0.97	0.43	0.96	0.36	0.96	0.36
Deprivation Quartile 4 (lowest deprivation)												0.94	0.24	0.93	0.19	0.93	0.19
Inequality Quartile 1 (highest inequality, referent)																	
Inequality Quartile 2														0.99	0.79	0.99	0.79
Inequality Quartile 3														0.97	0.40	0.97	0.41
Inequality Quartile 4 (lowest inequality)														0.98	0.71	0.98	0.70
Female*Barrio Quartile 2																1.10	0.11
Female*Barrio Quartile 3																1.10	0.19
Female*Barrio Quartile 4																1.11	0.29
Constant	0.26	0.26	<.0001	0.23	<.0001	0.13	<.0001	0.05	<.0001	0.07	<.0001	0.07	<.0001	0.07	<.0001	0.07	<.0001
ICC	0.03	0.03		0.03		0.01		0.01		0.001		0.001		0.001		0.001	
log likelihood	226626.3	226641.9		237678.7		237929.8		241279.5		241503.6		241513.1		241533.9		241563.8	

I present results for odds of having obesity among Hispanic patients in Table 4-8. As Table 4-3 demonstrated for the total population, primary Spanish speakers have substantially *lower* odds of obesity despite their higher odds of diabetes compared to primary English speakers. The initial difference (25%) is slightly attenuated after accounting for number of visits and type of insurance, but differences in relative odds remain at about 20% after accounting for all covariates. Similar to patterns in the total population, Hispanic women had 14% higher odds of having diabetes after accounting for covariates.

Level 2 models for obesity reveal a similar effect for barrio quartiles as they did for diabetes; Hispanics living in lower ranked barrio neighborhoods have lower odds of being obese.

Unlike diabetes models, however, socioeconomic deprivation had a statistically significant effect on odds of having obesity; quartiles with less socioeconomic deprivation had lower odds of obesity compared to the quartile with the most socioeconomic deprivation. Differences in economic inequality did not significantly impact odds of having obesity. Another difference between diabetes and obesity models was the gender interactions. Hispanic women living in lower ranked barrio neighborhoods (quartile 3 or 4) had lower odds of being obese compared to men living in barrio neighborhoods. These differences are not apparent when looking at the main effect for gender, and reveal a large gender disparity for Hispanic women living in quartile 4 (24% lower odds of obesity compared to men living in the highest ranked barrio neighborhoods).

Differences between diabetes and obesity models are important because the two conditions are physiologically related (higher BMI is strongly associated with increased risk of developing type-2 diabetes), so it would be logical that the social mechanisms driving differences in diabetes and obesity would be the same or similar. For example, Chapter 3 showed similar patterns of diabetes and obesity rates and inequality (although notably not exactly the same). Tables 4-7 and 4-8 suggest that distinct social processes may be associated with diabetes and obesity, particularly within the Hispanic population. First, the fact that primary Spanish speakers had higher odds of diabetes but lower odds of obesity is puzzling. Although there was no apparent health benefit for living in the highest ranked barrio neighborhoods for diabetes or obesity, there were no gender differences across barrio quartiles for diabetes but substantial gender differences for obesity. This suggests complex and heterogeneous processes occurring within the Hispanic population, and will be further discussed at the end of the chapter and in Chapter 5.

Table 4-8. Multilevel models predicting odds of having obesity for Hispanic adults 25-84 with an outpatient visit in 2014/2015 and examining influence of barrio neighborhoods, socioeconomic deprivation, and economic inequality at the neighborhood level (N=48,386)

	Baseline ICC	L1: Race		L1: demographics		L1: health behaviors, comorbidities		L1: visits, insurance		L2: barrio quartiles		L2: deprivation quartiles		L2: inequality quartiles		Interactions: gender*barrio	
		OR	p	OR	p	OR	p	OR	p	OR	p	OR	p	OR	p	OR	p
Level 1 covariates																	
Spanish speaking (English, referent)		0.76	<.0001	0.75	<.0001	0.76	<.0001	0.80	<.0001	0.80	<.0001	0.80	<.0001	0.80	<.0001	0.80	<.0001
Average Age (mean centered)				1.00	0.7168	1.00	<.0001	1.00	<.0001	1.00	<.0001	1.00	<.0001	1.00	<.0001	1.00	<.0001
Female				1.23	<.0001	1.17	<.0001	1.14	<.0001	1.14	<.0001	1.14	<.0001	1.14	<.0001	1.22	<.0001
Current smoker						0.74	<.0001	0.72	<.0001	0.72	<.0001	0.72	<.0001	0.72	<.0001	0.72	<.0001
Comorbidities (0 conditions, referent)																	
1 comorbid condition						1.32	<.0001	1.28	<.0001	1.28	<.0001	1.28	<.0001	1.28	<.0001	1.28	<.0001
2 comorbid conditions						1.40	<.0001	1.31	<.0001	1.31	<.0001	1.31	<.0001	1.31	<.0001	1.31	<.0001
3+ comorbid conditions						1.35	<.0001	1.21	<.0001	1.21	<.0001	1.21	<.0001	1.21	<.0001	1.21	<.0001
Visits (Less than 22 visits, referent)								1.03	0.2504	1.03	0.2558	1.03	0.25	1.03	0.2555	1.03	0.3272
22-52 (Q2)																	
53-114 (Q3)								1.09	0.0029	1.09	0.0027	1.09	0.00	1.09	0.0028	1.09	0.0045
115+ (Q4)								1.24	<.0001	1.24	<.0001	1.24	<.0001	1.24	<.0001	1.24	<.0001
Insurance type (private insurace, referent)								1.18	<.0001	1.18	<.0001	1.18	<.0001	1.18	<.0001	1.18	<.0001
Medicaid																	
Medicare								1.12	0.0228	1.12	0.0255	1.11	0.03	1.12	0.0256	1.12	0.0245
Self pay								0.99	0.8802	0.99	0.818	0.99	0.78	0.99	0.8047	0.99	0.7529
Other insurance								1.06	0.3105	1.05	0.3285	1.05	0.34	1.05	0.3359	1.05	0.3444
Other type of payment								0.96	0.5537	0.96	0.5554	0.96	0.55	0.96	0.5378	0.96	0.52
Missing payment information								1.22	<.0001	1.21	<.0001	1.21	<.0001	1.21	<.0001	1.21	<.0001
Level 2 covariates																	
Barrio Quartile 1 (Highest barrio rank, referent)																	
Barrio Quartile 2										0.95	0.15	0.94	0.13	0.98	0.65	1.02	0.68
Barrio Quartile 3										0.80	<.0001	0.80	<.0001	0.82	0.00	0.87	0.05
Barrio Quartile 4 (Lowest barrio rank)										0.63	<.0001	0.63	<.0001	0.65	<.0001	0.77	0.00
Deprivation index Quartile 1 (highest deprivation, referent)																	
Deprivation Quartile 2												0.94	0.04	0.94	0.03	0.94	0.04
Deprivation Quartile 3												0.94	0.09	0.93	0.06	0.93	0.07
Deprivation Quartile 4 (lowest deprivation)												0.99	0.82	0.96	0.42	0.96	0.44
Inequality Quartile 1 (highest inequality, referent)																	
Inequality Quartile 2														1.00	0.97	1.00	0.97
Inequality Quartile 3														0.93	0.11	0.93	0.11
Inequality Quartile 4 (lowest inequality)														0.96	0.41	0.96	0.41
Female*Barrio Quartile 2																0.94	0.18
Female*Barrio Quartile 3																0.91	0.09
Female*Barrio Quartile 4																0.76	<.0001
Constant	0.63	0.68	<.0001	0.60	<.0001	0.54	<.0001	0.50	<.0001	0.63	<.0001	0.65	<.0001	0.66	<.0001	0.63	<.0001
ICC	0.02	0.03		0.03		0.03		0.03		0.009		0.009		0.010		0.010	
log likelihood	205982.6	206214.3		206357.4		206781.5		206914.0		206873.9		206895.5		206921.6		206944.0	

I present results for odds of having hypertension among Hispanic patients in Table 4-9. After adjusting for age and gender, primary Spanish speakers had 29% lower odds of having hypertension compared to primary English speakers. After accounting for smoking and comorbid conditions (L1: health behaviors, comorbidities), the difference was reduced to 7%, but was still statistically significant. After accounting for the number of visits and health insurance (L1: visits, insurance) the differences in odds of having hypertension were no longer statistically significant between primary Spanish speakers and primary English speakers. Similar to diabetes, Hispanic women much lower odds of having hypertension compared to Hispanic men, and this difference was particularly exacerbated after accounting for differences in visits and insurance (L1: visits, insurance).

Level 2 models for hypertension reveal a similar effect for barrio quartiles as they did for obesity and diabetes; Hispanics living in the lowest two barrio quartiles have lower odds of having hypertension. The differences between barrio quartile 1 and barrio quartile 2 were not significant across level 2 models. Although accounting for deprivation and inequality quartiles did not reveal significant differences, adding these characteristics did affect the relationship between barrio quartiles. In the final model, the only significant and substantive differences were between the first and fourth barrio quartiles, in which Hispanics living in the fourth quartile had 19% lower odds of having hypertension. Although there were significant individual-level gender differences, the cross-level interactions between a patient's gender and the barrio quartiles were not significant. Thus, results for hypertension reveal no substantial effects for Hispanics by acculturation, lower odds of hypertension among Hispanic women compared to Hispanic men, and a small negative impact on odds of being hypertensive for those living in a barrio compared to the lowest ranked barrio neighborhoods.

Table 4-9. Multilevel models predicting odds of having hypertension for Hispanic adults 25-84 with an outpatient visit in 2014/2015 and examining influence of barrio neighborhoods, socioeconomic deprivation, and economic inequality at the neighborhood level (N=49,594)

	Baseline ICC	L1: Race		L1: demographics		L1: health behaviors, comorbidities		L1: visits, insurance		L2: barrio quartiles		L2: deprivation quartiles		L2: inequality quartiles		Interactions: gender*barrio	
		OR	p	OR	p	OR	p	OR	p	OR	p	OR	p	OR	p	OR	p
Level 1 covariates																	
Spanish speaking (English, referent)		0.79	<.0001	0.71	<.0001	0.93	0.003	1.00	0.9362	0.99	0.7117	0.99	0.70	0.99	0.694	0.99	0.687
Average Age (mean centered)				1.10	<.0001	1.08	<.0001	1.08	<.0001	1.08	<.0001	1.08	<.0001	1.08	<.0001	1.08	<.0001
Female				0.78	<.0001	0.66	<.0001	0.49	<.0001	0.49	<.0001	0.49	<.0001	0.49	<.0001	0.49	<.0001
Current smoker						0.94	0.04	0.90	0.00	0.90	0.00	0.90	0.00	0.90	0.00	0.90	0.00
Comorbidities (0 conditions, referent)																	
1 comorbid condition						1.91	<.0001	1.45	<.0001	1.45	<.0001	1.45	<.0001	1.45	<.0001	1.45	<.0001
2 comorbid conditions						3.07	<.0001	1.91	<.0001	1.91	<.0001	1.91	<.0001	1.91	<.0001	1.91	<.0001
3+ comorbid conditions						7.93	<.0001	3.88	<.0001	3.87	<.0001	3.87	<.0001	3.87	<.0001	3.87	<.0001
Visits (Less than 22 visits, referent)								2.18	<.0001	2.18	<.0001	2.18	<.0001	2.18	<.0001	2.18	<.0001
22-52 (Q2)																	
53-114 (Q3)								3.30	<.0001	3.30	<.0001	3.30	<.0001	3.30	<.0001	3.31	<.0001
115+ (Q4)								6.24	<.0001	6.24	<.0001	6.24	<.0001	6.24	<.0001	6.25	<.0001
Insurance type (private insurace, referent)								2.23	<.0001	2.20	<.0001	2.20	<.0001	2.20	<.0001	2.20	<.0001
Medicaid																	
Medicare								2.86	<.0001	2.83	<.0001	2.82	<.0001	2.82	<.0001	2.82	<.0001
Self pay								1.77	<.0001	1.75	<.0001	1.75	<.0001	1.75	<.0001	1.75	<.0001
Other insurance								2.29	<.0001	2.27	<.0001	2.27	<.0001	2.27	<.0001	2.27	<.0001
Other type of payment								1.16	0.0849	1.15	0.0891	1.15	0.09	1.15	0.0893	1.15	0.0894
Missing payment information								2.38	<.0001	2.34	<.0001	2.33	<.0001	2.33	<.0001	2.33	<.0001
Level 2 covariates																	
Barrio Quartile 1 (Highest barrio rank, referent)																	
Barrio Quartile 2										1.02	0.63	1.02	0.61	1.02	0.56	1.04	0.43
Barrio Quartile 3										0.91	0.01	0.91	0.02	0.92	0.06	0.89	0.06
Barrio Quartile 4 (Lowest barrio rank)										0.79	<.0001	0.80	<.0001	0.81	0.00	0.83	0.02
Deprivation index Quartile 1 (highest deprivation, referent)																	
Deprivation Quartile 2												0.98	0.50	0.98	0.45	0.98	0.46
Deprivation Quartile 3												0.98	0.56	0.97	0.45	0.97	0.47
Deprivation Quartile 4 (lowest deprivation)												0.96	0.39	0.95	0.31	0.95	0.32
Inequality Quartile 1 (highest inequality, referent)																	
Inequality Quartile 2														0.98	0.54	0.98	0.55
Inequality Quartile 3														0.98	0.65	0.98	0.65
Inequality Quartile 4 (lowest inequality)														0.97	0.42	0.97	0.43
Female*Barrio Quartile 2																0.97	0.59
Female*Barrio Quartile 3																1.06	0.43
Female*Barrio Quartile 4																0.96	0.63
Constant	0.65	0.70	<.0001	0.84	<.0001	0.45	<.0001	0.18	<.0001	0.19	<.0001	0.19	<.0001	0.20	<.0001	0.19	<.0001
ICC	0.01	0.01		0.01		0.00		0.00		0.001		0.001		0.001		0.001	
log likelihood	212068.9	212227.8		232851.9		239958.6		244095.4		244233.9		244252.2		244273.0		244293.0	

I present results for odds of having depression among Hispanic patients in Table 4-10. After accounting for age and gender, primary Spanish speakers had 33% lower odds of being diagnosed with depression (L1: demographics). This difference was attenuated to a 10-13% difference by accounting for differences in smoking and comorbid conditions (L1: health behaviors, comorbidities) and other individual-level covariates. Gender differences in depression were even more exacerbated between Hispanic women and men than in the total population. After accounting for acculturation differences, Hispanic women had 132% higher odds of being diagnosed with depression. Similar to the models with the total population, accounting for differences in the number of visits and insurance reduced the gender difference, but Hispanic women still had 78% higher odds of being diagnosed with depression.

Level 2 models for depression differed from the diabetes, obesity, and hypertension models. Although there were no substantial differences between Hispanics living in barrio quartiles 1 and 2, Hispanics living in barrio quartile 3 had 8-10% higher odds of depression compared to quartile 1, and Hispanics living in barrio quartile 4 had 16-19% higher odds of having depression compared to barrio quartile 1. This gradient effect suggests that as Hispanics move into neighborhoods that resemble barrios less and less, the odds of depression increase. These differences are not explained by differences in socioeconomic deprivation or inequality. Finally, although there was generally a health benefit for living in a highly ranked barrio neighborhood, Hispanic women living in the lowest ranked barrio neighborhoods had 23% lower odds of being diagnosed with depression compared to their counterparts living in the highest ranked barrio neighborhoods.

Table 4-10. Multilevel models predicting odds of having depression for Hispanic adults 25-84 with an outpatient visit in 2014/2015 and examining influence of barrio neighborhoods, socioeconomic deprivation, and economic inequality at the neighborhood level (N=49,594)

	Baseline ICC	L1: Race		L1: demographics		L1: health behaviors, comorbidities		L1: visits, insurance		L2: barrio quartiles		L2: deprivation quartiles		L2: inequality quartiles		Interactions: gender*barrio	
		OR	p	OR	p	OR	p	OR	p	OR	p	OR	p	OR	p	OR	p
Level 1 covariates																	
Spanish speaking (English speaking, referent)		0.70	<.0001	0.67	<.0001	0.90	<.0001	0.86	<.0001	0.87	<.0001	0.87	<.0001	0.87	<.0001	0.87	<.0001
Average Age (mean centered)				1.02	<.0001	1.00	0.6006	0.99	<.0001	0.99	<.0001	0.99	<.0001	0.99	<.0001	0.99	<.0001
Female				2.32	<.0001	2.31	<.0001	1.78	<.0001	1.78	<.0001	1.78	<.0001	1.78	<.0001	1.85	<.0001
Current smoker						1.73	<.0001	1.61	<.0001	1.61	<.0001	1.61	<.0001	1.61	<.0001	1.61	<.0001
Comorbidities (0 conditions, referent)																	
1 comorbid condition						1.72	<.0001	1.22	<.0001	1.22	<.0001	1.22	<.0001	1.22	<.0001	1.22	<.0001
2 comorbid conditions						2.66	<.0001	1.45	<.0001	1.45	<.0001	1.45	<.0001	1.45	<.0001	1.45	<.0001
3+ comorbid conditions						5.12	<.0001	2.02	<.0001	2.03	<.0001	2.03	<.0001	2.03	<.0001	2.03	<.0001
Visits (Less than 22 visits, referent)								2.59	<.0001	2.60	<.0001	2.59	<.0001	2.59	<.0001	2.59	<.0001
22-52 (Q2)																	
53-114 (Q3)								5.04	<.0001	5.04	<.0001	5.04	<.0001	5.04	<.0001	5.02	<.0001
115+ (Q4)								11.08	<.0001	11.10	<.0001	11.09	<.0001	11.09	<.0001	11.06	<.0001
Insurance type (private insurace, referent)								4.29	<.0001	4.33	<.0001	4.32	<.0001	4.32	<.0001	4.31	<.0001
Medicaid																	
Medicare								5.00	<.0001	5.04	<.0001	5.02	<.0001	5.02	<.0001	5.03	<.0001
Self pay								3.00	<.0001	3.03	<.0001	3.01	<.0001	3.01	<.0001	3.00	<.0001
Other insurance								3.97	<.0001	4.01	<.0001	4.00	<.0001	4.00	<.0001	4.00	<.0001
Other type of payment								1.78	<.0001	1.78	<.0001	1.78	<.0001	1.78	<.0001	1.78	<.0001
Missing payment information								5.03	<.0001	5.08	<.0001	5.06	<.0001	5.06	<.0001	5.05	<.0001
Level 2 covariates																	
Barrio Quartile 1 (Highest barrio rank, referent)																	
Barrio Quartile 2										1.06	0.12	1.06	0.09	1.06	0.16	1.05	0.48
Barrio Quartile 3										1.08	0.04	1.10	0.03	1.09	0.06	1.15	0.05
Barrio Quartile 4 (Lowest barrio rank)										1.16	0.00	1.19	0.00	1.18	0.00	1.42	<.0001
Deprivation index Quartile 1 (highest deprivation, referent)																	
Deprivation Quartile 2												0.97	0.43	0.97	0.43	0.97	0.41
Deprivation Quartile 3												0.99	0.88	1.00	0.97	1.00	1.00
Deprivation Quartile 4 (lowest deprivation)												0.93	0.11	0.93	0.19	0.94	0.20
Inequality Quartile 1 (highest inequality, referent)																	
Inequality Quartile 2														1.01	0.77	1.01	0.77
Inequality Quartile 3														1.03	0.49	1.03	0.48
Inequality Quartile 4 (lowest inequality)														1.01	0.87	1.01	0.87
Female*Barrio Quartile 2																1.01	0.86
Female*Barrio Quartile 3																0.93	0.34
Female*Barrio Quartile 4																0.77	0.01
Constant	0.31	0.35	<.0001	0.20	<.0001	0.09	<.0001	0.02	<.0001	0.02	<.0001	0.02	<.0001	0.02	<.0001	0.02	<.0001
ICC	0.01	0.01		0.01		0.01		0.00		0.001		0.001		0.001		0.001	
log likelihood	225391.6	225830.1		228566.4		233711.2		244077.4		244127.1		244131.3		244145.5		244167.3	

