MOVING TOWARDS DISASTER: EXAMINING THE CHANGING PATTERNS OF SOCIAL VULNERABILITY IN A MULTI-HAZARD URBAN ENVIRONMENT

BY

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DISSERTATION

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ABSTRACT

Studies of social vulnerability have repeatedly emphasized the importance of identifying the drivers of vulnerability, but very few studies have focused on empirically characterizing those drivers within the domain of vulnerability science that would help in effective policymaking. This dissertation is an initial step in this direction, examining social vulnerability in the context of multiple cities and evaluating the changing patterns of vulnerability in a multi-hazard urban environment. It adopts a political-economic framing of vulnerability production (Dooling and Simon 2012) that conceptualizes vulnerability as a dynamic condition, produced through the historic interaction of economic, cultural, and social processes. It hypothesizes that the nature and distribution of social vulnerability in urban areas changes over time, and that the provision of subsidized low-income housing influences the hazard exposure of socially vulnerable populations. This is accomplished first by studying three cities in the Gulf coast region (Houston, New Orleans, and Tampa) and then by focusing on Houston, Texas as a case study city for a more detailed empirical analysis. The initial component of this research integrates neighborhood change theories and theories of social vulnerability to explain the changing patterns of social vulnerability in Houston, New Orleans, and Tampa over a 30 year time period (1980-2010). Next, the Houston case study further explores how vulnerable groups navigate the multi-hazard urban environment and how subsidized housing policies have influenced this interaction over time.

The pattern of social vulnerability observed within the case study cities indicates that despite having drastically different population growth trajectories and being situated in different political and economic settings, the spatial concentration of social vulnerability has gradually decreased in the study cities in recent decades. Specific trends in vulnerability are identified for each of the cities and the potential for constraining climate adaptation efforts is discussed. After analyzing the location of subsidized housing in Houston, this study found that among the two most widespread housing subsidy programs (Housing Choice Vouchers and the Low Income Housing Tax Credit), supply based subsidies exemplified by the LIHTC significantly increases neighborhood social vulnerability when it is located in areas exposed to technological hazards. Limitations in the present administration of the subsidy programs are identified and policy alternatives are discussed that may help to reduce their contribution to vulnerability.

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CHAPTER 1
INTRODUCTION

1.1 Introduction

Prior studies of social vulnerability and disaster risk management have repeatedly emphasized identifying the drivers of vulnerability, but very few studies have focused on empirically characterizing those drivers. Understanding these drivers within a multi-hazard urban context is important given the differential hazard exposure and disaster outcomes experienced by vulnerable low-income and minority population groups (Crowder & Downey, 2010; Finch et al., 2010; Van Zandt et al., 2012). In recent years, urban sustainability and climate adaptation have gained increased attention due in large part to growing concerns related to the impacts of climate change (Blanco et al., 2009). The devastation wrought by Hurricanes Katrina and Sandy are two recent examples that clearly highlighted the vulnerabilities of major coastal cities and have renewed calls for a planning response. Billions of dollars are now being spent to restore the economies of impacted localities and to prepare for future climatic impacts but comparable resources have not been dedicated to the social dimensions of vulnerability, namely recovery of the urban poor or how to ensure secure and safe housing for vulnerable population groups. This neglect of social vulnerability is an important limitation of adaptation efforts, which promises to reduce climate change impacts but "tend to exclude the possibility of non-adaptation from consideration" (Orlove, 2009). Despite these efforts, socially vulnerable populations may be increasingly concentrated in hazard exposed areas (Mohai & Saha, 2006; Wisner et al., 2004), significantly increasing the overall vulnerability of cities. What is required now is to consider the dynamics of social vulnerability and to identify the drivers that make the vulnerable population groups less able to avoid hazardous areas. This dissertation explores the changing patterns of social vulnerability and adopts a political-economic framing of vulnerability production (Dooling & Simon, 2012) to critically examine the drivers of vulnerability. It offers policy recommendations that move beyond the conventional notion of vulnerability as static and exogenous to urban development and politics. Finally acknowledging that there are multiple drivers of social vulnerability in a multi-hazard urban environment, this study focuses on subsidized housing and evaluates how market dependent housing subsidy programs for low-income people can act as one of the drivers contributing to conditions that are ripe for disaster.

1.2 Study Background

Although vulnerability has been defined differently across disciplines, it generally refers to susceptibility to harm (Adger, 2006; Füssel & Klein, 2006). However, even within this general definition of vulnerability, there are significant differences in its conceptualization in the policy arena and scholarly discourse. In the climate change literature for example, vulnerability is often understood to be a function of exposure to a hazard, sensitivity to that hazard, and the ability to respond accordingly (Parry et al., 2007; Smit & Wandel, 2006). In this biophysical conception of vulnerability, risk is seen as exogenous to society (McLaughlin & Dietz, 2008) as something that can be projected onto a socially-static landscape. It has been widely recognized, however, that adaptive capacity, exposure, and sensitivity are not static, and instead vary widely over time and across subpopulations, as do the damages experienced (Handmer, Dovers, & Downing, 1999; Turner et al., 2003). From this point of view, a social constructivist approach to vulnerability locates risk within society and places the burden of explanation of vulnerability within the social system (Ribot, 2009). An integrative vulnerability framework on the other hand, links both risk-hazard and social constructivist models of vulnerability, and understands vulnerability as having "an external dimension, which is represented by the 'exposure' of a system, as well as internal dimension, which comprises the 'sensitivity' and 'adaptive capacity' to these stressors" (Füssel & Klein, 2006). This study adopts an integrative framework of vulnerability to explain social vulnerability dynamics, where the external dimensions of hazard risks interact with internal dimensions of social vulnerability within the broader political-economic context of a region.

While scholarship on hazard vulnerability (or biophysical risk) offers significant insights for understanding the geography of unequal risk, it provides an incomplete basis for examining contemporary generative processes (Collins, 2009, 2010). Political-economic theory and analysis focuses on this generative process by explicitly considering changes in economic policies, technological systems, institutional arrangements, and demographic processes, all of which shape social vulnerability (Collins & Jimenez, 2012). Politically and economically powerful institutions and individuals, through their political ideologies and strategies, influence access to human and natural resources for different social and economic groups, and thereby act as the drivers for production of vulnerability (Dooling & Simon, 2012; Pelling, 2003). Following the work on vulnerable spatialities of Findlay (2005), Dooling & Simon (2012) elaborated this production-oriented framework for analyzing how interactions between political economies of resource use and normative planning and management interventions influence which places and populations are made vulnerable. In recent years, a number of studies have examined the effects of neoliberal[1] policies on public space, neighborhood change, gentrification, and other forms of uneven development (Hackworth & Smith, 2001; Lees, 2003; Newman & Ashton, 2004; Perkins, 2012). It has also been argued that the increased concentration of poverty in the United States over the last 40 years was more a result of housing policy than the result of income inequality (Reardon & Bischoff, 2011). Given this contextualization, this study examines the extent to which subsidized housing programs functioning within a neoliberal policy environment contribute to hazard exposure for socially vulnerable communities.

Poverty and access to stable, affordable housing are key factors in determining a household's ability to withstand socio-economic stresses in urbanizing environments (Moser, 1998; Sanderson, 2000). But in recent decades, policies designed to facilitate the provision of affordable housing in U.S. cities have undergone important changes. Since the early 1970s, a significant number of public housing projects have been dismantled and replaced with market-oriented solutions such as rental assistance vouchers and HOPE VI housing developments. Disinvestment in inner-cities, the shifting of new investment to suburbs, designating areas as blighted, and post-disaster reconstruction have justified the clearance of "slummed" neighborhoods resulting in direct subsidies to private real estate investors and the demolition of public housing (Angotti, 2008; Crump, 2002; Kamel, 2012). However, these market-oriented programs suffered from funding deficits since their inception and subsequent reductions in federal housing spending have exacerbated unmet housing needs (Malpass, 2003; Popkin et al., 2004). A significant proportion of low-income households, especially inner-city minorities, remained trapped in substandard, overcrowded, and over-priced housing (HUD 1993; 2007). Prior research has considered whether programs for low-income housing succeeded in deconcentrating poverty (Goetz, 2005; Massey & Denton, 1993; Wilson, 1987) or provided any improvement in life outcomes for participating household and communities (Freeman, 2003; Goering et al., 2002; Van Zandt & Mhatre, 2009), but very few studies have explored the extent to which these housing provisions have increased or decreased the hazard exposure of vulnerable

[1] Harvey (2005) identifies neoliberal policies as emerging from political-economic practices that "proposes that human well-being can best be advanced by liberating individual entrepreneurial freedoms and skills within an institutional framework characterized by strong private property rights, free market, and free trade." As Perkins (2012) asserts, neoliberal modes of environmental governance usually prioritize market profitability and personal responsibility.

populations (e.g. Cutter et al. 2001; Houston et al. 2013).

Prior research on social vulnerability in urban areas has tended to focus on exposure to natural hazards (Maantay & Maroko, 2009b; Zahran et al., 2008) or differential outcomes in the context of recovery planning and disaster impacts (Van Zandt et al., 2012; Zhang & Peacock, 2009), but the changing pattern of social vulnerability and the generative process of vulnerability has yet to be examined. Adopting the production-oriented framework of vulnerability (Dooling & Simon, 2012) this dissertation investigates the intensity and persistence of conditions of social vulnerability (Collins, 2010; Davis, 1998; Peet & Watts, 1996). Since the location and availability of subsidized low-income housing is considered a critical determinant in the spatial distribution of socially vulnerable populations (Moser, 1998; Sanderson, 2000), it is important to understand how these programs, in their present form, may influence social vulnerability within a multi-hazard landscape.

Exponential population growth along the coasts of the United States in recent decades has increased the number of people and amount of property vulnerable to high winds, waves, and storm surge flooding of catastrophic coastal storms (Burby, 1998; Deyle et al., 2008; Godschalk et al., 1999). Therefore, coastal cities are the most appropriate test cases for the vulnerability framework discussed above. This dissertation selects three coastal cities (Houston, New Orleans, and Tampa) for exploring the changing pattern of social vulnerability over a 30 year time period (1980-2010). These cities were chosen due to the similarity of their geographic locations (i.e., all are located in Gulf Coast region) and because they exhibit significantly different patterns of population growth. The study then focuses exclusively on Houston to evaluate how subsidized housing programs may have influenced social vulnerability and hazard exposure. Houston is adopted as the subject of a detailed case study due to its high level of natural and technological hazard exposure (Nicholls et al., 2008; Schiller, 2010) and its situation within the archetypal neoliberal state of Texas (Miller et al., 2011).

1.3 Objectives, Research Questions, and Hypothesis

The primary objective of this study is to evaluate how urban growth and decline shapes and changes patterns of social vulnerability and how subsidized low-income housing programs influence social vulnerability in a multi-hazard environment. This dissertation will be guided by following central questions:

1. How do the spatial patterns of social vulnerability change over time in coastal metropolitan areas and how do these patterns vary across different cities (in terms of the distribution of vulnerable population groups and indicators of social vulnerability)?
2. Are socially vulnerable populations more likely to live in hazard exposed (both natural and technological) areas and if so, has this relationship changed over time?
3. To what extent have subsidized housing programs influenced the hazard exposure of socially vulnerable population groups?
4. How can existing subsidized housing programs be modified to better address the problems of hazard exposure and disaster risk reduction?

Considering the above research questions, this study tests three related hypotheses:

H1. With the growth of a city, vulnerable population groups become less concentrated over time. The suburbanization of poverty, limited availability of affordable housing, and gradual gentrification of inner-city poor neighborhoods can contribute to such trends. The dimensions of social vulnerability also vary through changing demographic composition.

H2. Over time, vulnerable population groups increasingly move into hazard exposed areas of a city, which further skews the already uneven geography of hazard exposure. A lack of housing security, decreasing provisions for a social safety net, and more limited housing options due to urban revitalization and gentrification are some of the key drivers behind this uneven geography.

H3. Subsidized housing programs have failed to reduce the overall hazard exposure of socially vulnerable populations and to some extent, have contributed to an increased level of hazard exposure. Exposure to technological hazards may be higher than exposure to natural hazards due to the concentration of these land uses in space over time and their attendant impacts on land values and rent in these areas of the city.

1.4 Dissertation Outline

To address the research questions mentioned above, this study begins by exploring the patterns of social vulnerability in three coastal cities, then narrows its focus to a detailed case study of subsidized low-income housing in Houston, Texas. Chapter 2 reviews literature on social vulnerability, and particularly how different schools of thought have contributed to formalizing the concept of urban social vulnerability. It also gives a brief review of low-income housing subsidy programs in the U.S. and how these programs may influence the location decisions of vulnerable populations in a multi-hazard environment. This chapter also presents the overall framework of the research, summarizing the key theoretical basis and how the study is conducted in two stages. Chapter 3 presents the study methodology and briefly describes the three case study cities before elaborating the data processing methods, procedure for calculating social vulnerability, approach for analyzing the temporal trends of vulnerability, methods for calculating natural and technological hazard exposure, and later how the modeling framework was selected for evaluating the impacts of subsidized housing and hazard exposure on changing patterns of social vulnerability at census tract level.

Chapter 4 discusses the results of analyzing the changing patterns of social vulnerability in three coastal cities over a thirty year time period (1980-2010). It also presents a brief review of relevant neighborhood change theories before synthesizing social vulnerability and neighborhood change theory to explain the identified patterns of social vulnerability. This chapter concludes with a call for developing a land use planning framework that is more responsive to the changing patterns of vulnerability in a city. Chapter 5 presents the results from the detailed case study of Houston (Harris County), Texas evaluating the spatial distribution of socially vulnerable populations within the multi-hazard landscape and how the subsidized low-income housing that existed there in 2000 and 2010 was distributed across different natural and technological hazard zones. This chapter also interprets the results of spatial econometric models that evaluate the interaction between subsidized housing and hazard exposure and how this may have contributed to an increase in social vulnerability within hazardous areas of the county.

Chapter 6 focuses on identifying limitations in present housing policies and policy alternatives that would ensure that low-income housing subsidies are channeled into lower hazard areas of the city. It evaluates the environmental requirements of housing projects that receive assistance from the U.S. Department of Housing and Urban Development (HUD), then looks at the requirements of two of the most popular subsidy programs—Housing Choice Vouchers (HCV) and Low Income Housing Tax Credit (LIHTC). Based on interviews with officials at the Houston Housing Authority and site visits to selected tax credit properties, this chapter further explains and contextualizes the findings from the spatial econometric models presented in Chapter 5. Later this chapter proposes policy alternatives for modifying existing provisions of HCV and LIHTC, particularly how these programs can be more responsive to the hazard characteristics of an area and how these programs can ensure that socially vulnerable populations are not concentrating in those areas. This dissertation concludes with Chapter 7, which summarizes the findings of this study and reiterates the importance of considering the changing patterns of vulnerability in the current initiatives for adaptation planning as well as how our subsidized housing programs can be an integral part of climate adaptation initiatives.

CHAPTER 2
LITERATURE REVIEW AND RESEARCH FRAMEWORK

2.1 Introduction

Vulnerability science is multidimensional with researchers working in the fields of disaster management and hazards, environmental justice, food and water security, and climate change contributing theories that have helped to define and advance the field of vulnerability studies (Eakin & Luers, 2006; Ionescu et al., 2009; Kasperson et al., 2005; Turner et al., 2003). Scholars evaluating the dynamic tensions of vulnerability[2] examine more explicitly the connections between pre-existing and emerging economic, environmental and social conditions that impact vulnerable communities (Andrey & Jones, 2008; Dooling & Simon, 2012; Hogan & Marandola, 2005; Pelling, 2003). Prior studies adopting a political-economic framing of vulnerability production have specifically explored these broader dynamic tensions, but detailed research that evaluates the outcomes of low-income housing programs can also make valuable theoretical contributions and yield useful policy recommendations. This dissertation represents an initial step in this direction. The remainder of this chapter discusses theoretical models of vulnerability itself, and then considers the political economic framing of vulnerability and the environmental justice framing of vulnerability. A brief overview of subsidized low-income housing programs is provided later, followed by a more detailed discussion of residential location choice and the hazard exposure of subsidized housing to explain their linkages under the political-economic and environmental justice framing of vulnerability.

2.2 Theoretical Models of Vulnerability

Interaction between biophysical and social vulnerability has always been a contentious issue among researchers. The biophysical conception of vulnerability considers risk as exogenous to society (McLaughlin & Dietz, 2008) and climate-related hazards can therefore, be mapped onto a socially-static landscape where adaptive capacity and sensitivity are assumed to be fixed in a particular geographic area. In contrast, a social constructivist approach relies on the theories of political economy and political ecology to uncover and evaluate the structural origins

[2] Dynamic tensions of vulnerability refer to the processes through which conditions of, and experiences with, vulnerability are produced through specific cross-scale interactions that are historic in nature (Dooling & Simon, 2012).

of vulnerability. Bohle et al. (1994) provided an early model of social vulnerability rooted in the political economy tradition and in their view, vulnerability is best understood and studied using concepts rooted in human ecology, political economy, and entitlement theory. Three of the most prominent theoretical models of vulnerability that draw upon this political economy tradition are briefly discussed here.

2.2.1 Pressure and Release Model

The Pressure and Release (PAR) model (Blaikie et al., 1994) addressed more specifically the construction of some of the contextual factors influencing vulnerability. In the PAR model, vulnerability is seen as part of a risk equation: Risk = Hazard + Vulnerability. Risk, in this application, is distinct from its traditional definition as the probability of event occurrence (Cutter, 1996), or as Sarewitz et al. (2003) put it, event risk. Risk in the above formula is what Sarewitz et al. called outcome risk—that is the probability of a *specific* outcome occurring. Vulnerability within the PAR model is conceptualized as stemming primarily from social structures and characteristics. Vulnerability originates from a variety of root causes, leading to what are termed as dynamic pressures. These dynamic pressures localize the influence of the broader root causes (e.g., poverty) into unsafe living conditions. Unsafe living conditions in turn interact with the probable or actual occurrence of hazard events to produce what may be called a higher outcome risk for less advantaged members of society. This model developed the idea that the consequences of a hazard event depend not only on the event in question, or even solely on the direct human-environmental systems, but also on the broader structure and characteristics of human society.

2.2.2 Hazards of Place Model

The Hazards of Place (HOP) model of vulnerability (Cutter, 1996) attempted to bridge the gap between vulnerability approaches focused solely on exposure, and those centered exclusively on social conditions related to resistance or resilience. Cutter proposed that the idea of *place* be used to unify these approaches and the diagram shown in Figure 2.1 offers an overview. Interactions between people and their environment occur within a particular place and places have a unique hazard potential, which arises from the interaction between hazard risk and socially determined mitigation activities (or lack thereof). Geographic contexts (characteristics) within the study area, such as elevation and proximity, work to modify hazard potential across space. This modified, spatially differentiated hazard potential is called biophysical vulnerability. The hazard potential is also modified by the social fabric of the area, which in turn modifies and differentiates the hazard potential across space. The social fabric consists of those characteristics that describe the distribution and composition of the population measured, for example, by socio-demographic, economic and welfare variables. The social contributions to the spatial differences are called *social vulnerability*.

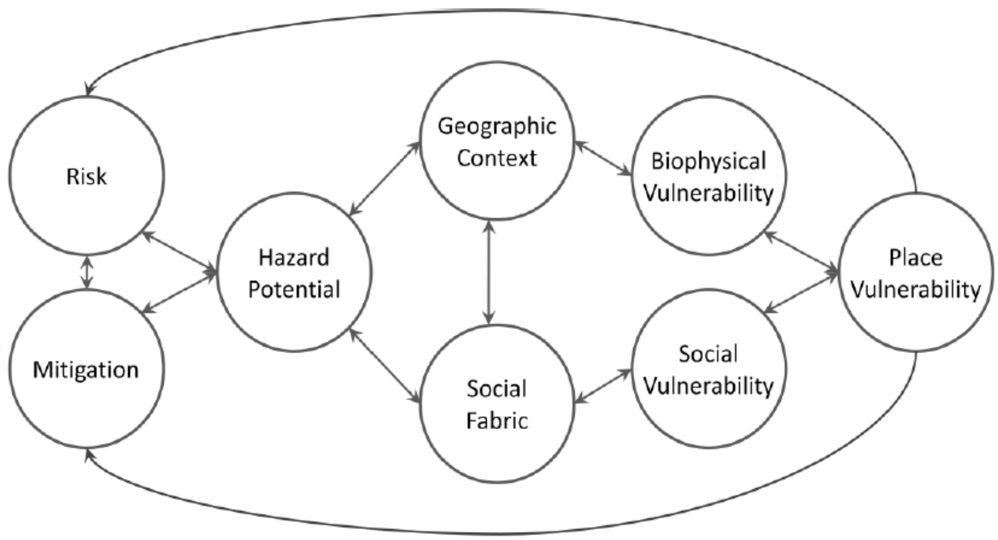

Figure 2.1 Hazards of Place (HOP) model of vulnerability (after Cutter (1996))

Biophysical and social vulnerability interact to create an overall place vulnerability, but place vulnerability can, in turn, modify both the event risk of an area as well as the mitigation approaches used in the area. The linkages displayed in the model (Figure 2.1) communicate an understanding of the dynamic nature of vulnerability—namely that changes in the physical and social setting of an area may result in changes in vulnerability, risk, mitigation, etc.

2.2.3 Vulnerability Framework for Sustainability Science Model

The Vulnerability Framework for Sustainability Science (VFSS) model (Turner et al., 2003) was also developed to bridge gaps in existing approaches to studying vulnerability. But while the HOP model reconciled competing understandings of the factors contributing to vulnerability (physical and social), the VFSS approach sought to bridge the risk-hazards and the political economy and political ecology traditions as different ways of conceptualizing vulnerability. While it includes vulnerability stemming from biophysical subsystems seen in the risk-hazards approaches, it also reconciles this with the multi-scaled and structural explanations of the political economy approaches[3]. Like the HOP model, it employs the geographic concept of place as the lens through which the interactions of social and physical systems are analyzed. In this framework, vulnerability occurs within a specific place, but is influenced by human and environmental influences at regional and global levels.

Although the models discussed above explore vulnerability from different perspectives, all of them can be traced to the political-economic framing of vulnerability. This dissertation makes use of these established theoretical frameworks, but draws most heavily on the HOP model (Cutter, 1996) and VFSS framework (Turner et al., 2003). In order to evaluate the pattern of social vulnerability within the study cities, it adopts Cutter's approach, but for exploring the generative dynamics of vulnerability it takes cues from Turner et al.'s VFSS framework given the latter's emphasis on political-economic explanations of vulnerability dynamics.

2.3 Political-Economic Framing of Vulnerability

A political-economic perspective on hazard exposure and vulnerability provides a foundation for describing uneven patterns of risk (Bolin & Stanford, 1998; Hewitt, 1983; Susman et al., 1983; Wisner et al., 1976, 2004). Like the PAR model of vulnerability (discussed above), this perspective considers risk as the product of people's exposure to an environmental hazard *and* their social vulnerability[4]. Political-economic theory and analysis focuses on the generative process of vulnerability by integrating changes in economic policies, technological systems, institutional arrangements, and demographic processes, all of which shape contemporary experiences of vulnerability. It questions the neoliberal objective of aggregate economic growth that promises to improve human well-being, but ultimately ignores the production of social vulnerability (Cannon & Müller-Mahn, 2010). Empirical analysis and theorizing about the neoliberal project provides the basis for understanding and challenging environmental injustice created by the neoliberal agenda.

While a political-economic framing allows us to understand the broader generative process of vulnerability, it too is insufficient to explore the vulnerability dynamics in an urban context when taken in isolation. Risk exposure to urban environmental hazards is a complex

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[3] Specifically the linkages outlined from global root causes to local unsafe living conditions in the PAR model.
[4] The capacity to anticipate, respond to, and recover from exposure to a chronic stressor or perturbation (Wisner et al., 2004).

phenomenon, with overlapping risks associated with the household, workplace, or neighborhood, and pollution risks from industrial contamination (Hardoy et al., 2001). Poverty and access to stable, affordable housing are key factors in determining a household’s ability to withstand socio-economic stresses in urbanizing environment (Dooling & Simon, 2012; Moser, 1998; Sanderson, 2000). In addition, people without access to safe housing are frequently the group most harmed by environmental hazards (Pelling, 2003), and on the other hand, neoliberal policies also impede a community’s ability to preserve and deliver affordable housing (Kamel, 2012). In addition to housing affordability, studies have also demonstrated the importance of local stresses as contributors to vulnerability in the context of health, racial, gender and age composition of affected households and communities (Phillips et al., 2009). Within the urban context, it is argued that social vulnerability emerges as a response to, and a byproduct of, phenomena operating at larger scales, including national policies, global financial markets, and regional environmental disasters (Collins, 2009; Dooling, 2012). In order to better conceptualize the role of these larger-scale phenomena vulnerabilities must be understood as conditions that are created and maintained through historical relationships and arise from the interaction of economic, cultural, and social processes (Andrey & Jones, 2008; Blaikie et al., 1994; Hogan & Marandola, 2005; Pelling, 2003).

A production-oriented framework of vulnerability (Dooling & Simon, 2012) analyzes how interactions between political economies of resource use and normative planning and management interventions—at both global and local scales—influence which places and populations are made vulnerable as well as the intensity and persistence of conditions of vulnerability (Collins, 2010; Davis, 1998; Mustafa, 2005; Orsi, 2004; Wisner et al., 2004). It focuses on articulating how the conditions and experience of vulnerability are produced, regulated, manipulated and resisted. By detailing the relationship between vulnerability and planning agendas that guide urban sustainability, gentrification, suburban development, climate change adaptation, and other planning initiatives, this production-oriented framing places vulnerability within the broader field of urban political ecology (Dooling, 2012; Heynen et al., 2006). This framing focuses on the contradictions of a planning agenda that ignores the dynamics of social vulnerability and thereby, exacerbates existing risks and harms groups of people that are the least able to avoid the risks (Dooling, 2012).

2.4 Environmental Justice Framing of Vulnerability

An environmental justice framing of vulnerability contributes important insights into the underlying dynamics of hazard exposure and vulnerability (Boone & Fragkias, 2013). The environmental justice literature examines inequalities in technological hazard exposure by race and class and has coalesced around concern and action regarding the societal distribution of environmental hazards and their health effects (Buzzelli, 2007). It specifically explores the nature and extent of disproportionate exposures to health hazards, ranging from toxic waste sites and air pollution to the landfill siting process, and how this exposure varies across population groups (Chakraborty & Armstrong, 2001; Crowder & Downey, 2010; Hamilton, 1995; Maantay, 2001). Buzzelli (2007) presents a schematic (Figure 2.2) of the environmental justice conundrum, indicating that as Socio-Economic Position (SEP) rises, the corresponding exposure to environmental health hazards among individuals and neighborhoods diminishes. This general framing of environmental justice is augmented by two competing viewpoints (Crowder & Downey, 2010): the *racial income inequality thesis* and *residential discrimination thesis*, which are briefly discussed below.

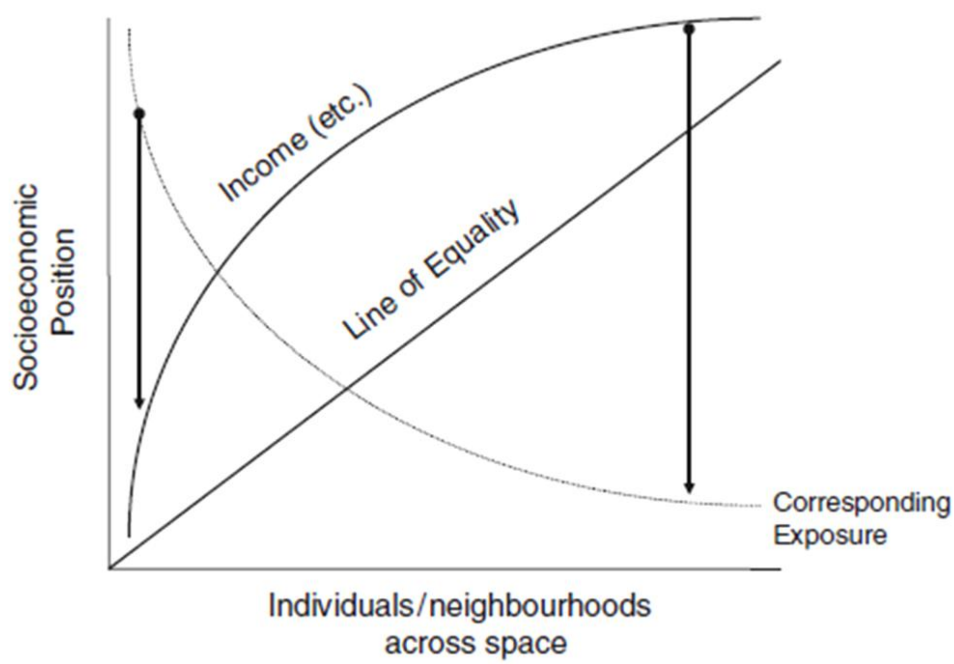

Figure 2.2 Schematic of environmental (in)justice (Buzzelli, 2007).

The *racial income inequality thesis* (Downey, 2005; Oakes et al., 1996) argues that, racial differences in exposure and proximity to environmental hazards largely reflect group differences in socioeconomic resources (Crowder & Downey, 2010). It holds that environmentally hazardous neighborhoods have relatively low property values and rents, which make those areas more accessible to lower-income families. Low-income families on the other hand are overrepresented by non-white families and as a result, higher proportions of non-white populations also live in hazardous areas.

The *residential discrimination thesis* (Bullard, 1999; Mohai & Bryant, 1998) is more critical than the racial income-inequality thesis in explaining differential exposure to hazards. It argues that housing market discrimination reduces the ability of minority households to move out of, or to avoid moving into, hazardous neighborhoods, thereby creating or maintaining environmental racial inequality (Crowder & Downey, 2010). Studies based on this thesis show how discriminatory actions by real estate agents (Pearce, 1979; Yinger, 1995), local governments (Shlay & Rossi, 1981), and mortgage lenders (Ross & Yinger, 2002) limit residential location choice for minority home seekers (Galster & Keeney, 1988; Massey & Denton, 1993).

Besides these two viewpoints some studies have assessed the argument that environmental injustice emerge because environmental hazards are disproportionately sited in minority neighborhoods who lack political influence to resist it (Downey, 2005; Pastor et al., 2001). However, it is argued that in the context of high levels of residential mobility, initial siting decisions may have relatively less influence on prevailing patterns of hazard exposure (Crowder & Downey, 2010). Also, as both the income-inequality and discrimination perspectives predict, in comparison to whites, members of minority groups will be less likely to leave and more likely to enter, polluted neighborhoods, thereby increasing their overall proximity and exposure to environmental hazards (Downey, 2005; Hamilton, 1995; Mohai & Bryant, 1998; Oakes et al., 1996). Although environmental justice studies focus more on assessing fairness and vulnerability studies focus on the biophysical and social system, combining them in a common framework can strengthen and advance the goals of each (Boone & Fragkias, 2013). This study facilitates this integration by exploring vulnerability dynamics in a multi-hazard environment.

2.5 Subsidized Low-Income Housing in the U.S.

Federally assisted public housing began in 1930s, primarily to stimulate employment after the crisis of the Great Depression in the U.S. (Cutter et al., 2001; Wyly & DeFilippis, 2010). Over time, low-income housing assistance has evolved with the federal government playing a reduced role that favors state and locally led partnerships supplemented with a blend of block grants, tax credits to private developers, and vouchers (Wyly & DeFilippis, 2010). After widespread criticism of public housing as a key contributor to the creation and exacerbation of social and economic segregation in cities, federal housing policy since the 1970s has focused on two objectives—to help depressed neighborhoods through the construction of new affordable housing and to deconcentrate poor subsidized-housing residents (Galster, 2013; Scally & Koenig, 2012), but these policies have had relatively little impact in improving the conditions of low income neighborhoods (Galster, 2013). Many studies have argued that the placement of subsidized housing creates negative spillover effects in neighborhoods such as the devaluation of land, increased crime, and middle class flight and eventually lead to further concentrations of poverty (Carter et al., 1998; Galster et al., 1999; Holloway et al., 1998). However, other studies have argued that much of the negative reaction to low-income subsidized housing developments is unwarranted (Freeman, 2003; Green et al., 2002; Oakley, 2008). Further complicating matters is the fact that the outcomes of subsidized housing programs tend to vary by specific program and across local housing markets. A brief review of relevant subsidized housing programs is presented here[5] and followed by a discussion of residential location choice and the hazard exposure of subsidized housing.

2.5.1 Scattered-Site Public Housing

As evidence mounted that public housing was contributing to the concentration of inner-city poverty, at the beginning of 1970s, the U.S. Department of Housing and Urban Development (HUD) encouraged local Public Housing Authorities (PHAs) to develop more housing on a "scattered-site" basis (Galster, 2013). This scattered-site housing was typically operationalized through the construction and/or acquisition of low-density buildings with fewer than 15 units per site in locations that were not disproportionately minority-occupied (Hogan, 1996). However, this strategy was not widely adopted across the nation due to the near-elimination of funding

[5] For a more detailed treatment, see Schwartz (2010).

from federal sources and there was huge variation in the density and locations of "scattered sites" across PHAs (Galster, 2013). In general, it is argued that scattered site public housing programs have offered superior neighborhood environments for low-income tenants compared to conventional, large-scale, concentrated public housing developments, but the outcome also vary by the contexts of local housing markets (Galster, 2013).

2.5.2 Housing Choice Vouchers Program

Vouchers, authorized by Section 8 of the Housing and Community Development Act of 1973, have been regarded as inherently superior to public housing in that they enable poor families to live in moderate- or middle-income neighborhoods (Wyly & DeFilippis, 2010). Since its inception in 1974, this housing assistance program had followed the general formula that the qualifying household must contribute a share of its income (currently 30%) toward rent of an apartment that meets certain quality standards and whose landlord agrees to sign a minimum one-year lease with the tenant and the PHA administering the voucher (Galster, 2013). In 1998 Section 8 was renamed the Housing Choice Voucher (HCV) program. By encouraging residents of high-poverty neighborhoods to relocate to outlying areas, the program is intended to make more jobs accessible to program participants (Briggs, 1997; Goering et al., 2002), but an enduring problem is that its effectiveness depends on the availability of affordable units in neighborhoods with low concentrations of poor persons. Pendall (2000) attributes the shrinking supply of affordable units to a combination of increased competition for land and unfavorable tax codes that hinder the development of multifamily housing. Efforts to close older public housing projects under the HOPE VI program (discussed later) also negatively affect the supply of affordable units. Further, despite the option to move out of high-poverty neighborhoods, many program participants choose not to move at all and instead opt to remain close to family, friends, and other social institutions (Briggs, 1997; Popkin et al., 2004).

Feins & Patterson (2005) conducted a longitudinal analysis using a national sample of those entering the HCV program from 1995 to 2002 and found that the trajectory of moves was not into significantly better neighborhoods (measured on many characteristics) over time. Research suggests that even after controlling for socioeconomic status, minorities are less likely than whites to move to predominantly white neighborhoods and more likely to move to minority or racially mixed neighborhoods (South & Crowder, 1998; Stearns & Logan, 1986). These results indicate that merely increasing the effective affordability of vacant apartments of decent quality via a voucher is not enough to realize much improvement (on average) in the geographic outcomes for program participants relative to comparable renters who are not subsidized (Galster, 2013).

2.5.3 Low-Income Housing Tax Credit Program

Established by Congress in 1986, the Low-Income Housing Tax Credit Program (LIHTC) provides tax credits to developers for the construction and rehabilitation of affordable rental housing. Administered by the Internal Revenue Service (IRS) in partnership with state housing finance agencies (HFAs), the LIHTC has subsidized the production of over 2.2 million rental units between 1987 and 2010 (Khadduri et al., 2012). Subject to broad guidelines, each state develops criteria for awarding these tax credits and holds annual competitions among prospective developers for projects designed with a minimum share of "affordable" units (Galster, 2013). Unlike the public housing or housing vouchers that often serve extremely poor households, the LIHTC targets households with incomes below 50 or 60 per cent of area median income (AMI) (Deng, 2011). While it has been criticized for failing to reach households with the most serious housing needs, this higher-income eligibility also makes the program popular among both non-profit and for-profit developers. However, studies evaluating the LIHTC program have revealed a more mixed picture. Freeman (2004) found that relative to other neighborhoods, LIHTC neighborhoods experienced larger declines in poverty and similar increases in home values, but Rosenthal (2008) argued that the concentration of LIHTC units lays the foundation for deterioration of a neighborhood's economic status in the next decade. On the other hand, (Green et al., 2002) found that LIHTC projects either increased nearby property value or had no impact, but they were less likely to generate a negative impact.

Oakley (2008) found that the LIHTC program is more successful than other programs at locating developments in less disadvantaged neighborhoods in terms of income level and minority concentration, but was not as successful at avoiding clustering. Abt Associates (2006) concluded that in large metropolitan areas, LIHTC units are likely to be located in high-growth tracts and in areas of increasing poverty, but that the majority of LIHTC units are located in moderate-poverty neighborhoods. These studies indicate a lack of consensus on whether the LIHTC program is successful in providing affordable housing in low poverty areas or with respect to how it impacts the characteristics of neighborhoods where it is built.

2.5.4 HOPE VI Program

Housing Opportunities for People Everywhere (HOPE) programs were initiated in 1994 with the aim of revitalizing “severely distressed” public housing sites (characterized by physical decay, high vacancies, drugs, gangs and violence) through locally developed PHA-private developer/financier partnerships (Galster, 2013). This program financed the demolition and rehabilitation of public housing units, the construction of new units on site, the temporary relocation of displaced tenants, and the provision of HCVs to displaced tenants who were unwilling or unable to return to the redeveloped sites. All totaled, HOPE VI demolished about 150,000 dilapidated public housing units in 224 different projects nationwide (Landis & McClure, 2010). The national HOPE VI tracking study found that after the first eight years of the program only 19% of original residents were living on the redeveloped sites, 29 % were in other public housing, 33% were using HCVs, and 18% had left housing assistance (Popkin et al., 2004). In summary, HOPE VI has had only minimal success in substantially increasing housing opportunities for former public housing residents in non-poor environments (Galster, 2013).

2.6 Location Choice and Hazard Exposure of Subsidized Housing

In light of the preceding discussion, the location of subsidized housing is clearly important for understanding the production of social vulnerability in urban areas. Housing policy has increasingly aimed to deconcentrate poverty and increase the employment opportunities available to low income households, but whether these programs have really been successful remains uncertain. Further, the degree to which subsidized housing has managed to avoid hazardous locations is another issue that has yet to be rigorously explored. The outcomes of residential location choice can vary based on the specific characteristics of local housing markets and program provisions (Pendall, 2000; Turner, 1998) and since the supply-side (i.e., scattered-site or LIHTC program) and demand-side (i.e., vouchers) policies have different mechanisms for providing housing assistance, their location outcomes can also be expected to vary (Kucheva, 2013). The location patterns of subsidized housing are discussed in the subsequent paragraph, and then prior studies on the hazard exposure of subsidized housing are briefly reviewed.

Studies have shown that the use of HCVs can be higher in disadvantaged neighborhoods because landlords in these areas often eagerly recruit HCV holders (Galster, 2013). Private landlords are more likely to be faced with high vacancies in these neighborhoods and respond by aggressively marketing their units to voucher holders (Galster et al., 1999). For the LIHTC, a number of studies have documented the effect of a specific location incentive called the qualified census tract (QCT), which provides additional credit for construction in designated low-income census tracts (Baum-Snow & Marion, 2009; Freeman, 2004; Hollar & Usowki, 2007; Oakley, 2008). However, Lang (2012) showed that, even after controlling for QCT designations, differences in the market rent level affect the location of subsidized housing and specifically, developers are more likely to build subsidized housing in locations with low rent. Lang (2012) argues that subsidization is less likely to be profitable in locations with relatively high market rent because the opportunity cost of building subsidized housing is also higher in these locations. Burge (2011) shows that only a small portion of the cost of the LIHTC subsidy is used to reduce rent for tenants and rent savings diminish over the lifetime of the apartment units. The outcome Burge demonstrates may be the result of incentives to build subsidized housing in locations where the prevailing rent is already low.

Although previous research has thoroughly examined the location of subsidized housing in terms of the socio-economic status of a neighborhood, very few studies have explored the level of hazard exposure experienced by participants in these programs. Cutter et al. (2001) examined the relationship between the location of environmental risks and federally assisted public housing in a sample of eight medium-sized United States metropolitan areas. They found that families living in HUD housing had a greater risk potential from hazardous facilities based on proximity and the reported releases from them, and that minority populations (defined as percentage non-White) had significantly greater locational exposure than non-minority populations. Houston et al. (2013) assessed the spatial distribution of subsidized housing units provided through two federally supported, low-income housing programs in Orange County, California, in relation to neighborhood walkability, transit access, and traffic exposure. They argued that, since LIHTC development proposals receive points in a competitive process for access to local amenities, these developments may be more sensitive to site feasibility considerations and may tend to be located in transportation corridors with lower property values and higher traffic. On the other hand, since the HCV program is not location based and allows participants to locate within the private rental market, their neighborhoods should differ spatially from areas prioritized by developers leveraging capital through the LIHTC program. From their analysis, Houston et al. (2013) also found LIHTC projects more likely to be located in high-traffic areas than voucher users.

