CONCENTRATED POVERTY, RACIAL SEGREGATION, AND HEALTH: AN ANALYSIS OF METROPOLITAN AREAS

By

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ABSTRACT OF THE DISSERTATION

The Spatial Dimensions of Concentrated Poverty, Racial Segregation, and Health: An Analysis of Metropolitan Areas

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Individual poverty has long been linked to poor health. With the increased importance of the social determinants of health, the literature on neighborhood effects has attempted to explain the independent effect on health of the ecological environment of daily life in order to lessen persistent health inequalities. Extant research on the topic of neighborhood effects has fallen short in addressing the problem of selection bias. This study overcomes this with a multilevel design modelling individual health outcomes aggregated at the metropolitan level as a function of metropolitan level poverty, poverty concentration, and segregation, controlling for individual and household level characteristics. I further compute spatial equivalents for poverty concentration and segregation at the metro level. The results suggest the spatial arrangement of poverty, at a set level of aspatial concentration, worsens health for lower income individuals. The aspatial measure of segregation, at a set level of spatial arrangement of race and ethnicity, worsens health for Hispanics, and Native Americans. Importantly, the study uncovers

some profound differences in the two sets of aspatial and explicitly spatial metro level measures: what they measure, how they interact, and the implications for their use.

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Chapter 1: Introduction and Literature Review

Research Problem

Conditions of individual poverty undoubtedly affect physical and mental health through various channels, both direct and indirect (Fitzpatrick, 2013). Poverty places downward pressure on ultimate health attainment by lessening the chances of exposure to health-promoting resources vital to preventing disease as well as limiting access to health care services for timely and effective treatment and management of illness. The immediate built environment such as the quality of housing and household circumstances are some of the most visible manifestations of micro level poverty on health distress.

Combating social and economic distress has been a pressing priority in the context of evolving urban redevelopment policy paradigms over the decades. Amid a widening spread of the distribution of earnings and wages across population subgroups, the gap between the top and bottom grew substantially in the closing decades of the twentieth century (Morris & Western, 1999). Indeed, this period has been termed “The Age of Extremes”, marked by the ushering in of deep divides between the polar opposites in terms of both income and wealth characterized by an ever shrinking middle class (Massey, 1996). Area level income inequality has been shown to have an independent relationship with mortality rates, after accounting for individual and family socioeconomic characteristics (Kahn, Wise, Kennedy, & Kawachi, 2000; Lochner, Pamuk, Makuc, Kennedy, & Kawachi, 2001).

The research has pointed to life in impoverished urban environments as a potent factor in explaining many areas of political, economic, and societal concern: among these are population health and quality of life issues. Understanding factors shaping health inequalities in particular poses great challenges for public health researchers and policy makers. More careful study of these inequalities thus has the potential to carry with it important insights and lessons for policy toward more effective interventions.

The implications of declining and disinvested urban areas for population health risk factors and outcomes have been studied on local and regional levels extensively in terms of all-cause age-adjusted mortality rates, suggesting a strong relationship between the two phenomena even after controlling for a number of demographic and socioeconomic characteristics at the individual level (Anderson, Sorlie, Backlund, Johnson, & Kaplan, 1997; Borrell, Diez Roux, Rose, Catellier, & Clark, 2004). In contrast to findings from the United States, related work from Canada (having less inequality and more equitable access to medical care) shows no detectable impact of contextual disadvantage on mortality (Roos, Magoon, Gupta, Chateau, & Veugelers, 2004).

Metropolitan-level residential segregation by race and ethnicity is another important factor shaping the health of urban populations. Segregated urban neighborhoods work to isolate mostly minority residents from resources and opportunities, among these health-promoting resources. Research has identified the association between racial segregation and poor health outcomes as manifesting both independently and indirectly through exposure to neighborhood poverty (Do, Frank, & Iceland, 2017).

Nevertheless, there has been limited attention paid to the relation of spatial patterns of the distribution of poverty and segregation within and across urbanized regions and measures of health outcomes. Although understanding fully the dynamics and mechanisms operating underneath this relationship is beyond the scope of this study, I seek to shed new light on some of the nuances and ways in which poverty, segregation, health, and geography collide to shape health and wellbeing for some of the most disadvantaged residents of urban regions.

As discussed in more detail later in this dissertation, a number of related studies of neighborhood effects, several of them multilevel in structure, have sought to successfully link contextual factors with measures of health. The problem of appropriately addressing and dealing with selection bias is one of the greatest design obstacles identified in this area of study. Although implementing various techniques to address this, the studies discussed prove ultimately deficient in their attempt to shield against bias arising from self-selection in and out of neighborhoods.

My dissertation will add to the knowledge in the field of neighborhood effects on health by bringing forth evidence of the specific ways in which metropolitan-level concentration of poverty and residential segregation by race and ethnicity interact with health outcomes burdening predominantly low income minority communities. The study will provide a clearer picture of these relationships through a unique analytical strategy designed to be less susceptible to neighborhood selection bias.

Research Questions and Hypotheses

In this study, I will seek to provide empirical evidence toward better understanding of the following broad research questions:

1. What are the determinants of poor health at the metropolitan level? What factors drive health at the regional scale?
2. What is the impact of spatial patterns of concentrated poverty / racial and ethnic residential segregation on health outcomes across U.S. metropolitan areas?
3. How do individual and metropolitan level characteristics interact to produce distinct conditions of health among urban populations?

Further, I provide evidence in support of the following key hypotheses:

Hypothesis I: I expect to observe a positive correlation, at the metro-level, between poor health outcomes and the level of concentration of poverty across U.S. metropolitan regions – the greater the spatial association between high poverty, racially and economically isolated areas the more pronounced the negative effect will be upon health within a given metropolitan statistical area, micropolitan statistical area, or metropolitan division, while holding median household income, and other covariates, constant.

Hypothesis II: Given the differences in the socioeconomic ecologic conditions of disadvantage characterizing predominantly minority versus non-minority neighborhoods, I hypothesize that health disparities in the former are significantly related to the clustering of high poverty neighborhoods through the spatial patterning of tract-level poverty within a metropolitan area.

Hypothesis III: I expect to observe a positive correlation, at the metropolitan level, between unfavorable health outcomes and the spatial concentration of predominantly minority neighborhoods – the greater the spatial association between highly racially and ethnically segregated areas the more pronounced the negative effect will be upon health within a given metropolitan statistical area, micropolitan statistical area, or metropolitan division, while controlling for race/ethnicity among other individual level covariates.

Poverty, Neighborhood Effects, and Health

For decades, social scientists, researchers, and policy scholars studying urban distress have pondered the question of precisely what societal phenomenon could be attributed with influencing the pattern of social and economic outcomes observed in America's core cities and metropolitan areas. Such outcomes include health-, residential-, educational-, and labor market attainment. A common thread tying these outcomes together is the concept of neighborhood effects, an argument that posits that the impact of one's immediate surroundings as a key factor driving long term trajectories of personal and social development in U.S. metropolitan areas (Wilson, 2012).

Individual level poverty could be viewed as the most powerful factor shaping health outcomes within the isolated built and social environment of mostly minority inner city communities (Lopez & Hynes, 2006). Overall social and economic disadvantage and lower socioeconomic status has been associated with a multifaceted detrimental effect on a person's physical and mental health. Accordingly, social stress theory suggests that poverty not only works to heighten exposure to such conditions but also reduce one's immunity through "limited psychosocial coping resources, which in turn leads to a higher risk of developing symptoms of mental illness" (Fitzpatrick, 2013, p. 36). Studies have connected some of the physical manifestations of poverty (inadequate housing, low quality public schools, job-related hardship, environmental degradation, and unsafe neighborhood conditions) with a list of physical ailments and chronic conditions (Fitzpatrick, 2013). Each of these areas on its own accord works to create an existence mired in poor health attainment for many generations of individuals and families.

More narrowly, the condition of poverty is characterized by a daily existence in an environment of low social support and self-efficacy, over and above the effects of absolute material deprivation, all of which work to exacerbate the exposure to persistent stressors. Residence in socially and materially distressed locales has on average been associated with poorer health on a variety of measures, relative to more advantaged areas (Ellen, Mijanovich, & Dillman, 2001).

In shedding light on the nexus of poverty and health, the empirical evidence on neighborhood effects suggests that the contextual disadvantage found in neighborhoods of lower socioeconomic status, or SES, commonly defined using a combination of factors such as area level income, percent below the poverty level, accrued assets, occupational status, percent unemployed, and the educational attainment of the resident population, is a significant driver of health in such environments, over and above individual and family factors (Anderson et al., 1997; Borrell et al., 2004; M. Haan, Kaplan, & Camacho, 1987; LeClere, Rogers, & Peters, 1997; Lochner et al., 2001; Schulz et al., 2000; Steenland, Henley, Calle, & Thun, 2004; Waitzman & Smith, 1998a; Winkleby & Cubbin, 2003; Yen & Kaplan, 1999). Collins et. al. (2009) refer to the “social conditions of daily living” to include the physical and built ecology of urban residence, work, schooling, and leisure activities (p. 156). The effect of the socioeconomic environment, or context, is shown to influence health independently above and beyond that of the agglomeration of the neighborhood compositional factors, that inter-locus variation in features characterizing the resident population (A.V. Diez-Roux, 1998; A.V. Diez-Roux et al., 1997; M. N. Haan, Kaplan, & Syme, 1989; Kaplan, 1996; Krieger, 1991; Macintyre, MacIver, & Sooman, 1993; O’Campo, Xue, Wang, & Caughy, 1997; O’campo & Wang, 1995; S.A. Robert, 1998; Schwartz, 1994; Wing, Casper, Riggan, Hayes, & Tyroler, 1988). Robert (1998) finds a consistently significant independent effect of socioeconomic context above and beyond individual socioeconomic position, however small in magnitude as compared to individual-level SES. Two other studies report similar results (Ana V Diez-Roux et al., 1997; LeClere et al., 1997).

This discussion points to a need for more in depth unpacking of relative effects for population subgroups as well as indirect effects of community level through individual level factors (Stephanie A Robert, 1998). It is important to note here that very few of the relevant studies on neighborhood effects on health outcomes have managed to set up research designs equipped to adequately address the issue of residential selection of individuals and families in and out of neighborhoods, especially as it relates to the limitations inherent in cross-sectional data and the dynamic nature of neighborhoods and their residents (Tienda, 1990). A notable exception is Evans, et. al. (1992) which explicitly tested for selection bias. The researchers found their neighborhood, or peer, effect erased after setting up a two-stage process whereby they explicitly deal with selection using simultaneous equation estimation. The article duly raises the import of the issue of endogeneity in modelling, however leaves open questions as to the selection of appropriate variables in estimating area-wide effects - namely the chosen social and geographic context as the scope within which to center the analysis.

Experimental study designs are one ideal solution to the selection problem as they allow for a fully controlled, randomized assignment of people into residential contexts of treatment and control. However, they are very rare in social science research. With good reason, as unlike in other sciences, there are serious ethical concerns arising from knowingly placing individuals or families in less than favorable, or even hazardous, neighborhood conditions. Furthermore, the complex logistical considerations entailed in random assignment often make the experiments impracticable.

One of the most oft cited large research experiments in the study of neighborhood effects, Moving To Opportunity (MTO) was a randomized, controlled trial implemented by the U.S. Department of Housing and Urban Development in the mid-to-late 1990’s in five large U.S. cities to study the effects of residential mobility to less disadvantaged environments on social and economic trajectories of public housing residents. The study design placed a total of 4,608 families with children into three groups: those offered Section 8 vouchers along with additional relocation assistance with stipulations on making a move from public housing to specifically less impoverished neighborhoods in the suburbs, those provided with vouchers with no stipulations, and finally, those remaining in public housing. A portion of the families who initially elected to move to low-poverty neighborhoods did not in fact remain there longer-term but moved back into more highly impoverished environments, oftentimes not far from the neighborhoods of the original public housing locations.

Some of the earlier results from post-MTO evaluations point to a measurable difference primarily in mental health, particularly among children (less psychological distress and depressive symptoms), as well as a drop in obesity rates, as among the areas of most notable improvement among the families to relocate to low poverty areas, relative to counterparts remaining in public housing (Gennetian, Sanbonmatsu, & Ludwig, 2011; J. Kling, Liebman, Katz, & Sanbonmatsu, 2004; J. R. Kling, Liebman, & Katz, 2007; Leventhal & Brooks-Gunn, 2003; Ludwig et al., 2012; Sampson, 2008). Thus, the MTO study is one of the rare attempts providing experimental evidence in support of the power of socioeconomic context on individual and family health.

Winkleby et. al. (2006) find quite an opposite effect from the MTO, with adult mortality increasing in lower SES individuals residing in 82 higher SES neighborhoods across four California cities, hinting toward a diffuse relationship between individual and neighborhood socioeconomic status in shaping health outcomes. However, Winkleby et al. (2006) did not measure the length of exposure or residence of their sample population within their respective neighborhoods, as well as maintenance of residence in comparable neighborhoods after relocating. Two other multilevel studies, both from Canada, arrived at similar findings to Winkleby et al. (2006) for all-cause mortality, in which individual income mattered most in higher SES environments (Roos et al., 2004; Veugelers, Yip, & Kephart, 2001). This structural and psychological relative deprivation experienced by lower SES families residing within higher SES communities is further supported by Robert (1998, 1999).

Chetty et. al. (2016) appear to contradict these previous findings in their recent work with a large detailed dataset following lower SES families' moves from impoverished to more advantageous areas (the research team here revisits the MTO study taking on a longer view on original study participants' socioeconomic outcomes). The positive effects identified were especially pronounced for families with younger children (pre-teen) exhibiting improved long term outcomes (on dimensions of employment, adulthood residence, family structure, and educational attainment), potentially providing a foundation for halting the inter-generational transmission of poverty. Indeed, Chetty et. al. (2016) posit the number of early childhood years spent living in a better neighborhood as a decisive factor explaining the observed variation in outcomes into adolescence and young adulthood.

Within the literature on the ecology of health, the theory of neighborhood disadvantage calls attention to the role of neighborhood material disadvantage or contextual poverty on health outcomes. The argument combines the multilevel confluence of neighborhood and personal disadvantage, and neighborhood disorder, including erosion of social support and control mechanisms (Cohen et al., 2003; Hill, Ross, & Angel, 2005; Latkin & Curry, 2003; Ross & Mirowsky, 2001). In the urban realm, (particularly younger) residents of high poverty neighborhoods enjoy prospects of consistently poorer health, among other outcomes, than others within the diverse human ecology of metropolitan areas (Sampson, Sharkey, & Raudenbush, 2008). In essence, a reduced length and quality of life due to ill health and limited access to health-related resources are some of the direct consequences of residing in a distressed urban environment.

One of the primary factors explored by the public health field is adequate access to medical care, and in particular access to reliable primary care. The effects of physical resource deprivation reach well beyond scarcity of access to medical care alone. The existence of food deserts in resource-depleted neighborhoods fuels unrestricted easy access to unhealthy food, conversely limiting adequate nutritious intake and contributing to obesity rates, especially in the case of youth (Kipke et al., 2007; Walker, Keane, & Burke, 2010).

Sampson's (2008) study follows a sample of African American children in Chicago through their moves from and into neighborhoods of varying levels of disadvantage anywhere in the U.S., and presents a research design in which addressing selection bias is attempted longitudinally using a series of baseline and time-varying covariates, and having as its focus a single, economically diverse, racial group sample. The study also controls for household income among other household socioeconomic factors and incorporates cumulative disadvantage to assess variability in later life attainment. The study does not however control for unobserved, time-invariant factors.

The importance of concentrated poverty is relevant more recently as the U.S. has seen an increase in the percentage of individuals residing in extreme-poverty neighborhoods by one third over the decade of the 2000's, much of it fueled by the economic recession in its latter years (Elizabeth, Carey, & Alan, 2011). As the geographic locus of intense poverty narrows, so do some of the major factors shaping health and well-being among the urban poor. Neighborhood- or community-level poverty operates beyond individual or family poverty to shape health outcomes and the life course of vulnerable urban populations.

In addition, there is research to suggest that economic segregation/inequality and concentrated disadvantage operate on separate spatial scales (Do et al., 2017). The former, in the form of resource distribution, bears most heavily on outcomes at the macro level (states or regions), while the latter, level of resource development or deprivation, is most pronounced within the confines of the neighborhood (Wilkinson, 1997).

Segregation and Health

There is an established literature cataloguing in depth the multitude of negative effects of racial residential segregation in urban contexts. The evidence suggests segregated urban neighborhood environments to be a strong determinant of poor physical and mental health outcomes, particularly for low income residents, persevering across generational boundaries (Burton, Kemp, Leung, Matthews, & Takeuchi, 2011). Burton et. al. (2011) in their review of the recent work on the subject note that African Americans carry a heavy and vastly disproportional burden imposed by the social and economic dynamics in such marginalizing conditions, in comparison to any other racial or ethnic group.

Persistent racial residential segregation is posited in the research as a significant contributing factor in the growth and magnitude of the gap between population groups, as this geographic isolation translates to unequal access to medical care, information, and institutional structures and resources (Wilson, 2012). Segregation based on race, ethnicity, and income is associated with divergent, and worse, outcomes for minorities (Bell, Zimmerman, Almgren, Mayer, & Huebner, 2006; S. C. Grady, 2006; Hart, Kunitz, Sell, & Mukamel, 1998; Jackson, Anderson, Johnson, & Sorlie, 2000; LaVeist, 2003; Lobmayer & Wilkinson, 2002; Roux et al., 2001). Racial segregation further reinforces health outcomes in minority populations related to the limited access to outlets for healthy and nutritional food options in the urban environment (Zenk et al., 2005).

With the close linkages between racial and ethnic minorities and poverty, this serves as further evidence as to the magnitude of the health disparities gap across population groups. Racial residential segregation and neighborhood context may operate in tandem as well as separately to shape health in complex ways (C. A. Collins & Williams, 1999).

A related concept closely connected to segregation of isolated minority populations is the one of ethnic or immigrant enclaves. These environments often can be not dissimilar from segregated, minority majority, urban neighborhoods in terms of their conditions of material deprivation and low attachment to the mainstream social and resource networks. Such enclaves however have been found to display a protective effect on health outcomes, especially for first generation Latino and Asian American populations (Kasinitz, Mollenkopf, Waters, & Holdaway, 2009; Logan, Zhang, & Alba, 2002; Zhou, 2010). The presence of co-ethnics sharing linguistic and cultural norms serves to reinforce and perpetuate positive health inducing habits and outlooks, helping to mitigate and even offset the disruptive influence of isolation and actual and perceived discrimination from the broader outside context of the metropolitan conglomeration of neighborhoods. This interconnectedness forms durable networks of mutual assistance in areas such as child care, securing of jobs, as well as support in entrepreneurial endeavors, working toward community-strengthening empowerment and self-reliance (Berkman & Glass, 2000; Weiss, Gonzalez, Kabeto, & Langa, 2005).

Further, a distinguishing characteristic of enclaves – that of perpetual demographic flux, the constant inflow (i.e. new immigrant arrivals) of a generationally diverse population at various points in the life cycle and the socioeconomic ladder, creates and reinforces attachment to place, forging closer attachment among residents (Jacobs, 1961; Osypuk, Roux, Hadley, & Kandula, 2009; Zhou & Portes, 2012). The above often give rise to conditions favorable to the achievement of better health outcomes across a spectrum of metrics relative to other, at least in a physical sense, similarly isolated urban environments.

Inter-group Disparities in Health

Beginning with the work of French sociologist Emil Durkheim at the turn of the 20th century, it has been known that wide differentials exist between social groups on measures of health outcomes based on religion, gender, familial and social status, etc. (Idler, 2014). Among these inequalities, health disparities by race and ethnicity have proven some of the most enduring spanning generations. Racial and ethnic disparities in health are inextricably mediated by the relationship between minority status, race as a social construct, and socioeconomic disadvantage. For instance, African American men at all points on the socioeconomic scale have shorter life expectancies than White males (Nelson, 2002). A preponderance of studies have shown that racial and ethnic minorities, especially African Americans, have poorer health and carry a disproportionate share of the burden of morbidity and early mortality as compared to the population overall (Fiscella, Franks, Gold, & Clancy, 2000; S. Grady & Darden, 2012). The differences extend to the level and quality of care extended (Nelson, 2002).

Moreover, self-assessed health, itself an important subjective measure of wellbeing (a reliable predictor of mortality and long-term morbidity among other health indicators) (Idler & Benyamini, 1997; Miilunpalo, Vuori, Oja, Pasanen, & Urponen, 1997) was found to be worse for Blacks and Hispanics relative to Whites, even after the relative effects moderated upon the introduction of controls for socioeconomic status (Ren & Amick, 1996). The quality of the living environment and with that its conduciveness to prospects for a healthy life varies greatly along racial and ethnic lines. An individual's absolute income level and their race interact to produce marked disparities in the daily exposure to air pollution levels leading to poor health. Air pollution from industrial sources, transportation, and other environmental stressors affect African Americans more heavily than any other group in the United States (Downey & Hawkins, 2008). Poor air quality is among the primary factors contributing to chronic lung disease, among which asthma affects heavily low income minority communities.

More broadly, ecological factors related to residence in a high poverty neighborhood influence the degree and extent of inequality in various health conditions and risk factors, as well as related matters of quality of life for minority residents. Persistent inequalities in health outcomes are of concern to public health officials and researchers – inequalities in measures such as self-assessed health status, premature/low weight births, overweight/obesity, diabetes, hypertension, cardiovascular disease, asthma, cancer, and HIV/AIDS among others (Franzini, Caughy, Spears, & Esquer, 2005; Lopez & Hynes, 2006; Ludwig et al., 2011). Relatedly, mental health is found to be strongly influenced by the neighborhood socio-economic status and conditions in distressed urban areas (Galea et al., 2007). Environmental degradation within neighborhoods, often imposed from the outside expose residents to a constant stream of diverse environmental hazards and sources of pollutants such as waste dumping grounds and former industrial lands (G. W. Evans & Kantrowitz, 2002).

Impetus for the Research

Disparities in health have become accentuated over the decade of the 2000’s by broader economic instability among other factors and remain a pressing issue in need of policy redress, particularly in an environment of rising concentration of poverty and inequality while many racial and ethnic minorities in urban regions remain on the margins of economic opportunity. Historical structural and institutional socioeconomic determinants of health outcomes invariably place a disproportionate burden of disease on those most disadvantaged in our society. In this climate, it is imperative to find better ways of understanding the dynamics that underlie the geography of interplay between neighborhood poverty and health. The current research aims to add to that understanding in order to elevate the social and public health policy discussion to incorporate vital life circumstances of disease burdened urban residents.

Methodological Arguments

The study of the relationship between neighborhood-level concentrated poverty and health outcomes necessitates the incorporation of a spatial analysis component, a research design that would account for the fact that neighborhoods do not exist in isolation from one another but are nested within broader urban regions and exist within a complex and interrelated geographical milieu of neighborhoods (Sampson, Morenoff, & Gannon-Rowley, 2002). The existent research is mixed on the issue of whether the spatial proximity of impoverished, minority neighborhoods (ethnic density) have a positive (informal social control, support, cohesion, collective efficacy) or deleterious effect (social disorganization) on certain health-related measures of outcomes and risk factors (S. C. Grady, 2006).

Self-selection into and out of neighborhoods is a significant impediment to designing research examining neighborhood level effects on health. Since people are not randomly distributed, processes of social stratification have a role in clouding effects that the neighborhood socioeconomic ecology exerts on residents' health (Oakes, 2004). This endogeneity problem arises when families choose (within varying degrees of constraint) to sort themselves into neighborhoods based on characteristics and preferences that then directly drive outcomes (G. J. Duncan, Connell, & Klebanov, 1997; Johnson, 2011). A comprehensive review of existing empirical papers between 1998 and 2005 on the subject cites a preponderance of cross-sectional studies in the field; the lack of longitudinal data in turn renders the respective research unable to address the issue of residential selection (Riva, Gauvin, & Barnett, 2007). Winkleby et al. (2006) recognize their research's limitation in relation to its ability to account for factors associated with selection bias. In order to ameliorate the selection problem, Sampson et al. (2002) propose "[combining] experimental assignment of neighborhood conditions with a longitudinal assessment of changes in social processes and individual behaviors" (p. 474). Indeed, point-in-time measures ignore effects of stability and change in a given community on the health of residents (Sampson, 1991). For the purpose of correct model specification selection bias could be seen as a left out variable bias. Thus, the omission of certain individual or household characteristics associated with residential location may bias estimates on the outcome variable (G. J. Duncan et al., 1997).

As discussed earlier, HUD's Moving To Opportunity experiment provided (at least conceptually) a nearly ideal data platform to study neighborhood treatment on a variety of child and adult outcomes over time, effectively eliminating potential bias on results from non-random residential sorting. With all its advantages, however, the study suffers from limited generalizability to a narrow segment of the population; it was further plagued by families' longer term residential mobility choices back to more or less similarly disadvantaged neighborhood environments (Sampson, 2008). Even so, since true experimental designs in this area are often impractical or even immoral/unethical to implement, a longitudinal multi-level approach provides great potential in uncovering neighborhood effects on individual level health outcomes. Relatedly, the Gautreaux Assisted Housing Program of the Chicago Housing Authority, initiated in 1976, is a notable example of other, quasi-experimental studies. In the course of the study nearly four thousand resident families were offered private housing choices in both city and suburbs. This design offered to somewhat address the problems of selection bias, however, again, localized scope and small sample sizes remain as limitations (Gephart, 1997).

A first study of its kind to examine the relationship between metropolitan economic segregation and mortality, Waitzman and Smith's (1998b) research examined the effect of concentrated poverty and concentrated affluence on individual mortality risk over the years 1986-1994 for adults over 30 residing in the 33 largest MSAs. They utilize several indices to represent poverty concentration: the C index- the proportion of poor persons residing in high poverty tracts, D index (or Index of Dissimilarity): measuring the evenness of the poor-non-poor distribution, and the P index – a measure of isolation or intergroup contact. However, the indices represent metropolitan-wide averages. The authors did find a significant association between a rise in metro-level concentrated poverty and risk of death among adults ages 30-64, controlling for individual level variables. The significance ceased however, after controlling for MSA poverty level. In this regard, a confounding interplay between overall area-wide poverty level and poverty concentration when controlling for race reemphasizes the importance of examining the role of race/ethnicity in the neighborhood-health relationship (Waitzman & Smith, 1998b).

Geographic Information Systems (GIS) have been used to analyze the complex spatial relationships of nested phenomena operating at different scales. Examples of previous research exist that combine spatial analysis and the metropolitan level of analysis, including an examination of the relationship between environmental health and applications of GIS (Jerrett et al., 2003).

Grady (2006) was the first study to explore the added contextual effect of racial residential segregation and neighborhood level poverty on individual risk of low birthweight among African American mothers and children (previous studies have considered the impact of MSA level segregation on birth outcomes). The cross-sectional study pairs fine grained birth outcome data with contextual predictor variables, racial residential segregation and poverty at the neighborhood level in New York City. The author finds that racial segregation operates at the smaller, neighborhood scale in determining the prevalence of low birth weight among African American women, while the rising concentration of neighborhood poverty effectively equalizes race-driven disparities in outcomes and all but removes the ‘ethnic density’ effect, or the protective effect of the neighborhood-level concentration of a single ethnic group. Thus, increasing neighborhood poverty works to exacerbate risk factors at the individual level in conjunction with racial residential segregation operating at the neighborhood scale. The findings at their core accentuate the importance of structural factors undergirding the historical processes of neighborhood residential sorting by race and socioeconomic deprivation, as well as the heightened physical and mental stressors extending from those structural forces through a complex mechanism deleterious to social cohesion. Further, ethnic concentration may exacerbate health stressors through racial isolation and associated social dysfunction (S. C. Grady, 2006).

Methodologically, Grady (2006) constructs a series of two-stage hierarchical generalized linear models (with the individual data modeled at level 1 and census tract data at level 2) – a random coefficients (level 1), level-2 predictor for intercepts-as-outcomes, and level-2 predictor for intercepts- and slopes-as-outcomes model. Two separate sets of models are set with racial residential segregation and neighborhood poverty at level 2; an additional model has segregation at level 2 while controlling for neighborhood poverty. The focus on a single outcome limits the study's versatility in assessing contextual effects; relatedly, additional racial and ethnic categories are omitted from the analysis. Situated in a single city, New York, further limits the study's generalizability. In its essence, the research is ultimately cross-sectional in its nature, rendering itself ill-fitted to capture the "dynamic trajectories" of neighborhood segregation and poverty over time (p. 3027). This inability to encapsulate the historic dynamism of neighborhoods ties back to controlling for selection bias where the longitudinal design element would account for neighborhood compositional and contextual changes over time. Further, the study lacks a measure of individual income level, but rather uses a dichotomous representation of Medicaid receivership status as a proxy. Finally, and most importantly, the above paper does not address selection bias due to its reliance on census tracts, proxies for neighborhoods, as the geography encompassing its level 2 predictors. The author attempts to address non-random residential sorting by controlling for additional individual maternal characteristics that would otherwise be left out of such models, however, this leaves off short of solving the issue. At the community level, there may always be present unobserved or unmeasured factors that simultaneously “affect both one’s health and where one lives” (Stephanie A Robert, 1999, p. 508). The neighborhood is hence a micro level geography susceptible to a myriad of variables determining residential location decisions of individuals and families.

In the way of correcting for the correlation between unobserved or unmeasured variables of individuals and families related to the treatment (neighborhood level factor), studies have used instrumental variables (Case & Katz, 1991; W. N. Evans et al., 1992; Foster & McLanahan, 1996). Aaronson (1997) conducted a study using 1968-1985 data from the Panel Study of Income Dynamics (PSID) in which the author designed a family fixed effects model around sibling pairs (at least three years apart in age) using sibling differences in neighborhood conditions to control for selection bias. The fixed effects approach allows for only within-family variation. Some of the drawbacks of the study were increased standard errors due to relatively low sample sizes as well as unmeasured between-sibling and family temporal differentials. Overall, the use of instrumental variables, even when good variables are identified, leaves room for potentially other, unaccounted for, latent confounders.

The current study proposes a novel methodological approach in that it uses a combination of a multilevel modeling technique employing longitudinal data where the health outcome of concern is available at the level of the individual. This approach also shields against potential selection bias seen in neighborhood effects and health research in reference to residential mobility (selective neighborhood in- and out-migration), and poverty and health more broadly, by relying on variables centered at their metropolitan level means, thus absorbing the within region migration processes. Individuals and families may sort themselves and reside within different neighborhoods based on a variety of reasons and influences by local mechanisms as well as broader pathways not captured by the proposed methodology. In this vein, the macro level approach of using entire urbanized regions encapsulates the above sorting at the micro level, thus controlling for the problem of residential selection in and out of neighborhoods.

Context matters in the study of the geographic distribution of social phenomena. In this vein, Tobler's first law of geography applies: "everything is related to everything else, but near things are more related than distant things" (Tobler, 1970). It follows that "…neighborhoods with similar characteristics tend to cluster together-a phenomenon that may indicate spatially based dependencies" (Browning, Cagney, & Wen, 2003, p. 1227). In the same vein, poverty is not a randomly occurring spatial phenomenon (Voss, Long, Hammer, & Friedman, 2006). The extant literature includes studies aimed at uncovering geographic patterns among different health-related metrics at varying scales (most often having the state or county as their unit of analysis), as well as that of concentrated poverty. In recent decades, multi-level or mixed models have been constructed and increasingly utilized in studying the neighborhood, or context-driven, effects on a number of health outcomes and risk factors. Some of the major shortcomings among them include the inconsistent control of individual level variables (as well as their incorrect conceptualization), and focus on reporting fixed effects over random (Riva et al., 2007). This study will control for left out variable bias, unmeasured variables constant over time within metros, through the estimation of fixed effects.

Yet, many studies (more specifically in the area of infant mortality) fail to recognize the importance of space and do not incorporate the spatial component into their methodological approach (Yang, Teng, & Haran, 2009). Some researchers have suggested looking beyond the local to include the broader milieu of adjacent neighborhoods in examining health-related factors, with an emphasis on disproportionate impacts on population subgroups (Sampson, Morenoff, & Earls, 1999). The relative position of such values vis-à-vis neighboring areas or analytic units is an aspect of the relationship between health and poverty not sufficiently explored in the literature and worthy of more in-depth study that could illuminate some of the causal mechanisms behind poor health in impoverished, minority communities.

Both Yang et. al. (2009) and Sparks et. al. (2013) utilize spatial statistical models to explore the relationship between infant mortality and socioeconomic factors. However, as common in many research studies in the public health they rely on aggregate data at the county level. The county is viewed as the lowest level of geographic aggregation at which much public health data is reported; it is also a convenient standard jurisdictional level to inform policy research. However, that unit of analysis falls short of encapsulating the full breath of data available in that it does not allow for the study of the association of individual health outcomes to neighborhood or area-wide factors. Also counties do not allow for individual level controls, thus making results vulnerable to the error of ecological fallacy – drawing inferences about individuals based on a group. Indeed, a multi-level study would lend itself to an ecological approach allowing for the optimal use of health outcome data for the individual paired with contextual determinants, enabling greater analytic precision utilizing available health data.

Prolonged exposure to the physical and mental stressors of residing within a marginalized neighborhood takes a material toll on residents felt in the course of everyday existence. One major caveat with existing studies is that they often attempt to measure effects over the short term or at a point in time (cross sectional). More narrowly, the data utilized in public health research is largely cross sectional in nature, omitting the temporal aspect of the respective relationships between dependent and predictor variables. However, the relationship between health outcomes and neighborhood residence necessitates a longitudinal exploration of dynamics of people and places.

In conjunction with this notion, a major shortcoming in both Yang et. al. (2009) and Sparks et. al. (2013) is that the cross sectional nature of the studies inhibits the identification of causal pathways. For illustration, a 1991 national survey examining the relationship between individual income and self-rated health (among other variables) was not able to circumvent the problem of neighborhood selection bias, or movement in and out of geographic units (states) without a longitudinal design to account for inter-areal sorting over time (Kahn et al., 2000). Geronimus' (1992) weathering theory relates to this issue of a cumulative contribution of exposure to conditions of disadvantage on health over time. In this direction, Clampet-Lundquist and Massey (2008) stress the importance of accounting for the duration of time spent in unfavorable neighborhood conditions for both adult and child health in future studies vying to extend knowledge on the effects of impoverished environments on health (in an effort to extend evaluations of the MTO study to non-economic outcomes).

Chapter 2: Methodology

This dissertation combines two national level datasets into a multilevel longitudinal design in order to tease out the effect of spatial concentration of high poverty neighborhoods and residential segregation on deleterious population health outcomes.

Measures of Health

Self-rated or self-assessed health is an important health outcome used within the public and population health fields. Although itself a variable measuring point-in-time assessment of overall health, it is an important subjective measure of wellbeing, evidenced to be a reliable indicator of current disease presence as well as predictor of morbidity throughout the life course and mortality, among other health indicators (Benyamini & Idler, 1999; Ferraro & Farmer, 1999; Idler & Benyamini, 1997; Idler, Russell, & Davis, 2000; Jylhä, 2009; Mackenbach, Simon, Looman, & Joung, 2002; Miilunpalo et al., 1997; Vuorisalmi, Lintonen, & Jylhä, 2005).

There are important and sizeable differences in the prevalence rates of the chronic conditions of asthma and diabetes among population subgroups, with a disproportionate share of disease burden carried by minority populations. The occurrence of asthma has been established to be highest for African American and Native American adults, with socioeconomic and environmental quality conditions explaining much of the difference with whites (Gorman & Chu, 2009). Together, members of the Hispanic heritage or ethnicity (with some notable within-group variation based upon national origin or ancestry) have been associated with unusually high rates of diabetes, compared to the national average (Ribble, PhD, & Keddie, 2001). ‘Inferior’ neighborhoods – deficient in nutritious food sources, proper recreational facilities, and compromised psychosocial safety increase the risk of obesity and uncontrolled hypertension, both of which are linked to diabetes and severity of complications (Spanakis & Golden, 2013). This puts minorities, especially African Americans, at greatest risk for this condition.

Poverty Concentration

Arguably the foundational and most frequently used measure of poverty concentration within the urban neighborhood context is the one put forth by Jargowsky and Bane (Jargowsky & Bane, 1990). It is the ratio of the count of persons living in high poverty neighborhoods to the count of the total metropolitan poor; in other words, the proportion of poor people residing within concentrated, or high, poverty census tracts – usually understood as tracts with a poverty rate of 40 percent or greater. This measure, although revealing of the level of within-tract composition and intensity of poverty, does not take into account the relative inter-dependence, positioning or organization of tracts in space (Greene, 1991). Nonetheless, this measure of poverty concentration provides information on an important dimension of the relative prevalence and magnitude of areas of socioeconomic disadvantage and deprivation within metropolitan area boundaries.