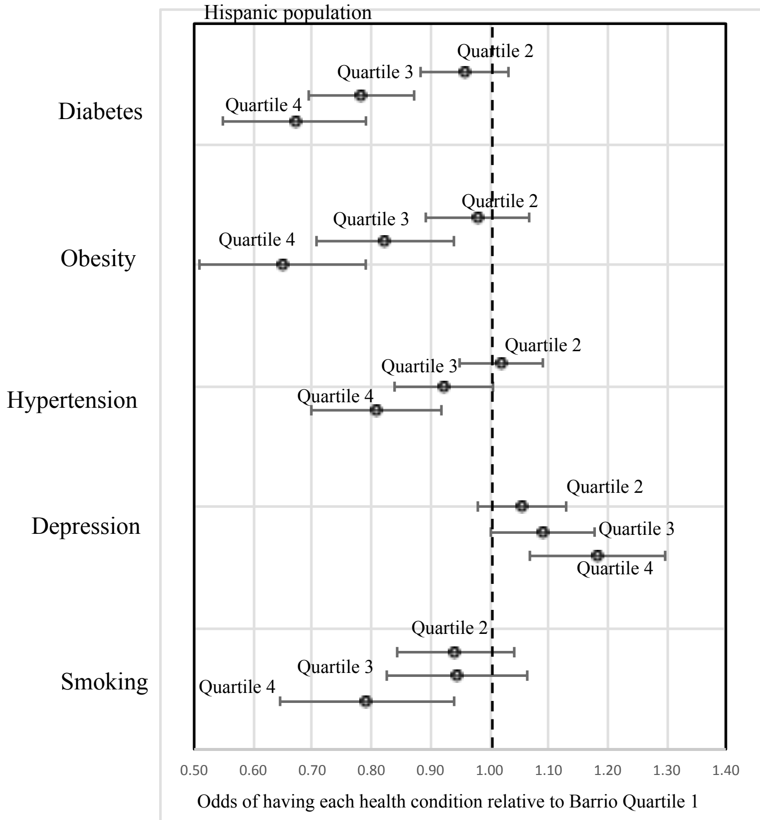
I present results for odds of being a current smoker among Hispanic patients in Table 4-11. Results for smoking revealed the largest differences by acculturation across all health conditions. After accounting for all covariates, primary Spanish speakers had 63% lower odds of current smoking than their English-speaking counterparts. Results also revealed large gender differences; Hispanic women had 38-40% of being current smokers compared to Hispanic men. Similar to the models in Table 4-6 that use the total patient population, the Hispanic models reveal that it is likely compositional factors that drove the apparent protective association between barrio neighborhoods and smoking in the Chapter 3 results. Again, Hispanics living in the lowest ranked barrio neighborhoods (quartile 4) had, on average, 21% lower odds of smoking compared to those living in the highest ranked barrio neighborhoods (quartile 1) after accounting for socioeconomic deprivation and inequality. Unlike other health conditions, inequality worked in the opposite direction as the barrio and deprivation associations. Hispanics living in more economically equitable neighborhoods actually had higher odds of smoking, on average. There was a gradient effect, wherein Hispanics living in the most economically equitable environments had 22% higher odds of smoking. It is likely that inequality in this context is another proxy for acculturation. Assuming economically equitable environments may be desirable, living in those neighborhoods may also be more achievable for Hispanics who had more resources. These Hispanics were likely not recent migrants, and thus the same difference between primary Spanish speakers and primary English speakers may have been highlighted in different types of neighborhood inequality. The cross-level gender and barrio interactions revealed significant gender differences in the third barrio quartile, but no others. Here, women living in lower ranked barrio neighborhoods had higher odds of smoking compared to their counterparts in barrio quartile 1. Thus, although there was not an overall protective association between highly ranked barrio neighborhoods and smoking, there may be a protective association for Hispanic women living in highly ranked barrio neighborhoods.

Table 4-11. Multilevel models predicting odds of being a current smoker for Hispanic adults 25-84 with an outpatient visit in 2014/2015 and examining influence of barrio neighborhoods, socioeconomic deprivation, and economic inequality at the neighborhood level (N=49,594)

	Baseline ICC	L1: Race		L1: demographics		behaviors, comorbidities		L1: visits, insurance		L2: barrio quartiles		deprivation quartiles		inequality quartiles		Interactions: gender*barrio	
		OR	p	OR	p	OR	p	OR	p	OR	p	OR	p	OR	p	OR	p
Level 1 covariates																	
Spanish speaking (English speaking, referent)		0.33	<.0001	0.33	<.0001	0.34	<.0001	0.37	<.0001	0.37	<.0001	0.37	<.0001	0.37	<.0001	0.36	<.0001
Average Age (mean centered)				1.00	0.004	1.00	<.0001	0.99	<.0001	0.99	<.0001	0.99	<.0001	0.99	<.0001	0.99	<.0001
Female				0.61	<.0001	0.60	<.0001	0.62	<.0001	0.62	<.0001	0.62	<.0001	0.62	<.0001	0.57	<.0001
Comorbidities (0 conditions, referent)																	
1 comorbid condition						1.09	0.01	1.13	<.0001	1.13	<.0001	1.13	<.0001	1.13	<.0001	1.13	<.0001
2 comorbid conditions						1.24	<.0001	1.31	<.0001	1.31	<.0001	1.31	<.0001	1.31	<.0001	1.31	<.0001
3+ comorbid conditions						1.10	0.01	1.17	<.0001	1.17	<.0001	1.17	<.0001	1.17	<.0001	1.17	<.0001
Visits (Less than 22 visits, referent)																	
22-52 (Q2)								0.84	<.0001	0.84	<.0001	0.84	<.0001	0.84	<.0001	0.84	<.0001
53-114 (Q3)								0.76	<.0001	0.76	<.0001	0.76	<.0001	0.76	<.0001	0.77	<.0001
115+ (Q4)								0.65	<.0001	0.65	<.0001	0.65	<.0001	0.65	<.0001	0.65	<.0001
Insurance type (private insurace, referent)																	
Medicaid								1.77	<.0001	1.75	<.0001	1.75	<.0001	1.75	<.0001	1.75	<.0001
Medicare								1.51	<.0001	1.50	<.0001	1.49	<.0001	1.49	<.0001	1.49	<.0001
Self pay								1.05	0.44	1.04	0.53	1.03	0.59	1.03	0.61	1.03	0.60
Other insurance								1.18	0.05	1.17	0.06	1.17	0.07	1.16	0.07	1.17	0.07
Other type of payment								1.00	0.99	1.00	0.98	1.00	0.99	1.00	0.99	1.00	0.99
Missing payment information								2.74	<.0001	2.71	<.0001	2.70	<.0001	2.70	<.0001	2.70	<.0001
Level 2 covariates																	
Barrio Quartile 1 (Highest barrio rank, referent)																	
Barrio Quartile 2										0.99	0.77	0.99	0.91	0.94	0.24	0.89	0.06
Barrio Quartile 3										0.95	0.38	1.02	0.78	0.95	0.36	0.87	0.06
Barrio Quartile 4 (Lowest barrio rank)										0.77	0.00	0.86	0.05	0.79	0.00	0.76	0.00
Deprivation index Quartile 1 (highest deprivation, referent)																	
Deprivation Quartile 2												0.97	0.46	0.99	0.70	0.99	0.71
Deprivation Quartile 3												0.90	0.02	0.92	0.07	0.92	0.08
Deprivation Quartile 4 (lowest deprivation)												0.78	<.0001	0.83	0.00	0.83	0.00
Inequality Quartile 1 (highest inequality, referent)																	
Inequality Quartile 2														1.11	0.05	1.11	0.05
Inequality Quartile 3														1.13	0.02	1.13	0.02
Inequality Quartile 4 (lowest inequality)														1.22	0.00	1.22	0.00
Female*Barrio Quartile 2																1.10	0.12
Female*Barrio Quartile 3																1.15	0.05
Female*Barrio Quartile 4																1.06	0.57
Constant	0.19	0.24	<.0001	0.32	<.0001	0.30	<.0001	0.26	<.0001	0.28	<.0001	0.29	<.0001	0.27	<.0001	0.28	<.0001
ICC	0.03	0.03		0.03		0.03		0.01		0.010		0.007		0.005		0.005	
log likelihood	241706.0	246780.5		246792.8		246944.1		249695.5		249733.6		249811.4		249852.4		249865.8	

I summarize results for the barrio quartile comparisons for the odds of having each health condition total population in Figure 4-2. Similar to Figure 4-1 for the total population, the visual comparison in Figure 4-2 shows the clear gradient of lower odds of having diabetes, obesity, and hypertension for Hispanics among neighborhoods with a lower barrio rank. For depression, Figure 4-2 shows a similar gradient reversal as Figure 4-1, with higher odds of having depression among neighborhoods with a lower barrio rank. For smoking, however, Figure 4-2 shows that although odds of smoking are likely lower among residents of lower ranked barrio neighborhoods, there is not a gradient between quartiles 2 and 3. Thus, there is only a significant difference in odds of smoking between barrio quartile 1 and quartile 4 (the lowest ranked barrio neighborhoods).

Figure 4-2. Comparison of odds of having five health conditions in barrio quartiles relative to barrio quartile 1 for the Hispanic population



Sensitivity Analyses

In Table 4-12 I compare final model results for census tracts versus socially defined neighborhoods for the total population and each health condition. Individual-level results are comparable for each geographic level. There are some differences in neighborhood-level estimates across geographies. For obesity, the differences between barrio quartiles and between inequality quartiles were larger for census tracts than for socially defined neighborhoods. The same conclusions could still be made for barrio quartiles, but conclusions would be different for the relationship between inequality quartiles 1 and 4. Using census tracts, there were statistically significant differences between inequality quartiles 1 and 4 that were absent using socially defined neighborhoods. Census-tract-level results suggest that residents living in the most economically equitable neighborhoods had 17% lower odds of being obese compared to those living in the most economically unequal environments. Similarly for hypertension, the size of the differences between census tracts and socially defined neighborhoods were slightly different. The only estimate that was significant for census tracts and not for socially defined neighborhoods was the lower odds of having hypertension in the inequality quartile 2 compared to quartile 1. Results were not substantially different between geographic levels for depression. For smoking, some results were significant using census tracts that were not significant using socially defined neighborhoods. Census-tract-level analyses revealed significantly lower odds of smoking in barrio quartile 2 compared to barrio quartile 1. Similarly, census-tract-level analyses revealed significantly lower odds of smoking in deprivation quartile 3 compared to deprivation quartile 1, overall demonstrating a stronger gradient of association between socioeconomic deprivation and smoking.

Table 4-12. Comparisons of final models for type 2 diabetes between census tract and socially defined neighborhoods for patients in Denver, Colorado (N=151,027)

	Diabetes				Obesity				Hypertension				Depression				Smoking			
	Census tracts		Socially-defined neighborhoods		Census tracts		Socially-defined neighborhoods		Census tracts		Socially-defined neighborhoods		Census tracts		Socially-defined neighborhoods		Census tracts		Socially-defined neighborhoods	
	OR	p	OR	p value	OR	p	OR	p value	OR	p	OR	p value	OR	p	OR	p value	OR	p	OR	p value
Level 1 covariates																				
Race (NH white, referent)																				
Hispanic - English speaking	2.17	<.0001	2.18	<.0001	1.66	<.0001	1.67	<.0001	1.21	<.0001	1.21	<.0001	0.84	<.0001	0.84	<.0001	0.95	0.016	0.95	0.019
Hispanic - Spanish speaking	2.88	<.0001	2.89	<.0001	1.32	<.0001	1.33	<.0001	1.23	<.0001	1.24	<.0001	0.75	<.0001	0.74	<.0001	0.33	<.0001	0.33	<.0001
NH black	1.98	<.0001	2.00	<.0001	1.59	<.0001	1.61	<.0001	2.06	<.0001	2.05	<.0001	0.59	<.0001	0.58	<.0001	1.30	<.0001	1.31	<.0001
NH Other race	1.95	<.0001	1.96	<.0001	0.68	<.0001	0.68	<.0001	1.08	0.012	1.08	0.013	0.62	<.0001	0.62	<.0001	0.67	<.0001	0.66	<.0001
Missing race/ethnicity	1.38	<.0001	1.38	<.0001	1.13	<.0001	1.13	<.0001	0.94	0.098	0.94	0.097	0.82	<.0001	0.82	<.0001	1.11	0.0053	1.11	0.0046
Average Age (mean centered)	1.05	<.0001	1.05	<.0001	1.00	0.296	1.00	0.254	1.07	<.0001	1.07	<.0001	0.99	<.0001	0.99	<.0001	0.99	<.0001	0.99	<.0001
Female	0.68	<.0001	0.68	<.0001	1.09	<.0001	1.09	<.0001	0.57	<.0001	0.57	<.0001	1.59	<.0001	1.59	<.0001	0.68	<.0001	0.68	<.0001
Current smoker	1.09	<.0001	1.10	<.0001	0.80	<.0001	0.80	<.0001	1.09	<.0001	1.09	<.0001	1.59	<.0001	1.60	<.0001				
Comorbidities (0 conditions, referent)																				
1 comorbid condition	1.12	<.0001	1.12	<.0001	1.28	<.0001	1.28	<.0001	1.39	<.0001	1.39	<.0001	1.24	<.0001	1.24	<.0001	1.18	<.0001	1.18	<.0001
2 comorbid conditions	1.37	<.0001	1.37	<.0001	1.38	<.0001	1.38	<.0001	1.96	<.0001	1.96	<.0001	1.53	<.0001	1.53	<.0001	1.41	<.0001	1.41	<.0001
3+ comorbid conditions	1.80	<.0001	1.80	<.0001	1.37	<.0001	1.37	<.0001	4.21	<.0001	4.21	<.0001	2.18	<.0001	2.18	<.0001	1.50	<.0001	1.50	<.0001
Average BMI (mean centered)	1.10	<.0001	1.10	<.0001																
Visits (Less than 22 visits, referent)																				
22-52 (Q2)	1.89	<.0001	1.89	<.0001	1.09	<.0001	1.09	<.0001	2.01	<.0001	2.01	<.0001	2.58	<.0001	2.58	<.0001	0.88	<.0001	0.88	<.0001
53-114 (Q3)	2.81	<.0001	2.81	<.0001	1.15	<.0001	1.15	<.0001	2.98	<.0001	2.98	<.0001	4.89	<.0001	4.90	<.0001	0.79	<.0001	0.79	<.0001
115+ (Q4)	4.30	<.0001	4.30	<.0001	1.26	<.0001	1.26	<.0001	5.34	<.0001	5.33	<.0001	11.53	<.0001	11.52	<.0001	0.63	<.0001	0.62	<.0001
Insurance type (private insurace, referent)																				
Medicaid	2.22	<.0001	2.23	<.0001	1.16	<.0001	1.17	<.0001	2.04	<.0001	2.04	<.0001	4.27	<.0001	4.27	<.0001	2.14	<.0001	2.15	<.0001
Medicare	2.36	<.0001	2.37	<.0001	1.22	<.0001	1.23	<.0001	2.82	<.0001	2.82	<.0001	5.51	<.0001	5.51	<.0001	2.15	<.0001	2.16	<.0001
Self pay	2.19	<.0001	2.19	<.0001	1.03	0.3467	1.03	0.303	1.59	<.0001	1.59	<.0001	2.94	<.0001	2.94	<.0001	1.16	0.002	1.16	0.002
Other insurance	2.32	<.0001	2.33	<.0001	0.98	0.6447	0.99	0.694	2.25	<.0001	2.25	<.0001	4.07	<.0001	4.06	<.0001	1.37	<.0001	1.37	<.0001
Other type of payment	1.01	0.831	1.02	0.809	0.87	<.0001	0.87	<.0001	1.11	0.015	1.11	0.015	1.29	<.0001	1.29	<.0001	0.88	0.0073	0.88	0.0091
Missing payment information	1.99	<.0001	1.99	<.0001	1.22	<.0001	1.22	<.0001	2.35	<.0001	2.35	<.0001	4.99	<.0001	4.99	<.0001	3.04	<.0001	3.04	<.0001
Level 2 covariates																				
Barrio Quartile 1 (Highest barrio rank, referent)																				
Barrio Quartile 2	0.97	0.391	0.98	0.458	0.92	0.155	1.00	0.913	1.00	0.976	1.05	0.170	1.05	0.105	1.06	0.049	0.86	0.027	0.93	0.129
Barrio Quartile 3	0.83	<.0001	0.83	<.0001	0.73	<.0001	0.82	<.0001	0.90	0.005	0.93	0.054	1.09	0.010	1.08	0.020	0.82	0.003	0.79	<.0001
Barrio Quartile 4 (Lowest barrio rank)	0.69	<.0001	0.71	<.0001	0.52	<.0001	0.70	<.0001	0.78	<.0001	0.82	<.0001	1.11	0.004	1.11	0.006	0.64	<.0001	0.69	<.0001
Deprivation index Quartile 1 (highest deprivation, referent)																				
Deprivation Quartile 2	0.93	0.039	0.95	0.041	0.96	0.460	0.99	0.677	0.99	0.763	1.00	0.949	0.99	0.578	1.00	0.890	0.95	0.305	1.00	0.989
Deprivation Quartile 3	0.93	0.047	0.95	0.053	0.98	0.660	0.97	0.321	0.96	0.201	0.97	0.250	0.96	0.117	0.97	0.199	0.82	0.000	0.96	0.165
Deprivation Quartile 4 (lowest deprivation)	0.86	0.000	0.89	0.001	0.98	0.766	0.96	0.2502	0.89	0.001	0.91	0.002	0.92	0.007	0.93	0.013	0.73	<.0001	0.86	0.001
Inequality Quartile 1 (highest inequality, referent)																				
Inequality Quartile 2	0.94	0.110	0.94	0.031	0.95	0.374	0.98	0.387	0.93	0.048	0.96	0.114	0.99	0.782	1.00	0.903	1.04	0.529	0.94	0.098
Inequality Quartile 3	0.93	0.039	0.94	0.039	0.87	0.012	0.91	0.002	0.90	0.002	0.91	0.002	0.97	0.350	0.98	0.449	1.02	0.771	0.96	0.321
Inequality Quartile 4 (lowest inequality)	0.87	0.000	0.89	0.001	0.83	0.000	0.98	0.4481	0.87	<.0001	0.92	0.007	0.97	0.262	0.97	0.242	1.01	0.829	0.99	0.857
Constant	0.03	<.0001	0.03	<.0001	0.43	<.0001	0.34	<.0001	0.17	<.0001	0.16	<.0001	0.02	<.0001	0.02	<.0001	0.27	<.0001	0.25	<.0001
ICC	0.003		0.002		0.01		0.01		0.00		0.00		0.00		0.00		0.01		0.01	
log likelihood	816367		816378		659131		659000		744244		744299		758586		758633		756753		756811	

In Tables 4-13 through 4-17 I show the same geographic comparisons for the Hispanic population. I separated results into discrete tables by health condition because I compare both the final level 2 results and the gender-barrio rank interactions across geographic levels, and putting all results in a single table was difficult to interpret.

I present geographic comparisons for diabetes among Hispanics in Table 4-13. There are no substantial differences between using census tracts and socially defined neighborhoods for diabetes.