2.7 Study Framework

The analysis of social vulnerability generally focuses on social, economic, political, and institutional factors that lead to differential susceptibility or sensitivity (of different social groups) in the face of risk exposures (Tate et al., 2010). It is argued that the mounting financial, human, and environmental impacts in the United States are a function of the increasing movement of people and property into highly exposed areas (Cutter et al., 2007), however, very few studies have explored how social vulnerability changes over time across cities with different population growth trends. The first stage of this dissertation explores how the dimensions and spatial distribution of social vulnerability changed over a 30 year time period (1980-2010) in three coastal cities (Houston, New Orleans, and Tampa). This analysis documents and interprets observed similarities and differences in the dynamics of social vulnerability across the study cities. This study recognizes that multiple drivers contribute to this changing pattern of social vulnerability, but focuses on subsidized low-income housing programs as a potentially important, yet understudied factor ripe for further exploration. In its second stage, this dissertation delves deeper into the relationship between subsidized housing and hazard exposure in Houston, Texas. Under the vulnerability production framing (Dooling & Simon, 2012), it explores the extent to which the market-based programs for providing low-income housing are contributing to vulnerability within the city.

The spatial clustering of minorities and low-income households in neighborhoods vulnerable to hazardous and toxic materials is not uncommon in the United States (Massey & Denton, 1993; Mohai & Saha, 2006). Previous studies have proposed different but not mutually exclusive explanations for this including a lack of financial capacity (Galster & Keeney, 1988), discriminatory siting of hazardous facilities (Pastor et al., 2001), housing market discrimination (Dawkins, 2004; Freeman, 2004; Galster & Godfrey, 2005), and a lack of adequate knowledge about the risks (Zhang, 2010). On the other hand, studies of subsidized housing have also shown that these programs usually fail to deconcentrate poverty, in some cases create negative spillover effects on neighborhoods, and may even further concentrate poverty (Galster, 2013; Galster et al., 1999; Schill & Wachter, 1995). There is also evidence that market-oriented housing programs can actually incentivize low-income households to live in disadvantageous, low-rent neighborhoods (Freeman, 2004; Galster et al., 1999; Hollar & Usowki, 2007; Oakley, 2008). Since both natural and technological hazards exert a negative effect on residential property values (Shultz & Fridgen, 2001; Speyrer & Ragas, 1991), it is reasonable to expect that subsidized housing programs may contribute to more low-income households living in those hazardous areas. Because minorities and low-income home owners usually do not have adequate knowledge about the risks associated with hazardous and toxic materials (Zhang, 2010), the probability that they may move into multi-hazard areas is even higher. However, it is also true that in some cases hazard exposure, in terms of distance to rivers and coastline, can also be perceived as an amenity (Smith et al., 2009) for the recreational opportunities and scenic views it may offer. As a result, such areas can serve as an important counterexample that defies the general trend (i.e., high hazard exposure coupled with low social vulnerability). These areas also can be expected to have fewer subsidized housing units due to higher land values. Ultimately, the above proposition should still hold that when located in hazardous areas, a higher proportion of subsidized units may be associated with a higher proportion of low-income minority households in the neighborhood.

The conceptual framework of this dissertation is presented in Figure 2.3 below. As shown, under the broader political-economic framing of vulnerability this dissertation examines the ways in which vulnerable populations may move into hazard exposed areas. The first stage of the study explores the changing pattern of social vulnerability (in three coastal cities) over time and in the second stage it delves into one case study city, hypothesizing that subsidized low-income housing programs may act as a key driver of social vulnerability in hazardous areas.

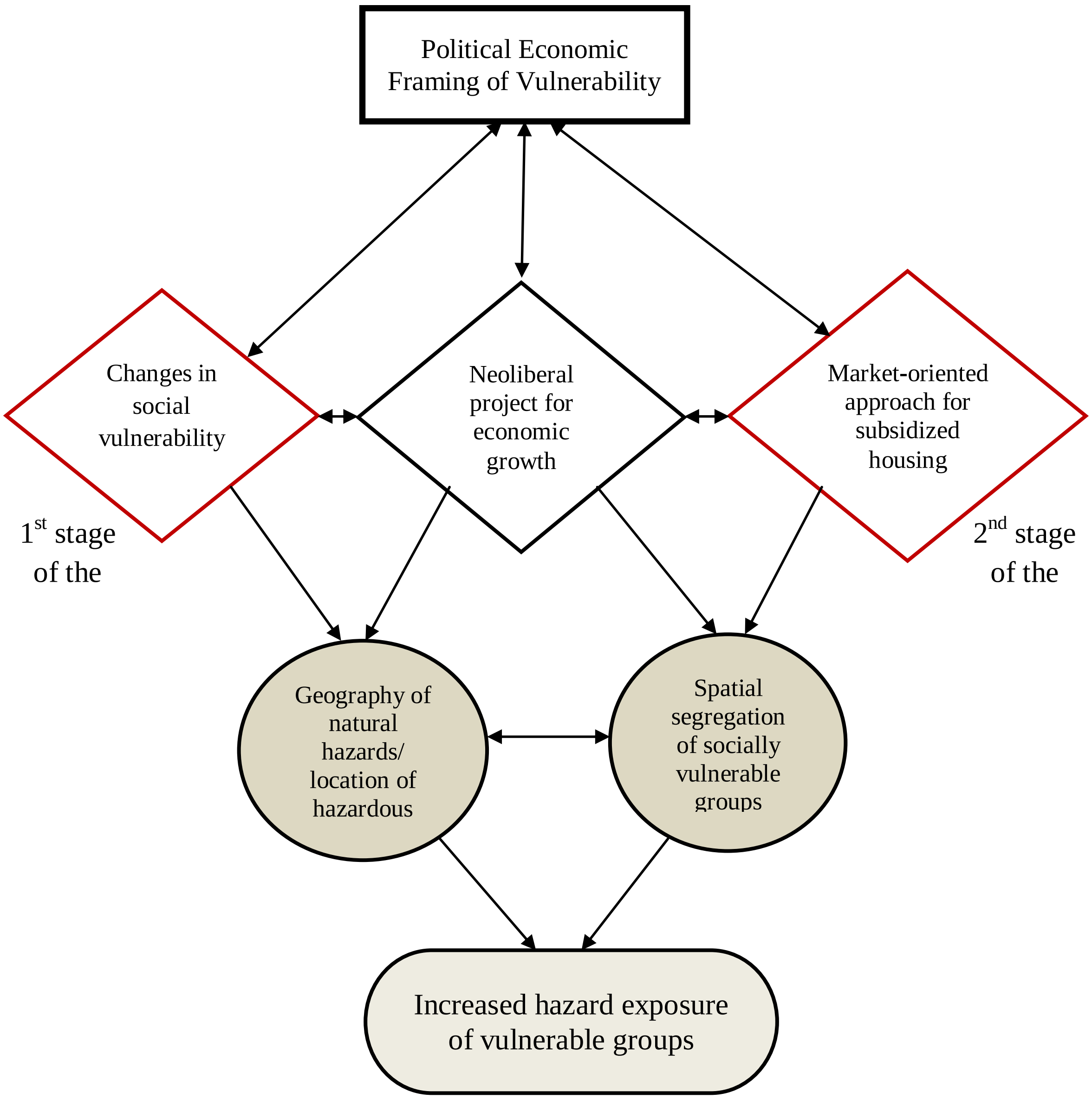

Figure 2.3: Conceptual framework of the dissertation

CHAPTER 3
RESEARCH METHODOLOGY

As discussed in the previous chapter, this dissertation is conducted in two stages—the first stage explores social vulnerability in three case study cities and the second stage examines the influence of subsidized housing programs on social vulnerability and hazard exposure in Houston, Texas. The methodology is discussed in detail here after a brief introduction to the case study cities.

3.1 Case Study Cities

For the first stage of the dissertation, similarity of geographic location and variation in population trends were the primary criteria for selecting case study cities. All three case study cities are located in the U.S. Gulf Coast region, but within different state jurisdictions—Houston in Texas, New Orleans in Louisiana, and Tampa in Florida. All of these cities are considered highly exposed to climate change impacts (Nicholls et al., 2008), but have varying levels of population and assets exposure (Table 3.1).

Table 3.1: Case Study Cities

Case study cities	**Population growth (2000-10)**	**Current climate exposed pop. (thousands)***	**Current climate exposed assets (billion $)***
Houston, TX (Harris County)	7.46%	59	12.21
New Orleans, LA (Orleans Parish)	-29.06%	1,124	233.69
Tampa, FL (Hillsborough County)	10.63%	415	86.26

* Estimates from Nicholls et al. (2008), Appendix 3: City Data and Rankings

Since the boundary of the cities has changed over time, their respective counties[6] are used to spatially delineate the study cities for this research. Figure 3.1 shows different trajectories of population change over time in each of the three study areas. While Houston has experienced consistent growth since 1960, Tampa was characterized by relatively moderate growth, and New Orleans experienced consistent decline.

[6] Counties encompassing the core cities are considered for this study to maintain a consistent geographic area over time. Metropolitan areas not considered since MSA boundaries have also changed over time and outlying rural areas may significantly influence the results of this study.

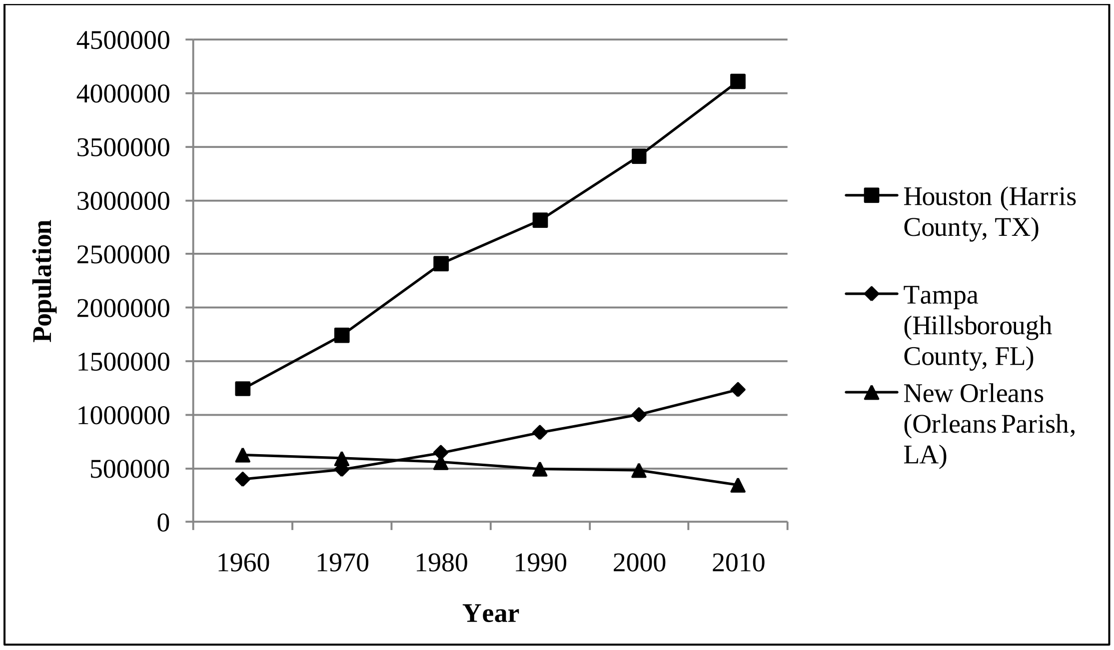

Figure 3.1: Population trends of case study cities

For the second stage of the dissertation, Houston (i.e., Harris County) serves as a detailed case study for examining the longitudinal relationship between subsidized low income housing and hazard exposure. The distinctly neoliberal approach to policy making that characterizes Texas also makes Houston the most suitable choice, given the political-economic framing of this study. Since the city boundary of Houston has changed, Harris County is adopted as the case study unit of analysis in order to maintain a consistent geographical extent over time. This area is also a prime candidate for the dissertation due to its multi-hazard environment. Harris County is the third most populous county in the United States[7] with about 4 million residents[8] and is located in the low-lying Texas coastal area that is exposed to both hurricane and flood hazards (Cutter, 2003). Besides natural hazards, there are also hundreds of petrochemical manufacturing and distribution facilities across the county, which elevates the potential for toxic chemical hazards (EPA, 2008). Harris County is also demographically and socioeconomically diverse. According to 2012 American Community Survey data, the Hispanic and Latino population accounted for 41.5 percent and the African American population accounted for 19.5 percent of the total

[7] Both in the 2000 and 2010 Decennial Census.
[8] Total population of Harris County was 3,400,578 in 2000, which increased to 4,092,459 in 2010, as per the 2000 and 2010 Decennial Census respectively.

population, with 17.3 percent of population below poverty level in this county. This diversity further recommends Harris County and the City of Houston as an interesting case for evaluating the location decisions of vulnerable low-income population groups in this urban agglomeration and how existing subsidized housing programs are influencing this vulnerability pattern.

3.2 Evaluating the Changing Patterns of Social Vulnerability

A variety of methods have been employed to measure social vulnerability at many different scales, but the one constant has been a consensus on the multidimensionality of this concept. For example, vulnerability is often understood to include poverty (Fothergill & Peek, 2004; Long, 2007), race and ethnicity (Fothergill et al., 1999; Peacock et al., 1997), gender (Enarson & Morrow, 1998; Enarson et al., 2007), and age (Anderson, 2005; Smith et al., 2009). In order to evaluate social vulnerability dynamics in the study cities (**Research Question 1**), the Social Vulnerability Index (SoVI) is calculated decennially at the census tract level over a 30 year time period (1980-2010). This was accomplished using the inductive approach for measuring social vulnerability developed by (Cutter et al., 2003) with some modifications considering data availability and suggested refinements to this foundational method by subsequent studies (Finch et al., 2010; Tate, 2012). Cutter et al. (2003) considered 42 variables for their study at the county level, but since this dissertation measures social vulnerability at the census tract level and focuses more on the social construction of vulnerability, it considers 26 variables, following the approach of (Finch et al., 2010). The list of variables used for SoVI calculation is presented in Table 4.1 of Chapter 4. For 2010, these variables were collected from U.S. Census American Community Survey (ACS) 2008-2012, and for 1980 to 2000, data were drawn from the decadal census reports of U.S. Census Bureau[9]. Since the ACS data are based on sample surveys over a five-year period, 2008-2012 is considered representative data for 2010. The boundaries of census tracts also changed significantly in 2010, which makes it very difficult to construct a longitudinal database of the type required here. For the purposes of longitudinal comparison, all the data (1980 to 2010) were converted to 2010 census geography following the Longitudinal Tract Data Base (LTDB) approach developed by Logan et al. (2014). Census tracts with high group quarters populations (e.g. jails, university campuses, etc.) or too few residents in any time period were excluded from the analysis. These collected data were then normalized to

[9] Census reports of 1980 to 2000 are collected from Social Explorer (http://www.socialexplorer.com/).

percent, per capita, or density functions given the differential population and area of census tracts. Each of the variables is standardized as a z-score[10] before being incorporated into the Principal Components Analysis (PCA) so that no individual variable influences the final vulnerability score more than another. Before applying PCA to calculate the SoVI, biplots with alpha-bags (La Grange et al., 2009) were created to explore distributions of data over the years and to visualize the changing patterns of the various dimensions of social vulnerability.

3.3. Multidimensional Biplots for Exploring Social Vulnerability

The distribution of selected vulnerability indicators and their relationship with each other can be visualized through two-dimensional scatter-plots, but such plots can only present two variables and cannot show how all the variables are distributed in relation to each other. Biplots were introduced by Gabriel (1971) as a graphical display tool consisting of a vector for each row and a vector for each column of a matrix of rank two. Here the prefix "bi-" refers to the simultaneous display of both the rows and columns of a data matrix and not to the dimension of the display space. It is also described as a multivariate analogue of the ordinary scatter plot (Gower & Hand, 1996). While a scatter-plot portrays the covariation of two variables, a biplot can contain as many axes as there are variables so as to provide information on all variables in a single plot. Biplots represent different variables by axes similar to ordinary scatter-plots and calibrate these axes in the original scales of measurement (Gardner et al., 2005). Here the individual observations are represented as points, and variables are represented as labeled, calibrated axes (La Grange et al., 2009). To accommodate more than two variables, the axes of biplots are not perpendicular as in ordinary scatter-plots, but they are still used in a similar way to provide information on all variables. As a multivariate extension of an ordinary scatter plot, non-statisticians should comfortably understand the basics of the biplot, enabling them to interpret the biplot display with relative ease (Walters & Roux, 2008).

Since this dissertation explores how different dimensions of vulnerability are distributed over time, correlation biplots are created for each of the time periods (and for each of the study cities) separately. The biplot follows an ordinary eigenvalue[11] problem and aims to optimally

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[10] The z-score was calculated as follows: $Z_{Tract} = (Score_{Tract} - Mean_{Metro}) / Standard\ Deviation_{Metro}$

[11] In Principal Component Analysis (PCA) the variance for each principal component is given by the eigenvalue of the corresponding eigenvector. The eigenvalue of each component indicates the percentage of variation in the total data explained by this component. For more discussion on eigenvectors and eigenvalues see Manly (1986).

represent the multidimensional variation of the observations in two dimensions (Gardner et al., 2005). Like ordinary scatter plots, biplot axes do not intersect perpendicularly. In this case angles among the axes indicate correlations among the variables, where a *smaller angle* refers to a *larger correlation* (Le Roux & Gardner, 2005). Such a biplot can be overlaid with an alpha-bag (Gardner, 2001) to better present and aid interpretation of a large number of variables. An alpha-bag is a contour enclosing the exact innermost α percentage of sample points in a biplot (Gardner et al., 2005). The distribution of the selected variables within the alpha-bags indicates how different dimensions of vulnerability are related and comparing alpha-bags of different time periods indicate how this relationship changes over time. Chapter 4 further elaborates on biplots and shows how the dimensions of social vulnerability have changed over time for each of the study cities.

3.4 Calculation of SoVI and Exploring Its Distribution

Biplots with alpha-bags (for all four census years) visually indicate the changing pattern of vulnerability dimensions, but for quantifying the relative levels of vulnerability, the Social Vulnerability Index (SoVI) is calculated at the census tract level. Since the SoVI algorithm of Cutter et al. (2003) has been found to be robust enough to withstand minor changes in variable composition and scale (Schmidtlein et al., 2008) and precision (Tate, 2012), this dissertation adapts this approach to measure social vulnerability at the census tract level. The SoVI is derived through Principal Component Analysis (PCA) which identifies a smaller set of independent factors that account for a majority of the overall variance within the original data. These component parts are then interpreted and assigned a general socioeconomic or demographic interpretation based on which factors loaded highest on each component. One of the key steps in this process is to choose the optimum number of factors to retain from the principal component analysis. Cutter et al. (2003) applied the Kaiser criterion[12] for selecting the number of factors, but recent studies have shown that use of the Kaiser criterion overestimates the number of factors to retain (O'Connor, 2000; Patil et al., 2008). Considering this limitation of the original approach of Cutter et al. (2003), this dissertation applies parallel analysis[13] for determining the optimum

[12]In which all components with an eigenvalue greater than one are retained.

[13] The rationale behind Parallel Analysis is that sampling variability may produce an eigenvalue greater than one even if all eigenvalues of a correlation matrix are exactly one and no large components exist (Zwick & Velicer, 1986). Parallel analysis applies principal components analysis to a random matrix of identical dimensionality and compares it to the research data set. Through a Monte Carlo simulation approach it produces a distribution of

number of factors as suggested by (Tate, 2012).

The aim of applying PCA to the standardized variables is to identify a certain number of factors that explain most of the variation in the dataset. These factors are interpreted and named based on the characteristics of the variables that are most closely associated with it and typically informed by one or more dominant variables. All factors are rescaled so that positive values indicated higher levels of vulnerability, while negative values are consistent with a decrease in vulnerability. The factor scores are then aggregated in an additive model to derive the overall composite social vulnerability score. The additive model assigns equal weight to all components, which makes no a priori assumptions about the relative importance of each component in producing social vulnerability (Cutter et al., 2003; Finch et al., 2010). This process of SoVI calculation is applied to each of the study areas (Houston, New Orleans, and Tampa) and for all time periods (1980, 1990, 2000, and 2010) separately. To determine the patterns of similarity and dissimilarity in the clustering of social vulnerability, the degree of spatial autocorrelation among the census tracts is evaluated. This portion of the analysis measures and visually depicts the spatial pattern of social vulnerability in each of the different study city contexts and how it has changed over time. Local Indicators of Spatial Association (LISA) cluster analysis (Anselin, 1995) helps to identify the areas with significantly higher concentrations of vulnerable populations.

Comparing the z-scores of the SoVI at the tract level shows which areas of the city (with respect to other parts of the city) have experienced a significant increase or decrease in vulnerability over time. The degree of spatial autocorrelation of the SoVI evaluates the pattern of change in social vulnerability throughout the study cities and how it varies in different city contexts. Chapter 4 discusses further on the statistical measures applied to compare SoVI and presents the results for all three study cities.

3.5 Subsidized Low-Income Housing as Driver of Social Vulnerability

This second stage of the study is conducted in two steps. First, the level of exposure to both natural (flood and hurricane) and technological hazards are evaluated for the entirety of

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eigenvalues for each principal component in the random dataset. Simulated eigenvalue distributions are compared to the observed eigenvalues and whatever number of eigenvalues in the observed dataset exceeds the corresponding value in the simulated dataset is considered as the optimal number of factors to retain. This procedure usually results in a fewer number of factors (compared to Kaiser criterion) and considered as a superior alternative for determining the optimal number of factors (Tate, 2012).

Harris County, Texas, and population trends (for different vulnerable groups) within these areas are explored (**Research Question 2**). In the second step, spatial econometric models are applied to evaluate the extent to which subsidized low-income housing is influencing the hazard exposure of vulnerable population groups in Harris County (**Research Question 3**). Given the availability of data on subsidized housing, this part of the study was conducted for the period of 2000 to 2010.

3.5.1 Hazard Exposure and Social Vulnerability

In order to capture the multi-hazard landscape of Harris County, both natural and technological hazards are included in this study. Given the high risk of floods and hurricanes in Harris County area, these two hazards are considered under the domain of natural hazards. For technological hazards, exposure through the facilities identified in the Toxic Release Inventory (TRI) of EPA is considered due to the prevalence of such industries in the low-lying areas of Houston. The impact areas for flooding and hurricane storm surge are identified based on publicly available outputs of computer modeling. The U.S. National Hurricane Center used the SLOSH (Sea, Land, and Overland Surge from Hurricanes) model to estimate worst-case-scenario storm-surge boundaries (Tate et al., 2010) and produced surge zones for each of the Saffir-Simpson categories. GIS floodplain-boundary representations of these model outputs are available from FEMA Digital Flood Insurance Rate Map (DFIRM) database. Category-1 hurricane risk zones and 100-year floodplains were identified from these sources and combined to identify and map the natural hazard exposed areas of Harris County. The proportion of residential lots falling within these areas was used as the indicator for determining the relative natural hazard exposure level of each census tract. This approach is similar to Cadastral-based Expert Dasymetric System (CEDS) methodology of Maantay et al. (2007) that considers residential area or the number of residential units as proxies for population distribution. This technique gives a more realistic population distribution compared to traditional mapping methods and is particularly useful for evaluating flood exposure in an urban environment (Maantay & Maroko, 2009a). Parcel information for Harris County was used in this study as the ancillary data required for the CEDS approach. These data were collected from the Harris County Appraisal District (HCAD) public downloads FTP site and the locations of residential lots were extracted. ArcGIS tools were used to combine the flood and hurricane risk maps, clip the residential lots located within risk areas, then intersect these layers with census tract layers to calculate the percentage of residential lots within the natural hazard areas of each census tract. Areas with a higher percentage of its residential lots falling in the flood or hurricane risk areas are considered to be more exposed to natural hazards.

For evaluating technological hazards, environmental pollution data collected by the United States Environmental Protection Agency's Toxic Release Inventory (TRI) were used for this study. The TRI is one of the most widely used data sources for environmental justice studies. Any facility that releases toxic chemicals is required to submit reports to the Environmental Protection Agency if certain minimum release thresholds and other criteria are met as mandated by the Emergency Planning and Community Right-to-Know Act (EPCRA) of 1986. The locations of Toxic Release Inventory (TRI) facilities in Harris County were obtained by querying the TRI.NET application of the US Environmental Protection Agency (EPA). This application allows users to select, sort, and filter TRI data by geography, year, and hazard type. The location and total toxic release data of all facilities in Harris County for all years from 2000 to 2010 were collected to evaluate the relative hazardousness of the county's census tracts. All the locations were checked after mapping them by both geocoding addresses and plotting latitude and longitude coordinates. Since the release levels may vary from year to year for a certain facility, data for all years were considered in calculating the average level of hazardousness.

An effective method for defining proximity and potential exposure to environmental hazards remains a widely debated issue in the environmental justice literature (Chakraborty & Maantay, 2011; Conley, 2011). Since this study is interested in proximity to hazards and its relative influence on social vulnerability, exposure based on distance decay or continuous distance from the hazard was deemed the best approach. But here as well there is no recognized standard for what the threshold distance of exposure from a facility should be or how the distance decay function should be defined. Considering this methodological uncertainty, two approaches were taken here that have contrasting distance decay specifications and can accommodate multiple threshold distances. The first approach uses a power function (Conley, 2011) and the second approach considers cumulative exposure (Cutter et al., 2001) within a specified threshold distance. For both of these approaches, the total release from a given TRI facility is used as an indicator of its relative level of influence without considering the toxicity level of the chemicals released by them. It can be assumed that the total release will be commensurate with facility size and hence, a better indicator of relative influence on its surrounding region. The two approaches taken for evaluating technological exposure are explained below.

The first approach uses the power equation, taken from the physical model of gravity, and considers that the impact of a facility is proportional to the size of the release and inversely proportional to the distance (from a census tract centroid) raised to a parameterized component (Conley, 2011). The equation can be shown as:

$$y_i = \sum_{j}^{\#Facilities} \frac{w_j^{\theta}}{d_{ij}^{\theta}}$$

Here y_i is the weighted cumulative exposure of census tract i, w_j is the total release from facility j and d_{ij} is the distance from facility j to tract i. In this equation θ is a positive constant that determines the rate of decrease to which a facility may impact its surrounding region. To operationalize a situation where a facility exerts a very high impact on its immediate neighboring area and then its influence decreases rapidly with distance, θ is assigned a value of 2 in this study (Figure 3.4). An additional reason for this specification is that no threshold distance or cutoff point for facility impact (which is considered in the second approach) is assumed and hence, a given facility will still have a minimal impact on far away tracts.

In the second approach, risk exposure at the census tract level was measured based on the potential exposure model of Cutter et al. (2001). Like the first approach, it is also based on the distance to existing hazard source and can incorporate multiple hazard sources, but has the option to impose a threshold distance or cutoff point on facility impact. The index measured through this model is labeled as *proximal exposure* as it does not purport to represent actual exposure. This proximal exposure model includes multiple hazard sources in order to compute a *cumulative proximal exposure* (CPE) for a census tract Cutter et al. (2001). Cumulative proximal exposure is defined as the sum of proximal exposure associated with each tract:

$$WCPE_i = \sum_{j}^{\#Facilities} w_j \left(1.0 - \frac{d_{ij}^{\theta}}{T}\right)$$

Here, $WCPE_i$ is the weighted cumulative proximal exposure to population in census tract i from distance to facility at locations 1 through j (total number of facilities), w_j is the total release from facility j, d_{ij} is the distance from tract i to facility j, T is the threshold distance at which exposure becomes negligible from a facility, and θ is the rate of reduction of exposure at increasing distance from *j*. Unlike the power function of the first model, this model assumes a distance, *T*, at which the proximal exposure becomes zero. This point is called the "negligible threshold" beyond which there is no locational risk. In this case the impact from a facility to its neighboring region decreases much more slowly (compared to power function), but does not assume any impact beyond the threshold distance (Figure 3.2). For the present analysis, θ is assigned a value of 2 (following Cutter et al. (2001)) and the negligible threshold is taken at multiple distances to evaluate whether the results change due to the threshold distances (i.e., sensitivity analysis). All the results presented in Chapter 5 were tested for threshold distances of 1, 3, and 5 miles[14], but only the results from conservative estimate of 1 mile are presented after finding that it yielded the most consistent results.

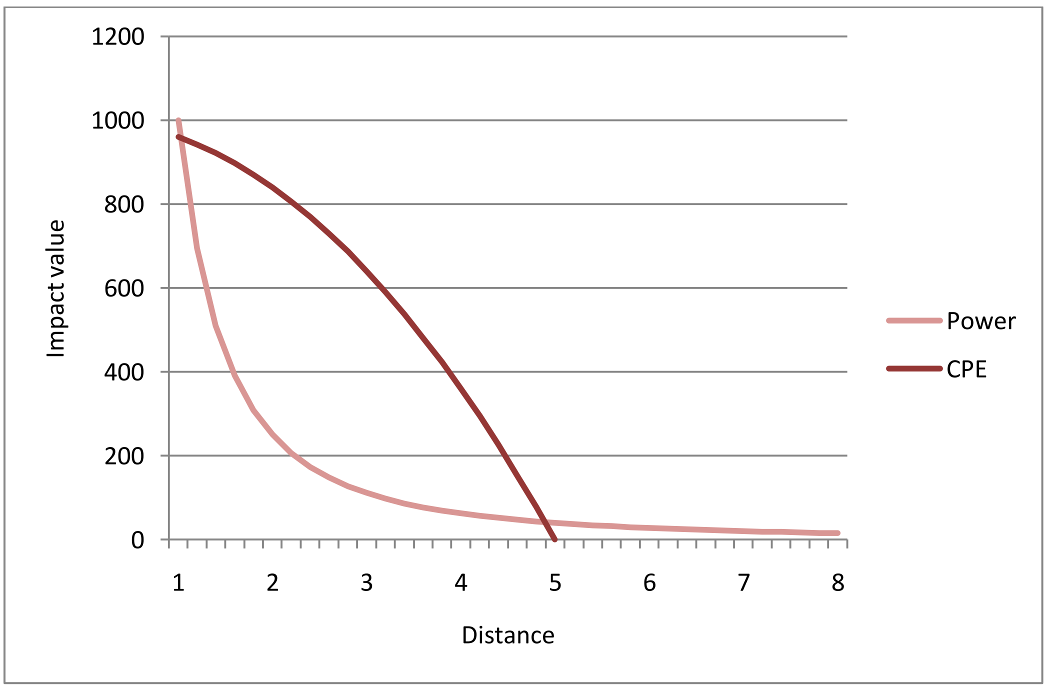


Figure 3.2: Comparison of distance decay functions. (For both functions θ =2, *w*=1000, and for CPE T=5 is considered to show a hypothetical TRI facility may impact its nearby region.)

The two approaches discussed above produce two different hazard landscapes for the study area and hence, should provide a deeper understanding of the dynamics between subsidized housing and social vulnerability in the study area. For both of the approaches,

[14] Since there is no widely accepted threshold distance, this study tested the results in these three distance bands of 1,3, and 5 miles following the approach of Cutter et al. (2001) who also evaluated their results on 1 to 5 miles distance range. While Cutter et al. (2001) tested it for census tract level analysis, a subsequent study of Conley (2011) applied it for County level data with much larger distance threshold (5, 10, 15,….500 miles).

technological exposures at the census tract level were calculated for all years from 2000 to 2010 and then the average level of exposure was calculated, which represents the relative hazardousness of an area. Population trends, for different dimensions of social vulnerability (i.e. minority, low-income, etc.) were explored within census tracts having different levels of exposure to natural or technological hazards.

3.5.2 Low-Income Housing in a Multi-Hazard Environment

Data on the location and type of subsidized housing from the Department of Housing and Urban Development (HUD) were used for this study. HUD maintains the LIHTC Database and the *Picture of Subsidized Households* data set, which disaggregates building-based public and private "fixed" subsidies (Public and Indian Housing, Section 236, Section 8 New Construction and Substantial Rehabilitation, FHA, LIHTC) from person-based "voucher" subsidies (Section 8 vouchers and certificates). These data were further verified against information collected from the Houston Housing Authority (HHA) and Texas Department of Housing and Community Affairs (TDHCA) to check the accuracy of the location and number of subsidized housing units. After geocoding the locations of the housing units, the total number of housing units (by type) in each of the census tracts was calculated. Considering variation in the coverage and approach of different housing assistance programs, this research focused on two programs that are among the most popular and widely used (Schwartz, 2010)—Section 8 or the Housing Choice Voucher (HCV) program and the Low Income Housing Tax Credit (LIHTC) program. These two programs also represent contrasting approaches for providing housing assistance, the supply-side (LIHTC program) and the demand-side (vouchers). However, HUD's *Picture of Subsidized Households* data set is consistently available only beginning in 1996 and to make it comparable with census data, 2000 and 2010 were chosen as the two time periods for HCV data. For the LIHTC data (collected from HUD's LIHTC Database), the locations of the properties were geocoded, then the year when a project was placed in service was extracted and used to assign them to either 2000 or 2010 (i.e. all active projects built before 2000 are assigned to year 2000, and all projects developed after 2000 are assigned to year 2010). For all of the LIHTC properties in a census tract the number of low income units available were aggregated to obtain total number of subsidized households in that tract attributable to this program.

Before applying regression analysis to the social vulnerability and housing subsidy dataset, some of the key variables were explored through descriptive statistics. Principal

Component Analysis (PCA), applied for developing the SoVI, revealed the key indicators that explain most of the variation in the original data, which were race and poverty. Whether an increase in housing subsidies in a hazardous area contributes to social vulnerability there (e.g., higher poverty) compared to other areas which did not experience an increase in housing subsidies between 2000 and 2010 is a question that emerged from this initial exploration of the data. As hypothesized here, we should see a significant increase in vulnerable populations in an area (compared to other areas) when it receives increased number of housing subsidy and is also located in a hazardous area. While prior studies have extensively explored the neighborhood impacts of housing subsidy and found mixed results (Freeman, 2003; Galster et al., 1999; Holloway et al., 1998; Oakley, 2008), this kind of interaction between hazard exposure and housing subsidies, alongside their combined effects on neighborhood social vulnerability is yet to be explored.

3.5.3 Model Selection and Analysis

Both standard OLS regression and spatial regression models were estimated to evaluate the above mentioned hypothesis, which necessitates controlling for base year neighborhood socio-economic characteristics along with changes in these characteristics in the 10 year period between 2000 and 2010. Particularly, considering the spatial pattern of vulnerability concentration and diffusion (as presented in Chapter 4), a spatial Durbin model (LeSage & Pace, 2009) was estimated to evaluate the extent to which subsidized housing may have contributed to the location of vulnerable populations in hazard exposed areas. Here the dependent variables are the number of residents exhibiting key dimensions (determined from the SoVI analysis) of social vulnerability (e.g., African-American population in poverty, Hispanic population in poverty, etc.) while four interaction variables (e.g., two hazard types by two subsidy types) are the key independent variables for this model. All other variables related to social vulnerability and hazard exposure were treated as control variables. The rationale for estimating a spatial Durbin model (SDM) is due to the patterns of spatial dependence among social vulnerability, hazard exposure, and housing subsidy observed by previous studies. First, prior studies have shown significant clustering of minorities and low-income households in neighborhoods vulnerable to hazardous and toxic materials (Bullard, 1999; Massey & Denton, 1993; Mohai & Saha, 2006). Second, subsidized low-income housing has been found to be geographically concentrated in certain areas (Oakley, 2008), and sometimes highly clustered in areas characterized by high poverty rates, minority concentrations, and poor educational opportunities (Van Zandt & Mhatre, 2009). The provision of incentives through qualified census tracts (QCTs) for the LIHTC program was also found to be contributing to higher numbers of low-income housing in high-poverty areas (Abt Associates, 2006; Hollar & Usowki, 2007). Thirdly, studies have found negative spill-over effects of subsidized housing on land value, crime, middle class flight, and concentration of poverty (Galster et al., 1999; Holloway et al., 1998; Massey & Kanaiaupuni, 1993). In light of this evidence, it can be expected that subsidized housing and poverty concentration are not only related within a neighborhood, but also influencing surrounding neighborhoods, and to capture the spill-over effects (if there are any) the SDM should be a better modeling approach. An unconstrained SDM is a general-to-specific approach which can consider such indirect spatial interactions as when the exogenous explanatory variables influence not only the dependent variable in an area, but also in neighboring areas as well (LeSage & Pace, 2009).

The most commonly encountered specification in spatial econometrics is the spatial lag model (Anselin, 1988; LeSage & Pace, 2009; Ord, 1975):

$$y = \rho W y + X\beta + \varepsilon \qquad (1)$$

where y is a vector of observations on a dependent variable taken at each locations, X is a matrix of exogenous variables, W is row-standardized n by n spatial weight matrix, β is a vector of parameters, ε is a vector of independent and identically distributed disturbances and ρ is a scalar spatial lag parameter. The spatial error model can be written as (Anselin, 1988; LeSage & Pace, 2009; Ord, 1975):

$$y = X\beta + u \qquad (2)$$

$$u = \lambda W u + \varepsilon \qquad (3)$$

Here λ is the spatial autoregression parameter of error term u. While spatial lag model (1) treats spatial correlation as a process or effect of interest and incorporates spatial dependence (Wy), the spatial error model treats spatial correlation as a nuisance and examines whether the error term has a spatial dependency (Wu). The spatial Durbin model, on the other hand, includes a spatial lag of the dependent variable as well as spatial lags of the explanatory variables:

$$y = \rho W y + X\beta + WX\theta + \varepsilon \qquad (4)$$

where θ is a vector of parameters. Here ρ is the spatial autoregressive parameter that measures the degree of spatial dependence between the numbers of vulnerable population of nearby census tracts. The WXθ term in Eq. (4) captures the extent to which the characteristics of neighboring areas (for hazard exposure and housing subsidy) influence the size of vulnerable populations in an area and specifically captures the spill-over effect of subsidized housing shown by previous studies (Galster, 2013; Galster et al., 1999; Schill & Wachter, 1995). The Wy term is expected to capture the clustering of minority and low-income populations in certain areas of the city and the SDM is solved using maximum likelihood estimation (Bivand & Gebhardt, 2000; LeSage & Pace, 2009).

Before applying the spatial Durbin model, Elhorst (2010) suggests that other modeling alternatives be explored to find out which model is the most likely candidate to explain the data and test hypothesized relationships. LeSage & Pace (2009) advocate for use of the SDM model as the model to test for spatial interaction effects for two main reasons. First, in the case that the true spatial process is one in which spatial dependence exists between the *dependent variable in one area* and the *exogenous covariates in neighboring areas*, and these variables happen to be correlated with independent variables not omitted from the model, the SDM will produce unbiased coefficient estimates (but a spatial lag model will not). This is considered to be a salient issue for this study, since vulnerability indicators (poverty, minority populations etc.) tend to be clustered in space, thus implying correlation between the values in neighboring tracts. Second, when the true spatial process is one in which the outcome variable is spatially correlated with the exogenous covariates within the same tract or in which there exists a spatially correlated error term (i.e. spatial error model), the SDM model will continue to produce unbiased coefficient estimates[15]. So it can be inferred that, except under circumstances in which the spatial lag or error model is an unequivocally better fit to the underlying spatial process, the SDM model is the preferred option. It should also be noted that in recent simulation experiments conducted by Beer & Riedl (2012), the spatial Durbin model also outperformed a structural equations model (SEM) specification.

Elhorst (2010) proposed a procedure to determine which model, among OLS, spatial lag, SEM, and SDM is the most likely candidate to explain the data. In this procedure, first an OLS model is tested to check if a spatial lag or spatial error model is more appropriate for describing the data. The classic LM-tests (Anselin, 1988) and the robust LM-tests (Anselin et al., 1996) can

[15] Spatial dependence in the error term modeled in the spatial error model is usually referred to as nuisance dependence (Anselin, 2003). The spatial error model usually loses its popularity given its lack of interpretation of spatial dependence and, more importantly, its susceptibility to omitted variables (Brown et al., 2009).

be used for this purpose. If the OLS model is rejected in favor of a spatial lag specification, the spatial error model, or in favor of both models (as indicated by LM tests), then the spatial Durbin model (SDM) should be estimated. If these models are estimated by maximum likelihood, Elhorst (2010) suggested using a likelihood ratio (LR) test to evaluate the hypothesis H_0: $\theta = 0$ and H_0: $\theta+\rho\beta = 0$. The first hypothesis examines whether SDM can be simplified to spatial lag model (Eq. 1) and if it cannot be rejected, then the spatial lag model best describes the data (provided that the robust LM also pointed to the spatial lag model). The second hypothesis examines whether the SDM can be simplified to the spatial error model (Eq. 2, if $\theta = -\rho\beta$ then $\lambda=\rho$), and if it cannot be rejected, then the spatial error model best describes the data (provided that the robust LM also pointed to the spatial error model). If none of these conditions are satisfied, then SDM should be adopted, because it generalizes both the spatial lag and spatial error models (Elhorst, 2010).

In case the estimated OLS model is not rejected in favor of both the spatial lag and the spatial error model, Elhorst (2010) suggested reestimating the OLS model with spatially lagged independent variables (*WX*). This approach allows testing of the hypothesis H_0: $\theta = 0$, and if this hypothesis also cannot be rejected, then the OLS model should be adopted. On the other hand, if this hypothesis is rejected, then there should be another iteration applying the SDM and testing the additional hypothesis H_0: $\rho = 0$. If this hypothesis is also rejected, then SDM should be considered; otherwise, the spatial lag model should be considered as the best description of the data[16]. This procedure proposed by Elhorst (2010) was adopted for this study to identify statistical models describing the changing patterns of social vulnerability in Harris County, Texas. Chapter 5 discusses these models and their findings in greater detail.