Segregation Measures

Several different metrics have been used to represent neighborhood racial segregation. Among the most widely used are the exposure or isolation index (P*) measuring the likelihood of interaction or physical contact in daily life between two groups by virtue of physical proximity; as well as the index of dissimilarity (D), an index measuring the evenness of the distribution of one group relative to another – its score representing the proportion of a group that would have to relocate in order to achieve perfect evenness of that group in the wider areal unit. Measures such as the index of exposure P* or the Neighborhood Sorting Index (NSI) are essentially aspatial, meaning that they do not take into account certain traits inherent in the arrangement of the values of a particular variable across space (Jargowsky, 1996).

Further, an areal unit's relative position in space vis-à-vis neighboring areas or units is an aspect of the relationship between health and poverty not sufficiently explored in the literature and worthy of in-depth study. In light of this, I will attempt to apply the concept of spatial autocorrelation (the clustering of geographical units across physical space) to elucidate the dynamic nature and nuances of the relationship between the spatial patterning of areas of high urban poverty and racial/ethnic segregation, and health outcomes over the period of analysis.

Measures of spatial autocorrelation

The Global Moran's I (GMI) is an index developed to measure the spatial autocorrelation (clustering) of neighboring values of a given variable based on a predefined characteristic. The index takes on a range of values between -1 and 1 from a fully random distribution toward a perfect clustering pattern (Ishizawa & Stevens, 2007). It is conceptually similar to a correlation coefficient as it relates to the distribution of neighboring characteristics in space (Sparks et al., 2013). A key prerequisite of the Moran's I calculation is the determination of a spatial weights matrix. In this respect, a first-order contiguity matrix is theoretically sound for application in the study of health outcomes as proximity matters in relation to health-relevant economic and social resources (Anselin, 2013).

The GMI has been applied in studies aimed at uncovering geographic patterns among different health-related metrics at varying scales (aggregated to areal unit), as well as that of concentrated poverty and racial segregation, however separately. The current study is different in that uses the GMI to generate metrics of metropolitan-level poverty and segregation, juxtaposing them with individual-level health outcomes, thus allowing for the measurement of the effect on health at varying levels of these area-wide measures. This approach also shields against potential selection bias seen in research on neighborhood effects and residential mobility, and poverty and health more broadly by including metrics aggregated to the metropolitan level, absorbing within region migration processes. The following section elaborates on the mechanism by which this paper addresses selection bias in more detail.

Data and Analytic Strategy

This study explores the relationship between the geographic patterns of poverty and racial/ethnic and economic segregation within urban areas and population health at the metropolitan scale within the United States. A multi-level fixed effects panel model (at the MSA level) is proposed in order to test the hypotheses stated above. The analysis models both individual and metro-level characteristics.

The individual-level measures derive from the Behavioral Risk Factor Surveillance System (BRFSS). The BRFSS represents a cross-sectional nationally representative random-digit-dial state-based telephone survey compiled and released by the Centers for Disease Control and Prevention (CDC) on an annual basis and administered monthly by the respective public health agency/body of each state; the survey has grown substantially since its introduction in 1984 (a more detailed summary of historical participation numbers for the BRFSS, 1984 to present, is provided in Appendix A). The data collected is used for the purposes of state, local and regional population health planning, policy evaluation, and related research. The geographic extent of the data used in this study includes the 48 contiguous United States and the District of Columbia (the states of Alaska and Hawaii, as well as Puerto Rico and the remaining overseas territories were excluded for the purposes of this project due to their unique geographic and socio-economic characteristics).

The primary unit of analysis at the 2nd level (ecological) is a set of selected metropolitan and micropolitan statistical areas as defined by the U.S. Bureau of the Census[1]. Both areas represent core-based statistical areas – areas defined by the Census as consisting of an urban core (city or town) at the center and its adjacent counties tied

[1] United States Census Bureau, Metropolitan and Micropolitan, Accessed from: https://www.census.gov/programs-surveys/metro-micro/about.html

together by shared socioeconomic conditions (average commuting distance as among the foremost of these). Further, the time-frame of analysis includes the years 2000 and 2010, period for which comparable data is available within the BRFSS annual survey program as well as Census/ACS data releases corresponding to those years (a rationale for setting the timeframe of the analysis is presented in Appendix E).

The analysis combines metropolitan and micropolitan statistical areas (core-based statistical areas or CBSAs), and metropolitan divisions (constituent components of combined statistical areas, CSAs).

Statistical Modeling and Analysis

Multilevel modeling has been established as a quantitative technique of great utility and possibility by public health researchers, particularly in accounting for and incorporating into the analysis the complex interrelationship between contextual and compositional factors in shaping health outcomes across space through the specification of cross-level interactions (C. Duncan, Jones, & Moon, 1998). As such, multilevel, also referred to as hierarchical linear or mixed, models are able to accurately represent the interactions between variables measured at different geographic levels (nested variables).

Further, utilizing a large, national level dataset affords the ability to discern patterns and relationships relative to studies of smaller areal units (Mehta & Chang, 2008). Using a combination of health related data at the individual level and spatial poverty, racial/ethnic and economic segregation at the metropolitan and micropolitan levels, we employ the following two-level hierarchical linear (multilevel) regression model specification.

General multilevel model structure:

Equation 1: Level 1 (individual)

$$H_{ij} = \beta_{0j} + \beta_{1j}X_{ij} + u_{ij}$$

Equation 2: Level 2 (metropolitan); random effect (intercept component)

$$\beta_{0j} = \beta_{00} + \beta_{01}RS_{j} + \beta_{02}CP_{j} + v_{j}$$

Equation 3: Level 2 (metropolitan); random effect (slope component)

$$\beta_{1j} = \beta_{10} + \beta_{11}RS_{j} + \beta_{12}CP_{j} + \beta_{13}MP_{j} + w_{j}$$

Equation 4: The complete multilevel structure with interaction effects (individual*metropolitan)

$$\begin{aligned} H_{ij} &= \beta_{00} + \beta_{01}RS_{j} + \beta_{02}CP_{j} + v_{j} \\ &\quad + (\beta_{10} + \beta_{11}RS_{j} + \beta_{12}CP_{j} + \beta_{13}MP_{j} + w_{j})X_{ij} + u_{ij} \\ &= \beta_{00} + \beta_{01}RS_{j} + \beta_{02}CP_{j} + \beta_{03}MP_{j} + (\beta_{10} + w_{j})X_{ij} + \beta_{11}RS_{j}X_{ij} \\ &\quad + \beta_{12}CP_{j}X_{ij} + v_{j} + u_{ij} \end{aligned}$$

Equation 1 represents the individual level regression model where both coefficients for the slope and intercept are written as a function of the level 2 factors (Equation 2 and Equation 3 respectively). Thus, the health outcome H of person i in metro j is modeled as a function of level 2 coefficients β_{0j} and β_{1j} where the latter (level 2 slope) carries the cross-level interaction with a vector of individual level sociodemographic characteristics X for a person i in metro j. The intercept and the slopes at the individual level are allowed to vary on the key 2nd level predictor variables:

residential segregation (RS), concentrated poverty (CP), metro poverty level (MP), and random components for the intercept and slope, v_j and w_j respectively.

Centrally to testing our hypotheses stated previously, within Equation 1, the slope coefficient on the interaction term, $\beta_{1j}X_{ij}$, will allow us to discern the additional effect of individual or household characteristics at the metro-level when a metro displays high levels of a metro area factor, at a set level of the remaining metro area factors. Equation 4 presents the full model after substituting in the two level 2 equations (for the intercept and slope respectively) into the original level 1 structure, showing each of the three interaction terms (highlighted); here, the term $\beta_{1j}X_{ij}$ is written out in its long form to show the interaction of the set of individual or household factors with each of the metropolitan level variables. We expect higher levels of the respective metropolitan factor to exacerbate the effect of individual or household characteristics when the effect is nonlinear – exhibiting an increasingly greater magnitude toward the upper extreme of the distribution. In particular (within Equation 4): β_{11} provides the added effect of individual or household characteristics on expected individual health outcome for a one percentage point increase in residential segregation, holding CP and MP constant (Hypothesis III); β_{12} provides the added effect of individual or household characteristics on expected health outcome for a one percentage point increase in concentrated poverty, holding RS and MP constant (Hypothesis I/II); finally, β_{13} provides the added effect of individual or household characteristics on expected health outcome for a one percentage point increase in metro poverty, holding CP and RS constant.

The multilevel analysis was conducted with the use of the -xtreg- command in Stata version 14, with clustering on the 2^{nd} (metropolitan) level and correcting for potential heteroscedasticity (common with MSAs) and correlation of residuals due to left out variables and/or measurement error. All variables will be centered at their metropolitan level means. The bias stemming from non-random selection in and out of neighborhoods is eliminated with the use of metro-level variables which absorb within-metro residential sorting processes. Left out variable bias is controlled through fixed effects. Fixed effects models are preferable when working with metro regions as the geography over random effects as there are expected to be latent factors within regions that are constant over time (e.g., climate, regional political arrangements), taking precedence over between-metro variability. The method utilized in this dissertation is a lower bound estimate. Lastly, the models are able to capture both within and between metro area variability in health measures, as the data will provide a relatively large minimum number of observations per areal unit for each of the years in the analysis.

Chapter 3: Trends, Data, and Descriptive Statistics

Trend in Health Outcomes over decade of the 2000's

The CDC produces the SMART (Selected Metropolitan/Micropolitan Area Risk Trends) BRFSS dataset, a subset of the BRFSS annual data for each year between 2002 to 2010 (as well as more current years) consisting of individuals residing in metros with representative numbers of observations, 500 or more respondents per metro per year[2]. The SMART BRFSS provides metro-level weights that can be used to produce area-wide disease prevalence rates and summary statistics on the various health measures. This subset provides data for 77 metros (metros appearing in every year between 2002 and 2010). The areas consist of 56 metropolitan statistical areas, 3 micropolitan statistical areas, and 18 metropolitan divisions. A review of these data shows a 2002 median rate prevalence of poor or fair health of about 13.6%. The same number for 2010 was just over 13.5% – a slight decrease of about 0.4%. The median rate of a diagnosis of asthma from among the same set of metros was under 12.1% in 2002, and 14.4% in 2010, an increase of 19.3%. Finally, the median rate of a diagnosis of diabetes was a little less than 6.2% in 2002 and 8.3% in 2010, an increase of 34.6%. Figure 3-1 shows the overall trend over this period.

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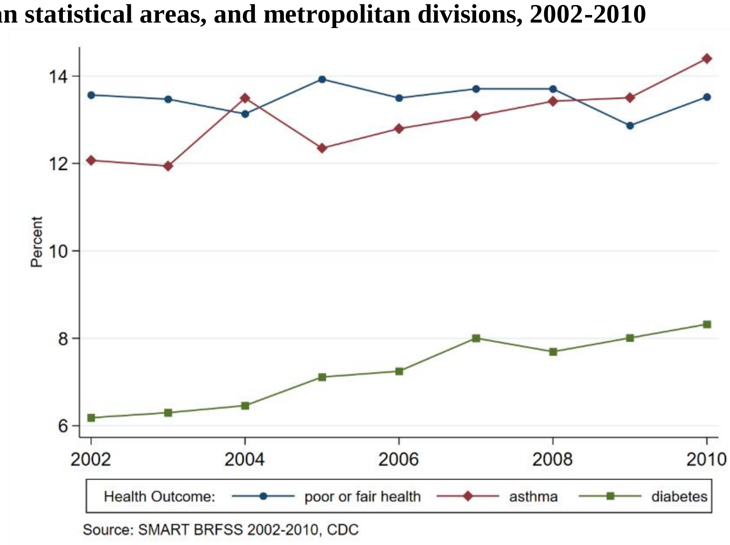
[2] Centers for Disease Control and Prevention, Behavioral Risk Factor Surveillance System, SMART: BRFSS City and County Data and Documentation. Accessed from https://www.cdc.gov/brfss/smart/Smart_data.htm

In comparison, the National Health Interview Survey (NHIS), also from the CDC, reports about a 58% increase (age-unadjusted) in the rate of diabetes diagnoses over the period 2000 to 2010 for the U.S. adult population overall (Pleis, Schiller, & Benson, 2003; Schiller, Lucas, & Peregoy, 2012). A study in the Journal of the American Medical Association used the NHIS to find a doubling in diagnosed diabetes rates in adults ages 20 to 79 between the years 1990 and 2008 (controlling for age, gender, race and ethnicity, education level, and weight status or body mass index), with a tapering off or slowing down thereafter until 2012, with exceptions for certain minority groups (Geiss et al., 2014). In terms of asthma, Zhang et. al., using BRFSS state level data, report a 33% increase in its prevalence rate among U.S. adults between 2000 and 2009 (2013). The authors find a significant rise in current asthma prevalence after adding relevant sociodemographic and risk factor controls (Zhang et al., 2013).

Figure 3-1: Median rates: poor or fair health, asthma, and diabetes for 77 metropolitan statistical areas, micropolitan statistical areas, and metropolitan divisions, 2002-2010

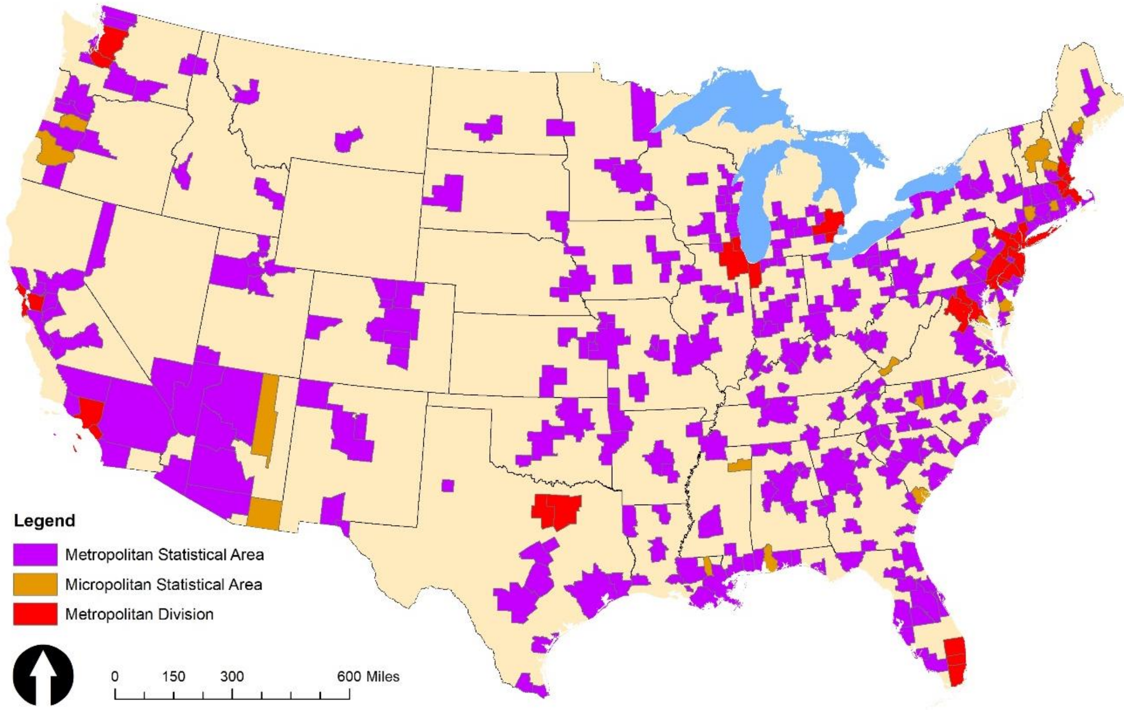


Sources of data and geographic scope

The quantitative models used in this dissertation rely primarily on these secondary publicly available sources of data: the 2000 Census (Summary File 3), American Community Survey (2008-2012 5-year release) as a source of data at the metropolitan level, and the Behavioral Risk Factor Surveillance System (BRFSS) 2000 and 2010 annual survey data releases for data at the individual level.

The analysis has as its geographic scope metropolitan- and micropolitan statistical areas, as well as metropolitan divisions (component parts of Core Based Statistical Areas, or CBSAs) within the contiguous United States with a total population of 100,000 residents and greater. This specific population cutoff threshold was chosen in order to ensure a minimum working number of Census tracts necessary in the calculations of the measures of metro-level concentration of poverty as well as race and ethnicity segregation indices, taking into account the relationship between area population size and tract density (a total count of Census tracts by consistent metropolitan-, micropolitan statistical area, and metropolitan division for the years 2000 and 2010 is presented in Appendix B). In total, there are 310 unique areas for each of the years 2000 and 2010 (for a panel of 620); in all, 909 counties comprise 263 metropolitan statistical areas, 18 micropolitan statistical areas, and 29 metropolitan divisions (Figure 3-2). The areas were standardized to the 2010 boundaries and naming conventions using the constituent counties.

Figure 3-2: Map of the 310 metropolitan statistical areas, micropolitan statistical areas, and metropolitan divisions



Time-frame of the Analysis

The study uses pooled 2000 and 2010 data for each U.S. metropolitan / micropolitan statistical area, and metropolitan division occurring in and having a sufficient number of responses in both BRFSS annual survey years. The analysis has the purpose of ascertaining the determinants of the change recorded in health outcomes in light of a number of factors operating at both the individual and metropolitan scale, as well as cross-level interactions. In this direction, the analysis runs models clustered on the 2nd level variable (metro) in order to explore both the within and between metro region variation. A fixed effects model takes into account factors/variables within regions that are constant over time and not otherwise captured or measured.

Since not all metros have sufficient number of responses for each of the survey years, an appropriate cutoff point was determined to be those areas with total population of 100,000 in at least one year (a summary of BRFSS survey response rates by consistent metropolitan-, micropolitan statistical area, and metropolitan division for the years 2000 and 2010 is presented in Appendix B).

Dependent Variables

The response or outcome variables used in the study are selected health outcome measures from the BRFSS dataset. All health outcomes are individual level measures of self-assessed general health status, diagnoses of asthma and diabetes, and the number of physically and mentally unhealthy days. The outcomes derive from the core section of the BRFSS questionnaire[3] (as this data is collected consistently across survey years). It is important to note here that all of the BRFSS individual-level variables are self-reported measures of health outcomes and risk factors as well as a number of socioeconomic and demographic characteristics.

The variable genhlth is the self-reported general health status of an individual measured on a scale of 1 through 5, going from excellent to poor health respectively. It is treated as first continuous and then ordinal within the analyses in sections to follow. The binary variable poorfairhlth was created to represent an overall unfavorable self-rated health and was derived from the above original (genhlth) variable by combining the two

[3] Centers for Disease Control and Prevention. (2015). Behavioral Risk Factor Surveillance System, BRFSS Questionnaires. Accessed from http://www.cdc.gov/brfss/questionnaires/index.htm

highest categories, 4 and 5 (corresponding to fair and poor health respectively), and is coded 1 if a person has self-assessed as being in fair or poor general health, and 0 otherwise.

The analyses presented in subsequent chapters treat one of the main dependent variables ‘general health status’ in one of three ways: a continuous variable with a possible range of 1 through 5, to be analyzed through the fitting of an ordinary least squares regression model; an ordinal variable with five discrete levels (cut points) ranging from 1 (excellent) 2 (very good) 3 (good) 4 (fair) and 5 (poor), fitted using an ordered logit model; and finally, a derived dummy variable ‘poor or fair health’ (coded as 1 if health status is 5 (poor) or 4 (fair), and 0 otherwise), where a logit regression is appropriate. The above three sets of models based on the three different variants of the dependent variable general health status were estimated as a robustness test to check for sensitivity of the model results to each of the three model specifications.

Next among the outcomes is a set of variables measuring chronic illness burden: incidence of asthma and diabetes. The binary variable asthma is coded 1 if a person has ever been diagnosed with asthma by a doctor, nurse, or other health professional (irrespective of current status of disease presence), and 0 otherwise. Similarly, the binary variable diabetes is coded as 1 if a person has ever been diagnosed with diabetes by a doctor or other health professional, and 0 otherwise (note: the responses “female told only during pregnancy” and “pre-diabetes or borderline diabetes” were coded as 0).

The dependent variables measuring adult incidence of chronic conditions (similarly to poor or fair health) are collectively of the binary type – indicating whether a condition has been met or not; thus necessitating a logistic regression as an analytic functional form.

Lastly, the variables named physhlth and menthlth represent counts of the number of physically and mentally unhealthy days respectively that a survey respondent has reported as having experienced in the last 30 days prior to the interview. There is significant clustering at zero (respondent reported no physically or mentally unhealthy days over the period) – constituting well over half of non-missing responses across the outcomes and survey years (63.7%-64.9%). Descriptive statistics including the respective means and proportions of minimum and maximum values for the physically and mentally unhealthy days variables of physhlth and menthlth are presented in Table 3-1. When examining the respective distributions of the variables, a noticeable spike occurs at the final response value of 30 (these are likely individuals living with long-running or chronic illness/distress). Given the likely presence of excessive dispersion negative binomial regression analysis was determined as the most appropriate and employed with this variable set.

Table 3-1: Summary statistics for BRFSS variables - number of physically and mentally unhealthy days

Year	**2000**			**2010**		
Variable	**Mean**	**Prop. (0)**	**Prop. (30)**	**Mean**	**Prop. (0)**	**Prop. (30)**
physhlth	3.23	64.89%	5.31%	3.49	63.7%	5.59%
menthlth	3.2	64.92%	4.24%	3.46	64.55%	4.74%

The pair of number of physically and mentally unhealthy days variables represent a new and different set of measures as contrasted to general health status. While the latter provides information on current health status, the former provides insight into a person's health through a longer time horizon. The set of unhealthy days variables introduces a more functional measure of health to the analysis capturing certain more objective aspects of health – an attempt at quantifying the degree of cumulative physical and mental limitations in the course of daily life. In turn, this potentially helps to ascertain a better understanding of processes of longer term health trajectories.

Independent Variables

Key independent variables in the model are measures of the spatial arrangement of concentration of poverty and segregation within the boundaries (constituent counties) of metropolitan areas. The metro-wide spatial indices were calculated using GIS software with corresponding data points measured at the census tract-level.

The review of the literature on disparities in health discussed earlier brought forth evidence of persistently poor outcomes for vulnerable populations, primarily low to moderate income households, African Americans, Hispanics, as well as Native Americans.

The controls consist of relevant individual level socioeconomic and demographic characteristics:

Socioeconomic and demographic - This study utilizes individual-level data from the CDC's Behavioral Risk Factor Surveillance System (BRFSS) for the following list of (level 1) control variables:

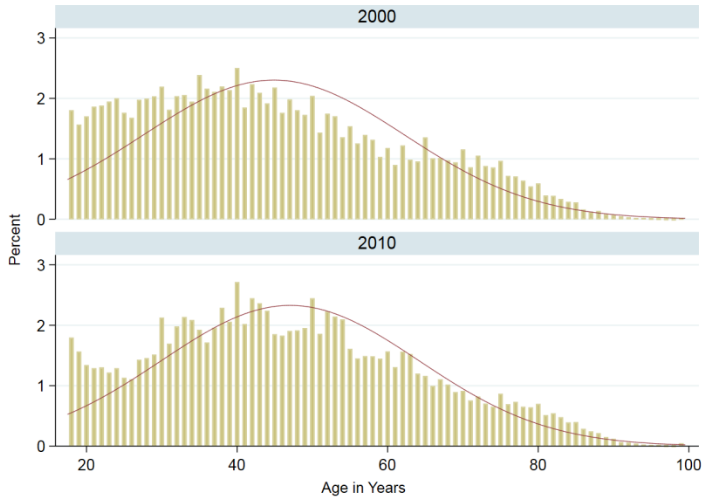
a. Age (continuous)
b. Race/Ethnicity (categorical)
c. Sex (binary variable)
d. Annual household income (categorical, income ranges)
e. Married status (binary variable)

Individual level variables

It has been long since established that socioeconomic status, or SES (usually defined as grouping income, education, and occupation status), is an important factor in the delineation of difference in health attainment among social groups. This is the well know SES gradient in health (Adler et al., 1994). Household income in its own right is found to be consequential to health, with lowest incomes bearing the brunt of the disease burden (Kahn et al., 2000). Likewise, consistent disparities on a variety of health indicators have been studied and well documented between racial and ethnic minority population groups in the United States (with a particular focus on African Americans) and whites (Williams & Collins, 1995). Further, a person's marital status is determined as among the social determinants to longer term wellbeing and health outcomes, accompanied by important variations by gender; married persons are generally healthier across categories (Liu & Umberson, 2008). Individual gender and age are variables used routinely as controls in research studying health outcomes.

The individual level variables utilized in regression analysis come from pooled data for the years 2000 and 2010 of the BRFSS annual survey releases. The variable Female is a binary variable, coded as 1 if person is female and 0 otherwise. The variable Marital is also a binary variable, coded with 1 if a person is married, and 0 otherwise. The variable age is a continuous variable indicating a person's age, in years, at the time of the survey. It includes adults 18 years of age and older (up to 99). The distribution of age in each of 2000 and 2010 is presented in Figure 3-3. The variable age2 or age-squared represents the addition of a quadratic function for age to more accurately model the effect of the progression of age on the set of health outcomes. The mean age in 2000 and 2010 was 44.9 and 47.1 respectively, while the median age in 2000 and 2010 was 43 and 46 respectively (the summary statistics were computed using sampling weights provided with the BRFSS data).

Figure 3-3: Histogram of survey respondent age in sample, by year



The categorical income variable used in the current analysis was derived from the original BRFSS INCOME2 variable for an individual's annual household income consisting of eight distinct categories or ranges of household income which were collapsed to four income categories. It must be noted here that the 2000 dollar amounts have not been adjusted for inflation to 2010. The 2000 household incomes were provided in the BRFSS data in categories of ranges of income not adjusted for inflation. An attempt was made by the author to adjust the amounts (bringing year 2000 incomes forward to 2010 dollars), however after exploring several ways to align the adjusted 2000 ranges to arrive at consistent bracket boundaries with those for 2010 a match was not possible. The original eight income ranges were reduced to the following four: Less than $25,000 (a coarse approximation for the federal poverty threshold for a five-person household in 2010), $25,000 to $49,999, $50,000 to $74,999, and $75,000 and over. The last income category was omitted from the models and stands as the base or reference case for comparison.

The five binary race and ethnicity variables used in the analysis are based on the original BRFSS variable RACE consisting of eight categories of race and ethnicity. The categories were consolidated and new categories were defined as follows: Non-Hispanic White, Non-Hispanic Black, Non-Hispanic Asian, Non-Hispanic Native American (original name: Native American or Alaska(n) Native), and Hispanic (of any race). The first variable in the preceding list, Non-Hispanic White, was omitted from the analysis as the base case. The race variable in the 2000 BRFSS had combined the categories of Non-Hispanic Asian and Non-Hispanic Pacific Islander, thus the corresponding original race category of Hawaiian or other Pacific Islander was added to the Non-Hispanic Asian race category in the 2010 data. Lastly, the remaining categories of Multiracial, and Other race as a whole comprised a relatively small proportion of the combined analytic sample and were dropped in the interest of a more simplified interpretation of the effect of the key race and ethnicity groups.

There were a number of other possible covariates isolated from among the BRFSS individual-level measures of behavioral risk factors. Such variables include patterns of tobacco use (past or current smoking), alcohol consumption (heavy and binge drinking), preventative screenings (mammograms, colonoscopies/sigmoidoscopies), physical exercise, and public of private health insurance coverage. The study ultimately does not include such factors as additional covariates in the regression models due to endogeneity concerns. After all, such behavioral risk patterns affecting health are to a large extent themselves influenced by both macro and micro social and economic forces left outside of the analysis.

Metropolitan level variables

The metropolitan level variables in this analysis were derived from the relevant poverty status in past year tables from the 2000 census and the 2012 ACS 5-year data release (2008-2012). The specific variables obtained at the census tract-level represent counts of individuals in poverty as well as total population by race and ethnicity for whom poverty status has been determined (this counts only those persons not in group quarters at the time of interview).

The above variables were used in the calculation of the race and ethnicity specific poverty rates, the variable Metro Poverty Rate. The measure for concentration of poverty, the variable Poverty Concentration, also utilizing race-specific figures, was calculated as an area-wide measure where the census tract is the inner geography contained within the broader unit - the metropolitan area. This variable is a ratio of the total population in poverty, by race and ethnicity, residing in tracts with a poverty rate of 40 percent or greater (known as high or concentrated poverty tracts) and the total group-specific population in poverty within the metro area. Although inherently aspatial, this measure provides insights into the level of regional concentration of the poor as it is unaffected by the physical location in metropolitan space of high poverty neighborhoods.

The measure of race and ethnicity specific segregation, seg, was calculated using the user-written -seg- command in Stata, version 15. The index of dissimilarity (D) is a measure of the evenness of the distribution of two groups. It gives the proportion of one group that would have to relocate in order to attain an equal distribution with the other group across a wider area. Here once again census tracts are nested within metropolitan areas. The index is generated by this method for every pair of minority group / non-Hispanic White (majority) race group combination of race and ethnicity (e.g. Non-Hispanic Black – Non-Hispanic White, Hispanic – Non-Hispanic White, etc.). In the case of whites the segregation index was calculated as Non-Hispanic Whites in relation to every other group.

Lastly, the measure of global spatial autocorrelation (Moran's index score), was calculated using a combination of ArcGIS and Stata for each metropolitan area by race and ethnicity-specific category for two groups of tract-level measures: percent race or ethnicity, the variable Moran's I (%race/ethnicity), and poverty rate, the variable Moran's I (poverty rate). A spatial weights matrix was generated from XY coordinate data extracted from U.S. Census Tigerline / Cartographic Boundary shapefile geographies using the –shp2dta- utility. This in turn was used to apply a first order contiguity rule (nearest neighbor) in the construction of the spatial indices. The Moran's I, as an explicitly spatial measure, quantifies the degree of geographic clustering of values of a variable across two dimensional space. Here again the smaller level unit of census tract was used as comprising metropolitan areas. The index score ranges from -1 (a perfect checkered pattern, indicating perfect dispersion, equidistance or proximity of dissimilar values) to 1 (perfect clustering along the range of values); scores near 0 exhibit patterns of random dispersion of values, where some clustering is expected by chance. These sets of measures provide an alternative means of capturing the area-wide distribution of racial and ethnic groups as well as poverty. More specifically, Moran's I (%race/ethnicity) measures a different aspect of the regional segregation by race and ethnicity, while Moran's I (poverty rate) offers a new perspective on the level of poverty concentration across the metropolitan space.

It is important to note that when merging the metropolitan and individual level datasets the assignment of the level 2 variables was made based on an individual's race or ethnicity. For example, the value for Non-Hispanic Asian concentration of poverty was assigned to a Non-Hispanic Asian individual; the respective value for White – non-White segregation (index of dissimilarity) was assigned to a person with race Non-Hispanic White, etc. This strategy ensured that each individual was correctly matched with the appropriate value for metropolitan level poverty, concentration of poverty, segregation, as well as the Moran's I measures corresponding to their own racial or ethnic group. This in fact is superior to the use of a single 'total' or overall measure of poverty, poverty concentration, segregation, and/or the Moran's I measure (itself a form of measurement error) as the approach takes into consideration the effects on an individual of the respective area-wide figure for one's own group. Another argument for selecting the two groups in calculating segregation is that minority-majority group segregation is more conceptually sound due to the aims of testing relative resource deprivation between the disadvantaged and advantaged groups (Jargowsky, 2018).

Descriptive Statistics

Table 3-2 presents summary statistics for the several sets of area variables used in the current analysis (race-specific numbers, and the respective totals where applicable). The figures in the table below were weighted by a metro's relative share of the aggregate population of the full analytic sample for each year in order to mitigate the potential biasing influence of smaller areas on the summary statistics.

We note a general divergence in the way that the pairings of Moran's I and corresponding aspatial measures. The total and race and ethnicity specific poverty rate almost universally increased in the inter-year period, with the exception of the Asian American poverty rate. The total and race and ethnicity specific concentration of poverty figures show a substantial increase, with the weighted sample means of the percent of the metropolitan poor population in high poverty tracts climbing between 28.3% for African Americans and by nearly 70% for Non-Hispanic whites between 2000 and 2010. The corresponding measure of Moran's I for poverty rate exhibits a reversal in trend or less spatially arranged total and race and ethnicity specific poverty rates, with the greatest drop for total poverty, 39% (except for Non-Hispanic White; that number climbed 38%).

In terms of segregation, the index of dissimilarity presents a mixed picture. The White – Non-White and White - Black segregation decreases between the two years while White – Asian and White – Native segregation increases. The White – Hispanic segregation remains unchanged. Conversely, the Moran's I for percent race/ethnicity has increases among all majority – non-majority group and majority – minority group pairs. In fact, the respective number for the spatial clustering of the tract-level percent Native increases almost 2.7 fold by 2010.

The summary statistics of the metro-level variables point to rather conflicting trends by the otherwise seemingly intuitively related pairs of aspatial and explicitly spatial measures of concentration and clustering, particularly for poverty concentration. Although by the numbers a greater proportion of the poor now reside in high poverty tracts, the average metropolitan landscape exhibits greater tract dispersion, tracts with similar poverty rates are less proximal to one another taking into account the complete spectrum of the poverty rate distribution. This condition to a large extent drives the divergence in regression analysis results obtained in subsequent sections.

Table 3-2: Race-specific summary statistics for the level 2 variables: poverty rate, poverty concentration, segregation (Index of Dissimilarity), and Moran's I measures, by year (figures weighted by metropolitan share of agregate sample population)

	2000						2010				
Variable	Obs.	Mean	StDev	Min	Max		Obs.	Mean	StDev	Min	Max
Total poverty rate	310	11.79	4.46	4.45	35.87		310	14.29	4.33	5.96	35.03
Non-Hisp White pov rate	310	7.08	3.29	3.25	20.58		310	9.02	3.71	3.72	22.50
Black poverty rate	310	23.34	7.90	5.20	62.61		310	25.82	9.49	10.91	73.27
Asian poverty rate	310	13.00	7.98	2.02	61.12		310	12.79	7.57	0	48.86
Native poverty rate	310	19.78	8.79	2.33	61.80		310	23.02	10.48	0	62.16
Hispanic poverty rate	310	21.13	6.51	5.26	43.56		310	24.55	7.34	4.62	53.69
Total conc of poverty	310	9.86	10.41	0	61.21		310	13.45	11.26	0	53.48
NH White conc of pov	310	4.16	9.13	0	47.80		310	7.06	9.72	0	49.58
Black conc of poverty	310	15.65	12.92	0	55.13		310	20.08	16.42	0	78.55
Asian conc of poverty	310	8.14	15.56	0	76.36		309	12.05	19.33	0	100
Native conc of poverty	310	8.96	11.54	0	80.05		309	12.56	17.58	0	100
Hispanic conc of poverty	310	9.52	11.20	0	61.37		310	14.62	14.27	0	61.73
Moran's I (total poverty rate)	310	0.56	0.23	-0.15	0.82		310	0.51	0.21	-0.25	0.78
Moran's I (NH Wht pov rate)	310	0.37	0.17	-0.15	0.75		310	0.34	0.18	-0.24	0.71
Moran's I (Black pov rate)	310	0.20	0.18	-0.40	0.64		310	0.13	0.15	-0.40	0.49
Moran's I (Asian pov rate)	310	0.12	0.16	-0.29	0.56		309	0.09	0.15	-0.60	0.71
Moran's I (Native pov rate)	310	0.05	0.16	-0.52	1.03		309	0.04	0.18	-1.00	0.61
Moran's I (Hisp pov rate)	310	0.23	0.20	-0.31	0.62		310	0.18	0.17	-0.44	0.54
Dissim (White--non-White)	310	0.49	0.14	0.07	0.78		310	0.46	0.12	0.12	0.71
Dissimilarity (White--Black)	310	0.62	0.15	0.29	0.87		310	0.60	0.12	0.24	0.82
Dissimilarity (White--Asian)	310	0.44	0.08	0.24	0.60		310	0.48	0.08	0.22	0.73
Dissimilarity (White--Native)	310	0.51	0.11	0.20	0.87		310	0.65	0.13	0.28	0.88
Dissimilarity (White--Hisp)	310	0.48	0.13	0.14	0.73		310	0.48	0.11	0.20	0.69
Moran's I (% Non-H White)	310	0.69	0.28	-0.14	0.90		310	0.71	0.25	-0.15	0.91
Moran's I (% Black)	310	0.63	0.31	-0.16	0.89		310	0.66	0.28	-0.13	0.90
Moran's I (% Asian)	310	0.42	0.26	-0.29	0.76		310	0.54	0.22	-0.09	0.79
Moran's I (% Native)	310	0.09	0.14	-0.21	0.79		310	0.24	0.18	-0.26	0.85
Moran's I (% Hispanic)	310	0.53	0.31	-0.23	0.87		310	0.62	0.25	-0.10	0.90

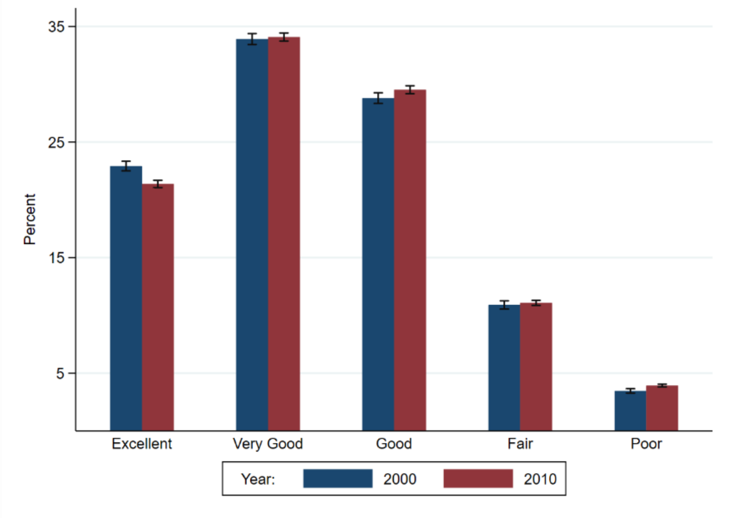
There is reason to believe that the two sets of aspatial and explicitly spatial measures of poverty/segregation concentration/clustering respectively are associated measures, at least to a certain extent. After all, they are understood to measure the same underlying poverty and residential dynamics. In order to better ascertain the level of association present, the below correlation matrix was produced for each year of analysis (Table 3-3). A high level of correlation between the following two measures is to be expected: metropolitan poverty and concentration of poverty (r=0.81 in 2000 and r=0.68 in 2010). There is considerable inverse association between metro poverty and the Moran's index for poverty (r=-0.54 in 2000 and r=-0.61 in 2010). There is a somewhat reduced however still negative relationship between poverty concentration and Moran's I for poverty, the two key paired measures in the poverty section (r=-0.29 in 2000 and r=-0.26 in 2010). Lastly, with regard to segregation, the index of dissimilarity and the Moran's index for percent race/ethnicity show a positive relationship in 2000 (r=0.22) which then moderates to virtually no association by 2010 (r=0.02). Overall, the correlation results fall in line with the race-specific figures presented in Table 3-2 above.