I present geographic comparisons for obesity among Hispanics in Table 4-14. There are a few differences between the geographic estimates for obesity. The size of the difference in odds of being obese is larger between barrio rank quartile 4 and barrio rank quartile 1 for socially defined neighborhoods compared to census tracts. However, the difference between deprivation quartiles 1 and 2 were not significant for socially defined neighborhoods but were significant for census tracts.

I present geographic comparisons for hypertension among Hispanics in Table 4-15. The primary difference between the geographic units is in the interpretation of the difference between barrio quartiles 1 and 3. Although the size of the effect is about the same, in the census tract model the difference is not statistically significant at the alpha=0.05 level, whereas it is significant for the socially defined neighborhoods. Depending on a researcher’s adherence to specific alpha levels, interpretation of the models could lead to different conclusions.

I present geographic comparisons for depression among Hispanics in Table 4-16. Similar to diabetes, there were no substantial differences between using census tracts and socially defined neighborhoods for depression.

I present geographic comparisons for smoking among Hispanics in Table 4-17. The primary difference between the two geographic units was between deprivation quartiles. The socially defined neighborhood analyses demonstrated a stronger gradient between the first deprivation quartile and the other three. Although census tract analyses generally showed a similar pattern, there was not a statistically significant difference between the quartiles 1 and 3 for census tracts, but there was a significant (and more substantive) difference for socially defined neighborhoods.

Table 4-13. Comparisons of final models for type 2 diabetes between census tract and socially defined neighborhoods for Hispanic patients in Denver, Colorado (N=48,386)

	Census tract		Socially-defined neighborhoods		Census tract		Socially-defined neighborhoods	
	L2: inequality quartiles		L2: inequality quartiles		Interactions: gender*barrio		Interactions: gender*barrio	
	OR	p	OR	p	OR	p	OR	p
Level 1 covariates								
Spanish speaking (English speaking, referent)	1.38	<.0001	1.38	<.0001	1.38	<.0001	1.38	<.0001
Average Age (mean centered)	1.06	<.0001	1.06	<.0001	1.06	<.0001	1.06	<.0001
Female	0.66	<.0001	0.66	<.0001	0.62	<.0001	0.62	<.0001
Current smoker	1.04	0.27	1.04	0.27	1.04	0.27	1.04	0.27
Comorbidities (0 conditions, referent)								
1 comorbid condition	1.05	0.14	1.05	0.15	1.05	0.14	1.05	0.15
2 comorbid conditions	1.22	<.0001	1.22	<.0001	1.22	<.0001	1.22	<.0001
3+ comorbid conditions	1.58	<.0001	1.58	<.0001	1.58	<.0001	1.58	<.0001
Average BMI (mean centered)	1.09	<.0001	1.09	<.0001	1.09	<.0001	1.09	<.0001
Visits (Less than 22 visits, referent)								
22-52 (Q2)	2.09	<.0001	2.09	<.0001	2.10	<.0001	2.10	<.0001
53-114 (Q3)	3.28	<.0001	3.28	<.0001	3.29	<.0001	3.29	<.0001
115+ (Q4)	5.12	<.0001	5.11	<.0001	5.13	<.0001	5.13	<.0001
Insurance type (private insurace, referent)								
Medicaid	1.86	<.0001	1.86	<.0001	1.86	<.0001	1.87	<.0001
Medicare	1.84	<.0001	1.84	<.0001	1.84	<.0001	1.84	<.0001
Self pay	2.03	<.0001	2.04	<.0001	2.04	<.0001	2.04	<.0001
Other insurance	1.87	<.0001	1.87	<.0001	1.87	<.0001	1.87	<.0001
Other type of payment	1.11	0.30	1.11	0.30	1.11	0.30	1.11	0.29
Missing payment information	1.77	<.0001	1.77	<.0001	1.77	<.0001	1.77	<.0001
Level 2 covariates								
Barrio Quartile 1 (Highest barrio rank, referent)								
Barrio Quartile 2	0.96	0.26	0.96	0.18	0.90	0.05	0.90	0.04
Barrio Quartile 3	0.78	<.0001	0.79	<.0001	0.74	<.0001	0.74	<.0001
Barrio Quartile 4 (Lowest barrio rank)	0.67	<.0001	0.67	<.0001	0.63	<.0001	0.63	<.0001
Deprivation index Quartile 1 (highest deprivation, referent)								
Deprivation Quartile 2	0.97	0.33	0.97	0.45	0.97	0.34	0.98	0.45
Deprivation Quartile 3	0.96	0.36	0.97	0.38	0.96	0.36	0.97	0.38
Deprivation Quartile 4 (lowest deprivation)	0.93	0.19	0.94	0.20	0.93	0.19	0.94	0.20
Inequality Quartile 1 (highest inequality, referent)								
Inequality Quartile 2	0.99	0.79	0.98	0.67	0.99	0.79	0.98	0.67
Inequality Quartile 3	0.97	0.40	0.97	0.40	0.97	0.41	0.97	0.41
Inequality Quartile 4 (lowest inequality)	0.98	0.71	0.98	0.65	0.98	0.70	0.98	0.65
Female*Barrio Quartile 2					1.10	0.11	1.10	0.11
Female*Barrio Quartile 3					1.10	0.19	1.10	0.19
Female*Barrio Quartile 4					1.11	0.29	1.12	0.28
Constant	0.069	<.0001	0.07	<.0001	0.072	<.0001	0.07	<.0001
ICC	0.001		0.00		0.001		0.0004	
log likelihood	241533.9		241511.0		241563.8		241541.2	

Table 4-14. Comparisons of final models for obesity between census tract and socially defined neighborhoods for Hispanic patients in Denver, Colorado (N=48,386)

	Census tract		Socially-defined neighborhoods		Census tract		Socially-defined neighborhoods	
	L2: inequality quartiles		L2: inequality quartiles		Interactions: gender*barrio		Interactions: gender*barrio	
	OR	p	OR	p	OR	p	OR	p
Level 1 covariates								
Spanish speaking (English speaking, referent)	0.80	<.0001	0.80	<.0001	0.80	<.0001	0.80	<.0001
Average Age (mean centered)	1.00	<.0001	1.00	<.0001	1.00	<.0001	1.00	<.0001
Female	1.14	<.0001	1.14	<.0001	1.22	<.0001	1.22	<.0001
Current smoker	0.72	<.0001	0.72	<.0001	0.72	<.0001	0.72	<.0001
Comorbidities (0 conditions, referent)								
1 comorbid condition	1.28	<.0001	1.28	<.0001	1.28	<.0001	1.28	<.0001
2 comorbid conditions	1.31	<.0001	1.31	<.0001	1.31	<.0001	1.31	<.0001
3+ comorbid conditions	1.21	<.0001	1.21	<.0001	1.21	<.0001	1.21	<.0001
Visits (Less than 22 visits, referent)	1.03	0.26	1.03	0.24	1.03	0.33	1.03	0.31
22-52 (Q2)								
53-114 (Q3)	1.09	0.003	1.09	0.003	1.09	0.005	1.09	0.004
115+ (Q4)	1.24	<.0001	1.24	<.0001	1.24	<.0001	1.24	<.0001
Insurance type (private insurace, referent)	1.18	<.0001	1.18	<.0001	1.18	<.0001	1.18	<.0001
Medicaid								
Medicare	1.12	0.03	1.12	0.02	1.12	0.02	1.12	0.02
Self pay	0.99	0.80	0.99	0.81	0.99	0.75	0.99	0.76
Other insurance	1.05	0.34	1.06	0.32	1.05	0.34	1.05	0.33
Other type of payment	0.96	0.54	0.96	0.53	0.96	0.52	0.96	0.51
Missing payment information	1.21	<.0001	1.22	<.0001	1.21	<.0001	1.22	<.0001
Level 2 covariates								
Barrio Quartile 1 (Highest barrio rank, referent)								
Barrio Quartile 2	0.98	0.65	0.94	0.27	1.02	0.68	0.98	0.75
Barrio Quartile 3	0.82	0.00	0.78	<.0001	0.87	0.05	0.82	0.01
Barrio Quartile 4 (Lowest barrio rank)	0.65	<.0001	0.55	<.0001	0.77	0.00	0.65	<.0001
(highest deprivation, referent)								
Deprivation Quartile 2	0.94	0.03	0.95	0.30	0.94	0.04	0.95	0.31
Deprivation Quartile 3	0.93	0.06	0.96	0.44	0.93	0.07	0.96	0.46
Deprivation Quartile 4 (lowest deprivation)	0.96	0.42	1.01	0.93	0.96	0.44	1.01	0.89
(highest inequality, referent)								
Inequality Quartile 2	1.00	0.97	1.04	0.48	1.00	0.97	1.04	0.49
Inequality Quartile 3	0.93	0.11	1.01	0.87	0.93	0.11	1.01	0.88
Inequality Quartile 4 (lowest inequality)	0.96	0.41	0.97	0.65	0.96	0.41	0.97	0.64
Female*Barrio Quartile 2					0.94	0.18	0.94	0.16
Female*Barrio Quartile 3					0.91	0.09	0.91	0.08
Female*Barrio Quartile 4					0.76	<.0001	0.76	<.0001
Constant	0.66	<.0001	0.67	<.0001	0.63	<.0001	0.65	<.0001
ICC	0.01		0.01		0.01		0.01	
log likelihood	206921.6		206894.0		206944.0		206916.6	

Table 4-15. Comparisons of final models for hypertension between census tract and socially defined neighborhoods for Hispanic patients in Denver, Colorado (N=49,493)

	Census tract		Socially-defined neighborhoods		Census tract		Socially-defined neighborhoods	
	L2: inequality quartiles		L2: inequality quartiles		Interactions: gender*barrio		Interactions: gender*barrio	
	OR	p	OR	p	OR	p	OR	p
Level 1 covariates								
Spanish speaking (English speaking, referent)	0.99	0.69	0.99	0.79	0.99	0.69	0.99	0.79
Average Age (mean centered)	1.08	<.0001	1.08	<.0001	1.08	<.0001	1.08	<.0001
Female	0.49	<.0001	0.49	<.0001	0.49	<.0001	0.49	<.0001
Current smoker	0.90	0.00	0.90	0.00	0.90	0.00	0.90	0.00
Comorbidities (0 conditions, referent)								
1 comorbid condition	1.45	<.0001	1.45	<.0001	1.45	<.0001	1.45	<.0001
2 comorbid conditions	1.91	<.0001	1.90	<.0001	1.91	<.0001	1.90	<.0001
3+ comorbid conditions	3.87	<.0001	3.87	<.0001	3.87	<.0001	3.87	<.0001
Visits (Less than 22 visits, referent)	2.18	<.0001	2.18	<.0001	2.18	<.0001	2.18	<.0001
22-52 (Q2)								
53-114 (Q3)	3.30	<.0001	3.30	<.0001	3.31	<.0001	3.30	<.0001
115+ (Q4)	6.24	<.0001	6.23	<.0001	6.25	<.0001	6.24	<.0001
Insurance type (private insurace, referent)	2.20	<.0001	2.20	<.0001	2.20	<.0001	2.20	<.0001
Medicaid								
Medicare	2.82	<.0001	2.83	<.0001	2.82	<.0001	2.83	<.0001
Self pay	1.75	<.0001	1.75	<.0001	1.75	<.0001	1.75	<.0001
Other insurance	2.27	<.0001	2.27	<.0001	2.27	<.0001	2.27	<.0001
Other type of payment	1.15	0.09	1.16	0.09	1.15	0.09	1.16	0.09
Missing payment information	2.33	<.0001	2.33	<.0001	2.33	<.0001	2.33	<.0001
Level 2 covariates								
Barrio Quartile 1 (Highest barrio rank, referent)								
Barrio Quartile 2	1.02	0.56	1.01	0.80	1.04	0.43	1.03	0.58
Barrio Quartile 3	0.92	0.06	0.91	0.02	0.89	0.06	0.88	0.03
Barrio Quartile 4 (Lowest barrio rank)	0.81	0.00	0.79	<.0001	0.83	0.02	0.81	0.01
(highest deprivation, referent)								
Deprivation Quartile 2	0.98	0.45	0.98	0.60	0.98	0.46	0.98	0.61
Deprivation Quartile 3	0.97	0.45	0.98	0.57	0.97	0.47	0.98	0.58
Deprivation Quartile 4 (lowest deprivation)	0.95	0.31	0.96	0.45	0.95	0.32	0.96	0.46
(highest inequality, referent)								
Inequality Quartile 2	0.98	0.54	0.98	0.53	0.98	0.55	0.98	0.54
Inequality Quartile 3	0.98	0.65	0.98	0.68	0.98	0.65	0.98	0.69
Inequality Quartile 4 (lowest inequality)	0.97	0.42	0.96	0.30	0.97	0.43	0.96	0.31
Female*Barrio Quartile 2					0.97	0.59	0.97	0.60
Female*Barrio Quartile 3					1.06	0.43	1.06	0.43
Female*Barrio Quartile 4					0.96	0.63	0.96	0.63
Constant	0.20	<.0001	0.20	<.0001	0.19	<.0001	0.20	<.0001
ICC	0.00		0.00		0.00		0.00	
log likelihood	244273.0		244242.8		244293.0		244262.8	

Table 4-16. Comparisons of final models for depression between census tract and socially defined neighborhoods for Hispanic patients in Denver, Colorado (N=49,493)

	Census tract		Socially-defined neighborhoods		Census tract		Socially-defined neighborhoods	
	L2: inequality quartiles		L2: inequality quartiles		Interactions: gender*barrio		Interactions: gender*barrio	
	OR	p	OR	p	OR	p	OR	p
Level 1 covariates								
Spanish speaking (English speaking, referent)	0.87	<.0001	0.87	<.0001	0.87	<.0001	0.87	<.0001
Average Age (mean centered)	0.99	<.0001	0.99	<.0001	0.99	<.0001	0.99	<.0001
Female	1.78	<.0001	1.78	<.0001	1.85	<.0001	1.85	<.0001
Current smoker	1.61	<.0001	1.61	<.0001	1.61	<.0001	1.61	<.0001
Comorbidities (0 conditions, referent)								
1 comorbid condition	1.22	<.0001	1.22	<.0001	1.22	<.0001	1.22	<.0001
2 comorbid conditions	1.45	<.0001	1.44	<.0001	1.45	<.0001	1.45	<.0001
3+ comorbid conditions	2.03	<.0001	2.02	<.0001	2.03	<.0001	2.02	<.0001
Visits (Less than 22 visits, referent)	2.59	<.0001	2.59	<.0001	2.59	<.0001	2.58	<.0001
22-52 (Q2)								
53-114 (Q3)	5.04	<.0001	5.04	<.0001	5.02	<.0001	5.02	<.0001
115+ (Q4)	11.09	<.0001	11.09	<.0001	11.06	<.0001	11.06	<.0001
Insurance type (private insurace, referent)	4.32	<.0001	4.32	<.0001	4.31	<.0001	4.31	<.0001
Medicaid								
Medicare	5.02	<.0001	5.02	<.0001	5.03	<.0001	5.03	<.0001
Self pay	3.01	<.0001	3.01	<.0001	3.00	<.0001	3.00	<.0001
Other insurance	4.00	<.0001	4.00	<.0001	4.00	<.0001	4.00	<.0001
Other type of payment	1.78	<.0001	1.78	<.0001	1.78	<.0001	1.78	<.0001
Missing payment information	5.06	<.0001	5.06	<.0001	5.05	<.0001	5.05	<.0001
Level 2 covariates								
Barrio Quartile 1 (Highest barrio rank, referent)								
Barrio Quartile 2	1.06	0.16	1.04	0.29	1.05	0.48	1.03	0.61
Barrio Quartile 3	1.09	0.06	1.08	0.08	1.15	0.05	1.14	0.07
Barrio Quartile 4 (Lowest barrio rank)	1.18	0.00	1.17	0.01	1.42	<.0001	1.41	<.0001
(highest deprivation, referent)								
Deprivation Quartile 2	0.97	0.43	0.96	0.25	0.97	0.41	0.96	0.25
Deprivation Quartile 3	1.00	0.97	0.99	0.89	1.00	1.00	1.00	0.93
Deprivation Quartile 4 (lowest deprivation)	0.93	0.19	0.93	0.16	0.94	0.20	0.93	0.17
(highest inequality, referent)								
Inequality Quartile 2	1.01	0.77	1.01	0.77	1.01	0.77	1.01	0.77
Inequality Quartile 3	1.03	0.49	1.03	0.50	1.03	0.48	1.03	0.48
Inequality Quartile 4 (lowest inequality)	1.01	0.87	1.01	0.80	1.01	0.87	1.01	0.80
Female*Barrio Quartile 2					1.01	0.86	1.01	0.85
Female*Barrio Quartile 3					0.93	0.34	0.93	0.33
Female*Barrio Quartile 4					0.77	0.01	0.77	0.01
Constant	0.02	<.0001	0.02	<.0001	0.02	<.0001	0.02	<.0001
ICC	0.00		0.00		0.00		0.00	
log likelihood	244145.5		244152.2		244167.3		244174.0	

Table 4-17. Comparisons of final models for smoking between census tract and socially defined neighborhoods for Hispanic patients in Denver, Colorado (N=49,493)

	Census tract		Socially-defined neighborhoods		Census tract		Socially-defined neighborhoods	
	L2: inequality quartiles		L2: inequality quartiles		Interactions: gender*barrio		Interactions: gender*barrio	
	OR	p	OR	p	OR	p	OR	p
Level 1 covariates								
Spanish speaking (English speaking, referent)	0.37	<.0001	0.36	<.0001	0.36	<.0001	0.36	<.0001
Average Age (mean centered)	0.99	<.0001	0.99	<.0001	0.99	<.0001	0.99	<.0001
Female	0.62	<.0001	0.62	<.0001	0.57	<.0001	0.57	<.0001
Comorbidities (0 conditions, referent)								
1 comorbid condition	1.13	<.0001	1.13	<.0001	1.13	<.0001	1.13	<.0001
2 comorbid conditions	1.31	<.0001	1.31	<.0001	1.31	<.0001	1.31	<.0001
3+ comorbid conditions	1.17	<.0001	1.17	<.0001	1.17	<.0001	1.17	<.0001
Visits (Less than 22 visits, referent)								
22-52 (Q2)	0.84	<.0001	0.84	<.0001	0.84	<.0001	0.84	<.0001
53-114 (Q3)	0.76	<.0001	0.76	<.0001	0.77	<.0001	0.77	<.0001
115+ (Q4)	0.65	<.0001	0.65	<.0001	0.65	<.0001	0.65	<.0001
Insurance type (private insurace, referent)								
Medicaid	1.75	<.0001	1.74	<.0001	1.75	<.0001	1.74	<.0001
Medicare	1.49	<.0001	1.48	<.0001	1.49	<.0001	1.48	<.0001
Self pay	1.03	0.61	1.03	0.63	1.03	0.60	1.03	0.62
Other insurance	1.16	0.07	1.16	0.07	1.17	0.07	1.16	0.07
Other type of payment	1.00	0.99	1.00	0.96	1.00	0.99	1.00	0.96
Missing payment information	2.70	<.0001	2.70	<.0001	2.70	<.0001	2.69	<.0001
Level 2 covariates								
(Highest barrio rank, referent)								
Barrio Quartile 2	0.94	0.24	0.93	0.21	0.89	0.06	0.88	0.06
Barrio Quartile 3	0.95	0.36	0.97	0.66	0.87	0.06	0.90	0.14
Barrio Quartile 4 (Lowest barrio rank)	0.79	0.00	0.82	0.01	0.76	0.00	0.79	0.01
(highest deprivation, referent)								
Deprivation Quartile 2	0.99	0.70	0.95	0.31	0.99	0.71	0.95	0.32
Deprivation Quartile 3	0.92	0.07	0.83	0.002	0.92	0.08	0.83	0.002
Deprivation Quartile 4 (lowest deprivation)	0.83	0.00	0.76	0.000	0.83	0.005	0.76	0.000
(highest inequality, referent)								
Inequality Quartile 2	1.11	0.05	1.17	0.01	1.11	0.05	1.17	0.01
Inequality Quartile 3	1.13	0.02	1.15	0.02	1.13	0.02	1.15	0.02
Inequality Quartile 4 (lowest inequality)	1.22	0.00	1.26	0.00	1.22	0.00	1.26	0.00
Female*Barrio Quartile 2					1.10	0.12	1.10	0.12
Female*Barrio Quartile 3					1.15	0.05	1.15	0.05
Female*Barrio Quartile 4					1.06	0.57	1.06	0.54
Constant	0.27	<.0001	0.27	<.0001	0.28	<.0001	0.28	<.0001
ICC	0.01		0.01		0.01		0.01	
log likelihood	249852.4		249738.1		249865.8		249750.9	

The next set of sensitivity analyses compares different conceptualizations of barrios. This chapter primarily focused on the barrio rank variable, which prioritized foreign born and non-citizens in characterizing barrios over purely using the percent of Hispanic residents in each neighborhood. Since this is a novel measure, it is important to compare it to other measures, specifically, percent of Hispanic residents and the LPA classes that were used in Chapter 3. Since the LPA classes combined demographic and socioeconomic characteristics (including all of the measures that were included in the deprivation quartiles), the LPA class comparisons were not calculated for the deprivation quartiles.