3.6 Analysis of Policy and Planning Practice for Subsidized Housing

Findings from the spatial analysis described above indicates the extent to which subsidized low-income housings are clustered in Houston and how they are contributing to the concentration of vulnerable populations in hazardous areas. In this last stage of the dissertation, policies and planning approaches for locating subsidized housing are evaluated and suggestions are offered for making them more consistent with climate change adaptation and disaster risk reduction efforts (**Research Question 4**). HUD regulations for locating subsidized housing in a

[16] For elaborate discussion on model comparison procedure and more statistical background, see Elhorst (2010)

multi-hazard environment were reviewed to compare those provisions with the HCV and LIHTC programs. Housing officials with the Houston Housing Authority were interviewed to gauge awareness of the prevailing issue of environmental justice in the study area and what factors are considered when permitting (or issuing tax credits) for construction of any subsidized housing. Since prior studies have found significant variation in location outcomes (of subsidized housing) depending on local housing markets and planning approaches (Galster, 2013; Pendall, 2000), it is necessary to evaluate how these aspects of Houston may have influenced the observed distribution of subsidized housing. A variety of documents on housing subsidy programs were collected and analyzed to determine how the allocation of funds for subsidized housing is made and which factors have guided the decision making process. Short visits to some of the LIHTC projects in Houston were made to see first-hand how they are situated with respect to hazard sources and to get a better sense of their surrounding neighborhoods. The findings from the interviews, document analysis, and field visits helped to highlight the limitations of present approaches for affordable housing and to identify opportunities for subsidized housing to become more consistent with climate change adaptation and disaster risk reduction efforts.

CHAPTER 4
CHANGING PATTERNS OF SOCIAL VULNERABILITY IN COASTAL CITIES

4.1 Theoretical Framework

Planning for climate adaptation tends to overemphasize future climate variability, which can lead to non-adaptive or even mal-adaptive outcomes (Barnett & O'Neill, 2010; Macintosh, 2013; Orlove, 2009). This approach runs the risk of focusing solely on identifying the climatic hazards of a place rather than exploring why people are located in hazard exposed areas in the first place. Recent research indicates that in addition to hazard exposure and physical vulnerability, social vulnerability, or the variation in characteristics such as income, race/ethnicity, gender, and household composition (among others), matters when predicting the impacts of coastal surge and flooding (Highfield et al., 2014). Adaptation approaches that ignore the social dynamics of a city can create an environment for non-adaptation when, despite efforts to climate-proof places, people are pushed into harm's way. This becomes more problematic in a multi-hazard urban environment where zoning restrictions or flood-proofing policies may further the climate adaptation of certain places, but the socially vulnerable population may only find it affordable to live in places which are exposed. The intersection of adaptation and social vulnerability demands a new approach to land use planning that is more responsive to how socially vulnerable people find their places within a multi-hazard urban area.

Although theories of neighborhood change and social vulnerability represent two distinct literatures, when considered jointly they should yield important insights into the vulnerability dynamics of a city. While neighborhood change theories explain the underlying forces that drive shifts in the demographic composition of neighborhoods (Glaeser et al., 2008; Peterman, 2000; Temkin & Rohe, 1996), social vulnerability theories explore how factors such as poverty, race, age, migration, etc. reduce the capacity of marginalized population groups to withstand hazard events or delay their recovery process (Blaikie et al., 1994; Hewitt, 1997; Peacock et al., 1997). This chapter integrates these two theoretical frameworks in order to explore changing patterns of social vulnerability in three coastal cities (Houston, New Orleans, and Tampa). Recognizing the historical path dependency of social vulnerability, this chapter analyzes three decades of data (1980-2010) to understand how the different dimensions of vulnerability interacted with each other over time and to identify emerging dimensions of vulnerability that warrant attention in future adaptation efforts. Since city boundaries often change significantly over time, the respective counties of the three coastal cities are taken as the study units to maintain geographic consistency. Houston is located in Harris County, Texas; New Orleans in Orleans Parish, Louisiana, and Tampa in Hillsborough County, Florida. As mentioned in Chapter 3, despite being located in the same Gulf Coast region, these cities are experiencing drastically different population trends, and also have different planning and policy approaches. One commonality among them is that all three cities are considered to be highly exposed to projected climate change impacts (Nicholls et al., 2008). Studying the changing pattern of social vulnerability within and across these cities should yield important insights for adaptation planning efforts in the region and beyond. The next section further discusses neighborhood change theories and how integrating those with social vulnerability theories will further the aims of this study. Changing patterns of vulnerability are explored through two different approaches, first by multidimensional biplots and then by measuring the Social Vulnerability Index (Cutter et al. 2003) and its spatial dimensions over time. Similarities and dissimilarities in longitudinal patterns of social vulnerability among the cities are identified and explained through the lens of neighborhood change theories.

4.2 Social Vulnerability and Neighborhood Change

Social vulnerability theorists contend that vulnerability is a social condition, a measure of societal resistance and resilience to hazards (Blaikie et al., 1994; Hewitt, 1997). In other words, this perspective emphasizes the socioeconomic characteristics that influence a community's ability to prepare for, respond to, cope with, and recover from a hazard event (Cutter et al., 2003; Laska & Morrow, 2006; Peacock et al., 1997) and is most often described using individual characteristics (e.g., age, race, health, income, type of dwelling unit, employment). This approach situates disasters and their impacts within broader social contexts and processes (Wisner et al., 2004) and emphasizes social factors that influence or shape the susceptibility of various groups to harm (Cutter et al., 2003). Studies of social vulnerability have extensively documented the disproportionate impacts of hazards events on socially vulnerable population groups (Cutter, 1996; Cutter et al., 2003; Fothergill & Peek, 2004; Highfield et al., 2014; Peacock et al., 2007; Zahran et al., 2008). Prior research has also shown that minority and low-income households usually have a lower level of disaster preparedness (Mileti & Darlington, 1997; Peacock, 2003; Russell et al., 1995), are less likely to hold earthquake or flood insurance instruments (Blanchard-Boehm, 1998; Fothergill, 2004), and are less likely to receive and believe official disaster warnings (Fothergill & Peek, 2004; Perry & Mushkatel, 1986; Perry & Nelson, 1991). Although these studies contribute important insights to better understanding the differential outcomes of disasters, they typically fail to explore the generative process of social vulnerability in a place—specifically, why vulnerable population groups move into hazardous areas and how present patterns of social vulnerability have evolved over time. Within the framework of social vulnerability there have been some efforts to incorporate societal processes and mechanisms of vulnerability (Eriksen & Kelly, 2007), but these studies are also limited in their scope by evaluating only cross-sectional variation. There have been attempts to explore longitudinal change in social vulnerability (Cutter & Finch, 2008), but very few studies (if any) have done so at the urban neighborhood level or attempted to explain the drivers for the changing geography and composition (of different dimensions) of social vulnerability.

Neighborhood change theorists have long investigated the underlying drivers of shifts in the social characteristics of urban neighborhoods and this literature also offers significant insights into the changing pattern of social vulnerability within the cities. While social vulnerability explores *what* makes people vulnerable to hazards, neighborhood change theories explain, among other things, *why* vulnerable people move to or concentrate in certain areas of a city. Integrating these two theoretical perspectives allows for a broader and more realistic framing of the changing patterns of social vulnerability, which is currently lacking in the vulnerability science literature. Neighborhood change theories explain the macro- and micro-level socioeconomic, political, and institutional forces that drive changes in neighborhood characteristics (Temkin & Rohe, 1996) and emphasize understanding the dynamics of neighborhood change to fully grasp the implications for urban planning and policy (Glaeser et al., 2008; Li & Morrow-Jones, 2010; Peterman, 2000). Within these theories there are three major schools of thought (Temkin & Rohe, 1996)—ecological, subcultural, and political economy. Within ecological change are the invasion-succession (Burgess, 2008), filtering (Hoyt, 1939), and neighborhood life-cycle models (Downs, 1981; Hoover & Vernon, 1959), which basically treat neighborhood change as a natural evolution process. Subcultural models (Firey, 1945; Gans, 1962; Suttles, 1972) reject the economic determinism of the ecological models and stress the attachment of residents to their neighborhoods as a key determinant of why and how residents live in certain parts of the city. Political economy models (Castells, 1983; Harvey, 1973; Logan & Molotch, 1987), on the other hand, highlight the institutional forces that influence neighborhood change. Rather than viewing urban development as a process of market equilibrium, as promoted by urban ecological theorists, political economists argue that social, economic, and political forces are the key drivers of neighborhood change. Considering the overall focus of this study and that it adopts a political economic framing of vulnerability production, political economy theories of neighborhood change are used to explain the changing patterns of social vulnerability within the study cities.

4.3 Political Economy Theories of Neighborhood Change

Political economy theorists explain neighborhood change through two broad streams of thought—the "urban growth machine" thesis (Logan & Molotch, 1987; Molotch, 1976), and the "urban restructuring" or "globalization" thesis (Borja & Castells, 1997; Sassen, 2000; Soja et al., 1983). While urban growth machine theorists argue that neighborhood change occurs through active exploitation of the real estate market and political process by local elites, theories of urban restructuring focus on how capital and labor restructuring at the global scale influences urban growth and movement within cities. One of the basic tenets of growth machine theorists is that the local growth coalition, driven by their fixation on economic growth, can bend the policy priorities of localities toward developmental rather than redistributional goals (Logan et al., 1997). This can be particularly problematic for vulnerable populations in poor neighborhoods who may face displacement and hardship, as happened through the 1960s "urban renewal" projects and now as a result of the gentrification process. Economic and labor restructuring, as argued by the urban restructuring theorists, also makes it harder for vulnerable populations to find better paying jobs or affordable housing. The transformation of the economy from manufacturing to services has relocated better paying jobs from the inner city to the suburban fringe and thereby, increased unemployment in poor neighborhoods (Dickens, 1999). Economic restructuring and increased liberalization also led the federal government to reduce funding for affordable housing (as discussed in Chapter 2) and made it difficult for vulnerable populations to find houses in safer areas. Decreased public spending on social services has strained low-income residents of many inner-city neighborhoods (Fainstein & Fainstein, 1985) and economic restructuring has contributed to poverty rates in predominantly black neighborhoods rising faster than in white neighborhoods (Galster et al., 1997).

Globalization of the economy coupled with local economic restructuring is rapidly changing the demographic composition of cities, particularly in the growing coastal cities of the U.S. Demand for low-wage workers fueled an influx of immigrant workers from Latin America and Asia, and thereby created a "heterogeneous mosaic of new and old ethnicities" (Soja, 2000) breaking down the dominant black-white race paradigm within the cities, as Soja et al. (1983) showed for Los Angeles. These forces are also changing the patterns of social vulnerability in urban neighborhoods and this reality needs to be accounted for in climate adaptation initiatives. The next section explores the evolving and increasingly heterogeneous nature of socially vulnerable groups within the three coastal urban counties using biplots and in later sections through the analysis of Social Vulnerability Index (SoVI).

4.4 Exploring Social Vulnerability through Biplots

An historical exploration of social vulnerability requires an evaluation of how the different dimensions of vulnerability are related to each other and how they have changed over time in different cities. Dimensionality reduction through Principal Component Analysis (PCA) is one approach, but visualizing these dimensions can help to explain and communicate how social vulnerability has evolved over time, given demographic shifts and urban growth. Biplots are effective for analyzing multivariate data in that they can simultaneously provide information on both the samples and the variables in a two- or three-dimensional representation (La Grange et al., 2009; Le Roux & Gardner, 2005). For this study, the neighborhoods or census tracts are the samples and variables selected for measuring social vulnerability (as shown in Table 4.1) are the variables represented as a calibrated axis on the biplot. The distribution of the sample points on a biplot indicates how different census tracts are located along the axis of all the variables and at the same time, how the variables (or axes) are related to one another. Correlation biplots are created for this analysis that scale all the variables to unit variance[17] and then adjusts the points and axes in such a way that the cosines of the angles between the axes approximate the correlations between the corresponding variables (La Grange et al., 2009). This means that if two

[17] For calculating unit variance, all elements of a data matrix X are divided by their standard deviations (i.e., $\frac{[X]_{ij}}{sd(X_{(j)})}$). For correlation biplots, data are also centered around their means (i.e., $[X]_{ij} - mean(X_{(j)})$).

axes are closer together they are positively correlated and if they are in opposite directions (around 180°) that would indicate a negative correlation between them. As a result, the relative position of the axes visually communicates the degree of similarity among the variables they represent in a concise and accessible way.

Table 4.1: Variables used for creating biplots and to calculate the SoVI.

#	Variables	Normalized Variable
1	Black or African-American population	% of Black population
2	Hispanic population	% of Hispanic population
3	Asian population	% of Asian population
4	Native American population	% of Native American population
5	Population under 5 years old	% of population under 5 years old
6	Population 65 years or older	% of population 65 years or older
7	Group quarters population	% of population living in group quarters
8	Foreign born population	% of foreign-born population
9	Household size	Average number of people per household
10	Female population	% of female population
11	Female-headed households	% of families with female-headed households with no spouse present
12	Female labor force participation	% of female population in civilian labor force
13	Public transportation dependence	% of workers (Civilian pop. 16+ and employed) using public transport
14	Education attainment	% of population over 25 years old with less than 12 years of education
15	Unemployment rate	% of the civilian labor force unemployed
16	Manufacturing employment	% of persons (16+ years old) employed in manufacturing, transportation and public administration

Table 4.1 (cont.)

#	Variables	Normalized Variable
17	Employment in service occupations	% of persons (16+ years old) employed in service occupations
18	Poverty rate	% of population in poverty
19	Social security recipients	% of population who are social security recipients
20	Average household income	Average household income last year ($)
21	Renter-occupied housing units	% of renter-occupied housing units in total occupied housing units
22	Number of mobile homes	% of housing units that are mobile homes
23	Average gross rent	Average gross rent ($) for renter-occupied housing units
24	Average home value	Average dollar value of owner occupied housing units
25	Population in civilian labor force	% of population in civilian labor force
26	Housing density	Number of houses per sq. mile

All biplots created for this analysis are presented in Appendix Figures A1 to A3. Figures 4.1 to 4.3 presented below also show the same biplots, but highlight three important race/ethnicity and poverty variables for easier interpretation of the findings from this biplot analysis. Alpha bags (Gardner, 2001; La Grange et al., 2009), containing 90% of the samples (i.e. $\alpha = 0.9$) are superimposed on the biplots to identify the prominent dimensions of vulnerability at different time periods. Alpha bags can be understood as a multivariate extension of the univariate boxplot which can contain any specified proportion of data nearest to the median (unlike the central 50% contained by boxplots) and as a result, is effective in highlighting differences in variation or the role of outlying values (Walters & Le Roux, 2008). When data points are more dispersed in the biplot, there would be an alpha bag of larger size to encompass defined percentage of samples (i.e. 90% for this study) and if some data points (i.e., census tracts) deviate significantly from the median value due to a higher value of any particular variable (e.g., higher concentration of Hispanic or African-American population), the alpha bag will be elongated along the axis of that variable.

Figure 4.1 shows Harris County, Texas biplots for the four years delineating the three decade study period. Changes in the shape of the alpha bag and the relationship among the race/ethnicity and poverty axes are evident, particularly after 1990. Changes in the angles between the axes can be attributed to high growth of the Hispanic population and the increase of poverty in suburban census tracts, which was more concentrated in inner city areas prior to 1990. Harris County has experienced enormous growth in its Hispanic population in recent decades. In 1980 the Hispanic population was only about 15% but increased to 22% in 1990 and then rapidly climbed to 33% and 40% in 2000 and 2010 respectively[18]. The black or African American population remained consistent at about 18 to 20% of the total population at all three decades, and although absolute numbers increased, their percentage remained at a significantly lower rate than the Hispanic population. As a result, in 1980 and 1990 (when the Hispanic and African-American population shares were not that different) there were high correlations among poverty rate and minority population, as indicated by smaller angles among these axes (Figure 4.1). In 2000 however, when the Hispanic population jumped to 33%, a sizable number of census tracts exhibited a higher share of Hispanic population and this reduced the historically high correlation between concentration of Hispanic and black population. With growth of Hispanic population, this pattern continued in 2010 when the axes showed angles similar to those observed for 2000. Angles between the axis of poverty rate and race/ethnicity increased after 1990 primarily due to a greater negative correlation between the Hispanic and black populations in 2000 and 2010. Since the areas with higher minority populations continued to hold higher percentages of the population living in poverty, the axis for poverty rate is located in almost equal distance from these two axes, indicating a positive correlation with both the Hispanic and black population percentage. In 1980, mobile homes comprised a higher percentage of the housing stock in some census tracts of Harris County along with a higher percentage of the population employed in manufacturing jobs. This is the reason for the 1980 alpha bag having a second spike besides the one associated with high poverty and minority population (Figure 4.1, top left box). This distortion gradually decreased in subsequent decades and for 2000 and 2010 the alpha bags

[18] Calculated from 1980, 1990, 2000 decadal census data and 2008-2012 ACS data (considered as representation of 2010). All values are rounded to nearest whole number for easies interpretation.

indicated two spikes for census tracts with a higher share of black population and Hispanic population. This indicates that for Harris County, poverty and minority populations are the dominant social vulnerability factors in recent decades, whereas other indicators (e.g. percentage of mobile homes) were dominant in previous decades.

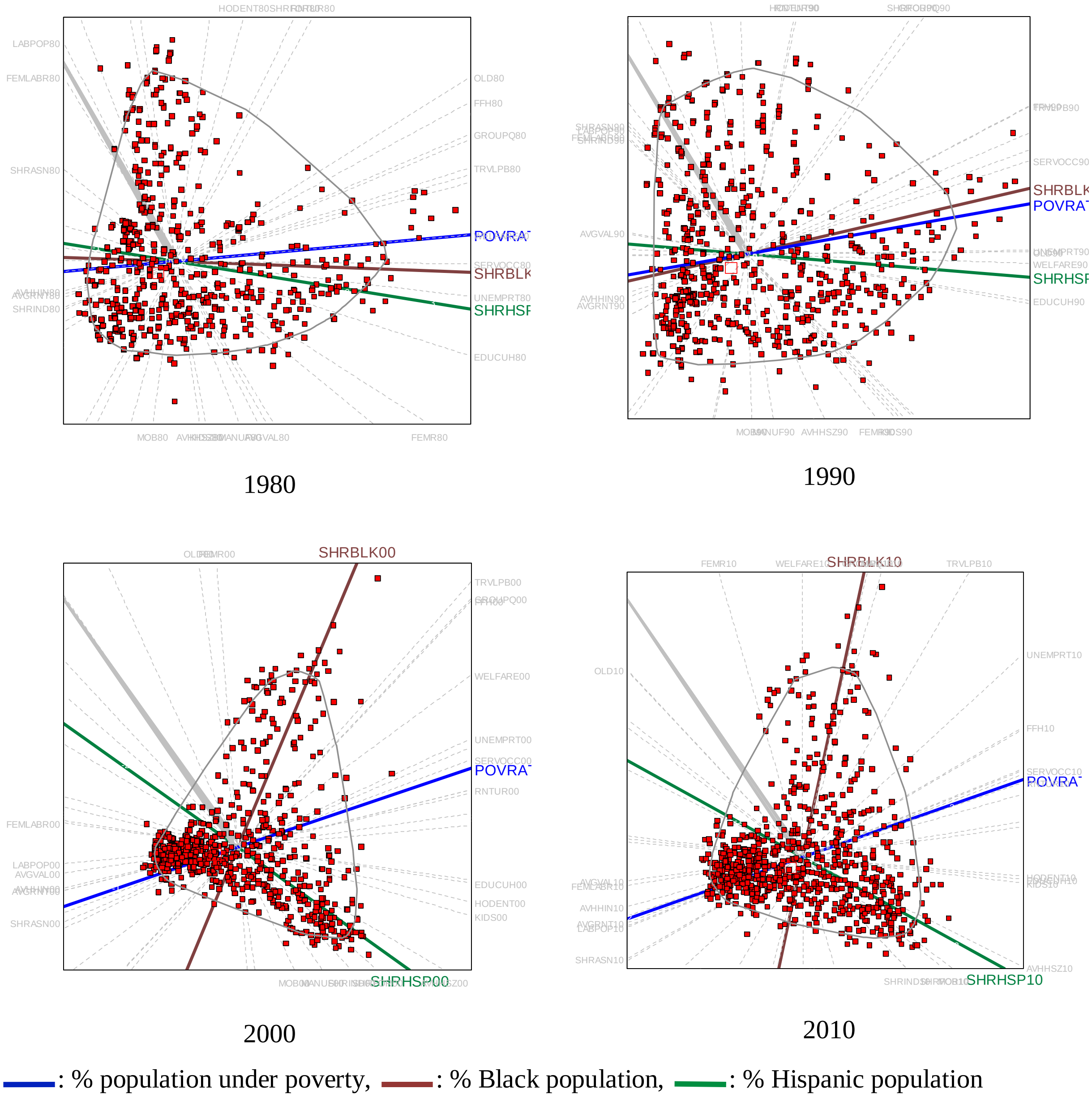
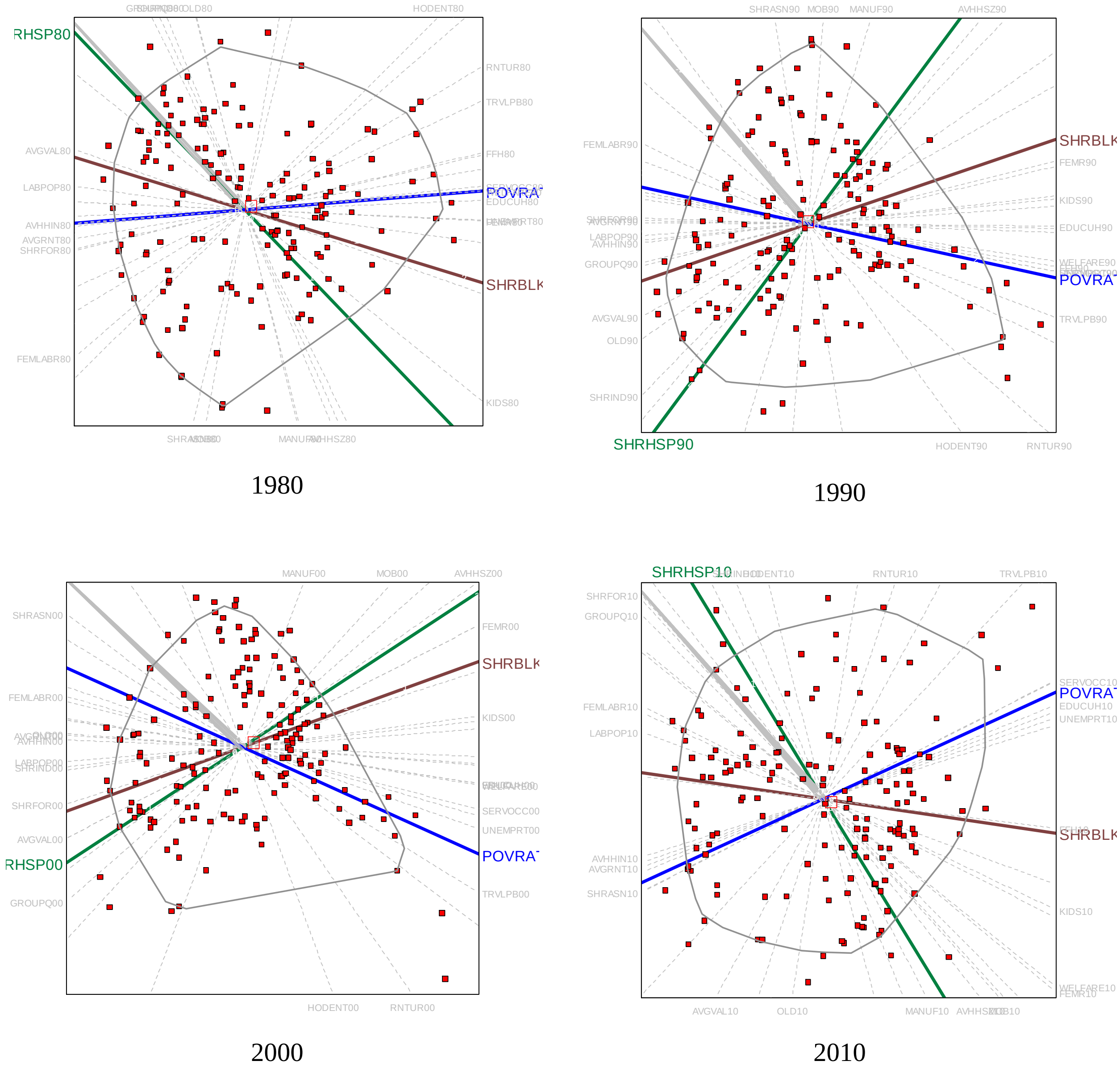


Figure 4.1: Correlation biplots (with alpha bag) of Harris County with poverty rate, % black population and % Hispanic population highlighted

Unlike Harris County, which experienced consistently high population growth, Orleans Parish, Louisiana saw a gradual decrease in population over time—specifically, it lost about 145,000 people between 2000 and 2010[19]. Hurricane Katrina in 2005 is one of the key factors behind this population loss as the storm displaced thousands of people and the parish has yet to fully recover from that devastation. In terms of racial/ethnic composition, Orleans Parish did not experience any significant shift in contrast to Harris County. The black or African American population was the largest racial group in the parish in 2000 (about 55%) and remained so in 2010 (about 60%), while the Hispanic or Latino population continued to constitute a small minority (about 3% in 1980 to only 5% in 2010). These trends are also reflected in the biplots of Orleans Parish presented in Figure 4.2. In this case, the poverty rate has a higher correlation with the black population percentage (as indicated by smaller angle between these two axes) in all time periods. The very low presence of Hispanic population also contributed to the negative correlation between Hispanic population percentage with poverty rate and Black population percentage. Here, none of the vulnerability dimensions are significantly influencing the shape of the alpha bag, in contrast to the Harris County case. Still, the poverty rate and black population percentage are the two key factors that are moving in tandem with other dimensions of vulnerability (particularly after 1990), as evidenced by the concentration of the axes of other variables near these two axes (Figure 4.2). Principal Components Analysis for calculating the Social Vulnerability Index, as discussed in next section, revisits and further examines those other dimensions of vulnerability that correlate with poverty and race in Orleans Parish.

[19] In 2000 total population of Orleans Parish was 484,674, which decreased to 339,016 in 2010, as documented by Census 2000 and ACS 2008-2012 respectively.



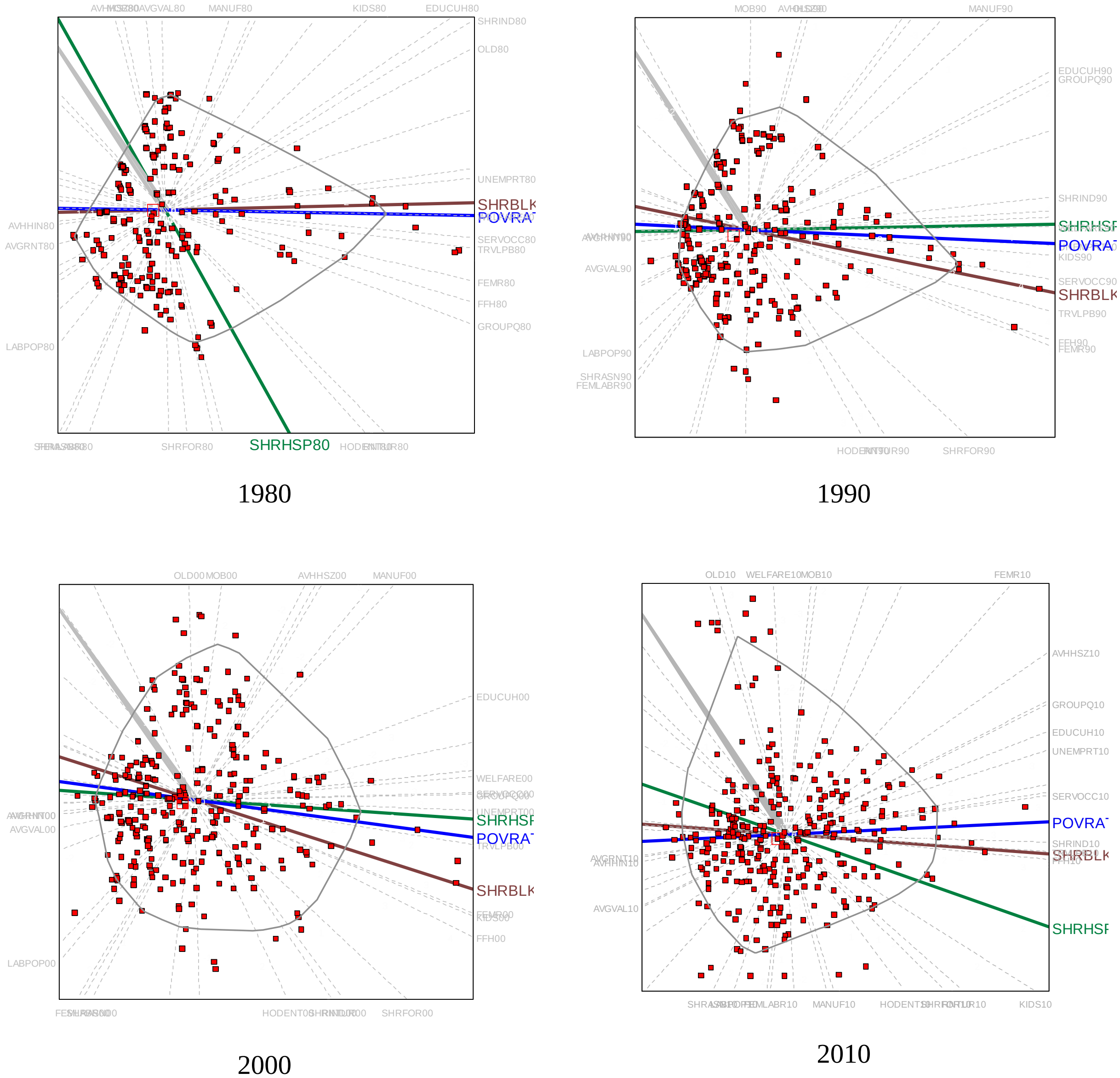
: % population under poverty, : % Black population, : % Hispanic population

Figure 4.2: Correlation biplots (with alpha bag) of Orleans County with poverty rate, % Black population and % Hispanic population highlighted

The vast majority of the population in Hillsborough County in Florida has historically been white. Although the county experienced gradual growth of its black and Hispanic populations in recent decades, it neither experienced a high growth rate (like the Hispanic population in Harris County) nor a high concentration of racial or ethnic minorities (like the black population in Orleans Parish). As shown in the biplots in Figure 4.3, in all three time periods (with the exception of 1980) the poverty rate and concentration of minority populations were highly correlated with each other in Hillsborough County (as indicated by the smaller angles between the three axes). The departure from this trend seen in 1980 is due to the fact that the Hispanic population was smaller compared to the black population (10% vs. 13% respectively), but by 1990 these populations were almost equal (both comprising about 13% of the total population)[20]. In 2000 the Hispanic population surpassed the black population (18% vs. 16%) and the gap increased further by 2010 (25% Hispanic and 17% black population)[21]. Census tracts with a higher share of minority populations also tend to have higher poverty rates, as indicated by the small angles between axis of the poverty rate and Black and Hispanic population percentage variables (Figure 4.3). Besides poverty and minority population, the alpha bags for Hillsborough County indicate other emerging dimensions of social vulnerability in this county. While in 1980 and 1990, the shape of the alpha bags was primarily determined by poverty and minority population, in 2010 the percent elderly population is associated with another spike or elongation. This indicates that census tracts where the elderly comprise a larger percentage of the overall population also tend to exhibit higher social vulnerability.

[20] Calculated from 1980 and 1990 census report collected through Social Explorer

[21] Calculated from 2000 census and 2008-2012 ACS data. All values are rounded to nearest whole number for easies interpretation.



: % population under poverty, : % Black population, : % Hispanic population

Figure 4.3: Correlation biplots (with alpha bag) of Hillsborough County with poverty rate, % Black population and % Hispanic population highlighted

4.5 Results of PCA Analysis

The SoVI was calculated by applying Principal Component Analysis (PCA) to 26 variables (table 4.1) that have been established in the literature and were described in Chapter 2. After reducing the number of variables through PCA, the resulting component scores were aggregated using the additive approach pioneered by Cutter et al. (2003). The PCA results indicate how the prominent dimensions of vulnerability have evolved over time, as well as how the role of different variables used to construct the SoVI changed along with the shifting demographic composition of the counties. As mentioned in Chapter 3, this study used parallel analysis (Zwick & Velicer, 1986) rather than the Kaiser criterion applied in the original SoVI methodology of Cutter et al. (2003) to determine how many components to retain. Parallel analysis usually retains fewer components than the Kaiser criterion and is considered a superior alternative for determining the optimal number of components (Tate, 2012). After applying PCA, the selected components were interpreted and labeled based on the characteristics of the variables, specifically the loadings of the variables. Tables 4.2 to 4.4 show the selected vulnerability components along with the percentage of overall variance explained by those components for each of the three study counties. Appendix Tables A1 to A4 present a more detailed version of these tables and show which variables are contributing most to each of the components.

Among the three study counties, one common trend from the PCA was that the percentage of total variance explained by the SoVI components gradually decreased over time. Further, the parallel analysis approach retained a different number of components for each of the counties (and even in different years) and the variance explained by the individual components also changed across time periods. This suggests actual changes in the composition and significance of the underlying dimensions of social vulnerability in different time periods. For census tracts in Harris County (Table 4.2), the overall variance explained by the selected components decreased from 74.4% in 1990 to 72.5% in 2000 and 65.5% in 2010. In all four years, five components were consistently retained by the parallel analysis with *Race and socio-economic status* (i.e., percent Black, poverty, unemployment, income, etc.) as the leading component in all years. While *Housing and labor force* was the second most important component in 1980 and 1990 (explaining 16.5% and 15.1% variance), it was replaced by the *Hispanic and foreign-born* component in 2000 and 2010 (explaining 17.6% and 13.9%

variance), which can be attributed to the rapid growth of the Hispanic population during this time period.

The PCA components explained 71% of the overall variance among the census tracts of Orleans Parish in 1980, 70.5% in 1990, 69.6% in 2000, and 67.7% in 2010. While four components were retained by the parallel analysis in 1980, 1990, and 2000, five components were retained in 2010. Race and socio-economic variables consistently emerged as the leading component, although the percentage of variance it explained decreased significantly in 2010. This can be attributed to the massive loss of population in Orleans County between 2000 and 2010 as a result of Hurricane Katrina, which may also have contributed to the retention of more components in 2010 (i.e., previously insignificant components became more prominent in the wake of population loss).

In the case of Hillsborough County, the PCA did not indicate any consistent trend (in terms of the percentage of variance explained or for the number of components retained) unlike Harris or Orleans County. In 1990, 73.6% of the variance among the census tracts of Hillsborough County were explained by five components, by 2000 74.3% was explained by six components, and in 2010 only 65.8% was explained by the five components retained. Race and socio-economic variables also comprised the leading component for all four decades here. A growing concentration of elderly population in certain census tracts (as mentioned in previous section) contributed to the significantly higher percentage of variance explained by the *Age and labor force* component in 2010 (increased from 13.3% in 2000 to 16.2%).

Table 4.2: PCA results for Harris County

	1980	1990	2000	2010
% variance explained	71.8	74.4	72.5	65.5
No. of components	5	5	5	5
Major components (% variance explained)	Race and socio-economic status (28.9)	Race and socio-economic status (29.4)	Race and socio-economic status (27.5)	Race and socio-economic status (23.4)
	Housing and labor force (16.5)	Housing and labor force (15.1)	Hispanic and foreign-born (17.6)	Hispanic and foreign-born (13.9)
	Hispanic and foreign-born (9.9)	Hispanic and foreign-born (12)	Employment and housing (11.4)	Age and labor force (11.4)
	Age and gender (8.9)	Age (10)	Age and labor force (10)	Employment, housing (9.2)
	Employment, mob. Homes (7.6)	Employment, mob. Homes (7.9)	Gender (6)	Gender (7.6)

Table 4.3: PCA results for Orleans Parish

	1980	1990	2000	2010
% variance explained	71	70.5	69.6	67.7
No. of components	4	4	4	5
Major components (% variance explained)	Race and socio-economic status (40.3)	Race and socio-economic status (39.8)	Race and socio-economic status (38.7)	Race and socio-economic status (26.5)
	Age and Hispanic (13.4)	Hispanic population (11.9)	Hispanic and employment (15)	Employment, gender (12.7)
	Foreign-born and Asian (8.7)	Foreign-born, Asian, mob. Homes (10.5)	Foreign-born and Asian (8.7)	Hispanic and foreign-born (10.9)
	Employment, Gender (8.6)	Employment and Gender (8.3)	Age and gender (7.2)	Age and gender (10.1)
				Housing, employment (7.5)

Table 4.4: PCA results for Hillsborough County

	1980	1990	2000	2010
% variance explained	75.5	73.6	74.3	65.8
No. of components	6	5	6	5
Major components (% variance explained)	Race and socio-economic status (31.1) Age, labor force (11.5) Household size, age (9.1) Hispanic, foreign-born (8.6) Employment, housing (8.5) Gender (6.7)	Race and socio-economic status (32.6) Age, labor force (13.9) Household size, employment (10.7) Hispanic, foreign-born (9) Gender and Housing (7.4)	Race and socio-economic status (27.6) Age, labor force (13.3) Household size, employment (10.9) Hispanic, foreign-born (9.5) Income, home value (7.3) Employment, housing (5.7)	Race and socio-economic status (23.8) Age, labor force (16.2) Hispanic, foreign-born (10) Household size, housing (8.6) Gender, employment (7.2)

4.6 Spatial Changes in the SoVI

Component scores calculated through PCA were aggregated to derive the overall composite social vulnerability index (SoVI). Since the composition of the vulnerability factors varies from place to place and even over time in the same area (as the biplots in section 4.3 showed), the SoVI was calculated for each county and each decadal period separately. Figures 4.4 to 4.6 present the SoVI maps for the three study counties in all four decades. In these maps, the SoVI is classified based on standard deviations from the mean, which helps to better visualize comparative vulnerability of the census tracts within a county and longitudinally. In the case of Harris County, Texas (Figure 4.4) in 1980 and 1990, high concentrations of SoVI near the inner-city (surrounding the downtown) areas were evident. Between 2000 and 2010 social vulnerability decreased, particularly in the north-west and western parts of the downtown area, due to gentrification in the Heights, Memorial Park, and other surrounding neighborhoods consistent with the findings of prior studies (Podagrosi et al., 2011). An increase in vulnerability in the south and south-west part of the county, particularly in the Central Southwest, Sunnyside, and Southwest Houston neighborhoods is also evident during the same time period.

In Orleans Parish, Louisiana (Figure 4.5) changes in the SoVI between 2000 and 2010 are more apparent, which can be attributed to displacement after Hurricane Katrina, particularly in the Gentilly, Upper Ninth Ward, and Lower Ninth Ward neighborhoods in the north and north-east parts from the downtown area. For Hillsborough County, Florida (Figure 4.6) the SoVI appears to be less spatially concentrated in 2010 than in earlier years, particularly in the inner-city areas of Tampa. During the same time period vulnerability has increased in southern part of county in the census tracts along Hillsborough Bay.