Table 3-3: Correlation matrix for the main metro-level variables, by year (population-weighted)

2000			
	Metro pov. rate	Poverty conc.	I. of dissim.
Poverty concentration	0.81	-	-
Morans I (pov. rate)	-0.54	-0.29	-
Morans I (%race/eth.)	-	-	0.22
2010			
	Metro pov. rate	Poverty conc.	I. of dissim.
Poverty concentration	0.68	-	-
Morans I (pov. rate)	-0.61	-0.26	-
Morans I (%race/eth.)	-	-	0.02

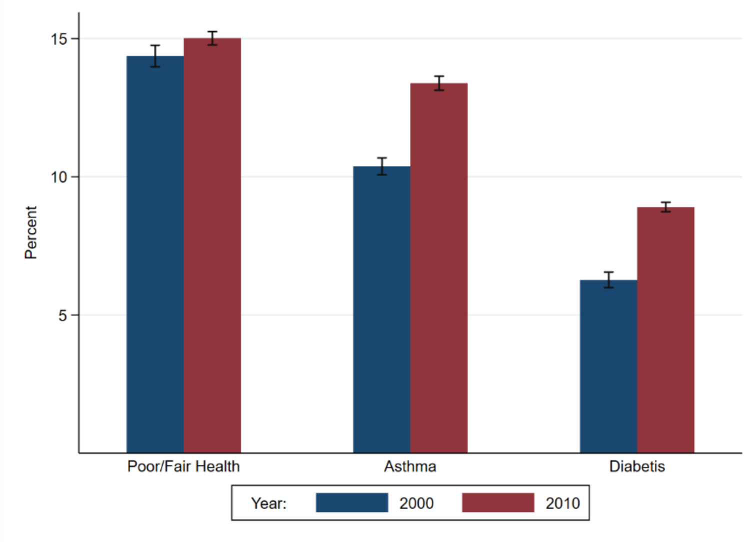
As seen in Figure 3-4, the relative distribution of the component categories of general health status has remained largely similar across the two years of data, with a noticeable drop in the proportion of reports of Excellent health, and an uptick in the proportion of those reporting Good as well as Poor health. On average, a little over 63 percent of respondents self-assess to be in Good or Very Good health.

Figure 3-4: General health status categories, by year (w/ 95% C.I.)



As seen in Figure 3-5 the weighted proportions of persons reporting poor or fair health increased from 14.4% in 2000 to 15% in 2010. The weighted proportions of those individuals ever diagnosed with asthma also rose markedly between the years 2000 and 2010 from 10.4% to 13.4% (up full three percentage points). Lastly, the corresponding proportions for persons ever diagnosed with diabetes rose from 6.3% to 8.9% in the inter-year period.

Figure 3-5: Health outcome prevalence: poor or fair health, asthma, and diabetes, by year (w/ 95% C.I.)

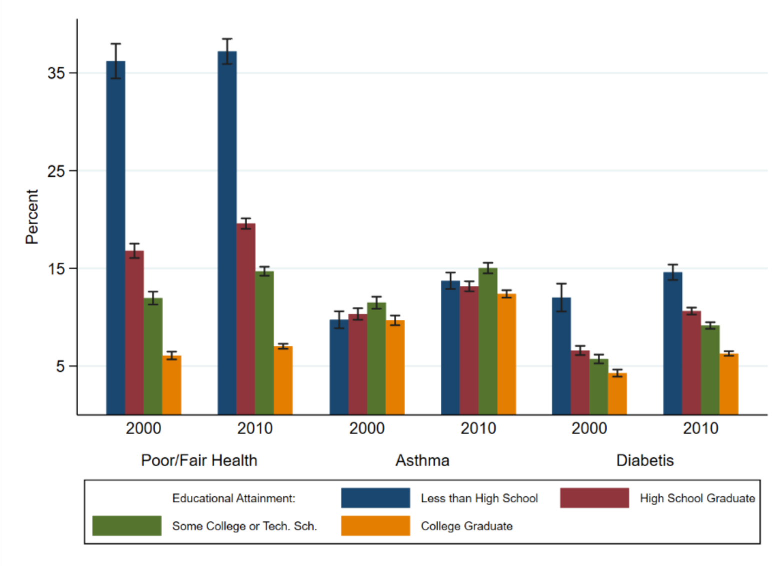


All six outcome variables are coded in such a way as to indicate progressively poor health outcomes, i.e. worsening of overall health with greater values. For instance, a higher numerical code for **genhlth** corresponds to worse general health.

The following series of graphs will further aid in getting a better understanding of the ways in which the several health outcomes relate to socioeconomic and demographic groups within the individual level sample.

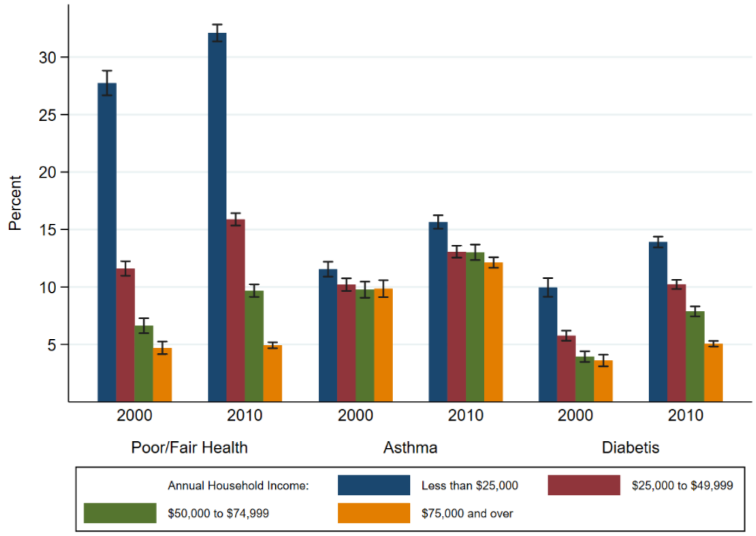
Figure 3-6 points to a rather conspicuous gradient of health outcomes and years of education completed (of the population 18 years and older). Outcomes improve as one moves up the levels of attainment. This is most striking in the case of Less than high school where just over 36% and 37% of all respondents reported poor or fair health in 2000 and 2010 respectively. The prevalence of asthma is the exception in this regard, appearing to be at its peak for persons who have completed Some college or technical school.

Figure 3-6: Health outcome prevalence: poor or fair health, asthma, and diabetes, by year and educational attainment (w/ 95% C.I.)



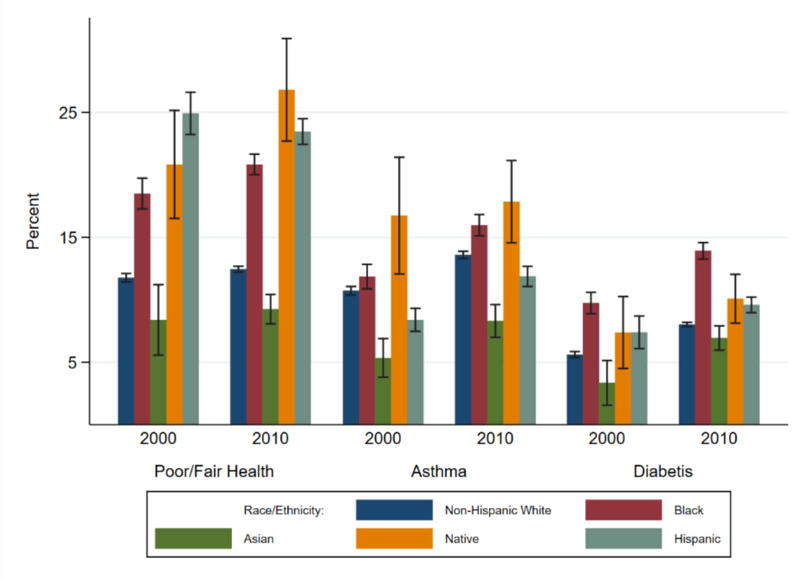
A similar picture arises when examining the distribution of health outcomes by annual household income ranges (Figure 3-7). There is a clear gradient of worsening health moving toward near poverty income levels. In fact, nearly 28% (2000) and 32% (2010) of all respondents with household incomes of less than $25,000 reported poor or fair health. Asthma once again defies this pattern; however, it does exhibit a slight downward trend with rising incomes.

Figure 3-7: Health outcome prevalence: poor or fair health, asthma, and diabetes, by year and income (w/ 95% C.I.)



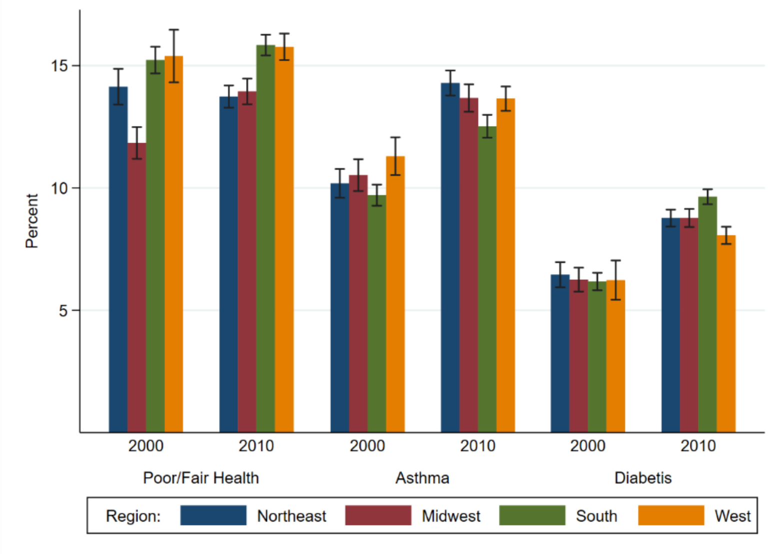
With respect to the racial and ethnic composition (Figure 3-8), there is a clear general trend of worsening in health over the decade. For Hispanics, there is pronounced high proportion of respondents with poor or fair health (25% in 2000 and 23.5% in 2010). The rates are similar, however to a degree lower, for Non-Hispanic Blacks; this group also has the highest proportions of persons diagnosed with asthma and diabetes, in any year (nearly 14% of Non-Hispanic Blacks reported a diabetes diagnosis in 2010). One of the race groups fairing worst among the health outcomes are Non-Hispanic Native Americans, with a rate of poor or fair health reaching close to 27% in 2010 (up by six percentage points from the year 2000 and the highest of any group by decade's end). This population further had some of the highest rates of asthma in both years.

Figure 3-8: Health outcome prevalence: poor or fair health, asthma, and diabetes, by year and race and ethnicity (w/ 95% C.I.)



When considering the Census region of the country in which a person resides (Figure 3-9), we note a general worsening of health over the period of study. An exception here is improvement in general health status seen in the Northeast; however, this region also had a rise in asthma by four percentage points, from 10.2% in 2000 to 14.2% in 2010. The South and West regions have markedly higher proportions of residents with poor or fair health in both years.

Figure 3-9: Health outcome prevalence: poor or fair health, asthma, and diabetes, by year and census region (w/ 95% C.I.)



Next, we look at the distribution of the health outcomes by an individual's marital status (Figure 3-10). Here once again we observe a general worsening across the health outcomes over the period, with the exception of a narrow decline in poor or fair health for married individuals in 2010 relative to 2000. Widowed and separated persons exhibit the highest proportions of poor or fair health across the two years, while those divorced and separated experienced a considerable worsening in health status (with the prevalence of poor or fair health increasing by 5.9 percentage points each, from 24.6% (2000) to 30.5% (2010) for divorced, and from 17.7% (2000) to 23.6% (2010) in the case of separated). Overall, married persons enjoy measurably better health (poor/fair health and asthma), however less conclusively so with respect to diabetes (Figure 3-11).

Figure 3-10: Health outcome prevalence: poor or fair health, asthma, and diabetes, by year and marital status (w/ 95% C.I.)

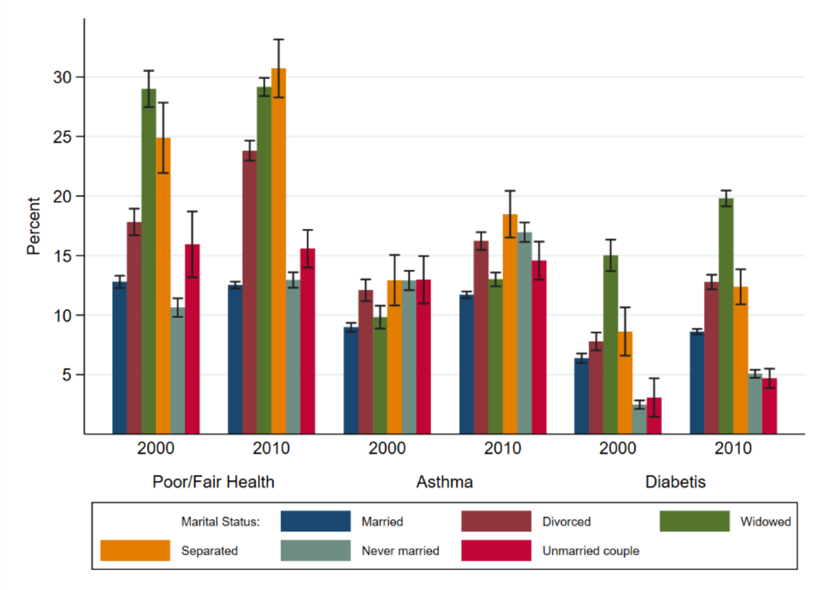
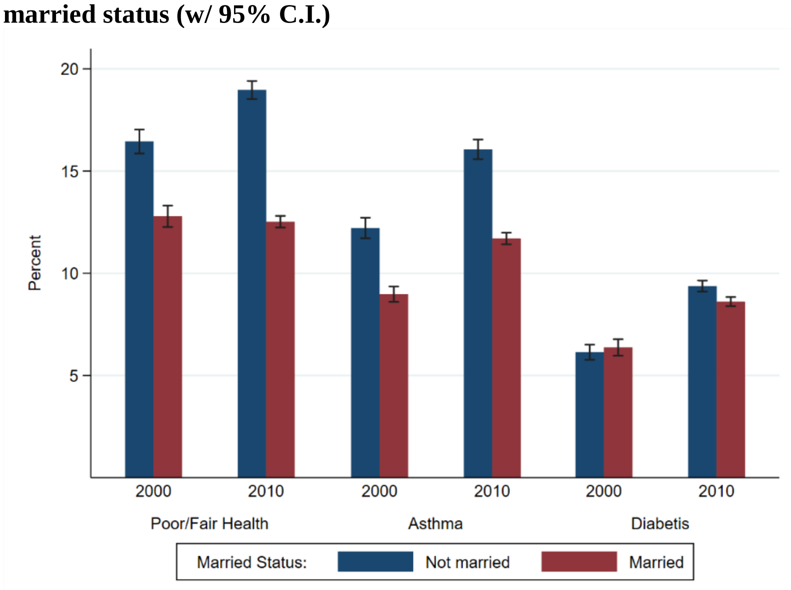
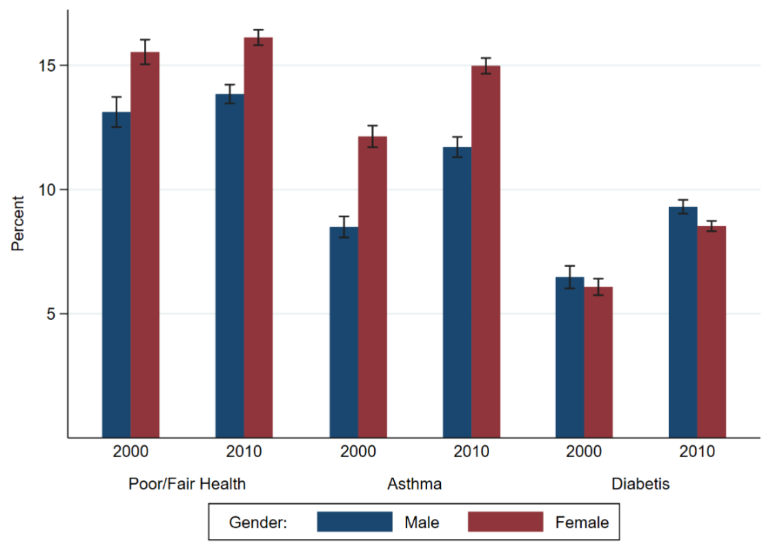


Figure 3-11: Health outcome prevalence: poor or fair health, asthma, and diabetes, by year and married status (w/ 95% C.I.)



Lastly, the breakdown of the health outcomes by gender (Figure 3-12) reveals females to be overall worse off relative to males, in all outcomes but diabetes where females maintain slightly better outcomes. Once again there is a notable trend of worsening health across the measures over the course of the decade of the 2000's for both genders.

Figure 3-12: Health outcome prevalence: poor or fair health, asthma, and diabetes, by year and gender (w/ 95% C.I.)



Summary of Descriptive Statistics

To synthesize the above, the descriptive statistics point to an overall downward pressure over the period of analysis on the measures of health: poor or fair health, diagnose of asthma, and diagnose of diabetes. The general trend of worsening health outcomes observed here is consistent with other studies dealing with a similar period having as their key outcome various measures of morbidity and mortality. Moreover, the outcome measures, the focus of the current study, vary considerably on a number of socioeconomic and demographic factors. We observe particularly worse health among individuals with the lowest household incomes, those with the lowest educational attainment, as well as minorities, relative to the more advantaged comparison groups.

When looking at the change in average statistics for the period 2000-2010, nearly all measures display a worsening of conditions over the period. From time spent in non-work related physical activity/exercise, to chronic conditions and other risk factors, the samples show a general downward trend in health across the spectrum of the nation's adult, non-elderly population.

Given the observed trends, a closer examination is needed to establish a more direct connection between concurrent trends in health and increasing concentration of poverty and inequality in the first decade of the new millennium.

The Combined Dataset

The dataset matches BRFSS data (2000 and 2010) to Decennial Census (2000 and 2010) and American Community Survey (ACS) 2010 1-year and 2008-2012 5-year release data. The pooled 2000 and 2010 individual (level 1) and metropolitan (level 2) data represents the full analytical sample used in the analyses conducted in subsequent sections and has a total of 373,183 observations (n=373,183) distributed as follows for the two years of data: 105,868 observations for the year 2000 (28.4%), and 267,315 for the year 2010 (71.6%). The fewest number of observations by metro for the year 2000 are 49 (the Vallejo-Fairfield, CA MSA), while the most are 4,179 (the Providence-New Bedford-Fall River, RI-MA MSA); the mean number of observations per metro in that year was 338.7, and the 50th percentile (median) was 156. For the year 2010, the fewest number of observations by metro are 39 (the Bloomington-Normal, IL MSA), while the most are 8,933 (the Providence-New Bedford-Fall River, RI-MA MSA); the mean number of observations per metro in 2010 was 862.3, and the median was 507; the corresponding statistics for 2000 are 341.5 and 158 (Table 3-4). Table 3-5 shows the breakdown of observations by area type for each of the years.

Table 3-4: Summary statistics (respondent counts/observations) by metro and year

Year	Groups	Median	Mean	Standard Dev.	Min	Max
2000	310	158	341.51	459.43	49	4,179
2010	310	507	862.31	1,025.75	39	8,933

Table 3-5: Number of observations by metro type and year

Metro Type	2000	2010	Total
Micropolitan	3,740	7,710	**11,450**
Metropolitan	77,051	200,303	**277,354**
Metropolitan Division	25,077	59,302	**84,379**
Total	**105,868**	**267,315**	**373,183**

Study Limitations

The present study has several important limitations whose careful consideration is needed in order to provide the reader a more comprehensive context when interpreting the findings. The time period under investigation spans only the decade of the 2000's, offering a limited ability for utilization of available quantitative tools for longitudinal analysis, revealing more clearly some of the causal mechanisms at work in the concentrated poverty to health and racial segregation to health relationship.

Moreover, while the study design addresses the problem of selection bias in the form of residential sorting of individuals at the local level by extending the focus of the analysis to the broader, metropolitan area level, it operates under the assumption that all relevant sorting takes place within metropolitan areas. Thus, it does not take into account possible bias introduced by varying degrees and nature of migration flows between metropolitan areas, metropolitan areas and population centers outside of metropolitan areas (small towns and rural areas), both within and between regions, as well as international migration flows (potentially biasing the impact of immigrant populations).

Lastly, in terms of the analytical sample, there are three metropolitan statistical areas, all fully contained in the state of Illinois, with total year 2000 observation counts under 30 per group (specifically between 22 and 26), for the asthma models. This presents a potential limitation on the statistical power in drawing conclusions regarding this subset of metropolitan areas.

Chapter 4: Metropolitan level poverty, concentration, and spatial clustering of poverty

Research Inquiry

The following set of models explore the effect of the overall metropolitan level of poverty, concentration of poverty, and spatial clustering of poverty on selected health outcomes measured at the level of the individual and mediated by several groups of both individual and household level covariates in order of increasing complexity.

The data and variables

The complete dataset used in the analyses contains a total of 373,183 pooled records for the years 2000 and 2010. The regression models were specified to treat the data as a panel of U.S. metros (a combined total of 310 metropolitan and micropolitan statistical areas, and metropolitan divisions). The individual respondents are not the same across the two years of data.

In the initial set of models the -xtreg- command in Stata version 15 was employed, with fixed effects in order to pick up influence of unobserved time-invariant factors within metropolitan areas. Robust and metro area clustered standard errors were applied uniformly across all models with the purpose of accounting for the nested nature of observations (individuals) within metros, an essentially multilevel structure, as well as addressing heteroscedasticity as a common concern when working with metropolitan areas. In some models, individual metro area dummies were inserted as explanatory variables as a fixed effects specification form. The outcome variable **genhlth** is treated as first containing continuous then ordinal data within the sequence of models in this section. The continuous form assumes equidistant levels, for instance moving within the coding scheme from 1 (excellent health) to 2 (very good health) on the variable scale is equal to going from 4 (fair health) to 5 (poor health). A continuous response allows for the use of ordinary least squares (OLS) regressions aiding in the interpretation of model coefficients; following, ordered logit models were then specified, conceptualizing **genhlth** in its ordinal form. Logit models were fitted for the remaining indicator outcomes of poor or fair health, asthma, and diabetes. Lastly, negative binomial functions were estimated in the case of the count variables **physhlth** and **menthlth**, number of physically and mentally unhealthy days respectively.

Key predictor variables in this portion of the analysis are the metropolitan level poverty rate and concentration of poverty, as well as an alternative measure of the geographic (spatial) concentration, or clustering, of poverty (the tract-level poverty rate). These area measures are race and ethnicity specific, meaning that, in the combined dataset, each level 2 value is assigned to an individual record based on the race and/or ethnicity of the specific respondent in the BRFSS data (level 1). This ensures that each individual in the analyses is correctly paired with the corresponding overall metropolitan area-wide measure pertaining to their own racial and/or ethnic group as these measures of disadvantage (and especially concentrated disadvantage) directly bear on individual experiences within the broader spatial context of metropolitan areas.

For the purposes of the analysis the metropolitan poverty rate and poverty concentration pair of measures were rescaled to assume the range of values from 0 to 1 (in effect a transformation from percent to decimal form) so as to render each more readily comparable to the Moran's I measure for poverty rate (itself with a range of possible values between -1 and 1).

The standard set of level 1 controls include dummy variables for race and ethnicity, as well as four categories (quartiles) of annual household income, gender, marital status, an individual's age in years, and age-squared (to incorporate the nonlinear, or quadratic, effect of age). The four-model structure is consistent across the analyses, with models arranged such that they range from the simplest (1) to most complete (4). Model 1 contains the two key predictor variables of interest: race and ethnicity specific metropolitan area level poverty rate, concentration of poverty, and the Global Moran's index for poverty rate, as well as the individual level race and ethnicity dummies: Non-Hispanic Black, Non-Hispanic Asian, Non-Hispanic Native, and Hispanic (reference category of Non-Hispanic White). Model 2 adds the income dummies: Less than $25,000, $25,000 to $49,999, and $50,000 to $74,000 (reference category of $75,000 and over). Model 3 further adds the level 1 dichotomous variables of Female and Married. Model 4 includes the pair of respondent age variables: age and age2 (age-squared).

Finally, the complete model presents results of two sets of cross-level interactions corresponding to the key level 2 predictor variables subject of the current analysis, which help to probe further for potential nuances in the impact of these measures by category of household income (income ranges). The interactions are instituted in order to better ascertain the differential effect (both in terms of direction and magnitude) of overall concentration of poverty and spatial clustering of poverty by household income category, in reference to the base category of incomes of 75,000 and over. It is precisely here that the multilevel model structure described in Chapter 2: comes to light allowing for the specification of separate effects of the metro variables for each of the household-level characteristics (annual income). The slope of the effect of the level 1 factor on the health outcomes varies for different levels of the level 2 factor.

Multivariate Regressions

Table 4-1: Fixed effects OLS models of general health status on metropolitan poverty rate, concentration of poverty, and spatial clustering of poverty, with cross-level interactions

Model #	(1)		(2)		(3)		(4)	
Constant	2.386**	(90.50)	2.003**	(64.75)	2.010**	(64.92)	1.016**	(30.66)
Metro-level variables								
Metro Poverty Rate	0.884**	(3.83)	0.866**	(4.05)	0.875**	(4.07)	0.372**	(2.82)
Poverty Concentration	0.390**	(4.47)	0.437**	(4.90)	0.444**	(4.94)	0.276**	(3.54)
Moran's I (Poverty Rate)	-0.199**	(-4.04)	-0.257**	(-4.34)	-0.259**	(-4.33)	-0.0961*	(-2.40)
Person-level variables								
Race/ethnicity								
Non-Hispanic Black	0.0866+	(1.83)	-0.151**	(-4.13)	-0.146**	(-3.99)	0.0587**	(2.75)
Non-Hispanic Asian	-0.179**	(-7.36)	-0.159**	(-7.59)	-0.166**	(-7.89)	0.0429*	(2.52)
Non-Hispanic Native	0.186**	(4.72)	0.000539	(0.02)	-0.00359	(-0.11)	0.183**	(6.69)
Hispanic	0.145**	(3.46)	-0.125**	(-3.76)	-0.132**	(-3.96)	0.147**	(5.26)
Income								
less than $25,000			0.960**	(122.47)	0.989**	(118.97)	0.950**	(59.35)
$25,000-$49,999			0.460**	(76.54)	0.476**	(75.89)	0.447**	(32.81)
$50,000-$74,999			0.222**	(36.53)	0.230**	(36.94)	0.216**	(15.78)
Other person-level controls								
Female					-0.0668**	(-14.31)	-0.0711**	(-16.22)
Married					0.0342**	(7.58)	0.0121**	(2.91)
Age in years							0.0280**	(27.34)
Age (squared)							-0.000149**	(-16.10)
Cross-level interactions								
Inc. < $25,000 # Pov. Conc.							-0.153*	(-2.18)
Inc. $25,000-$49,999 # Pov. Conc.							-0.0186	(-0.31)
Inc. $50,000-$74,999 # Pov. Conc.							-0.0940	(-1.49)
Inc. < $25,000 # Moran's I							-0.0843*	(-2.20)
Inc. $25,000-$49,999 # Moran's I							-0.0388	(-1.16)
Inc. $50,000-$74,999 # Moran's I							0.0334	(1.06)
N	367,561		318,366		318,366		317,011	

t statistics in parentheses; models use robust (due to heteroskedasticity) and metropolitan area clustered standard errors
race/ethnicity reference category: non-Hispanic white; income reference category: $75,000 and over
+ p < .10, * p < .05, ** p < .01

A high level of correlation between metropolitan poverty concentration and the Moran's measure for the geographic distribution, or clustering, of tract-level poverty rates was suspected due to an intuitive original assumption that the two merely represent alternative ways of capturing the degree, or character, of the distribution of poverty across metropolitan space. Upon testing for the presence of correlation between the pair of aspatial and explicitly spatial metro-level explanatory variables in the set of poverty-specific regression models, there appears to be a moderate association present. The Pearson's correlation coefficient shows an inverse relationship ($r = -0.27$). In order to probe for any potential effects of multicolinearity, a new set of models were estimated in which each of the health outcomes was regressed on the two main metro-level measures of interest separately. When looking at the two different specifications the corresponding coefficients on the poverty concentration and Moran's I measures behave almost identically, both in terms of effect size and direction. There is however a narrow tendency for the estimates in the separate models to be statistically weaker, particularly with respect to the concentration measure. The complete results of those models are presented in Appendix C. In the interest of parsimony and preserving a more complete set of results in the final presentation, as limited multicollinearity was found, only the sets of models including both metro-level measures simultaneously are used in the main text in order to facilitate comparison and observe the mutual interaction among the two main measures of poverty concentration and clustering for each of the health outcomes.

Table 4-1 presents the results from the set of metropolitan fixed effect models examining the effect of overall metropolitan level poverty, concentration of poverty, and geographic clustering of poverty on self-rated general health status.

The coefficients on all three key level 2 explanatory variables of race-specific metro poverty rate, poverty concentration, and the Moran's I measure for poverty rate are highly significant across the model specifications, from model (1) through model (3), with the first two showing a positive relationship (worsening health status), while the Moran's measure has a protective effect on health status. Model (4) adds the pair of age variables and two sets of interaction terms (the estimates on the metro variables are now specified, standing for the reference income category of $75,000 and over). The Moran's measure here takes on a moderate significance at an alpha level of 0.05. It follows that a greater overall level of poverty and spatial concentration of poverty for one's own race/ethnicity maintain opposing and relatively highly statistically significant effects on the general health status score (indicating worsening and improving health for the high incomes respectively). The last of the metropolitan level predictors, spatial clustering of poverty, indeed has a protective effect – a metro with a more highly clustered geographic pattern of tract-level poverty shields the base income category against worsening health after controlling for the levels of poverty and poverty concentration.

Of the cross-level interactions, the (detrimental) relative impact of residing in a metro with higher concentrations of poverty is reduced by 0.153 for those in the lowest income category relative to those in the highest income category. However, this only partly offsets the large direct effect of being in the low income category of 0.95 in Model

4. The effect of poverty concentration is not significantly different from the base case for the two intermediate income categories.

From among the second set of interactions (between each of the income categories and the Moran's measure for poverty rate), only the coefficient on the first interaction achieves (moderate) significance, speaking to an effect of residence in a metro with a greater degree of spatial ordering of poverty not harmful for those individuals with the lowest incomes ($25,000 and under) compared to what would be expected for the highest income group. The small, seemingly protective effect for the lowest income category is more than annulled by the standalone estimate on low income.

The first set of individual level predictors, race and ethnicity, vary greatly in both directionality of effect and significance. Generally, all groups but Non-Hispanic Asian begin with having a detrimental effect compared to Non-Hispanic White, turn to protective in models (2) and (3), then return to detrimental to health in model (4). Asian race status appears as highly significant and protective, relative to whites in model (1), changing to detrimental, however weakened and only moderately significant by model (4). The estimate on Non-Hispanic Black has only marginal statistical significance in the first model, but ends as highly significant in models (4). The estimates for Native American respondents in models (2) and (3) appear to weaken considerably and lose any significance.

The set of household income categories exhibit highly statistically significant detrimental effects uniformly across model specifications, progressively increasing in magnitude moving down the income ranges, relative to persons with annual household incomes of $75,000 and over. There is a clearly identifiable income gradient effect on health.

In model (3) female status has a significant and protective effect relative to males, while being married worsens general health compared to those unmarried (a result highly significant at an alpha level of .01).

Table 4-2: Ordered logit models of general health status on metropolitan poverty rate, concentration of poverty, and spatial clustering of poverty, with cross-level interactions

Model#	(1)		(2)		(3)		(4)	
Metro-level variables								
Metro Poverty Rate	1.443**	(3.70)	1.538**	(3.99)	1.559**	(4.01)	0.656**	(2.70)
Poverty Concentration	0.671**	(4.60)	0.788**	(4.89)	0.802**	(4.93)	0.571**	(3.90)
Moran's I (Poverty Rate)	-0.330**	(-3.96)	-0.450**	(-4.20)	-0.455**	(-4.21)	-0.172*	(-2.16)
Person-level variables								
Race/ethnicity								
Non-Hispanic Black	0.173*	(2.16)	-0.229**	(-3.43)	-0.220**	(-3.28)	0.140**	(3.50)
Non-Hispanic Asian	-0.258**	(-6.30)	-0.246**	(-6.33)	-0.262**	(-6.67)	0.108**	(3.27)
Non-Hispanic Native	0.316**	(4.62)	0.00485	(0.08)	-0.00278	(-0.04)	0.340**	(6.62)
Hispanic	0.282**	(3.94)	-0.182**	(-3.00)	-0.196**	(-3.22)	0.304**	(5.78)
Income								
less than $25,000			1.690**	(119.34)	1.749**	(117.86)	1.734**	(58.94)
$25,000-$49,999			0.827**	(75.61)	0.860**	(75.94)	0.835**	(33.31)
$50,000-$74,999			0.415**	(37.06)	0.432**	(37.72)	0.414**	(15.80)
Other person-level controls								
Female					-0.129**	(-15.64)	-0.139**	(-17.41)
Married					0.0668**	(8.44)	0.0292**	(3.84)
Age in years							0.0490**	(26.84)
Age (squared)							-0.000257**	(-15.40)
Cross-level interactions								
Inc. < $25,000 # Pov. Conc.							-0. 364**	(-2.74)
Inc. $25,000-$49,999 # Pov. Conc.							-0. 0930	(-0.82)
Inc. $50,000-$74,999 # Pov. Conc.							-0. 203+	(-1.69)
Inc. < $25,000 # Moran's I							-0.191**	(-2.65)
Inc. $25,000-$49,999 # Moran's I							-0.0719	(-1.12)
Inc. $50,000-$74,999 # Moran's I							0.0724	(1.20)
N	367,561		318,366		318,366		317,011	

t statistics in parentheses; models use robust (due to heteroskedasticity) and metro area clustered standard errors
models include 310 metro dummies (coefficients not displayed); race/ethnicity reference category: non-Hispanic white; income reference category: $75,000 and over
+ p < .10, * p < .05, ** p < .01

Table 4-2 displays a set of models that mirror the setup in Table 4-1 using general health status as the response, only this time ordered logit models were estimated, with robust and metropolitan area-clustered standard errors. These, as well as all remaining models in this section, were estimated with the inclusion of 310 metropolitan area dummies. The output reports untransformed coefficients, or log odds, for ease of result interpretation, particularly with regard to the cross-level interaction terms. These coefficients are interpreted as the change (increase or decrease) in the log odds of observing the outcome with a unit increase in the predictor.