In Tables 4-18 through 4-22 I compare final models for the three different barrio characterizations for the total population. I present results for diabetes in Table 4-18. The best fitting model was percent Hispanic, followed by barrio rank and the LPA classes. The percent Hispanic and LPA models revealed statistically significant differences between the first and second quartiles that were not present for the barrio rank, but deprivation differences between quartile 1 and 2 were significant in the barrio rank models, and they were not for percent Hispanic. Generally the biggest differences between groups were among LPA classes, which is not surprising because the classes incorporate demographic and socioeconomic factors. Economic inequality was significant at all levels for barrio rank, not significant for differences between quartiles 1 and 3 for the percent Hispanic models or LPA classes. Economic inequality quartiles had larger differences in the barrio rank models.

I present results for obesity in Table 4-19. The best fitting model was barrio rank, followed by percent Hispanic and LPA classes, but all log likelihood values were very similar. Percent Hispanic and LPA classes revealed statistically significant differences between the first and second groups that were not present for the barrio rank. Percent Hispanic had biggest differences between quartiles 1 and 3 and 1 and 4, whereas LPA had biggest differences between classes 1 and 2. Deprivation differences were not significant for any measure. Economic inequality was not significant between quartiles 1-2 or 1-4 for any measure. There were significant differences between inequality quartiles 1-3 for each measure, and the effect size was the largest for barrio rank measure.

I present results for hypertension in Table 4-20. The best fitting model was percent Hispanic, followed by barrio rank and LPA classes. Percent Hispanic and LPA class models revealed statistically significant differences between the first and second groups that were not present for the barrio rank model. Similar to obesity, percent Hispanic had biggest differences between quartiles 1 and 3 and 1 and 4, whereas LPA had biggest differences between class 1 and class 2. Deprivation differences were not significant for any measure except for between the first and fourth groups. Economic inequality differences were not significant between groups 1-2 for any measure. There were significant differences in economic inequality between groups 1-3 and 1-4 for each, and the effect was the largest for barrio rank measure.

I present results for depression in Table 4-21. The best fitting model was the LPA classes, followed by barrio rank and percent Hispanic, but all had similar log likelihood values. There were no differences between groups 1-2 for percent Hispanic or the LPA classes, but there were significant difference for barrio rank. There were significant differences between groups 1-3 for each measure, and between groups 1-4 for barrio rank and percent Hispanic. Deprivation differences were only significant between the first and fourth groups. Economic inequality was not significant between any groups for any measure.

I present results for smoking in Table 4-22. The best fitting model was percent Hispanic, followed by LPA classes and barrio rank. There were no differences between groups 1 and 2 for barrio rank, but significant differences for percent Hispanic and LPA. There were significant differences between groups 1 and 3 and 1 and 4 for each measure, with the largest differences between percent Hispanic quartiles. Deprivation differences were only significant between the first and fourth groups for the barrio rank measure, and for groups 1 and 3 and 1 and 4 for percent Hispanic. Economic inequality was only significant between groups 1 and 2 for the percent Hispanic measure, and not significant between any groups for the other measures.

Table 4-18. Comparison of odds of having type-2 diabetes across three measures of neighborhood-level "barrio" characterizations for adults 25-84 with an outpatient visit in 2014/2015 (N=149,234)

	Barrio rank		Percent Hispanic		LPA classes	
	OR	p value	OR	p value	OR	p value
Level 1 covariates						
Race (NH white, referent)						
Hispanic - English speaking	2.18	<.0001	2.15	<.0001	2.17	<.0001
Hispanic - Spanish speaking	2.89	<.0001	2.87	<.0001	2.89	<.0001
NH black	2.00	<.0001	1.99	<.0001	2.00	<.0001
NH Other race	1.96	<.0001	1.95	<.0001	1.95	<.0001
Missing race/ethnicity	1.38	<.0001	1.37	<.0001	1.38	<.0001
Average Age (mean centered)	1.05	<.0001	1.05	<.0001	1.05	<.0001
Female	0.68	<.0001	0.68	<.0001	0.68	<.0001
Current smoker	1.10	<.0001	1.09	<.0001	1.10	<.0001
Comorbidities (0 conditions, referent)						
1 comorbid condition	1.12	<.0001	1.12	<.0001	1.12	<.0001
2 comorbid conditions	1.37	<.0001	1.37	<.0001	1.37	<.0001
3+ comorbid conditions	1.80	<.0001	1.80	<.0001	1.81	<.0001
Average BMI (mean centered)	1.10	<.0001	1.10	<.0001	1.10	<.0001
Visits (Less than 22 visits, referent)						
22-52 (Q2)	1.89	<.0001	1.89	<.0001	1.89	<.0001
53-114 (Q3)	2.81	<.0001	2.81	<.0001	2.81	<.0001
115+ (Q4)	4.30	<.0001	4.30	<.0001	4.30	<.0001
Insurance type (private insurace, referent)						
Medicaid	2.23	<.0001	2.22	<.0001	2.23	<.0001
Medicare	2.37	<.0001	2.36	<.0001	2.38	<.0001
Self pay	2.19	<.0001	2.18	<.0001	2.20	<.0001
Other insurance	2.33	<.0001	2.33	<.0001	2.33	<.0001
Other type of payment	1.02	0.8088	1.02	0.8042	1.02	0.7876
Missing payment information	1.99	<.0001	1.99	<.0001	2.00	<.0001
Level 2 covariates						
(Highest barrio/% Hispanic/barrio class)						
Barrio/% HispanicQuartile 2 or Class 2	0.98	0.4575	0.90	0.0008	0.83	<.0001
Barrio/% HispanicQuartile 3 or Class 3	0.83	<.0001	0.80	<.0001	0.77	<.0001
(Highest barrio/% Hispanic/barrio class)	0.71	<.0001	0.66	<.0001	0.69	<.0001
(highest deprivation, referent)						
Deprivation Quartile 2	0.95	0.0406	0.96	0.0991		
Deprivation Quartile 3	0.95	0.0529	0.95	0.058		
Deprivation Quartile 4 (lowest deprivation)	0.89	0.0005	0.88	0.0002		
(highest inequality, referent)						
Inequality Quartile 2	0.94	0.031	0.93	0.0175	0.95	0.1169
Inequality Quartile 3	0.94	0.0392	0.95	0.0631	0.96	0.1627
Inequality Quartile 4 (lowest inequality)	0.89	0.0007	0.91	0.0025	0.91	0.0053
Constant	0.03	<.0001	0.03	<.0001	0.03	<.0001
ICC	0.002		0.00		0.00	
log likelihood	816378		816535.5		816139.8	

Table 4-19. Comparison of odds of having obesity across three measures of neighborhood-level "barrio" characterizations for adults 25-84 with an outpatient visit in 2014/2015 (N=149,234)

	Barrio rank		Percent Hispanic		LPA classes	
	OR	p value	OR	p value	OR	p value
Level 1 covariates						
Race (NH white, referent)						
Hispanic - English speaking	1.67	<.0001	1.67	<.0001	1.67	<.0001
Hispanic - Spanish speaking	1.33	<.0001	1.32	<.0001	1.33	<.0001
NH black	1.61	<.0001	1.61	<.0001	1.61	<.0001
NH Other race	0.68	<.0001	0.68	<.0001	0.68	<.0001
Missing race/ethnicity	1.13	<.0001	1.13	<.0001	1.13	<.0001
Average Age (mean centered)	1.00	0.254	1.00	0.279	1.00	0.184
Female	1.09	<.0001	1.09	<.0001	1.09	<.0001
Current smoker	0.80	<.0001	0.80	<.0001	0.80	<.0001
Comorbidities (0 conditions, referent)						
1 comorbid condition	1.28	<.0001	1.27	<.0001	1.28	<.0001
2 comorbid conditions	1.38	<.0001	1.38	<.0001	1.38	<.0001
3+ comorbid conditions	1.37	<.0001	1.37	<.0001	1.37	<.0001
Visits (Less than 22 visits, referent)						
22-52 (Q2)	1.09	<.0001	1.09	<.0001	1.09	<.0001
53-114 (Q3)	1.15	<.0001	1.15	<.0001	1.15	<.0001
115+ (Q4)	1.26	<.0001	1.26	<.0001	1.26	<.0001
Insurance type (private insurace, referent)						
Medicaid	1.17	<.0001	1.16	<.0001	1.16	<.0001
Medicare	1.23	<.0001	1.22	<.0001	1.23	<.0001
Self pay	1.03	0.303	1.03	0.37	1.03	0.307
Other insurance	0.99	0.694	0.98	0.657	0.98	0.679
Other type of payment	0.87	<.0001	0.87	<.0001	0.87	<.0001
Missing payment information	1.22	<.0001	1.22	<.0001	1.22	<.0001
Level 2 covariates						
(Highest barrio/% Hispanic/barrio class)						
Barrio/% HispanicQuartile 2 or Class 2	1.00	0.913	0.88	9E-04	0.73	<.0001
Barrio/% HispanicQuartile 3 or Class 3	0.82	<.0001	0.67	<.0001	0.70	<.0001
Barrio/% HispanicQuartile 4 or Class 4 (Highest barrio/% Hispanic/barrio class)	0.70	<.0001	0.56	<.0001	0.64	<.0001
(highest deprivation, referent)						
Deprivation Quartile 2	0.99	0.677	1.01	0.734		
Deprivation Quartile 3	0.97	0.321	1.00	0.859		
Deprivation Quartile 4 (lowest deprivation)	0.96	0.25	0.97	0.286		
Inequality Quartile 1						
Inequality Quartile 2	0.98	0.3870	0.98	0.481	1.02	0.546
Inequality Quartile 3	0.91	0.002	0.93	0.004	0.95	0.036
Inequality Quartile 4 (lowest inequality)	0.98	0.448	0.97	0.331	1.00	0.928
Constant	0.34	<.0001	0.36	<.0001	0.36	<.0001
ICC	0.01		0.01		0.02	
log likelihood	658999.9		658980.7		658971.2	

Table 4-20. Comparison of odds of having hypertension across three measures of neighborhood-level "barrio" characterizations for adults 25-84 with an outpatient visit in 2014/2015 (N=151,027)

	Barrio rank		Percent Hispanic		LPA classes	
	OR	p value	OR	p value	OR	p value
Level 1 covariates						
Race (NH white, referent)						
Hispanic - English speaking	1.21	<.0001	1.21	<.0001	1.22	<.0001
Hispanic - Spanish speaking	1.24	<.0001	1.23	<.0001	1.24	<.0001
NH black	2.05	<.0001	2.05	<.0001	2.06	<.0001
NH Other race	1.08	0.013	1.08	0.0167	1.08	0.0118
Missing race/ethnicity	0.94	0.097	0.94	0.0889	0.94	0.1029
Average Age (mean centered)	1.07	<.0001	1.07	<.0001	1.07	<.0001
Female	0.57	<.0001	0.56	<.0001	0.57	<.0001
Current smoker	1.09	<.0001	1.09	<.0001	1.10	<.0001
Comorbidities (0 conditions, referent)						
1 comorbid condition	1.39	<.0001	1.39	<.0001	1.39	<.0001
2 comorbid conditions	1.96	<.0001	1.96	<.0001	1.96	<.0001
3+ comorbid conditions	4.21	<.0001	4.21	<.0001	4.22	<.0001
Visits (Less than 22 visits, referent)						
22-52 (Q2)	2.01	<.0001	2.01	<.0001	2.01	<.0001
53-114 (Q3)	2.98	<.0001	2.98	<.0001	2.98	<.0001
115+ (Q4)	5.33	<.0001	5.33	<.0001	5.33	<.0001
Insurance type (private insurace, referent)						
Medicaid	2.04	<.0001	2.03	<.0001	2.04	<.0001
Medicare	2.82	<.0001	2.82	<.0001	2.82	<.0001
Self pay	1.59	<.0001	1.58	<.0001	1.59	<.0001
Other insurance	2.25	<.0001	2.25	<.0001	2.25	<.0001
Other type of payment	1.11	0.015	1.11	0.015	1.11	0.0146
Missing payment information	2.35	<.0001	2.35	<.0001	2.36	<.0001
Level 2 covariates						
(Highest barrio/% Hispanic/barrio class)						
Barrio/% HispanicQuartile 2 or Class 2	1.05	0.17	0.93	0.0192	0.87	0.0003
Barrio/% HispanicQuartile 3 or Class 3	0.93	0.054	0.87	<.0001	0.92	0.0317
Barrio/% HispanicQuartile 4 or Class 4 (Highest barrio/% Hispanic/barrio class)	0.82	<.0001	0.76	<.0001	0.77	<.0001
(highest deprivation, referent)						
Deprivation Quartile 2	1.00	0.949	1.00	0.8872		
Deprivation Quartile 3	0.97	0.25	0.97	0.235		
Deprivation Quartile 4 (lowest deprivation)	0.91	0.002	0.91	0.0012		
Inequality Quartile 1						
Inequality Quartile 2	0.96	0.1142	0.96	0.1736	0.99	0.6783
Inequality Quartile 3	0.91	0.002	0.94	0.0234	0.94	0.0361
Inequality Quartile 4 (lowest inequality)	0.92	0.007	0.94	0.0488	0.95	0.0622
Constant	0.16	<.0001	0.16	<.0001	0.16	<.0001
ICC	0.00		0.00		0.00	
log likelihood	744298.6		744317.9		744154.7	

Table 4-21. Comparison of odds of having depression across three measures of neighborhood-level "barrio" characterizations for adults 25-84 with an outpatient visit in 2014/2015 (N=151,027)

	Barrio rank		Percent Hispanic		LPA classes	
	OR	p value	OR	p value	OR	p value
Level 1 covariates						
Race (NH white, referent)						
Hispanic - English speaking	0.84	<.0001	0.85	<.0001	0.84	<.0001
Hispanic - Spanish speaking	0.74	<.0001	0.75	<.0001	0.74	<.0001
NH black	0.58	<.0001	0.58	<.0001	0.59	<.0001
NH Other race	0.62	<.0001	0.62	<.0001	0.62	<.0001
Missing race/ethnicity	0.82	<.0001	0.82	<.0001	0.82	<.0001
Average Age (mean centered)	0.99	<.0001	0.99	<.0001	0.99	<.0001
Female	1.59	<.0001	1.59	<.0001	1.59	<.0001
Current smoker	1.60	<.0001	1.60	<.0001	1.59	<.0001
Comorbidities (0 conditions, referent)						
1 comorbid condition	1.24	<.0001	1.24	<.0001	1.24	<.0001
2 comorbid conditions	1.53	<.0001	1.53	<.0001	1.53	<.0001
3+ comorbid conditions	2.18	<.0001	2.18	<.0001	2.18	<.0001
Visits (Less than 22 visits, referent)						
22-52 (Q2)	2.58	<.0001	2.58	<.0001	2.58	<.0001
53-114 (Q3)	4.90	<.0001	4.89	<.0001	4.90	<.0001
115+ (Q4)	11.52	<.0001	11.52	<.0001	11.52	<.0001
Insurance type (private insurace, referent)						
Medicaid	4.27	<.0001	4.27	<.0001	4.27	<.0001
Medicare	5.51	<.0001	5.52	<.0001	5.52	<.0001
Self pay	2.94	<.0001	2.94	<.0001	2.94	<.0001
Other insurance	4.06	<.0001	4.06	<.0001	4.07	<.0001
Other type of payment	1.29	<.0001	1.28	<.0001	1.29	<.0001
Missing payment information	4.99	<.0001	5.00	<.0001	5.00	<.0001
Level 2 covariates						
(Highest barrio/% Hispanic/barrio class)						
Barrio/% HispanicQuartile 2 or Class 2	1.06	0.0489	1.04	0.1457	1.02	0.4941
Barrio/% HispanicQuartile 3 or Class 3	1.08	0.0203	1.10	0.0011	1.12	0.0002
Barrio/% HispanicQuartile 4 or Class 4 (Highest barrio/% Hispanic/barrio class)	1.11	0.0057	1.08	0.0192	1.01	0.706
(highest deprivation, referent)						
Deprivation Quartile 2	1.00	0.8897	0.99	0.6962		
Deprivation Quartile 3	0.97	0.1986	0.96	0.0791		
Deprivation Quartile 4 (lowest deprivation)	0.93	0.013	0.93	0.0077		
Inequality Quartile 1						
Inequality Quartile 2	1.00	0.9031	1.00	0.9404	1.01	0.5698
Inequality Quartile 3	0.98	0.4488	0.99	0.6166	0.99	0.7206
Inequality Quartile 4 (lowest inequality)	0.97	0.2421	0.97	0.317	0.99	0.6569
Constant	0.02	<.0001	0.02	<.0001	0.02	<.0001
ICC	0.00		0.00		0.00	
log likelihood	758633.1		758628.8		758648.8	

Table 4-22. Comparison of odds of being a current smoker across three measures of neighborhood-level "barrio" characterizations for adults 25-84 with an outpatient visit in 2014/2015 (N=151,027)

	Barrio rank		Percent Hispanic		LPA classes	
	OR	p value	OR	p value	OR	p value
Level 1 covariates						
Race (NH white, referent)						
Hispanic - English speaking	0.95	0.0189	0.95	0.0124	0.96	0.0274
Hispanic - Spanish speaking	0.33	<.0001	0.33	<.0001	0.33	<.0001
NH black	1.31	<.0001	1.31	<.0001	1.32	<.0001
NH Other race	0.66	<.0001	0.66	<.0001	0.66	<.0001
Missing race/ethnicity	1.11	0.0046	1.11	0.0055	1.11	0.0043
Average Age (mean centered)	0.99	<.0001	0.99	<.0001	0.99	<.0001
Female	0.68	<.0001	0.68	<.0001	0.68	<.0001
Comorbidities (0 conditions, referent)						
1 comorbid condition	1.18	<.0001	1.18	<.0001	1.18	<.0001
2 comorbid conditions	1.41	<.0001	1.41	<.0001	1.41	<.0001
3+ comorbid conditions	1.50	<.0001	1.50	<.0001	1.50	<.0001
Visits (Less than 22 visits, referent)						
22-52 (Q2)	0.88	<.0001	0.88	<.0001	0.88	<.0001
53-114 (Q3)	0.79	<.0001	0.79	<.0001	0.79	<.0001
115+ (Q4)	0.62	<.0001	0.62	<.0001	0.62	<.0001
Insurance type (private insurace, referent)						
Medicaid	2.15	<.0001	2.14	<.0001	2.15	<.0001
Medicare	2.16	<.0001	2.16	<.0001	2.17	<.0001
Self pay	1.16	0.0016	1.16	0.0019	1.17	0.0013
Other insurance	1.37	<.0001	1.37	<.0001	1.38	<.0001
Other type of payment	0.88	0.0091	0.88	0.0089	0.88	0.0089
Missing payment information	3.04	<.0001	3.04	<.0001	3.05	<.0001
Level 2 covariates						
(Highest barrio/% Hispanic/barrio class)						
Barrio/% HispanicQuartile 2 or Class 2	0.93	0.1285	0.86	0.0008	0.79	0.0001
Barrio/% HispanicQuartile 3 or Class 3	0.79	<.0001	0.76	<.0001	0.85	0.015
Barrio/% HispanicQuartile 4 or Class 4 (Highest barrio/% Hispanic/barrio class)	0.69	<.0001	0.63	<.0001	0.69	<.0001
Deprivation index Quartile 1 (highest deprivation, referent)						
Deprivation Quartile 2	1.00	0.9885	1.00	0.9747		
Deprivation Quartile 3	0.96	0.165	0.94	0.0431		
Deprivation Quartile 4 (lowest deprivation)	0.86	0.0005	0.84	<.0001		
Inequality Quartile 1 (highest inequality, referent)						
Inequality Quartile 2	0.94	0.0981	0.93	0.0414	0.97	0.3681
Inequality Quartile 3	0.96	0.3208	0.96	0.2136	0.98	0.5084
Inequality Quartile 4 (lowest inequality)	0.99	0.8567	0.99	0.7309	1.01	0.7279
Constant	0.25	<.0001	0.26	<.0001	0.23	<.0001
ICC	0.01		0.01		0.02	
log likelihood	756810.7		756747.8		756746.6	

In Tables 4-23 through 4-27 I present the same comparisons of barrio characteristics for the Hispanic population, and also include comparisons for the gender interactions for each measure. I present results for diabetes among Hispanics in Table 4-23. The best fitting model was percent Hispanic, followed by barrio rank and LPA classes. There were only two substantial differences between all of the measures. The group 1 and group 2 differences were not significant for the barrio rank measure but were significant for percent Hispanic and LPA classes. Additionally, Hispanic women living in Class 3 neighborhoods (mid/high SES) had higher odds of diabetes compared to women living in Class 1 neighborhoods, but these differences were not significant for the other measures.