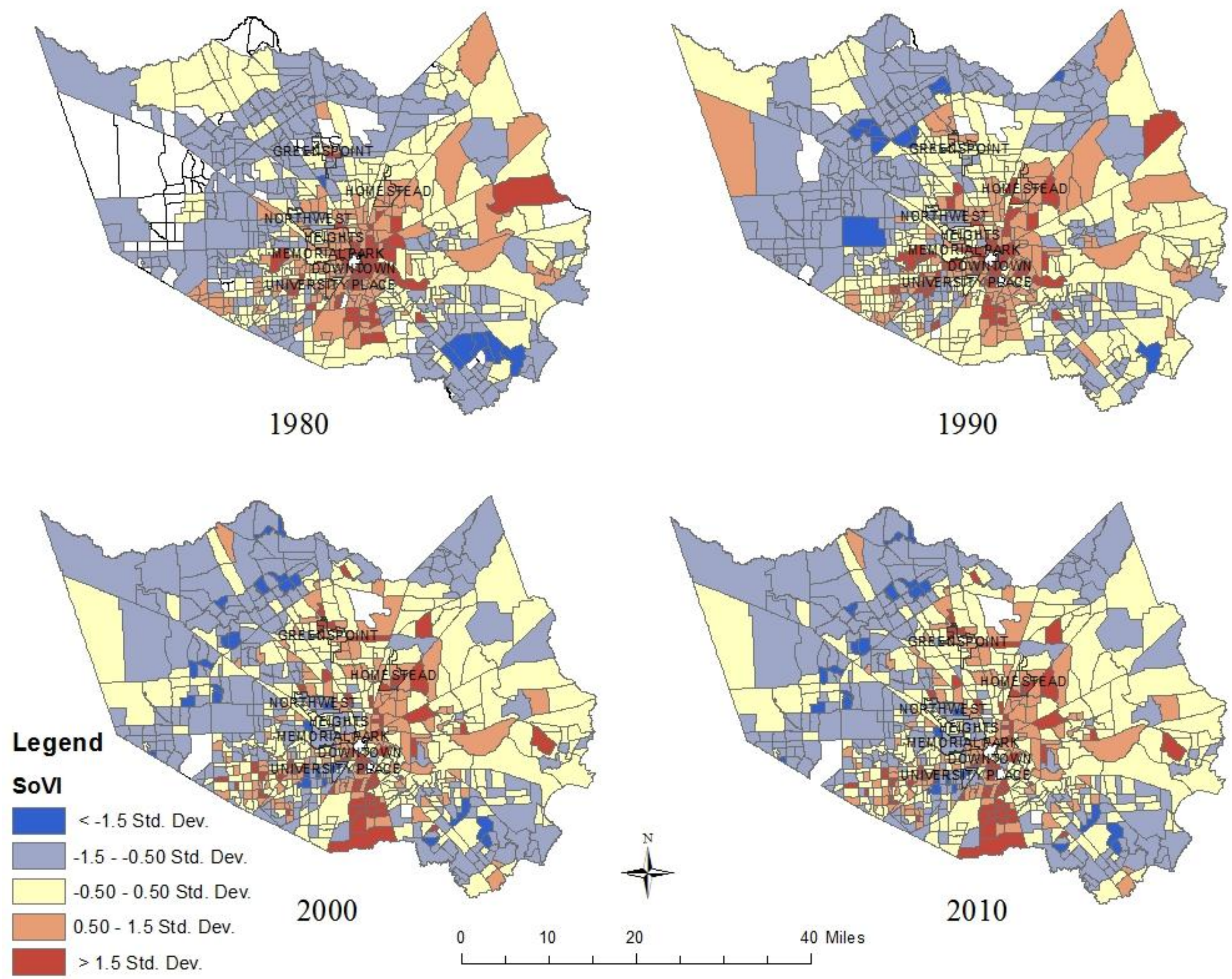


Figure 4.4: Social Vulnerability in Harris County, TX (1980-2010)

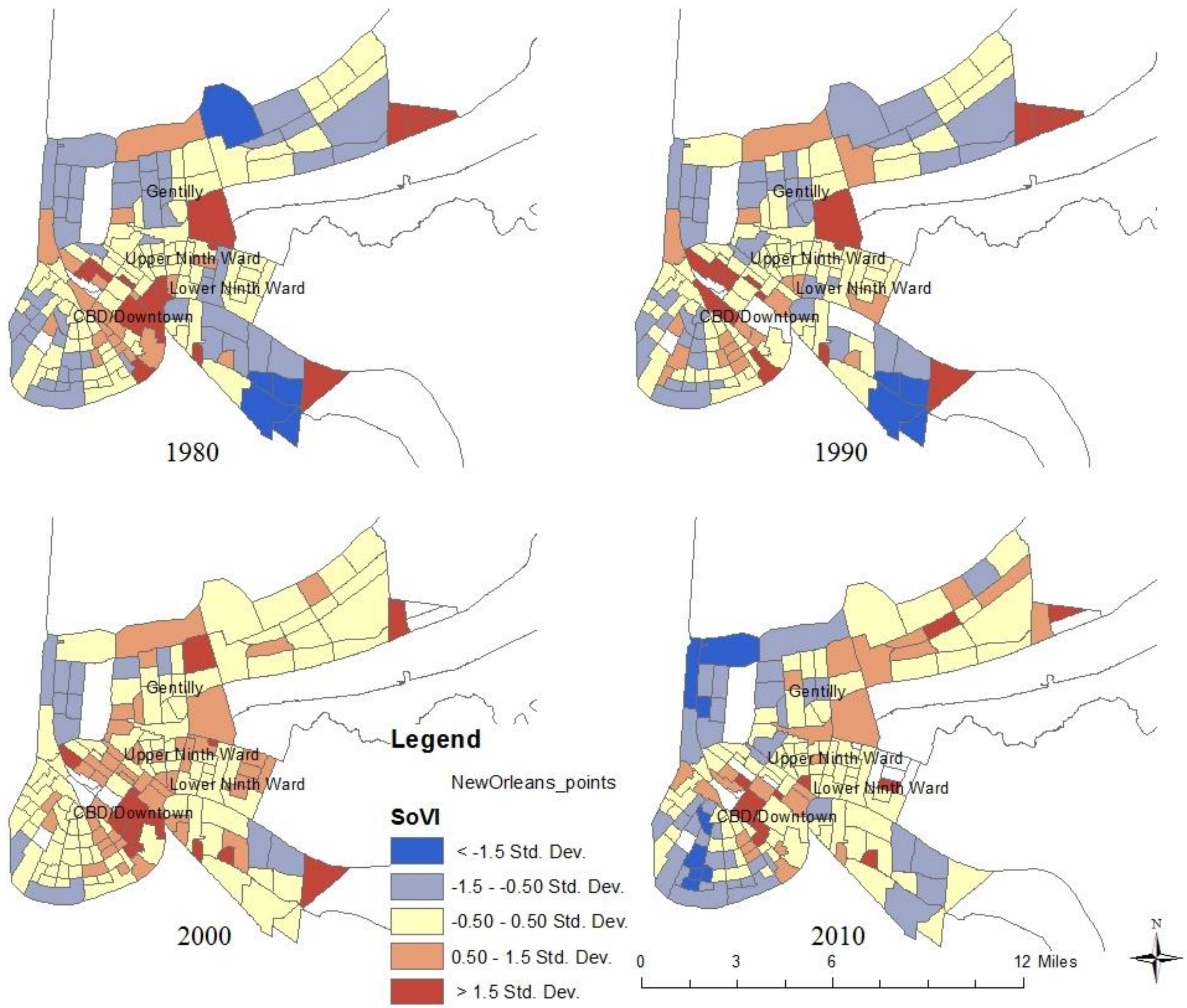


Figure 4.5: Social Vulnerability in Orleans County, LA (1980-2010)

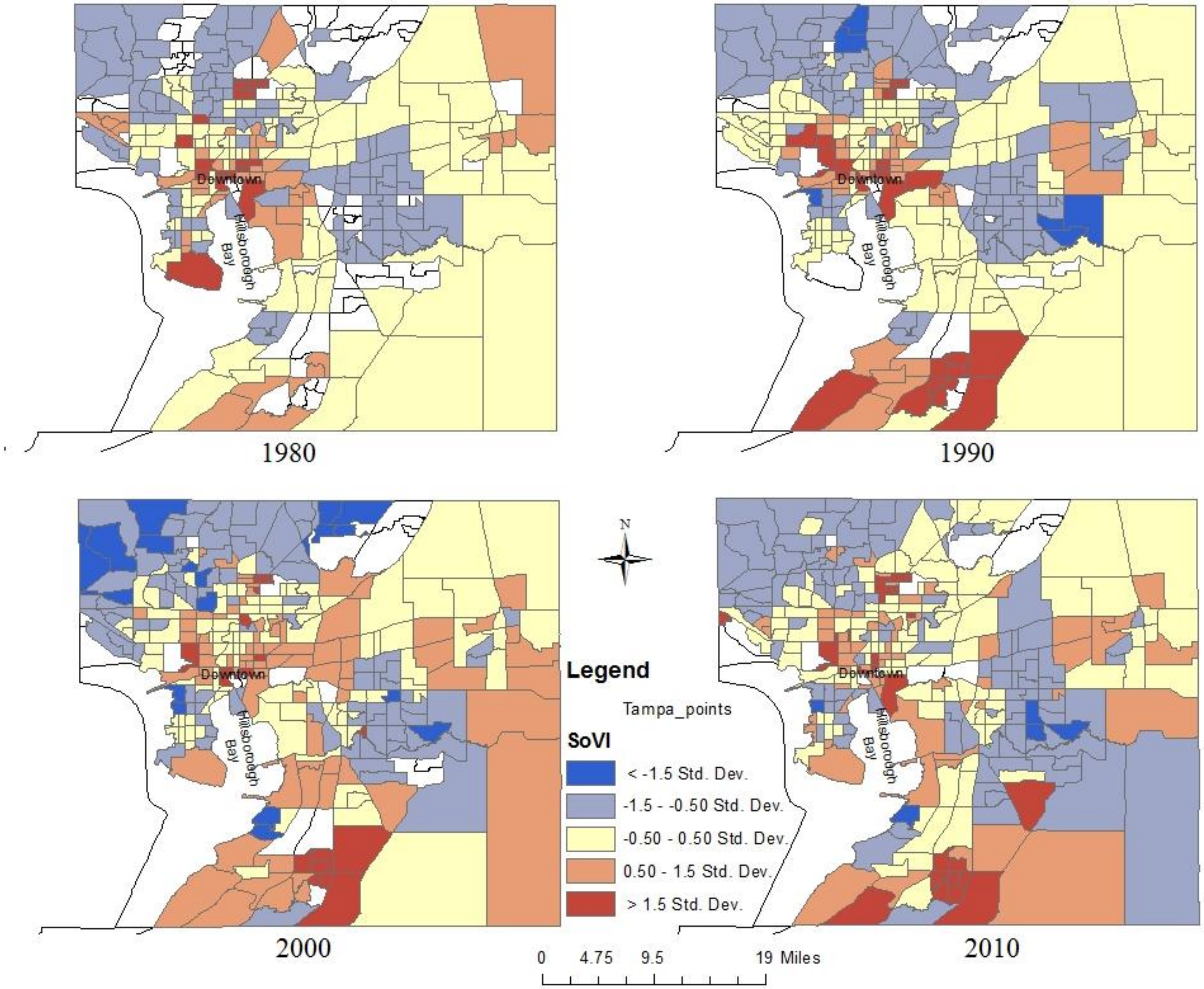


Figure 4.6: Social Vulnerability in Hillsborough County, FL (1980-2010)

4.7 Cluster Analysis of the SoVI

While the SoVI maps presented in previous section show the spatial distribution of vulnerability within the counties, they do not indicate the extent to which census tracts with higher SoVI are clustered together and how this spatial distribution changed over time. To identify the patterns of similarity and dissimilarity in the clustering of social vulnerability, spatial autocorrelation of the SoVI among the census tracts was evaluated. Both global and local measures of spatial autocorrelation were calculated and when considered jointly, they reveal two distinct but complementary spatial characteristics of vulnerability. The global autocorrelation measure involves studying the entire map pattern and identifies whether the observed pattern is clustered, dispersed, or random (Cliff & Ord, 1981; Goodchild, 1986) and in this case, indicates whether overall social vulnerability within the county has become more or less concentrated over time. Local indicators of spatial of spatial autocorrelation or LISA statistics (Anselin, 1995), on the other hand, capture local variability and identify significant clusters of similar SoVI values (high or low social vulnerability). Tables 4.5 to 4.7 present the global Moran's I[22] and number of census tracts within clusters based on local Moran's I of the SoVI for all three study counties, while Figures 4.7 to 4.9 present the corresponding LISA cluster maps for the three counties.

One important trend that emerged from the global analysis of SoVI is that the Moran's I value decreased over time for all of the counties. This suggests that, despite experiencing different patterns of population growth (as mentioned in section 4.1) and different compositions of vulnerability (as revealed through the biplots and PCA earlier), in all three study counties the overall concentration of social vulnerability has decreased over time. Although the positive values of Moran's I (all of which were statistically significant at $p < 0.05$) indicate that social vulnerability is highly concentrated in all of the counties, their decreasing values indicate that the level of concentration of vulnerability has lessened. In Harris County, Texas (Table 4.4), the global Moran's I was 0.63 in 1980, but gradually decreased to 0.46 in 2010 and the number of census tracts in high-high clusters (indicating concentration of high values of the SoVI) also decreased from 88 (12.34% of tracts) in 1980 to 70 (9% of tracts) in 2010.

[22] The Moran's I statistic is interpreted as follows: a value close to +1 represents strong similarity between the values of the SoVI (i.e. higher concentration); a value of -1 indicates dissimilarity (i.e. higher dispersion); while a value of zero represents a random pattern.

Table 4.5: Spatial clustering statistics and LISA cluster categories for Harris County

Global Moran's I	1980		1990		2000		2010	
	0.63		0.62		0.58		0.46	
LISA categories	Count	%total	Count	%total	Count	%total	Count	%total
Significant local spatial clusters								
High-High	88	12.34	100	12.95	81	10.51	70	9.00
Low-Low	0	0.00	0	0.00	0	0.00	0	0.00
Spatial outliers								
Low-High	62	8.70	79	10.23	72	9.34	57	7.33
High-Low	1	0.14	2	0.26	0	0.00	2	0.26
No statistically significant spatial clustering								
Tracts	562	78.82	591	76.55	618	80.16	649	83.42
Total	713	100	772	100.00	771	100.00	778	100.00

In the case of Orleans Parish, Louisiana (Table 4.6) the global Moran's I was lower in earlier years (0.40 in 1980 and 0.37 1990), but increased in 2000 (0.47) and then decreased in 2010 (0.44). This suggests an overall decrease in the concentration of social vulnerability in recent years, but the number of tracts in high-high clusters barely changed. There were 10 census tracts in high-high clusters in 1980, which decreased in 1990 and 2000 only to climb back to 10 in 2010.

Table 4.6: Spatial clustering statistics and LISA cluster categories for Orleans Parish

Global Moran's I	1980		1990		2000		2010	
	0.40		0.37		0.47		0.44	
LISA categories	Count	%total	Count	%total	Count	%total	Count	%total
Significant local spatial clusters								
High-High	10	5.99	8	4.85	9	5.42	10	6.21
Low-Low	0	0.00	0	0.00	0	0.00	0	0.00
Spatial outliers								
Low-High	5	2.99	5	3.03	5	3.01	14	8.70
High-Low	1	0.60	1	0.61	0	0.00	0	0.00
No statistically significant spatial clustering								
Tracts	151	90.42	151	91.52	152	91.57	137	85.09
Total	167	100.00	165	100.00	166	100.00	161	100.00

For Hillsborough County in Florida (Table 4.7) the concentration of vulnerability (measured with global Moran's I) followed a consistent downward trend, similar to Harris County in Texas. Although Hillsborough County had a low concentration of vulnerability in 1980 (0.53), it increased in 1990 (0.62) before gradually decreasing in 2000 (0.57) and 2010 (0.42). For a number of tracts in high vulnerability clusters (i.e. high-high spatial clusters), however, the number of census tracts did not follow the downward trend of the global Moran's I. While there were 44 census tracts located in high vulnerability clusters in 1990, this number decreased to 33 in 2000, then increased to 46 in 2010. The larger number of census tracts (326 versus 300 in 2000) included in the 2010 analysis (which were excluded[23] in earlier years due to low population counts) may have had an effect, but this is not a sufficient explanation since even with a lower number of census tracts in 1990, a greater number of census tracts were part of high-high SoVI clusters than in 2000.

[23] Since both global and local spatial autocorrelations were measured separately for every year (i.e. with separate weight matrix), excluding any feature in one year shouldn't influence the result of another year. Although having different number of features may make the temporal comparison difficult, as the result shows here, number of features are not influencing the results. Also, in most cases excluded features are located nearby (i.e. tracts with fewer population clustered together), and as a result it can be expected that they will not affect the results in subsequent years.

Table 4.7: Spatial clustering statistics and LISA cluster categories for Hillsborough County

Global Moran's I	1980		1990		2000		2010	
	0.53		0.62		0.57		0.42	
LISA categories	Count	% total	Count	% total	Count	% total	Count	%total
Significant local spatial clusters								
High-High	24	11.37	44	17.89	33	11.00	46	14.11
Low-Low	0	0.00	0	0.00	0	0.00	1	0.31
Spatial outliers								
Low-High	17	8.06	6	2.44	27	9.00	23	7.06
High-Low	0	0.00	0	0.00	2	0.67	0	0.00
No statistically significant spatial clustering								
Tracts	211	100.00	246	100.00	238	79.33	256	78.53
Total	252	119.43	296	120.33	300	100.00	326	100

The LISA cluster maps in Figures 4.7 to 4.9 show the locations of clusters and spatial outliers within the study counties and how they changed over time. One trend that can be identified from these maps is, the high vulnerability clusters (i.e. high-high clusters) have become relatively less spatially concentrated in all three counties, and this is most evident in Harris County. In Harris County some of the high-high clusters have shifted from the immediate north and north-west vicinity of the downtown to further northern location. For Orleans Parish (Figure 4.8) some shifts in the high-high cluster near the downtown area can be identified between 2000 and 2010. In Hillsborough County (Figure 4.9) there is also evidence of fragmentation of established high-high clusters during the same time period. Compared to 2000, in 2010 there were fewer census tracts in the high vulnerability cluster near the downtown area (of Tampa) and there were more tracts in high vulnerability clusters located in northern and southern parts of Hillsborough County.

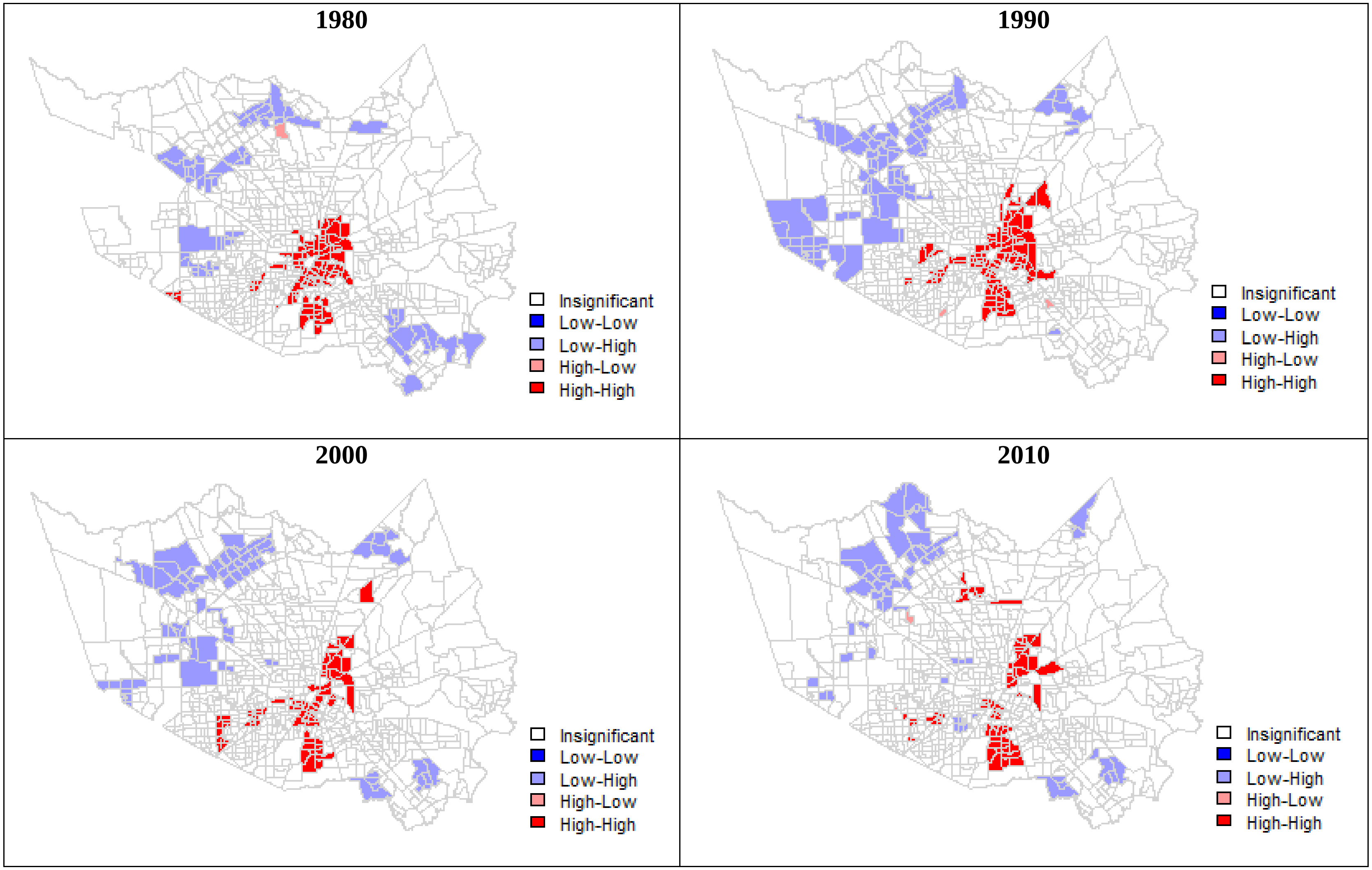


Figure 4.7: LISA cluster maps of SoVI, Harris County, TX (1980-2010)

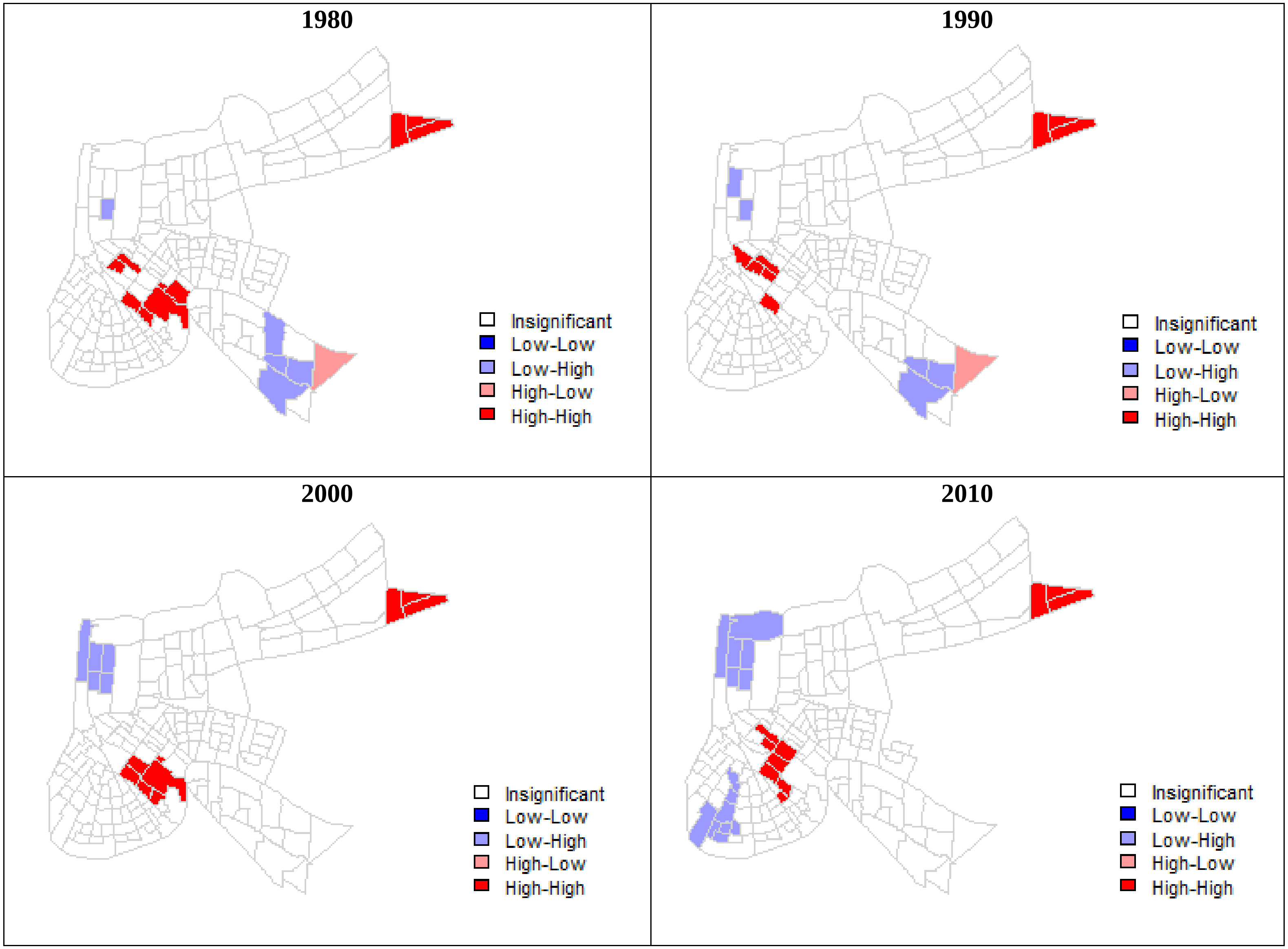


Figure 4.8: LISA cluster maps of SoVI, Orleans Parish, LA (1980-2010)

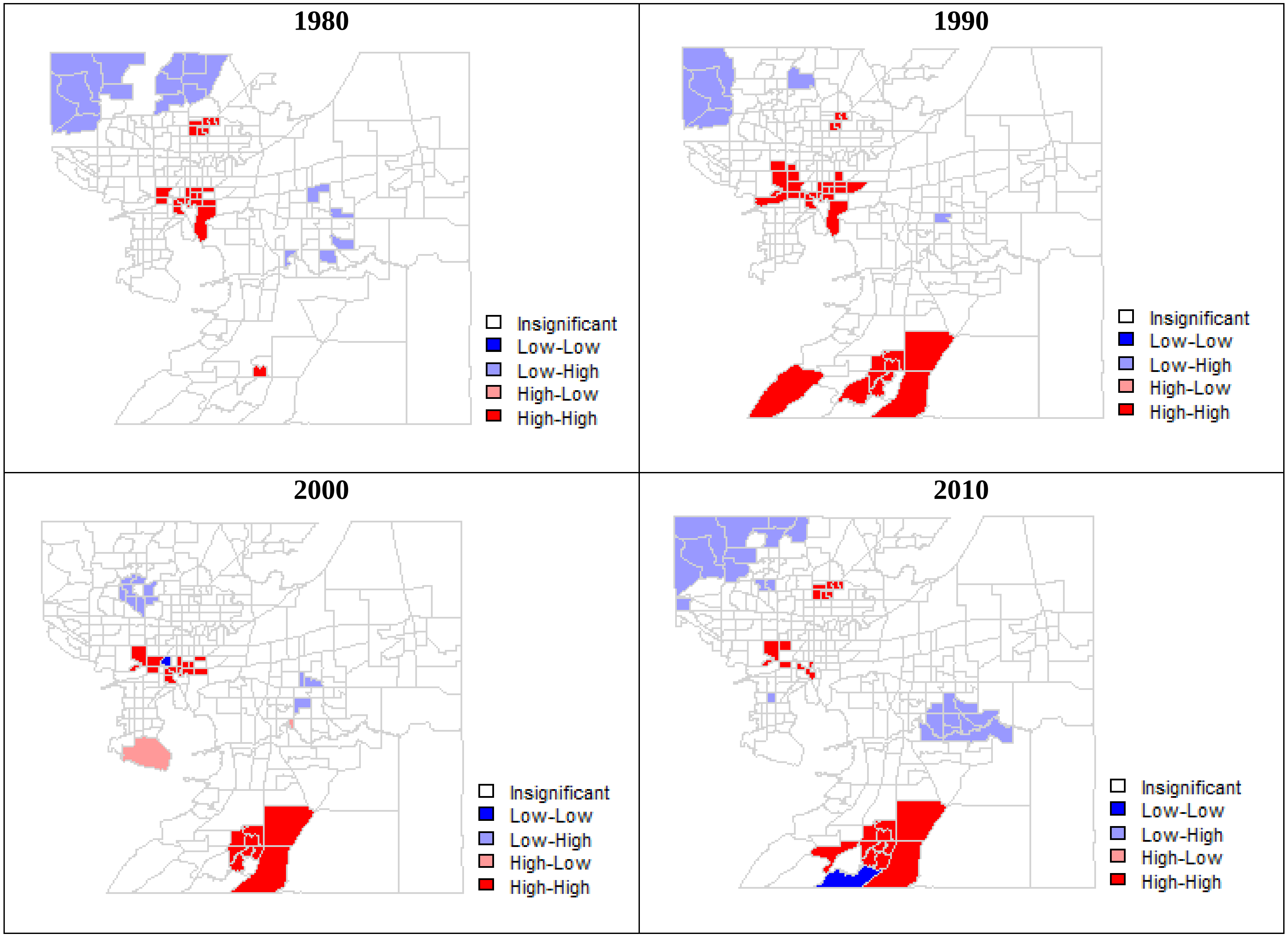


Figure 4.9: LISA cluster maps of SoVI, Hillsborough County, FL (1980-2010)

4.8 Temporal Changes in the SoVI

Measuring temporal change in social vulnerability is a challenging task due to shifts in the composition of vulnerability at the different time periods considered. Still, if we consider the SoVI as a relative measure of vulnerability within a county, it can be useful in examining how the degree of social vulnerability among all census tracts in the county has changed over time and for identifying areas that have experienced an increase or decrease in social vulnerability. Keeping this in mind, the approach taken by Cutter & Finch (2008) is applied here to identify historical trends of social vulnerability within the three study counties. Although Cutter & Finch (2008) focused on U.S. counties, this study adapted their methods for temporal trend analysis at the census tract level. Specifically, individual SoVI scores of census tracts were converted to z-scores (based on county mean score per decade) in order to improve their comparability over time. If this transformed score consistently increased over time in a census tract, that tract can be viewed as an area experiencing a gradual increase in social vulnerability. Applying simple linear regression, a line of best fit from 1980 to 2010 was calculated for each of the census tracts (with their transformed SoVI score for all time periods considered). The slope of the line of best fit indicates the directionality of vulnerability over time and the resulting R^2 captures the strength of this best fit line in capturing the trend in the transformed SoVI score. A positive slope of the best fit line indicates an increasing trend of social vulnerability and a negative slope indicates decreasing social vulnerability in a census tract. For all regressions, F-statistics were used to determine the statistical significance of the best fit lines at a 0.05 alpha level. This is an inherently aspatial approach to evaluating longitudinal trends of social vulnerability since each of the census tract is analyzed as a separate entity without considering changes in vulnerability in surrounding regions, but it still helps to visually locate areas that experienced a consistent increase or decrease in social vulnerability over time. Another potential issue with this approach is that it is based on the vulnerability of a census tract with respect to the whole county. As a result, even if a census tract experienced an increase in vulnerability in a certain time period, a much higher increase or decrease of vulnerability in other areas may influence its transformed SoVI score. Also, census tracts having a high increase or decrease in vulnerability only in recent decades (with opposite trends in previous decades) may end up showing an insignificant overall trend. Accepting these limitations, this study adopted the Cutter & Finch (2008) approach for evaluating longitudinal trends of social vulnerability, given its establishment in the literature and because there is no other widely accepted alternative for performing this kind of analysis.

SoVI trend maps for the three study counties are presented in Figures 4.10 to 4.12 and include the coefficient of the best fit trend line of SoVI scores for each of the tracts, outlining the tracts for which the trends were found to be statistically significant (at the 0.05 alpha level). As mentioned previously, here a positive slope indicates a consistent increase in social vulnerability and a negative slope indicates a consistent decrease in social vulnerability over time. From these maps one common trend can be identified for all three counties—the decrease of social vulnerability in inner city census tracts and increase of vulnerability in suburban census tracts. This can be attributed to the general phenomenon of suburbanization of poverty in major U.S. cities, which is widely discussed by the neighborhood change theorists (Dickens, 1999). Although these trends were statistically significant for only a few census tracts, these maps still provide an overall representation of the longitudinal trend of social vulnerability in the study counties.

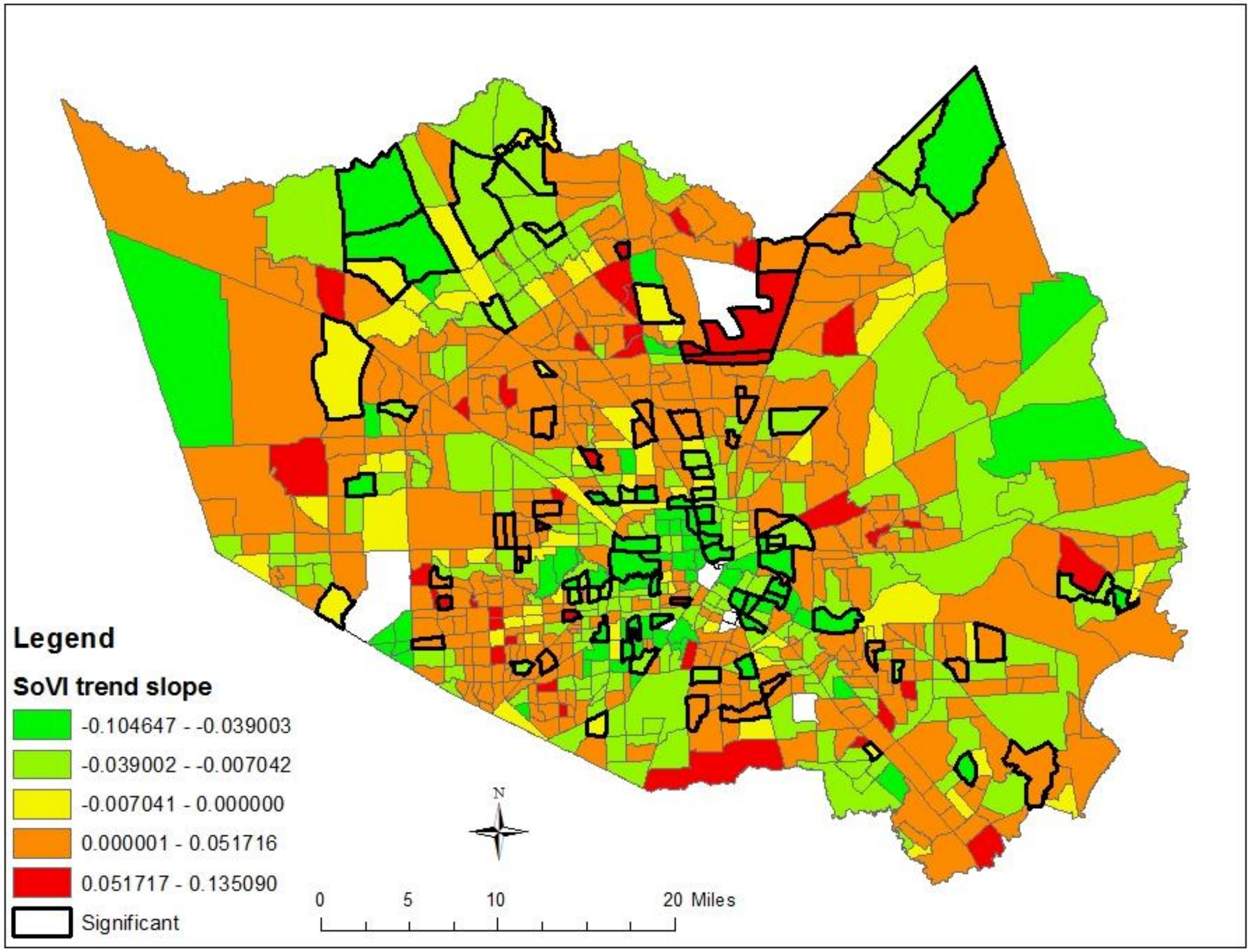


Figure 4.10: Temporal trends of SoVI in Harris County, TX (1980-2010)

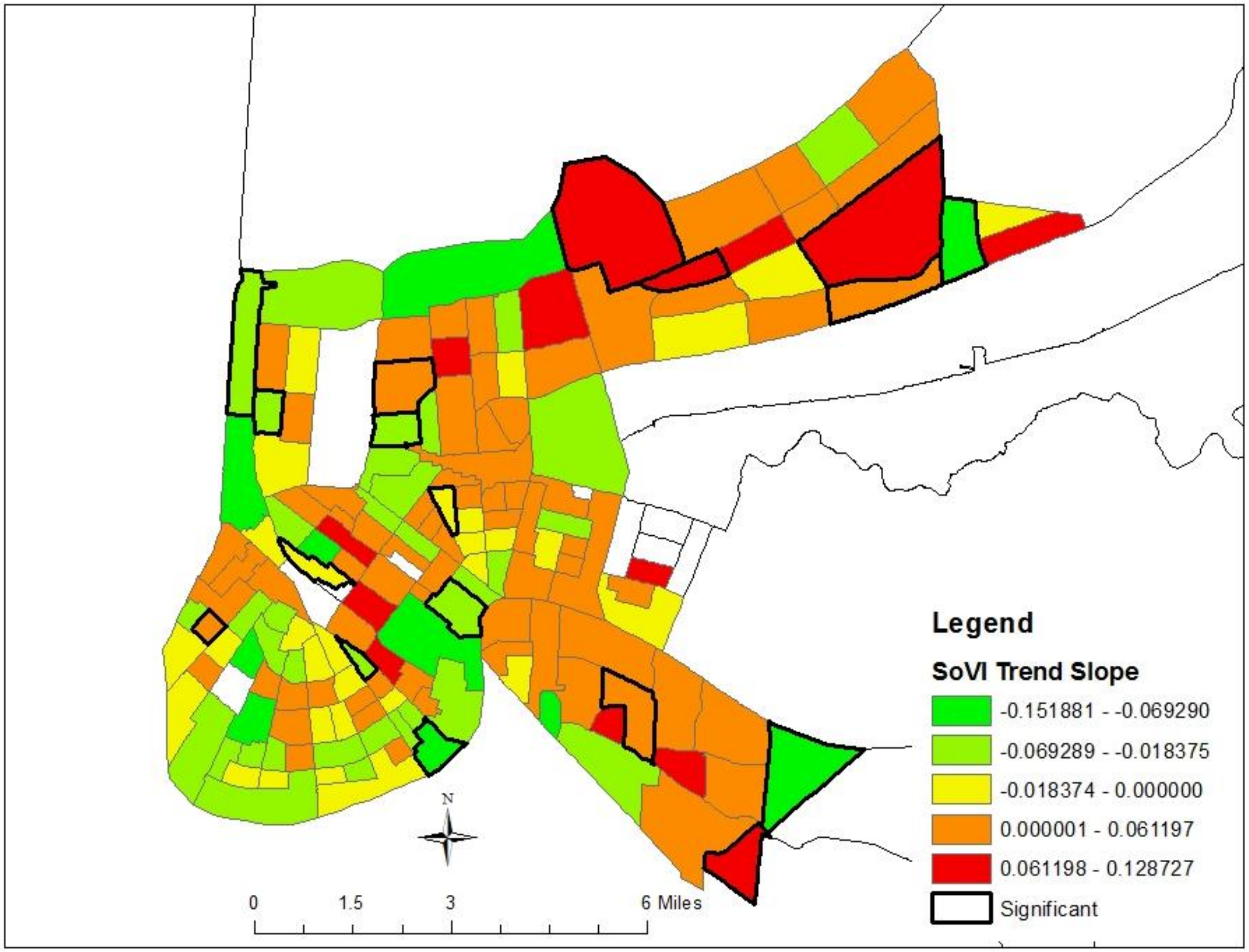


Figure 4.11: Temporal trends of SoVI in Orleans County, LA (1980-2010)

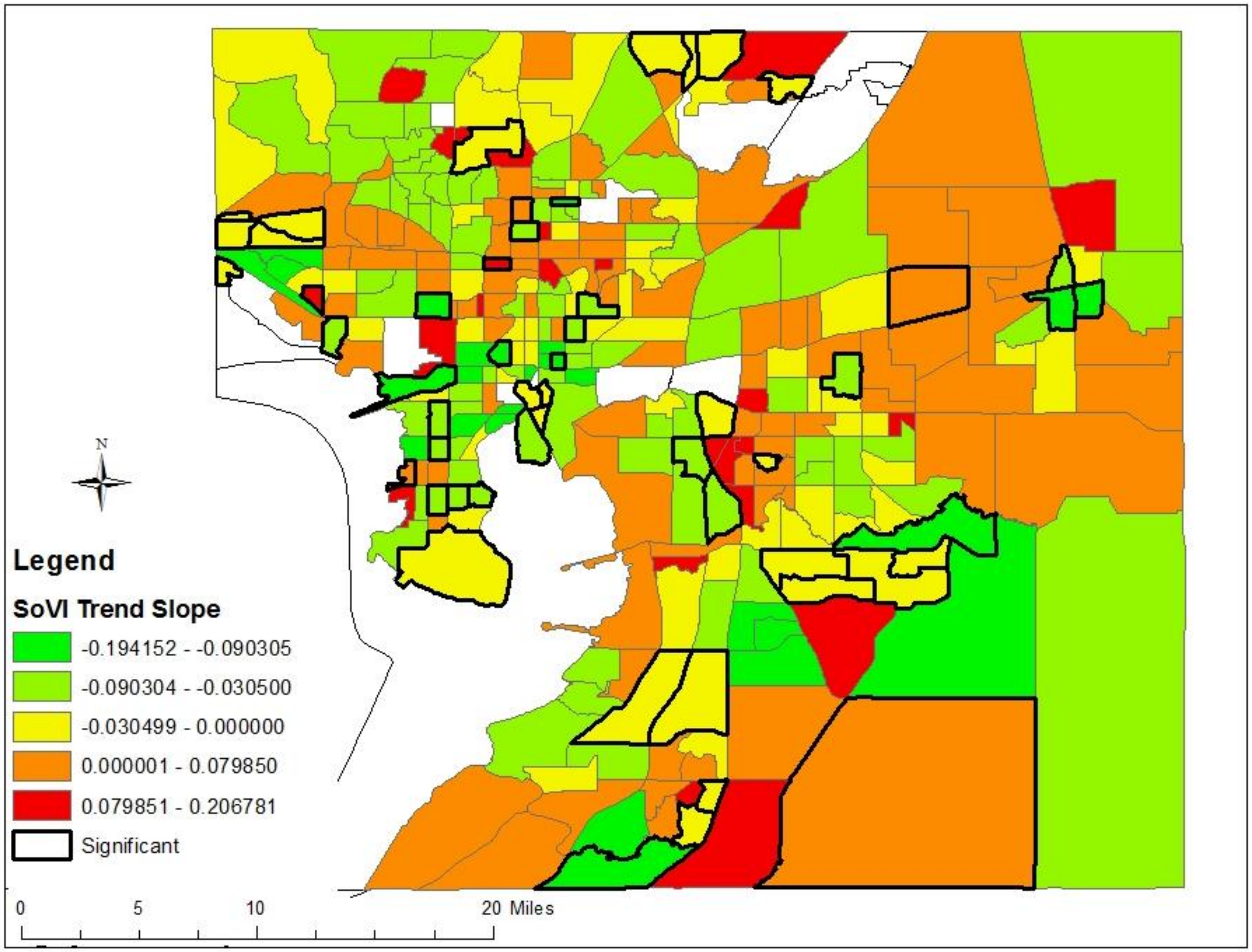


Figure 4.12: Temporal trends of SoVI in Hillsborough County, FL (1980-2010)

4.9 Challenges for Adaptation Planning

This chapter identified several commonalities in the observed pattern of social vulnerability change among the study counties. Despite having drastically different population growth trajectories and being located in different political and economic settings, in recent decades the spatial concentration of social vulnerability has gradually decreased in all of them. However, the composition of social vulnerability was different in each of the counties and also changed in a non-uniform way over time. For Harris County (Houston) in Texas, the high growth of the Hispanic and immigrant populations in recent decades elevated the importance of these factors in the SoVI, along with the percentage of black or African-American population and the poverty rate. This trend is consistent with the "urban restructuring" or "globalization" thesis of neighborhood change (Borja & Castells, 1997; Sassen, 2000; Soja et al., 1983) that attributes these demographic changes to capital and labor restructuring both at the global and local level. Demand for cheap labor has attracted sizeable immigrant and minority populations, which will make adaptation planning efforts more challenging because of the tendency of these groups to exhibit higher vulnerability. Ensuring equity and the legitimacy of adaptation efforts (Adger et al., 2005) would be problematic in this changed context when these new ethnic minority and immigrant population lack adequate political participation to have their voices heard in the planning process.