We note here that, with reference to the level 2 variables, a similar pattern is observed as in the OLS models. A one-unit increase in the race-specific metro poverty rate results in about 0.66 greater log odds of observing worse general health for incomes $75,000 and over (model (4)) ceteris paribus. Model (4) specifies the metro estimates with the inclusion of the cross-level interactions – they now stand for the effect on the person-level base category: household incomes of $75,000 and greater. Similar to the initial model specification, the coefficient on poverty concentration holds a high level of significance in the last model as the estimate becomes income group-specified, having greater practical significance this time – a unit increase raising the log odds of worse health for the base income group by 0.57, all else equal. The Moran's measure once again retains moderate significance and protective status in model (4) – a unit increase in the measure lowers the log odds of the outcome for the highest incomes by 0.17.

We find a divergence in the behavior of the coefficients on the first set of cross-level interactions as contrasted with the OLS results. The signs here have flipped;

however, all effect sizes are relatively minor. Residence in metropolitan areas with a heightened level of poverty concentration exerts a slight shielding influence on those of lowest incomes compared with the highest incomes, with a high level of significance. Further, we find a similar effect for the medium income range, at only marginal significance.

The second set of interactions (household income categories and Moran's I) once again maintain a protective, and this time highly significant, effect on overall health for the low income group relative to the high incomes. Locating within a metro with comparably higher degree of geographical sorting of poverty, relative to what we would expect to find by random chance, does not appear to harm the health attainment of persons with low household incomes, in relation to the highest incomes (residence in metros with a greater clustering of poverty results in a change in the log odds of worse health for low income individuals of -0.36 compared to those with high incomes (with significance at an alpha of .01)).

Among the level 1 indicators, beginning with the race and ethnicity categories, we note here a nearly identical pattern among the categories as in Table 4-1: the coefficients behave almost uniformly as protective between models (2) and (3) when the signs change, rendering group membership detrimental to health in the complete model, with high significance mostly retained throughout the models. Asian is the sole category to start off as protective, while the addition of household income temporarily flips the signs on Non-Hispanic Black and Hispanic from detrimental to protective.

The coefficients on the three income categories, the Female and Married dummies, as well as age follow much a similar pattern as was found in the OLS metro-fixed effects regressions.

The change in model specification (treatment of the dependent variable) between the first and second set of models made for a substantial difference primarily in a single set of explanatory variables - the effects observed in the first group of cross-level interactions between household income and the (aspatial) measure of poverty concentration.

Table 4-3: Logit models of poor or fair health status on metropolitan poverty rate, concentration of poverty, and spatial clustering of poverty, with cross-level interactions

Model#	(1)		(2)		(3)		(4)	
Constant	-1.678**	(-24.78)	-2.912**	(-33.11)	-2.910**	(-32.90)	-6.056**	(-66.76)
Metro-level variables								
Metro Poverty Rate	1.386**	(3.53)	1.424**	(3.74)	1.439**	(3.77)	0.581*	(2.18)
Poverty Concentration	0.627**	(3.85)	0.745**	(4.08)	0.755**	(4.11)	0.562**	(2.90)
Moran's I (Poverty Rate)	-0.400**	(-4.22)	-0.543**	(-4.67)	-0.544**	(-4.66)	-0.473**	(-4.06)
Person-level variables								
Race/ethnicity								
Non-Hispanic Black	0.166*	(2.03)	-0.323**	(-5.30)	-0.316**	(-5.19)	0.112**	(2.59)
Non-Hispanic Asian	-0.613**	(-8.93)	-0.593**	(-9.38)	-0.609**	(-9.62)	-0.138*	(-2.39)
Non-Hispanic Native	0.381**	(4.99)	0.00358	(0.05)	-0.00206	(-0.03)	0.390**	(5.75)
Hispanic	0.333**	(4.38)	-0.223**	(-3.45)	-0.236**	(-3.64)	0.392**	(6.72)
Income								
less than $25,000			2.155**	(92.84)	2.204**	(87.83)	2.063**	(44.48)
$25,000-$49,999			1.148**	(54.70)	1.175**	(53.93)	1.041**	(21.46)
$50,000-$74,999			0.545**	(24.88)	0.559**	(25.02)	0.477**	(9.22)
Other person-level controls								
Female					-0.101**	(-7.98)	-0.128**	(-10.36)
Married					0.0597**	(5.11)	0.0165	(1.39)
Age in years							0.0976**	(41.24)
Age (squared)							-0.000642**	(-31.02)
Cross-level interactions								
Inc. < $25,000 # Pov. Conc.							-0. 366*	(-2.22)
Inc. $25,000-$49,999 # Pov. Conc.							-0. 170	(-1.01)
Inc. $50,000-$74,999 # Pov. Conc.							-0. 304	(-1.56)
Inc. < $25,000 # Moran's I							0.175	(1.63)
Inc. $25,000-$49,999 # Moran's I							0.214+	(1.81)
Inc. $50,000-$74,999 # Moran's I							0.256*	(1.98)
N	367,561		318,366		318,366		317,011	

t statistics in parentheses; models use robust (due to heteroskedasticity) and metro area clustered standard errors; models include 310 metro dummies (coefficients not displayed); race/ethnicity reference category: non-Hispanic white; income reference category: $75,000 and over
+ p < .10, * p < .05, ** p < .01

The next set of models (Table 4-3) comprise of logit regression results based on the dichotomous dependent variable, poor or fair health, created by combining levels 4 and 5 of the original general health status variable in order to arrive at a summary indicator of generally poor overall subjective health. This set of results represents the third and final specification variant based on general health status conducted as an added sensitivity check to model specification of the dependent variable.

In this instance, the three metro-level variables maintain generally similar patterns as in the previous two tables. The coefficient on metro poverty rate in model (4) with the estimate income group-specified retains moderate significance – a unit rise in the rate leads to a change in the log odds of poor/fair health for incomes $75,000 and over by 0.58; likewise, there is a detrimental effect of poverty concentration – a unit increase in concentration changes the log odds of poor/fair health for high incomes by 0.56, at 99% confidence; as well as the more pronounced (and very statistically significant) beneficial effect of the race-specific Moran's I measure (resulting in a change in the log odds of poor or fair health for the base income group of -0.47, significant at 99% confidence).

The first set of interactions between household income and poverty concentration remains similar to the results in Table 4-2 (although the coefficients have weakened) – the effect of poverty concentration on poor/fair health for the low incomes is slightly less detrimental than that for the high incomes, all else equal.

On the other hand, we see a much different picture in the second set of interactions (between household income and clustering of poverty) where the estimates have changed signs to become detrimental, with now progressively more deleterious effects on health ascribed to the moderate through to medium income categories (both in magnitude and significance level) relative to incomes of $75,000 and over. Specifically, we now note a substantial worsening in the effect of the estimate on the Moran's I for poverty for persons reporting household incomes of $25,000 to $49,999 and $50,000 to $74,999, compared to incomes of $75,000 and over. Residence in metros characterized by a comparably higher spatial ordering of poverty produces a change in the log odds of the outcome for the moderate income group of -0.26 relative to the high income group, at 90% confidence, while the corresponding change in the log odds of poor/fair health for the low income group is -0.22 relative to the high income group, at an alpha level of .05).

Of the person-level controls, Non-Hispanic Asian here for the first time is able to maintain its protective status against poor health, everything else held constant, through to the complete model (although the estimate loses some significance). Thus, in model (4), Asian Americans maintain lower log odds of poor or fair health by 0.14 in relation to whites (at 90% confidence). As in previous specifications, the remaining race and ethnicity categories maintain a familiar effect pattern.

The three income dummies respond much in a way established by the previous two models specifications, exposing a clear income gradient. Notably, the lowest household income range here achieves both high practical and statistical significance - raising the log odds of observing poor or fair health status by 2.1 compared to the highest incomes, while controlling for race, gender, marital status, and age.

It is also interesting here that the estimate on Married remains positive, however loses significance in the complete model. Finally, age maintains a similar pattern as observed in prior models.

In summary, when collapsing general health status into an indicator of overall worse off health as the dependent variable the findings point to two key departures from the earlier specifications: an unraveling in the positive association between poor/fair health and married status, as well as a reversal in the structure of the added effect of the income-spatial clustering of poverty interaction – the relationship becomes positive and increasingly significant for the moderate and medium income ranges (relative to incomes of $75,000 and greater); thus coming near to cancelling out the protective effect of the Moran’s I measure for poverty for those higher income groups.

Table 4-4: Logit models of ever diagnosed with asthma on metropolitan poverty rate, concentration of poverty, and spatial clustering of poverty, with cross-level interactions

Model#	(1)		(2)		(3)		(4)	
Constant	-1.854**	(-26.33)	-1.958**	(-25.55)	-2.057**	(-25.90)	-2.157**	(-20.99)
Metro-level variables								
Metro Poverty Rate	0.818*	(2.43)	0.685+	(1.95)	0.633+	(1.82)	0.914*	(2.44)
Poverty Concentration	0.541**	(3.08)	0.540**	(2.99)	0.507**	(2.85)	0.874**	(3.65)
Moran's I (Poverty Rate)	-0.508**	(-5.22)	-0.497**	(-4.83)	-0.494**	(-4.88)	-0.691**	(-5.62)
Person-level variables								
Race/ethnicity								
Non-Hispanic Black	-0.0688	(-1.24)	-0.141*	(-2.49)	-0.158**	(-2.84)	-0.276**	(-4.47)
Non-Hispanic Asian	-0.689**	(-11.76)	-0.679**	(-11.32)	-0.644**	(-10.69)	-0.763**	(-12.34)
Non-Hispanic Native	0.207**	(2.92)	0.181*	(2.44)	0.205**	(2.78)	0.100	(1.29)
Hispanic	-0.323**	(-4.59)	-0.409**	(-5.60)	-0.379**	(-5.28)	-0.528**	(-6.90)
Income								
less than $25,000			0.381**	(19.44)	0.257**	(11.50)	0.292**	(6.68)
$25,000-$49,999			0.0686**	(4.39)	-0.00134	(-0.08)	0.0133	(0.36)
$50,000-$74,999			0.0462**	(2.62)	0.00950	(0.51)	0.0378	(0.86)
Other person-level controls								
Female					0.376**	(30.48)	0.377**	(30.80)
Married					-0.126**	(-9.29)	-0.138**	(-10.39)
Age in years							0.0123**	(5.65)
Age (squared)							-0.000185**	(-8.99)
Cross-level interactions								
Inc. < $25,000 # Pov. Conc.							-0. 405*	(-2.04)
Inc. $25,000-$49,999 # Pov. Conc.							-0. 231	(-1.30)
Inc. $50,000-$74,999 # Pov. Conc.							-0. 156	(-0.88)
Inc. < $25,000 # Moran's I							0.260*	(2.41)
Inc. $25,000-$49,999 # Moran's I							0.154	(1.61)
Inc. $50,000-$74,999 # Moran's I							-0.0109	(-0.09)
N	366,656		317,464		317,464		316,106	

t statistics in parentheses; models use robust (due to heteroskedasticity) and metro area clustered standard errors
models include 310 metro dummies (coefficients not displayed); race/ethnicity reference category: non-Hispanic white; income reference category: $75,000 and over
+ p < .10, * p < .05, ** p < .01

The following set of models is based on the binary variable: individual ever diagnosed with asthma (Table 4-4). Aligned with the models treating general health status, this set of logit models shows a clear positive association between asthma and the overall metropolitan poverty rate and concentration of poverty, and an inverse relationship between asthma and the spatial clustering of census tract-level poverty rates. The effect sizes markedly stand out. First of the level 2 measures, the metropolitan poverty rate appears to raise the log odds of asthma for the base group by 0.9 (at 95% confidence), showing a wavering significance record across the models. The estimates on poverty concentration and Moran's I hold very significant throughout the model sequence (1-3), assuming opposing signs. Both (specified) estimates are highly significant in model (4) - poverty concentration raises the log odds of an asthma diagnosis for the reference income group by 0.87, and Moran's I for poverty lowers the odds of diagnosis for high incomes by 0.7, all else held constant.

The coefficients on the first set of cross-level interactions (household income and poverty concentration) display recognizably low, and not harmful, effect sizes, where only the interaction between poverty concentration and the low income group (less than $25,000) reaches moderate significance.

The second set of interactions (household income and the spatial organization of poverty) follows an inverse pattern compared to earlier model iterations - detrimental in the case of the interaction of spatial clustering of poverty and the low income group; only the first interaction shows as only moderately statistically significant. Residence in metros with relatively more spatially clustered tract-level poverty rates produces a change in the log odds of an asthma diagnosis for household incomes under $25,000 of -0.43 in relation to high income households (result significant at 95% confidence).

Proceeding to the individual level variables, the race and ethnicity categories share a decidedly protective influence against the incidence of asthma, with relatively large effect sizes. The coefficients on Non-Hispanic Asian and Hispanic, highly significant throughout, indicate lower log odds of asthma by 0.76 and 0.53 respectively, compared to Non-Hispanic White. The estimate on Non-Hispanic Black starts off insignificant then builds up to high statistical significance, resulting in lower log odds of an asthma diagnosis by 0.28 compared to whites. The exception here is the estimate on Native, which loses all significance by model (4).

Of note, the estimates on the household income categories are highly significant in model (1), however only the low income dummy (income less than $25,000) manages to maintain a sizeable effect as well as high significance through to model (4) – a change in the log odds of asthma of 0.3 compared to the highest incomes.

The effect of the variable combination of Female and Married introduced in model (3) departs from convention in this set of models in that the coefficients change signs. Female status now changes the log odds of an asthma diagnosis by 0.38 compared to males, while married status is protective, changing the log odds of a diagnosis by -0.14 (model (4)); both at an alpha=.01).

Table 4-5: Logit models of ever diagnosed with diabetes on metropolitan poverty rate, concentration of poverty, and spatial clustering of poverty, with cross-level interactions

Model#	(1)		(2)		(3)		(4)	
Constant	-2.103**	(-19.79)	-2.721**	(-22.05)	-2.647**	(-21.62)	-9.928**	(-85.12)
Metro-level variables								
Metro Poverty Rate	1.807**	(2.87)	2.012**	(3.06)	2.050**	(3.09)	1.002**	(2.60)
Poverty Concentration	1.123**	(4.59)	1.164**	(4.44)	1.192**	(4.48)	0.658**	(2.89)
Moran's I (Poverty Rate)	-0.701**	(-4.56)	-0.784**	(-4.44)	-0.788**	(-4.40)	-0.763**	(-6.36)
Person-level variables								
Race/ethnicity								
Non-Hispanic Black	0.0394	(0.32)	-0.252*	(-2.11)	-0.239*	(-1.99)	0.391**	(5.57)
Non-Hispanic Asian	-0.584**	(-7.82)	-0.554**	(-7.21)	-0.585**	(-7.54)	0.148*	(2.23)
Non-Hispanic Native	-0.0000863	(-0.00)	-0.244*	(-2.25)	-0.262*	(-2.39)	0.290**	(3.75)
Hispanic	-0.384**	(-3.61)	-0.706**	(-6.45)	-0.730**	(-6.59)	0.211**	(2.91)
Income								
less than $25,000			1.079**	(48.21)	1.167**	(48.90)	0.803**	(19.81)
$25,000-$49,999			0.631**	(31.34)	0.678**	(32.76)	0.405**	(8.98)
$50,000-$74,999			0.338**	(14.91)	0.363**	(16.05)	0.217**	(4.52)
Other person-level controls								
Female					-0.290**	(-19.25)	-0.316**	(-20.97)
Married					0.0755**	(5.28)	0.0115	(0.78)
Age in years							0.226**	(68.06)
Age (squared)							-0.00155**	(-55.06)
Cross-level interactions								
Inc. < $25,000 # Pov. Conc.							-0. 320+	(-1.80)
Inc. $25,000-$49,999 # Pov. Conc.							-0. 216	(-1.26)
Inc. $50,000-$74,999 # Pov. Conc.							-0. 0523	(-0.28)
Inc. < $25,000 # Moran's I							0.441**	(4.63)
Inc. $25,000-$49,999 # Moran's I							0.414**	(4.08)
Inc. $50,000-$74,999 # Moran's I							0.309*	(2.48)
N	368,431		319,023		319,023		317,661	

t statistics in parentheses; models use robust (due to heteroskedasticity) and metro area clustered standard errors
models include 310 metro dummies (coefficients not displayed); race/ethnicity reference category: non-Hispanic white; income reference category: $75,000 and over
+ p < .10, * p < .05, ** p < .01

The next set of models in this section (Table 4-5) reports the results of a series of logit regressions based on the binary dependent variable: ever diagnosed with diabetes. The coefficients on all three metropolitan area level variables are very significant, as well as carry large effect sizes in models (1) through (3). The metro explanatory variables maintain the familiar association pattern with the health outcome in the complete model with the level 2 estimate specified by income – a positive relationship with the base income group in the case of overall poverty level and concentration of poverty, as well as a corresponding negative relationship with the Moran's Index for poverty. The magnitude of the coefficient on metro poverty rate is of note here – a one-unit increase in the mean metropolitan area poverty rate raises the log odds of a diabetes diagnosis for the high incomes by 1, holding all other factors constant. A unit increase in poverty concentration raises the log odds of diabetes for this group by 0.66. Further, the estimate associated with the Moran's measure reaches a new low – a one-unit increase in the spatial clustering of poverty lowers the log odds of diabetes for the reference group by 0.76.

The first group of interactions giving the income group-specific effect of a person's household income category at a given level of poverty concentration (relative to the base income group) behaves in ways much consistent with results recorded in previous model runs – not harmful, however small and inconclusive, with the exception of the first income category which seemingly deviates only minimally from the detrimental effect of poverty concentration on diabetes incidence with reference to the highest incomes.

For the second group of interactions between household income and the measure of spatial sorting of poverty there is largely a positive and highly statistically significant association between the three income categories and the Moran's index, compared with incomes of $75,000 and over. This signals a relatively strong added deleterious income group-specific effect for the lower to medium incomes of residence in metros characterized by a comparatively higher degree of tract-level spatial arrangement of poverty, with practical and statistical significance dropping somewhat moving up the income ladder. Thus, the effect of poverty clustering is indeed most worsening of health for the first, low household income, category, relative to high incomes (now seeing a change in the log odds of -0.32 relative to the base category, at 99% confidence); similarly, the effect is comparatively worse for the latter two categories as well (the change in the log odds for the moderate incomes is -0.35 compared to the high incomes, again at 99% confidence; the corresponding change in the log odds for the medium incomes is -0.45 compared to the high incomes, at 95% confidence).

With respect to the person-level variables, race and ethnicity demonstrate as protective against diabetes, at relatively high significance (with the exception of model (1)) before the familiar flip in the signs occurs between models (3) and (4). The coefficients on all of the race and ethnicity covariates flip considerably at the end, going from raising to lowering the log odds of a diabetes diagnosis (-0.24 to 0.4, -0.59 to 0.15, -0.26 to 0.29, and -0.73 to 0.2 for Non-Hispanic Black, Non-Hispanic Asian, Non-Hispanic Native, and Hispanic respectively) prior to which they exhibit a protective effect (while achieving high significance and with reference to Non-Hispanic White).

It is of interest that the set of household income variables displays a clearly identifiable gradient - an increasingly worsening effect on diabetes moving from the medium to low incomes, in comparison with high incomes.

The Female and Married dummies have an inverse effect on diabetes – female status is protective relative to males (leading to a change in the log odds of having received a diagnosis of -0.32, ceteris paribus), while married status is detrimental. However, the coefficient on Married loses all significance in model (4), mimicking the results in Table 4-3 earlier.

Lastly, the linear effect of an individual's age is quite amplified in this set of models – one additional year of age raises the log odds of diabetes by 0.23 (with 99% confidence).

Table 4-6: Negative binomial models of number of physically unhealthy days on metropolitan poverty rate, concentration of poverty, and spatial clustering of poverty, with cross-level interactions

Model#	(1)		(2)		(3)		(4)	
Constant	1.442**	(25.58)	0.687**	(10.75)	0.613**	(9.60)	-0.819**	(-12.59)
Metro-level variables								
Metro Poverty Rate	1.035**	(2.70)	1.290**	(4.02)	1.285**	(4.00)	0.571*	(2.48)
Poverty Concentration	0.332*	(2.35)	0.353**	(2.74)	0.355**	(2.74)	0.205	(1.34)
Moran's I (Poverty Rate)	-0.276**	(-3.69)	-0.331**	(-4.01)	-0.329**	(-3.99)	-0.196*	(-2.43)
Person-level variables								
Race/Ethnicity								
Non-Hispanic Black	-0.0972	(-1.24)	-0.424**	(-7.62)	-0.426**	(-7.63)	-0.185**	(-4.79)
Non-Hispanic Asian	-0.704**	(-14.48)	-0.651**	(-13.48)	-0.649**	(-13.31)	-0.405**	(-9.09)
Non-Hispanic Native	0.187**	(2.73)	-0.0633	(-0.94)	-0.0556	(-0.82)	0.149**	(2.58)
Hispanic	-0.161*	(-2.53)	-0.494**	(-9.71)	-0.494**	(-9.61)	-0.162**	(-4.00)
Income								
less than $25,000			1.255**	(98.77)	1.252**	(88.13)	1.144**	(41.78)
$25,000-$49,999			0.602**	(51.75)	0.601**	(50.91)	0.531**	(18.65)
$50,000-$74,999			0.307**	(23.04)	0.306**	(22.71)	0.312**	(9.95)
Person-level controls								
Female					0.108**	(11.47)	0.122**	(13.73)
Married					0.0173^{+}	(1.69)	-0.0200^{+}	(-1.89)
Age in years							0.0435**	(24.49)
Age (squared)							-0.000265**	(-16.55)
Cross-level interactions								
Inc. < $25,000 # Pov. Conc.							-0.230^{+}	(-1.95)
Inc. $25,000-$49,999 # Pov. Conc.							-0.0870	(-0.70)
Inc. $50,000-$74,999 # Pov. Conc.							-0.107	(-0.71)
Inc. < $25,000 # Moran's I							0.0637	(0.97)
Inc. $25,000-$49,999 # Moran's I							0.0400	(0.53)
Inc. $50,000-$74,999 # Moran's I							-0.0552	(-0.67)
N	361,675		314,162		314,162		312,853	

t statistics in parentheses; models use robust (due to heteroskedasticity) and metro area clustered standard errors; models include 310 metro dummies (coefficients not displayed); race/ethnicity reference category: non-Hispanic white; income reference category: $75,000 and over

$^{+}$ $p < .10$, * $p < .05$, ** $p < .01$

The next table (Table 4-6) presents the results of a set of negative binomial regressions treating the first of the two functional health count response variables: number of physically unhealthy days. The output of the final two model sets reports the estimates in terms of untransformed coefficients. These are expressed as log odds of expected counts, for ease of result interpretation, particularly with regard to the cross-level interaction terms. In the case of regressions based on count data the coefficients are interpreted as the change (increase or decrease) in the difference in the logs of expected counts of the outcome (count of physically or mentally unhealthy days) with a unit increase in the predictor, while holding all other covariates constant.

These models regress the above dependent variable on the three level 2 variables: metropolitan poverty rate, concentration of poverty, and Global Moran's index for poverty rate.

Following from the above table, we note a general continuation in the effect pattern of the three metropolitan area level variables as with all previous response variables examined in the current chapter. The overall race-specific poverty rate and poverty concentration show a positive, while the Moran's index for poverty shows a negative association to the number of physically unhealthy days with regard to incomes of $75,000 and over. This holds true almost universally at very high levels of statistical significance from model (1) through model (3). In model (4), however, once the metro-level estimates have been specified by income group, the statistical power of the reference category-specific estimates is attenuated. In fact, the concentration of poverty measure falls fully out of significance (although still remaining sizable in magnitude). A single-unit increase in the metro poverty rate raises the difference in the logs of expected counts of physically unhealthy days for household incomes less than $25,000 by 0.57, all else equal; and inversely, a one-unit increase in the Moran’s I score leads to a decrease in the incidence in the difference in the logs of expected counts of physically unhealthy days for the base income group by 0.2 (both at medium, 95% level of confidence).

The first set of cross-level interactions (household income and poverty concentration) is very similar to previous several model iterations in that it depicts a relative group-specific effect on each of the household income categories that is not harmful (by narrow margins and largely insignificant), in relation to the base omitted category, as interacted with the level 2 measure of poverty concentration. Interestingly, the base group coefficient on poverty concentration is not significant here. None of the coefficients on the second set of interactions of income with the Moran’s measure show as statistically significant.

In reference to the person-level variables, the race categories exhibit a mixed pattern of influence on the outcome across models. All but the estimate on Native American ultimately result as very significant and protective against the incidence of physically unhealthy days. Non-Hispanic Black is first not significant (model (1)), then turns very significant and protective, reducing the difference in the logs of expected counts by 0.19, relative to whites. Asian American starts off as having the largest effect size and retains a considerable magnitude to model (4) where this race status lowers the difference in the odds of expected counts of physically unhealthy days by 0.4, compared to Non-Hispanic White.

Universally across models the income ranges continue to show as very significant and progressively detrimental going from medium to low, in relation to the high income base category.

Female status this time has a positive association with physically unhealthy days (at 99% confidence) relative to males, while married status flips from only marginally detrimental to protective between models (3) and (4). An individual's age remains detrimental to this health outcome, however at a slightly diminishing rate.

Table 4-7: Negative binomial models of number of mentally unhealthy days on metropolitan poverty rate, concentration of poverty, and spatial clustering of poverty, with cross-level interactions

Model#	(1)		(2)		(3)		(4)	
Constant	1.299**	(30.49)	0.793**	(17.96)	0.781**	(16.40)	0.279**	(3.71)
Metro-level variables								
Metro Poverty Rate	0.0879	(0.38)	0.0941	(0.46)	0.0547	(0.27)	0.587*	(2.30)
Poverty Concentration	0.150	(1.55)	0.108	(1.13)	0.0875	(0.91)	0.502**	(3.06)
Moran's I (Poverty Rate)	-0.0956	(-1.58)	-0.139*	(-2.43)	-0.141*	(-2.37)	-0.449**	(-5.30)
Person-level variables								
Race/Ethnicity								
Non-Hispanic Black	0.140**	(3.46)	-0.0912**	(-2.87)	-0.122**	(-3.81)	-0.337**	(-7.64)
Non-Hispanic Asian	-0.422**	(-10.34)	-0.392**	(-11.49)	-0.370**	(-10.35)	-0.557**	(-13.74)
Non-Hispanic Native	0.456**	(9.04)	0.272**	(5.01)	0.301**	(5.33)	0.101	(1.59)
Hispanic	0.153**	(3.63)	-0.0727*	(-2.06)	-0.0553	(-1.55)	-0.315**	(-6.88)
Income								
less than $25,000			0.987**	(64.98)	0.859**	(52.79)	0.945**	(30.06)
$25,000-$49,999			0.459**	(32.77)	0.390**	(26.52)	0.432**	(13.20)
$50,000-$74,999			0.274**	(19.33)	0.237**	(16.39)	0.222**	(5.95)
Person-level controls								
Female					0.337**	(30.63)	0.325**	(27.30)
Married					-0.200**	(-18.87)	-0.218**	(-19.68)
Age in years							0.0373**	(18.33)
Age (squared)							-0.000508**	(-25.28)
Cross-level interactions								
Inc. < $25,000 # Pov. Conc.							-0.256+	(-1.74)
Inc. $25,000-$49,999 # Pov. Conc.							-0.223	(-1.35)
Inc. $50,000-$74,999 # Pov. Conc.							-0.339+	(-1.86)
Inc. < $25,000 # Moran's I							0.245**	(3.44)
Inc. $25,000-$49,999 # Moran's I							0.223**	(2.91)
Inc. $50,000-$74,999 # Moran's I							0.203*	(2.23)
N	362,874		315,045		315,045		313,733	

t statistics in parentheses; models use robust (due to heteroskedasticity) and metro area clustered standard errors

models include 310 metro dummies (coefficients not displayed); race/ethnicity reference category: non-Hispanic white; income reference category: $75,000 and over

$^{+}$ $p < .10$, * $p < .05$, ** $p < .01$

Lastly in this section, we turn attention to the second of the pair of count dependent variables: number of mentally unhealthy days. Table 4-7 presents results from a series of negative binomial models regressing the above dependent variable on the three metropolitan level variables, as well as person-level controls and including cross-level interactions.

Of the level 2 variables, only the Moran's I for poverty maintains significance back to model (2), while the metro poverty and concentration of poverty only first achieve significance in the final model – upon the relevant estimates' specification by income group. Following a pattern consistently observed in the current section, the metro poverty and concentration of poverty both increase the difference in the logs of counts of mentally unhealthy days for the reference income group (by 0.6 and 0.5 respectively), and Moran's I decreases that difference for the base group (by 0.45, at 99% significance), in the full model (4).

Looking at the interactions of household income and poverty concentration, there again we find a group-specific effect to be not harmful, at a marginal statistical significance, for the low and medium income categories relative to high incomes.

The second set of interactions tells a very different story (household income and the metro-level spatial organization of poverty). All three interaction terms are moderately to highly statistically significant and detrimental. These group-specific interaction effects manage to effectively counter the protective effect of the Moran's I measure on the base income group – changing its direction toward contributing to diminished health for the three household income groups included in the analysis in reference to incomes $75,000 and over. The largest impact is observed in the coefficient on the first interaction term (low household incomes and Moran's I). The equivalent effect of the spatial sorting of tract-level poverty for the, taken together, group of comparatively lower income ranges places the change in the difference in the logs of expected counts of mentally unhealthy days for the low, moderate, and medium incomes at -0.2, -0.23, and -0.25 respectively relative to the high incomes, with all other factors held constant (at 99%, 99%, and 95% confidence respectively).

In relation to the level 1 indicators, two of the race and ethnicity categories, Non-Hispanic Black and Hispanic, begin very significant and detrimental in model (1), then change signs to become strongly protective against mentally unhealthy days beginning with model (2) and remaining as such to the last model. Asian Americans' effect is highly protective throughout the specifications, with the estimate much accentuated at the end – reducing the difference in the logs of expected counts of mentally unhealthy days by 42.7% by model (4) relative to Non-Hispanic White, ceteris paribus, at 99% confidence. Native status appears very significant and strongly detrimental however loses all significance in the last model.

As expected, the three income categories display a clearly identifiable gradient of increasingly worsening effect on the outcome across models, moving from moderate to low incomes, all compared to household incomes of 75,000 and over.

As with the previous set of results, the current outcome maintains a reversal in the role of the pair of person-level controls introduced in model (3) – Female shows as worsening the outcome relative to males (increasing the difference in the log of expected counts by 0.33, at 99% confidence), while married status protects against the incidence of mentally unhealthy days (this time at high significance in the last two models) – depressing the same difference by 0.22.

Finally, as established by all previously discussed model results, the pair of age variables reveals a positive relationship, however so at a decreasing rate at more advanced ages.

Marginal Effects

Average marginal effects for each race/ethnicity and household income category were calculated in order to compare with the cross-level interaction effects in previous model results. These are the changes in probability in each of the health outcomes while holding all other variables at their mean values. The set of marginal effects are presented for each of the two main metro-level variables (Table 4-8). The results confirm the discussion above in that poverty concentration increases the probability of worse self-reported health, asthma, and diabetes. The effects are largest for those in the lowest income bracket. The spatial concentration of the poverty rate as measured by the Moran's I has the opposite effect on poor health outcomes.

Table 4-8: Average marginal effects, poverty concentration and Moran's I (poverty rate)

	Poor/Fair Hlth			Asthma			Diabetes	
Poverty Concentration								
Race/Ethnicity	Margins	Std. Err.		Margins	Std. Err.		Margins	Std. Err.
Non-Hisp. White	0.035	0.016		0.077	0.022		0.037	0.014
Non-Hisp. Black	0.038	0.017		0.063	0.018		0.049	0.019
Non-Hisp. Asian	0.032	0.015		0.042	0.012		0.042	0.016
Non-Hisp. Native	0.044	0.020		0.083	0.024		0.046	0.018
Hispanic	0.044	0.020		0.052	0.015		0.043	0.017
H.H. Income								
< $25,000	0.040	0.031		0.061	0.025		0.038	0.022
$25,000-$49,999	0.049	0.019		0.068	0.021		0.038	0.017
$50,000-$74,999	0.021	0.015		0.075	0.024		0.045	0.016
$75,000<	0.030	0.010		0.090	0.025		0.039	0.013
Moran's I (poverty rate)								
Race/Ethnicity								
Non-Hisp. White	-0.035	0.009		-0.067	0.013		-0.034	0.009
Non-Hisp. Black	-0.037	0.010		-0.054	0.011		-0.045	0.011
Non-Hisp. Asian	-0.032	0.008		-0.037	0.007		-0.038	0.010
Non-Hisp. Native	-0.042	0.011		-0.072	0.014		-0.042	0.011
Hispanic	-0.042	0.011		-0.045	0.008		-0.040	0.009
H.H. Income								
< $25,000	-0.061	0.018		-0.056	0.017		-0.036	0.014
$25,000-$49,999	-0.032	0.011		-0.057	0.012		-0.030	0.010
$50,000-$74,999	-0.018	0.011		-0.073	0.015		-0.034	0.011
$75,000<	-0.025	0.006		-0.071	0.013		-0.045	0.007

Results Summary

Overall, the above series of models provide some insight into the association between metropolitan level poverty, concentration of poverty, the spatial clustering of poverty and health outcomes. Specifically, the OLS fixed effects models indicate a tangible negative effect of both metropolitan level poverty and concentration of poverty on an individual's self-assessed general health status, conceptualized as assuming a continuous form, while the measure of spatial clustering of tract-level poverty rates is protective. Likewise, the set of ordinal logit models, as well as logit models treating the derivative 'poor or fair health' measure point to a positive relationship of both metropolitan poverty and poverty concentration to general health for the reference income group. The latter two sets of models also corroborate the result of an inverse association between the geographic patterning of poverty and general health. Thus, the first three model sets treating general health status add support to the conclusion of a divergence of impact between the aspatial and explicitly spatial level 2 measures. This finding appears to be robust to model specification.

The next pair of logit models treating the chronic disease diagnoses of asthma and diabetes shows a similar pattern of effect as above – a detrimental effect of overall poverty and poverty concentration, and a protective spatial clustering of poverty for the base group. Only in the asthma models does the effect of metro-level poverty appear tenuous. Lastly, the effect of the pair of functional measures of health diverges in several significant ways from the other outcomes.

The detrimental effect of poverty concentration for the incidence of physically unhealthy days goes away (at least in terms of significance) once age is controlled for and that estimate is specified to now represent the effect for the base income group in the full model. Further, the respective effects of metro-level poverty and spatial clustering of poverty weaken in the last model specification. Overall, the area-wide measures prove least consequential to the outcome (both practically and statistically) in the last set of models. All three measures only reach (high) statistical significance in the complete model (with the exception of spatial clustering, brought to significance after the addition of household income). The metro-level effect only comes to the forefront when parsed out by income group in the set of mentally unhealthy days models.

The addition of age and specification with interaction terms further serve to weaken somewhat the effect of spatial clustering of poverty on general health, as well as that of metro poverty on poor/fair health, and diabetes – the effects generally lose potency when the estimate comes to stand for the base income category as compared to all groups (expectedly so since the effect has been further refined). Thus, the introduction of the age variables and interactions with household income prove as material to mediating the relationship between the area measures and health outcomes.