I present results for obesity among Hispanics in Table 4-24. Model fit was slightly better for the LPA classes, followed by barrio rank and percent Hispanic. Comparisons across LPA classes revealed lower odds of obesity for Hispanics living in Class 2 neighborhoods compared to Class 1 neighborhoods, and these differences were not present between quartiles 1 and 2 for barrio rank or percent Hispanic. The effect size was largest between quartiles 1 and 4 for percent Hispanic, indicating that Hispanics living in the least Hispanic neighborhoods had much lower odds of obesity compared to those living in neighborhoods with the most Hispanic residents. In the gender interaction results, women living in Class 2 (low SES) neighborhoods had lower odds of obesity than their counterparts in Class 1 neighborhoods, and these differences were not present for quartiles 1 and 2 for the other measures. Women living in the third quartile of percent Hispanic neighborhoods also had lower odds of obesity compared to their counterparts living in the most concentrated Hispanic neighborhoods, and these differences were not present for the other measures.

I present results for hypertension among Hispanics in Table 4-25. Model fit was the best for the percent Hispanic measure, followed by barrio rank and LPA classes. The only substantial difference between all measures was that there were significant differences between quartiles 1 and 2 for percent Hispanic. Those living in slightly less concentrated Hispanic neighborhoods had 7% lower odds of having hypertension compared to those living in the most concentrated Hispanic neighborhoods.

I present results for depression among Hispanics in Table 4-26. Model fit was best for the LPA classes in all models, followed by barrio rank and percent Hispanic in the models without the interaction, and percent Hispanic followed by barrio rank in the interaction models. The barrio rank and percent Hispanic models showed lower odds of depression for Hispanics living in the highest ranked barrio neighborhoods compared to the lowest ranked barrio neighborhoods (quartile 1 vs. quartile 4), but the LPA classes showed similar differences between Class 1 (barrio) and Class 3 (mid/high SES) neighborhoods. Differences were not significant between Class 1 and Class 4 (high SES) neighborhoods. Similarly for the gender interactions, the differences in the LPA classes were between Class 1 and Class 3 neighborhoods instead of the first and fourth quartiles for the other two measures. The percent Hispanic measure revealed the largest differences in gender across quartiles, with women living in neighborhoods with fewer Hispanics having 20-30% lower odds of being diagnosed with depression.

Finally, I present results for smoking among Hispanics in Table 4-27. Model fit was best for percent Hispanic in all models, followed by barrio rank and LPA classes in the models without the interaction, and LPA classes followed by barrio rank in the interaction models. For the barrio rank and percent Hispanic measures, quartile 4 neighborhoods have lower odds of smoking than quartile 1 neighborhoods, but this difference was not found between Class 1 and

Class 4 neighborhoods. Additionally, higher odds of smoking in quartiles 2 and 3 compared to quartile 1 for barrio rank and percent Hispanic were not significant between LPA classes. Gender interaction models revealed significantly higher odds of smoking among Hispanic women in quartile 3 compared to quartile 1 for barrio rank, and between Class 2 and Class 1 for the LPA models, but no gender interactions were significant for percent Hispanic models.

Table 4-23. Comparisons of final models for type 2 diabetes between neighborhood barrio rank, percent Hispanic, and four classes from latent profile analysis for Hispanic patients in Denver, Colorado (N=48,386)

	L2: inequality quartiles						Interactions: gender*barrio					
	Barrio Rank		Percent Hispanic		LPA Classes		Barrio Rank		Percent Hispanic		LPA Classes	
	OR	p	OR	p	OR	p	OR	p	OR	p	OR	p
Level 1 covariates												
Spanish speaking (English speaking, referer	1.38	<.0001	1.39	<.0001	1.39	<.0001	1.38	<.0001	1.39	<.0001	1.38	<.0001
Average Age (mean centered)	1.06	<.0001	1.06	<.0001	1.06	<.0001	1.06	<.0001	1.06	<.0001	1.06	<.0001
Female	0.66	<.0001	0.66	<.0001	0.66	<.0001	0.62	<.0001	0.64	<.0001	0.64	<.0001
Current smoker	1.04	0.27	1.04	0.30	1.04	0.24	1.04	0.27	1.04	0.31	1.04	0.25
Comorbidities (0 conditions, referent)												
1 comorbid condition	1.05	0.14	1.05	0.15	1.05	0.14	1.05	0.14	1.05	0.15	1.05	0.14
2 comorbid conditions	1.22	<.0001	1.22	<.0001	1.22	<.0001	1.22	<.0001	1.22	<.0001	1.22	<.0001
3+ comorbid conditions	1.58	<.0001	1.58	<.0001	1.58	<.0001	1.58	<.0001	1.58	<.0001	1.58	<.0001
Average BMI (mean centered)	1.09	<.0001	1.09	<.0001	1.09	<.0001	1.09	<.0001	1.09	<.0001	1.09	<.0001
Visits (Less than 22 visits, referent)												
22-52 (Q2)	2.09	<.0001	2.09	<.0001	2.09	<.0001	2.10	<.0001	2.10	<.0001	2.09	<.0001
53-114 (Q3)	3.28	<.0001	3.27	<.0001	3.28	<.0001	3.29	<.0001	3.28	<.0001	3.29	<.0001
115+ (Q4)	5.12	<.0001	5.10	<.0001	5.12	<.0001	5.13	<.0001	5.11	<.0001	5.12	<.0001
Insurance type (private insurace, referent)												
Medicaid	1.86	<.0001	1.85	<.0001	1.86	<.0001	1.86	<.0001	1.86	<.0001	1.86	<.0001
Medicare	1.84	<.0001	1.84	<.0001	1.84	<.0001	1.84	<.0001	1.84	<.0001	1.84	<.0001
Self pay	2.03	<.0001	2.02	<.0001	2.03	<.0001	2.04	<.0001	2.02	<.0001	2.04	<.0001
Other insurance	1.87	<.0001	1.87	<.0001	1.87	<.0001	1.87	<.0001	1.87	<.0001	1.87	<.0001
Other type of payment	1.11	0.30	1.11	0.29	1.11	0.29	1.11	0.30	1.11	0.29	1.11	0.28
Missing payment information	1.77	<.0001	1.76	<.0001	1.77	<.0001	1.77	<.0001	1.76	<.0001	1.77	<.0001
Level 2 covariates												
Barrio/Hispanic Quartile/Class 1 (Highest barrio rank, referent)												
Barrio/Hispanic Quartile/Class 1	0.96	0.26	0.87	<.0001	0.86	0.0003	0.90	0.05	0.82	<.0001	0.83	0.001
Barrio/Hispanic Quartile/Class 1	0.78	<.0001	0.76	<.0001	0.79	<.0001	0.74	<.0001	0.74	<.0001	0.69	<.0001
Barrio/Hispanic Quartile/Class 1 (Lowest barrio rank)	0.67	<.0001	0.59	<.0001	0.73	<.0001	0.63	<.0001	0.59	<.0001	0.78	0.0013
Deprivation index Quartile 1 (highest deprivation, referent)												
Deprivation Quartile 2	0.97	0.33	0.98	0.56	0.96	0.24	0.97	0.34	0.98	0.57	0.96	0.24
Deprivation Quartile 3	0.96	0.36	0.95	0.14	0.96	0.28	0.96	0.36	0.95	0.14	0.95	0.27
Deprivation Quartile 4 (lowest deprivation)	0.93	0.19	0.91	0.06	0.92	0.13	0.93	0.19	0.91	0.06	0.91	0.12
Inequality Quartile 1 (highest inequality, referent)												
Inequality Quartile 2	0.99	0.79	0.97	0.41	0.97	0.47	0.99	0.79	0.97	0.42	0.97	0.46
Inequality Quartile 3	0.97	0.40	0.96	0.24	0.95	0.20	0.97	0.41	0.96	0.24	0.95	0.19
Inequality Quartile 4 (lowest inequality)	0.98	0.71	0.97	0.47	0.95	0.29	0.98	0.70	0.97	0.47	0.95	0.28
Female* Quartile/Class 2							1.10	0.11	1.10	0.11	1.06	0.31
Female*Quartile/Class 3							1.10	0.19	1.04	0.68	1.28	0.01
Female*Quartile/Class 4							1.11	0.29	1.01	0.92	0.91	0.25
Constant	0.07	<.0001	0.07	<.0001	0.07	<.0001	0.07	<.0001	0.07	<.0001	0.07	<.0001
ICC	0.001		0.000		0.002		0.001		0.000		0.002	
log likelihood	241533.9		241562.2		241467.5		241563.8		241587.5		241522.4	

Table 4-24. Comparisons of final models for obesity between neighborhood barrio rank, percent Hispanic, and four classes from latent profile analysis for Hispanic patients in Denver, Colorado (N=48,386)

	L2: inequality quartiles							Interactions: gender*barrio					
	Barrio Rank		Percent Hispanic		LPA Classes			Barrio Rank		Percent Hispanic		LPA Classes	
	OR	p	OR	p	OR	p		OR	p	OR	p	OR	p
Level 1 covariates													
Spanish speaking (English speaking, referent)	0.80	<.0001	0.80	<.0001	0.80	<.0001		0.80	<.0001	0.80	<.0001	0.80	<.0001
Average Age (mean centered)	1.00	<.0001	1.00	<.0001	1.00	<.0001		1.00	<.0001	1.00	<.0001	1.00	<.0001
Female	1.14	<.0001	1.14	<.0001	1.14	<.0001		1.22	<.0001	1.20	<.0001	1.21	<.0001
Current smoker	0.72	<.0001	0.72	<.0001	0.72	<.0001		0.72	<.0001	0.72	<.0001	0.72	<.0001
Comorbidities (0 conditions, referent)													
1 comorbid condition	1.28	<.0001	1.28	<.0001	1.28	<.0001		1.28	<.0001	1.28	<.0001	1.28	<.0001
2 comorbid conditions	1.31	<.0001	1.31	<.0001	1.31	<.0001		1.31	<.0001	1.31	<.0001	1.31	<.0001
3+ comorbid conditions	1.21	<.0001	1.21	<.0001	1.21	<.0001		1.21	<.0001	1.20	<.0001	1.21	<.0001
Visits (Less than 22 visits, referent)	1.03	0.2555	1.03	0.2489	1.03	0.2493		1.03	0.3272	1.03	0.31	1.03	0.3344
22-52 (Q2)													
53-114 (Q3)	1.09	0.0028	1.09	0.003	1.09	0.0027		1.09	0.0045	1.09	0.0045	1.09	0.0048
115+ (Q4)	1.24	<.0001	1.24	<.0001	1.24	<.0001		1.24	<.0001	1.24	<.0001	1.24	<.0001
Insurance type (private insurace, referent)	1.18	<.0001	1.18	<.0001	1.18	<.0001		1.18	<.0001	1.17	<.0001	1.18	<.0001
Medicaid													
Medicare	1.12	0.0256	1.11	0.0282	1.12	0.0245		1.12	0.0245	1.11	0.0272	1.12	0.0228
Self pay	0.99	0.8047	0.99	0.6819	0.99	0.8442		0.99	0.7529	0.98	0.6315	0.99	0.802
Other insurance	1.05	0.3359	1.05	0.354	1.05	0.3282		1.05	0.3444	1.05	0.3622	1.05	0.3276
Other type of payment	0.96	0.5378	0.96	0.5475	0.97	0.5596		0.96	0.52	0.96	0.5301	0.96	0.5429
Missing payment information	1.21	<.0001	1.21	<.0001	1.21	<.0001		1.21	<.0001	1.21	<.0001	1.21	<.0001
Level 2 covariates													
Barrio/Hispanic Quartile/Class 1 (Highest barrio rank, referent)													
Barrio/Hispanic Quartile/Class 2	0.98	0.65	0.95	0.18	0.87	0.02		1.02	0.68	1.00	0.96	0.95	0.40
Barrio/Hispanic Quartile/Class 3	0.82	0.00	0.73	<.0001	0.71	<.0001		0.87	0.05	0.80	0.00	0.71	<.0001
Barrio/Hispanic Quartile/Class 4 (Lowest barrio rank)	0.65	<.0001	0.51	<.0001	0.73	<.0001		0.77	0.00	0.62	<.0001	0.85	0.06
Deprivation index Quartile 1 (highest deprivation, referent)													
Deprivation Quartile 2	0.94	0.03	0.95	0.07	0.93	0.03		0.94	0.04	0.95	0.07	0.93	0.03
Deprivation Quartile 3	0.93	0.06	0.94	0.08	0.94	0.11		0.93	0.07	0.94	0.08	0.94	0.11
Deprivation Quartile 4 (lowest deprivation)	0.96	0.42	0.95	0.28	0.93	0.22		0.96	0.44	0.96	0.30	0.93	0.22
Inequality Quartile 1 (highest inequality, referent)													
Inequality Quartile 2	1.00	0.97	1.01	0.85	1.01	0.85		1.00	0.97	1.01	0.87	1.01	0.87
Inequality Quartile 3	0.93	0.11	0.97	0.41	0.94	0.15		0.93	0.11	0.97	0.39	0.94	0.15
Inequality Quartile 4 (lowest inequality)	0.96	0.41	0.98	0.70	0.93	0.15		0.96	0.41	0.98	0.70	0.93	0.14
Female* Quartile/Class 2								0.94	0.18	0.92	0.07	0.88	0.00
Female*Quartile/Class 3								0.91	0.09	0.87	0.04	0.99	0.94
Female*Quartile/Class 4								0.76	<.0001	0.74	<.0001	0.80	<.0001
Constant	0.66	<.0001	0.66	<.0001	0.67	<.0001		0.63	<.0001	0.64	<.0001	0.64	<.0001
ICC	0.010		0.003		0.012			0.010		0.003		0.012	
log likelihood	206921.6		206920.9		206927.0			206944.0		206939.4		206955.8	

Table 4-25. Comparisons of final models for hypertension between neighborhood barrio rank, percent Hispanic, and four classes from latent profile analysis for Hispanic patients in Denver, Colorado (N=49,594)

	L2: inequality quartiles							Interactions: gender*barrio					
	Barrio Rank		Percent Hispanic		LPA Classes			Barrio Rank		Percent Hispanic		LPA Classes	
	OR	p	OR	p	OR	p		OR	p	OR	p	OR	p
Level 1 covariates													
Spanish speaking (English speaking, refe	0.99	0.694	0.99	0.725	0.99	0.7478		0.99	0.687	0.99	0.722	0.99	0.7326
Average Age (mean centered)	1.08	<.0001	1.08	<.0001	1.08	<.0001		1.08	<.0001	1.08	<.0001	1.08	<.0001
Female	0.49	<.0001	0.49	<.0001	0.49	<.0001		0.49	<.0001	0.48	<.0001	0.48	<.0001
Current smoker	0.90	0.00	0.90	0.00	0.90	0.00		0.90	0.00	0.90	0.00	0.90	0.00
Comorbidities (0 conditions, referent)													
1 comorbid condition	1.45	<.0001	1.45	<.0001	1.45	<.0001		1.45	<.0001	1.45	<.0001	1.45	<.0001
2 comorbid conditions	1.91	<.0001	1.90	<.0001	1.90	<.0001		1.91	<.0001	1.90	<.0001	1.90	<.0001
3+ comorbid conditions	3.87	<.0001	3.87	<.0001	3.87	<.0001		3.87	<.0001	3.87	<.0001	3.87	<.0001
Visits (Less than 22 visits, referent)	2.18	<.0001	2.18	<.0001	2.18	<.0001		2.18	<.0001	2.18	<.0001	2.18	<.0001
22-52 (Q2)													
53-114 (Q3)	3.30	<.0001	3.30	<.0001	3.30	<.0001		3.31	<.0001	3.30	<.0001	3.30	<.0001
115+ (Q4)	6.24	<.0001	6.23	<.0001	6.25	<.0001		6.25	<.0001	6.24	<.0001	6.25	<.0001
Insurance type (private insurace, referen	2.20	<.0001	2.19	<.0001	2.20	<.0001		2.20	<.0001	2.19	<.0001	2.20	<.0001
Medicaid													
Medicare	2.82	<.0001	2.82	<.0001	2.83	<.0001		2.82	<.0001	2.81	<.0001	2.83	<.0001
Self pay	1.75	<.0001	1.73	<.0001	1.75	<.0001		1.75	<.0001	1.73	<.0001	1.75	<.0001
Other insurance	2.27	<.0001	2.26	<.0001	2.27	<.0001		2.27	<.0001	2.26	<.0001	2.27	<.0001
Other type of payment	1.15	0.089	1.16	0.084	1.16	0.0817		1.15	0.089	1.16	0.084	1.16	0.0812
Missing payment information	2.33	<.0001	2.31	<.0001	2.33	<.0001		2.33	<.0001	2.31	<.0001	2.33	<.0001
Level 2 covariates													
Barrio/Hispanic Quartile/Class 1 (Highest barrio rank, referent)													
Barrio/Hispanic Quartile/Class 2	1.02	0.56	0.93	0.04	0.96	0.26		1.04	0.43	0.89	0.02	0.95	0.28
Barrio/Hispanic Quartile/Class 3	0.92	0.06	0.85	0.00	0.86	0.00		0.89	0.06	0.83	0.01	0.82	0.01
Barrio/Hispanic Quartile/Class 4 (Lowest barrio rank)	0.81	0.0002	0.74	<.0001	0.84	0.001		0.83	0.02	0.74	0.00	0.87	0.05
Deprivation index Quartile 1 (highest deprivation, referent)													
Deprivation Quartile 2	0.98	0.45	0.98	0.58	0.97	0.34		0.98	0.46	0.98	0.58	0.97	0.34
Deprivation Quartile 3	0.97	0.45	0.97	0.45	0.97	0.48		0.97	0.47	0.97	0.46	0.97	0.48
eprivation Quartile 4 (lowest deprivation)	0.95	0.31	0.96	0.35	0.96	0.44		0.95	0.32	0.96	0.36	0.96	0.43
Inequality Quartile 1 (highest inequality, referent)													
Inequality Quartile 2	0.98	0.54	0.97	0.41	0.97	0.43		0.98	0.55	0.97	0.42	0.97	0.43
Inequality Quartile 3	0.98	0.65	0.99	0.88	0.99	0.85		0.98	0.65	1.00	0.90	0.99	0.84
Inequality Quartile 4 (lowest inequality)	0.97	0.42	0.98	0.55	0.96	0.31		0.97	0.43	0.98	0.55	0.96	0.30
Female* Quartile/Class 2								0.97	0.59	1.08	0.18	1.03	0.67
Female*Quartile/Class 3								1.06	0.43	1.03	0.74	1.09	0.33
Female*Quartile/Class 4								0.96	0.63	0.99	0.90	0.94	0.47
Constant	0.20	<.0001	0.20	<.0001	0.20	<.0001		0.19	<.0001	0.20	<.0001	0.20	<.0001
ICC	0.001		0.001		0.001			0.001		0.001		0.001	
log likelihood	244273.0		244301.0		244262.3			244293.0		244320.2		244290.1	