In Orleans Parish (New Orleans) Louisiana, displacement by Hurricane Katrina has significantly influenced the pattern of social vulnerability, which has become less concentrated and less dominated by race and socio-economic indicators. As the Katrina recovery process moves forward and planning for climate adaptation continues, this changed vulnerability pattern should be kept in mind both to ensure equitable outcomes from the planning process and to identify effective ways of avoiding future disasters. Hillsborough County (Tampa) in Florida exhibits two notable trends in its social vulnerability patterns, along with the decreased concentration of vulnerability found in the other two counties. In this county, gentrification in the inner city areas is pushing socially vulnerable populations (primarily minority and low income groups) to suburban and coastal census tracts and at the same time, some of the coastal locations are experiencing high growth of elderly populations due to the development of retirement communities there. These trends can be explained by urban 'growth machine' theories of neighborhood change (Logan & Molotch, 1987; Molotch, 1976) that emphasize how the economic interests of local elites drive policy decisions, which are in turn changing the pattern of social vulnerability on the ground. Both of these trends will make adaptation planning more challenging in the future and reveal two priorities—first evaluating the climatic risks of census tracts being populated by low-income and minority population and finding safer places for them, and second ensuring that climatic uncertainties are considered when developing retirement communities and that steps are taken to prevent displacement of other vulnerable groups.

CHAPTER 5
SUBSIDIZED HOUSING AND SOCIAL VULNERABILITY IN A MULTI-HAZARD URBAN AREA

5.1 Study Area

Harris County, Texas is taken as a detailed case study based on its level of risk exposure to both natural and technological hazards (Cutter et al., 2003; EPA, 2008; Nicholls et al., 2008; Sexton et al., 2007) and its high racial/ethnic diversity. As reported in the 2012 American Community Survey (ACS), this county has more than 4 million residents with 41.5 percent identifying as Hispanic/Latino, 19.5 percent as Black/African American, and about 17.3 percent living below the poverty level. The population of this county is primarily centered in the city of Houston (Figure 5.1), the largest cultural and economic center of the Southwestern United States. Houston is also the only major city in the United States without zoning as an element of its land use planning and is often portrayed as an archetype of the free enterprise, capitalist, or *laissez-faire* city (Lamare, 1998; Lin, 1995). Despite a lack of zoning, local land use regulatory policies made by the municipality significantly influence urban development in Harris county (Qian, 2010), but the high natural and technological risk of this area makes it a complex environment for socially vulnerable populations to navigate. Efforts to minimize costs for potential investors as an economic development strategy in the metropolitan area have created less than ideal living conditions, especially for socially vulnerable groups (Vojnovic, 2003). Similar to other large U.S. cities, Houston is also faced with environmental justice problems as a result of disproportionately placing environmental hazards in areas occupied by lower income groups and non-whites (Bullard & Wright, 1993; Chakraborty et al., 2014; Pulido, 2000). While this issue is extensively studied in the environmental justice literature, the role of policies like low-income housing subsidies in placing marginalized groups in harm’s way in a multi-hazard urban environment like Houston has not yet been explored. The spatial distribution of housing subsidies under the broader umbrella of two different programs (HCV and LIHTC) is explored here and ways in which housing subsidies influence neighborhood social vulnerability over time are examined through spatial econometric models.

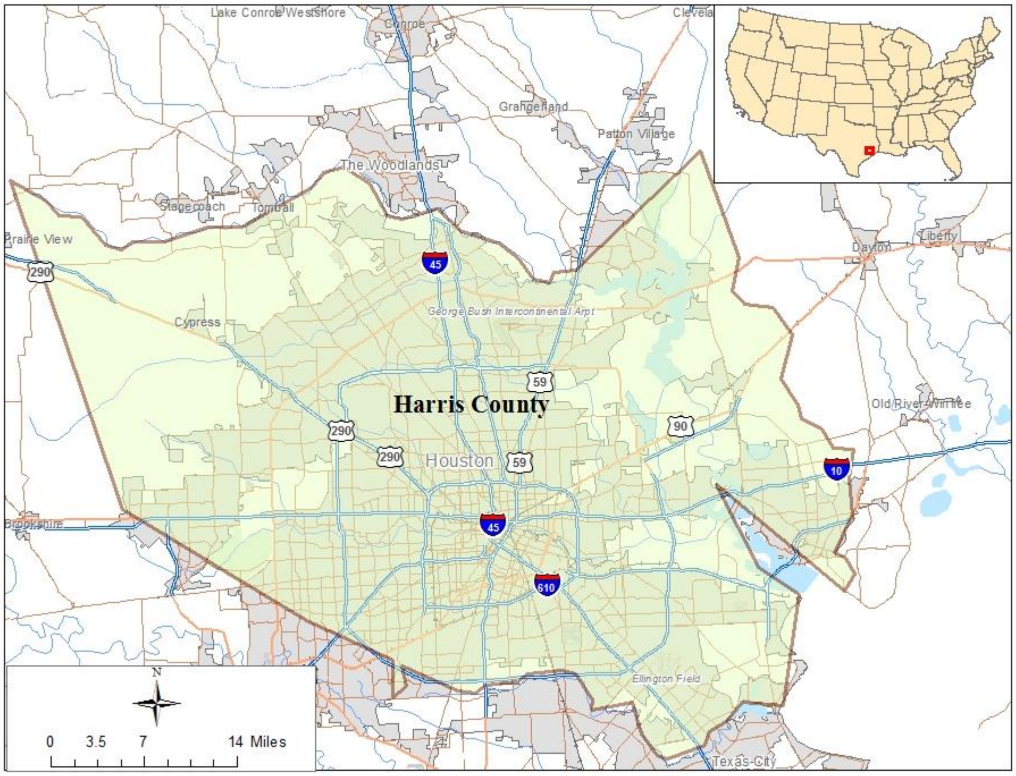


Figure 5.1: Map of Harris County, Texas

5.2 Hazard Risk Exposure in Harris County

In order to portray the multi-hazard risk context of Harris County, both natural and technological risks are considered in this study. Specifically, natural hazard risk due to flood and hurricane storm surge and technological hazard risk due to the locations of TRI facilities, with Chapter 3 detailing the methodological steps followed for creating these multi-hazard risk measures. Figure 5.2 shows the natural hazard risks identified at the census tract level and in this case, risk is measured as the percentage of residential lots in each census tract that fall in either the 100 year flood plain or a Category-1 hurricane risk zone. Some census tracts are excluded from this analysis (shown in grey) that had very few people (less than 1,000 in both 2000 and 2010) or a high percentage (greater than 30%) of residents living in group quarter housing (i.e., jails, senior housing, university campuses, etc.). Although Houston has a vast amount of low-lying land in its south-east and eastern region, natural hazard exposure was not found to be significantly higher in these parts of that region (compared to other areas) due to the lower percentage of residential areas falling in the 100 year flood plain or Category 1 hurricane risk zone. Still, the map (Figure 5.2) shows a high number of census tracts having at least 40 percent of their residential lots in the natural hazard risk zone, particularly concentrated in the southwest and northern part of the county.

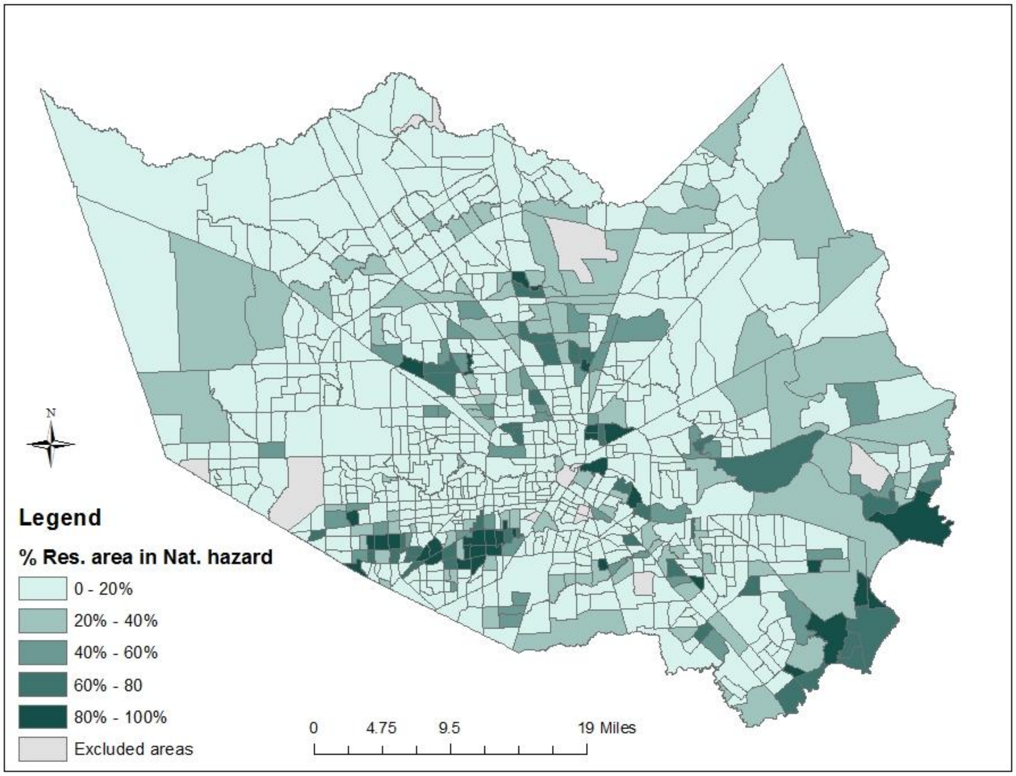


Figure 5.2: Natural hazard risk (i.e. % of residential lots in flood and hurricane risk zone) of Harris County

As detailed in Chapter 3, technological hazard risk for Harris County is estimated using two different measures of distance decay which, produce significantly different hazard exposure patterns. Since there is no theoretical consensus on the ideal specification for distance decay or what the threshold distance for impacts from a facility should be, this study considers both approaches in order to capture as wide a spectrum of technological risk as possible. Since this study is more interested in relative hazard risk and how people locate within this hazard context, proximal exposure due to distance and total toxic emission from TRI facilities is considered more relevant than the actual health risks posed by a specific type of toxic chemical. Further, prior studies have extensively examined such health risks due to both point and non-point sources of emissions in Harris County or Houston (Chakraborty et al., 2014; Linder et al., 2008;

Sexton et al., 2007). Considering the variability of emissions in different years, all reported TRI locations and their emissions from 2000 to 2010 were included in the hazard calculation and then an average level of hazard exposure is identified for the whole study period. Although it can be argued that new facilities appearing during this time period could in theory alter this risk measure, the data do not indicate that this is the case. Firstly, there was not a large increase in reported TRI facilities during this time (349 in 2001 increased to 367 in 2010) and secondly, the new facilities were located mostly in the areas which already had other facilities nearby. Due to these two factors, the relative risk measures should not change significantly, which is a key assumption of this study.

Figures 5.3 and 5.4 show quantile maps for risk measures calculated using the two distance decay approaches adopted for this study. Since it takes the average of exposure (for 2000 to 2010) weighted by the total emissions, measures using the power function were denoted AWPOWR, while measures based on the WCPE function were named AWCPE. Drastic differences in the hazard landscapes created under the two distance decay specifications are evident in Figures 5.3 and 5.4. Since the power function considers high exposure in the immediate vicinity of a facility with a rapid decrease in impact thereafter and does not consider any distance threshold or cutoff, it results in a relatively larger area identified as exposed to technological hazards. On the other hand, since the WCPE function imposes a distance threshold (Figure 5.4 shows a one mile threshold) it confines exposure to areas within that threshold distance and does not consider impacts for areas located far away from the facilities. Still, there are some common areas identified as high technological risk zones in both of the maps and in particular, near the south-eastern ship channel and along the north-west corridor (Highway 290).

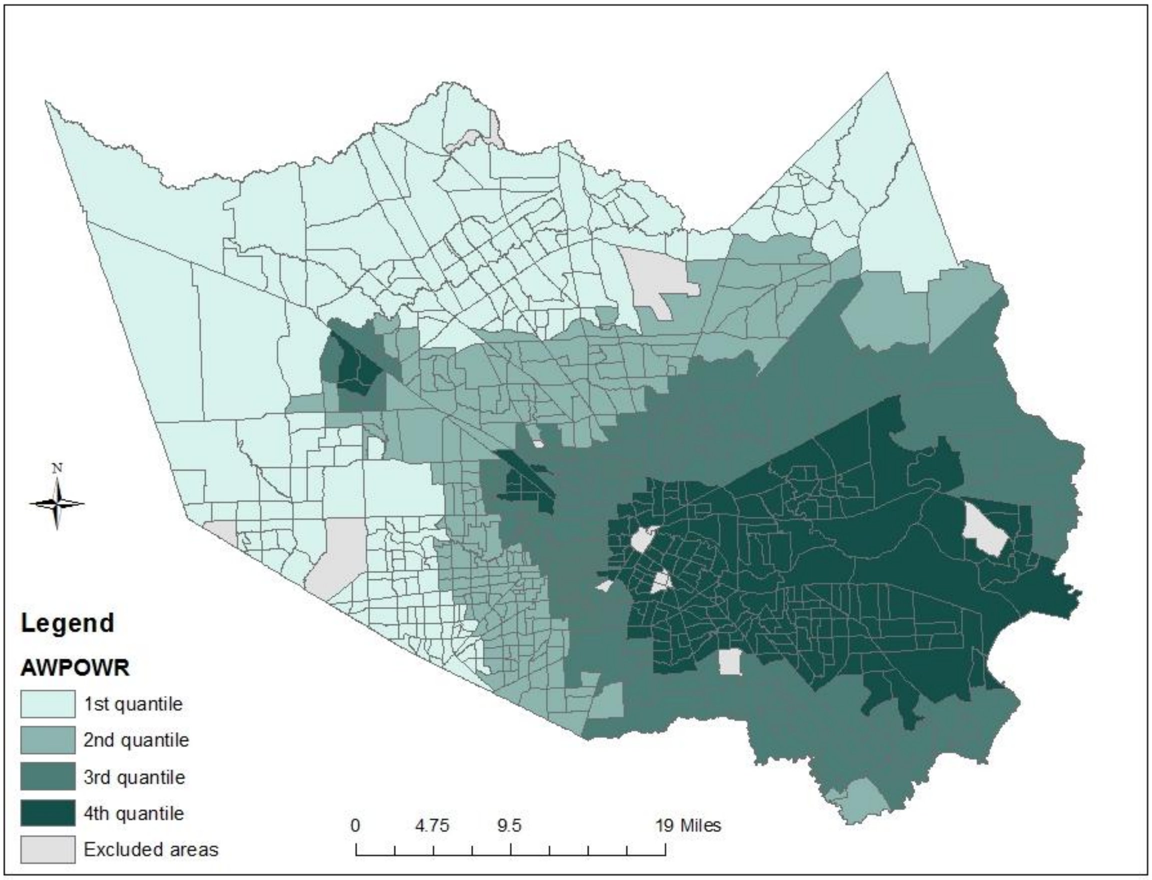


Figure 5.3: Technological risk exposure (measured by power function) in Harris County

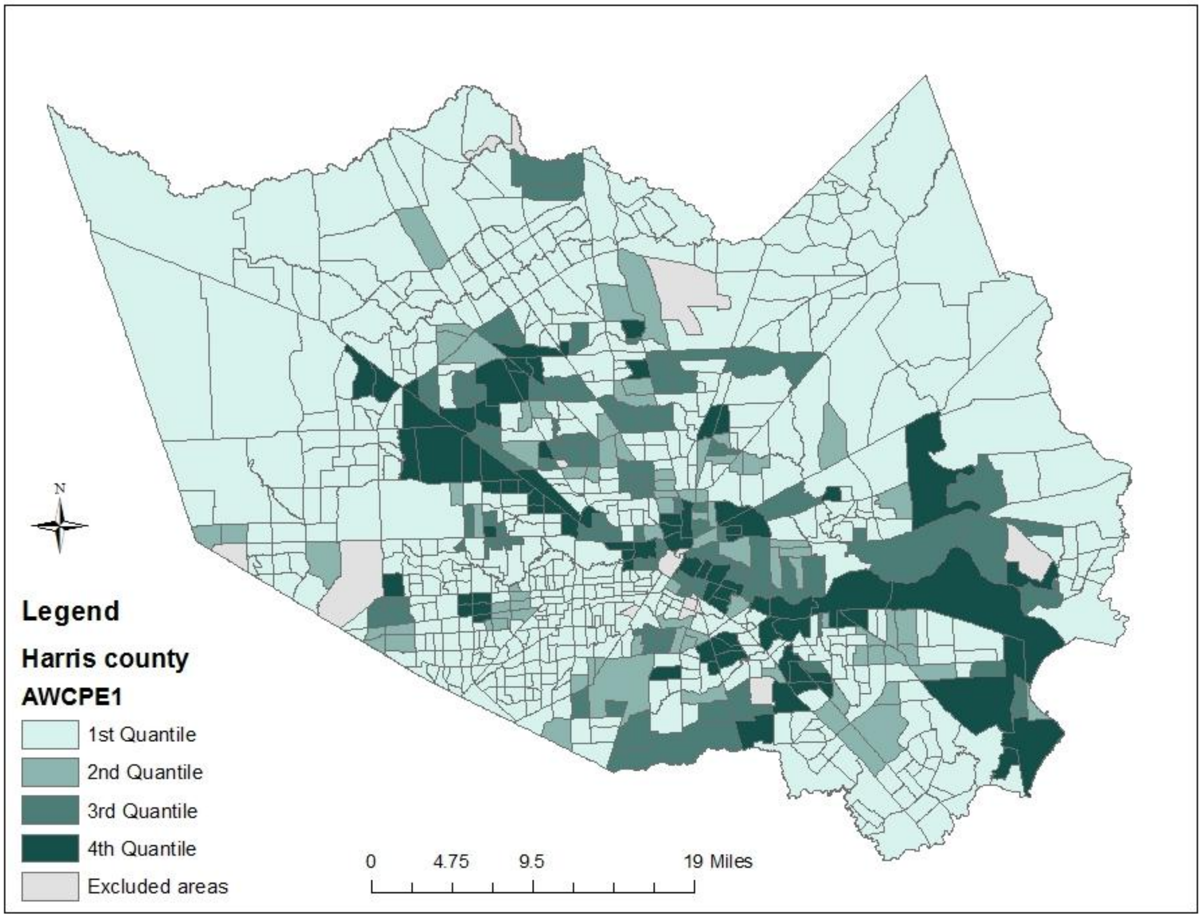
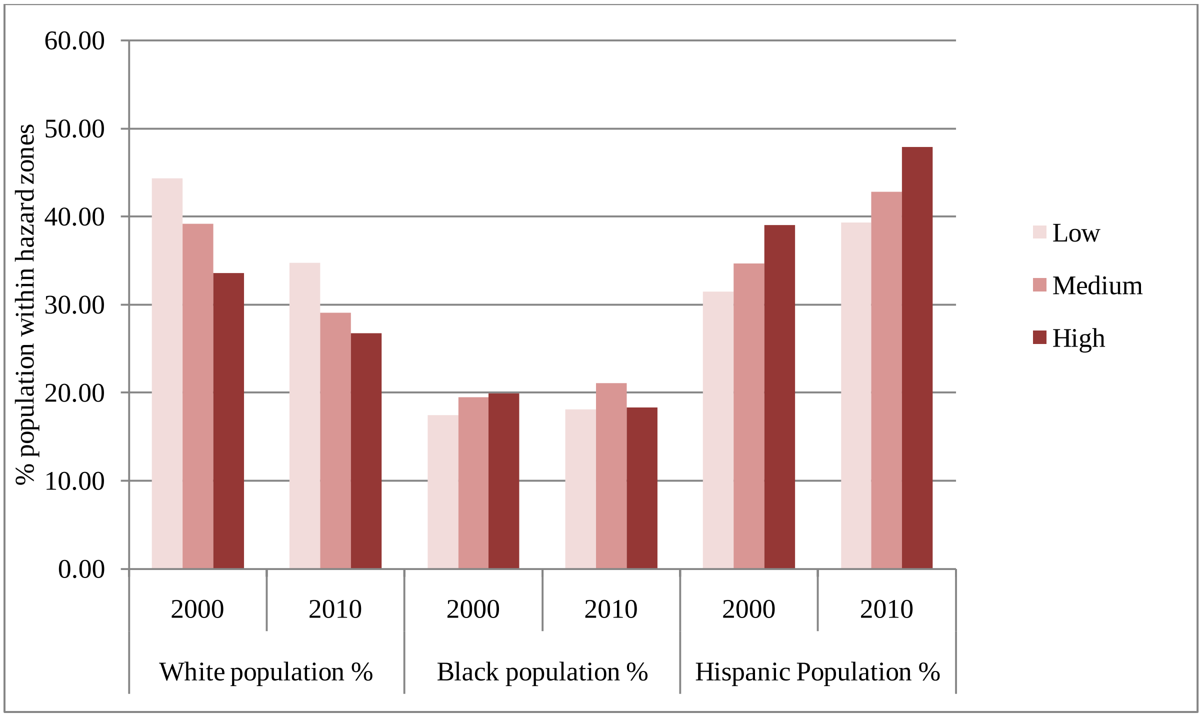


Figure 5.4: Technological risk exposure (measured by WCPE function, 1 mile distance threshold) in Harris County

5.3 Social Vulnerability in the Hazard Zones

The hazard risk measures discussed in previous section were used in a spatial regression analysis to understand the interaction between hazard risk and social vulnerability. This section discusses how the population in different racial/ethnic groups and poverty statuses are spatially distributed within this hazard context of Harris County in the year 2000 and 2010. Figures 5.5 to 5.7 show the race/ethnicity distribution within different levels of natural and technological hazard areas. Contrasting trends in the spatial distribution of Non-Hispanic White (henceforth mentioned as ‘white’) and Hispanic populations is evident here, while for the Non-Hispanic Black or African-American population (henceforth mentioned as ‘black’) this trend is unclear. With the growth of the Hispanic population in Harris County, the white population percentage has decreased significantly between 2000 and 2010, but within the identified hazard zones the relative distribution is consistent in both time periods. While the White population percentage is higher in safer areas (i.e., less risk from flood or hurricane storm surge), in hazardous areas the percentage of Hispanic population is higher consistently in both 2000 and 2010.



Low: Less than 20% residential area in hazard zone, Medium: 20%-40% area in hazard zone, High: More than 40% area in hazard zone

Figure 5.5: Race/ethnicity distribution in natural hazard areas

Considering the different hazard landscapes created by the power function and the WCPE function (Figures 5.3 and 5.4) it could be expected that the pattern of racial/ethnic distribution within hazard exposed areas would be different, but as shown in Figures 5.6 and 5.7 the patterns are actually similar in both 2000 and 2010. Since the power function assigns risk measures to all census tracts, its median value is used as the cutoff point for technological hazards (Figure 5.6) and in the case of the WCPE function, areas within the threshold distance of one mile is taken as the cutoff point (Figure 5.7). Despite these different approaches, both of the methods for technological risk measures indicate that the percent white is significantly lower and percent Hispanic is significantly higher in hazardous areas in both 2000 and 2010. For the black population however, these two approaches show different distributions. While the hazard zones from the power function do not show any consistent trend (Figure 5.6), from the WCPE function

(Figure 5.7) it appears that the black population percentage within technological hazard areas was higher compared to that in non-hazard areas.

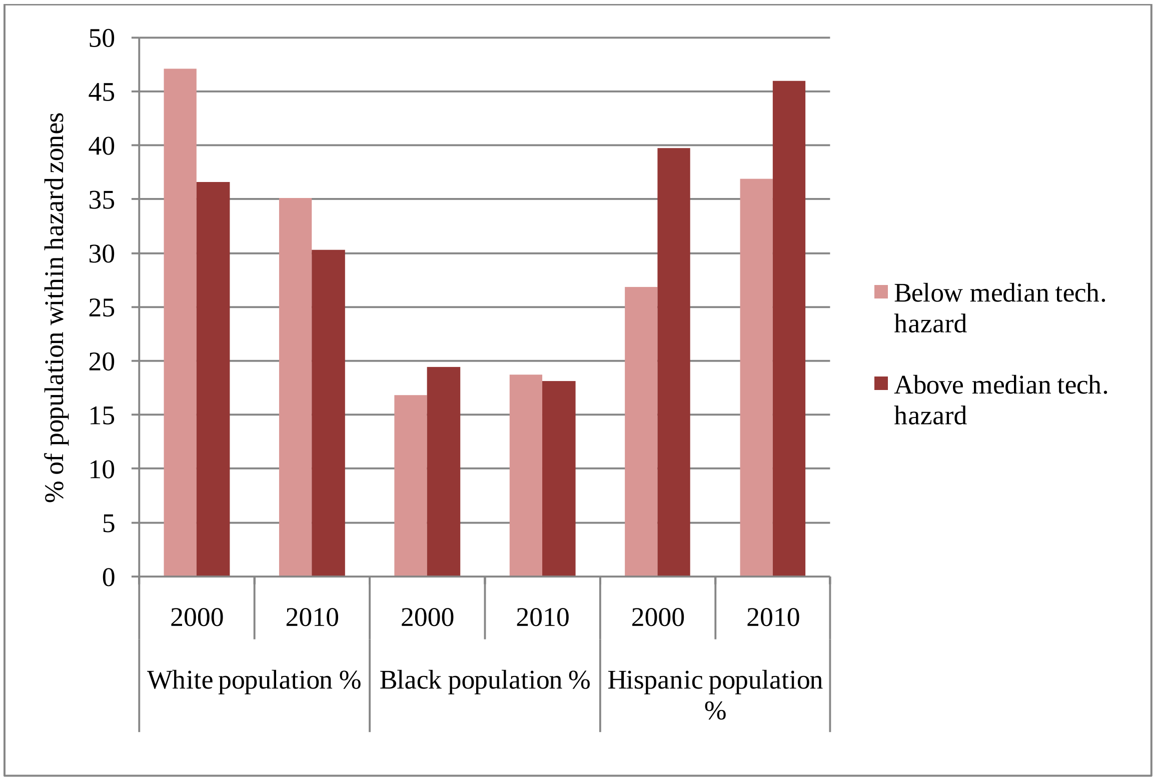


Figure 5.6: Race/ethnicity distribution within technological hazard zones (power function)

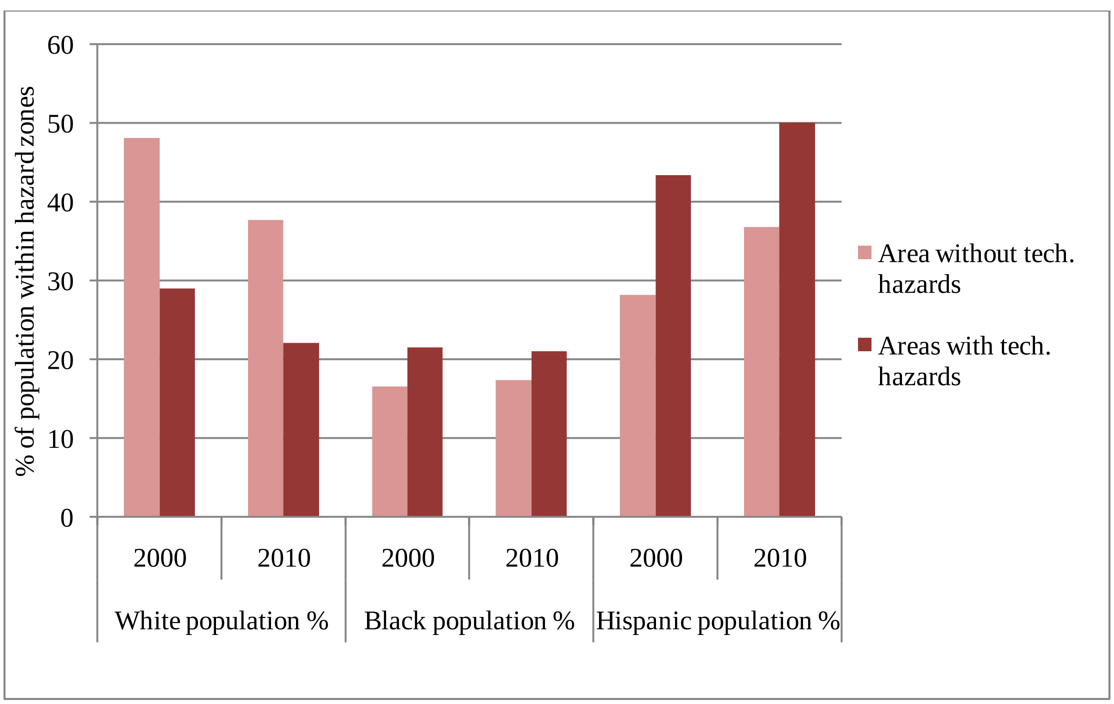
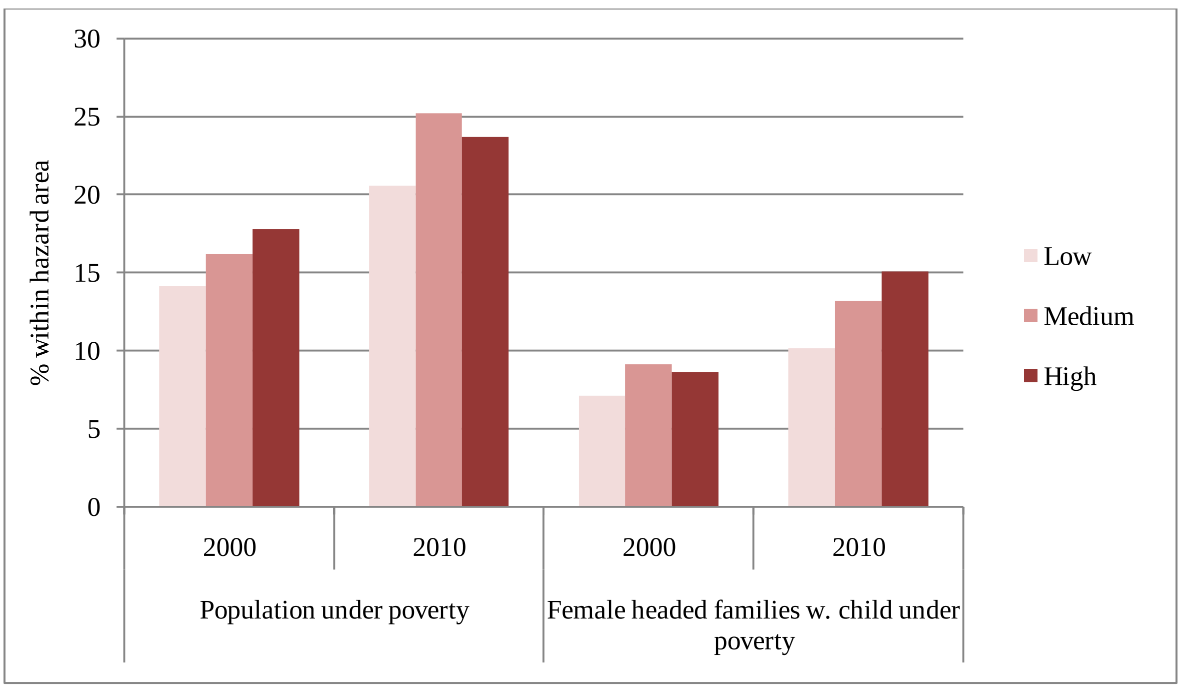


Figure 5.7: Race/ethnicity distribution within technological hazard zones (WCPE function)

Poverty rates within the natural and technological hazard areas are comparatively higher than the non-hazard areas and Figures 5.8 to 5.10 show this trend for both 2000 and 2010. Since the total poverty rate has increased in Harris County between these two time periods, the percentages of people under the poverty level has increased in all areas, but within hazardous areas, the concentration of poverty is consistently higher throughout the study period. All three figures (5.8 to 5.10) also show similar trends for female-headed families in poverty (as a percentage of all families with children). This indicator is considered here based on its enduring status in the principal component analysis as a significant contributor to social vulnerability. Although it can be expected to move in tandem with the findings for overall poverty rate, it is included here considering the higher degree of vulnerability experienced by female-headed households during any disaster event (Donner, 2003; Rodriguez & Russell, 2006). As Figures 5.8 to 5.10 indicate, among all the families with children living in different hazard zones, the presence of female-headed families living in poverty is significantly higher in natural or technological hazard areas.



Low: Less than 20% residential area in hazard zone, Medium: 20%-40% area in hazard zone, High: More than 40% area in hazard zone

Figure 5.8: Percentage of population under poverty and Percentage of female headed families (with children) under poverty by natural hazard zones

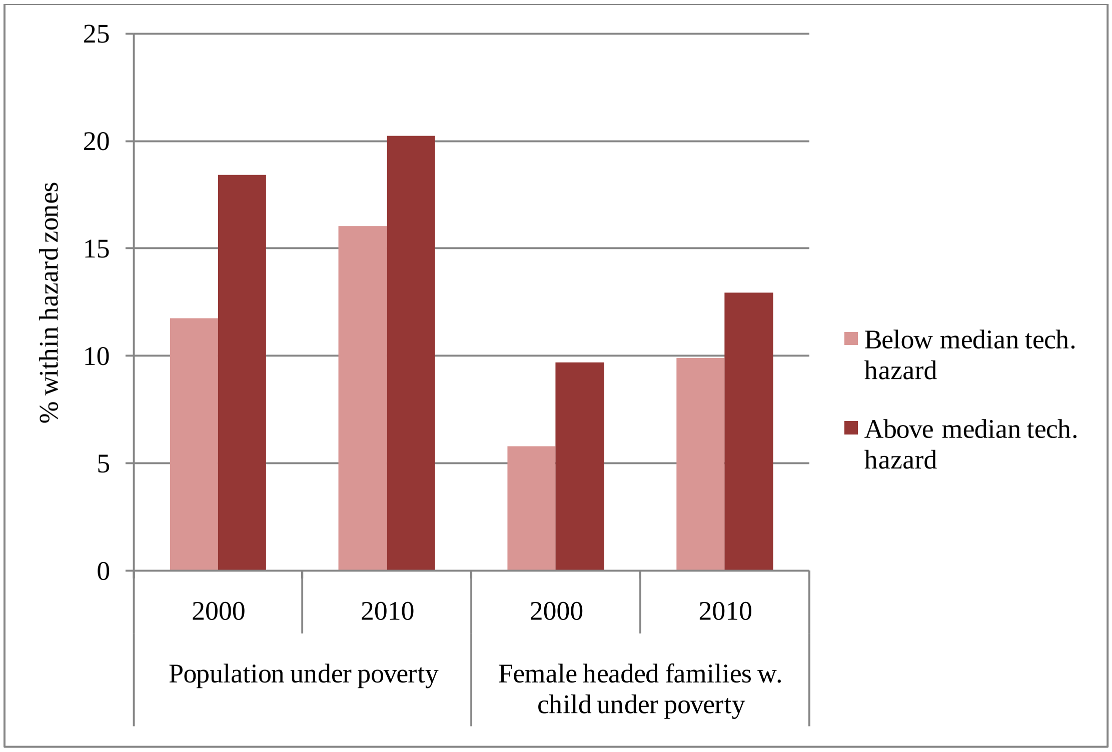


Figure 5.9: Percentage of population under poverty and Percentage of female headed families under poverty (with children) by technological hazard zones (power function)

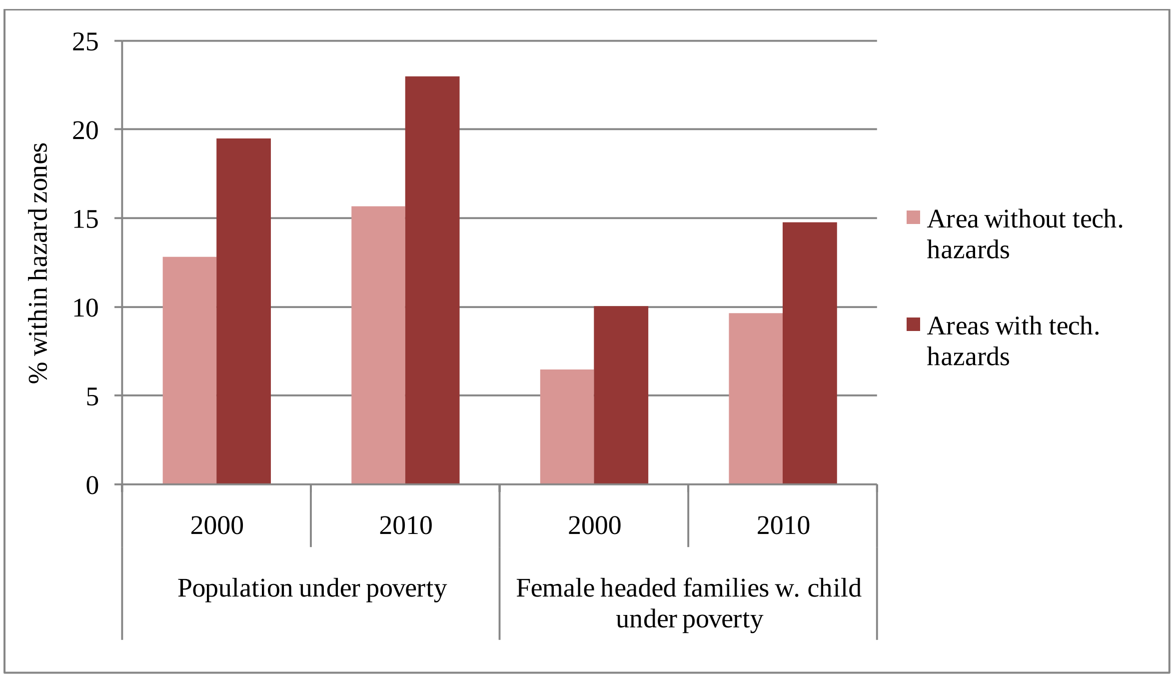
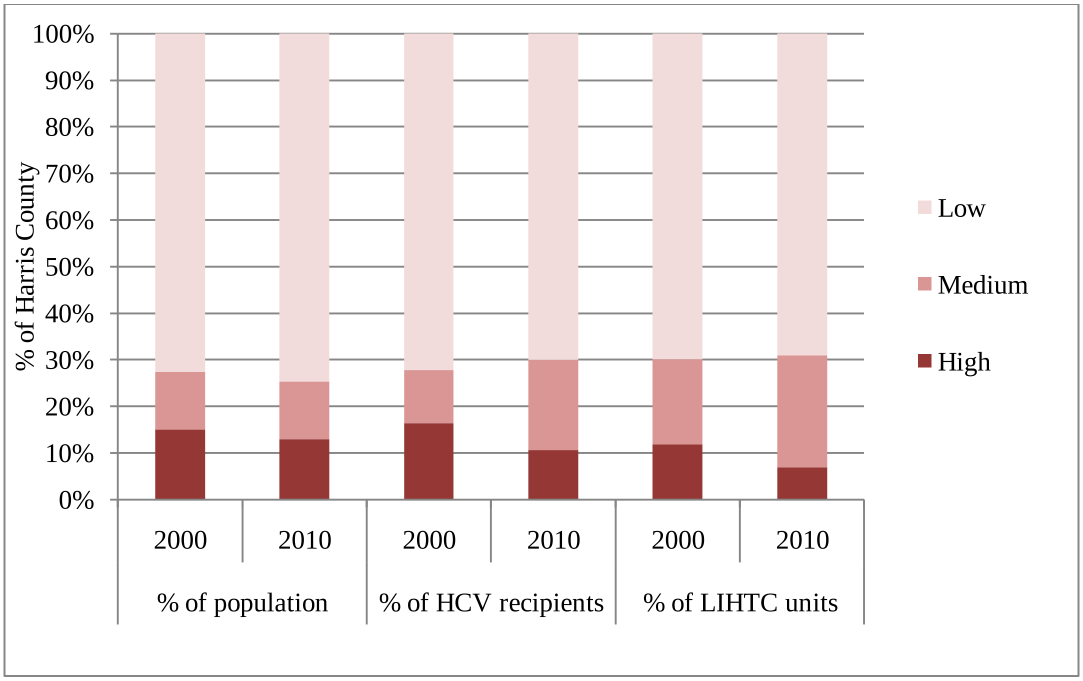


Figure 5.10: Percentage of population under poverty and Percentage of female headed families under poverty (with children) by technological hazard zones (WCPE function)

5.4 Housing Subsidies in the Hazard Zones

While the above findings on race/ethnicity or poverty distribution in urban hazard zones is not surprising, there is yet to be any study that explores the location outcomes produced by housing subsidies within these multi-hazard contexts (Cutter et al., 2001; Houston et al., 2013). This section centers on how the two housing subsidy programs considered in this study are performing in terms of avoiding hazardous areas. Although the findings discussed in previous section were for the distribution of population groups within the hazard zones, in the interest of having a better reference for comparison, the population distribution throughout the county is compared to the distribution of housing subsidies among the hazard zones. If the distribution of housing subsidies follows the overall distribution of population, it can be argued that housing units provided under these programs are not concentrated within hazardous areas. However, considering the broader objective of poverty deconcentration associated with these programs, it can be expected that the housing subsidies would be located in less hazardous areas compared to the overall population distribution. Since the two programs have different approaches for providing housing subsidies (demand based HCV and supply oriented LIHTC), different outcomes are to be expected.