The two sets of cross-level interactions between income and each of the concentration of poverty and spatial clustering of poverty measures largely display a counterbalancing added effect for each of the low to medium household income categories relative to the base (high) income group impact of the metropolitan level measures. The OLS models show interaction effects for the lower incomes attaining moderate statistical significance, providing a measurable protective effect of poverty concentration on the lowest incomes relative to the highest incomes. Spatial clustering is further beneficial to health for the low incomes here, relative to high incomes. Results from the ordered logit models are mixed. The effect of concentration on individuals in low income households is reversed, and now matches that of clustering, somewhat beneficial relative to the high incomes. Both aspatial concentration and spatial clustering are protective for low income households. The low incomes experience a protective effect of spatial clustering in both specifications of general health status. The two specifications produce disparate directionality of effect for the concentration measure. This measure proves adverse for the moderate incomes in the OLS models, whereas the effect on the medium income category flips between the OLS and ordered logit models (all relative to high incomes). Notably however, the effect sizes of the poverty concentration interaction terms are relatively minor across virtually all outcomes in this section of the analysis. Only the low incomes continue to see a negative effect of poverty concentration in the third specification variant of general health – poor or fair health status. Here, the spatial clustering of poverty arises as protective of the moderate and medium incomes compared to the base category (households with the highest incomes). These models commence a pattern of countervailing influences of income level-parsed metro-level factors relative to the base category. For the chronic conditions of asthma and diabetes the concentration and spatial clustering measures trade off against each other in their effect on the low incomes, while in the latter outcome spatial clustering emerges once again detrimental to the moderate and medium incomes. Among the functional health outcomes the first produces a single protective effect of concentration on low household incomes, while the second shows a duality in effect between concentration and spatial clustering for both low and medium income levels. In the final outcome, the spatial measure of poverty exerts worsening pressure on moderate household incomes, similar to the pattern in the poor/fair health and diabetes models.

Racial and ethnic category membership holds a mixture of associations to the health outcomes, relative to the base race category (Non-Hispanic White). African American status acts as worsening of general health, poor/fair health, and diabetes; it is protective against a diagnosis of asthma, and the incidence of both physically and mentally unhealthy days. Asian status results in a worsening in general health and diabetes, and it is protective in the case of poor/fair health, asthma, and the incidence of physically and mentally unhealthy days. Native status produces a worsening in general health, poor/fair health, diabetes, and physically unhealthy days. Lastly, Hispanic status shows as worsening of general health, poor/fair health, and diabetes, while shielding against asthma, and physically and mentally unhealthy days. Overall, minority status leads to worse outcomes in general health and diabetes; it is protective against asthma and physically and mentally unhealthy days (Native is an exception), compared to Non-Hispanic whites.

Adding the age controls and interaction sets once again proves profoundly influential in shaping effect direction and magnitude. This is observed in the flip in effect of Asian for general health, and that of all four groups in the diabetes models, and loss of significance of Native in the Asthma and mentally unhealthy days models. Further, inclusion of the set of household income controls was instrumental in bringing statistical significance to Non-Hispanic Black in the asthma, diabetes, and physically unhealthy days models, and Native in the diabetes models; it further changes the signs on Non-Hispanic Black and Hispanic in the mentally unhealthy days models.

Regarding household income itself across outcomes in this chapter there is an observable clear gradient of worsening in health for individuals with progressively decreasing annual incomes, relative to the highest of incomes. In terms of effect size, this condition bears highly on general health, and poor/fair health more specifically. The exception to this are findings from the set of asthma models in which this pattern is fully disrupted for the moderate and medium incomes as the Married and Female indicators are introduced.

Female status proves protective against worse general health, poor/fair health, and diabetes; it affects adversely the outcomes of asthma, and incidence of physically and mentally unhealthy days, compared to males. Married individuals exert a worsening influence on general health, and a protection against asthma and incidence of mentally unhealthy days. Age is cross-cutting in its worsening of health, carrying a marginally diminishing effect. It has its largest effect size in diabetes.

Speaking more broadly across the three area measures, there is a palpable downward pressure on health from the overall metropolitan poverty level and concentration of poverty; this trend falters for the poverty concentration measure only in the incidence of physically unhealthy days. The measure of metropolitan wide spatial clustering of poverty appears to exert a sizeable and oftentimes strong protective influence on the health outcomes almost universally. Household income provides important, however mixed, adjustments to these area effects, setting a pattern of reversed effects between the three lower income groups and the base case. On the whole, poverty concentration is protective against worse outcomes for low to medium incomes, as the spatial clustering proves to worsen outcomes for these income ranges.

The nearly universal discord in the effect of the metro-level factors presents in itself an interesting finding. This is consistent with the analysis of descriptive statistics presented in Chapter 3: demonstrating a visible divergence in trends among the set of measures over the inter-year period. Seemingly related, the two measures of metro-level poverty concentration prove fundamentally different. One, the aspatial concentration of poverty, represents a threshold measure taking into account high poverty tracts alone. The other, explicitly spatial measure of the distribution of tract-level poverty, uses the full gamete of poverty rates.

A metropolitan area with more concentrated poverty is worse for persons of all incomes; this of course without regard to the spatial arrangement of poverty. Incorporating the physical arrangement of tracts across the poverty spectrum finds that greater proximity of tracts similar on this metric promotes better health across income groups (the effect is notably lessened for the lower incomes). This condition might favor those with higher incomes by shear geographic separation from their lower income counterparts, while the same provides (although limited) benefits to the latter group through increased access to focused health supportive resources. The protective effect of clustering is markedly attenuated for the lower income groups versus higher incomes in the case of diabetes and mentally unhealthy days possibly hinting at challenges posed by larger spatial concentrations of low income neighborhoods for these outcomes.

Importantly, it appears that specifying the models with metropolitan area fixed effects made for stronger, accentuated effects of the area poverty measures on health.[4] This would imply the existence of left out variable bias – variables not included or factors unmeasured within the sample of metropolitan areas, variables that are correlated with the key area-wide predictor variables of interest in the current set of models. This suggests that incorporating the adjustment for a set of unobserved factors operating within metropolitan areas over the period, as well as historically, was important to finding an unbiased effect of overall poverty and poverty concentration/clustering on the health outcomes, as mediated by the confounding variables. This could indicate the relevance of a potential set of omitted variables relating to the unique trajectory of historical development of these urban regions, particularly in the way of local land use and housing policies, issues of race, and spatial residential patterning over time.

[4] A note must be made that these point estimates may indeed be conservative. There is more recent research pointing to a negative bias present in estimates when smaller area fixed effects are applied, relative to, for example, state fixed effects (Lindo, 2015). Among the reasons are potential spillover effects of surrounding areas outside of metropolitan boundaries, as well as overarching state-specific policy and other environment. The use of state fixed effects in this study was not feasible as a number of the metropolitan areas in the sample span multiple states.

Chapter 5: Metro-level Segregation and Clustering by Race and Ethnicity

Research Inquiry

The analysis in this section explores the effect of metropolitan level residential segregation as well as spatial clustering by race and ethnicity on select health outcomes measured at the level of the individual and mediated by several groups of both individual and household level explanatory measures presented within the models in order of increasing complexity.

The data and variables

The complete dataset used in the analyses contains a total of 373,183 pooled records for the years 2000 and 2010. The regression models were specified to treat the data as a panel of contiguous U.S. metros (a combined total of 310 metropolitan and micropolitan statistical areas, and metropolitan divisions). The individual respondents are not the same across the two years of data.

In the initial set of models the -xtreg- command in Stata version 15 was employed, with fixed effects in order to pick up influence of unobserved time-invariant factors within metros. Robust and clustered standard errors were applied uniformly across all models with the purpose of accounting for the nested nature of observations (individuals) within metro regions, an essentially multilevel structure, as well as addressing heteroscedasticity as a common concern when working with metropolitan areas. Individual metro area dummies were inserted as explanatory variables in each of the subsequent regression models as an alternative fixed effects specification form. The outcome variable **genhlth** is treated first as containing continuous then ordinal data within the sequence of models in this section. The continuous form assumes equidistant levels, for instance moving within the coding scheme from 1 (excellent health) to 2 (very good health) on the variable scale is equal to going from 4 (fair health) to 5 (poor health). A continuous response allows for the use of ordinary least squares (OLS) regressions aiding in the interpretation of model coefficients; following, ordered logit models were then specified, conceptualizing **genhlth** in its ordinal form. Logit models were fitted for the remaining indicator outcomes of poor or fair health, asthma, and diabetes. Lastly, negative binomial functions were estimated in the case of the count variables **physhlth** and **menthlth**, number of physically and mentally unhealthy days respectively.

The key predictor variables of interest in this portion of the current study are the metro-level residential segregation by race and ethnicity as measured by the index of dissimilarity, and the spatial, or geographic, clustering by race and ethnicity (measured as the census tract-level proportion of each race and ethnicity group) provided by the Global Moran's index of spatial autocorrelation. The Moran's I score calculation has been set up using first order polygon contiguity, i.e. comparing each census tract's value to the value of its nearest (contiguous) neighbors. With respect to the segregation measure, pair-wise indices were computed for every race and ethnicity minority group relative to the majority group (Non-Hispanic White), as well as majority group to every other (e.g. segregation of Hispanics from Non-Hispanic Whites, Non-Hispanic Whites from every other group, etc.). As with the area level measures of the level of poverty, concentration of poverty, and spatial clustering of poverty examined in the previous section, the area-wide segregation and spatial clustering measures are race and ethnicity specific, meaning that each level 2 value is matched with an individual record based on the race and/or ethnicity of the specific individual at level 1 in the combined dataset. This approach ensures that each individual in the analyses is correctly paired with the specific metropolitan area-wide measure pertaining to their own racial and/or ethnic group membership as these are the measures of racial and ethnic divides and related processes of marginalization with a direct influence on individual experiences within the broader spatial arrangement of metropolitan areas.

The standard set of level 1 covariates includes dummy variables for race and ethnicity, as well as four categories (quartiles) of annual household income, gender, marital status, an individual's age in years, as well as age-squared (to incorporate the nonlinear, or quadratic, effect of age). The four-model structure is consistent across the analyses, with models arranged such that they range from the simplest (1) to most complete (4). Model 1 contains the two level 2 predictor variables of interest: race and ethnicity specific metropolitan area level group/non-group measure of segregation, the variable seg, and the Moran's index for percent race and ethnicity, as well as the individual level race and ethnicity dummies: Non-Hispanic Black, Non-Hispanic Asian, Non-Hispanic Native, and Hispanic (reference category of Non-Hispanic White). Model 2 adds the income dummies: Less than $25,000, $25,000 to $49,999, and $50,000 to $74,000 (reference category of $75,000 and over). Model 3 further ads the dichotomous person-level variables of Female and Married. Model 4 includes the pair of respondent age variables: age and age2 (age-squared).

Importantly, the complete model presents results of two sets of cross-level interactions corresponding to the key level 2 predictor variables subject of the current analysis, which help to probe further for potential nuances, or variability, in the impact of these measures by race and ethnicity. The interactions were employed in order to gauge the differential effect (both direction and magnitude) of overall inter-group segregation and spatial clustering by racial and ethnic group, in reference to the base category of Non-Hispanic White. As in the previous chapter, through the cross-level interactions the multilevel model structure described in Chapter 2: is operationalized with the specification of separate effects (slopes) of the metropolitan-level variables for each of the individual-level characteristics (in this case the minority racial and ethnic groups, relative to the majority group). The slope of the effect of the level 1 factor on the health outcomes varies for different levels of the level 2 factor.

Multivariate Regressions

Table 5-1: Fixed effects OLS models of general health status on segregation and spatial clustering by race and ethnicity, with cross-level interactions

Model #	(1)		(2)		(3)		(4)	
Constant	2.353**	(51.61)	1.847**	(40.63)	1.850**	(41.29)	1.082**	(21.62)
Metro-level variables								
Segregation (Dissim.)	-0.338**	(-3.37)	-0.440**	(-3.88)	-0.445**	(-3.88)	-0.522**	(-5.74)
Moran's I (% Race/Ethnicity)	0.326**	(5.16)	0.553**	(8.39)	0.563**	(8.51)	0.279**	(5.40)
Person-level variables								
Race/ethnicity								
Non-Hispanic Black	0.365**	(21.01)	0.154**	(9.29)	0.161**	(9.68)	0.127**	(3.43)
Non-Hispanic Asian	-0.0223	(-1.23)	0.0482**	(2.72)	0.0432*	(2.43)	0.159+	(1.73)
Non-Hispanic Native	0.417**	(15.65)	0.269**	(9.56)	0.268**	(9.56)	0.308**	(3.36)
Hispanic	0.565**	(14.10)	0.433**	(9.94)	0.434**	(9.88)	0.0614	(0.98)
Income								
less than $25,000			0.962**	(119.33)	0.990**	(116.17)	0.911**	(111.34)
$25,000-$49,999			0.458**	(75.38)	0.474**	(75.52)	0.433**	(69.68)
$50,000-$74,999			0.221**	(37.07)	0.229**	(37.66)	0.220**	(38.99)
Other person-level controls								
Female					-0.0672**	(-14.44)	-0.0718**	(-16.55)
Married					0.0337**	(7.47)	0.0122**	(2.96)
Age in years							0.0279**	(27.21)
Age (squared)							-0.000149**	(-16.02)
Cross-level interactions								
Non-Hispanic Black # Seg.							0.0842	(0.81)
Non-Hispanic Asian # Seg.							-0.131	(-0.62)
Non-Hispanic Native # Seg.							0.141	(0.50)
Hispanic # Seg.							0.715**	(6.01)
Non-Hisp. Black # Moran's I							0.0848	(1.14)
Non-Hisp. Asian # Moran's I							0.0740	(0.89)
Non-Hisp. Native # Moran's I							-0.110	(-0.79)
Hispanic # Moran's I							-0.0988	(-1.31)
N	367,569		318,373		318,373		317,018	

t statistics in parentheses; models use robust (due to heteroskedasticity) and metropolitan area clustered standard errors
race/ethnicity reference category: non-Hispanic white; income reference category: $75,000 and over
+ p < .10, * p < .05, ** p < .01

As discussed in the previous section, considerable correlation between the metropolitan inter-group segregation by race and ethnicity (as measured by the Index of Dissimilarity), and the Moran's measure of the spatial distribution, or clustering, of the tract-level proportion of each race/ethnic group within metros had been expected due to the underlying assumption that the two represent alternative ways of capturing essentially the same phenomenon – the nature of the distribution of race/ethnicity across metropolitan space. Upon closer inspection for the presence of correlation between the pair of aspatial and explicitly spatial metro-level explanatory variables in the set of segregation-specific regression models, there appears to be only a very small amount of association present. The corresponding Pearson's correlation coefficient indeed shows a weak positive relationship (r=0.07). As a test, separate sets of models were estimated where each of the health outcomes was regressed on the metro-level measures separately. When examining the two different specifications the estimates on the segregation and Moran's I metrics exhibit an overall similar pattern, with a few notable exceptions – in select instances in the model runs with the main level 2 predictors included separately (the Moran's Index in the poor/fair health models, and the Index of Dissimilarity in the asthma, and physically and mentally unhealthy days models) these explanatory variables do manage to achieve a matching direction of effect in the full model specification as in the counterpart combined models, however exhibit no statistical significance. In addition, statistical significance appears to be somewhat diminished in other instances where the level 2 estimates are otherwise relatively similar, though not identical. The complete results of those models are reported in Appendix D. In the interest of parsimony and to preserve a more complete set of results, as once again very little amount of multicollinearity was detected, only the combined sets of models including both metro-level measures simultaneously are retained in the main text in order to facilitate comparison and observe the mutual interaction of the two main measures of segregation and clustering by race and ethnicity for each of the health outcomes.

Table 5-1 presents the results from the set of metropolitan OLS fixed effects models examining the association of area-wide residential segregation as well as the spatial patterning by race and ethnicity on self-rated general health status.

The coefficients on the pair of level 2 explanatory variables in this section reverse roles from the section prior, in that each maintains a highly significant, and opposite, effect with regard to general health status across the four model specifications (more specifically segregation is protective, while clustering is detrimental for the base race/ethnic group). The complete model (4) now represents the metro-level effect for Non-Hispanic White - with the specification of the level 2 effect by race and ethnicity (introduction of the two sets of cross-level interactions). A greater overall level of majority to minority group (as well as majority group to all others) segregation corresponding to one's own race or ethnicity is associated with a lower general health status score for Non-Hispanic White, indicating improving self-reported health, all else held constant. The converse is observed for the measure of spatial clustering of the distribution of census tract-wide proportions of each race and ethnicity group across metropolitan space.

The coefficients on both groups of cross-level interactions vary considerably in direction and size, however, only the interaction term between Hispanic and Dissimilarity is significant. With regard to Hispanics, the base group effect of segregation is not only counteracted but the sign is changed, making higher levels of metropolitan segregation actually worsening of general health for this ethnicity, compared to whites (at 99% confidence).

Of the person-level covariates, among the estimates on the race and ethnicity variables: Non-Hispanic Black and Native show a detrimental effect maintained at a high level of statistical significance across the model specifications, relative to Non-Hispanic White. The estimate on Hispanic behaves much the same way, until model (4) where it plummets both in size and significance. Lastly, Asian achieves only a marginally significant detrimental effect to general health by the final model compared to whites (after starting off as protective in model (1)).

The three household income categories exhibit a pattern of consistency transferring over into this section a previously well-established gradient of worsening health when moving toward lower (near poverty) income levels (relative to incomes of $75,000 and over). A detrimental effect of an especially pronounced magnitude is noted for the low incomes.

Once again females have a highly significant and protective effect on general health status in relation to males, while being married worsens general health (also at an alpha of .01).

The last two person-level additions unique to model (4), age and age2 (age-squared), are both highly statistically significant. As in the previous chapter, each additional year of age worsens general health status. Again, the effect curve slopes slightly downward, as indicated by the negative quadratic term.

Table 5-2: Ordered logit models of general health status on segregation and spatial clustering by race and ethnicity, with cross-level interactions

Model#	(1)		(2)		(3)		(4)	
Metro-level variables								
Segregation (Dissim.)	-0.621**	(-3.69)	-0.826**	(-3.99)	-0.835**	(-3.99)	-0.987**	(-5.75)
Moran's I (% Race/Ethnicity)	0.525**	(4.96)	0.987**	(8.23)	1.008**	(8.35)	0.518**	(5.33)
Person-level variables								
Race/ethnicity								
Non-Hispanic Black	0.643**	(21.84)	0.318**	(10.57)	0.334**	(11.00)	0.278**	(4.18)
Non-Hispanic Asian	-0.000144	(-0.00)	0.122**	(3.71)	0.112**	(3.41)	0.319+	(1.77)
Non-Hispanic Native	0.695**	(15.57)	0.482**	(9.70)	0.482**	(9.71)	0.599**	(3.63)
Hispanic	0.976**	(14.67)	0.816**	(10.30)	0.818**	(10.21)	0.149	(1.27)
Income								
less than $25,000			1.692**	(116.62)	1.751**	(115.67)	1.647**	(116.03)
$25,000-$49,999			0.826**	(74.36)	0.858**	(75.54)	0.805**	(71.17)
$50,000-$74,999			0.413**	(37.80)	0.430**	(38.64)	0.423**	(39.80)
Other person-level controls								
Female					-0.130**	(-15.73)	-0.141**	(-17.75)
Married					0.0659**	(8.29)	0.0297**	(3.92)
Age in years							0.0488**	(26.72)
Age (squared)							-0.000256**	(-15.33)
Cross-level interactions								
Non-Hispanic Black # Seg.							0.112	(0.59)
Non-Hispanic Asian # Seg.							-0.233	(-0.56)
Non-Hispanic Native # Seg.							0.185	(0.38)
Hispanic # Seg.							1.318**	(5.90)
Non-Hisp. Black # Moran's I							0.175	(1.27)
Non-Hisp. Asian # Moran's I							0.136	(0.84)
Non-Hisp. Native # Moran's I							-0.198	(-0.83)
Hispanic # Moran's I							-0.183	(-1.29)
N	367,569		318,373		318,373		317,018	

t statistics in parentheses; models use robust (due to heteroskedasticity) and metro area clustered standard errors
models include 310 metro dummies (coefficients not displayed); race/ethnicity reference category: non-Hispanic white; income reference category: $75,000 and over
+ p < .10, * p < .05, ** p < .01

Table 5-2 displays a set of models that mirror the setup of the models presented in Table 5-1 using general health status as the outcome, only this time ordered logit models were estimated, with robust and metropolitan area-clustered standard errors. These, as well as all remaining models in this section, were estimated with the inclusion of 310 metropolitan area dummies. The output reports untransformed coefficients, or log odds, for ease of result interpretation, particularly the cross-level interaction terms. These coefficients are interpreted as the change (increase or decrease) in the log odds of observing the outcome with a unit increase in the predictor.

It can be noted here that, as seen previously, for the two key metro-level explanatory variables - majority to minority (as well as majority to all others) group segregation by race and ethnicity and the spatial arrangement of the tract-level proportions of each race and ethnicity, the coefficients follow a very similar however inverse path across the model specifications. Dissimilarity is highly significant and protective of general health status, while the Moran's I for percent race/ethnicity is highly significant and detrimental moving from model (1) to model (4) as the level 2 estimate becomes group-specified in the final model (the index of dissimilarity leading to a change in the log odds of worse general health status for the reference race group of -0.99, and the Moran's I changing those log odds of un upward movement on the general health status scale by 0.52, all else equal).

The cross-level interactions behave much in the same manner as in the OLS models. Once again, we find the only (highly) significant result on the estimate for the Hispanic – Dissimilarity interaction term. The effect size is well over 0.99 in absolute value, meaning that the relative effect of metro-level segregation for this ethnic group is not only reversed from that of the base group, but turned considerably detrimental. Residence in a metropolitan area with a higher dissimilarity index score results in a change in the log odds of worse general health for Hispanics of 0.33 relative to Non-Hispanic whites, all else held constant (at 99% confidence).

Turning to the individual level variables, all four of the race and ethnicity categories appear as worsening health. Between model (1) and (3), all but Non-Hispanic Asian appear highly statistically significant. However, the race/ethnicity coefficients see their statistical power reduced by the complete model. Hispanic loses all significance; Asian raises the log odds of worse general health by 0.32 over Non-Hispanic White, at only 90% confidence; while Non-Hispanic Black and Native raise the log odds of worse health status compared to Non-Hispanic White by 0.28 and 0.6 respectively (at 99% confidence). Here the addition of age and interaction terms appears to have been instrumental to affecting the significance levels of the race/ethnicity final estimates.

The sequence of household income indicators once again shows a clear progression of worsening influence on health moving down the income ladder – by model (4) the low incomes (less than $25,000) have higher log odds of observing a worse general health status by 1.65, over the high income group ($75,000 and over).

The Female and Married dummies present similar results as in the previous table – the former maintains as protective relative to males, while the latter is detrimental (both remaining very significant). Lastly, age remains to be very important to health (contributing to a worsening in general health), however doing so at a slowly decreasing pace.

Overall these findings strongly resemble the results in Table 5-1 above where general health status was treated as a continuous measure. With respect to comparing the two, we observe not identical but highly similar patterns: the coefficients on the race/ethnicity and income categories, Female and Married dummies, as well as age follow much a similar pattern as in the OLS outcomes - an overarching theme characterizing the vast majority of past models. The Hispanic – Dissimilarity interaction proves as the sole significant and highly potent adjustment to the base group effect of segregation for this ethnicity.

Table 5-3: Logit models of poor or fair health status on segregation and spatial clustering by race and ethnicity, with cross-level interactions

Model#	(1)		(2)		(3)		(4)	
Constant	-1.847**	(-15.69)	-3.396**	(-29.99)	-3.399**	(-30.42)	-5.940**	(-43.59)
Metro-level variables								
Segregation (Dissim.)	-0.273	(-1.26)	-0.500*	(-2.03)	-0.504*	(-2.03)	-0.905**	(-3.73)
Moran's I (% Race/Ethnicity)	0.414**	(3.06)	0.927**	(6.33)	0.940**	(6.40)	0.344**	(2.67)
Person-level variables								
Race/ethnicity								
Non-Hispanic Black	0.597**	(17.60)	0.186**	(5.24)	0.197**	(5.53)	0.123	(1.39)
Non-Hispanic Asian	-0.355**	(-5.86)	-0.217**	(-3.95)	-0.229**	(-4.18)	-0.393	(-1.08)
Non-Hispanic Native	0.754**	(14.07)	0.476**	(7.19)	0.475**	(7.20)	0.424+	(1.92)
Hispanic	0.941**	(11.24)	0.713**	(7.35)	0.710**	(7.26)	0.248+	(1.71)
Income								
less than $25,000			2.154**	(92.87)	2.203**	(88.44)	2.086**	(84.52)
$25,000-$49,999			1.144**	(55.05)	1.171**	(54.65)	1.095**	(49.98)
$50,000-$74,999			0.542**	(24.86)	0.556**	(25.07)	0.534**	(24.62)
Other person-level controls								
Female					-0.101**	(-8.02)	-0.129**	(-10.49)
Married					0.0592**	(5.07)	0.0151	(1.26)
Age in years							0.0973**	(41.42)
Age (squared)							-0.000640**	(-31.09)
Cross-level interactions								
Non-Hispanic Black # Seg.							0.285	(1.10)
Non-Hispanic Asian # Seg.							0.388	(0.52)
Non-Hispanic Native # Seg.							0.638	(0.94)
Hispanic # Seg.							1.135**	(4.09)
Non-Hisp. Black # Moran's I							0.174	(0.93)
Non-Hisp. Asian # Moran's I							0.448	(1.39)
Non-Hisp. Native # Moran's I							-0.185	(-0.57)
Hispanic # Moran's I							-0.189	(-1.12)
N	367,569		318,373		318,373		317,018	

t statistics in parentheses; models use robust (due to heteroskedasticity) and metro area clustered standard errors
models include 310 metro dummies (coefficients not displayed); race/ethnicity reference category: non-Hispanic white; income reference category: $75,000 and over
+ p < .10, * p < .05, ** p < .01

The next set of models, results of which are presented in Table 5-3, are a set of logit regressions based on the dichotomous dependent variable, poor or fair health, created by combining levels 4 (fair health) and 5 (poor health) of the original general health status variable.

This case follows a pattern similar to the ologit set of models above for both area-wide predictors, with small discrepancies; both maintain their opposing signs throughout: segregation (Dissimilarity) starts off as insignificant, with only attaining medium significance in models (2) and (3), to then solidify its very significant and protective status in Model (4) as the estimate becomes specified by race - greater race and ethnicity specific segregation lowers the log odds of observing poor or fair health among Non-Hispanic whites by 0.9, all else equal; and the coefficient on the Moran's measure of percent race and ethnicity is very significant and exacerbating of poor/fair health - raising the log odds of the outcome for whites by 0.34 in the last (specified) model, all else equal (a deleterious effect with regard to the attainment of poor or fair health).

From among the interaction sets – again, the sole (highly) significant, and negative, estimate is found on the Hispanic – Dissimilarity interaction term. Thus, for Hispanics, the net effect of segregation runs fully opposite from that of the base group (changing the sign from protective to detrimental), in relation to whites – a metro with a higher degree of Non-Hispanic White to Hispanic segregation sees the log odds of observing poor/fair health status for its Hispanic residents raised by 0.23 relative to Non-Hispanic whites, all else constant (a result significant at an alpha level of .01).

For the level 1 variables: the race/ethnicity categories follow a pattern similar to the previous table, with the following differences: all but Non-Hispanic Asian maintain a highly significant and detrimental effect on reporting poor or fair general health, all through to model (3); Asian is the only highly significant and protective of the race categories throughout those model specifications. However, by model (4), significance levels drop substantially for all four groups, when only Native and Hispanic are able to retain only a marginally significant and negative effect.

The set of three income categories once again displays a recognizable gradient of worsening health moving toward the lower incomes. In fact, in these models, a formidable effect is observed maintained through to model (4) in the case of persons member of a household with an annual income of less than $25,000 – these raise the log odds of reporting poor or fair health by 2.1, relative to those incomes $75,000 and over (at 99% confidence).

While females show a familiar protective effect relative to males, a divergence is seen in the case of married status in which this indicator holds as negative and highly significant in model (3) before the magnitude of its effect becomes greatly diminished and in fact significance is fully lost by model (4). Finally, age is detrimental to this outcome, at a diminishing rate.

Table 5-4: Logit models of ever diagnosed with asthma on segregation and spatial clustering by race and ethnicity, with cross-level interactions

Model#	(1)		(2)		(3)		(4)	
Constant	-2.407**	(-20.47)	-2.546**	(-20.92)	-2.632**	(-21.82)	-2.658**	(-15.98)
Metro-level variables								
Segregation (Dissim.)	0.140	(0.59)	0.186	(0.78)	0.217	(0.93)	-1.210**	(-3.99)
Moran's I (% Race/Ethnicity)	0.457**	(3.69)	0.465**	(3.54)	0.415**	(3.21)	1.340**	(7.93)
Person-level variables								
Race/ethnicity								
Non-Hispanic Black	0.213**	(6.33)	0.111**	(3.14)	0.0755*	(2.18)	0.0826	(0.66)
Non-Hispanic Asian	-0.431**	(-7.71)	-0.431**	(-7.51)	-0.409**	(-7.13)	0.258	(0.58)
Non-Hispanic Native	0.507**	(9.50)	0.459**	(7.79)	0.468**	(7.88)	0.592*	(2.51)
Hispanic	0.195*	(2.10)	0.0789	(0.84)	0.0701	(0.77)	-0.906**	(-5.36)
Income								
less than $25,000			0.380**	(19.11)	0.256**	(11.27)	0.342**	(13.83)
$25,000-$49,999			0.0641**	(4.06)	-0.00610	(-0.35)	0.0504**	(2.72)
$50,000-$74,999			0.0422*	(2.40)	0.00542	(0.29)	0.0254	(1.35)
Other person-level controls								
Female					0.376**	(30.58)	0.375**	(30.80)
Married					-0.126**	(-9.25)	-0.140**	(-10.37)
Age in years							0.0113**	(5.22)
Age (squared)							-0.000177**	(-8.67)
Cross-level interactions								
Non-Hispanic Black # Seg.							0.389	(1.02)
Non-Hispanic Asian # Seg.							-0.360	(-0.36)
Non-Hispanic Native # Seg.							1.461*	(2.18)
Hispanic # Seg.							3.069**	(8.74)
Non-Hisp. Black # Moran's I							-0.159	(-0.67)
Non-Hisp. Asian # Moran's I							-0.786*	(-2.34)
Non-Hisp. Native # Moran's I							-1.327**	(-3.96)
Hispanic # Moran's I							-1.392**	(-5.13)
N	366,664		317,471		317,471		316,113	

t statistics in parentheses; models use robust (due to heteroskedasticity) and metro area clustered standard errors
models include 310 metro dummies (coefficients not displayed); race/ethnicity reference category: non-Hispanic white; income reference category: $75,000 and over
+ p < .10, * p < .05, ** p < .01

The next set of model results is based on the dichotomous variable: individual ever diagnosed with asthma, presented in Table 5-4. Interestingly, this set of logit models show somewhat of a positive association between the overall majority to minority group (as well as majority group to all others) segregation by race and ethnicity and an asthma diagnosis. More specifically, the estimate on the segregation measure indeed has a substantial (however wholly statistically insignificant) detrimental influence in the first three model specifications. However, the estimate then finally changes sign and lowers considerably to produce a powerful protective effect on the probability of an asthma diagnosis once the corresponding effect is specified - lowering the log odds of an asthma diagnosis for Non-Hispanic whites by 1.2 by the final model (at 99% confidence). The estimate on the Moran's index for clustering by race and ethnicity exemplifies very much the same pattern as in previous model sets in this section. We note here the large spike in the magnitude of the coefficient obtained by model (4) with the effect group-specified - finally increasing the log odds of an asthma diagnosis for whites by 1.34, all else equal (again at 99% confidence).

We observe a much different picture among the two sets of cross-level interactions as compared to previous models. In terms of the first set - the coefficients on the Native – Dissimilarity and Hispanic – Dissimilarity interaction terms both show as significant and sizably detrimental. The effect of segregation on Native status thus goes fully counter to the one observed for Non-Hispanic White, resulting in raised log odds of observing asthma for Native Americans by 0.25 compared to Non-Hispanic whites (at 95% confidence). The largest effect size by a great margin in any of the models presented in this project is found for Hispanic – the net effect of Hispanic residence in on average more segregated metros is to increase considerably their susceptibility to the condition – the log odds of an asthma diagnosis for this ethnic group are here greater by 1.86 relative to Non-Hispanic whites, all else held constant (at a high 99% confidence).

The current models introduce for the first time significance among the second set of cross-level interactions, those probing the differential effect by race and ethnicity of the measure of spatial segregation. Although all four interaction terms show as protective, only the estimates on the interactions including Asian, Native, and Hispanic have significance. The interactions here manage to mitigate considerably the deleterious base group effect of the Moran's Index for these groups (the latter two in particular), relative to Non-Hispanic whites. The net effect for Asian Americans and Native Americans is an increase in the log odds of asthma in metros with more spatial clustering of the respective races/ethnicities by 0.55 (at 95% confidence) and 0.013 (at 99% confidence), while decreasing those log odds by 0.05 for Hispanics (at 99% confidence), all else held equal, compared to what we would expect to observe for whites. Thus, Hispanics in fact experience a protective effect (however small in magnitude).

Turning to the person-level covariates, the race/ethnicity categories display a diverse trend in both effect size and sign across specifications. The coefficient on Non-Hispanic Black is detrimental and very significant in the first two models, to only fall out of significance entirely by model (4). The estimate on Asian is protective from model (1) through model (3), then suddenly flips considerably to become detrimental making a considerable departure between models (3) and (4), however insignificant. Native is highly significant and detrimental in the first three models, managing to maintain a moderate significance through to the full model – raising the log odds of asthma by about 0.6 in relation to Non-Hispanic White (at 95% confidence). Lastly, Hispanic is at first moderately significant and detrimental, loses significance in the subsequent two models, to then flip entirely and produce a strong and substantial protective effect - lowering the log odds of asthma by over 0.91 compared to Non-Hispanic White (at 99% confidence).

It is of interest to note here that the effect of household income departs from convention in this set of models in that the detrimental effect sizes appear greatly suppressed across the categories, and only the coefficient on less than $25,000 is (highly) significant throughout the models, raising the log odds of a lifetime diagnosis (an effect that is indeed sustained through to the last model) by 0.34 relative to incomes $75,000 and over; whereas the next, moderate income range ($25,000 to $49,999) although ultimately maintaining a highly significant and weak detrimental effect, appears somewhat inconclusive, fluctuating across the models; the last category of medium incomes ($50,000 to $74,999) only shows a medium level of significance and a negative effect in Model (1), however loses all significance thereafter. It appears that, unique to the asthma set of models, the detrimental impact of the moderate and medium income categories isn't nearly as well defined or conclusive as that of the low incomes, having the high incomes as the overall reference group.

In addition, the respective effects of Female and Married have flipped here as well (female status raises the log odds of asthma by 0.38 relative to male, and married status lowers those log odds by 0.14 in the complete model). Age is once again revealed as worsening this health outcome, at a decreasing rate.