Table 4-26. Comparisons of final models for hypertension between neighborhood barrio rank, percent Hispanic, and four classes from latent profile analysis for Hispanic patients in Denver, Colorado (N=49,594)

	L2: inequality quartiles							Interactions: gender*barrio					
	Barrio Rank		Percent Hispanic		LPA Classes			Barrio Rank		Percent Hispanic		LPA Classes	
	OR	p	OR	p	OR	p		OR	p	OR	p	OR	p
Level 1 covariates													
Spanish speaking (English speaking, refe	0.87	<.0001	0.87	<.0001	0.86	<.0001		0.87	<.0001	0.87	<.0001	0.87	<.0001
Average Age (mean centered)	0.99	<.0001	0.99	<.0001	0.99	<.0001		0.99	<.0001	0.99	<.0001	0.99	<.0001
Female	1.78	<.0001	1.78	<.0001	1.78	<.0001		1.85	<.0001	1.89	<.0001	1.89	<.0001
Current smoker	1.61	<.0001	1.61	<.0001	1.60	<.0001		1.61	<.0001	1.61	<.0001	1.60	<.0001
Comorbidities (0 conditions, referent)													
1 comorbid condition	1.22	<.0001	1.22	<.0001	1.22	<.0001		1.22	<.0001	1.22	<.0001	1.21	<.0001
2 comorbid conditions	1.45	<.0001	1.45	<.0001	1.45	<.0001		1.45	<.0001	1.45	<.0001	1.44	<.0001
3+ comorbid conditions	2.03	<.0001	2.03	<.0001	2.03	<.0001		2.03	<.0001	2.03	<.0001	2.02	<.0001
Visits (Less than 22 visits, referent)	2.59	<.0001	2.59	<.0001	2.59	<.0001		2.59	<.0001	2.58	<.0001	2.59	<.0001
22-52 (Q2)													
53-114 (Q3)	5.04	<.0001	5.04	<.0001	5.04	<.0001		5.02	<.0001	5.02	<.0001	5.03	<.0001
115+ (Q4)	11.09	<.0001	11.10	<.0001	11.08	<.0001		11.06	<.0001	11.06	<.0001	11.06	<.0001
Insurance type (private insurace, referen	4.32	<.0001	4.33	<.0001	4.31	<.0001		4.31	<.0001	4.31	<.0001	4.30	<.0001
Medicaid													
Medicare	5.02	<.0001	5.03	<.0001	5.01	<.0001		5.03	<.0001	5.03	<.0001	5.01	<.0001
Self pay	3.01	<.0001	3.02	<.0001	3.00	<.0001		3.00	<.0001	3.00	<.0001	2.99	<.0001
Other insurance	4.00	<.0001	4.00	<.0001	3.99	<.0001		4.00	<.0001	4.00	<.0001	3.98	<.0001
Other type of payment	1.78	<.0001	1.78	<.0001	1.78	<.0001		1.78	<.0001	1.78	<.0001	1.78	<.0001
Missing payment information	5.06	<.0001	5.07	<.0001	5.04	<.0001		5.05	<.0001	5.06	<.0001	5.03	<.0001
Level 2 covariates													
Barrio/Hispanic Quartile/Class 1 (Highest barrio rank, referent)													
Barrio/Hispanic Quartile/Class 2	1.06	0.16	1.05	0.17	1.05	0.16		1.05	0.48	1.10	0.12	1.10	0.09
Barrio/Hispanic Quartile/Class 3	1.09	0.06	1.08	0.10	1.19	0.00		1.15	0.05	1.27	0.00	1.49	<.0001
Barrio/Hispanic Quartile/Class 4 (Lowest barrio rank)	1.18	0.00	1.23	0.00	1.00	0.94		1.42	<.0001	1.55	<.0001	1.01	0.92
Deprivation index Quartile 1 (highest deprivation, referent)													
Deprivation Quartile 2	0.97	0.43	0.97	0.31	0.97	0.33		0.97	0.41	0.97	0.31	0.97	0.31
Deprivation Quartile 3	1.00	0.97	1.00	0.98	1.03	0.49		1.00	1.00	1.00	0.93	1.03	0.46
eprivation Quartile 4 (lowest deprivation)	0.93	0.19	0.95	0.27	1.01	0.90		0.94	0.20	0.95	0.30	1.01	0.88
Inequality Quartile 1 (highest inequality, referent)													
Inequality Quartile 2	1.01	0.77	1.01	0.71	1.03	0.46		1.01	0.77	1.01	0.72	1.03	0.46
Inequality Quartile 3	1.03	0.49	1.04	0.31	1.04	0.32		1.03	0.48	1.04	0.30	1.04	0.32
Inequality Quartile 4 (lowest inequality)	1.01	0.87	1.01	0.76	1.03	0.48		1.01	0.87	1.01	0.76	1.03	0.48
Female* Quartile/Class 2								1.01	0.86	0.94	0.35	0.94	0.29
Female*Quartile/Class 3								0.93	0.34	0.80	0.01	0.71	0.00
Female*Quartile/Class 4								0.77	0.01	0.70	0.00	0.98	0.84
Constant	0.02	<.0001	0.02	<.0001	0.02	<.0001		0.02	<.0001	0.02	<.0001	0.02	<.0001
ICC	0.001		0.001		0.001			0.001		0.001		0.001	
log likelihood	244145.5		244157.6		244178.7			244167.3		244164.3		244245.3	

Table 4-27. Comparisons of final models for hypertension between neighborhood barrio rank, percent Hispanic, and four classes from latent profile analysis for Hispanic patients in Denver, Colorado (N=49,594)

	L2: inequality quartiles						Interactions: gender*barrio					
	Barrio Rank		Percent Hispanic		LPA Classes		Barrio Rank		Percent Hispanic		LPA Classes	
	OR	p	OR	p	OR	p	OR	p	OR	p	OR	p
Level 1 covariates												
Spanish speaking (English speaking, referer	0.37	<.0001	0.36	<.0001	0.37	<.0001	0.36	<.0001	0.36	<.0001	0.37	<.0001
Average Age (mean centered)	0.99	<.0001	0.99	<.0001	0.99	<.0001	0.99	<.0001	0.99	<.0001	0.99	<.0001
Female	0.62	<.0001	0.62	<.0001	0.62	<.0001	0.57	<.0001	0.60	<.0001	0.58	<.0001
Comorbidities (0 conditions, referent)												
1 comorbid condition	1.13	<.0001	1.13	<.0001	1.13	<.0001	1.13	<.0001	1.13	<.0001	1.13	<.0001
2 comorbid conditions	1.31	<.0001	1.31	<.0001	1.31	<.0001	1.31	<.0001	1.31	<.0001	1.31	<.0001
3+ comorbid conditions	1.17	<.0001	1.17	<.0001	1.17	<.0001	1.17	<.0001	1.17	<.0001	1.17	<.0001
Visits (Less than 22 visits, referent)												
22-52 (Q2)	0.84	<.0001	0.84	<.0001	0.84	<.0001	0.84	<.0001	0.84	<.0001	0.84	<.0001
53-114 (Q3)	0.76	<.0001	0.76	<.0001	0.76	<.0001	0.77	<.0001	0.76	<.0001	0.77	<.0001
115+ (Q4)	0.65	<.0001	0.65	<.0001	0.65	<.0001	0.65	<.0001	0.65	<.0001	0.65	<.0001
Insurance type (private insurace, referent)												
Medicaid	1.75	<.0001	1.74	<.0001	1.75	<.0001	1.75	<.0001	1.74	<.0001	1.76	<.0001
Medicare	1.49	<.0001	1.48	<.0001	1.49	<.0001	1.49	<.0001	1.48	<.0001	1.49	<.0001
Self pay	1.03	0.61	1.03	0.65	1.03	0.55	1.03	0.60	1.03	0.65	1.04	0.53
Other insurance	1.16	0.07	1.16	0.08	1.17	0.06	1.17	0.07	1.16	0.08	1.17	0.06
Other type of payment	1.00	0.99	1.00	1.00	1.00	1.00	1.00	0.99	1.00	1.00	1.00	0.99
Missing payment information	2.70	<.0001	2.68	<.0001	2.71	<.0001	2.70	<.0001	2.68	<.0001	2.71	<.0001
Level 2 covariates												
Barrio/Hispanic Quartile/Class 1 (Highest barrio rank, referent)												
Barrio/Hispanic Quartile/Class 2	0.94	0.24	0.93	0.16	0.95	0.36	0.89	0.06	0.89	0.06	0.88	0.04
Barrio/Hispanic Quartile/Class 3	0.95	0.36	0.92	0.20	1.00	0.98	0.87	0.06	0.87	0.09	0.93	0.34
Barrio/Hispanic Quartile/Class 4 (Lowest barrio rank)	0.79	0.00	0.69	<.0001	0.91	0.22	0.76	0.00	0.72	0.00	0.89	0.19
Deprivation index Quartile 1 (highest deprivation, referent)												
Deprivation Quartile 2	0.99	0.70	1.00	0.93	0.98	0.58	0.99	0.71	1.00	0.93	0.98	0.58
Deprivation Quartile 3	0.92	0.07	0.93	0.10	0.92	0.09	0.92	0.08	0.93	0.10	0.92	0.10
Deprivation Quartile 4 (lowest deprivation)	0.83	0.00	0.83	0.00	0.81	0.00	0.83	0.00	0.83	0.00	0.81	0.00
Inequality Quartile 1 (highest inequality, referent)												
Inequality Quartile 2	1.11	0.05	1.11	0.05	1.09	0.10	1.11	0.05	1.11	0.05	1.09	0.10
Inequality Quartile 3	1.13	0.02	1.12	0.02	1.09	0.08	1.13	0.02	1.12	0.02	1.09	0.08
Inequality Quartile 4 (lowest inequality)	1.22	0.00	1.23	0.00	1.18	0.00	1.22	0.00	1.23	0.00	1.18	0.00
Female* Quartile/Class 2							1.10	0.12	1.08	0.20	1.15	0.02
Female*Quartile/Class 3							1.15	0.05	1.10	0.29	1.16	0.10
Female*Quartile/Class 4							1.06	0.57	0.93	0.55	1.04	0.67
Constant	0.27	<.0001	0.27	<.0001	0.26	<.0001	0.28	<.0001	0.27	<.0001	0.27	<.0001
ICC	0.005		0.006		0.006		0.005		0.005		0.006	
log likelihood	249852.4		249893.8		249847.3		249865.8		249905.5		249885.8	

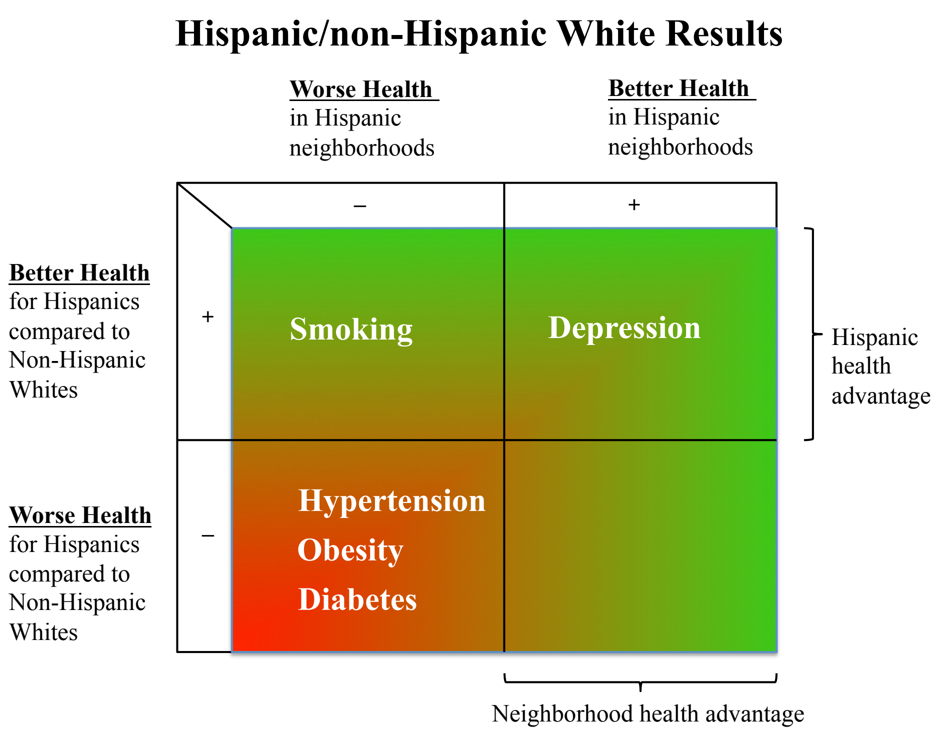
CONCLUSION

Chapter 4 results are complex and portray heterogeneous results across subpopulations, health conditions, geographic units of analysis, and characterizations of barrio neighborhoods. Overall, results suggest that a framework for understanding within-neighborhood heterogeneity and intersectionality is important. Diverse results should not be considered problematic, but rather symptomatic of the types of complex neighborhood dynamics and measures examined in the analyses. I lay out the overall findings in the following sections and figures.

Hispanic Health Advantage

Figure 4-3 summarizes results from the total population. After accounting for social, demographic and health factors, Hispanic patients had lower odds of being current smokers and lower odds of being diagnosed with depression compared to NHWs. This suggests a Hispanic health advantage was present for smoking and depression, which has been supported in other studies (for example, Mair et al. 2010, Shaw et al. 2010). However, a Hispanic health advantage was not present for diabetes, obesity, or hypertension.

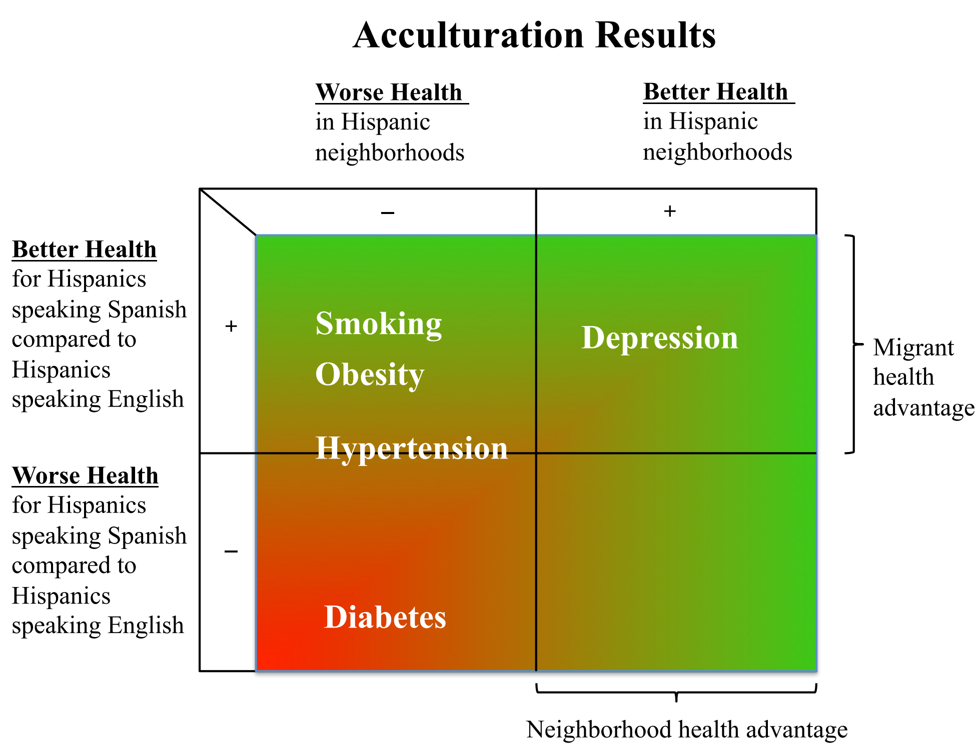
Figure 4-3: Summary of results from total population analyses and their implications for the Hispanic health paradox and neighborhood health advantage



Acculturation and Health

Figure 4-4 summarizes the findings from the analyses with the Hispanic population. Assuming that Hispanic patients who are primary Spanish speakers are migrants or the least acculturated, results suggest a negative association between acculturation and odds of smoking, being diagnosed with depression, and obesity. Results do not reveal clear or significant differences in odds of having hypertension between less and more acculturated Hispanic patients. Results also suggest a positive association between acculturation and odds of diabetes. Overall, results indicate that less acculturated Hispanics have better health across a number of health conditions compared to more acculturated Hispanics, but this health advantage is likely not due to living in barrio neighborhoods.