Figures 5.11 to 5.13 indicate that for all hazard measures, subsidized housing units are not successfully avoiding hazardous areas; rather they are slightly more concentrated in hazard zones compared to the overall population distribution. Although both of the subsidy programs performed better in avoiding highly exposed natural hazard zones (i.e. census tracts with more than 40% in natural hazard zone), in the case of moderate exposure (i.e. census tracts with more than 20% in natural hazard zone) they exhibit a slightly higher presence compared to the overall population distribution in both 2000 and 2010 (Figure 5.11). Between the two programs, the HCV program appears to be performing marginally better than the LIHTC in avoiding moderate hazard zones, but in the case of high exposure areas, the LIHTC is performing better.



Low: Less than 20% residential area in hazard zone, Medium: 20%-40% area in hazard zone, High: More than 40% area in hazard zone

Figure 5.11: Comparing distribution of HCV recipients and LIHTC units to population distribution within natural hazard zones of Harris County

For technological hazards, both of the hazard measures indicate similar outcomes for the subsidy programs, although they vary in terms of the extent of their differences (between the programs). Following the trends of natural hazards, in the case of technological hazards both of the housing subsidy programs also failed to find safer areas and instead their placement in hazardous areas is marginally higher compared to the overall distribution of the population. For example, if we consider the hazard zones identified by the WCPE function (Figure 5.13), in 2010 about 30 percent of the population of Harris County lived in a hazardous area, but about 33 percent of HCV recipients and 40 percent of LIHTC units were found in those areas during the same time period. Between the two programs, despite performing better in terms of avoiding technological hazard areas in 2000 (33% LIHTC versus 36% HCV, Figure 5.13), in 2010 a higher proportion of LIHTC units were found in hazardous areas (40% versus 33% for HCV).

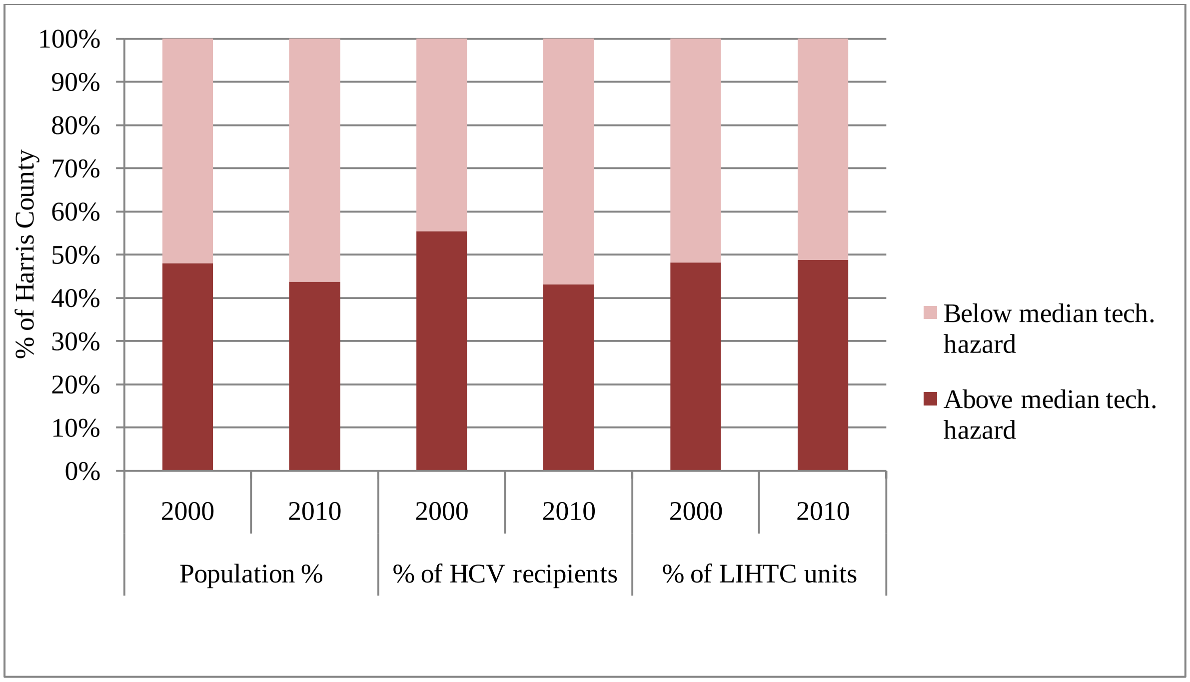


Figure 5.12: Comparing distribution of HCV recipients and LIHTC units to population distribution within technological hazard zones (power function) of Harris County

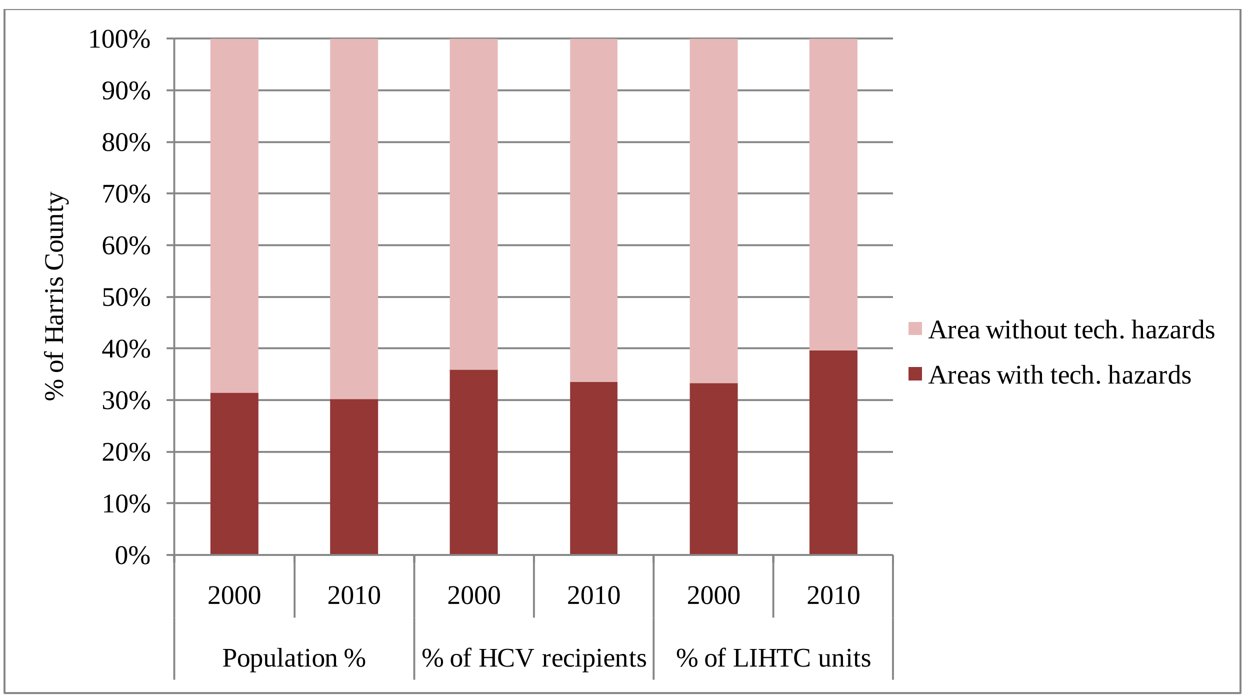


Figure 5.13: Comparing distribution of HCV recipients and LIHTC units to population distribution within technological hazard zones (WCPE function) of Harris County

5.5 Subsidized Housing in a Multi-hazard Area: Impacts on Social Vulnerability

The broad objective of this study is to explore the drivers of social vulnerability and examine how housing subsidy programs may act as a driver to locate more vulnerable population in harm's way. The previous sections advance this objective by clearly depicting the higher presence of vulnerable populations in hazardous areas and at the same time, how housing subsidies are failing to avoid the hazard zones of Harris County. This outcome can be attributed to limitations in the present mechanisms of subsidized housing provision (detailed in Chapter 6), while the political economic and environmental justice framing of vulnerability (discussed in Chapter 2) explains the location decisions of vulnerable populations in a contested urban space. Now the critical question to be asked is how the ostensibly progressive agenda of providing housing subsidies in a neoliberal political setting can influence and even exacerbate vulnerability in a multi-hazard urban area. This is where the idea of the *production of urban vulnerability* (Dooling, 2012), that examines how political economies of resource use and normative planning and management interventions influence which places and populations are made vulnerable (Collins, 2009; Orsi, 2004), reenters the discussion. Keeping this broader theoretical underpinning in mind, this study explores the impacts of placing subsidized housing in hazardous areas on the social vulnerability outcomes in Harris County. While the regression analysis discussed in the next section helps to empirically examine the relationship, a descriptive exploration is conducted before estimating the models.

Since social vulnerability is a multidimensional concept, it makes sense to explore it through an index (SoVI) as discussed in Chapter 4. But such an index is difficult to interpret for specific policy outcomes due to its changing composition from year to year. Keeping these limitations of the SoVI in mind, this study considers prominent indicators that contribute significantly to the overall social vulnerability index. As discussed in Chapter 4, poverty was found to be a consistent indicator that met this criterion for all study years. But it is also true that the experience of poverty is not the same across all population sub-groups. For example, analyzing the neighborhood crime rate of HCV recipients, Lens et al. (2011) found that black voucher holders lived in significantly safer areas than poor households of the same race, but that Hispanic and white voucher holders did not experience the same outcome. Considering this possible difference in the location patterns of those in poverty among population sub-groups, this study considers the poverty rate of racial and ethnic subgroups (e.g., Hispanic, Non-Hispanic

White, Non-Hispanic Black) along with the overall poverty rate. Before exploring the poverty rate for different subgroups, Table 5.1 shows population growth in different areas of Harris County categorized by the presence of natural hazard zones (greater than 40% residential land in natural hazard area) and increase in vouchers between 2000 and 2010. As this table shows, safer areas (away from natural hazards) that had an increase in HCV recipients experienced the highest population growth (32.34%), but it also shows significant population growth (7.46%) in hazardous areas with HCV growth between 2000 and 2010.

Table 5.1: Population growth by location in natural hazard* areas and HCV growth

	Population		
Natural Hazard and HCV growth	2000	2010	Growth (%)
Nat. Haz. Areas with increased HCV	246,399	264,782	7.46
Other areas with increased HCV	1,878,958	2,486,683	32.34
Nat. Haz. Areas without increased HCV	263,199	263,380	0.07
Other areas without increased HCV	991,011	1,063,400	7.30

*Areas with more than 40% residential land in natural hazard Area

While all the areas irrespective of hazard level or HCV presence experienced significant population growth, a question of interest for this study is how the poverty profile changed in those areas during the study period. Table 5.2 presents changes in vulnerability by the overall poverty rate and also by the poverty rate of major racial and ethnic population subgroups. As shown, the incidence of poverty for all groups was significantly higher in natural hazard areas that experience any growth in voucher households. These areas also witnessed an increase in poverty rate between 2000 and 2010.

Table 5.2: Changes in vulnerability by location in natural hazard* areas and HCV growth

Natural hazard and HCV growth	%population under poverty			%population under poverty (White)			%population under poverty (Black)			%population under poverty (Hispanic)		
	2000	2010	(+/-) %	2000	2010	(+/-) %	2000	2010	(+/-) %	2000	2010	(+/-) %
Nat. Haz. Areas with increased HCV	16.57	23.32	6.75	5.88	12.49	6.62	5.25	6.64	1.39	7.87	13.91	6.04
Other areas with increased HCV	13.06	16.43	3.37	5.24	8.23	2.99	3.71	4.57	0.86	5.88	8.52	2.63
Nat. Haz. Areas without increased HCV	18.91	22.34	3.42	7.78	13.08	5.30	4.12	4.14	0.01	11.54	15.27	3.73
Other areas without increased HCV	17.05	18.82	1.77	7.01	11.41	4.40	4.82	3.86	-0.96	9.46	12.25	2.79

*Areas with more than 40% residential land in natural hazard areas

In the same fashion, if we categorize all census tracts based on their natural hazard exposure and growth of LIHTC units, the results are the same. As Table 5.3 shows, natural hazard areas with any growth of LIHTC units had comparatively higher poverty rates in both 2000 and 2010. The overall poverty rate in those areas also increased significantly between 2000 and 2010 compared to other areas.

Table 5.3: Changes in vulnerability by location in natural hazard* areas and LIHTC units growth

Natural hazard and change in poverty %	%population under poverty			%population (White) under poverty			%population (Black) under poverty			%population (Hispanic) under poverty		
	2000	2010	(+/-) %	2000	2010	(+/-) %	2000	2010	(+/-) %	2000	2010	(+/-) %
Nat. Haz. Areas with increased TCU	24.42	34.22	9.80	7.79	17.26	9.47	8.83	11.29	2.46	12.3	20.34	7.99
Other areas with increased TCU	18.66	22.93	4.27	5.98	10.01	4.03	8.12	8.96	0.84	7.51	10.83	3.32
Nat. Haz. Areas without increased TCU	17.48	22.21	4.74	6.82	12.55	5.73	4.48	5.07	0.59	9.65	14.28	4.63
Other areas without increased TCU	13.55	15.78	2.23	5.83	8.99	3.17	3.25	3.27	0.03	7.04	9.35	2.32

*Areas with more than 40% residential land in natural hazard areas

Like natural hazards, areas with technological hazards showed a similar pattern of population growth and social vulnerability. Since both measures of technological hazards showed similar trends, only the results from the power function are presented here. Table 5.4 shows population growth of different areas categorized by their technological hazards (i.e., above the median value of AWPOWR) and increased presence of HCV households. The pattern of population growth observed in all areas is similar to that of natural hazards.

Table 5.4: Population growth (2000-2010) by location in technological hazards* areas and HCV growth

	Population		
Technological Hazard and population growth	2000	2010	Growth (%)
Tech. Haz. Areas with increased HCV	44,746,302	48,654,600	8.73
Other areas with increased HCV	167,789,527	226,491,900	34.99
Tech. Haz. Areas without increased HCV	40,005,169	40,249,300	0.61
Other areas without increased HCV	85,415,935	92,428,700	8.21

*Areas with above median value of AWPOWR

In the case of vulnerability measures however, technological hazard areas yielded different results than natural hazard areas. Although hazardous areas with an increase in HCV households had comparatively higher poverty rates than other areas also experiencing HCV growth, the highest poverty rates were found in hazardous areas without any growth in HCV. This finding is consistent with the hypothesis that housing subsidies when placed in hazardous areas significantly increase neighborhood vulnerability compared to other non-hazardous areas also having such subsidies. Although for the overall population the change in poverty rate was higher in non-hazardous areas (4.03 versus 2.93) and the actual poverty rate in 2010 was higher in hazardous areas with HCV growth (21.42% versus 16.16%). However, for the white and Hispanic population living in poverty even the change in the rate of poverty is higher in hazardous areas with HCV growth compared to other areas also experiencing an increase in HCV households.

Table 5.5: Changes in vulnerability by location in technological hazard* areas and HCV growth

Tech. hazard and change in poverty%	%population under poverty			%population (White) under poverty			%population (Black) under poverty			%population (Hispanic) under poverty		
	2000	2010	(+/-) %	2000	2010	(+/-) %	2000	2010	(+/-) %	2000	2010	(+/-) %
Tech. Haz. Areas with increased HCV	18.49	21.42	2.93	7.10	11.13	4.03	5.54	5.60	0.05	9.35	12.71	3.37
Other areas with increased HCV	12.13	16.16	4.03	4.85	8.11	3.26	3.45	4.59	1.14	5.25	8.24	2.99
Tech. Haz. Areas without increased HCV	23.90	26.22	2.32	9.93	15.62	5.69	5.87	5.39	-0.5	15.4	18.68	3.27
Other areas without increased HCV	14.43	16.61	2.19	5.88	10.06	4.18	4.12	3.28	-0.8	7.33	10.32	2.99

*Areas with above median value of AWPOWR

As for the increase of LIHTC units in technological hazard areas, the findings also fit well with the hypothesis of this study. As Table 5.6 shows, hazardous areas with increased LIHTC units had significantly higher poverty rates in both 2000 and 2010 compared to other areas also receiving new LIHTC units during this time period. For the racial and ethnic population subgroups considered the same trend holds with the exception of the black population living in poverty.

Table 5.6: Changes in vulnerability by location in technological hazard* areas and LIHTC units growth

Tech. hazard and change in poverty%	%population under poverty			%population (White) under poverty			%population (Black) under poverty			%population (Hispanic) under poverty		
	2000	2010	(+/-) %	2000	2010	(+/-) %	2000	2010	(+/-) %	2000	2010	(+/-) %
Tech. Haz. Areas with increased TCU	21.04	26.66	5.62	7.68	12.48	4.80	7.63	8.49	0.87	9.72	14.71	4.99
Other areas with increased TCU	18.09	22.39	4.30	5.44	9.64	4.20	8.35	9.21	0.86	6.94	10.15	3.20
Tech. Haz. Areas without increased TCU	21.05	22.91	1.87	8.59	13.32	4.73	5.30	4.83	-0.5	12.7	15.57	2.85
Other areas without increased TCU	12.00	15.04	3.04	5.15	8.48	3.33	2.86	3.18	0.33	5.78	8.58	2.80

*Areas with above median value of AWCPE

5.6 Spatial Regression Model for Social Vulnerability

The exploration of changes in social vulnerability with respect to hazard exposure and housing subsidies in Harris County as presented in previous section appear to confirm the hypothesis of this study that housing subsidies exacerbate social vulnerability when located in hazardous areas, controlling for background or baseline rates of vulnerability attributable to population growth. This finding conflicts with the central objectives of the subsidy programs to revitalize depressed neighborhoods and to provide safer housing to low-income people. As this study posits, present attempts to achieve these objectives through the provision of market dependent housing subsidies is likely to fail, particularly in hazard exposed neighborhoods. To confirm these results, a spatial regression analysis was performed (as explained in Chapter 3). This kind of regression analysis not only controls for other factors that may contribute to social vulnerability, but also can account for spatial autocorrelation of the dependent variables. All four dependent variables considered in this study (Table 5.7) were found to exhibit significant spatial autocorrelation, warranting spatial regression analysis. In addition to standard ordinary least squares (OLS), spatial lag, spatial error, and spatial Durbin (SDM) models were estimated to compare their results. Each of these model results along with the Lagrange Multiplier (LM) diagnostics (Anselin, 1988; Anselin et al., 1996) for model selection are presented in Appendix C. Following the procedures suggested by Elhorst (2010), likelihood ratio (LR) tests were conducted to identify the model that best describes the data[24].

Identifying neighboring areas and assigning spatial weights for those neighboring areas is a key issue for spatial regression. The spatial weight matrix specifies which neighboring tracts are most important in defining the characteristics of an area and thereby formally articulates the spatial dependence relationships assumed by the regression analysis. Neighborhood change studies have documented how areas surrounding a neighborhood influences white flight (Crowder & South, 2008; Denton & Massey, 1991), minority composition (Denton & Massey, 1991; Massey & Mullan, 1984), housing values and appreciation rates (Burnell, 1988; Sampson et al., 1999), and loss of population (Morenoff & Sampson, 1997). Studies of subsidized housing have also shown spill-over effects on surrounding neighborhoods (Galster, 2013; Galster et al., 1999; Schill & Wachter, 1995). These studies indicate spatial dependence in the characteristics of a given neighborhoods on the characteristics of neighboring areas and the spatial matrix is designed to capture this influence. Since spatial dependence tends to decline with distance (Downey, 2006), an inverse distance weighting strategy is adopted for this study in which the influence of neighboring census tracts is assumed to be inversely related to distance. This distance-decay strategy defines the elements of the spatial weights matrix as $W_{ij} = 1/d_{ij}$ where d_{ij} is the geographic distance[25] between the centroid of tract i and the centroid of the neighboring tract j. In this case another critical factor is the distance beyond which a zero influence will be assumed (i.e., threshold distance for negligible influence). Voss & Chi (2006) tested multiple distance thresholds (and matrices) and selected the one that achieved a high coefficient of spatial

[24] See Chapter 3 section 3.3.2 for detail procedure followed in this study. Elhorst (2010) gives elaborate discussion.
[25] This distance can also be powered by two or more value.

autocorrelation along with a high level of statistical significance, while Crowder & South (2008), selected a much larger distance (100 miles) without a clear theoretical foundation[26]. In this study, a smaller threshold distance (eight miles) is selected, which was found to be the minimum distance (for Harris County) to assign all census tracts at least one neighbor (i.e., eight miles is the maximum distance between all the tract centroids) and which also gives the highest coefficient of spatial autocorrelation[27]. Since the traditional adjacency approach ignores tracts that do not share a boundary, a distance decay approach offers important theoretical and practical advantages. While, both approaches emphasize neighboring tracts, the distance-decay function produces a more realistic spatial pattern of neighborhood characteristics and residential location choice. This approach is consistent with the argument that householders consider conditions in a broad range of geographic areas when making their residential location choices (Crowder & South, 2008; Krysan, 2008).

Table 5.7 lists all variables used for the regression analysis. Change in social vulnerability (ΔSoVI) between 2000 and 2010 is one of the key dependent variables and is used to model how the independent variables are contributing to overall changes of vulnerability throughout Harris County. This variable is calculated from the SoVI values (as described in Chapter 4), by subtracting the standardized value of the 2000 SoVI from that of 2010. It should be noted that because the SoVI is a composite measure of social vulnerability, it may mask changes in specific dimensions of vulnerability. Similarly, as explained in Chapter 4 (section 4.7), temporal comparison of the SoVI can be problematic since the composition of vulnerability dimensions (and variables) may change over time. Considering these limitations of the SoVI, individual dimensions of social vulnerability are also explored here alongside changes in the SoVI. The poverty rate is one of the key measures of social vulnerability (as also found through the PCA results discussed in Chapter 4) and change in the poverty rate between 2000 and 2010 (Δpoverty_rate) is evaluated to determine how subsidized housing and hazard exposure interacted with the overall poverty rate at the census tract level. Since the experience of poverty is also not the same across all population subgroups (Lens et al., 2011), the change in the percentage of the population who are black and living in poverty (Δblack_poverty) as well as

[26] Spatial weights by inverse distance are quite small beyond distance of about 10 miles, as contended by Crowder & South (2008) in support of taking 100 mile distance threshold.

[27] It is quite obvious that higher distance threshold will produce lower spatial autocorrelation, but in this case the minimum distance was taken that would assign all neighborhood with at least one neighborhood and would better help to capture the spatial spill over patterns of neighborhood characteristics through distance decay function.

Hispanic and living in poverty (Δhispanic_poverty) is also examined to determine if poor people within these subgroups are experiencing differential outcomes.

Table 5.7: Variables used for the models

Dependent Variables	
ΔSoVI	Change in standardized values of SoVI (2000-2010)
Δpoverty_rate	Change in % of population under poverty (2000-2010)
Δblack_poverty	Change in % of population who are Non-Hispanic Black and under poverty (2000-2010)
Δhispanic_poverty	Change in % of population who are Hispanic and under poverty (2000-2010)
Independent Variables	
zpowr*pchcvgr	Standardized value of technological exposure from power function*change in % of households with HCV
zpowr*pctcugr	Standardized value of technological exposure from power function*change in % of households in LIHTC units
zcpe1*pchcvgr	Standardized value of technological exposure from CPE function* change in % of households with HCV
zcpe1*pctcugr	Standardized value of technological exposure from CPE function* change in % of households in LIHTC units
zfldrt*pchcvgr	Standardized value of % residential lot in natural hazard area* change in % of households with HCV
zfldrt*pctcugr	Standardized value of % residential lot in natural hazard area* standardized growth of LIHTC units
pchcvgr	change in % of households with HCV (2000-2010)
pctcugr	change in % of households in LIHTC units (2000-2010)
zfldrt	Standardized value of % residential lot in natural hazard area
zpowr	Standardized value of technological exposure from power function
zcpe1	Standardized value of technological exposure from CPE function
Control variables	
Popgr	% growth of population (2000-2010)
Blkgr	Change in % of Black population (2000-2010)
Hspgr	Change in % of Hispanic population (2000-2010)
pov2000	% of population under poverty in 2000
hsp2000	% of Hispanic population in 2000
blk2000	% of Non-Hispanic Black population in 2000
mdrnt2000	Median rent of renter-occupied units in 2000
cbd_dist	Distance from CBD in miles

Among the independent variables, the key variables of interest for this study are the interaction terms for hazard exposure and housing subsidy. If those variables are statistically significant and carry a positive coefficient, this would confirm the hypothesis of this study. Each of the hazard exposure and housing subsidy variables were standardized (using the z-score transformation[28]) before incorporating them in the regression analysis to enhance the interpretability of the regression coefficients (Schielzeth, 2010). Centering variables through standardization is important when the interaction of two continuous variables is included in a model, because without centering the input variables will result in an interaction predictor that is collinear with the main effects (Schielzeth, 2010). Standardization of the input variables before estimating the model will largely eliminate this problem of correlation (Aiken & West, 1991; Neter et al., 1999) and also allows tests for interaction effects[29] (Schielzeth, 2010). For the present analysis, the estimated coefficient for the interaction term will indicate if the combination of hazard risk and housing subsidy significantly impacts social vulnerability beyond the individual effect of these two variables that are estimated as main effects. Since this study adopted two different measures of technological hazards (i.e., the power function and WCPE function), all the models are estimated for both of these measures separately.

Several control variables were included in the models that may influence the changes of social vulnerability indicators of an area. The growth of the total population and growth of different racial and ethnic groups are included, assuming that they may influence the percentage of the population under poverty in an area. Base year poverty (pov2000) and racial/ethnic composition (blk2000 and hsp2000) are included in the model because prior studies have shown that poor people usually find it easier to move into areas that already have high poverty rates and high minority concentrations (Galster et al., 2008; Logan & Zhang, 2010). The median rent of housing units in 2000 (mdrnt2000) represents the affordability of an area, while distance from the central business district (cbd_dist) indicates accessibility to employment opportunities, which can also be important decision factors whether people living in poverty will move to a certain area (Brueckner & Rosenthal, 2009). After controlling for all these relevant factors, it can be expected that the independent variables will capture their net effects on the dependent variables. Procedures for preparing all the data used in the models are discussed in detail in Chapter 3.

[28] The z-score is derived as follows: $Z_{Tract} = (Score_{Tract} - Mean_{county}) / \text{Standard Deviation}_{county}$

[29] For example, if combinations of the two variables produce differential responses in addition to what is explained by the sum of the main effects.

5.7 Model Results Discussion

Model estimates for change in social vulnerability (ΔSoVI) in the census tracts between 2000 and 2010 are presented in Table 5.8. The Lagrange Multiplier (LM) diagnostics of the OLS models (Appendix Table C2 and C5, for both measures of technological hazard) indicated that both a spatial lag and error model specification can be selected for this variable, but the Likelihood Ratio (LR) test (Table C3 and C6) recommended by Elhorst (2010) indicated the Spatial Durbin Model (SDM) would be a better choice. As a result, OLS and SDM estimates are presented in Table 5.8 for both measures of technological hazard. As the OLS model results indicate, tracts with an increase in the percentage of households with HCV (pchcvgr) have experienced an increase in social vulnerability between 2000 and 2010. Although the SDM using the power function did not find a significant relationship, the SDM using the WCPE function did and for all models the interaction terms did not indicate any significant influence on changes in social vulnerability at the census tract level. As discussed in previous section, since the SoVI is a composite measure of vulnerability, it may mask the impacts of specific dimensions of social vulnerability. While the models for change in SoVI (Table 5.8) indicate the outcomes for the overall vulnerability pattern, it may also have suppressed underlying heterogeneity for different dimensions of vulnerability.

Table 5.8: Models estimating change in standardized value of SoVI between 2000 and 2010 (ΔSoVI)

	Power function for tech. hazard		WCPE function for tech. hazard	
Variables	OLS	Spatial Durbin	OLS	Spatial Durbin
(Intercept)	-0.472 (0.194)*	-0.192 (0.506)	-0.492 (0.195)*	-0.277 (0.503)
zfldrt:pchcvgr	-0.013 (0.018)	-0.007 (0.017)	-0.013 (0.018)	-0.009 (0.017)
zfldrt:pctcugr	0.004 (0.007)	0 (0.007)	0.004 (0.007)	0.002 (0.007)
pchcvgr:zpowr	-0.007 (0.011)	-0.012 (0.011)		
pctcugr:zpowr	-0.008 (0.01)	-0.014 (0.009)		
pchcvgr:zcpe1			-0.016 (0.011)	-0.019 (0.011)
pctcugr:zcpe1			-0.015 (0.012)	-0.02 (0.012)
Pchcvgr	0.046 (0.015)**	0.028 (0.014)	0.048 (0.015)**	0.03 (0.014)*
Pctcugr	0.002 (0.005)	0.001 (0.005)	0.001 (0.005)	0 (0.005)
zfldrt	-0.012 (0.029)	-0.036 (0.033)	-0.01 (0.029)	-0.028 (0.033)
zpowr	-0.075 (0.036)*	-0.005 (0.044)		
zcpe1			-0.005 (0.036)	0.062 (0.039)
Popgr	0 (0)	0 (0)	0 (0)	0 (0)
Blkgr	0.03 (0.004)***	0.026 (0.004)***	0.03 (0.004)***	0.026 (0.004)***

Table 5.8 (cont.)

	Power function for tech. hazard		WCPE function for tech. hazard	
Variables	OLS	Spatial Durbin	Variables	OLS
Hspgr	0.033 (0.003)***	0.029 (0.003)***	0.033 (0.003)***	0.029 (0.003)***
mdrnt2000	0 (0)	0 (0)*	0 (0)	0 (0)*
pov2000	-0.021 (0.005)***	-0.018 (0.005)***	-0.022 (0.005)***	-0.017 (0.005)**
hsp2000	0.01 (0.002)***	0.012 (0.003)***	0.009 (0.002)***	0.013 (0.003)***
shrblk2000	0.01 (0.002)***	0.015 (0.003)***	0.01 (0.002)***	0.015 (0.003)***
cbd_dist	0.01 (0.006)	-0.026 (0.045)	0.01 (0.006)	-0.033 (0.045)
lag.pchcvgr		- 0.006 (0.061)		0.009 (0.06)
lag.pctcugr		0.019 (0.027)		0.008 (0.028)
lag.zfldrt		0.161 (0.097)		0.123 (0.097)
lag.zpowr		0.022 (0.152)		
lag.zcpe1				-0.193 (0.187)
lag.popgr		0 (0.001)		0 (0.001)
lag.blkgr		0.015 (0.013)		0.016 (0.013)
lag.hspgr		-0.003 (0.009)		-0.008 (0.009)
lag.mdrnt2000		0.001 (0.001)		0.001 (0)
lag.pov2000		0.012 (0.016)		0.009 (0.016)
lag.hsp2000		-0.01 (0.006)		-0.008 (0.006)
lag.shrblk2000		- 0.017 (0.006)**		-0.014 (0.006)*
lag.cbd_dist		0.013 (0.05)		0.021 (0.05)
lag.zfldrt:pchcvgr		0.087 (0.072)		0.088 (0.071)
lag.zfldrt:pctcugr		0.002 (0.033)		0.019 (0.031)
lag.pchcvgr:zpowr		0.003 (0.061)		
lag.pctcugr:zpowr		-0.062 (0.061)		
lag.pchcvgr:zcpe1				0.024 (0.072)
lag.pctcugr: zcpe1				-0.094 (0.091)
rho/lambda		0.516 (0.076)***		0.518 (0.075)***
Adj.R2	0.2896		0.2834	
AIC	1780.967	1719.9	1787.633	1717.7
Log likelihood	-872.4837	-824.9665	-875.8167	-823.8262
Moran's I for residuals	0.117***		0.125***	

*$p< .05$, **$p< .01$, ***$p< .001$

OLS and SDM estimates for the change in poverty rate between 2000 and 2010 variable (Δpoverty_rate) are presented in Table 5.9 while the full model results including LM diagnostics and LR test results are presented in Appendix Tables C7 to C12. While the LM test favored the spatial error model specification, the LR test again identified the SDM as the preferred alternative. As the model results indicate (Table 5.9), for both measures of technological hazard the interaction of tax credit units (i.e., LIHTC units) and technological hazards (pctcugr: zpowr and pctcugr: zcpe1) are statistically significant predictors for an increase in poverty rate. This effect is in addition to the positive effect of the growth of such subsidized units (pctcugr) considered individually (i.e., its main effect). However, for HCV households or natural hazard exposure, the models do not indicate any significant influence. On the other hand, while technological hazard (zcpe1 and zpowr) itself is not significantly related to change in poverty rate, when those hazardous areas experience an increase in the number of tax credit units (pctcugr: zpowr and pctcugr: zcpe1), poverty rates increase significantly in the neighborhood. This result confirms the key hypothesis of this study that subsidized housing contributes to increased social vulnerability in an area, although it was only found to be significant for tax credit units (i.e. LIHTC) and not for vouchers (i.e. HCV).

Table 5.9: Models estimating change in % of population under poverty between 2000 and 2010 (Δpoverty_rate)

	Power function for tech. hazard		WCPE function for tech. hazard	
Variables	OLS	Spatial Durbin	OLS	Spatial Durbin
(Intercept)	-0.146 (1.822)	2.308 (4.876)	-0.173 (1.821)	0.524 (4.846)
zfldrt:pchcvgr	-0.158 (0.172)	-0.181 (0.167)	-0.122 (0.172)	-0.159 (0.166)
zfldrt:pctcugr	0.029 (0.068)	0 (0.065)	-0.002 (0.067)	-0.013 (0.064)
pchcvgr:zpowr	-0.017 (0.104)	-0.12 (0.102)		
pctcugr:zpowr	0.278 (0.093)**	0.212 (0.089)*		
pchcvgr:zcpe1			-0.096 (0.1)	-0.105 (0.109)
pctcugr:zcpe1			0.38 (0.116)**	0.341 (0.115)**
Pchcvgr	0.343 (0.141)*	0.256 (0.139)	0.308 (0.141)*	0.239 (0.138)
Pctcugr	0.154 (0.051)**	0.142 (0.049)**	0.167 (0.051)**	0.155 (0.05)**
zfldrt	0.551 (0.272)*	0.304 (0.319)	0.559 (0.272)*	0.324 (0.32)
zpowr	-0.849 (0.341)*	0.219 (0.421)		
zcpe1			-0.181 (0.333)	0.359 (0.38)
Popgr	-0.01 (0.003)***	-0.01 (0.003)**	-0.01 (0.003)***	-0.01 (0.003)**
Blkgr	0.174 (0.037)***	0.22 (0.039)***	0.171 (0.037)***	0.217 (0.039)***
Hspgr	0.312 (0.027)**	0.334 (0.032)***	0.317 (0.028)***	0.336 (0.032)***
mdrnt2000	-0.003 (0.002)	-0.003 (0.002)	-0.002 (0.002)	-0.003 (0.002)
pov2000	-0.274 (0.046)***	-0.288 (0.051)***	-0.279 (0.046)***	-0.283 (0.051)***
hsp2000	0.139 (0.018)***	0.184 (0.027)***	0.135 (0.018)***	0.183 (0.028)***
shrblk2000	0.09 (0.018)***	0.166 (0.029)***	0.09 (0.018)***	0.163 (0.029)***
cbd_dist	0.062 (0.052)	-0.305 (0.439)	0.071 (0.052)	-0.256 (0.439)
lag.pchcvgr		0.068 (0.589)		0.324 (0.581)

Table 5.9 (cont.)

	Power function for tech. hazard		WCPE function for tech. hazard	
Variables	OLS	Spatial Durbin	Variables	OLS
lag.pctcugr		-0.079 (0.261)		-0.084 (0.273)
lag.zfldrt		1.155 (0.938)		0.785 (0.938)
lag.zpowr		-1.308 (1.481)		
lag.zcpe1				-3.002 (1.815)
lag.popgr		0.01 (0.009)		0.012 (0.009)
lag.blkgr		-0.123 (0.12)		-0.092 (0.121)
lag.hspgr		-0.061 (0.091)		-0.083 (0.092)
lag.mdrnt2000		0.002 (0.005)		0.003 (0.005)
lag.pov2000		0.206 (0.152)		0.19 (0.152)
lag.hsp2000		-0.137 (0.062)*		-0.122 (0.061)*
lag.shrblk2000		-0.209 (0.062)***		-0.182 (0.061)**
lag.cbd_dist		0.233 (0.481)		0.179 (0.479)
lag.zfldrt:pchcvgr		1.581 (0.694)*		1.616 (0.691)*
lag.zfldrt:pctcugr		-0.067 (0.319)		0.126 (0.3)
lag.pchcvgr:zpowr		-0.136 (0.588)		
lag.pctcugr:zpowr		-0.565 (0.59)		
lag.pchcvgr:zcpe1				0.252 (0.701)
lag.pctcugr: zcpe1				0.204 (0.88)
Rho		0.284 (0.091)**		0.316 (0.089)***
Adj.R2	0.2872		0.2869	
AIC	5222.408	5198.1	5222.682	5198.1
Log likelihood	-2593.204	-2564.032	-2593.341	-2564.033
Moran's I for residuals	0.069***		0.075***	

**p*< .05, ***p*< .01, ****p*< .001

Since the experience of poverty is not the same across population subgroups (Lens et al., 2011), separate models were estimated for change in the percentage of population who are black and living in poverty (Δblack_poverty) as well as Hispanic and living in poverty (Δhispanic_poverty). Despite significant impacts on change in the overall poverty rate for technological hazard and LIHTC units, for the black population (under poverty), as Table 5.10 shows, no such influence was found. This measure in particular follows the overall change in social vulnerability, indicating that an increase of voucher recipient households (pchcvgr) in a census tract also increases the percentage of poor black residents there. This pattern persists even after controlling for the overall trends of black population (blkgr) growth during the same period and similar results were found for both measures of technological hazards. The full model results, including LM diagnostics and LR test results for this variable are presented in Appendix Table C13 to C18.