Table 5-5: Logit models of ever diagnosed with diabetes on segregation and spatial clustering by race and ethnicity, with cross-level interactions

Model#	(1)		(2)		(3)		(4)	
Constant	-3.006**	(-21.70)	-3.763**	(-22.73)	-3.699**	(-22.11)	-10.34**	(-64.93)
<u>**Metro-level variables**</u>								
Segregation (Dissim.)	-0.643*	(-2.13)	-0.813*	(-2.33)	-0.833*	(-2.35)	-1.304**	(-4.98)
Moran's I (% Race/Ethnicity)	1.605**	(9.08)	1.889**	(9.85)	1.927**	(9.91)	1.315**	(7.31)
<u>**Person-level variables**</u>								
Race/ethnicity								
Non-Hispanic Black	0.718**	(16.10)	0.504**	(10.24)	0.531**	(10.55)	0.747**	(7.20)
Non-Hispanic Asian	-0.0244	(-0.47)	0.0728	(1.29)	0.0528	(0.93)	0.585	(1.39)
Non-Hispanic Native	0.656**	(11.49)	0.491**	(8.14)	0.485**	(8.03)	0.821**	(3.23)
Hispanic	1.018**	(8.30)	0.902**	(6.68)	0.907**	(6.62)	0.270	(1.51)
Income								
less than $25,000			1.083**	(47.71)	1.170**	(48.58)	0.914**	(42.80)
$25,000-$49,999			0.629**	(31.29)	0.676**	(32.85)	0.522**	(25.96)
$50,000-$74,999			0.336**	(14.56)	0.361**	(15.70)	0.313**	(13.35)
Other person-level controls								
Female					-0.291**	(-19.21)	-0.318**	(-21.08)
Married					0.0744**	(5.33)	0.00912	(0.63)
Age in years							0.225**	(67.80)
Age (squared)							-0.00155**	(-54.78)
<u>**Cross-level interactions**</u>								
Non-Hispanic Black # Seg.							0.416	(1.37)
Non-Hispanic Asian # Seg.							0.0220	(0.02)
Non-Hispanic Native # Seg.							-0.0266	(-0.04)
Hispanic # Seg.							1.963**	(5.40)
Non-Hisp. Black # Moran's I							-0.203	(-0.99)
Non-Hisp. Asian # Moran's I							-0.120	(-0.32)
Non-Hisp. Native # Moran's I							-0.218	(-0.55)
Hispanic # Moran's I							-0.614*	(-2.25)
N	368,439		319,030		319,030		317,668	

t statistics in parentheses; models use robust (due to heteroskedasticity) and metro area clustered standard errors
models include 310 metro dummies (coefficients not displayed); race/ethnicity reference category: non-Hispanic white; income reference category: $75,000 and over
$^{+}$ *p* < .10, * *p* < .05, ** *p* < .01

Next, Table 5-5 holds the results of a series of logit regression models based on the dichotomous dependent variable, the other chronic ailment: ever diagnosed with diabetes. Moving from model (1) to model (3) the coefficient on area-wide measure of race and ethnicity specific segregation maintains as detrimental at only medium significance, to then strengthen substantively and become highly significant by model (4) where the estimate is specified – lowering the log odds of a diabetes diagnosis for Non-Hispanic whites by 1.3, all else held constant (at 99% confidence). The Moran's measure for percent race and ethnicity mirrors its behavior in past model sets and shows as detrimental throughout the specifications, with a sizeable drop between the last two models, however maintaining its practical and statistical strength - producing increased log odds of observing diabetes in Non-Hispanic whites by over 1.3 in the full model, all else equal (at 99% confidence).

The first set of cross-level interaction measures has a very similar trajectory to a previously observed pattern – the estimate on the Hispanic – Dissimilarity term is the sole having (high) significance and a sizeable negative impact, producing an opposite and detrimental effect of segregation for Hispanics, relative to whites – a metropolitan area exhibiting a higher segregation of Hispanic residents results in raised log odds of diabetes for this group by 0.66 relative to Non-Hispanic White, all else equal (at 99% confidence).

Interestingly, the second set of interactions involving the race and ethnicity groups and the Moran's I measure, seem to imply the opposite in terms of group-specific effect. The coefficient on the Hispanic – Moran's I term this time is protective (although at a slightly lessened 95% level of confidence). Thus, on average, a relatively higher score on the Moran's Index (greater degree of spatial clustering) of the Hispanic ethnicity results in a less detrimental effect for this group relative to the reference group, still raising the log odds of a diagnosis for Hispanic by 0.7 relative to Non-Hispanic White, all else equal.

In relation to the individual level variables, from among the race/ethnicity categories the estimates on Non-Hispanic Black and Native parallel each other in their very highly significant and considerably potent across specifications detrimental effect on this health outcome. Non-Hispanic Black and Native raise the log odds of a diagnosis by 0.75 and 0.82 respectively in the last model, relative to whites (at an alpha of .01). The estimate on Asian eventually shows as highly detrimental by model (4), however at no point attaining significance. Lastly, Hispanic maintains high significance and effect size in its negative effect over the first three models, only to drop considerably and lose all significance by model (4).

The group of household income categories returns here to point once again to a pattern of highly statistically significant and increasingly detrimental effects (or worsening influence on diabetes) as household incomes decrease. A person member of a household with an annual income of less than $25,000 has greater log odds of having been diagnosed with diabetes by over 0.9, compared to those with incomes of 75,000 and higher (at 99% confidence).

Once again, the coefficient on Female is highly significant and protective – lowering the log odds of diabetes by 0.32 in comparison to males, while Married appears deleterious but loses all significance once age and the interactions are introduced in the complete model (a result pattern similar to those in the diabetes and poor/fair health models in this and the previous section). Of note here (once again, as in the diabetes models of the previous chapter) is the effect size of the estimate on age - an additional year of age raises the log odds of a diabetes diagnosis by 0.23, all else equal (at 99% confidence).

Table 5-6: Negative binomial models of No. of physically unhealthy days on segregation and clustering by race and ethnicity, w/ cross-level interactions

Model#	(1)		(2)		(3)		(4)	
Constant	1.141**	(13.40)	0.321**	(3.53)	0.256**	(2.77)	-0.894**	(-8.97)
Metro-level variables								
Segregation (Dissim.)	-0.0955	(-0.57)	-0.183	(-0.96)	-0.187	(-0.98)	-0.398*	(-2.24)
Moran's I (% Race/Ethnicity)	0.462**	(4.54)	0.615**	(5.41)	0.607**	(5.33)	0.351**	(3.16)
Person-level variables								
Race/Ethnicity								
Non-Hispanic Black	0.181**	(6.25)	-0.0783**	(-2.78)	-0.0808**	(-2.84)	-0.141	(-1.63)
Non-Hispanic Asian	-0.508**	(-12.06)	-0.406**	(-9.20)	-0.405**	(-9.03)	-0.233	(-0.82)
Non-Hispanic Native	0.467**	(9.71)	0.282**	(5.30)	0.287**	(5.40)	0.283	(1.30)
Hispanic	0.339**	(4.92)	0.144+	(1.84)	0.139+	(1.77)	-0.245**	(-2.59)
Income								
less than $25,000			1.255**	(99.78)	1.251**	(89.52)	1.144**	(80.83)
$25,000-$49,999			0.600**	(52.24)	0.599**	(51.54)	0.538**	(44.84)
$50,000-$74,999			0.305**	(23.16)	0.304**	(22.84)	0.286**	(21.51)
Person-level controls								
Female					0.108**	(11.47)	0.121**	(13.65)
Married					0.0165	(1.64)	-0.0211*	(-2.01)
Age in years							0.0433**	(24.55)
Age (squared)							-0.000263**	(-16.53)
Cross-level interactions								
Non-Hispanic Black # Seg.							0.275	(1.27)
Non-Hispanic Asian # Seg.							0.0546	(0.08)
Non-Hispanic Native # Seg							0.557	(0.87)
Hispanic # Seg.							0.907**	(4.64)
Non-Hisp. Black # Moran's I							-0.0405	(-0.33)
Non-Hisp. Asian # Moran's I							-0.120	(-0.50)
Non-Hisp. Native # Moran's I							-0.400	(-1.49)
Hispanic # Moran's I							-0.415**	(-3.10)
N	361,683		314,169		314,169		312,860	

t statistics in parentheses; models use robust (due to heteroskedasticity) and metro area clustered standard errors
models include 310 metro dummies (coefficients not displayed); race/ethnicity reference category: non-Hispanic white; income reference category: $75,000 and over
$^{+}$ $p < .10$, * $p < .05$, ** $p < .01$

The next table (Table 5-6) presents the results of a set of negative binomial regressions treating the first of the two count response variables: number of physically unhealthy days. As with the previous table, these models report the estimates in terms of untransformed coefficients, expressed as log odds of expected counts of mentally unhealthy days. These models regress the above dependent variable on the two level 2 variables: metropolitan segregation (as measured by the index of dissimilarity) and Global Moran's index for percent race and ethnicity.

Reading from the table above, there is a general continuity in the effect pattern of the two metropolitan area level variables on the outcome as with all previous response variables examined in the current chapter. The race-specific inter-group, and majority-minority group segregation (Dissimilarity) shows a positively sloping effect in models (1) through (3), although it only achieves (moderate) significance and magnitude in model (4) once the effect becomes specified by group – a one-unit increase in the dissimilarity index reduces the difference in the logs of expected counts of physically unhealthy days among Non-Hispanic whites by 0.4, all else equal (at an alpha of .05). Inversely, the Moran's index for percent race/ethnicity shows the familiar negative association to the number of physically unhealthy days experienced. This holds true universally at very high levels of statistical significance from model (1) through model (4), however with somewhat of a precipitous drop in magnitude by that final model specification when the effect is specified; nonetheless, the coefficient's effect holds, and in fact, a one unit increase in the metro-level spatial segregation by race and ethnicity (the Moran's I score) leads to an increase in the difference in the logs of expected counts of physically unhealthy days for whites by 0.35, all else held equal (at an alpha of .01).

The pair of cross-level interactions show a result pattern very similar to the one found in the previous Table 5-5 (treating the outcome variable of diabetes). The interactions between segregation as measured by the index of dissimilarity and race/ethnicity group point to a strong negative (and highly significant) group-specific effect for the Hispanic ethnic category in relation to Non-Hispanic White, in contrast with the (generally very protective) effect of segregation for the reference race group. The Hispanic – Dissimilarity interaction term transforms the effect of segregation for Hispanic relative to Non-Hispanic White from protective to strongly detrimental, resulting in a change in the difference in the logs of expected counts of physically unhealthy days for Hispanics of over 0.5 in relation to for whites (at 99% confidence).

Conversely, with respect to the set of interactions based on race/ethnicity status and the Moran's index for Census tract-level percent race/ethnicity, the overall detrimental effect of the spatial clustering by race and ethnicity is countered by a protective effect specifically for Hispanics relative to Non-Hispanic whites, bringing forth a minor protective effect of clustering – a change in the difference in the logs of expected counts for Hispanic of -0.06 compared to whites (the interaction term again significant at 99% confidence). The coefficients on the interaction terms between Hispanic and the respective measure of segregation/clustering are the only (highly) significant results from among the cross-level interactions; in both instances, their effect counters the base race group effect of the corresponding level-2 measures.

Among the person-level variables, the race/ethnicity categories display a mix of behaviors across model specifications. The coefficient on Non-Hispanic Black is first detrimental, (model (1)), before turning and remaining protective in the following two models (maintaining high significance throughout), to finally further its protective influence by size in model (4), only without any significance left. From model (1) through model (3), the estimates on both Asian and Native are very significant, with opposing effects on the outcome – protective and detrimental respectively; however, once again, they both lose significance in the complete model. Last among the categories, the effect of the Hispanic ethnicity appears to transform from very significant and detrimental, to end as very significant and protective against the incidence of physically unhealthy days – ultimately helping to reduce the difference in the logs of expected counts of physically unhealthy days by 0.25, relative to whites (model (4), at 99% confidence).

Looking at the household income categories, the three resume a pattern of an income gradient effect on this health outcome – a greater incidence of physically unhealthy days is promoted moving toward the lower ranges, relative to high incomes.

The Female dummy mirrors the pattern observed in the asthma set of models. Female status here worsens the outcome, compared to males; however, married status, although beginning as nominally detrimental (and non-significant), in fact ends as mildly protective with moderate significance in model (4). Age is detrimental here as well, with a diminishing effect.

Table 5-7: Negative binomial models of No. of mentally unhealthy days on segregation and clustering by race and ethnicity, w/ cross-level interactions

Model#	(1)		(2)		(3)		(4)	
Constant	1.098**	(15.41)	0.544**	(7.14)	0.541**	(7.36)	-0.0882	(-0.76)
Metro-level variables								
Segregation (Dissim.)	0.289*	(2.49)	0.188	(1.55)	0.165	(1.38)	-0.513**	(-2.71)
Moran's I (% Race/Ethnicity)	0.0258	(0.38)	0.125+	(1.79)	0.119+	(1.78)	0.741**	(6.61)
Person-level variables								
Race/Ethnicity								
Non-Hispanic Black	0.155**	(7.29)	-0.0612**	(-2.94)	-0.0984**	(-4.76)	-0.139	(-1.37)
Non-Hispanic Asian	-0.384**	(-10.59)	-0.329**	(-10.62)	-0.310**	(-10.00)	-0.0772	(-0.40)
Non-Hispanic Native	0.495**	(13.94)	0.331**	(7.73)	0.353**	(7.81)	0.339	(1.26)
Hispanic	0.179**	(4.18)	0.0258	(0.60)	0.0372	(0.87)	-0.0676	(-0.56)
Income								
less than $25,000			0.987**	(65.04)	0.859**	(52.95)	1.006**	(58.63)
$25,000-$49,999			0.458**	(32.70)	0.389**	(26.52)	0.491**	(33.15)
$50,000-$74,999			0.274**	(19.42)	0.237**	(16.47)	0.266**	(17.61)
Person-level controls								
Female					0.337**	(30.48)	0.325**	(27.07)
Married					-0.200**	(-18.85)	-0.220**	(-19.88)
Age in years							0.0369**	(18.24)
Age (squared)							-0.000504**	(-25.27)
Cross-level interactions								
Non-Hispanic Black # Seg.							-0.0222	(-0.09)
Non-Hispanic Asian # Seg.							0.230	(0.52)
Non-Hispanic Native # Seg.							0.732	(0.83)
Hispanic # Seg.							0.794**	(3.27)
Non-Hisp. Black # Moran's I							0.0932	(0.59)
Non-Hisp. Asian # Moran's I							-0.643**	(-3.09)
Non-Hisp. Native # Moran's I							-0.594+	(-1.65)
Hispanic # Moran's I.							-0.501**	(-3.36)
N	362,882		315,052		315,052		313,740	

t statistics in parentheses; models use robust (due to heteroskedasticity) and metro area clustered standard errors
models include 310 metro dummies (coefficients not displayed); race/ethnicity reference category: non-Hispanic white; income reference category: $75,000 and over
$^{+}$ $p < .10$, * $p < .05$, ** $p < .01$

The final analysis for this chapter, above are presented negative binomial regression results for the second of the pair of count dependent variables: number of mentally unhealthy days. Table 5-7 presents results of models regressing the dependent variable on two main metropolitan level variables: segregation (index of dissimilarity) and Moran's index for percent race/ethnicity.

It is of interest to note that from among the metropolitan level variables, the segregation measure for the first time attains detrimental and significant status in model (1) (at an alpha of .95); this estimate next loses statistical significance to finally experience a marked reversal to protective status in model (4) once specified – reducing the difference in the logs of expected counts of mentally unhealthy days for Non-Hispanic whites by 0.5, all else held equal (at an alpha level of .01). A pattern similar to this is only previously found in the asthma set of models, only none of those positive coefficients reaches significance. The Moran's measure presents another notable departure from previous models: the estimate is inconclusive in its positive association with the outcome for much of the model specifications. The measure is only marginally statistically significant in models (2) and (3), strengthening and attaining high significance only in the last model with the effect specified by group – ultimately increasing the difference in the logs of expected counts of unhealthy days for Non-Hispanic White by 0.74, all else equal (at an alpha of .01).

From the first of the cross-level interactions between the index of dissimilarity and race/ethnic group only the Hispanic – Dissimilarity interaction term shows as (highly) significant, having an inverse group-specific relationship to this measure of segregation, meaning that among the race and ethnicity groups Hispanics are the sole group expected to experience a relative worsening in the incidence of mentally unhealthy days in on average more segregated metros with Non-Hispanic White as the reference category, controlling for other factors. In quantifying this difference – the net effect of segregation for Hispanics relative to whites is a change in the difference in the logs of expected counts of mentally unhealthy days of 0.28 relative to Non-Hispanic whites, all else constant (at 99% confidence). The estimate on Native here has a pronounced magnitude, however without any significance.

With regard to the second set of interaction terms (race/ethnicity status and spatial ordering of tract-level proportions of race/ethnicity), the coefficients on the interactions including Asian, Native, and Hispanic are all protective in reference to Non-Hispanic White. The first two having high statistical significance, while that of Native only marginally significant. Each produces a group-specific protective effect relative to Non-Hispanic White opposite to the detrimental impact of the spatial clustering of race and ethnicity for the base race group – a change in the difference in the logs of expected counts of mentally unhealthy days for Asian Americans, Native Americans, and Hispanics of 0.1 (at 99% confidence), 0.15 (at 90% confidence), and 0.24 (at 99% confidence) respectively in comparison with whites, ceteris paribus.

Discussing now the first group of person-level variables, we note that none of the four race and ethnicity categories retains any statistical significance by the complete model, upon the introduction of age and interaction sets. The estimates on Non-Hispanic Black, Asian, and Native all have high significance through model (3): Non-Hispanic

Black changes signs going from detrimental to protective between the first two models; Asian and Native are negatively and positively associated with the health outcome, respectively; and Hispanic further shows as detrimental and highly significant, an effect however limited to the first model.

The three household income ranges maintain a continuum of worsening effects on health across model specifications moving toward the lower incomes, relative to those incomes 75,000 and over.

As observed in the previous table, as well as the asthma models, there is a switch in the direction of the effect of the Female and Married indicators. Both coefficients are highly significant in the two model specifications. Female appears to be worsening the outcome relative to males - increasing the difference in the logs of expected counts of mentally unhealthy days by 0.33, and Married shields against the outcome – reducing the difference in the logs of expected counts of unhealthy days by 0.22.

Finally, as established by virtually all previous analysis results, the age variables reveal a positive relationship, once again at a decreasing rate as age progresses.

Marginal Effects

Average marginal effects for each race/ethnicity and household income category were calculated in order to compare with the cross-level interaction effects in previous model results. These are the changes in probability in each of the health outcomes while holding all other variables at their mean values. The set of marginal effects are presented for each of the two main metro-level variables (Table 5-8). Once again, the results confirm the above discussion – segregation (as measured by the index of dissimilarity) by race and ethnicity appears to reduce the probability of worse self-reported health, asthma, and diabetes (with the exception of the Hispanic ethnicity). The spatial clustering by race and ethnicity group as measured by the Moran's I has the opposite effect on poor health outcomes. The negative effects are felt strongest in relation to diabetes.

Table 5-8: Average marginal effects, Index of Dissimilarity and Moran's I (% race/ethnicity)

	Poor/Fair Hlth			Asthma			Diabetes	
Index of Dissimilarity								
Race/Ethnicity	Margins	Std. Err.		Margins	Std. Err.		Margins	Std. Err.
Non-Hisp. White	-0.101	0.027		-0.129	0.032		-0.097	0.019
Non-Hisp. Black	-0.083	0.039		-0.098	0.048		-0.110	0.041
Non-Hisp. Asian	-0.059	0.088		-0.124	0.079		-0.135	0.103
Non-Hisp. Native	-0.040	0.101		0.036	0.090		-0.153	0.075
Hispanic	0.035	0.035		0.153	0.017		0.081	0.033
H.H. Income								
< $25,000	-0.158	0.045		-0.124	0.035		-0.126	0.026
$25,000-$49,999	-0.095	0.027		-0.101	0.029		-0.096	0.020
$50,000-$74,999	-0.063	0.018		-0.099	0.028		-0.083	0.017
$75,000<	-0.040	0.012		-0.097	0.028		-0.065	0.013
Moran's I (%race/ethnicity)								
Race/Ethnicity								
Non-Hisp. White	0.038	0.014		0.142	0.017		0.098	0.013
Non-Hisp. Black	0.069	0.026		0.141	0.032		0.138	0.028
Non-Hisp. Asian	0.091	0.037		0.044	0.027		0.126	0.041
Non-Hisp. Native	0.024	0.049		0.002	0.048		0.126	0.046
Hispanic	0.024	0.022		-0.004	0.017		0.086	0.028
H.H. Income								
< $25,000	0.072	0.024		0.157	0.020		0.140	0.018
$25,000-$49,999	0.044	0.014		0.128	0.016		0.108	0.014
$50,000-$74,999	0.029	0.010		0.125	0.016		0.092	0.012
$75,000<	0.019	0.006		0.123	0.015		0.072	0.009

Results Summary

Overall, the model results discussed above elucidate important aspects of the association between metropolitan level residential segregation and spatial clustering by race and ethnicity and measures of health. It is of note that the findings of the analysis presented in this chapter represent a complete reversal in the direction of influence exerted on the health outcomes of the aspatial and explicitly spatial factors measured at the metropolitan level. Specifically, the initial set of OLS fixed effects models indicates a strong and tangible positive (protective) effect of race and ethnicity-specific segregation on individual self-assessed general health status for the base race group. The race-specific spatial patterning, or clustering, of each race and ethnicity had an opposite, detrimental, effect on general health. Here, the outcome was conceptualized as assuming a continuous form. The following, ordered logit, set of models treated the outcome as an ordinal variable. These too point to an inverse relationship: rising segregation is associated with improved general health, while an increase in the level of geographic clustering is associated with worsening of the general health status. The next set of logit models presents yet another variant of general health models – treating the dichotomous depending variable poor or fair health status. These models provide further evidence of a protective effect of segregation on poor or fair health for whites; however, showing a noticeably diminished statistical power this time in the earlier models and only recovering in the full model with all covariates included. This speaks to the relevance of specifying the metro-level variables by race - the level 2 estimate comes to represent the corresponding effect on the outcome for the base race/ethnicity group (Non-Hispanic whites). The spatial clustering by race and ethnicity is again proving as worsening of this outcome.

It could be summarized that the first three model sets estimated on general health status do provide supportive concurrent evidence triangulating the above findings, showing that these are not particularly sensitive to and are robust across specifications. The only divergence is found in the poor/fair health set of models where the effect of the aspatial measure of segregation shows as somewhat inconclusive in the earlier model specifications coming to light only after being specified by race category. These results appear as mildly less robust than those from the OLS and ordered logic models.

The two sets of logit models treating the chronic conditions of asthma and diabetes as the outcome mimic the above general result trend in this respect and provide support for a protective effect of the segregation measure for the base group; however only (highly statistically significantly so) in the last, complete, model, showing segregation as protective for Non-Hispanic whites. These models continue the result pattern of a positive association between spatial clustering of Non-Hispanic whites and these two health outcomes, while the association is reversed for Hispanics.

Lastly, the pair of functional measures of health indicates (in the aggregate) similar results. This only applies to those results observed in the complete model specified by race/ethnicity (except of the last specification in the physically unhealthy days models where it only reaches medium significance). A higher dissimilarity score benefits Non-Hispanic whites, but is quite harmful for Hispanics; the converse is true for the Moran's I. Only the Moran's measure in the physically unhealthy days models maintains a strong (detrimental) impact on the outcome under all specifications. All other instances appear rather inconclusive, with indeed the aspatial segregation measure in the mentally unhealthy days models starting off as detrimental. Specifying the level 2 factors solidified the race/ethnicity specific effects – segregation is highly protective of Non-Hispanic whites and detrimental to Hispanics; the opposite holds true for the spatial measure as it relates to Non-Hispanic whites and all minority groups but Non-Hispanic Black, closely resembling the asthma set of models.

Overall, segregation (as measured by the index of dissimilarity) has a fully statistically powerful protective effect throughout all specifications only in the first two model sets. All other models show an attenuated effect on the health outcome in the earlier model specifications with a single estimate of metro-level effects for all racial and ethnic groups. Specification of the estimate on dissimilarity delivers a strong protective effect for Non-Hispanic whites and a compensating harmful one for Hispanics (severely so with asthma and diabetes), and Native Americans for the outcome of asthma. The Moran's index measure of spatial clustering shows a strong detrimental effect throughout the specifications of all model sets but the last – greater spatial segregation hurts Non-Hispanic whites, but helps minority residents (particularly Hispanics, and to a lesser degree Asians and Native Americans). The addition of household income enables significance for the estimates on segregation and spatial clustering in the poor/fair health and mentally unhealthy days models respectfully, while the sole presence of the race/ethnicity categories exacts a single instance of a positively related and significant estimate on segregation in the mentally unhealthy days models.

The results of two sets of cross-level interactions between individual race/ethnicity and both the segregation and spatial clustering by race and ethnicity are marked by a pattern of countervailing impacts for selected race and ethnicity groups. The first three tables show higher levels of Hispanic – Non-Hispanic White metropolitan segregation exerting a strongly negative (detrimental) effect on the general health status score for Hispanics over that of whites, going counter to the base group effect (that of the segregation of Non-Hispanic White to everyone else on Non-Hispanic whites). This trend continues throughout the remaining health outcomes in the analysis. Indeed, this countering effect for Hispanics alone is especially and extraordinarily high in the asthma models – reversing the effect on whites by over 2.5 fold; it further maintains as relatively high in the diabetes models. A new pattern begins to manifest for this ethnic group over the outcomes of diagnoses of asthma and diabetes, and the reported number of physically and mentally unhealthy days in the past 30. In these models, metropolitan areas exhibiting a higher degree of spatial clustering of Hispanic residents serves to potently guard this ethnic group against unfavorable health outcomes. Thus, for all outcomes but general health (and the derivative poor/fair health), there is a dichotomy of effects operating in an opposite direction from those of the two respective indicators for the majority race group in this analysis specifically affecting Hispanics. For this ethnic group, aspatial segregation appears to be adverse while spatial clustering is simultaneously beneficial. A similar duality of effects exists for Native Americans only in the case of asthma, while this group counters the effect of the spatial clustering for Non-Hispanic White alone in the mentally unhealthy days models. Asian Americans counter that respective effect of spatial clustering on whites in both the asthma and mentally unhealthy days models.

Racial and ethnic group membership demonstrates a mixed palette of effects across specifications and outcomes, with the addition of age and interactions in the complete model proving most consequential. African Americans see a worsening in health in the first two tables treating general health status, as well as diabetes, relative to whites. Asian Americans have a worsening only in general health. Native Americans experience a worse outcome for general health, poor/fair health, asthma, and diabetes. Hispanics experience a worse outcome for poor/fair health, and a protective status against asthma and physically unhealthy days. In this group of controls, household income appears to fully reverse the influence of African American race status on the incidence of both physically and mentally unhealthy days.

Throughout the models in this chapter, there emerges a consistent gradient of worsening in health along the spectrum of outcomes for persons in households of decreasing annual incomes, over those furthest up along the income distribution – affecting general health (poor/fair health) with particular force. The exception to this (akin to the findings in the previous set of analyses) is asthma, where this pattern somewhat breaks down for the moderate and medium income households.

Female status appears as protective in the case of general health, poor/fair health, and diabetes, and worsening of health for the outcomes of asthma, and incidence of physically and mentally unhealthy days, compared to males. Married status worsens general health, while shielding against an asthma diagnosis and the incidence of physically and mentally unhealthy days. Age once again proves as universally worsening of health, taking on a statistically significant quadratic form. Similar to the previous analysis dealing with poverty, it has its largest bearing on diabetes.

Once again an interesting finding emerges from a consistent dissonance in the effect of the metropolitan level measures of segregation for the majority race and minority racial/ethnic groups. This is consistent with the analysis of descriptive statistics presented in Chapter 3: demonstrating a visible divergence in trends among the set of metro-level measures over the period 2000 to 2010 (only the indices of dissimilarity for Asian and Native deviate from this). Expected to be closely related, the two measures of metro-level segregation are fundamentally different. The set of relationships are reversed here. The index of dissimilarity, as an aspatial measure of segregation, is generally protective across outcomes, and the spatial measure of tract-level clustering by prevalence of race/ethnicity proves worsening of health for Non-Hispanic whites. This time the pattern of dual countering of minority-specific effects of the level 2 factors manage to fully overturn the respective base group effect; this with a particular emphasis on Hispanic, and to a much lesser extent Native. Again, it must be noted that, largely, the impact of metropolitan segregation on Hispanics is fully opposite to the one for whites and considerable in magnitude across the outcomes.

The index of dissimilarity, like the poverty concentration measure, is not situated in geographic space: in other words, it does not consider each tract's value on the measure in relation to adjacent tracts. Thus, while the index of dissimilarity provides information on the overall level of racial segregation within a metropolitan area, it measures solely within tract segregation with no awareness of the wider arrangement of neighborhoods. On the other hand, the Moran's index measures segregation over a wider aerial unit. The findings here suggest that the geographic arrangement of neighborhood-level segregation matters in shaping the outcomes – namely, by counteracting the respective metro-level effects on minority versus majority group residents.

Similarly to the findings in Chapter 4: there is a nearly universal divergence between the respective relationships of the metro-level factors to the health outcomes. The result corresponds somewhat to the descriptive statistics observed in Chapter 3: the 2000-2010 inverse trends of the index of dissimilarity and Moran's I break down for Asians and Native Americans. Although related in principle, the two measures of metropolitan level segregation are in fact different, signaling that the two may be measuring two distinct dimensions of concentration/clustering. The two variables can be imagined as capturing residential sorting processes on different geographic scales: the index of dissimilarity at the census tract (micro) level, and the Moran's index at the metropolitan (macro) level.

The explicitly spatial measure of the distribution of tract-level proportion of race/ethnicity appears to worsen the outcome across all race/ethnic groups on all three model specifications of general health status. Greater metropolitan segregation (dissimilarity) acts as protective for the majority group and detrimental for Hispanics; this of course without regard to the spatial arrangement of race and ethnicity. Once the overall metropolitan area level of segregation is accounted for the spatial arrangement of proximal similar neighborhood-level proportions of race and ethnicity becomes largely favorable for minority residents. The spatial clustering of Non-Hispanic White neighborhoods - physical distance from minority neighborhoods - works to depress the health of whites. Clustering in this instance, or across-tract segregation, is protective for Hispanics in terms of chronic conditions and number of unhealthy days. This may be indicative of historic processes of immigration and settlement patterns, especially as it relates to the cross-generational maintenance of cultural norms and beliefs (e.g. nutrition). However, the within-tract intensity of segregation still works to worsen health of members of this ethnicity.

It can be inferred from these findings that, in this portion of the study too, it appears that specifying the models with metropolitan area fixed effects made for stronger, more pronounced effects of the area poverty and poverty concentration measures on the health outcomes.[5] It leads in the direction of the existence of substantive left over variable bias – variables not included or factors unmeasured within the sample of metropolitan areas, variables that are correlated with the key area-wide predictor

[5] A note must be made that these point estimates may indeed be conservative. There is more recent research pointing to a negative bias present in estimates when smaller area fixed effects are applied, relative to, for example, state fixed effects (Lindo, 2015). Among the reasons are potential spillover effects of surrounding areas outside of metropolitan boundaries, as well as overarching state-specific policy and other environment. The use of state fixed effects in this study was not feasible as a number of the metropolitan areas in the sample span multiple states.

variables of interest in the current set of regression models. This would suggest that incorporation of the adjustment for a set of unobserved factors operating within metropolitan areas over the period was important to finding an unbiased effect of segregation and clustering on the health outcomes, as mediated by the person-level controls. Thus once again the existence of a set of omitted factors relating to the unique trajectory and historical context of development of urban regions, particularly in the way of governmental housing, education, and transportation policy, historic race relations, immigrant settlement patterns, and overall spatial residential sorting over time is made salient to arriving at a better understanding of the underlying relationships between segregation, spatial clustering and health outcomes.

Chapter 6: Conclusions and Implications for Policy

Poverty Concentration, Poverty Clustering, and Health Outcomes

The analysis in Chapter 4: points to a consistently positive relationship between the overall metropolitan level of poverty and the non-spatial measure of poverty concentration and ill health, almost universally across the outcomes (with a notable exception found in the number of physically unhealthy days for the concentration measure). Metropolitan areas characterized by a higher degree of poverty concentration see a worsening in health, after accounting for the overall area-wide level of poverty, the spatial concentration of poverty, as well as a number of individual and household level covariates. Other researchers have alluded to a similar association between concentrated neighborhood socioeconomic disadvantage and measures of health. This stands particularly in reference to residence in neighborhoods where the effects of a person's own material deprivation are compounded by that of their neighbors. As the concentration measure employed in this analysis gages the magnitude of the within-neighborhood sorting of individuals and households living environments of aggregate deep poverty irrespective of the relative geographic co-location of neighborhoods, it represents those neighborhoods marked by conditions of inadequate housing conditions and depleted public resources among other factors, all inextricably linked to many risk factors and ultimately unfavorable health outcomes. These findings largely align with the findings of previous studies discussed within the literature review section above.

On the other hand, the analysis reveals a very different result with regard to the explicitly spatial measure of the concentration, or clustering, of neighborhood level poverty across metropolitan space. The spatial clustering of poverty has an inverse relationship to the health measures. Indeed, when the effect of concentration is controlled, clustering appears to lead to improved health overall. Metropolitan areas characterized by a higher degree of geographic clustering of poverty, an arrangement where neighborhoods of similar poverty are nearer to each other rather than further away, is thus associated with improved outcomes of health, after accounting for the overall metro-level of poverty, the non-spatial concentration of poverty, as well as the relevant individual and household factors.

The cross-level interaction results although mixed overall, direct attention to important insights. The effects observed from the interactions of within neighborhood concentrations of poverty demonstrate only a tenuous relationship to the health outcomes at best. The finding that individuals members of relatively lower income households in metros where poverty is more spatially clustered enjoy better general health while having worse outcomes on asthma, diabetes, and number of mentally unhealthy days (compared to high income households) is instructive. These individuals may benefit from the proximity of poor neighborhoods (up to a certain level) where a greater level of social capital and internal networks ties can work to improve perceptions of health and overall wellbeing, while poor access to nutrition and environmental conditions remain to fuel chronic conditions, and sustained psychological stressors such as exposure to crime work to limit mental function.

It is plausible that the more proximal positioning of poor neighborhoods along a continuum (as measured by poverty clustering) rather than the application of a rigid high poverty threshold (poverty concentration measure) is instrumental in accounting for the divergent effects of these two contextual measures; this potentially points to the importance of a threshold effect. It is apparent that the clustering of poverty provides health benefits to residents, so long as that inter-neighborhood clustering over space does not cross a boundary, morphing into micro-level, or intra-tract concentration of poverty – in other words, the production of localized levels of poverty substantial enough to wield a depressing force on the health ecology of place.

Indeed, there may be a relative advantage to residence within a cluster of moderately poor neighborhoods of varying levels (however (once again), below a level of extreme high poverty). Such positioning could allow for residents to benefit from targeted local government policy interventions using as a foundation the potentially wider scope or reach of the programs, where such investment of even limited funds may be viewed as carrying promise of disproportionate impact, (as contrasted to isolated neighborhoods of very high poverty where conditions and needs are complex). This can take the form of the extension or provision of health maintenance and promotion resources, tailored specifically to the unique needs and circumstances of low to moderate income households. These environments can offer better realized access to health-related resources, as contrasted with wealthier neighborhoods, which however replete with resources remain out of reach to such residents.

Of particular relevance in this section is the role of household income as assessed on its own merit. As documented by previous work on health outcomes, individual or household income bears a consistent and palpable imprint on health. This study adds further evidence of the injurious effects of low income and impoverishment. Urban residents with lowest of incomes unmistakably bear the brunt of the burden of ill health.

Segregation and Clustering by Race and Ethnicity, and Health Outcomes

The analysis presented in Chapter 5: arrives at roughly diametrically opposite conclusions from those of the preceding chapter. The results hint at an inverse relationship between racial segregation, as measured by the index of dissimilarity, and health - after controlling for spatial racial and ethnic clustering as well as person and household level factors. This measure is once again non-spatial, not accounting for the physical location and positioning of constituent metropolitan neighborhoods vis-à-vis one another.

A protective effect of racial segregation here is quite an unusual finding as for instance one recent study has come to a contrary finding utilizing the index of dissimilarity as the segregation measure - they find a highly statistically significant association between segregation and poor self-rated health for African Americans, an effect exacerbated by residence in high poverty neighborhoods (Do et al., 2017).

Inversely, the explicitly spatial measure of tract-level clustering by race and ethnicity is observed to have an overall worsening effect across the outcomes. Thus, the geographic co-location of neighborhoods of similar racial and/or ethnic composition along a continuum of tract-level proportions for each group results in poorer self-rated health, and heightened incidence of disease, and more days of physical and mental dysfunction.

As in the section dealing with poverty, the cross-level interactions are largely mixed in the group-specific effects they portray. However, they offer some nuanced results pertaining to certain minority groups. The effects on Hispanics stand out in that there is a pattern in many of the outcomes in which segregation of the group is detrimental while spatial clustering is protective, relative to whites. This falls in line with previous arguments detailing a negative effect on health of concentrated disadvantage, corresponding to highly racially/ethnically isolated and segregated neighborhoods. On the other side is the argument of immigrant ethnic enclaves, contiguous areas that may span a larger portion of a metropolitan area, such as several or more neighborhoods. These develop over time containing generations of immigrants, often host to a variable mix of nationalities and ethnic backgrounds or origins from one neighborhood to another. As discussed previously, a body of existing research has indicated a protective effect of such ethnic clustering for certain more recent immigrant subgroups of Hispanics and Asian Americans. These unique contexts are hypothesized to lead to improved health through a cultural and linguistic environment conducive to slowing the process of acculturation through the strengthening of social ties, informal supports, and facilitating access to mainstream economic and education resources (Kasinitz et al., 2009; Logan et al., 2002; Zhou & Portes, 2012).

Other studies have found a beneficial result in terms of birth outcomes for African Americans when their neighborhood level proportions exhibited greater clustering (Bell et al., 2006). The current analysis found no significant results for African American clustering on any of the outcome measures.