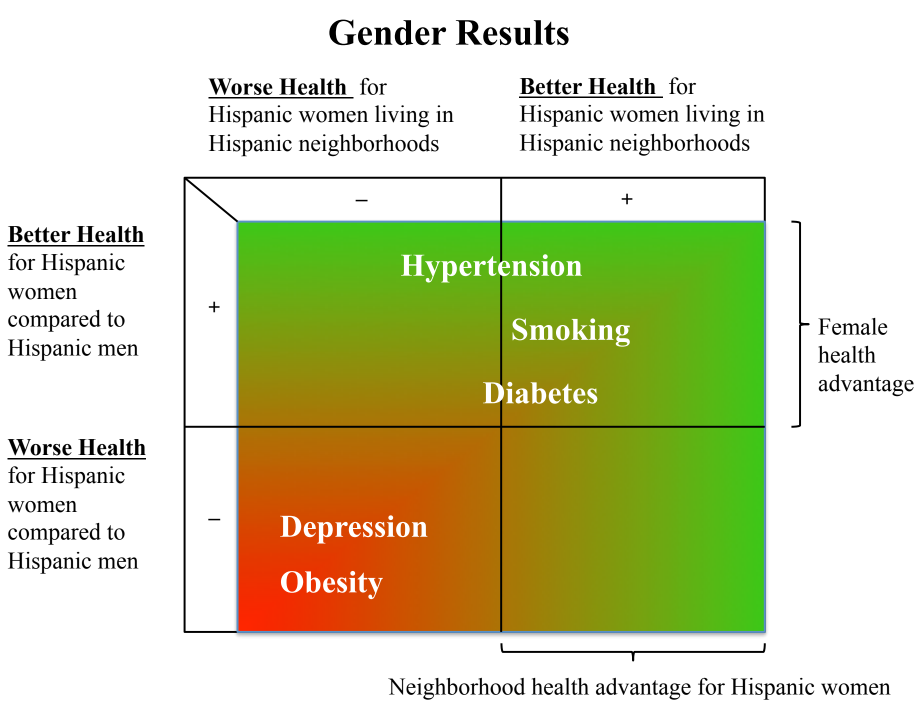
Figure 4-4. Summary of results from Hispanic population analyses and their implications for the migrant health advantage and neighborhood health advantage



Gender Differences among Hispanics

Figure 4-5 summarizes results for Hispanic women compared to Hispanic men and the interactions between being female and living in a barrio neighborhood. Again, results were split across health conditions. Hispanic women had lower odds of hypertension, smoking, and diabetes compared to Hispanic men, but higher odds of obesity and depression. There was a weak advantage of living in the highest ranked barrio neighborhoods for odds of smoking and potentially for diabetes, but women living in highly ranked barrio neighborhoods had higher odds of depression and obesity compared to their counterparts living in lower ranked barrio neighborhoods.

Figure 4-5. Summary of results from Hispanic population analyses and their implications for the Hispanic women compared to Hispanic men and interactions for women living in barrio neighborhoods



Barrio Neighborhood Health Advantage

Figures 4-3, 4-4, and 4-5 also demonstrate results for whether a living in barrio neighborhoods provided a health advantage for residents. In Figure 4.1, for the total population, there is a positive association between living in a highly ranked barrio neighborhood and odds of depression. However, there is a negative association between living in a barrio neighborhood and odds of hypertension, obesity, and diabetes. Thus, not only are odds of having hypertension, obesity, and diabetes higher among Hispanics compared to NHWs, they are also higher for those living in barrio neighborhoods.

Among the Hispanic population, living in a highly ranked barrio neighborhood is only protective for odds of being diagnosed with depression, and is negatively associated with all other health conditions.

Comparison of Measures of Barrio Neighborhoods

Table 4-28 summarizes model fit across three measures of barrio neighborhoods: quartiles of the barrio rank, quartiles of percent of Hispanic residents in the neighborhood, and the four LPA classes. The percent Hispanic measure had better model fit across the most health conditions, including all diabetes, hypertension, and smoking models. The LPA classes had better model fit for obesity models among Hispanics and all depression models. The barrio rank only had the best model fit for the obesity models using the total population.

Table 4-28. Summary of best model fit for different measures of barrios based on log likelihood values for final multilevel logistic regression models

	Barrio Rank	Percent Hispanic	LPA Classes
Diabetes Total		✔	
Hispanic		✔	
Obesity Total	✔		
Hispanic			✔
Hypertension Total		✔	
Hispanic		✔	
Depression Total			✔
Hispanic			✔
Smoking Total		✔	
Hispanic		✔	

Comparison of Geographic Units

This chapter also compared results across census tracts and socially defined neighborhoods to understand whether using larger, aggregated, socially defined neighborhoods produced different results compared to using census tracts. The modifiable areal unit problem (MAUP) is present when the size and statistical significance of effects change due to the geographic scale. Typically, using larger, aggregated geographic units produces inflated correlation coefficients and stronger effect sizes (Wong 2009). However, in this chapter the effect sizes are not consistently better for larger socially defined neighborhoods compared to smaller census tracts. Thus, although there is not evidence of a clear scaling effect, the fact that results are sensitive to geographic units warrants caution in interpretation.

Limitations

One of the primary limitations that is unique to Chapter 4 is the absence of better socioeconomic measures at the individual level. The best potential proxy for SES was the insurance variable (and may have been somewhat captured by the number of visits). Existing research suggests that health insurance and access may largely mediate the association between SES and health for Hispanics (Bacon, Riosmena, and Rogers 2017). Nonetheless, it was not possible to test how well insurance and visit characteristics mapped onto the SES of patients. The impact of not including individual-level SES is that more of the variation in each outcome could have been attributed to level 2 measures when in fact the variation could be explained by individual-level characteristics. Thus, it is more likely to overestimate the impact of neighborhood associations when key individual-level characteristics are omitted.

Chapter 5: Conclusion

Understanding the relationship between neighborhoods and the Hispanic health paradox (HHP) has implications for the ways in which we understand place-based associations and health, for the methods we use to examine population health for Hispanics living in the United States, and for the types of interventions that public health officials use to improve the health of residents and reduce health inequality. In this dissertation, I conducted the first analysis of the relationship between Hispanic neighborhoods and the health of residents in Denver, Colorado. Denver has been an understudied city, but one that should warrant more attention from researchers. Out of the 100 largest metropolitan areas in the United States, Denver ranks 22nd in the percent of Hispanic residents, and it has established Hispanic neighborhoods throughout the city. There was also immense diversity between and within Denver neighborhoods for each of the health conditions I studied, making it an appropriate site for examining the relationship between neighborhoods and health. As Denver continues to rapidly gentrify, similar to many American cities, it is important to capture how Hispanic neighborhoods are associated with residents' health, how the beneficial health associations may be fostered or preserved over time, and the detrimental health associations can be actively addressed.

The heterogeneity of results in this study can be understood in the context of how multiple mechanisms may affect the relationship between neighborhoods and health. Galster (2012) provides an overview of mechanisms through which neighborhood effects emerge, including social-interactional effects that I have discussed in this dissertation. He uses the medical concept of "dosage-response" to understand neighborhood effects. The existence, strength, and persistence of neighborhood effects depend on how the effects are administered (i.e., dosage) and the type of response produced by and through residents.

Although Galster discusses fifteen potential causal pathways for neighborhood effects, the social-interactive mechanisms are most relevant to this study and the application of culture that I use in the neighborhood health heterogeneity framework. Social-interactive mechanisms related to adult health include social contagion, collective socialization, social networks, social cohesion and control, competition, and relative deprivation. These mechanisms have been well established in the sociological literature, but some recent studies have questioned the static nature of the application of social mechanisms (for example, Harding and Hepburn 2014 and Sharkey and Faber 2014).

Static understandings of social-interactive mechanisms do not help to explain the findings of this study, particularly in their inability to explain the variation of health patterns within and between neighborhoods. For example, it is unclear how collective socialization and relative deprivation may function as they relate to health. The theory of collective socialization suggests that strong social ties within a community may be associated with positive *or* negative health behaviors, but not that positive *and* negative behaviors may coexist. Similarly, the theory of relative deprivation suggests that increased inequality is associated with worse health and increased anomie among the least advantaged residents (Kawachi et al. 1999). In this study, Hispanic neighborhoods had more health equity, but higher rates of multiple health conditions.

Broad applications of collective socialization and relative deprivation to an entire community may be vulnerable to a sociologistic fallacy, in that they may not account for how individual-level characteristics shape observed community-level associations (Diez-Roux 2003). Furthermore, individual and group statuses may interact to form unique social environments within neighborhoods that are masked when examining neighborhood patterns as a whole.

Galster's application of dosage-response to understand neighborhood effects allows these social-interactive mechanisms to operate in appropriately complex ways. The impact of the dosage depends primarily on two factors: neighborhood composition and how the dose is administered. Neighborhood composition refers to a combination of factors that make up each neighborhood, including demographic characteristics of residents, social norms and interactions, and geographic and environmental attributes. These compositional characteristics can vary *between* and *within* neighborhoods, setting the stage for potential neighborhood heterogeneity in effects. For example, variation in the composition of Hispanic residents across barrio neighborhoods in Denver may contribute to the heterogeneity of disparities between Hispanic-NHW health conditions found in Chapter 3 (and demonstrated spatially in Figures 3-2 through Figure 3-11 maps).

Administration of the dosage depends on eight factors: frequency, duration, intensity, consistency, trajectory, spatial extent, passivity, and mediation. In the context of social-interactive mechanisms, the ways in which residents are exposed to and interact with their social environment may predict how social environments affect health. One of the major limitations of many existing datasets used to understand neighborhood effects on health is the dearth of questions addressing the administration of social-interactive characteristics through the avenues discussed above. For example, even if a study asks residents about their interactions with neighbors, it is important to also assess how often these interactions occur, for how long, and how rich the interactions are for residents.

The movement towards more dynamic understandings of neighborhood effects, particularly in the context of social-interactive mechanisms, provides an opportunity for researchers to develop new measures and methods. Galster specifically calls for more mixed-method studies within the same sampling frame. While combining qualitative and quantitative methods is perhaps an ideal approach to test neighborhood mechanisms, it should not dissuade researchers from continuing to develop better quantitative measures of neighborhood social environments. An essential component of this development process is to test which of the eight administration factors appear to matter the most, since it is likely unrealistic to develop new measures across all of the ways that a dosage of neighborhood effects could be administered. Pilot testing and applying new measures across different neighborhoods in different geographies would reveal whether specific patterns emerge for the utility of more complex applications of social-interactive neighborhood mechanisms.

NEIGHBORHOOD HEALTH HETEROGENEITY

In this dissertation, I propose a new framework that better incorporates findings from existing studies on Hispanic neighborhoods and health, and is supported by my empirical findings in Denver. The neighborhood health heterogeneity framework suggests that neighborhood social and cultural processes are multifaceted and interact with intersectional identities to create a great deal of cultural heterogeneity within the same neighborhood. This cultural heterogeneity is one of the mechanisms through which neighborhood factors can be associated with both positive and negative health outcomes within the same neighborhood.

The neighborhood health heterogeneity framework provides a possible explanation for the mixed results in existing studies on Hispanic neighborhoods and health, which I presented in Table 1.1. in Chapter 1. However, there are methodological gaps in existing studies that I was able to fill using EHRs for patients in Denver. First, most existing studies examined a single health condition or related health conditions. Studying five common health conditions – type 2 diabetes, obesity, hypertension, depression, and smoking –is a more appropriate strategy to examine the extent to which the same neighborhood may be associated with better or worse health patterns among residents, compared to only examining one health condition. I tested this in two ways. In Chapter 3, I conducted an ecological analysis examining the relationship between four classes of neighborhoods and both prevalence and inequality for each health condition. I identified 30 Hispanic census tracts, or "barrios," which overall had higher rates of diabetes and obesity, no significant associations for hypertension or depression, and lower rates of smoking, after accounting for neighborhood-level demographics, health behaviors, and health care insurance/access. These mixed findings provide evidence for culturally heterogeneous processes coexisting within the same neighborhood, some of which may be associated with increased obesity and diabetes among residents, and others that may reduce the risk of smoking. For example, it is possible that some residents living in Hispanic neighborhoods may adhere to particular diet norms or food preferences that increase risk of obesity (as found by Reyes-Ortiz et al. 2009, but not Dubowitz et al. 2008) but that other norms or forces of social control facilitate low rates of smoking (as found by Finch et al. 2000 and Shaw et al. 2010).

I also used the same five health conditions to conduct the first analysis of within-neighborhood health inequality between Hispanics and NHWs. Studying the difference between race/ethnic groups *within* neighborhoods helps test the extent to which neighborhoods are associated with similar prevalence rates for different race/ethnic groups. It also speaks to potentially distinct selection processes for NHWs and Hispanics into particular neighborhoods. My findings revealed that Hispanic neighborhoods in Denver had less inequality in prevalence of diabetes, obesity, hypertension, and smoking between Hispanics and NHWs. This indicates that there may be more variation within race/ethnic groups (for example, by gender, class, or other social statuses) than between race/ethnic groups living in Hispanic neighborhoods.

In Chapter 4, I examined individual-level odds of each health condition, accounting for differences in individual- and neighborhood-level factors. I found that, overall, Hispanics had higher rates of diabetes, obesity, and hypertension compared to NHWs. The higher odds were exacerbated by living in Hispanic neighborhoods, particularly neighborhoods with high concentrations of foreign-born and non-citizen residents. However, Hispanics had lower odds of smoking and depression compared to NHWs. Hispanic neighborhoods appeared to foster lower odds of depression, but not smoking. Again, these findings reinforce complex neighborhood processes. Generally, Hispanic neighborhoods were not protective of individual-level odds of most health conditions, but the protective association for depression prevents an overall conclusion that Hispanic neighborhoods were less healthy places to live.

The second methodological gap that I filled in this study was examining how odds of having each health condition varied by gender and acculturation within the Hispanic community, and how individual-level gender interacted with living in a Hispanic neighborhood. Other studies have examined intersecting statuses within the Hispanic population (for example, Finch and colleagues (2000) study of U.S. and foreign-born pregnant Hispanic women). The contribution that I made in this study was to examine these statuses across diverse health conditions using a large sample of Hispanic residents.

My results from gender and acculturation models in Chapter 4 revealed distinct health patterns within the Hispanic patient population. The most puzzling of these results is that patients speaking primarily Spanish have higher odds of diabetes than patients speaking primarily English, but lower odds of obesity. In other analyses in the dissertation, obesity and diabetes followed generally similar patterns, since the two health conditions are correlated and obesity is precursor to diabetes. It was particularly interesting that language/acculturation appeared to be protective for obesity but not for diabetes for Hispanics. It is unclear which compositional or social processes may be associated with these differences, and warrants future study.

Acculturation results also support healthy migrant theories, suggesting that those who primarily spoke Spanish also had lower odds of depression and smoking, in addition to obesity, compared to those who spoke primarily English. As discussed in the limitations section, it is possible that some of the apparent advantage in depression could be due to undiagnosed depression among Spanish-speaking Hispanic patients, who may be less likely to have access to and seek care or associate more social stigma with the diagnosis. However, the independent effect of living in a Hispanic neighborhood on depression suggested that there may have been a protective force present in Hispanic neighborhoods above and beyond the composition of many Spanish-speaking residents.

As a brief side note, when I was planning to include a qualitative portion of the dissertation I did some preliminary participant-observation with a group of Spanish speaking women in one of Denver's Hispanic neighborhoods. The group met weekly to discuss mental health and depression issues. It included 6-8 regular attendees, all foreign-born Hispanic women who spoke primarily Spanish. They discussed complex and multifaceted frameworks for understanding their mental health challenges, including ways to think about adverse childhood experiences, their own identities as mothers, and the role their spirituality could play in assisting with the healing process. Qualitative studies that observe these types of groups could help shed light on potentially protective mechanisms that residents use to improve mental health for some residents (noting, of course, that this group only included Spanish-speaking women), and should be a focus of future research.

Relatedly, the role that gender played in health of Hispanic residents was equally heterogeneous to the roles of acculturation and race/ethnicity broadly. Hispanic women had lower rates of hypertension, smoking, and diabetes compared to Hispanic men, but higher rates of obesity and depression. Again, there were distinct patterns for obesity and diabetes that were not apparent when examining the population as a whole or the Hispanic population overall. The gender differences in smoking and depression were coherent with other studies examining how stress may be externalized or internalized differently by men and women, with women more likely to have stress manifest internally as depression and men more likely to have stress manifest externally through substance use (Leadbeater et al. 1995). Thus, while patterns were heterogeneous by gender and acculturation, many of the findings related to specific outcomes were coherent with existing studies.

The third methodological gap that I addressed in this study was to compare results across multiple geographic definitions of neighborhoods. Unlike the few studies that have compared multiple administrative boundaries (for example, Franzini and Spears (2003) comparison of counties versus census tracts), this study compared administratively defined census tracts to socially defined neighborhoods. Notably, social definitions may not fit all residents' ideas of which boundaries constitute their neighborhood, and the social boundaries do map onto administrative boundaries, so they are not wholly "socially" defined. However, the different boundaries provided an opportunity to examine whether results were consistent at each geographic level and the extent to which aggregation impacted strength of associations, since socially defined neighborhoods were bigger than census tracts. In Chapter 4, I found that aggregation did not appear to inflate the strength of results for the total population, and in fact some results were significant at the census tract level and not at the socially defined neighborhood level (for example, significantly lower odds of hypertension for residents living in barrio quartile 2 compared to barrio quartile 1 in tract comparisons but not socially defined neighborhood comparisons). However, many of the socially defined neighborhood results among the Hispanic population did have slightly lower p-values than the census tract results, suggesting a potential modifiable areal unit problem (MAUP). There were few cases where socially defined neighborhood results were significant at the alpha=0.05 level and census tracts were not.

Overall, these comparisons contribute to the debate about using census tracts to define neighborhoods (Lee et al. 2008). While many researchers have criticized the use of census tracts as neighborhood proxies, and indeed have at times dismissed results from studies that have used census tracts, results from this study suggest that census tracts were close approximations of results from socially defined neighborhoods and the observed differences may have been primarily due to issues of scale. The availability of data at the census tract level is a rich resource for researchers. While researchers should continue to examine how definitions of neighborhoods may impact results, this debate should not discourage studies using census tract boundaries.

The fourth methodological gap that I addressed in this study was examining multiple definitions of what constitutes a Hispanic neighborhood. Because existing studies have overwhelmingly not tested multiple measurements of Hispanic neighborhoods, it is unclear how much neighborhood health associations may hinge upon the way Hispanic neighborhoods are categorized and defined. In the context of neighborhood health heterogeneity, does it matter whether Hispanic neighborhoods are defined solely by the percent of Hispanic residents, by immigration status (i.e. the concentration of foreign-born and non-citizens), or by a mix of factors related to ethnicity, immigration, socioeconomic status, and stability? In Chapter 3, I used latent profile analysis (LPA) to create a new measure of Hispanic neighborhoods that incorporated multiple neighborhood factors from the ACS. In the resulting 4-class solution, I found that one class accurately captured Hispanic neighborhoods in Denver, and the other classes categorized low SES, mid/high SES, and high SES neighborhoods. Results for the LPA analysis were presented above. In comparing results using 4 classes to a simple measure of quartiles of the percent of Hispanic residents in each tract, I found some variation in results. Although overall conclusions were similar, there were different effect sizes, levels of statistical significance, and model fit across the two measures of Hispanic neighborhoods.

In Chapter 4, I created a new, ranked measure to capture Hispanic and immigrant neighborhood characteristics, which I called a barrio rank. The barrio rank incorporated the percent of Hispanic, foreign-born, and non-citizen residents. Comparing the barrio rank to both the percent of Hispanic residents in the neighborhood and the LPA classes created in Chapter 3, I again observed some differences in results. Although the overall stories did not change dramatically across measures, researchers' reliance on thresholds of statistical significance could produce different conclusions in cases where one measure was not significant at the alpha=0.05 level and another measure was. This could pose a particular problem in studies with a smaller sample size because p values may generally be larger for level 2 measures, and any sign of statistical significance could be used to draw overall conclusions about the role neighborhoods play in health. Because many studies do not test multiple neighborhood-level measures, it is unclear how robust and externally valid the neighborhood-level findings may be.

Different results across different measures of Hispanic neighborhoods also have implications for neighborhood health heterogeneity. The extent to which results were stable across measures relates to the extent of confidence we can have that strong, unified neighborhood-level processes were taking place. Instead, the variation in effect sizes, model fit, and statistical significance across health conditions suggests a reframing of how we think about the relationship between Hispanic neighborhoods and health. If there was variation and potential instability across neighborhood measures and health conditions, should we even continue to examine health processes at the neighborhood level?