Table 5.10: Models estimating change in % of population Black and under poverty between 2000 and 2010 (Δblack_poverty)

	Power function for tech. hazard		WCPE function for tech. hazard	
Variables	OLS	Spatial Durbin	OLS	Spatial Durbin
(Intercept)	0.162 (0.886)	2.481 (2.365)	0.181 (0.885)	2.407 (2.346)
zfldrt:pchcvgr	0.072 (0.084)	0.069 (0.081)	0.08 (0.083)	0.082 (0.08)
zfldrt:pctcugr	-0.037 (0.033)	-0.045 (0.032)	-0.043 (0.032)	-0.046 (0.031)
pchcvgr:zpowr	-0.016 (0.05)	-0.054 (0.05)		
pctcugr:zpowr	0.054 (0.045)	0.038 (0.043)		
pchcvgr:zcpe1			-0.01 (0.049)	-0.045 (0.053)
pctcugr:zcpe1			0.094 (0.056)	0.069 (0.056)
pchcvgr	0.37 (0.069)***	0.296 (0.067)***	0.362 (0.068)***	0.296 (0.067)***
pctcugr	0.026 (0.025)	0.025 (0.024)	0.031 (0.025)	0.026 (0.024)
zfldrt	0.272 (0.132)*	-0.049 (0.155)	0.271 (0.132)*	-0.046 (0.155)
zpowr	-0.044 (0.166)	0.328 (0.204)		
zcpe1			-0.006 (0.162)	0.283 (0.184)
popgr	-0.003 (0.001)*	-0.003 (0.001)	-0.003 (0.001)*	-0.003 (0.001)
blkgr	0.255 (0.018)***	0.273 (0.019)***	0.254 (0.018)***	0.272 (0.019)***
hspgr	0.003 (0.013)	0.003 (0.016)	0.004 (0.013)	0.004 (0.015)
mdrnt2000	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)
pov2000	-0.135 (0.022)***	-0.113 (0.025)***	-0.135 (0.022)***	-0.109 (0.025)***
hsp2000	0.053 (0.009)***	0.04 (0.013)**	0.052 (0.009)***	0.042 (0.013)**
shrblk2000	0.043 (0.009)***	0.064 (0.014)***	0.043 (0.009)***	0.064 (0.014)***
cbd_dist	0.003 (0.025)	-0.069 (0.213)	0.004 (0.025)	-0.104 (0.213)
lag.pchcvgr		0.079 (0.288)		0.161 (0.284)
lag.pctcugr		-0.069 (0.126)		-0.16 (0.132)
lag.zfldrt		1.09 (0.455)*		0.988 (0.456)*
lag.zpowr		-0.363 (0.711)		
lag.zcpe1				-0.363 (0.872)
lag.popgr		0.006 (0.004)		0.007 (0.004)
lag.blkgr		-0.173 (0.061)**		-0.17 (0.061)**
lag.hspgr		-0.024 (0.041)		-0.04 (0.042)
lag.mdrnt2000		-0.001 (0.002)		-0.001 (0.002)
lag.pov2000		-0.025 (0.074)		-0.038 (0.074)
lag.hsp2000		0.014 (0.03)		0.017 (0.03)
lag.shrblk2000		-0.07 (0.03)*		-0.065 (0.029)*
lag.cbd_dist		0.039 (0.233)		0.072 (0.232)
lag.zfldrt:pchcvgr		-0.086 (0.336)		-0.01 (0.334)
lag.zfldrt:pctcugr		0.128 (0.154)		0.183 (0.145)

Table 5.10 (Cont.)

Variables	Power function for tech. hazard		WCPE function for tech. hazard	
	OLS	Spatial Durbin	OLS	Spatial Durbin
lag.pchcvgr:zpowr		-0.146 (0.285)		
lag.pctcugr:zpowr		-0.295 (0.285)		
lag.pchcvgr:zcpe1				-0.137 (0.339)
lag.pctcugr: zcpe1				-0.789 (0.424)
rho/lambda		0.395 (0.085)***		0.4 (0)***
Adj.R2	0.3327		0.3338	
AIC	4113.338	4087	4112.064	4085.1
Log likelihood	-2038.669	-2008.487	-2038.032	-2007.56
Moran's I for residuals	0.07***		0.069***	

**p*< .05, ***p*< .01, ****p*< .001

In the case of change in the percentage of the poor Hispanic population (Δhispanic_poverty), the two measures of technological hazard exhibited different patterns of relationships with the independent variables. As Table 5.11 shows, for interaction between technological hazard and an increase in LIHTC units the power function did not indicate any significant contribution (pctcugr:zpowr), but the WCPE function (pctcugr:zcpe1) model specification suggested a positive relationship between LIHTC units and poor Hispanic residents. This result persists after controlling for the growth of the Hispanic population (hspgr) during the same time period and given the main effect of LIHTC growth (pctcugr) indicating a significant positive impact on the change in the percentage of the poor Hispanic population. Different results from the two interaction terms (pctcugr:zpowr and pctcugr:zcpe1) are primarily due to the different hazard measures produced by the two models and how poor Hispanic people have located themselves with high growth of Hispanic population in Harris County. All the model results, including LM diagnostics and LR test results for this variable are presented in Appendix Table C19 to C24. In this case too, although LM tests favored a spatial error model specification, the LR test identified SDM as a better alternative.

Table 5.11: Models estimating change in % of population Hispanic and under poverty between 2000 and 2010 (Δhispanic_poverty)

	Power function for tech. hazard		WCPE function for tech. hazard	
Variables	OLS	Spatial Durbin	OLS	Spatial Durbin
(Intercept)	-1.812 (1.401)	-0.432 (3.794)	-1.887 (1.402)	-2.05 (3.771)
zfldrt:pchcvgr	-0.2 (0.132)	-0.242 (0.13)	-0.175 (0.132)	-0.229 (0.129)
zfldrt:pctcugr	0.043 (0.052)	0.022 (0.051)	0.023 (0.051)	0.015 (0.05)
pchcvgr:zpowr	-0.028 (0.08)	-0.099 (0.079)		
pctcugr:zpowr	0.182 (0.071)*	0.135 (0.069)		
pchcvgr:zcpe1			-0.092 (0.077)	-0.075 (0.084)
pctcugr:zcpe1			0.258 (0.089)**	0.249 (0.09)**
Pchcvgr	0.004 (0.109)	0 (0.108)	-0.013 (0.108)	-0.008 (0.107)
Pctcugr	0.097 (0.039)*	0.084 (0.038)*	0.107 (0.039)**	0.097 (0.038)*
Zfldrt	0.404 (0.209)	0.458 (0.248)	0.408 (0.209)	0.475 (0.248)
Zpowr	-0.772 (0.262)**	-0.042 (0.327)		
zcpe1			-0.273 (0.256)	0.073 (0.295)
Popgr	-0.005 (0.002)*	-0.006 (0.002)*	-0.005 (0.002)*	- 0.006 (0.002)*
Blkgr	-0.017 (0.028)	0.018 (0.03)	-0.019 (0.028)	0.016 (0.03)
Hspgr	0.387 (0.021)***	0.402 (0.025)***	0.39 (0.021)***	0.403 (0.025)***
mdrnt2000	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)
pov2000	-0.077 (0.035)*	-0.107 (0.039)**	-0.082 (0.035)*	-0.106 (0.039)**
hsp2000	0.091 (0.014)***	0.136 (0.021)***	0.089 (0.014)***	0.134 (0.021)***
shrblk2000	0.038 (0.014)**	0.085 (0.022)***	0.039 (0.014)**	0.083 (0.022)***
cbd_dist	0.011 (0.04)	-0.072 (0.341)	0.018 (0.04)	-0.007 (0.34)
lag.pchcvgr		-0.074 (0.455)		0.138 (0.448)
lag.pctcugr		-0.048 (0.203)		0.012 (0.212)
lag.zfldrt		-0.208 (0.726)		-0.454 (0.724)
lag.zpowr		-1.166 (1.151)		
lag.zcpe1				-2.99 (1.414)*
lag.popgr		0.005 (0.007)		0.007 (0.007)
lag.blkgr		-0.053 (0.093)		0.022 (0.093)
lag.hspgr		-0.032 (0.077)		-0.039 (0.077)
lag.mdrnt2000		0.001 (0.004)		0.003 (0.004)
lag.pov2000		0.2 (0.117)		0.192 (0.117)
lag.hsp2000		-0.13 (0.048)**		-0.117 (0.047)*
lag.shrblk2000		-0.131 (0.048)**		-0.109 (0.047)*
lag.cbd_dist		-0.007 (0.373)		-0.076 (0.372)
lag.zfldrt:pchcvgr		1.69 (0.54)**		1.653 (0.536)**
lag.zfldrt:pctcugr		-0.103 (0.247)		0.028 (0.232)
lag.pchcvgr:zpowr		-0.093 (0.457)		

Table 5.11 (cont.)

	Power function for tech. hazard		WCPE function for tech. hazard	
Variables	OLS	Spatial Durbin	Variables	OLS
lag.pctcugr:zpowr		-0.145 (0.458)		
lag.pchcvgr:zcpe1				0.357 (0.544)
lag.pctcugr: zcpe1				0.917 (0.684)
rho/lambda		0.227 (0.095)*		0.243 (0.093)**
Adj.R2	0.4099		0.4081	
AIC	4818.134	4807.5	4820.529	4804.3
Log likelihood	-2391.067	-2368.733	-2392.265	-2367.154
Moran's I for residuals	0.059***		0.052***	

*$p < .05$, **$p < .01$, ***$p < .001$

5.8 Summary of Findings

Although the descriptive analyses at the beginning of this chapter suggested that an increase of both forms of housing subsidy (HCV and LIHTC) in both natural and technological hazard zones contributed to increased social vulnerability, the spatial regression found this relationship to be statistically significant only for an increase of LIHTC units in technological hazard zones. Also, further nuance was discovered when the outcomes for different racial and ethnic subgroups of the population living in poverty were examined. For tracts experiencing an increase in the share of black population living in poverty, none of the interactions (between hazards and housing subsidies) were found to be significant, but for the Hispanic population a significant relationship was found when technological hazards are measured using the WCPE function. The different approaches for providing affordable housing exemplified by the HCV and LIHTC programs may have also contributed to the different outcomes identified in this study. One of the key aspects of the LIHTC program is that it is project based and thereby, tends to concentrate low-income units in a neighborhood. Exploration of the spatial distribution of subsidized housing units also revealed a higher percentage of LIHTC units in the hazard zones. Taken together, these two factors help to explain the positive relationship between social vulnerability and an increase of LIHTC units in technological hazard zones.

For natural hazards, the locations of subsidized housing units did not deviate very much from the distribution of the overall population. Although Harris County exhibits a high degree of social vulnerability in natural hazard areas, because those areas did not experience a significant increase in subsidized housing units, this study also did not find any evidence that the HCV or LIHTC programs are contributing to social vulnerability in natural hazard areas for the time period considered. These findings suggest that while tax credit properties significantly increase social vulnerability when they are located in technological hazard areas, since there were not many new LIHTC developments in natural hazard zones between 2000 and 2010, their contribution to vulnerability in those areas was not found to be significant. The results of this analysis argue for scrutinizing the location requirements of the LIHTC program in terms of neighborhood environmental quality and proximity to hazardous facilities. Chapter 6 discusses existing environmental location requirements of housing subsidy programs, first in general for all HUD assisted housing, and then specifically for the HCV and LIHTC programs. Interviews of officials at the Houston Housing Authority and selected examples of LIHTC developments are also presented in Chapter 6 to further contextualize the findings presented in this chapter.

CHAPTER 6
HOUSING POLICY FOR A MULTI-HAZARD ENVIRONMENT

6.1 Introduction

Housing is more than just a shelter. Besides providing a place to sleep and to store belongings, it plays a vital role in the health and wellbeing of individuals and communities. Housing is an integral part of human identity and shapes the way that current residents and future generations interact with others. Further, housing affordability is one of the key determinants of how individuals and households locate themselves within the housing market, which in turn, shapes a variety of life outcomes. Low-income and marginalized groups have a more difficult time finding and retaining decent quality housing, which would better enable them to overcome the cycle of social vulnerability. Since the 1949 Housing Act when the U.S. Congress envisioned ensuring "a decent home in a suitable living environment for every American family", the federal government has helped to fund the construction and rehabilitation of more than 5 million housing units for low-income households and provided rental vouchers to nearly 2 million additional families (Schwartz, 2010). But these programs have undergone significant changes over time, starting with public housing type direct subsidy provision to the present market dependent approaches of the Low Income Housing Tax Credit (LIHTC) program and Housing Choice Voucher (HCV) program (McClure & Johnson, 2014; Schwartz, 2010). Recently the LIHTC and HCV programs have grown and currently rank as the largest components of the federal portfolio of assisted households and units. The two programs now serve in excess of 2 million households each[30] and considering the overall focus of these subsidy programs, prior studies have evaluated their outcomes in terms of whether housing units and households are being placed in low poverty, low crime neighborhoods with better opportunities (Baum-Snow & Marion, 2009; Freeman, 2004; Galster, 2013; Hollar & Usowki, 2007; Lang, 2012; Oakley, 2008). However, very few studies have explored their location outcomes in terms of environmental justice. As discussed in the previous chapter (through the case of Harris County, Texas) these programs are placing proportionally more subsidized housing units and households

[30] It is commonplace to add up all of the federal housing programs to generate a total, but this process exaggerates the count somewhat because there is some unknown amount of overlap between the two programs in that voucher households may lease units in LIHTC developments (O'Regan & Horn, 2013). The overlap may be 16% or more of all vouchers (Williamson et al., 2009).

(compared to overall population distribution) in environmentally hazardous areas and are therefore, failing to achieve their desired neighborhood impact (of providing safer places to low-income people) and in some cases increasing social vulnerability. This chapter argues that these failures are due to oversights in the locational provisions of these programs and discusses policy changes that should be considered to address these issues. It begins with a discussion of low-income housing and its implications for environmental justice, then explores what the environmental quality provisions of the Department of Housing and Urban Development (HUD) are and why those provisions are not being applied in the LIHTC and HCV programs. Finally, the housing subsidy program administered by Houston Housing Authority is discussed and selected cases of LIHTC properties in Houston that underscore these points are presented.

6.2 Environmental Justice and Low-income Housing

Although the concerns of environmental justice (EJ) have been widely researched, the present provisions for low-income housing and their possible EJ outcomes have garnered less attention. This section briefly discusses EJ theories and then explores why low-income housing subsidies need to consider EJ issues more explicitly. Broadly speaking, EJ theories emphasize social justice aspects of disproportionate environmental quality and illustrate how certain communities face greater environmental risks than others. In the United States, early studies on EJ linked exposure to environmental risks and pollution to both class and race, and explicitly showed that it was not only poor communities that bear disproportionate environmental burdens, but communities of color as well (Buzzelli, 2007; Schlosberg, 2013). Studies have widely documented the nature and extent of disproportionate exposures to health hazards, ranging from toxic waste sites and air pollution to the landfill siting process, and how it varies by population subgroups (Chakraborty & Armstrong, 2001; Crowder & Downey, 2010; Hamilton, 1995; Maantay, 2001). However, EJ scholarship has also moved beyond the simple description and documentation of inequity into a thorough analysis of the underlying reasons for that injustice and specifically, the question of why those communities were devalued in the first place (Schlosberg, 2013). As discussed in Chapter 2 (section 2.4), the *racial income inequality thesis* (Downey, 2005; Oakes et al., 1996) and the *residential discrimination thesis* (Bullard, 1999; Mohai & Bryant, 1998) both answer this question following two different perspectives, emphasizing the lower affordability thresholds of minority people and discriminatory housing practices respectively. The location outcomes of housing subsidy programs can be explained by both theses. First, since non-white households are overrepresented in the universe of low-income households, they are more likely to receive a housing subsidy. Second, real estate agents and local governments, even without any intent to discriminate, will locate housing subsidies in low rent and hazardous areas since this is where resistance is likely to be lowest (Mohai et al., 2009). Seicshnaydre (2010) documented this problem in post-Katrina New Orleans recovery process.

One issue that is still being debated in the EJ literature is the establishment of causation through the question of "which came first" (Boone et al., 2014)—whether the polluting facility was already there and then minority population moved in, or whether the areas was already minority dominated before the facility located there. In both cases the issue of EJ holds—minority people moving in near the polluting industry can still be an EJ problem, since the tight housing market plus discrimination and unfair housing practices, might diminish opportunities for minorities to find safer places (Boone et al., 2014). If we allow housing subsidies to be placed in polluted areas then EJ concerns will be intensified, and in this case through an institutional process. Another debated issue in EJ scholarship is identifying the evidence of harm (Bowen, 2002). To ensure the health and wellbeing of nearby residents, determining what a safe distance from the hazardous facility is can be an important piece of information (Brulle & Pellow, 2006; Hynes & Lopez, 2012). While this distance can be measured through a complex epidemiological study and applied for evaluating EJ (Osiecki et al., 2013), there are several strong arguments against this approach (Boone et al., 2014). First, waiting for the scientific demonstration to establish the causal link can be perilous for residents living near a polluting facility and this can also be a time consuming process for planning decision making (e.g., permitting process). Second, the proof of harm should not rest with victims, as is typically the case, but with the polluters themselves. So, there should be defined guidelines for the polluters (or for the developers, who propose to develop any housing project) to show that the polluting facility will not harm the residents. As shown in the next section, HUD already has such regulations for assisted housing, but those are not applicable for the particular case of the HCV or LIHTC programs.

Section 3604(b) of the Fair Housing Act (Title VIII of the Civil Rights Act of 1968) makes it unlawful to "discriminate against any person in the terms, conditions, or privileges of sale or rental of a dwelling, or in the provision of services or facilities in connection therewith."

For the last fifteen years or so, Title VIII has been an area of some commentary in the environmental-justice movement (Kaswan, 1997). Although it has been widely applied and debated in the cases for locating new public housing or during post-disaster recovery process (Rajotte, 2007; Seicshnaydre, 2010), its appropriateness as a general provision for the HCV and LIHTC programs, the problems of EJ, or how these programs may violate section 3604(b) has not yet to received much attention. Since this study does not intend to give an extensive review of legal provisions, some limitations of these popular housing subsidy programs that need further scrutiny are highlighted here without going into specifics of the legislation.

6.3 Environmental Quality Requirements for HUD Assisted Housing

Considering the possible impacts of placing low-income people in hazardous areas, HUD has established detailed guidelines for any HUD assisted housing through *Title 24 Code of Federal Regulations* (CFR), which outlines all the rules and regulation to be followed by HUD officials and for any HUD assisted activity (i.e., those receiving HUD funding). The discussion here is limited to those rules that focus on the environmental requirements of subsidized housing and that should play significant roles in preventing any housing from being placed in natural or technological hazard areas. As it is shown in this section and later (section 6.4 and 6.5), most of these regulations do not apply for the HCV or LIHTC programs since they do not fall under the umbrella of typical HUD assisted housing projects. Despite this fact, these regulations are described to give a better sense of the problems associated with moving to market dependent housing subsidies.

6.3.1 Technological Hazards

The Environmental quality requirements of HUD assisted housing are outlined in 24 CFR §50.3 (2014), which states, "[i]t is the policy of the Department to reject proposals which have significant **adverse environmental impacts** and to encourage the modification of projects in order to enhance environmental quality and **minimize environmental harm**." While it is more concerned with specific impacts of the housing, it also addresses the environmental quality of housing locations in §50.3(i):

> "(1) It is HUD policy that all property proposed for use in HUD programs be free of hazardous materials, contamination, toxic chemicals and gasses, and radioactive

substances, where a hazard could **affect the health and safety of occupants** or conflict with the intended utilization of the property.

(2) HUD environmental review of multifamily and non-residential properties shall include evaluation of previous uses of the site and other **evidence of contamination on or near the site**, to assure that occupants of proposed sites are not adversely affected by the hazards listed in paragraph (i)(1) of this section.

(3) Particular attention should be given to any proposed site on or in the general proximity of such areas as dumps, landfills, **industrial sites** or other locations that contain hazardous wastes.

(4) HUD shall require the use of current techniques by qualified professionals to undertake investigations determined necessary."

Particularly, §50.3(i)(3) is specifically mentioning the proximity to hazardous facilities for any HUD assisted housing. Besides specific HUD regulations (discussed later), 24 CFR §50.3(b) gives a list of related federal laws and authority that also guide the HUD assisted housing. Particularly, this section mentions that HUD housing should comply with Flood Disaster Protection Act, The Coastal Zone Management Act, The Safe Drinking Water Act, The Clean Air Act, etc.

24 CFR §51 (Environmental Criteria and Standard) gives the detailed guidelines for environmental quality of HUD assisted housing. Subpart B of §51 outlines regulations for noise abatement and control, while Subpart C gives regulations regarding proximity to technological hazards. In these regulations (Subpart C) the acceptable distance from specific, stationary, hazardous operations (which store, handle, or process hazardous substances) is termed as acceptable separation distances or ASD[31]. Subpart C gives detailed technical guidance for identifying hazard operations, evaluating the anticipated degree of danger, and based on these factors, how to measure ASD for any HUD assisted housing. For calculating ASD, §51.203 (of 24 CFR) dictates:

"The following standards shall be used in determining the acceptable separation distance of a proposed HUD-assisted project from a hazard:

[31] ASD is defined as "the distance beyond which the explosion or combustion of a hazard is not likely to cause structures or individuals to be subjected to blast overpressure or thermal radiation flux levels in excess of the safety standards in § 51.203. The ASD is determined by applying the safety standards established by this subpart C to the guidance set forth in HUD Guidebook, "Siting of HUD-Assisted Projects Near Hazardous Facilities."

(a) Thermal Radiation Safety Standard. Projects shall be located so that:

(1) The allowable thermal radiation flux level at the building shall not exceed 10,000 BTU/sq. ft. per hr.;

(2) The allowable thermal radiation flux level for outdoor, unprotected facilities or areas of congregation shall not exceed 450 BTU/sq. ft. per hour.

(b) Blast Overpressure Safety Standard. Projects shall be located so that the maximum allowable blast overpressure at both buildings and outdoor, unprotected facilities or areas shall not exceed 0.5 psi.

(c) If a hazardous substance constitutes both a thermal radiation and blast overpressure hazard, the ASD for each hazard shall be calculated, and the larger of the two ASDs shall be used to determine compliance with this subpart.

(d) Background information on the standards and the logarithmic thermal radiation and blast overpressure charts that provide assistance in determining acceptable separation distances are contained in appendix II to this subpart C."

Appendix I and II of subpart C (of 24 CFR §51) gives list of hazardous liquids and gases, and detailed calculation methods for determining ASD. Appendix D of this dissertation presents those appendices that can be used by planners for determining the acceptable distance from hazardous facilities (as required by HUD) for locating any assisted housing.

Two limitations in the approach for calculating ASD can be identified. The first involves the amount of hazardous material stored at certain point in time and the type of material. As the TRI data shows, the amount and type of hazardous material for certain facility can change over time and 24 CFR §51.203 (Safety Standards) does not give any guidance on how to calculate ASD in such a case. Second, it only considers the location of hazardous facilities, not the access road to the facility (although 'road' can come in as part of noise level mentioned in Subpart B of 24 CFR §51). Carrying hazardous materials to the facility can pose threat to the assisted housing if the access road is located nearby. These regulations are detailed enough to be followed in case of location decisions for any HUD assisted housing, but are most often applied to HUD assisted public housing or any other project-based developments and not for tax credit properties or vouchers (as discussed in section 6.4 and 6.5).

6.3.2 Flood and Natural Hazards

HUD regulations are also specific enough to strictly control any development in flood or natural hazard areas. 24 CFR §55 gives the required guidelines for developing and maintaining HUD assisted housing located in floodplains. Particularly, §55.1(b) instructs:

> "(b) Under section 202(a) of the Flood Disaster Protection Act of 1973, 42 U.S.C. 4106(a), proposed HUD financial assistance (including mortgage insurance) for acquisition or construction purposes in any "area having special flood hazards" (a flood zone designated by the Federal Emergency Management Agency (FEMA)) shall not be approved in communities identified by FEMA as eligible for flood insurance but which are not participating in the National Flood Insurance Program…."

So, instead of categorically denying any development in flood plain areas, this legislation mandates denial of any subsidized housing in areas which are identified by FEMA to be located in floodplains, but are not participating in the National Flood Insurance Program (NFIP). Instead of giving its own regulation (like technological hazard), in this case the regulations mostly refer to FEMA guidelines. For example, 24 CFR §55.1I(3) instructs to deny any subsidy in these cases:

> "(3) Any non-critical action located in a coastal high hazard area, unless the action is designed for location in a coastal high hazard area or is a functionally dependent use. An action will be considered to be designed for location in a coastal high hazard area if:
>
> (i) In the case of new construction or substantial improvement, the work meets the current standards for V zones in FEMA regulations (44 CFR 60.3(e)) and, if applicable, the Minimum Property Standards for such construction in 24 CFR 200.926dI(4)(iii); or
>
> (ii) In the case of existing construction (including any minor improvements):
>
> (A) The work met FEMA elevation and construction standards for a coastal high hazard area (or if such a zone or such standards were not designated, the 100-year floodplain) applicable at the time the original improvements were constructed; or
>
> (B) If the original improvements were constructed before FEMA standards for the 100-year floodplain became effective or before FEMA designated the location of the action as within the 100-year floodplain, the work

> would meet at least the earliest FEMA standards for construction in the 100-year floodplain".

Although this section clarifies that any development in a floodway or coastal high hazard area will not get approval for HUD assistance or will need to meet necessary construction standards (in case of 100-year floodplain), through 24 CFR §55.12(c) it excludes such requirements for any housing voucher. As §55.12(c) mentions:

> "(c) This part **shall not apply** to the following categories of proposed HUD actions:
>
> …….
>
> > (11) Issuance or use of Housing Vouchers, Certificates under the Section 8 Existing Housing Program, or other forms of rental subsidy where HUD, the awarding community, or the public housing agency that administers the contract awards rental subsidies that are not project-based (i.e., do not involve site-specific subsidies);"

So, the above mentioned regulations regarding flood hazards are mainly for public housing or other project-based HUD assistance and not for housing vouchers or any other development not directly assisted by HUD (like the LIHTC program).

6.4 Environmental Requirements for the HCV Program

Since its inception in the mid-1970s, the Section 8 housing voucher program (later renamed Housing Choice Voucher or HCV program) has grown from a small pilot project to become one of the primary programs for providing housing assistance to low-income households in the United States (Carlson et al., 2012). HUD spends about 19 billion dollars[32] every year through the Housing Choice Voucher program to provide rental assistance to over two million households. Moving away from the concept of public housing, this program is premised on the notion that the existing private market will provide an adequate number of quality units and that households will use their rental assistance to locate in quality neighborhoods (Winnick, 1995). Since it is dependent on the private market, this program does not have much control over the location outcomes of voucher recipients. The general expectation in this case is that the voucher will increase the rental affordability of low-income people and will enable them to find better

[32] Based on Department of Housing and Urban Development budget outlays by program Comparative summary, fiscal years 2013-2015, available at: http://portal.hud.gov/hudportal/documents/huddoc?id=fy15cj_bdgt_otly_tbl.pdf

places that require payment of higher rent. Through this program, HUD allocates certificates to participating Public Housing Authorities (PHA), which maintains waiting lists of eligible households, ordered according to both local and federal preference criteria. The PHAs allocate the vouchers following the waiting list and the voucher recipient households negotiate a lease with a landlord in the private market under the condition that the rent must be reasonable, the unit must be appropriately sized for the household, and the unit must pass a physical inspection (McClure & Johnson, 2014). In this case the unit rent cannot be more than the fair market rent and the tenant pays between 30 to 40 percent of their annual income for rent.

Since HCV is a rental support program, for determining eligible housing units (to be supported by HCV) it focuses more on the quality of the housing unit itself rather than the neighborhood quality or the distance of the unit from any kind of hazard. 24 CFR Section 982.401- Housing Quality Standard (HQS) defines “standard housing” and establishes the minimum criteria necessary for the health and safety of program participants. It gives detailed requirements for sanitary facilities, space and security, thermal environment, water supply, etc. that must be checked before considering any unit eligible for accepting HCV recipients. HUD developed an inspection manual for conducting this physical inspection for use by the PHA and also provides the necessary Inspection Form (HUD-52580) and Inspection Checklist (form HUD 52580-A). While CFR 24§982.401 gives detailed guidelines for HQS and HUD provides supporting checklists for the physical inspection, the regulations for site and neighborhood quality are comparatively lax. As part of the HQS, §982.401(l) gives this guideline for neighborhood quality of the HCV unit:

“(l) Site and Neighborhood—

> (1) Performance requirement. The site and neighborhood must be **reasonably free** from disturbing noises and reverberations and other dangers to the health, safety, and general welfare of the occupants.
>
> (2) Acceptability criteria. The **site and neighborhood** may not be subject to serious adverse environmental conditions, natural or manmade, such as dangerous walks or steps; instability; flooding, poor drainage, septic tank back-ups or sewage hazards; mudslides; abnormal air pollution, smoke or dust; excessive noise, vibration or vehicular traffic; excessive accumulations of trash; vermin or rodent infestation; or fire hazards.”

There is considerable room for subjectivity in the evaluation of site quality compared to the detailed guidelines provided for any project-based HUD assistance (as discussed in previous section). HUD can allow PHAs to accommodate variations in the acceptability criteria outlined by HQS to make it compatible with the standards of local housing codes or other codes adopted by the PHA or because of local climatic or geographic conditions. The Houston Housing Authority (HHA) could use this option to impose more restrictions on neighborhood quality requirements considering the density of hazardous facilities in certain areas of this city (as discussed in Chapter 5), but as the administrative plan for HCV[33] adopted by the HHA shows, they have adopted some additional criteria (on top of HUD requirements) but those are also only for unit characteristics[34] rather than the site or neighborhood quality of the unit.

As this study showed (Chapter 5), in Harris County, Texas (primarily served by the HHA for housing vouchers), compared to the overall population distribution, a higher proportion of HCV recipients are living in hazardous areas. With high population growth and an increasingly tight housing market, more HCV recipients may have to move into hazardous areas in the absence of any safeguards against such movement. Considering the key focus of HCV program to provide "decent, safe, and sanitary[35]" affordable housing to low-income people, the focus on the quality of the HCV unit is understandable, but in terms of 'safe' housing this program is failing to fully achieve its objective. One study exploring crime patterns in the neighborhoods of HCV households found that although they tend to live in safer neighborhoods than households in supply-side subsidized housing, these households still lag behind the general population in terms of neighborhood safety (Lens, 2013). Van Zandt & Mhatre (2013) also found that due to a lack of adequate voucher accepting units in safer areas, HCV households tend to live in higher crime neighborhoods. Comparing the locations of voucher households to other households living in project-based housing subsidies (like LIHTC), another study found that schools near voucher holders have lower performing students than the schools near other poor households without a housing subsidy (Horn et al., 2014). Apart from these findings, in general, existing research on the neighborhoods of voucher holders indicates that, on average, voucher holders live in slightly less disadvantaged neighborhoods than other poor households (Pendall, 2000; Wood et al.,

[33] Administrative Plan for Section 8 Housing Programs, Houston Housing Authority (2014), available at: http://www.housingforhouston.com/voucher-program/the-administrative-plan.aspx

[34] Page 34 of the Administrative Plan. for Section 8 Housing Programs, Houston Housing Authority (2014)

[35] Page 5 of the Administrative Plan. for Section 8 Housing Programs, Houston Housing Authority (2014)

2008), but, as this study shows, if we consider the hazard levels of different neighborhoods, in case of Harris County, Texas, HCV households are not in a significantly better position.

6.5 Environmental Requirements for the LIHTC Program

The LIHTC program was created by the Tax Reform Act of 1986 and is administered by the Department of the Treasury, as opposed to HUD. The portfolio of LIHTC properties grew dramatically over the last 2 decades and the program now supports more than 39,000 projects and 2.4 million units (HUD, 2014). Despite suffering a significant setback with the financial crisis of 2008–2010, the LIHTC program has now become the primary program that adds to the supply of rental housing for low- and moderate-income households (McClure & Johnson, 2014). Under this program, the federal government grants tax credits to states on a per capita basis and the states distribute the tax credit to developers (proposing projects) on a competitive basis. For distributing the tax credits, each state publishes a Qualified Allocation Plan (QAP), which details the criteria for evaluation of the proposed projects. Proposed projects should designate a minimum share of "affordable" units[36] within the development and projects that obtain the highest score as per the criteria outlined in QAP to receive the tax credits. After completion of the project, the developer receives a tax credit over a 10-year period, but the project must remain in low- or moderate-income occupancy for at least 15 years (McClure & Johnson, 2014). Developers awarded the credits sell them to investors to pay for some of the project's total development costs[37]. The tax credit amounts are generally 9% of the non-land development costs and in case it is financed through bonds with interest that is exempt from federal income taxes, it decreases to 4%. To encourage affordable rental developments in difficult development areas (a location with particularly high development costs relative to incomes) or in a qualified census tract (a census tract with a high incidence of low-income households), the tax credit amounts are boosted by an additional 30% if it is located in those areas. Following the scoring criteria of the QAP, developers generally try to maximize the amount of subsidy and as a result they are attracted to sites located in difficult development areas and qualified census tracts, which are often badly deteriorated neighborhoods (Oakley, 2008).

[36] To be eligible to apply for the program, developments must have a minimum of 20% of the units affordable to households earning 50 % of the metropolitan area's median family income or, a minimum of 40 % of the units are affordable to households earning 60% of the metropolitan area's median family income (Schwartz, 2010)s.

[37] Additional costs are usually paid via a combination of debt and other subsidy programs. (McClure & Johnson, 2014)

Since the LIHTC program is primarily guided by the QAP of state housing financing agency, to get better idea of their location requirements the state's regulations need to be evaluated. In the case of Texas (where the primary case study Harris County is located), the Texas Department of Housing and Community Affairs (TDHCA) is assigned the responsibility of awarding and allocation of housing tax credits. Following the general guidelines for the LIHTC program discussed above, TDHCA also publishes a QAP every year[38] to establish the procedures and requirements relating to an award and allocation of housing tax credits. Besides outlining the procedures for administering the program, it details the scoring criteria upon which the proposed housing developments will be selected for awarding tax credits. As per the 2015 QAP, there are criteria like size and quality of units (15 points), income level of tenants (16 points), rent level of tenants (13 points), tenant services (11 points), and other criteria that would promote community support and engagement. While this scoring criteria favors development in low poverty area (giving 7 points for development in census tracts with poverty rate below 15 percent), it does not have any criteria that would encourage development in safer areas or discourage development in hazardous areas. The only criteria that talk about such hazards are under the broad criteria for community support and engagement, and actually *gives additional points* (6 points) when the development is located in a hazardous area and there is a community revitalization plan for that area. One of the factors for such revitalization plan is mentioned as:

> "adverse environmental conditions, natural or manmade, that are material in nature and are inconsistent with the general quality of life in typical average income neighborhoods. By way of example, such conditions might include significant and recurring flooding, presence of hazardous waste sites or ongoing localized emissions not under appropriate remediation, nearby heavy industrial uses, or uses presenting significant safety or noise concerns such as major thoroughfares, nearby active railways (other than commuter trains), or landing strips; significant and widespread (e.g. not localized to a small number of businesses or other buildings) rodent or vermin infestation acknowledged to present health risks requiring a concerted effort; or fire hazards;"[39]

This encompasses both natural and technological hazards and supports any revitalization initiative taken by a municipality or county for those hazardous areas. Other than this criterion,

[38] 2014 and 2015 QAP of TDHCA are available at: http://www.tdhca.state.tx.us/multifamily/nofas-rules.htm
[39] Page 25 of 2015 QAP, available at: http://www.tdhca.state.tx.us/multifamily/docs/15-QAP.pdf

which indirectly supports any clean-up or hazard mitigation activity, the QAP does not give any specific provision that would disincentivize development in the floodplain or near hazardous facilities.

6.6 Subsidized Housing in Houston, Texas

Besides analyzing subsidized housing data and exploring its location in the multi-hazard environment of Harris County (as discussed in Chapter 5), the author visited Houston in Spring 2014 to gain a better sense of the social vulnerability scenarios there and how subsidized housing is being managed, particularly in the city of Houston. Several neighborhoods were visited, both declining and gentrifying, and officials with the Houston Housing Authority (HHA)—the public housing agency that manages housing vouchers in Houston and also maintains some public housing and tax credit properties—were interviewed. The key objective of this visit was to relate the findings of the spatial analysis (presented in Chapter 5) to actual developments on the ground in Houston. Due to time and resource constraints, extensive surveys or interviews could not be conducted, but short visits to selected sites were able to provide a deeper understanding of how the location of housing subsidies interacts with the multi-hazard context of Houston. This section briefly discusses gentrifying and declining neighborhoods in Houston and then describes the key informant interviews with HHA officials focusing on their provision of housing vouchers. Finally, the chapter examines selected housing projects funded through the LIHTC program.

6.6.1 Gentrification and Low-Income Housing

As identified in Chapter 4, certain neighborhoods of Houston have gradually gentrified over time, while others have consistently been characterized by high poverty and high minority concentration (i.e., high social vulnerability). The juxtaposition of neighborhoods with vastly different levels of affordability combined with strong population growth means that low-income households are likely to encounter difficulty in obtaining quality housing in safe neighborhoods. Midtown is an example of a gentrifying neighborhood located just west of Houston Downtown (Figure 6.1) and shown in Photo 6.1. The gentrification process has advanced by demolishing old houses and developing new upscale condominiums on several blocks. In 2010, about 57%[40] of the population (25 years and above) in this neighborhood had a bachelor's degree or higher

[40] Data collected from City-Data.com; http://www.city-data.com/neighborhood/Midtown-Houston-TX.html

education, a poverty rate of 17.4% (compared to 23.8% in Houston), and was comprised of about 50% non-Hispanic white population. Compared to the Midtown neighborhood, the Park Place neighborhood located southwest of the downtown (Figure 6.2) is a depressed neighborhood with high concentration of poverty and minority population and also mostly contains dilapidated housing structures (Photo 6.2). In 2010, this neighborhood had only about 27% of its population (25 years or above) with a bachelor's degree or higher education, about 34% population living under the poverty line, and more than 75% Hispanic population.

Photo 6.1: Midtown Neighborhood (near Gray St. and Bagby St.)

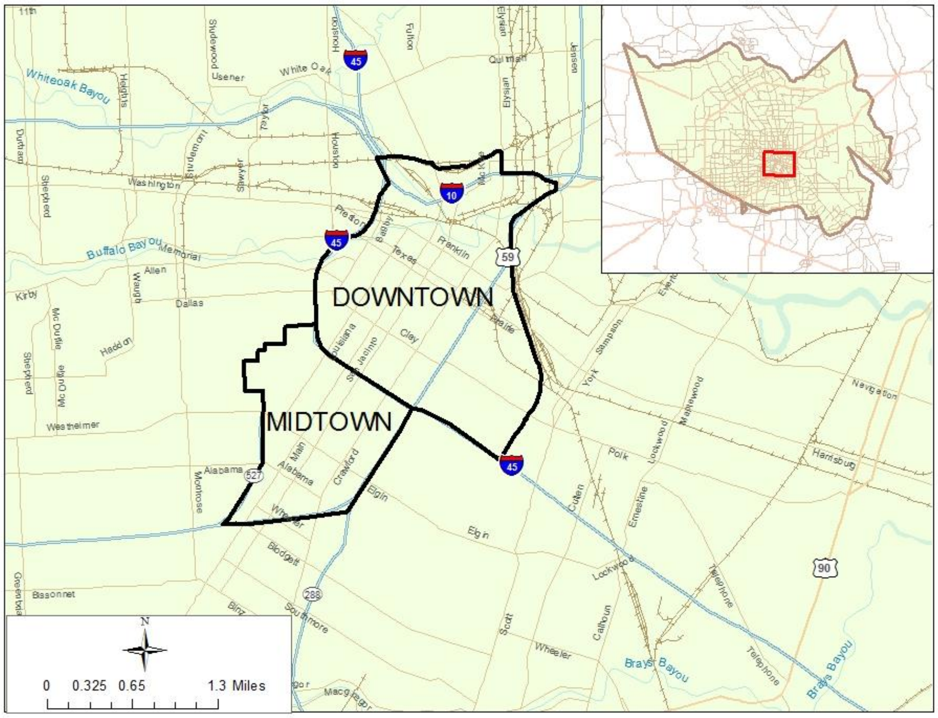


Figure 6.1: Map of Midtown neighborhood

Photo 6.2: Park Place Neighborhood (near Broadway St. and Detroit St.)

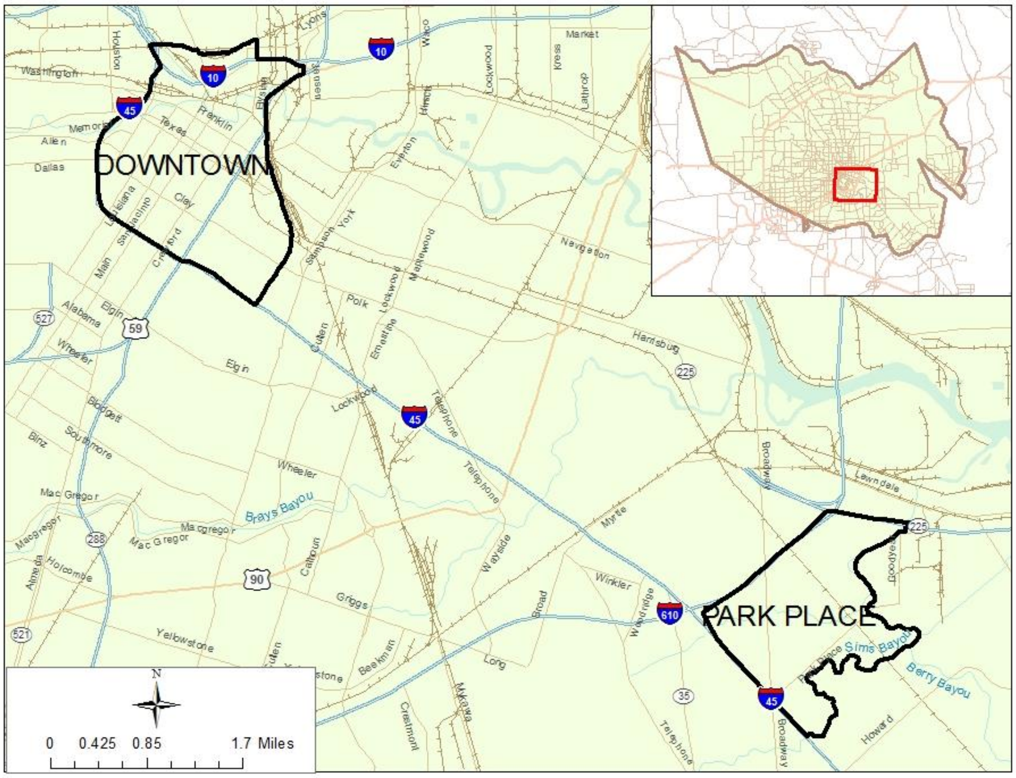


Figure 6.2: Map of Park Place Neighborhood, Houston

Due to the differences in their physical and socio-economic conditions, these two neighborhoods also exhibit different levels of affordability. In 2011, the median rent in the Midtown neighborhood was $936, and at the same time the median rent in the Park Place neighborhood was $575[41]. Given these different levels of affordability, poor people coming into the city find it more affordable to move into low rent neighborhoods like Park Place and if the present trend of gentrification continues (which can be expected with population growth), poor people may find it even more difficult to rent places in better neighborhoods even with housing vouchers. These conclusions are echoed in the interviews[42] conducted with HHA officials.