There is undoubtedly vast overlap between racial residential segregation and concentrated disadvantage. This condition has been well written about and documented in the neighborhood effects literature. Segregation’s enduring and durable effects have been primarily carried out through its ability to create concentrated poverty (Massey, 2016; Quillian, 2012). The relegation of minorities and, most of all, African Americans, to isolated, deteriorated, and disinvested sections of cities and urban regions has put concentrating poverty as the foremost driver of health, among other outcomes, as well as health disparities.

As discussed with regard to the results of the analysis in Chapter 4: here too individual or household level incomes pose serious challenges to the attainment of good health, even after accounting for a number of relevant both micro and macro level factors. In that respect as a policy implication this study adds credence to the usefulness of strategies targeting micro level conditions of low incomes and impoverishment as foundational to reducing health inequalities.

This dissertation shows that the specific distributional dynamics of racial and ethnic subgroups across the metropolitan landscape can have disparate, and sometimes conflicting, effects on the outcomes treated in the analysis examining the association between segregation and health. The effect of segregation depends to a large extent on the type of measure used, in this instance whether the aspatial index of dissimilarity, or the explicitly spatial Moran's index. The unforeseen nuances and cross-directionality of effects among the metropolitan measures brings to the forefront the complexity of the concept of segregation. This in turn alludes strongly to the importance of combining both types of measures within analyses in order to more accurately model the effect of segregation on an outcome of interest.

Chapter 7: Avenues for Future Research

The analysis presented in this dissertation produces important empirical findings regarding the direction and magnitude of the causal relationships between both aspatial and explicitly spatial measures of poverty concentration and racial residential segregation and health outcomes, accounting for a number of individual level factors. The analysis does not however contribute to the theory in the way of answering questions regarding the processes by which these area-wide characteristics help drive individual outcomes. Future studies on the subject of area influences on individual health outcomes could benefit from focusing on identification of some of the causal pathways or mechanisms, either exerted directly by the broader metropolitan and neighborhood environment, or their indirect influence through health related behaviors and response to stressors.

The current study represents a high level analysis covering the vast space of the contiguous United States, with a relatively large number of metropolitan areas that differ widely across a number of dimensions, taking on distinct characteristics of the different regions of the country. Thus while having a large breadth it is deficient in depth. In this direction, more narrowly focused case studies on metropolitan areas possibly combining mixed method inquiries hold potential for researchers to delve deeper into regional and metropolitan area settings in order to uncover some of the nuances of these relationships at a more localized scale, with that adding important substantive pieces of understanding to a cumulative body of knowledge within the study of public and population health.

This research could further be improved by the inclusion of a set of metro-level control variables providing information on immigrants, and more specifically, recent immigrants, absorbed within each of the sample metropolitan area populations corresponding to the period of analysis. This may help account for differentials in health related behaviors and other cultural beliefs and practices associated with immigrant communities, which could sharpen and strengthen overall results.

Moreover, the current study could be usefully extended with additional years of analysis or historical data points for the purpose of providing a greater longitudinal focus and enabling the application of additional methodological tools, such as year fixed effects. This would help to add credence and lend greater strength to causal relationships identified in potential future results.

Finally, the dataset providing the bulk of the variables for this research study, the BRFSS, is replete with measures of person-level behavioral risk factors, such as patterns of tobacco use and alcohol consumption; preventative screenings, level of physical exercise, or the possession of health insurance coverage (public of private). The addition of such factors as covariates in future model iterations (after the application of adequate statistical tools and techniques to address problems of endogeneity) could potentially help further isolate the effects of the key metro-level predictors on the outcomes. Relatedly, the BRFSS could provide some additional individual-level factors that could potentially be added as new dependent variables to be tested, such as the body mass index (BMI), a standard measure of overweight/obesity, as well as utilization of preventative care and services such as diagnostic screenings.

Appendix A

Historical survey participation rates, variables by year and state/territory, 1984-2017 (Behavioral Risk Factor Surveillance System annual data)

Survey year	Variable count	No. of states/territories	Total respondents
1984	98	15	12,258
1985	100	22	25,221
1986	108	26	34,395
1987	116	33	50,081
1988	152	37	56,448
1989	162	40	66,867
1990	193	45	81,557
1991	180	48	87,846
1992	181	49	96,213
1993	197	50	102,263
1994	209	50	105,853
1995	212	50	113,934
1996	263	52	124,085
1997	268	52	135,582
1998	326	52	149,342
1999	281	52	159,989
2000	289	52	184,450
2001	291	54	212,510
2002	310	54	247,964
2003	294	54	264,684
2004	293	52	303,821
2005	329	53	356,112
2006	302	53	355,710
2007	342	54	430,912
2008	292	54	414,509
2009	405	54	432,607
2010	378	54	451,075
2011	450	53	506,022
2012	359	53	475,687
2013	359	53	491,773
2014	279	53	464,664
2015	330	53	441,456

2016	275	54	486,303
2017	358	53	450,648

Appendix B

2000 and 2010 BRFSS annual survey response rates and Census tract counts: metropolitan-, micropolitan statistical areas, and metropolitan divisions

Met. type	Metro name	Resp.	Tract
Survey year 2000			
Metropoli	Providence-New Bedford-Fall River, RI-MA	4179	349
Met. Div.	Washington-Arlington-Alexandria, DC-VA-MD-WV	2919	802
Met. Div.	Boston-Quincy, MA	2246	387
Met. Div.	New York-White Plains-Wayne, NY-NJ	2049	2867
Met. Div.	Chicago-Joliet-Naperville, IL	1980	1712
Metropoli	Portland-Vancouver-Hillsboro, OR-WA	1766	426
Metropoli	Baltimore-Towson, MD	1644	622
Met. Div.	Cambridge-Newton-Framingham, MA	1508	297
Met. Div.	Seattle-Bellevue-Everett, WA	1413	506
Metropoli	Minneapolis-St. Paul-Bloomington, MN-WI	1408	742
Metropoli	Kansas City, MO-KS	1394	509
Metropoli	Hartford-West Hartford-East Hartford, CT	1338	281
Metropoli	New Orleans-Metairie-Kenner, LA	1259	386
Metropoli	Portland-South Portland-Biddeford, ME	1244	108
Metropoli	Sioux Falls, SD	1234	37
Metropoli	Salt Lake City, UT	1213	205
Metropoli	Albuquerque, NM	1169	190
Metropoli	Springfield, MA	1164	139
Metropoli	Boise City-Nampa, ID	1114	80
Met. Div.	Wilmington, DE-MD-NJ	1093	166
Metropoli	Oklahoma City, OK	1091	332
Metropoli	Burlington-South Burlington, VT	1027	43
Metropoli	Atlanta-Sandy Springs-Marietta, GA	1008	689
Metropoli	Omaha-Council Bluffs, NE-IA	989	237
Met. Div.	Edison-New Brunswick, NJ	967	494
Met. Div.	Philadelphia, PA	943	973
Metropoli	Denver-Aurora-Broomfield, CO	941	524
Met. Div.	Los Angeles-Long Beach-Glendale, CA	937	2041
Metropoli	Worcester, MA	923	163
Metropoli	Dover, DE	903	34
Met. Div.	Bethesda-Rockville-Frederick, MD	892	209

Metropoli	Bridgeport-Stamford-Norwalk, CT	891	209
Met. Div.	Newark-Union, NJ-PA	883	491
Metropoli	Houston-Sugar Land-Baytown, TX	870	887
Micropoli	Seaford, DE	862	36
Metropoli	New Haven-Milford, CT	858	184
Met. Div.	Peabody, MA	823	156
Metropoli	Wichita, KS	748	143
Metropoli	Tulsa, OK	743	264
Metropoli	St. Louis, MO-IL	724	552
Metropoli	Milwaukee-Waukesha-West Allis, WI	723	416
Metropoli	Las Vegas-Paradise, NV	718	342
Metropoli	Rapid City, SD	692	25
Metropoli	Phoenix-Mesa-Glendale, AZ	687	691
Met. Div.	Dallas-Plano-Irving, TX	686	687
Micropoli	Lebanon, NH-VT	685	45
Met. Div.	Miami-Miami Beach-Kendall, FL	674	345
Metropoli	Little Rock-North Little Rock-Conway, AR	674	147
Metropoli	Tucson, AZ	670	198
Metropoli	Tampa-St. Petersburg-Clearwater, FL	668	547
Metropoli	Baton Rouge, LA	666	143
Metropoli	Pittsburgh, PA	646	721
Metropoli	Reno-Sparks, NV	625	69
Met. Div.	Rockingham County-Strafford County, NH	600	79
Metropoli	Cincinnati-Middletown, OH-KY-IN	582	485
Metropoli	Akron, OH	578	166
Metropoli	Lincoln, NE	560	61
Metropoli	Des Moines-West Des Moines, IA	559	107
Metropoli	Memphis, TN-MS-AR	552	283
Metropoli	Manchester-Nashua, NH	526	81
Metropoli	Indianapolis-Carmel, IN	514	314
Metropoli	Nashville-Davidson--Murfreesboro--Franklin, TN	511	266
Metropoli	Huntington-Ashland, WV-KY-OH	489	75
Metropoli	Charlotte-Gastonia-Rock Hill, NC-SC	482	266
Metropoli	Jacksonville, FL	478	201
Met. Div.	Camden, NJ	478	314
Micropoli	Augusta-Waterville, ME	472	31
Metropoli	Idaho Falls, ID	462	26
Metropoli	Columbia, SC	462	143
Met. Div.	Nassau-Suffolk, NY	452	583
Metropoli	Louisville/Jefferson County, KY-IN	448	267
Metropoli	Orlando-Kissimmee-Sanford, FL	447	328

Metropoli	Charleston-North Charleston-Summerville, SC	442	117
Metropoli	Shreveport-Bossier City, LA	433	90
Met. Div.	Detroit-Livonia-Dearborn, MI	427	614
Metropoli	Birmingham-Hoover, AL	419	226
Met. Div.	Ft Lauderdale-Pompano Beach-Deerfield Beach, FL	419	279
Metropoli	Greenville-Mauldin-Easley, SC	417	126
Metropoli	Lewiston-Auburn, ME	414	28
Met. Div.	Warren-Troy-Farmington Hills, MI	408	667
Met. Div.	Tacoma, WA	402	157
Metropoli	Coeur d'Alene, ID	401	21
Metropoli	Dayton, OH	400	208
Metropoli	Youngstown-Warren-Boardman, OH-PA	388	167
Metropoli	Toledo, OH	380	174
Metropoli	Salem, OR	362	63
Metropoli	Riverside-San Bernardino-Ontario, CA	359	584
Metropoli	Fargo, ND-MN	357	40
Metropoli	Ogden-Clearfield, UT	351	93
Metropoli	Eugene-Springfield, OR	342	78
Met. Div.	Fort Worth-Arlington, TX	340	357
Metropoli	Las Cruces, NM	334	32
Met. Div.	Santa Ana-Anaheim-Irvine, CA	331	577
Metropoli	Colorado Springs, CO	330	117
Metropoli	San Diego-Carlsbad-San Marcos, CA	319	604
Metropoli	Fayetteville-Springdale-Rogers, AR-MO	318	68
Metropoli	Norwich-New London, CT	305	62
Metropoli	Hagerstown-Martinsburg, MD-WV	304	46
Metropoli	Charleston, WV	302	76
Met. Div.	West Palm Beach-Boca Raton-Boynton Beach, FL	298	264
Metropoli	Austin-Round Rock-San Marcos, TX	286	254
Metropoli	Topeka, KS	283	54
Metropoli	Bismarck, ND	278	21
Metropoli	Spokane, WA	276	106
Met. Div.	Oakland-Fremont-Hayward, CA	275	489
Metropoli	St. Joseph, MO-KS	273	35
Metropoli	San Antonio-New Braunfels, TX	272	338
Metropoli	Augusta-Richmond County, GA-SC	266	95
Metropoli	Provo-Orem, UT	265	84
Metropoli	Jackson, MS	256	115
Metropoli	Lafayette, LA	254	50
Metropoli	Santa Fe, NM	250	37
Metropoli	Knoxville, TN	238	127

Metropoli	Barnstable Town, MA	237	50
Metropoli	Raleigh-Cary, NC	233	128
Met. Div.	Gary, IN	232	147
Met. Div.	Lake County-Kenosha County, IL-WI	232	181
Metropoli	Davenport-Moline-Rock Island, IA-IL	222	103
Metropoli	Virginia Beach-Norfolk-Newport News, VA-NC	217	364
Metropoli	Buffalo-Niagara Falls, NY	216	297
Metropoli	Billings, MT	216	32
Micropoli	Concord, NH	215	31
Metropoli	Houma-Bayou Cane-Thibodaux, LA	206	42
Metropoli	Flagstaff, AZ	204	26
Metropoli	Madison, WI	203	109
Metropoli	Deltona-Daytona Beach-Ormond Beach, FL	203	78
Metropoli	Sioux City, IA-NE-SD	202	36
Metropoli	Lake Charles, LA	200	43
Metropoli	Prescott, AZ	199	25
Metropoli	Spartanburg, SC	196	51
Metropoli	Mobile, AL	195	114
Metropoli	Lexington-Fayette, KY	194	95
Metropoli	Missoula, MT	191	19
Metropoli	Savannah, GA	191	75
Metropoli	Monroe, LA	190	47
Metropoli	Clarksville, TN-KY	189	49
Metropoli	Medford, OR	187	36
Metropoli	Myrtle Beach-North Myrtle Beach-Conway, SC	183	43
Metropoli	Springfield, MO	182	85
Metropoli	San Jose-Sunnyvale-Santa Clara, CA	181	349
Metropoli	Lake Havasu City-Kingman, AZ	180	30
Metropoli	Cedar Rapids, IA	174	55
Metropoli	North Port-Bradenton-Sarasota, FL	173	143
Metropoli	Owensboro, KY	172	30
Met. Div.	San Francisco-San Mateo-Redwood City, CA	170	381
Metropoli	Fort Wayne, IN	170	104
Micropoli	Torrington, CT	170	51
Metropoli	Richmond, VA	169	276
Metropoli	Pittsfield, MA	168	41
Metropoli	Cleveland-Elyria-Mentor, OH	167	685
Micropoli	Willimantic, CT	165	25
Micropoli	Show Low, AZ	163	23
Metropoli	Lawrence, KS	162	22
Metropoli	Columbus, OH	162	385

Metropoli	Scranton--Wilkes-Barre, PA	158	168
Metropoli	Chattanooga, TN-GA	158	98
Metropoli	Rochester, NY	156	252
Metropoli	Evansville, IN-KY	155	85
Metropoli	Florence, SC	152	45
Metropoli	Elizabethtown, KY	150	22
Metropoli	Trenton-Ewing, NJ	150	73
Metropoli	Manhattan, KS	149	24
Metropoli	Farmington, NM	149	22
Metropoli	Bowling Green, KY	147	22
Metropoli	Greensboro-High Point, NC	146	142
Metropoli	Grand Rapids-Wyoming, MI	146	159
Metropoli	Sacramento--Arden-Arcade--Roseville, CA	144	403
Metropoli	Harrisburg-Carlisle, PA	143	111
Metropoli	Gulfport-Biloxi, MS	142	52
Metropoli	Palm Bay-Melbourne-Titusville, FL	140	92
Metropoli	Salisbury, MD	136	23
Metropoli	Yuma, AZ	136	32
Metropoli	Cape Coral-Fort Myers, FL	134	117
Metropoli	Alexandria, LA	134	39
Metropoli	Bremerton-Silverdale, WA	134	51
Metropoli	El Paso, TX	133	126
Metropoli	Anderson, SC	133	34
Metropoli	Lakeland-Winter Haven, FL	132	110
Metropoli	Allentown-Bethlehem-Easton, PA-NJ	129	163
Metropoli	Lancaster, PA	125	94
Metropoli	Parkersburg-Marietta-Vienna, WV-OH	125	46
Micropoli	Lexington Park, MD	123	15
Metropoli	Huntsville, AL	122	87
Metropoli	Cumberland, MD-WV	120	30
Metropoli	Bangor, ME	119	49
Metropoli	Reading, PA	119	82
Metropoli	Yakima, WA	118	34
Metropoli	Waterloo-Cedar Falls, IA	118	49
Micropoli	Sierra Vista-Douglas, AZ	118	21
Metropoli	Olympia, WA	117	34
Metropoli	St. George, UT	117	18
Metropoli	Green Bay, WI	117	64
Metropoli	Pensacola-Ferry Pass-Brent, FL	117	77
Micropoli	Roseburg, OR	116	22
Metropoli	Columbus, GA-AL	116	75

Metropoli	Bend, OR	116	21
Metropoli	Fort Smith, AR-OK	116	52
Micropoli	Hammond, LA	115	18
Metropoli	Poughkeepsie-Newburgh-Middletown, NY	115	132
Metropoli	Boulder, CO	114	68
Metropoli	Columbia, MO	114	32
Metropoli	Gainesville, FL	114	45
Metropoli	Winston-Salem, NC	113	97
Metropoli	South Bend-Mishawaka, IN-MI	113	84
Metropoli	Iowa City, IA	112	27
Metropoli	Tallahassee, FL	112	63
Metropoli	York-Hanover, PA	112	82
Metropoli	McAllen-Edinburg-Mission, TX	111	80
Metropoli	Logan, UT-ID	110	24
Metropoli	Duluth, MN-WI	109	90
Metropoli	Fort Collins-Loveland, CO	108	56
Metropoli	Flint, MI	108	131
Metropoli	Lawton, OK	107	29
Metropoli	Bellingham, WA	106	27
Metropoli	Montgomery, AL	106	82
Micropoli	Albany-Lebanon, OR	106	20
Micropoli	Hilton Head Island-Beaufort, SC	105	30
Metropoli	Fayetteville, NC	104	55
Metropoli	Lansing-East Lansing, MI	102	117
Metropoli	Pascagoula, MS	101	32
Metropoli	Fresno, CA	99	157
Metropoli	Pine Bluff, AR	98	33
Metropoli	Morgantown, WV	98	29
Metropoli	Erie, PA	96	72
Metropoli	Elkhart-Goshen, IN	96	28
Metropoli	Kingsport-Bristol-Bristol, TN-VA	93	65
Micropoli	Bluefield, WV-VA	92	27
Metropoli	Atlantic City-Hammonton, NJ	92	63
Metropoli	Kennewick-Pasco-Richland, WA	90	37
Metropoli	Ocala, FL	89	46
Metropoli	Ann Arbor, MI	88	97
Metropoli	Appleton, WI	87	42
Metropoli	Jonesboro, AR	86	20
Metropoli	Oxnard-Thousand Oaks-Ventura, CA	84	155
Metropoli	Syracuse, NY	83	189
Metropoli	Joplin, MO	83	32

Metropoli	Bakersfield-Delano, CA	83	137
Metropoli	Rockford, IL	82	82
Metropoli	Sumter, SC	80	22
Metropoli	Valdosta, GA	80	35
Metropoli	Durham-Chapel Hill, NC	80	89
Metropoli	Tuscaloosa, AL	80	54
Metropoli	Greeley, CO	79	36
Metropoli	Asheville, NC	77	78
Metropoli	St. Cloud, MN	76	34
Metropoli	Wausau, WI	75	27
Metropoli	Oshkosh-Neenah, WI	75	38
Metropoli	Stockton, CA	75	121
Metropoli	Lafayette, IN	72	46
Metropoli	Santa Rosa-Petaluma, CA	72	86
Metropoli	Brunswick, GA	71	18
Metropoli	Lubbock, TX	71	64
Metropoli	Naples-Marco Island, FL	69	52
Metropoli	Racine, WI	69	39
Metropoli	Peoria, IL	68	94
Metropoli	Ocean City, NJ	68	24
Metropoli	Jefferson City, MO	67	30
Metropoli	Beaumont-Port Arthur, TX	67	98
Metropoli	Kalamazoo-Portage, MI	67	76
Micropoli	Daphne-Fairhope-Foley, AL	67	23
Metropoli	Anderson, IN	67	36
Metropoli	Macon, GA	67	53
Metropoli	Warner Robins, GA	67	19
Metropoli	Janesville, WI	67	36
Metropoli	Holland-Grand Haven, MI	66	35
Metropoli	Bloomington, IN	66	42
Metropoli	Rochester, MN	65	44
Metropoli	Anniston-Oxford, AL	65	28
Metropoli	Greenville, NC	63	25
Metropoli	Michigan City-La Porte, IN	63	29
Metropoli	Johnson City, TN	63	40
Metropoli	Killeen-Temple-Fort Hood, TX	63	62
Metropoli	Bloomington-Normal, IL	63	41
Metropoli	Wilmington, NC	62	48
Metropoli	Corpus Christi, TX	62	83
Metropoli	Crestview-Fort Walton Beach-Destin, FL	61	33
Metropoli	Albany, GA	61	46

Metropoli	Vineland-Millville-Bridgeton, NJ	61	31
Metropoli	Auburn-Opelika, AL	60	21
Metropoli	Grand Junction, CO	60	28
Metropoli	Brownsville-Harlingen, TX	60	86
Metropoli	Panama City-Lynn Haven-Panama City Beach, FL	60	29
Metropoli	Pueblo, CO	60	50
Metropoli	Springfield, IL	59	55
Metropoli	Canton-Massillon, OH	59	87
Metropoli	Albany-Schenectady-Troy, NY	59	212
Metropoli	Terre Haute, IN	59	46
Metropoli	Gadsden, AL	58	28
Metropoli	Hickory-Lenoir-Morganton, NC	58	68
Micropoli	Pottsville, PA	58	39
Metropoli	Champaign-Urbana, IL	57	50
Metropoli	Waco, TX	57	51
Metropoli	Muncie, IN	57	31
Metropoli	Wheeling, WV-OH	57	49
Metropoli	Saginaw-Saginaw Township North, MI	56	56
Metropoli	Utica-Rome, NY	56	92
Metropoli	Mount Vernon-Anacortes, WA	55	27
Micropoli	Tupelo, MS	54	21
Micropoli	Thomasville-Lexington, NC	54	21
Metropoli	Modesto, CA	53	89
Metropoli	Hattiesburg, MS	53	25
Metropoli	Jacksonville, NC	52	26
Metropoli	Vallejo-Fairfield, CA	51	79
Metropoli	Sheboygan, WI	51	24
Metropoli	Johnstown, PA	51	48
Metropoli	Florence-Muscle Shoals, AL	50	31
Metropoli	Athens-Clarke County, GA	50	44
Metropoli	Gainesville, GA	50	22
Metropoli	Binghamton, NY	49	65
Metropoli	Fond du Lac, WI	49	20
Survey year 2010			
Metropoli	Providence-New Bedford-Fall River, RI-MA	8933	365
Met. Div.	Washington-Arlington-Alexandria, DC-VA-MD-WV	6215	1063
Met. Div.	New York-White Plains-Wayne, NY-NJ	5798	2871
Metropoli	Minneapolis-St. Paul-Bloomington, MN-WI	4713	769
Metropoli	Denver-Aurora-Broomfield, CO	4664	614
Met. Div.	Seattle-Bellevue-Everett, WA	4556	546
Metropoli	Salt Lake City, UT	4169	233

Met. Div.	Chicago-Joliet-Naperville, IL	3525	1856
Metropoli	Kansas City, MO-KS	3253	521
Metropoli	Baltimore-Towson, MD	3232	672
Met. Div.	Newark-Union, NJ-PA	3176	502
Met. Div.	Boston-Quincy, MA	3063	425
Metropoli	Portland-Vancouver-Hillsboro, OR-WA	2910	490
Met. Div.	Cambridge-Newton-Framingham, MA	2799	317
Metropoli	Houston-Sugar Land-Baytown, TX	2683	1070
Metropoli	Orlando-Kissimmee-Sanford, FL	2609	389
Metropoli	Portland-South Portland-Biddeford, ME	2559	114
Met. Div.	Los Angeles-Long Beach-Glendale, CA	2519	2320
Metropoli	Jacksonville, FL	2516	258
Metropoli	Pittsburgh, PA	2375	705
Metropoli	Oklahoma City, OK	2343	363
Metropoli	Omaha-Council Bluffs, NE-IA	2318	255
Met. Div.	Philadelphia, PA	2284	988
Metropoli	Atlanta-Sandy Springs-Marietta, GA	2244	941
Metropoli	Indianapolis-Carmel, IN	2210	360
Met. Div.	Edison-New Brunswick, NJ	2186	510
Met. Div.	Wilmington, DE-MD-NJ	2148	172
Metropoli	Albuquerque, NM	2139	202
Metropoli	Bridgeport-Stamford-Norwalk, CT	2096	210
Metropoli	Tulsa, OK	1990	272
Metropoli	Tallahassee, FL	1988	84
Metropoli	Tampa-St. Petersburg-Clearwater, FL	1979	734
Met. Div.	Peabody, MA	1972	162
Metropoli	Worcester, MA	1934	171
Metropoli	Springfield, MA	1921	156
Metropoli	Hartford-West Hartford-East Hartford, CT	1907	286
Metropoli	Burlington-South Burlington, VT	1867	47
Met. Div.	Detroit-Livonia-Dearborn, MI	1845	602
Metropoli	Wichita, KS	1814	149
Metropoli	Riverside-San Bernardino-Ontario, CA	1802	818
Met. Div.	Warren-Troy-Farmington Hills, MI	1753	686
Metropoli	St. Louis, MO-IL	1671	625
Metropoli	Charlotte-Gastonia-Rock Hill, NC-SC	1665	424
Met. Div.	Tacoma, WA	1653	172
Metropoli	Cincinnati-Middletown, OH-KY-IN	1642	499
Met. Div.	Camden, NJ	1641	304
Metropoli	San Diego-Carlsbad-San Marcos, CA	1630	623
Metropoli	Phoenix-Mesa-Glendale, AZ	1600	985

Metropoli	Ogden-Clearfield, UT	1597	106
Metropoli	New Haven-Milford, CT	1594	189
Met. Div.	Bethesda-Rockville-Frederick, MD	1589	276
Metropoli	Boise City-Nampa, ID	1547	95
Met. Div.	Rockingham County-Strafford County, NH	1536	89
Micropoli	Lebanon, NH-VT	1490	47
Metropoli	New Orleans-Metairie-Kenner, LA	1474	387
Metropoli	Milwaukee-Waukesha-West Allis, WI	1453	428
Met. Div.	Santa Ana-Anaheim-Irvine, CA	1401	581
Metropoli	Columbus, OH	1345	418
Met. Div.	Oakland-Fremont-Hayward, CA	1332	567
Metropoli	Manchester-Nashua, NH	1320	85
Metropoli	Sacramento--Arden-Arcade--Roseville, CA	1240	484
Metropoli	Reno-Sparks, NV	1238	108
Metropoli	Dover, DE	1222	32
Micropoli	Seaford, DE	1212	53
Metropoli	Las Vegas-Paradise, NV	1192	487
Metropoli	Spokane, WA	1180	105
Metropoli	Birmingham-Hoover, AL	1173	264
Metropoli	Baton Rouge, LA	1157	150
Met. Div.	Gary, IN	1130	159
Metropoli	Colorado Springs, CO	1129	135
Metropoli	Lincoln, NE	1120	76
Metropoli	Greensboro-High Point, NC	1119	167
Metropoli	North Port-Bradenton-Sarasota, FL	1116	172
Metropoli	Charleston-North Charleston-Summerville, SC	1113	154
Metropoli	Columbia, SC	1112	190
Metropoli	Memphis, TN-MS-AR	1108	307
Metropoli	San Antonio-New Braunfels, TX	1096	453
Metropoli	Provo-Orem, UT	1076	129
Metropoli	Allentown-Bethlehem-Easton, PA-NJ	1059	179
Metropoli	Cleveland-Elyria-Mentor, OH	1055	632
Met. Div.	Nassau-Suffolk, NY	1051	598
Metropoli	Youngstown-Warren-Boardman, OH-PA	1024	155
Metropoli	Durham-Chapel Hill, NC	1004	107
Metropoli	Raleigh-Cary, NC	999	223
Metropoli	Sioux City, IA-NE-SD	998	34
Metropoli	Pensacola-Ferry Pass-Brent, FL	981	96
Metropoli	Virginia Beach-Norfolk-Newport News, VA-NC	979	410
Metropoli	Des Moines-West Des Moines, IA	967	130
Metropoli	Austin-Round Rock-San Marcos, TX	954	349

Met. Div.	San Francisco-San Mateo-Redwood City, CA	925	405
Metropoli	Gainesville, FL	912	61
Metropoli	Bremerton-Silverdale, WA	895	54
Metropoli	San Jose-Sunnyvale-Santa Clara, CA	881	383
Metropoli	Atlantic City-Hammonton, NJ	875	69
Metropoli	Louisville/Jefferson County, KY-IN	872	316
Metropoli	Augusta-Richmond County, GA-SC	840	116
Metropoli	Deltona-Daytona Beach-Ormond Beach, FL	834	113
Metropoli	Rapid City, SD	831	28
Metropoli	Toledo, OH	828	177
Metropoli	Fargo, ND-MN	827	46
Metropoli	Dayton, OH	827	220
Metropoli	Nashville-Davidson--Murfreesboro--Franklin, TN	811	362
Metropoli	El Paso, TX	804	160
Metropoli	Akron, OH	784	170
Metropoli	Little Rock-North Little Rock-Conway, AR	780	163
Micropoli	Hilton Head Island-Beaufort, SC	780	44
Metropoli	Bismarck, ND	763	24
Metropoli	Greenville-Mauldin-Easley, SC	762	156
Metropoli	Sioux Falls, SD	759	57
Metropoli	Jackson, MS	750	123
Metropoli	Charleston, WV	737	79
Metropoli	Olympia, WA	735	49
Metropoli	Lubbock, TX	734	70
Metropoli	Topeka, KS	733	57
Metropoli	Richmond, VA	729	301
Metropoli	Yakima, WA	727	45
Metropoli	Canton-Massillon, OH	722	93
Met. Div.	Fort Worth-Arlington, TX	717	414
Metropoli	Fort Wayne, IN	703	110
Met. Div.	Dallas-Plano-Irving, TX	699	897
Metropoli	Fayetteville-Springdale-Rogers, AR-MO	678	89
Metropoli	Shreveport-Bossier City, LA	675	92
Metropoli	Tucson, AZ	670	233
Metropoli	Farmington, NM	665	33
Metropoli	Bangor, ME	663	46
Metropoli	Mobile, AL	658	113
Metropoli	Idaho Falls, ID	649	25
Metropoli	Kingsport-Bristol-Bristol, TN-VA	639	75
Metropoli	Huntington-Ashland, WV-KY-OH	638	78
Metropoli	Kennewick-Pasco-Richland, WA	637	49

Metropoli	Hagerstown-Martinsburg, MD-WV	627	49
Micropoli	Augusta-Waterville, ME	625	31
Micropoli	Concord, NH	613	36
Metropoli	Grand Rapids-Wyoming, MI	610	162
Metropoli	Buffalo-Niagara Falls, NY	601	293
Metropoli	Santa Fe, NM	598	50
Metropoli	Hickory-Lenoir-Morganton, NC	585	73
Metropoli	McAllen-Edinburg-Mission, TX	578	112
Metropoli	Ocala, FL	572	61
Metropoli	Coeur d'Alene, ID	563	25
Metropoli	Cedar Rapids, IA	555	57
Metropoli	Rochester, NY	552	261
Metropoli	Fort Collins-Loveland, CO	547	73
Metropoli	Myrtle Beach-North Myrtle Beach-Conway, SC	540	71
Met. Div.	West Palm Beach-Boca Raton-Boynton Beach, FL	538	331
Metropoli	Scranton--Wilkes-Barre, PA	537	170
Metropoli	Panama City-Lynn Haven-Panama City Beach, FL	526	43
Metropoli	Evansville, IN-KY	524	88
Metropoli	Knoxville, TN	523	170
Metropoli	Asheville, NC	523	103
Metropoli	Chattanooga, TN-GA	521	117
Metropoli	Palm Bay-Melbourne-Titusville, FL	514	111
Met. Div.	Ft Lauderdale-Pompano Beach-Deerfield Beach, FL	511	361
Metropoli	Cape Coral-Fort Myers, FL	511	165
Metropoli	Naples-Marco Island, FL	509	73
Metropoli	Lakeland-Winter Haven, FL	505	154
Metropoli	Las Cruces, NM	496	41
Metropoli	Ocean City, NJ	490	32
Metropoli	Greeley, CO	489	76
Metropoli	Lewiston-Auburn, ME	488	28
Metropoli	South Bend-Mishawaka, IN-MI	486	86
Metropoli	Trenton-Ewing, NJ	485	76
Metropoli	Tuscaloosa, AL	478	56
Met. Div.	Miami-Miami Beach-Kendall, FL	478	508
Metropoli	Billings, MT	475	37
Metropoli	Fresno, CA	471	198
Metropoli	Davenport-Moline-Rock Island, IA-IL	469	104
Metropoli	Albany-Schenectady-Troy, NY	467	217
Metropoli	Missoula, MT	462	20
Metropoli	Eugene-Springfield, OR	458	86
Metropoli	Boulder, CO	433	68

Metropoli	Wilmington, NC	430	90
Metropoli	Harrisburg-Carlisle, PA	429	122
Metropoli	Crestview-Fort Walton Beach-Destin, FL	428	41
Metropoli	Huntsville, AL	426	89
Metropoli	Santa Rosa-Petaluma, CA	422	99
Metropoli	Salem, OR	420	70
Metropoli	Bellingham, WA	418	34
Metropoli	Lake Havasu City-Kingman, AZ	417	43
Metropoli	Fayetteville, NC	417	72
Metropoli	Flint, MI	415	130
Metropoli	Bakersfield-Delano, CA	408	148
Metropoli	Pueblo, CO	406	54
Metropoli	Flagstaff, AZ	403	28
Metropoli	Gulfport-Biloxi, MS	400	54
Metropoli	Duluth, MN-WI	397	85
Metropoli	Grand Junction, CO	393	29
Metropoli	Oxnard-Thousand Oaks-Ventura, CA	393	172
Metropoli	Salisbury, MD	392	26
Metropoli	Norwich-New London, CT	390	65
Micropoli	Tupelo, MS	383	29
Metropoli	Barnstable Town, MA	379	56
Metropoli	Prescott, AZ	379	42
Metropoli	Brownsville-Harlingen, TX	375	84
Metropoli	Lafayette, LA	371	54
Metropoli	Waterloo-Cedar Falls, IA	369	50
Metropoli	Erie, PA	367	70
Metropoli	Lansing-East Lansing, MI	362	125
Metropoli	Yuma, AZ	362	52
Metropoli	Spartanburg, SC	358	69
Metropoli	Winston-Salem, NC	354	116
Micropoli	Thomasville-Lexington, NC	351	34
Metropoli	Fort Smith, AR-OK	349	61
Micropoli	Daphne-Fairhope-Foley, AL	347	31
Metropoli	Logan, UT-ID	342	28
Metropoli	Houma-Bayou Cane-Thibodaux, LA	341	44
Metropoli	St. George, UT	340	21
Metropoli	Greenville, NC	336	36
Metropoli	Florence, SC	332	49
Metropoli	Vineland-Millville-Bridgeton, NJ	332	31
Metropoli	Florence-Muscle Shoals, AL	330	36
Metropoli	Montgomery, AL	329	96

Metropoli	Stockton, CA	324	139
Metropoli	York-Hanover, PA	323	90
Metropoli	Hattiesburg, MS	323	28
Metropoli	Syracuse, NY	322	176
Metropoli	Cumberland, MD-WV	320	30
Metropoli	Lexington-Fayette, KY	318	129
Metropoli	Mount Vernon-Anacortes, WA	315	29
Metropoli	Iowa City, IA	302	29
Metropoli	Anniston-Oxford, AL	296	30
Metropoli	Lake Charles, LA	292	44
Metropoli	Jacksonville, NC	288	30
Metropoli	Alexandria, LA	283	38
Micropoli	Lexington Park, MD	276	17
Metropoli	Monroe, LA	275	45
Metropoli	Pascagoula, MS	274	33
Metropoli	St. Joseph, MO-KS	272	34
Metropoli	Poughkeepsie-Newburgh-Middletown, NY	272	156
Metropoli	Lawrence, KS	269	22
Metropoli	Madison, WI	267	123
Metropoli	Manhattan, KS	265	25
Metropoli	Wheeling, WV-OH	264	47
Met. Div.	Lake County-Kenosha County, IL-WI	262	187
Metropoli	Anderson, SC	261	39
Metropoli	Parkersburg-Marietta-Vienna, WV-OH	259	46
Metropoli	Modesto, CA	259	94
Metropoli	Pittsfield, MA	254	39
Micropoli	Torrington, CT	252	51
Metropoli	Morgantown, WV	252	32
Metropoli	Springfield, MO	251	91
Metropoli	Clarksville, TN-KY	251	62
Metropoli	Kalamazoo-Portage, MI	250	72
Metropoli	Sumter, SC	250	23
Metropoli	Medford, OR	249	41
Metropoli	Columbus, GA-AL	248	78
Metropoli	Johnson City, TN	248	43
Metropoli	Terre Haute, IN	238	44
Metropoli	Ann Arbor, MI	233	100
Metropoli	Elkhart-Goshen, IN	231	36
Metropoli	Bloomington, IN	230	45
Metropoli	Saginaw-Saginaw Township North, MI	228	56
Metropoli	Lancaster, PA	222	98