Decades of research about the presence and importance of neighborhoods and communities in shaping factors directly and distally related to health should give us confidence that this line of inquiry is important. The problem is that by claiming that segregated neighborhoods are either associated with positive or negative health outcomes creates overly simplistic and potentially inaccurate notions about the complex, heterogeneous health experiences that can coexist in the same social space. Instead of abandoning this avenue for research, researchers should embrace the complexity through two approaches. First, these findings should encourage researchers to be very specific about what they are studying. Examining the relationship between a neighborhood environment and a single health condition does not tell us very much about the neighborhood *as a whole.* It may tell us much more about factors that influence that specific health condition. Thus, paper titles such as: "Are immigrant enclaves healthy places to live: the multi-ethnic study of atherosclerosis" are potentially problematic, because they suggest that examining one or a few related health conditions can answer broader questions about communities. Relatedly, researchers should avoid claiming that broader social or cultural forces exist in a neighborhood based on findings for a single or few health conditions. A number of studies claim that Hispanic neighborhoods may have stronger social cohesion or networks because of observed positive associations between neighborhoods and a given health condition, but these broad claims ignore how these social forces may vary within and between groups living in the same neighborhood. For example, do all residents share the same association between neighborhood factors and health, or are there some residents that appear to benefit more than others? If researchers cannot explicitly study group differences, it is problematic to claim that broad social forces exist for all residents, or even for all members of a specific race/ethnic group.

Second, researchers should incorporate frameworks such as the neighborhood health heterogeneity framework that I introduced in this dissertation, because they provide theoretical validation for heterogeneous findings. Homogenous frameworks can reinforce presenting homogeneous results; complex frameworks can reinforce presenting complex results. Our empirical studies and findings will more accurately reflect collective social processes if they can embrace social complexity. My framework hinges on cultural heterogeneity within neighborhoods. There are other mechanisms that may also drive heterogeneity, and thus other neighborhood health heterogeneity frameworks can be developed to incorporate nuanced findings into our broader understanding of how neighborhoods function in relation to health. Once more diverse frameworks are introduced, it encourages development of new survey measures that may capture this heterogeneity quantitatively.

Finally, this study is part of a newly emerging trend of using EHRs to answer demographic and sociological research questions. As discussed in greater detail in the section on future research, EHRs provide opportunities to conduct analyses using rich clinical data and provide timely results that can be used for public health surveillance and interventions. This is the only study that I am aware of that uses EHRs to examine the relationship between Hispanic neighborhoods and health. Using a large sample of patients facilitated analyses that were intersectional and revealed the immense diversity of Hispanic neighborhoods. Going forward, this study contributes to a growing body of evidence that EHRs can be important tools in understanding population health (Casey et al. 2016).

LIMITATIONS

At the end of Chapters 3 and 4 I discussed limitations to those analyses specifically. In this chapter, I assess broader limitations of the study. Limitations fell primarily into three categories: issues of internal validity, external validity, and understanding the neighborhood health heterogeneity framework.

Internal Validity

Because EHRs are not collected systematically in the same way as health survey data, there are perhaps greater threats to the internal validity of the data. Data in EHRs were entered by health care providers for the primary purpose of recording and improving clinical care. Records were entered by different providers who may each have different habits or standards for entering or coding diagnoses. For example, not all patients with high blood pressure are formally diagnosed with hypertension. Factors such as the patient's age and general health may influence whether the provider coded the patient as having hypertension. A formal diagnosis is generally necessary for receiving a prescription, but some patients may not be medicated for their condition. In this study, diabetes, hypertension, and depression were the three health conditions for which this is particularly an issue because I used diagnosis codes to count the number of patients who had the condition. To minimize the impact of different coding procedures across providers, I used multiple categories of records to identify patients with diabetes and hypertension, including diagnosis codes, laboratory records/vital records, and pharmacy records.

By using three categories of data to determine whether a patient has a condition, it was more likely that patients were accurately categorized. For example, if a health care provider mistakenly entered a diagnosis code for hypertension when he or she meant to enter a diagnosis for a different condition, the patient would have to either have been previously coded as having hypertension, have multiple systolic or diastolic blood pressure measurements indicating the patient had hypertension, or been given a prescription for hypertension. Otherwise, the patient would not have been considered to have hypertension.

Depression was the dependent variable most subject to issues of internal and external validity (discussed later) because I based prevalence estimates solely on diagnosis codes. There is no lab test for depression, and I did not use pharmaceutical data to validate diagnoses. Thus, depression diagnoses had the highest odds of being misclassified compared to the other dependent variables.

In addition to threats to internal validity from different data entry standards or practices by individual health care professionals, it is possible that DH and KPCO have systematically different standards or practices for entering EHRs. Each organization may have internal screening processes that require providers to enter data in a specific way, or they may have different systems for identifying errors. Based on my experience working with EHRs, there were not robust systems in place to flag data entry errors. For example, many patients were given diagnosis codes for both type 1 and type 2 diabetes and some patients had height and weight values outside of the plausible ranges. Some of these errors have implications for clinical care, but they are arguably less problematic in a care setting than when EHRs are being used for research or surveillance. Since research/surveillance with EHRs is newly emerging and its users are still making the case to organization leaders about the utility of EHRs for research/surveillance, it may be awhile before systems are put in place to flag inconsistencies in the data.

Another threat to internal validity when using data from multiple health systems was the possibility of patient duplication in the data. As I mentioned briefly in Chapter 2, it was possible that a patient could have been seen at both DH and KPCO and could have been included in both datasets. I did not have access to patient-identifying information that would have allowed me to screen for duplicate records. However, there are a couple reasons to believe that there were not many duplicate records. First, I only included patients who had an encounter at DH or KPCO in 2014/2015. For duplication to occur, a patient would have had to be seen in both health systems during that two-year period. Second, because KPCO requires membership and the two organizations serve generally different patient populations, I do not expect that many patients would have seen providers at both health systems in a two-year period. Furthermore, if a few patients were duplicated in the data, the study's large sample size means that these duplicated patients would not have a large influence over the results as a whole. Currently, researchers working on the CHORDS project are addressing patient duplication because it is a bigger problem when EHRs are used from many health care providers, some of which have large overlapping patient populations. Within the next few years, their goal is to develop a master-patient index that uniquely identifies patients across health systems. This work will increase confidence in research and surveillance results in future studies.

External Validity

The most important threat to external validity in this project is that patient data from EHRs are not representative of the population of Denver, Colorado. This is apparent in the comparisons between the prevalence rates of chronic conditions from EHRs compared to representative survey estimates; generally prevalence rates from EHRs are higher than population estimates, indicating that the EHR population is generally not capturing some healthy individuals. Work is currently being done by the CHORDS team and others around the country to assess *how* representative EHRs are of the general population and the healthcare seeking population. They are also working on weighting procedures to see if estimates from EHRs can be representative of either the general population or the healthcare seeking population. For now, however, results from this dissertation should not be interpreted as representing all adult residents in Denver. Furthermore, results from Denver may not apply to other cities. The history of the Hispanic population in Denver, the history of Denver neighborhoods, and patient selection into one of the health care providers included in the study all factor into preventing results from being applicable outside of Denver.

However, national representativeness in neighborhood studies is rare. Of the 36 studies about Hispanic neighborhoods and health outlined in Table 1.1, only 3 studies used national data, and the rest used specific cities, a single state, or a region in the United States. Furthermore, results from this study are still useful even though the patient population may not be representative of all Denver residents. Because this study includes roughly one third of all adults living in Denver, results have implications for the health of a large number of residents. Furthermore, conducting a neighborhood study with a large sample size provides the opportunity to test new measures of defining Hispanic neighborhoods and for understanding experiences of subpopulations (e.g. Hispanic women). Many neighborhood studies relying on health surveys lack statistical power to assess these factors.

One of the issues in producing reliable results when studying the HHP is that some Hispanic adults may not be captured in health surveys or that undiagnosed disease may contribute to seemingly lower rates of health conditions (Palloni and Arias 2004, Riosmena, Wong, and Palloni 2013, Barcellos et al. 2012). This data artifact problem in health surveys is also a potential problem in EHRs, particularly for some health conditions. First, although Denver Health effectively serves many people without health insurance in Denver, undocumented immigrants may still be less likely to seek care. It is possible that those who do seek care are sicker than those who do not. This would inflate prevalence estimates to make it appear that prevalence rates were higher for Hispanics than they actually were in the general Hispanic population. Contrarily, results could also be biased towards better health for Hispanics, particularly for health conditions like depression, which is based on a single indicator. Those who are less likely to seek regular care also potentially less likely to be screened for depression or tobacco use, thus misplacing undiagnosed patients in the denominator of estimates rather than the numerator. EHRs can potentially improve upon rates of undiagnosed disease for conditions like diabetes and hypertension that can be assessed using multiple sources of clinical data. However, for conditions such as depression, they suffer from the same issues of bias as health surveys.

There are also limitations in the accuracy of neighborhood-level data. The ACS data is limited in its ability to accurately measure social/demographic characteristics at the census tract level due to small sample sizes. Individual measures in the ACS at the census tract level are plagued with extremely high margins of error, particularly for subgroups such as Hispanics, the foreign-born population, and non-citizens (all of which are critical to identifying barrio neighborhoods). To address this limitation, the study combined many ACS measures using LPA techniques. By combining multiple measures, it is less likely that error from a single variable will bias results (Spielman & Singleton 2016).

Data from the 500 Cities Project is limited in two primary ways. First, it relies on BRFSS data, which has typically has a less than 50% response rate (Schneider et al. 2012). Second, BRFSS data were not sampled at the census tract level, so all data produced for the 500 Cities Project relied on small area estimation techniques, which may not accurately capture health behaviors and utilization for neighborhood residents. Nonetheless, combining these data sources produces the best possible opportunity to examine neighborhood-level health and can be applied to other cities (pending availability of EHRs). It poses an opportunity for neighborhoods and health research that does not hinge on expensive and time-consuming surveys, such as L.A.FANS or the PHDCN, and is more amenable to longitudinal follow-up.

Understanding Neighborhood Health Heterogeneity

This study helped propel the field of Hispanic neighborhoods and health forward by conducting analyses on prevalence in addition to inequality in health conditions between Hispanics and NHWs, testing new measures of Hispanic neighborhoods, and examining the relationship between Hispanic neighborhoods and multiple population subgroups. This study is limited in its ability to fully test the neighborhood health heterogeneity model. As mentioned in Chapter 1, fully understanding mechanisms driving both positive and negative health experiences within the same neighborhood requires either a qualitative approach that can examine social processes unfold through intensive interviews and observation, or better quantitative measures that capture how multifaceted cultural environments and intersectional identities shape how social and physical environmental factors become embodied.

Furthermore, there are a number of social statuses that could have helped to understand health heterogeneity among Hispanics, but data were not available. For example, typical socioeconomic indicators such as level of education or income were not available, and insurance status has not yet been validated as an accurate proxy for SES. Also, EHRs did not contain information about whether patients were U.S. or foreign born. Relatedly, EHRs did not contain information about country of origin, time spent in the United States, or citizenship status, all of which could influence settlement in a particular neighborhood and experiences therein. The best measure of immigration and acculturation that was available in EHRs was whether the patient was a primary Spanish speaker or needed an interpreter during his or her visit. This measure has also been used in other studies as a proxy for foreign-born status and low acculturation. Even so, there is much debate about the notion of acculturation, its definition, and how it relates to health (Abraído-Lanza et al. 2006) that was beyond the scope of this dissertation to explore.

This study examined health inequality between Hispanics and NHWs, but did not provide explicit comparisons between Hispanics and other race/ethnic groups. Important comparisons for future research would be between Hispanics and NHBs, and highly concentrated Hispanic neighborhoods versus highly concentrated NHB neighborhoods. Because Hispanics and NHBs have both been studied extensively in relation to neighborhood ethnic density and health, and because different paradigms are often used to describe the relationship between ethnic density and health for these groups (as detailed in Chapter 1), it would be interesting to compare the extent to which neighborhood health heterogeneity exists for each group. Do Hispanics (or a subgroup therein) experience more neighborhood health heterogeneity compared to NHBs? If so, what individual- and neighborhood-level factors may help explain these differences? It was beyond the scope of this analysis to examine these comparisons, but is an important area for future research.

Finally, this study does not address the common challenges of assessing neighborhood exposure and selection versus protection in neighborhoods and health research. Patients were categorized as living in a particular neighborhood if they ever had an address in that neighborhood in their retrospective EHRs. Because changes in address are only assessed when patients come in for a new visit, it is impossible to evaluate how long patients have been exposed to a neighborhood environment. Exposure is likely a non-random process, with younger adults and those with fewer socioeconomic resources likely to be more transient than older adults and those with higher SES who can own homes and afford the rapidly increasing property taxes in a growing metropolitan area. This study did not attempt to assess whether or how certain types of individuals selected into Hispanic or other types of neighborhoods. These issues of selection versus protection are common challenges in neighborhoods and health research (Sampson 2008), and for the HHP more broadly (Riosmena, Wong, and Palloni 2013). However, because of the large sample size in EHRs, future analyses could examine matching techniques to see whether individuals with similar characteristics living in different neighborhoods have different health outcomes.

POLICY IMPLICATIONS

My findings have policy implications that can be divided into philosophical and practical implications. At the philosophical level, my results discourage assumptions that there is necessarily less variation within than between neighborhoods and groups. Policy makers, public health officials, and researchers should incorporate complex and dynamic meanings of places and groups into their policies and interventions. As more social indicators become available to policy makers and healthcare providers, there is a risk that this information can encourage or reinforce group stereotypes. For example, if providers were given information about which neighborhood their patients lived in so that they could recommend local resources (e.g. a local mental health center), it also poses the risk that providers may associate specific neighborhoods as “good” or “bad” environments, and these stereotypes could impact how they treat their patients. This is similar to unintended consequences of increased information about racial disparities in health, in which the process of instructing providers on racial health disparities actually reinforces stereotypes that assume all patients of a particular race/ethnicity may be similar (Blair et al. 2013, Johnson et al. 2004). The neighborhood health heterogeneity framework provides an opportunity for a complexity of cultural experiences and health outcomes to be formalized and acceptable, not problematic. This acceptance of dynamic social spaces can encourage policies that are more inductive and do not assume particular social environments will exist because of the racial/ethnic composition of a neighborhood.

At the practical level, my results demonstrate distinct health patterns across Denver that could be targeted for public health interventions or observed to learn about potentially positive social environments. For example, results from the ecological analyses suggest that Hispanic neighborhoods have higher rates of many health conditions but lower rates of inequality for the same conditions. Policy makers may want to understand factors that exacerbate inequality between the health of Hispanic and NHW patients outside of Hispanic neighborhoods. What issues shape the widened gap between Hispanic and NHWs patients in some Denver neighborhoods, and what policies may encourage more equitable environments?

FUTURE RESEARCH

Future research should continue to examine the extent to which the HHP may be diminishing *and* resilient, and how health patterns may vary for Hispanic subgroups, particularly by country of origin, acculturation, gender, and neighborhood residence. This dissertation provided a framework for understanding neighborhood health heterogeneity in the context of Hispanic neighborhoods, but a better framework for understanding heterogeneity in the HHP more broadly would be an important contribution to researchers' understandings of Hispanic health trends in the United States.

Future research should also continue to examine the extent to which neighborhoods are associated with positive and negative health outcomes for residents, and whether there are characteristics of neighborhoods that appear to exacerbate or minimize this heterogeneity. As mentioned earlier, this study did not compare Hispanic communities to NHB communities, but future research should examine the extent to which segregated NHB communities also produce diverse health outcomes and experiences among residents, and the role that race, gender, and class identities play in shaping these experiences.

There are also a number of opportunities for future research using EHRs that were be scope the scope of this study. Although I outlined many of the limitations of EHRs above, there are many future opportunities for EHR-based studies that can compliment health surveys. EHRs provide longitudinal data on many patients, making it possible to track conditions over time. This process involves an immense amount of data cleaning and sensitivity analyses, because some patients have records that date back decades and others only have one recorded visit, and the differences are not random. Nonetheless, samples could be created for patients who have had similar numbers of visits in specific health systems, and prevalence and severity of chronic conditions could be examined over time. Additionally, both DH and KPCO had retrospective address data available for patients. Although the quality of these data is subject to scrutiny, particularly because address information is likely only changed when patients come in for a new visit, it is possible to assess how prevalence and severity of conditions is related to duration or changes in neighborhood location. Similarly, longitudinal measures of neighborhood exposure may be able to be constructed for particular patients. Little research has been done to assess how effective retrospective address data in EHRs may in measuring exposure to neighborhood environments. If researchers can develop methods and validity for using retrospective address data, EHRs could present an immensely less time consuming and cost saving alternative to longitudinal neighborhood health surveys.

As briefly mentioned earlier, EHRs also present an opportunity to examine severity of chronic conditions. Some current studies, such as NHANES or the Health and Retirement Study (HRS) comprise of clinical examinations that allow for measures of disease severity. Health records are much more extensive in scope, and when combined with retrospective data can provide the opportunity to develop health trajectories for patients. Although it was beyond the scope of this study, it would have been valuable to examine the relationship between neighborhoods and severity of diabetes (through A1c), obesity (through BMI), and hypertension (through multiple blood pressure readings) for particular groups.

Finally, there are also opportunities to include or merge individual-level SES data with EHRs. For example, KPCO is working to develop social needs indicators for patients, and part of this effort involves collecting rich social data as part of patients' EHRs (Gold 2017). There are also opportunities to merge individual-level EHRs with individual-level U.S. Census data through secure systems such as research data centers (RDCs). These methods require rigorous evaluation of patient privacy and merging strategies, but once systems are developed these data sources could provide multifaceted patient information that could be used for timely research and public health surveillance.

This study also had complex results for depression that could have implications for practical public health interventions. Hispanic neighborhoods appeared to have a protective association for being diagnosed with depression, but Hispanic women had much higher odds of being depressed compared to Hispanic men. Are there policies that could potentially harness benefits of social environments within Hispanic neighborhoods to address higher rates of depression among Hispanic women? By examining intersecting statuses within neighborhoods, this study facilitates the development more specific programs or interventions.

CONCLUSION

In this dissertation, I advance our understandings of the relationship between Hispanic neighborhoods and health by proposing a new framework of neighborhood health heterogeneity and by expanding on the existing methodological techniques. I explore the use of electronic health records to answer sociological and demographic research questions and conduct the first analysis of the association between Hispanic neighborhoods and health in Denver, Colorado. My complex findings pave the way for myriad future research that can continue to examine new methods and theories for understanding how the places we live shape our health and our lives.

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APPENDIX

Office of Regulatory Compliance
UNIVERSITY OF COLORADO
DENVER | ANSCHUTZ MEDICAL CAMPUS
Clinical Research Administration

April 13, 2018

Re: How neighborhood environments impact racial and ethnic health disparities in Denver, Colorado, with particular focus on the Hispanic population
To: Emily Bacon

Thank you for sharing the information about your research project. Your study has two aims:

Study Aim 1: Examine whether there is a health advantage for Hispanic adults living in Denver compared to non-Hispanic white and non-Hispanic black residents that is similar to the Hispanic health advantage observed nationally. Electronic health records will be used to examine prevalence of five health conditions and behaviors: diabetes, obesity, hypertension, smoking, and depression, and compare them across racial/ethnic groups and across neighborhoods.

Study Aim 2: Understand the relationship between types of Denver County neighborhoods and common health conditions for adult residents compared to non-Hispanic white and non-Hispanic black adult residents and its implications for public health surveillance.

In order to conduct your study, you receive an aggregate data set with data points relevant to your study. This dataset does not include any privately identifiable information, nor does this dataset include protected health information. Based on my review of this activity, and review of the regulations, this activity does not meet the definition of research involving human subjects and does not require IRB review and approval.

Sincerely,

Deborah Barnard

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