Micropoli	Sierra Vista-Douglas, AZ	217	32
Metropoli	Owensboro, KY	217	29
Metropoli	St. Cloud, MN	216	38
Metropoli	Green Bay, WI	214	67
Micropoli	Willimantic, CT	208	25
Metropoli	Lawton, OK	206	31
Metropoli	Holland-Grand Haven, MI	204	53
Micropoli	Bluefield, WV-VA	196	27
Metropoli	Anderson, IN	195	37
Micropoli	Hammond, LA	194	20
Metropoli	Rochester, MN	194	44
Metropoli	Lafayette, IN	190	46
Metropoli	Bend, OR	189	24
Metropoli	Appleton, WI	189	51
Metropoli	Elizabethtown, KY	188	26
Metropoli	Savannah, GA	185	86
Metropoli	Pine Bluff, AR	183	30
Micropoli	Show Low, AZ	178	31
Metropoli	Gadsden, AL	167	30
Metropoli	Vallejo-Fairfield, CA	167	94
Metropoli	Binghamton, NY	162	65
Metropoli	Bowling Green, KY	158	28
Metropoli	Utica-Rome, NY	158	87
Metropoli	Reading, PA	157	90
Micropoli	Albany-Lebanon, OR	155	21
Metropoli	Michigan City-La Porte, IN	153	28
Micropoli	Roseburg, OR	152	22
Metropoli	Muncie, IN	148	30
Metropoli	Valdosta, GA	140	34
Metropoli	Oshkosh-Neenah, WI	139	41
Metropoli	Johnstown, PA	134	42
Metropoli	Peoria, IL	131	94
Metropoli	Rockford, IL	125	83
Metropoli	Jefferson City, MO	124	31
Metropoli	Janesville, WI	122	38
Metropoli	Racine, WI	120	44
Metropoli	Killeen-Temple-Fort Hood, TX	118	86
Metropoli	Beaumont-Port Arthur, TX	113	101
Metropoli	Macon, GA	113	60
Metropoli	Athens-Clarke County, GA	113	46
Metropoli	Albany, GA	111	43

Metropoli	Columbia, MO	108	32
Metropoli	Jonesboro, AR	98	24
Metropoli	Wausau, WI	97	27
Metropoli	Auburn-Opelika, AL	94	27
Metropoli	Joplin, MO	91	34
Metropoli	Sheboygan, WI	90	26
Micropoli	Pottsville, PA	81	40
Metropoli	Fond du Lac, WI	77	20
Metropoli	Corpus Christi, TX	75	101
Metropoli	Champaign-Urbana, IL	72	52
Metropoli	Warner Robins, GA	72	23
Metropoli	Springfield, IL	68	56
Metropoli	Gainesville, GA	62	36
Metropoli	Brunswick, GA	59	21
Metropoli	Waco, TX	57	50
Metropoli	Bloomington-Normal, IL	39	41

Appendix C

Regression model results: Health outcomes on metropolitan-level poverty, concentration of poverty, and Moran's I (poverty rate) – separately by level-2 factor

	GenHlth(OLS)	GenHlth(ologit)	Poor/Fair Hlth	Asthma	Diabetes	Physhlth	Menthlth
Constant	0.973**		-6.296**	-2.554**	-10.29**	-0.936**	0.05
	(32.50)		(-83.68)	(-37.52)	(-104.93)	(-18.10)	(0.90)
Metro Poverty Rate	0.447**	0.800**	0.717**	1.222**	1.191**	0.658**	0.711**
	(3.59)	(3.47)	(2.73)	(3.41)	(3.18)	(2.99)	(2.91)
Poverty Concentration	**0.251****	**0.523****	**0.491***	**0.754****	**0.568***	**0.17**	**0.419***
	(3.34)	**(3.71)**	**(2.52)**	**(3.06)**	**(2.43)**	**(1.16)**	**(2.57)**
Non-Hispanic Black	0.0703**	0.161**	0.142**	-0.228**	0.432**	-0.170**	-0.311**
	(3.24)	(3.99)	(3.13)	(-3.76)	(6.59)	(-4.66)	(-7.56)
Non-Hispanic Asian	0.0674**	0.153**	(0.07)	-0.630**	0.257**	-0.365**	-0.488**
	(4.57)	(5.33)	(-1.32)	(-10.63)	(4.16)	(-8.73)	(-13.55)
Non-Hispanic Native	0.202**	0.376**	0.435**	0.174*	0.348**	0.174**	0.141*
	(7.46)	(7.46)	(6.51)	(2.26)	(4.66)	(3.11)	(2.27)
Hispanic	0.181**	0.367**	0.467**	-0.399**	0.308**	-0.121**	-0.248**
	(6.58)	(7.13)	(8.02)	(-5.25)	(5.04)	(-3.24)	(-6.26)
Income less than $25,000	0.923**	1.675**	2.115**	0.368**	0.935**	1.162**	1.020**
	(92.95)	(95.53)	(70.07)	(13.07)	(33.28)	(67.16)	(54.14)
Income $25,000-$49,999	0.434**	0.810**	1.107**	0.0599**	0.532**	0.543**	0.502**
	(57.40)	(58.77)	(39.36)	(2.79)	(20.65)	(36.63)	(29.46)
Income $50,000-$74,999	0.226**	0.436**	0.557**	0.03	0.312**	0.294**	0.287**
	(31.59)	(32.16)	(19.53)	(1.44)	(10.74)	(18.02)	(14.92)
Female	-0.0711**	-0.139**	-0.128**	0.377**	-0.316**	0.122**	0.325**
	(-16.21)	(-17.41)	(-10.36)	(30.83)	(-20.92)	(13.74)	(27.14)
Married	0.0125**	0.0302**	0.02	-0.140**	0.01	-0.0207*	-0.220**
	(3.00)	(3.97)	(1.33)	(-10.50)	(0.62)	(-1.97)	(-19.68)
Age in years	0.0281**	0.0492**	0.0977**	0.0124**	0.226**	0.0435**	0.0374**
	(27.41)	(26.92)	(41.19)	(5.68)	(68.30)	(24.47)	(18.35)
Age (squared)	-0.000150**	-0.000259**	-0.000643**	-0.000184**	-0.00155**	-0.000265**	-0.000508**
	(-16.21)	(-15.52)	(-31.04)	(-8.94)	(-55.21)	(-16.52)	(-25.18)
Inc. < $25,000 # Pov. Conc.	-0.148*	-0.352**	-0.343*	-0.390+	-0.297	-0.226+	-0.226
	(-2.16)	(-2.73)	(-2.04)	(-1.87)	(-1.57)	(-1.94)	(-1.53)
Inc. $25,000-$49,999 # Pov. Conc.	(0.02)	-0.101	-0.154	-0.207	-0.186	-0.0803	-0.19
	(-0.38)	(-0.90)	(-0.91)	(-1.15)	(-1.07)	(-0.65)	(-1.15)
Inc. $50,000-$74,999 # Pov. Conc.	(0.09)	-0.197	-0.287	-0.153	-0.0261	-0.109	-0.309+
	(-1.45)	(-1.62)	(-1.45)	(-0.86)	(-0.14)	(-0.72)	(-1.67)
N	317,011	317,011	317,011	316,106	317,661	312,853	313,733

t statistics in parentheses; models use robust (due to heteroskedasticity) and metro area clustered standard errors

ologit, logit, and negative binomial models include 310 metro dummies (coefficients not displayed)

race/ethnicity reference category: non-hispanic white; income reference category: $75,000 and over

+ p < .10, * p < .05, ** p < .01

	GenHlth(OLS)	GenHlth(ologit)	Poor/Fair Hlth	Asthma	Diabetes	Physhlth	Menthlth
Constant	1.011**		-6.040**	-2.150**	-9.917**	-0.808**	0.291**
	(30.21)		(-67.14)	(-21.07)	(-84.42)	(-12.61)	(3.82)
Metro Poverty Rate	0.536**	0.958**	0.814**	1.456**	1.370**	0.611**	0.817**
	(4.69)	(4.54)	(3.51)	(4.19)	(4.14)	(3.12)	(3.59)
Moran's I (Poverty Rate)	**-0.0813***	**-0.142+**	**-0.449****	**-0.643****	**-0.732****	**-0.188***	**-0.423****
	(-2.02)	**(-1.77)**	**(-3.81)**	**(-5.20)**	**(-5.90)**	**(-2.33)**	**(-4.80)**
Non-Hispanic Black	0.0609**	0.145**	0.116**	-0.275**	0.396**	-0.181**	-0.333**
	(2.72)	(3.43)	(2.65)	(-4.13)	(5.37)	(-4.58)	(-7.10)
Non-Hispanic Asian	0.0470**	0.117**	-0.130*	-0.751**	0.159*	-0.401**	-0.551**
	(2.82)	(3.61)	(-2.26)	(-11.49)	(2.43)	(-9.01)	(-13.19)
Non-Hispanic Native	0.172**	0.320**	0.376**	0.06	0.266**	0.147**	0.09
	(6.43)	(6.38)	(5.63)	(0.79)	(3.52)	(2.62)	(1.39)
Hispanic	0.139**	0.289**	0.381**	-0.558**	0.191**	-0.162**	-0.326**
	(5.08)	(5.63)	(6.63)	(-7.24)	(2.64)	(-4.08)	(-7.04)
Income less than $25,000	0.936**	1.702**	2.033**	0.258**	0.774**	1.125**	0.928**
	(69.15)	(67.98)	(47.96)	(6.11)	(21.00)	(44.35)	(29.59)
Income $25,000-$49,999	0.447**	0.831**	1.032**	(0.00)	0.389**	0.527**	0.419**
	(35.70)	(35.49)	(23.11)	(-0.03)	(9.29)	(19.38)	(13.49)
Income $50,000-$74,999	0.211**	0.402**	0.457**	0.03	0.214**	0.306**	0.202**
	(16.17)	(16.08)	(9.53)	(0.69)	(4.81)	(10.08)	(5.67)
Female	-0.0709**	-0.139**	-0.128**	0.377**	-0.315**	0.122**	0.325**
	(-16.20)	(-17.40)	(-10.34)	(30.79)	(-20.91)	(13.73)	(27.22)
Married	0.0118**	0.0285**	0.02	-0.139**	0.01	-0.0205+	-0.218**
	(2.82)	(3.75)	(1.33)	(-10.45)	(0.72)	(-1.94)	(-19.68)
Age in years	0.0281**	0.0491**	0.0977**	0.0125**	0.226**	0.0435**	0.0374**
	(27.36)	(26.87)	(41.13)	(5.77)	(68.27)	(24.59)	(18.40)
Age (squared)	-0.000150**	-0.000258**	-0.000643**	-0.000186**	-0.00155**	-0.000265**	-0.000508**
	(-16.10)	(-15.39)	(-30.96)	(-9.04)	(-55.07)	(-16.58)	(-25.29)
Inc. < $25,000 # Moran's I	-0.0836*	-0.190**	0.17	0.259*	0.441**	0.06	0.238**
	(-2.22)	(-2.71)	(1.62)	(2.39)	(4.53)	(0.97)	(3.28)
Inc. $25,000-$49,999 # Moran's I	(0.04)	(0.08)	0.206+	0.14	0.408**	0.03	0.214**
	(-1.25)	(-1.26)	(1.73)	(1.49)	(3.96)	(0.46)	(2.73)
Inc. $50,000-$74,999 # Moran's I	0.03	0.06	0.249+	(0.02)	0.304*	(0.06)	0.189*
	(0.92)	(1.04)	(1.91)	(-0.16)	(2.43)	(-0.73)	(2.05)
N	317,011	317,011	317,011	316,106	317,661	312,853	313,733
t statistics in parentheses; models use robust (due to heteroskedasticity) and metro area clustered standard errors							
ologit, logit, and negative binomial models include 310 metro dummies (coefficients not displayed)							
race/ethnicity reference category: non-hispanic white; income reference category: $75,000 and over							
+ p < .10, * p < .05, ** p < .01							

Appendix D

Regression model results: Health outcomes on segregation by race and ethnicity, and Moran's I (% race/ethnicity) – separately by level-2 factor

	GenHlth(OLS)	GenHlth(ologit)	Poor/Fair Hlth	Asthma	Diabetes	Physhlth	Menthlth
Constant	1.183**		-5.805**	-2.147**	-9.816**	-0.759**	0.173+
	(27.34)		(-47.36)	(-13.60)	(-67.19)	(-8.19)	(1.64)
Segregation (Dissim.)	**-0.362****	**-0.692****	**-0.718****	**(0.39)**	**-0.575***	**(0.19)**	**(0.04)**
	(-4.25)	**(-4.27)**	**(-3.20)**	**(-1.38)**	**(-2.42)**	**(-1.23)**	**(-0.22)**
Non-Hispanic Black	0.115**	0.257**	0.11	0.00	0.688**	-0.163+	-0.188*
	(3.27)	(4.08)	(1.26)	(0.03)	(6.77)	(-1.95)	(-2.02)
Non-Hispanic Asian	0.10	0.19	(0.41)	(0.24)	0.24	(0.35)	-0.429*
	(1.09)	(1.14)	(-1.27)	(-0.55)	(0.59)	(-1.25)	(-2.26)
Non-Hispanic Native	0.268**	0.522**	0.37	0.39	0.657*	0.23	0.23
	(2.90)	(3.18)	(1.63)	(1.56)	(2.45)	(1.03)	(0.82)
Hispanic	(0.02)	(0.00)	0.14	-1.365**	(0.11)	-0.370**	-0.288*
	(-0.36)	(-0.02)	(1.03)	(-8.34)	(-0.63)	(-3.82)	(-2.52)
Income less than $25,000	0.909**	1.642**	2.083**	0.330**	0.904**	1.142**	1.002**
	(111.72)	(116.54)	(85.01)	(13.44)	(42.80)	(80.63)	(58.38)
Income $25,000-$49,999	0.431**	0.800**	1.092**	0.0376*	0.512**	0.535**	0.486**
	(69.47)	(71.05)	(50.14)	(2.05)	(25.53)	(44.54)	(32.87)
Income $50,000-$74,999	0.218**	0.419**	0.533**	0.02	0.307**	0.284**	0.263**
	(38.29)	(39.01)	(24.60)	(0.92)	(13.11)	(21.36)	(17.39)
Female	-0.0711**	-0.139**	-0.129**	0.377**	-0.316**	0.122**	0.325**
	(-16.37)	(-17.57)	(-10.45)	(30.83)	(-20.86)	(13.73)	(27.13)
Married	0.0120**	0.0292**	0.01	-0.142**	0.01	-0.0218*	-0.220**
	(2.90)	(3.86)	(1.24)	(-10.57)	(0.50)	(-2.08)	(-19.74)
Age in years	0.0282**	0.0494**	0.0978**	0.0125**	0.226**	0.0437**	0.0379**
	(27.66)	(27.21)	(41.72)	(5.86)	(68.65)	(24.58)	(18.61)
Age (squared)	-0.000150**	-0.000260**	-0.000643**	-0.000183**	-0.00155**	-0.000265**	-0.000510**
	(-16.25)	(-15.57)	(-31.24)	(-9.03)	(-55.22)	(-16.57)	(-25.40)
Non-Hisp. Black # Seg.	0.167**	0.285*	0.465**	0.17	0.13	0.22	0.06
	(2.73)	(2.55)	(3.11)	(0.81)	(0.75)	(1.58)	(0.37)
Non-Hisp. Asian # Seg.	0.00	0.03	0.86	(0.67)	0.22	0.05	(0.03)
	(0.02)	(0.08)	(1.20)	(-0.70)	(0.25)	(0.08)	(-0.07)
Non-Hisp. Native # Seg.	0.03	(0.01)	0.45	(0.03)	(0.24)	0.10	0.07
	(0.13)	(-0.03)	(0.87)	(-0.06)	(-0.40)	(0.20)	(0.11)
Hispanic # Seg.	0.558**	1.024**	0.926**	2.076**	1.180**	0.634**	0.28
	(4.93)	(4.82)	(3.54)	(6.94)	(3.91)	(3.78)	(1.26)
N	317,018	317,018	317,018	316,113	317,668	312,860	313,740

t statistics in parentheses; models use robust (due to heteroskedasticity) and metro area clustered standard errors
ologit, logit, and negative binomial models include 310 metro dummies (coefficients not displayed)
race/ethnicity reference category: non-hispanic white; income reference category: $75,000 and over
+ p < .10, * p < .05, ** p < .01

	GenHlth(OLS)	GenHlth(ologit)	Poor/Fair Hlth	Asthma	Diabetes	Physhlth	Menthlth
Constant	0.940**		-6.233**	-2.946**	-10.76**	-0.995**	-0.252**
	(22.97)		(-61.35)	(-24.16)	(-84.37)	(-11.66)	(-2.95)
Moran's I (% Race/Ethn.)	**0.130***	**0.240***	**0.08**	**0.816****	**0.920****	**0.189***	**0.581****
	(2.34)	**(2.30)**	**(0.62)**	**(5.27)**	**(6.40)**	**(1.96)**	**(5.87)**
Non-Hispanic Black	0.126**	0.265**	0.159*	0.11	0.795**	(0.09)	-0.175*
	(4.35)	(5.14)	(2.13)	(1.39)	(10.09)	(-1.54)	(-2.30)
Non-Hispanic Asian	0.03	0.08	-0.393*	(0.14)	0.36	-0.295*	(0.07)
	(0.56)	(0.83)	(-2.20)	(-0.76)	(1.60)	(-2.26)	(-0.62)
Non-Hispanic Native	0.321**	0.602**	0.548**	0.861**	0.736**	0.399**	0.507**
	(5.44)	(5.58)	(4.34)	(5.80)	(3.98)	(3.70)	(4.43)
Hispanic	0.305**	0.592**	0.608**	0.328**	0.969**	0.112+	0.213**
	(9.37)	(9.65)	(7.91)	(2.73)	(9.00)	(1.73)	(2.96)
Income less than $25,000	0.910**	1.644**	2.084**	0.340**	0.912**	1.144**	1.006**
	(110.96)	(115.72)	(84.80)	(13.80)	(42.83)	(81.36)	(58.91)
Income $25,000-$49,999	0.431**	0.801**	1.092**	0.0454*	0.518**	0.537**	0.490**
	(69.13)	(70.50)	(50.02)	(2.46)	(25.90)	(44.59)	(33.23)
Income $50,000-$74,999	0.218**	0.420**	0.533**	0.02	0.311**	0.285**	0.265**
	(38.55)	(39.32)	(24.51)	(1.16)	(13.31)	(21.57)	(17.63)
Female	-0.0710**	-0.139**	-0.128**	0.377**	-0.316**	0.122**	0.325**
	(-16.31)	(-17.51)	(-10.37)	(30.88)	(-20.88)	(13.74)	(27.10)
Married	0.0120**	0.0292**	0.01	-0.141**	0.01	-0.0216*	-0.220**
	(2.88)	(3.83)	(1.22)	(-10.44)	(0.59)	(-2.06)	(-19.84)
Age in years	0.0282**	0.0494**	0.0979**	0.0126**	0.226**	0.0438**	0.0374**
	(27.43)	(26.96)	(41.42)	(5.82)	(67.83)	(24.70)	(18.43)
Age (squared)	-0.000151**	-0.000260**	-0.000644**	-0.000186**	-0.00155**	-0.000266**	-0.000508**
	(-16.20)	(-15.52)	(-31.14)	(-9.06)	(-54.84)	(-16.67)	(-25.33)
Non-Hisp. Black # Moran's I	0.07	0.11	0.207*	(0.09)	(0.15)	0.06	0.03
	(1.59)	(1.53)	(1.99)	(-0.74)	(-1.32)	(0.74)	(0.27)
Non-Hisp. Asian # Moran's I	0.168*	0.313*	0.692*	(0.51)	0.18	(0.01)	-0.510**
	(2.30)	(2.20)	(2.25)	(-1.58)	(0.50)	(-0.04)	(-2.69)
Non-Hisp. Native # Moran's I	(0.06)	(0.12)	0.03	-0.768**	(0.18)	(0.21)	-0.366+
	(-0.52)	(-0.62)	(0.13)	(-3.15)	(-0.57)	(-1.07)	(-1.67)
Hispanic # Moran's I	0.07	0.14	0.10	-0.566+	(0.14)	(0.19)	-0.306*
	(0.86)	(0.84)	(0.57)	(-1.77)	(-0.64)	(-1.41)	(-2.20)
N	317,018	317,018	317,018	316,113	317,668	312,860	313,740

t statistics in parentheses; models use robust (due to heteroskedasticity) and metro area clustered standard errors

ologit, logit, and negative binomial models include 310 metro dummies (coefficients not displayed)

race/ethnicity reference category: non-hispanic white; income reference category: $75,000 and over

+ p < .10, * p < .05, ** p < .01

Appendix E

Rationale for selecting BRFSS Annual Survey Years 2000 and 2010 for Analysis

Beginning with the 2011 BRFSS data, a new sample weighting methodology known as iterative proportional fitting, or raking, replaced post-stratification, the weighting methodology used prior to the change, in order to adjust and account for the changing structure of the sample and its target population. A move toward surveying of cellular-telephone-only households in addition to landlines in the BRFSS precipitated a change in the sample weighing methodology. The change renders any post-2010 data difficult to compare with corresponding variables in previous years.

There were only a handful of states in the inaugural 1984 BRFSS, with participation becoming universal by the mid 1990's (Figure 0-1). Several key variables are not included in earlier survey years (1990's), or measured in ways as to make them incomparable/incompatible with more recent iterations of the survey (2000's), (i.e., asthma, extra-employment exercise/physical activity, smoking, and drinking behaviors).

The Selected Metropolitan Micropolitan Area Risk Trends (SMART BRFSS) which provides prevalence rates for counties and MMSAs sets 500 as the minimum representative sample size for MMSAs and 250 for individual MMSA component counties (Figure 0-2).

Figure 0-1: BRFSS annual survey historic variable counts and response rates (1984-2014)

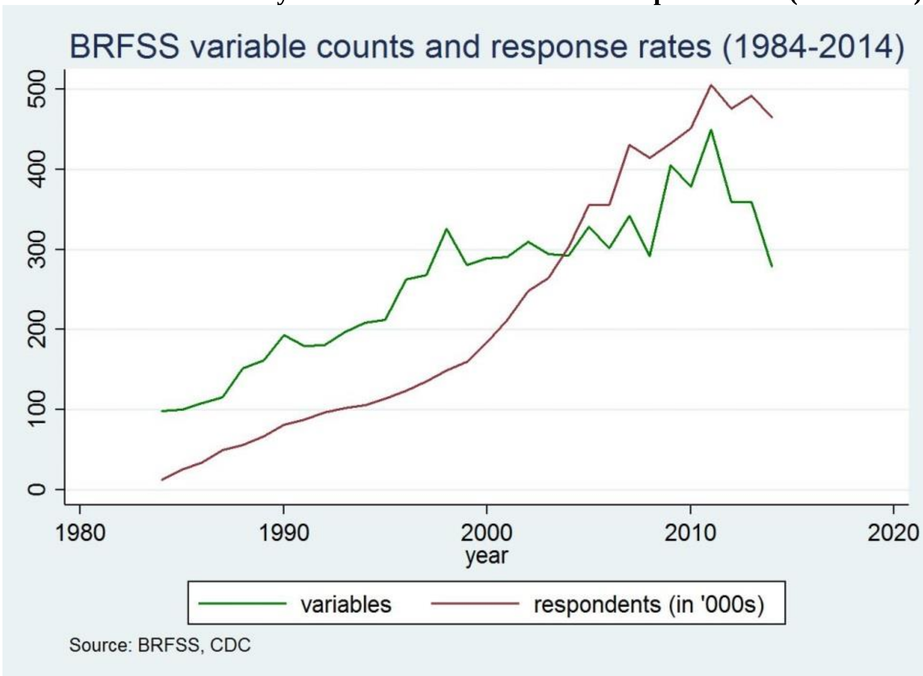
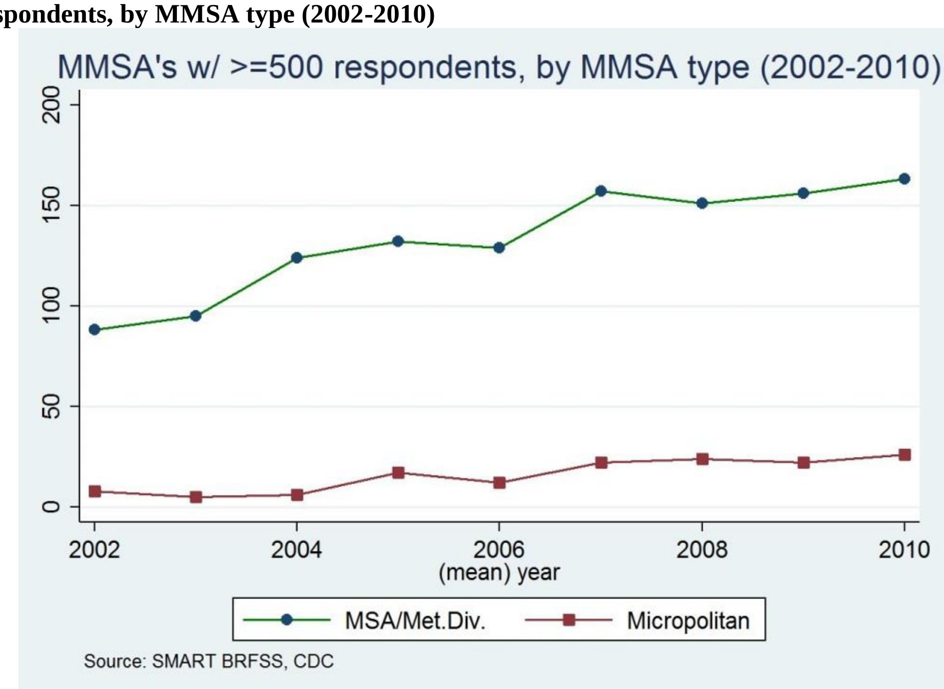


Figure 0-2: Metropolitan and Micropolitan Statistical Areas (MMSAs) with greater than or equal to 500 respondents, by MMSA type (2002-2010)



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M.A. in Public Affairs – Rutgers, The State University of New Jersey – Camden, NJ (October 2015)

M.A. in Geography, West Chester University of Pa, West Chester, PA (2011)
Graduate Certificates: Urban & Regional Planning and Geographic Information Systems (2011)

M.S. in Community and Regional Planning
Temple University, Ambler, PA (2008)

B.B.A., with a concentration in Computer Information Systems (CIS)
Lincoln Memorial University (LMU), Harrogate, TN. (2005, magna cum laude)

Awards & Honors

2018 Graduate School Summer Research Support Award, Office of the Dean, Graduate School - Camden
Dean's Graduate Conference Travel Grants, Office of the Dean, Faculty of Arts and Sciences, Camden
ARNOVA 2015 Diversity Fellow, Assoc. for Research on Nonprofit Organizations and Voluntary Action
2016 APPAM Equity and Inclusion Fellowship, Association for Public Policy Analysis and Management
Recognition, Graduate Student Advisory Council participant, Annual Meeting of the Graduate Faculty, Rutgers University – Camden, 2015-2016, 2016-2017

Certificate of Achievement for outstanding performance in CIS, April 2005 (LMU)
Dean's List, 2001-2005 (LMU)
Trustee's full tuition Academic Scholarship recipient, 2001-2005 (LMU)
"Who's Who Among Students in American Universities and Colleges" distinction, 2005 (LMU)

Technical Skills

Intermediate knowledge of Microsoft Office, Front Page, Visual Studio; Adobe Acrobat, Photoshop; WordPress
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SketchUp, Google (Earth, Fusion Tables, Maps API); ArcInfo ext.: HAZUS-MH MR3, 3D Analyst, Network Analyst, and Spatial Analyst; ArcGIS Online; Geodatabases; ArcGIS for Server 10.1; QGIS; Linux Shell
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Proficient in English and Macedonian; Basic knowledge of Spanish, Serbian, Croatian

Research Interests

Public health policy, city and urban planning, community and economic development, environmental sustainability, environmental justice, Geographic Information Systems

Training

Inter-university Consortium for Political and Social Research, Summer Program in Quantitative Methods of Social Research, Institute for Social Research, The University of Michigan, Ann Arbor, sponsored workshops:
"Designing, Conducting, and Analyzing Multi-Racial/Ethnic Political Surveys" (2014)
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Research/Industry Experience

September 2012 – Present
Project Research Assistant: Center for Urban Research and Education, Rutgers University, Camden, NJ

- GIS data collection and management; preparation of maps and running of spatial analyses of GIS shapefile overlays
- Research contribution to collaborative NSF grant-supported project (GIS consultant)

- Design of interactive mapping site for the Cramer Hill Neighborhood Change Study; design of web-mapping portal based on ArcGIS for Server 10.1 and the ArcGIS Javascript API

December 2014 – July 2018

Project Assistant: The Senator Walter Rand Institute for Public Affairs, Rutgers University, Camden, NJ

- Data management (Stata); assistance with web-mapping (ArcGIS Online), and preparation of GIS mapping products; creating heat maps of juvenile and adolescent crime
- Data gathering and maintenance for the South Jersey Data Project county and municipal infographics and data access; managed and updated data, tables, and graphics
- Statistical data analysis assistance, data management; designed project data storage, filing, and collaboration system for Pascale Sykes Foundation's South Jersey Strengthening Families Initiative

August 2011 – June 2018

Department of Policy and Public Administration, Rutgers University, Camden, NJ

Graduate Research Assistant:

- Research, manuscript editing, and (grant) writing tasks; data gathering and entry (Excel)
- web development for departmental website (WordPress) – maintenance and updates
- GIS data acquisition, management & analysis, map design; spatial statistics

Teaching Assistant:

- Introductory courses in statistics and quantitative analysis, research methods, regional and economic development, and GIS/ public sector data

February - August 2011

Planning Intern: City of Chester Planning Department, Chester, PA

- Consolidated and acquired geospatial data relating to different planning needs in the City
- Produced maps and other products as requested by planning department and city personnel.
- Conducted research study assessing parking needs and residential neighborhood impact mitigation for PPL Park soccer stadium in Chester.

August 2009 - May 2011

Graduate Assistant: Office of the Dean, College of Business & Public Affairs, West Chester University of Pennsylvania

- Academic research, teaching assistance, and related duties in support of faculty and staff.
- Project assistance to the Cottrell Center for Entrepreneurial Leadership.

July - August 2010
Temp. Project Assistant - GIS Analyst: John Milner & Associates, Inc., West Chester, Pa.

- Assisted with locational/report data capture and transfer to an online, digital format (map and database) of archeological sites for State of Louisiana, Office of Cultural Development, Division of Archaeology, Baton Rouge, La., under contract with U.S. Army Corps of Engineers, New Orleans District.

August 2006 - August 2008
Graduate Research Assistant: Department of Community and Regional Planning and Center for Sustainable Communities, Temple University.

- Data collection, entry and analysis for planning-related research projects, areas include: floodplain mapping, storm-water management, environmental preservation.
- Prepared, edited, and designed GIS maps; 3-D modeling of built environment.
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August 2005 - May 2006
Graduate Research Assistant: School of Business, LMU

- Assisted with instruction-related activities such as proctoring, grading exams, advising students, videoconferencing and other classroom technical support.
- Conducted online research and prepared written reports and summaries.

August 2004 - July 2006
Undergraduate Research Assistant, Resident/Student Technology Assistant: School of Business and Department of Computer and Information Services, LMU.

- Aided in interactive television (ITV) class instruction; academic hardware/software installation/support; network connectivity and security assistance to residential halls.
- Attended instructional technology workshops and STA training at the ACA 2004 summit.

<u>Conference Presentations</u>

Urban Affairs Assoc. annual conference posters – "Women of Faith and Hope: A Case Study Approach to Community Healthcare Education, Outreach, and Social Change". (co-authored paper with Spencer T. Clayton), April 2013, San Francisco, CA.; "Community Healthcare Redefined: The Role of Grass-Roots Community Health Organizations and Outreach Workers in Education and Access", March 2014, San

Antonio, TX; “Health Care for All: A Case Study of a Local Health Alliance and its Pursuit of Better Health Outcomes While Reducing Costs”, April 2015, Miami, FL; “The Spatial Dimension of the Relationship between Concentrated Poverty and Health: An Analysis of U.S. Metropolitan and Micropolitan Areas, 2001-2010”, March 2016, San Diego, CA; “Concentrated Poverty, Racial Segregation, and Health: The Spatio-temporal Dynamics Shaping Health Outcomes across U.S. Metropolitan Regions”, April 2017, Minneapolis, MN
Moderated poster session – "Widening the Insurance Coverage Net: Policy Implications from the Massachusetts Health Reform". Midwestern Political Science Assoc. Conference, April 2013, Chicago, IL
Assoc. for Public Policy Analysis and Management Fall Research Conference posters – “Community Healthcare Redefined: The Role of Grass-Roots Community Health Organizations and Outreach Workers in Bridging the Gap in Education, Access, and Equity”, Nov. 2013, Washington, DC; “Health Care for All: A Case Study of a Local Health Alliance and Its Pursuit of Better Health Outcomes for Residents While Reducing Costs in Camden, New Jersey”, Nov. 2014, Albuquerque, NM; “The Spatial Dimensions of Inequality and Wealth: An Analysis of U.S. Metropolitan Areas”, Nov. 2015, Miami, FL; “Assessing Economic Revitalization in NJ: A Comparative Study of Camden and Neighboring Municipalities”, Nov. 2016, Washington, DC; "Concentrated Poverty, Racial Segregation, and Health: The Spatio-temporal Dynamics Shaping Health Outcomes across U.S. Metropolitan Regions", Nov. 2017, Chicago, IL
Assoc. for Research of Nonprofit Organizations and Voluntary Action annual meeting posters – "Community Healthcare Redefined: The Role of Grass-Roots Community Health Organizations and Outreach Workers in Education and Access", Nov. 2013, Hartford, CT; “Health Care for All: A Case Study of a Local Health Alliance and its Pursuit of Enhanced Health Outcomes for Residents”, Nov. 2014, Denver, CO
Society for the Study of Social Problems annual meeting moderated panels – “Mapping Risk: An Examination of the Spatial Relationship between Adolescents, Resource Availability, and Risky Places in Camden,” co-presenter with Stacia Gilliard-Matthews, Robin Stevens, Spencer Clayton and Straso Jovanovski, Rutgers University, August 2013, New York, NY; “The Spatial Dimensions of the Relationship Between Concentrated Poverty and Health Outcomes in U.S. Metropolitan Regions”, student panel on environment and health, harm and inclusivity, August 2016, Seattle, WA.

Publications

“Assessing Economic Revitalization in New Jersey: A Comparative Study of Camden and Neighboring Municipalities”. Conference Proceedings Publication (with David Okereke), presented at State and Local Economic Development Policy Graduate Student conference, Camden NJ, April, 2016 (forthcoming).

Works in Progress

"Public Health Disparity, Health Disparity, and Disparity Measurement"
"Assessment of sleep deprivation, hypertension, and medication: Behavioral modification vs. medication"
"Determinants of Social Violence Among Youth and their Risky Health Behaviors: Policy Implications"

Professional and Academic Affiliations

Executive Board Member:
Public Administration Student Association, Rutgers University – Camden (2014-2016)
Student Member:
Planning committee, State and Local Economic Development Policy Graduate Student conference, 2016/2017, PhD program in Public Affairs and Dept. Public Policy & Admin., Rutgers-Camden
American Planning Association, PA/NJ Chapters, SE-PA section
Urban Affairs Association
Midwestern Political Science Association
Association for Public Policy Analysis and Management
Association for Research on Nonprofit Organizations and Voluntary Action
The Society for the Study of Social Problems
Scholars Strategy Network – New Jersey chapter (policy brief accepted and admitted January 2018)