6.6.2 Housing Vouchers and the HHA

The Houston Housing Authority (HHA) is the public agency in Houston responsible for administering and managing the Housing Choice Voucher (HCV), Moderate Rehabilitation,

[41] Data collected from city-data.com

[42] Necessary approval from Institutional Review Board (IRB) at the University of Illinois was obtained prior to conducting these interviews.

Single Room Occupancy (SRO), Disaster Voucher, and other Houston Housing Authority Section 8 special programs. In order to learn about the HCV program and how the voucher award process shapes housing outcomes, interviews were conducted with two HHA officials—Senior Policy Advisor Brian Gage, and Policy Analyst Ross LaFour. As they informed in the interviews, HHA currently supports about 17,000 households through its HCV program and owns about 3,000 project-based units (combination of public housing, tax credit projects, and Section 8 projects). The waiting list for awarding HCVs was initiated about two years ago when roughly 80,000 people applied. Through a lottery they selected 20,000 households to support and currently they have about 13,000 households on the waitlist to receive vouchers. The same procedures outlined by HUD (see section 6.4) are used to identify housing units eligible for selection by HCV households. In response to the question of whether HHA is concerned about vouchers being used primarily in low-income neighborhoods and whether HHA takes any measure to recruit landlords in better neighborhoods, the interviewees acknowledged that although they try do this, funding is a substantial obstacle. According to Brian:

> "One of the things we have been looking into implementing is, how do we go out to these areas where we have very few voucher holders now and get landlords interested in the program…, but the honest truth of the matter is our funding level for administering the program is declining sharply. In the past three to five years or so they (i.e., HUD) only give us 75 cents on a dollar what is actually cost to run the program. So, doing those extras make it much more difficult to fit in budget-wise. You know, there are lots of things that we know we can do if we had the administrative funding to go out and build our relationships with landlords."

As this response conveys, although the HHA knows about the problem of poverty concentration, budgetary constraints do not allow them to make a concerted effort to find housing units in higher rent areas that would accept housing vouchers. In response to the question of whether vouchers allow or perhaps encourage people to move to better neighborhoods, as suggested in literature (Carlson et al., 2012), the interviewees have not seen significant evidence of this in Houston. As Brian said:

> "Yes, we have people that want to stay in their neighborhood, they don't want to move into neighborhood they are not familiar with, because of their churches, kids go to school,

> because their cousin lives around the corner… because they are comfortable with that. We did a major relocation initiative down here (after demolishing public housing units)… and… I want to say about half stayed in the same zip code although they had the choice to go anywhere in the city. And, there were some who moved, even moved to California, cause you can move anywhere in the country, but they are just one or two individuals…"

According to Brian and Ross, currently the HHA is identifying areas which have fewer vouchers and planning to offer the maximum allowable subsidy (110% of Fair Market Rent) to households moving into those areas. Still, they expressed their concern that such a task will be hard to accomplish since Houston is a majority minority city and there simply are not very many areas with low minority populations and where the vouchers can be allocated.

The Housing Quality Standard (HQS) checklist required by HUD is the basis for evaluating the eligibility of any unit (for giving vouchers), but Brian found this approach too restrictive and he thinks that more flexible inspection protocol would allow more landlords to participate in the program. As per this current checklist, any minor problem may make an otherwise good housing unit ineligible to accept voucher households. However, Brian also acknowledged the fact that due to this strict checklist, people are moving into higher quality units overall. In terms of the location requirement of the HCV housing unit, as mentioned in Section 6.4, the HHA does not follow any particular provision for avoiding hazardous areas, since this is not required by HUD.

6.6.3 Selected Examples of LIHTC Developments

In addition to interviewing HHA officials, a selected number of tax credit developments were visited to get a better sense of such developments and how their neighborhoods fit within the broader context of Houston. During the interviews at the HHA, Brian Gage noted that developing gated communities through the LIHTC is particularly popular in Houston since it gives a sense of security to the prospective tenants. One of the aims of the visits to a few of the LIHTC projects was to see whether that is the case and to observe the degree of integration between those developments and their surrounding neighborhoods. South Houston and Pasadena were chosen since the analysis of natural and technological hazards (presented in Chapter 5) found this part of Houston to be significantly exposed to both kinds of hazards. Most of the census tracts in this part of the city also have higher poverty rates and larger minority populations. Of the eight LIHTC developments visited, six were gated housing projects. A brief overview of three of those tax credit developments is presented here and the question of how those developments may have been impacting their neighborhoods is considered later. Data on these developments were collected from the Texas Department of Housing and Community Affairs (TDHCA).

Vista Bonita Apartments

Vista Bonita Apartments (Photo 6.3) is a gated community of 118 tax credit units located in South Houston (9313 Tallyho Road, Houston, TX). Due to its location just east of the Gulf Freeway (I-45) it has easy access to Houston downtown and Hobby Airport (Figure 6.3). Approved by the TDHCA in 2008, it is a competitive (9%) Housing Tax Credit (HTC)[43] development. The site visit revealed that this project is not assimilating very much with its surrounding neighborhood. There is another gated community (non-LIHTC) just opposite of this development on Tallyho road and other than that, there are few residential developments in its immediate vicinity. The surrounding blocks are mostly commercial and light industrial uses (storage, construction yards, motel, etc.) with some scattered houses, but being a recent development, the units here are in very good condition.

Granada Terrace Apartments

Granada Terrace Apartments (Photo 6.4) is an older LIHTC project also located in South Houston (1301 Avenue A, Houston, TX). The TDHCA awarded tax credit status for this development in 1991 and it has a total of 154 tax credit units. Unlike Vista Bonita Apartments, it is not gated and mostly surrounded by residential development. As an older development, the physical condition of the units does not seem to be very high and most of the houses in the surrounding neighborhood are in a shabby state, suggesting that they are mostly occupied by low-income people.

[43] For 9% HTC the tax credit amount is 9% of the non-land development cost

Photo 6.3: Vista Bonita Apartments

Figure 6.3: Location of Vista Bonita Apartments

Photo 6.4: Granada Terrace Apartments

Figure 6.4: Location of Granada Terrace Apartments

Gardenview Apartments

Gardenview Apartments (Photo 6.5) is located in Pasadena (2730 Lafferty Road, Pasadena, TX) and about two miles away from Granada Terrace Apartments. It is also an older development (tax credit status awarded in 1993), but unlike Granada Terrace it is a gated community. It has a total of 309 tax credit units and despite being an older development, most of the units here seem to be in a good condition. A park and an elementary school isolate this project from the single family housing in its neighborhood, which appears to be home to mostly middle-income households. Although this development is somewhat detached from rest of the neighborhood and there are few similar residential developments in its vicinity, there is a mobile home park just south of this project, indicating a concentration of low-income households. So while this project is located in a middle-income neighborhood, the fact that it is a gated community and separated by physical barriers (park and school) means that it is not well integrated with its neighboring areas. In fact the concentration of low-income households (i.e., mobile home park) provides further evidence of the heterogeneity and incongruity characterizing this neighborhood.

Photo 6.5: Gardenview Apartments

Figure 6.5: Location of Gardenview Apartments

The preceding cases focus on one recent LIHTC project and two older projects (one gated and another non-gated). While the recent project was not found to be well integrated with its surrounding neighborhood, the older two projects present interesting examples of how they may be influencing their neighborhoods. The older non-gated community (Granada Terrace) is located in a low-income neighborhood and may have contributed to the changes there over time. Similarly, the older gated community (Grandview Apartments), despite being located in a middle-income neighborhood, may have contributed to the emergence of a low-income community in its immediate vicinity. More detailed case studies may have helped to understand these specific developments, but they also indicate the heterogeneity of location and patterns of tax-credit developments, which makes it harder to isolate the influences of these developments. Still, the popularity of developing gated communities through the LIHTC program invites further scrutiny. For more than a decade scholars have debated the consequences of the socio-economic differentiation and particularly the residential segregation created by the gated communities (Atkinson & Blandy, 2006; Blakely & Snyder, 1997; Gordon, 2004; Le Goix, 2005; Vesselinov, 2008). In terms of property values, while some studies indicate that such gated residential developments can play an instrumental role in avoiding decay and other externalities in a neighborhood (LaCour-Little & Malpezzi, 2001), others have argued that sometimes such development can be detrimental to property values in non-gated developments nearby (Le Goix & Vesselinov, 2013). While this study found that LIHTC developments are associated with increasing vulnerability in hazardous areas, the role played by gated developments in the particular case of Houston warrants further research.

6.4 Opportunities for Policy Intervention

Although HUD has specific environmental regulations in place that would better ensure the safety (i.e., areas less exposed to natural or technological hazards) of low income households, those regulations are not applicable for the two most popular low-income housing programs—the HCV and LIHTC programs. Given that these are market driven approaches operating within a neoliberal policy environment, this lack of regulatory safeguards against natural or technological hazards increases the possibility that they will concentrate low-income people in hazardous areas of the city (as this study found was particularly true for the LIHTC program). As in the case of Houston, this can be more problematic at times when the city is experiencing high rates of population growth alongside an influx of low-income and minority residents. An increasingly competitive housing market may push these socially vulnerable people into hazardous areas and thereby create a breeding ground for catastrophic disaster, whether by natural hazards exemplified by Hurricanes Katrina or Ike, or via a technological hazard like the fertilizer plant explosion in West, Texas[44]. While mitigation of those hazards can be one approach for avoiding such a catastrophic disaster, at the same time we need to examine how our plans and policies are influencing people's location choices within this multi-hazard environment. Several recommendations have emerged from the analysis presented in this dissertation that if implemented, should help to ensure that we are not placing socially vulnerable people in harm's way.

First, despite being a HUD assisted program, the HCV program does not require that the location criteria applicable to other HUD assisted project-based developments be followed. This is an administrative challenge because applying the present checklists for Housing Quality

[44] The explosion killed 15 and wounded another 226 people in West, Texas. More on this explosion here: http://www.cnn.com/2014/04/22/us/west-texas-fertilizer-plant-explosion-investigation/

Standard (HQS) to identify eligible housing units is already a difficult and time-consuming task for public housing officials (as confirmed by the HHA interviewees). Particularly, conducting case by case inspection of housing units, while ensuring good quality housing for HCV households can become problematic if environmental quality or the hazard exposure of the units must also be considered. Instead, it can be suggested that for such measurement of environmental quality and hazard exposure, public housing authorities can make use of the already available data from U.S. Environmental Protection Agency (EPA) and Federal Emergency Management Agency (FEMA). The EPA provides data on air quality and the location of contaminated sites or facilities handling toxic materials (i.e., TRI sites) while FEMA maintains and distributes data on floodplains and coastal hazard zones. As previously noted, HUD regulations already mandate the use of these data sources for identifying the location of housing projects, which is done on a case by case basis. The issue is that while such a case by case evaluation can be financially and administratively feasible for multi-family units, it is much more difficult for housing vouchers which are more flexible in terms of potential locations and more widely scattered across a broad region. In this case, housing officials can look at neighborhood or census tract data, much like they already do for poverty level or minority concentration, but also incorporate EPA and FEMA data to simultaneously evaluate the environmental quality and hazard exposure of areas under consideration. During the process of allocating vouchers, housing officials can check whether the candidate housing units are located in those census tracts and thereby determine the eligibility of the unit for accepting vouchers.

Second, since the LIHTC program is not administered or assisted by HUD, these developments are not required to follow the regulations like HUD assisted housing projects currently do, but because this program also targets low- and medium-income households, there is no reason why the same environmental regulations cannot be applicable to LIHTC projects as well. It is true that in the absence of any strict guidelines from the federal level the state housing finance agency (e.g., TDHCA in Texas) enjoys much freedom and flexibility to adjust the program requirements to meet local needs. But as it turns out, despite being a state frequently ravaged by different natural and technological hazards, there are not clear and detailed guidelines for locating tax credit properties in this state. The current scoring criteria outlined by the QAP of TDHCA gives scores based on neighborhood socio-economic condition, but there is no specific scoring mechanism that would disincentivize development in hazardous areas. In this case, it can be suggested that the TDHCA (and for that matter any other housing finance agency in states with a higher frequency of hazards) should take cues from HUD for the environmental requirements of the tax credit properties. Like HUD assisted projects, they can adopt acceptable separation distances (ASD) for locating tax credit properties near hazardous sites and can ask developers to not propose projects (or give negative scores) in areas not participating in the National Flood Insurance Program (NFIP).

Third, the problems inherent in these market dependent housing subsidy approaches need to be reevaluated at the national level, particularly in the present context of high population growth in coastal metro areas which are also experiencing increases in poverty and the spatial concentration of minority populations. Gentrification and increasingly tight housing markets will make it gradually more difficult for HCV households to find safe and secure places to live. While the growth of LIHTC is vulnerable to economic downturns because of its dependence on the tax credit market, in terms of location outcomes it can become concentrated in depressed neighborhood to maximize the tax credit benefits. With the increased price of tax credits, LIHTC units may be able to gradually enter the suburbs (McClure, 2006), but it also indicates the limitation of this approach. How the location of low-income housing will turn out is totally dependent on the market's profitability from such investments. This outcome needs to be analyzed in the broader context of environmental justice to determine if this market dependent subsidy approach will push more low-income minority people in hazardous areas of the city. As the results of this study suggest, this is precisely what is happening in the case of Houston.

With the increased emphasis on climate change and adaptation planning, particularly in coastal metro areas, the provision of low-income housing subsidies needs to be further scrutinized. When these market-dependent approaches fail to provide safe housing to socially vulnerable population groups, any climate adaptation effort that do not consider their housing needs (or pose any threat to existing stock of affordable housing) may turn out to be a mal-adaptive approach in the long term.

CHAPTER 7

CONCLUSION

With recent enthusiasm for urban sustainability and climate change adaptation (Blanco et al., 2009), planners need to be more careful and attentive to the equity outcomes in this policy environment. Climate change is expected to increase the frequency and severity of natural hazards and in the near future more disaster events are a likely outcome. In a multi-hazard urban environment a clear challenge for planners is to ensure that socially marginalized populations are not disproportionately exposed to hazards. Differential hazard exposure and disaster outcomes for vulnerable low-income and minority population groups are already well documented (Crowder & Downey, 2010; Finch et al., 2010; Van Zandt et al., 2012), but how the present pattern of vulnerability has evolved over time and how political-economy of cities may play a role in this process has not been extensively studied. Moving beyond the conventional notion of vulnerability as static and exogenous to urban development and politics, this study demonstrates how social vulnerability has changed over time in three coastal cities and calls for planning approaches that are more responsive to prevailing trends in vulnerability. Through a vulnerability production framing (Dooling & Simon, 2012) this study further explored how our present provision of subsidized low-income housing is failing to provide safer housing, and in some cases, is increasing vulnerability.

Present scholarship on social vulnerability, while highlighting the underlying cause of differential disaster outcomes and rightly identifying the social factors that need to be emphasized, paints an incomplete picture of how vulnerability evolves over time. By integrating neighborhood change theories and social vulnerability theories, this study explores three different coastal cities to explain the dynamics behind the changing patterns of vulnerability observed there. As this study found, despite having drastically different population growth trajectories and being located in different political and economic settings, in recent decades the spatial concentration of social vulnerability has gradually decreased in the study cities. However, in terms of the composition of social vulnerability, the study cities exhibited different trends. In the case of Harris County (Houston) in Texas, the high growth of the Hispanic and immigrant populations in recent decades made these the key factors in social vulnerability, along with the percentage of Black or African-American population and poverty rate. In the case of Orleans

Parish (New Orleans) Louisiana, displacement by Hurricane Katrina has significantly influenced the pattern of social vulnerability, which has become less concentrated and less dominated by race and socio-economic indicators. For Hillsborough County (Tampa) in Florida, gentrification in the inner city areas is pushing socially vulnerable populations to suburban and coastal census tracts and at the same time, some of the coastal locations are experiencing high rates of growth of elderly populations due to the development of retirement communities there. These trends imply drastically different adaptation challenges in these counties.

Analyzing the location outcomes of subsidized housing in Houston, this study found that among the two most popular housing subsidy programs (HCV and LIHTC), the supply-side based subsidy provision of LIHTC program significantly increases neighborhood social vulnerability when it is located in technological hazard areas. In comparison to the total population distribution however, it was found that both of these subsidies have a proportionally higher presence in both natural and technological hazard areas. A potential explanation for the significant contribution of the LIHTC program can be that it is a project based approach and necessarily concentrates low-income units within a given neighborhood. On the other hand, it was found that a substantial number of these projects are gated communities, which may also exert negative neighborhood impacts by devaluing adjacent property values (i.e., spillover effects).

Evaluating the environmental requirements of different subsidized housing programs, this study identified limitations that may have contributed to unfavorable location outcomes from the HCV and LIHTC programs. While HUD has explicit regulations regarding the placement of assisted projects in natural or technological hazard zones, those provisions are not applicable for these two subsidy programs. Since the HCV program is not project based and the LIHTC is administered by the U.S. Treasury Department, the location requirements for traditional public housing established by HUD cannot be directly applied to these programs. Because these are market driven approaches operating within a neoliberal policy environment, this lack of regulatory safeguards increases the possibility that they will concentrate low-income people in hazardous areas of the city (as this study found was particularly true for the LIHTC program). While this study emphasizes reevaluating the provisions of these market-based programs, policy modifications were also proposed that should help to ensure that housing subsidies are not placed in natural or technological hazard zones if implemented.

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APPENDIX A

RESULTS OF PCA ANALYSIS

Table A1: PCA results for Harris County

Major components (% variance explained)	Major contributing variables
1980 (total variance explained: 71.8%)	
Race and socio-economic status (28.9)	SHRBLK80, FFH80, TRVLPB80, EDUCUH80, UNEMPRT80, SERVOCC80, POVRAT80, WELFARE80, AVHHIN80, AVGRNT80
Housing and labor force (16.5)	KIDS80, AVHHSZ80, FEMLABR80, RNTUR80
Hispanic and foreign-born (9.9)	SHRHSP80, SHRFOR80
Age and gender (8.9)	SHRASN80, OLD80, FEMLABR80
Employment and mobile homes (7.6)	MANUF80, MOB80
1990 (total variance explained: 74.4%)	
Race and socio-economic status (29.4)	SHRBLK90, FFH90, TRVLPB90, EDUCUH90, UNEMPRT90, SERVOCC90, POVRAT90, WELFARE90, AVHHIN90, AVGRNT90
Housing and labor force (15.1)	AVHHSZ90, FEMLABR90, RNTUR90, LABPOP90, HODENT90
Hispanic and foreign-born (12)	SHRHSP90, SHRFOR90, FEMR90
Age (10)	KIDS90, OLD90, AVGVAL90
Employment and mobile homes (7.9)	SHRASN90, MANUF90, MOB90
2000 (total variance explained: 72.5%)	
Race and socio-economic status (27.5)	SHRBLK00, FFH00, TRVLPB00, EDUCUH00, UNEMPRT00, SERVOCC00, POVRAT00, WELFARE00, AVHHIN00, AVGVAL00, AVGRNT00
Hispanic and foreign-born (17.6)	SHRHSP00, KIDS00, SHRFOR00, AVHHSZ00, EDUCUH00
Employment and housing (11.4)	MANUF00, RNTUR00, MOB00, HODENT00
Age and labor force (10)	OLD00, FEMLABR00, LABPOP00
Gender (6)	GROUPQ00, FEMR00
2010 (total variance explained: 65.5%)	
Race and socio-economic status (23.4)	SHRBLK10, FFH10, TRVLPB10, EDUCUH10, UNEMPRT10, SERVOCC10, POVRAT10, WELFARE10, AVHHIN10, AVGVAL10, AVGRNT10
Hispanic and foreign-born (13.9)	SHRHSP10, SHRFOR10, AVHHSZ10, EDUCUH10
Age and labor force (11.4)	OLD10, FEMLABR10, WELFARE10
Employment and housing (9.2)	MANUF10, HODENT10
Gender (7.6)	GROUPQ10, FEMR10

Table A2: PCA results for Orleans Parish

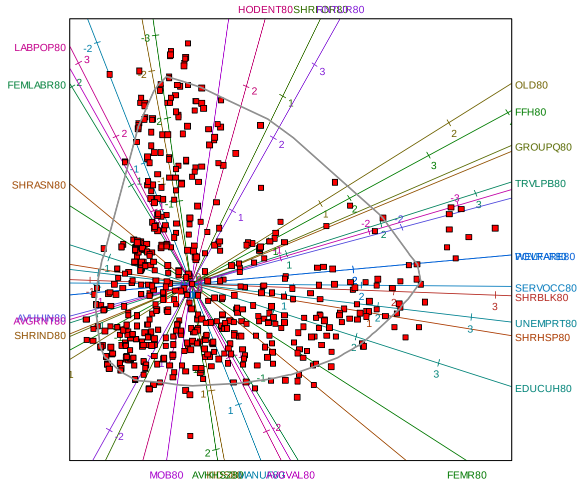
Major components (% variance explained)	Major contributing variables
1980 (total variance explained: 71%)	
Race and socio-economic status (40.3)	SHRBLK80, FFH80, TRVLPB80, EDUCUH80, UNEMPRT80, SERVOCC80, POVRAT80, WELFARE80, AVHHIN80, RNTUR80, AVGVAL80, AVGRNT80, LABPOP80, HODENT80
Age and Hispanic population (13.4)	SHRHSP80, KIDS80, OLD80, AVHHSZ80
Foreign-born and Asian population (8.7)	SHRASN80, SHRFOR80, MOB80
Employment and Gender (8.6)	FEMR80, FEMLABR80, MANUF80
1990 (total variance explained: 70.5%)	
Race and socio-economic status (39.8)	SHRBLK90, FFH90, TRVLPB90, EDUCUH90, UNEMPRT90, SERVOCC90, POVRAT90, WELFARE90, AVHHIN90, RNTUR90, AVGRNT90, LABPOP90, HODENT90
Hispanic population (11.9)	SHRHSP90, SHRFOR90, AVHHSZ90
Foreign-born, Asian, mobile homes (10.5)	SHRASN90, SHRFOR90, MOB90
Employment and Gender (8.3)	FEMLABR90, AVHHIN90, AVGVAL90
2000 (total variance explained: 69.6%)	
Race and socio-economic status (38.7)	SHRBLK00, FFH00, TRVLPB00, EDUCUH00, UNEMPRT00, SERVOCC00, POVRAT00, WELFARE00, AVHHIN00, RNTUR00, AVGVAL00, AVGRNT00, LABPOP00, HODENT00
Hispanic population and employment (15)	SHRHSP00, AVHHSZ00, FEMR00, MANUF00, AVGVAL00, HODENT00
Foreign-born and Asian (8.7)	SHRASN00, SHRFOR00
Age and gender (7.2)	OLD00, GROUPQ00, FEMLABR00
2010 (total variance explained: 67.7%)	
Race and socio-economic status (26.5)	SHRBLK10, FFH10, TRVLPB10, EDUCUH10, UNEMPRT10, SERVOCC10, WELFARE10, AVHHIN10, RNTUR10, AVGVAL10, AVGRNT10, LABPOP10
Employment, gender (12.7)	KIDS10, AVHHSZ10, FFH10, LABPOP10, HODENT10
Hispanic and foreign-born (10.9)	SHRHSP10, SHRASN10, SHRFOR10
Age and gender (10.1)	OLD10, FEMLABR10, WELFARE10
Housing, employment (7.5)	GROUPQ10, MANUF10,

Table A3: PCA results for Hillsborough County

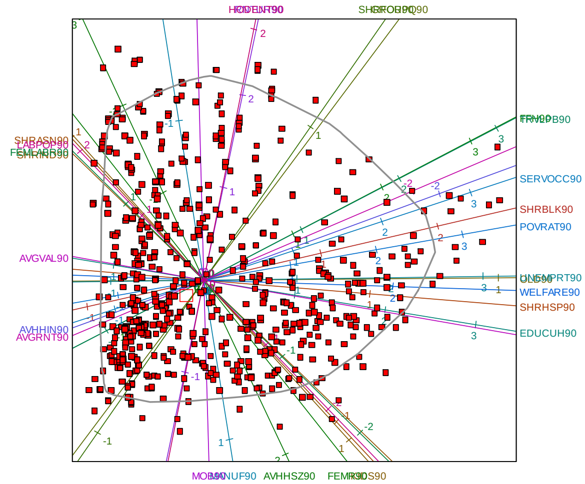
Major components (% variance explained)	Major contributing variables
1980 (total variance explained: 75.5%)	
Race and socio-economic status (31.1)	SHRBLK80, FFH80, TRVLPB80, EDUCUH80, UNEMPRT80, SERVOCC80, POVRAT80, WELFARE80, AVHHIN80, RNTUR80, AVGRNT80, HODENT80
Age, labor force (11.5)	OLD80, FEMLABR80, LABPOP80
Household size, age (9.1)	KIDS80, OLD80, AVHHSZ80
Hispanic, foreign-born (8.6)	SHRHSP80, SHRFOR80
Employment and housing (8.5)	GROUPQ80, EDUCUH80, MANUF80
Gender (6.7)	SHRIND80, FEMR80, MOB80
1990 (total variance explained: 73.6%)	
Race and socio-economic status (32.6)	SHRBLK90, FFH90, TRVLPB90, EDUCUH90, UNEMPRT90, SERVOCC90, POVRAT90, WELFARE90, AVHHIN90, RNTUR90, AVGRNT90, HODENT90
Age, labor force (13.9)	SHRASN90, OLD90, FEMLABR90, LABPOP90
Household size, employment (10.7)	AVHHSZ90, MOB90, HODENT90
Hispanic, foreign-born (9)	SHRHSP90, SHRFOR90
Gender and Housing (7.4)	GROUPQ90, FEMR90, MOB90
2000 (total variance explained: 74.3%)	
Race and socio-economic status (27.6)	SHRBLK00, FFH00, TRVLPB00, EDUCUH00, UNEMPRT00, SERVOCC00, POVRAT00, WELFARE00, AVHHIN00, RNTUR00, AVGRNT00
Age, labor force (13.3)	SHRASN00, OLD00, FEMLABR00, LABPOP00
Household size, employment (10.9)	AVHHSZ00, MANUF00, RNTUR00, HODENT00
Hispanic, foreign-born (9.5)	SHRHSP00, SHRFOR00
Income, home value (7.3)	SHRIND00, AVHHIN00, AVGVAL00
Employment and housing (5.7)	GROUPQ00, UNEMPRT00
2010 (total variance explained: 65.8%)	
Race and socio-economic status (23.8)	SHRBLK10, FFH10, TRVLPB10, EDUCUH10, UNEMPRT10, SERVOCC10, POVRAT10, WELFARE10, AVHHIN10, RNTUR10, AVGVAL10, AVGRNT10
Age, labor force (16.2)	OLD10, FEMLABR10, WELFARE10, LABPOP10
Hispanic, foreign-born (10)	SHRHSP10, SHRFOR10
Household size, housing (8.6)	KIDS10, AVHHSZ10
Gender and employment (7.2)	FEMR10, MANUF10, MOB10, HODENT10

APPENDIX B

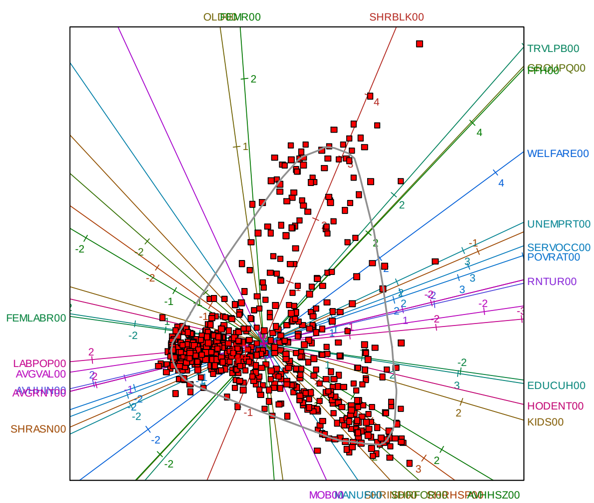
CORRELATION BIPLOTS



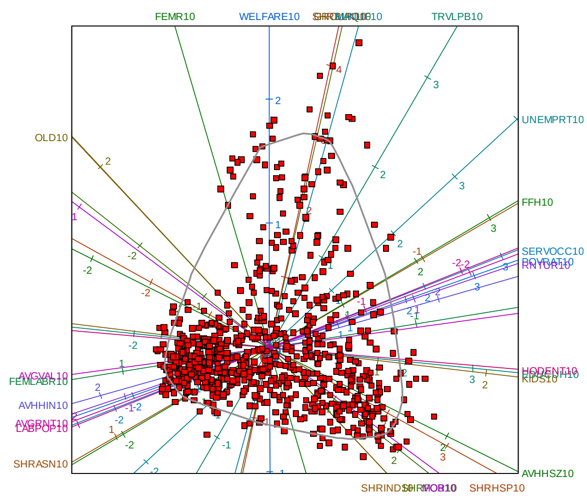
1980



1990



2000



2010

Figure B1: Correlation biplots (with alpha bag) of Harris County

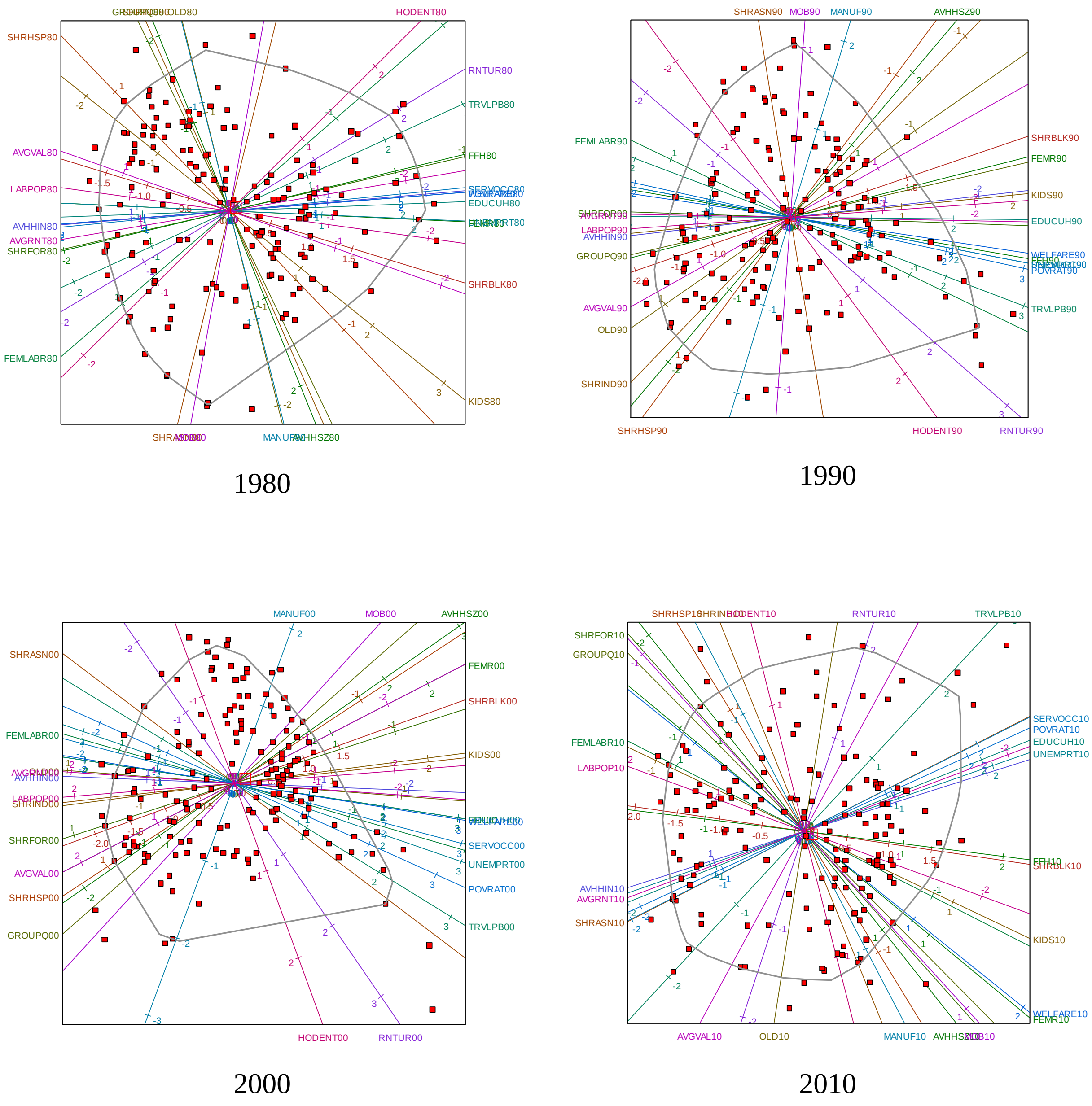


Figure B2: Correlation biplots (with alpha bag) of Orleans Parish

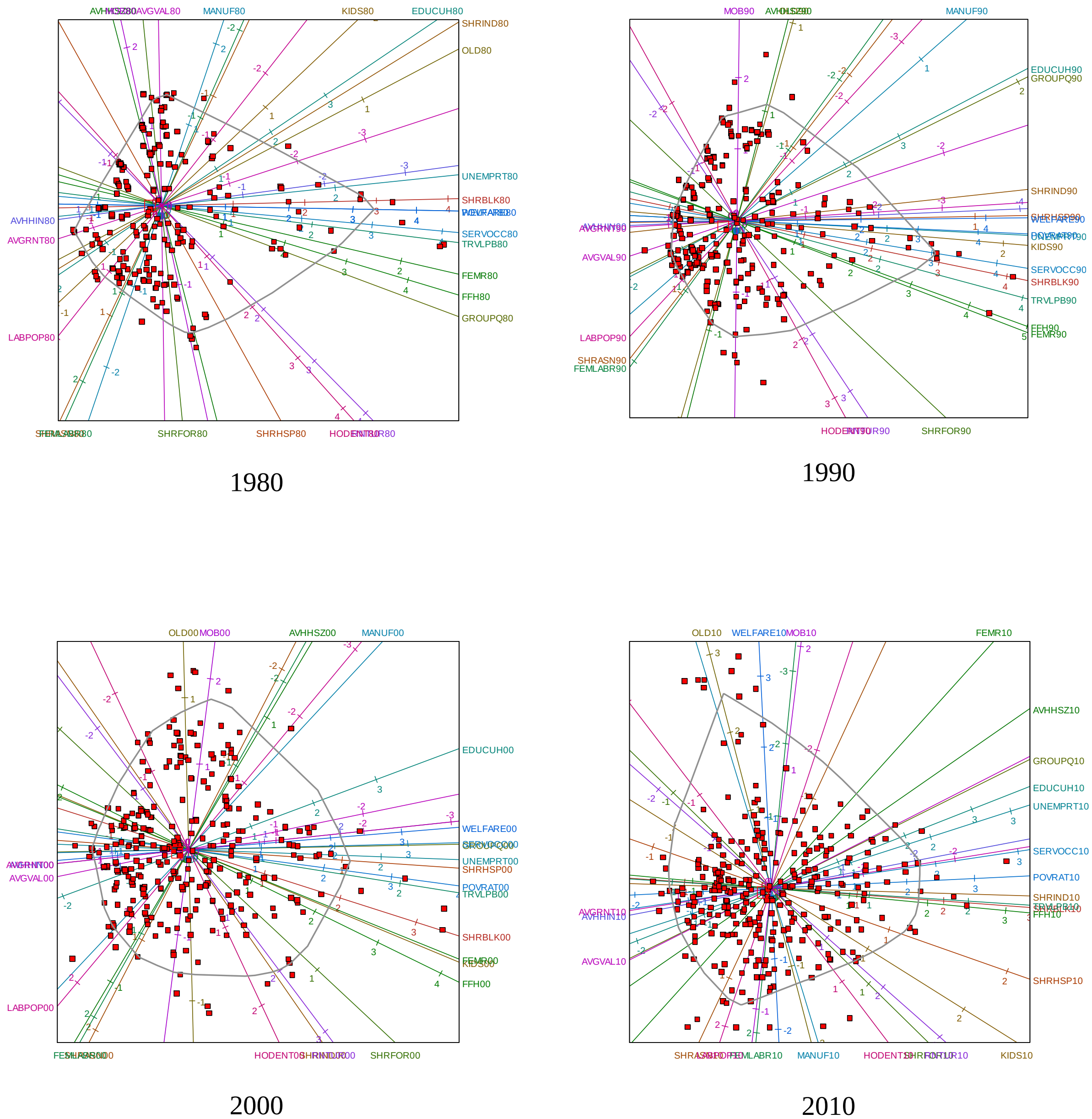


Figure B3: Correlation biplots (with alpha bag) of Hillsborough County

APPENDIX C
MODEL RESULTS AND COMPARISONS

Table C1: Models estimating change in standardized value of SoVI (using power function for technological hazards)

Variables	OLS	Spatial Lag	Spatial Durbin	Spatial Error
(Intercept)	-0.472 (0.194)*	-0.125 (0.188)	-0.192 (0.506)	-0.61 (0.25)*
zfldrt:pchcvgr	-0.013 (0.018)	-0.014 (0.017)	-0.007 (0.017)	-0.015 (0.017)
zfldrt:pctcugr	0.004 (0.007)	0.001 (0.007)	0 (0.007)	0 (0.007)
pchcvgr:zpowr	-0.007 (0.011)	-0.009 (0.01)	-0.012 (0.011)	-0.01 (0.01)
pctcugr:zpowr	-0.008 (0.01)	-0.009 (0.009)	-0.014 (0.009)	-0.009 (0.009)
Pchcvgr	0.046 (0.015)**	0.034 (0.014)*	0.028 (0.014)	0.034 (0.014)*
Pctcugr	0.002 (0.005)	0.001 (0.005)	0.001 (0.005)	0.001 (0.005)
Zfldrt	-0.012 (0.029)	-0.013 (0.027)	-0.036 (0.033)	-0.024 (0.031)
Zpowr	-0.075 (0.036)*	-0.033 (0.034)	-0.005 (0.044)	-0.027 (0.039)
Popgr	0 (0)	0 (0)	0 (0)	0 (0)
Blkgr	0.03 (0.004)***	0.022 (0.004)***	0.026 (0.004)***	0.025 (0.004)***
Hspgr	0.033 (0.003)***	0.025 (0.003)***	0.029 (0.003)***	0.03 (0.003)***
mdrnt2000	0 (0)	0 (0)*	0 (0)*	0 (0)*
pov2000	-0.021 (0.005)***	-0.015 (0.005)***	-0.018 (0.005)***	-0.019 (0.005)***
hsp2000	0.01 (0.002)***	0.006 (0.002)***	0.012 (0.003)***	0.01 (0.002)***
shrblk2000	0.01 (0.002)***	0.007 (0.002)***	0.015 (0.003)***	0.011 (0.002)***
cbd_dist	0.01 (0.006)	-0.002 (0.005)	-0.026 (0.045)	0.018 (0.011)
lag.pchcvgr			-0.006 (0.061)	
lag.pctcugr			0.019 (0.027)	
lag.zfldrt			0.161 (0.097)	
lag.zpowr			0.022 (0.152)	
lag.popgr			0 (0.001)	
lag.blkgr			0.015 (0.013)	
lag.hspgr			-0.003 (0.009)	
lag.mdrnt2000			0.001 (0.001)	
lag.pov2000			0.012 (0.016)	
lag.hsp2000			-0.01 (0.006)	
lag.shrblk2000			-0.017 (0.006)**	
lag.cbd_dist			0.013 (0.05)	
lag.zfldrt:pchcvgr			0.087 (0.072)	
lag.zfldrt:pctcugr			0.002 (0.033)	
lag.pchcvgr:zpowr			0.003 (0.061)	
lag.pctcugr:zpowr			-0.062 (0.061)	

Table C1 (cont.)

rho/lambda		0.574 (0.061)***	0.516 (0.076)***	0.661 (0.064)***
Adj.R2	0.2896			
AIC	1780.967	1715.4	1719.9	1714.5
Log likelihood	-872.4837	-838.7081	-824.9665	-838.2343

**p*< .05, ***p*< .01, ****p*< .001

Table C2: Lagrange Multiplier diagnostics for OLS model estimating change in standardized value of SoVI (using power function for technological hazards)

	Statistic	df	p-value
LM (error)	92.88	1	0.000
LM (lag)	95.908	1	0.000
Robust LM (error)	6.864	1	0.009
Robust LM (lag)	9.892	1	0.002
SARMA	102.772	2	0.000

Table C3: Likelihood Ratio (LR) test for spatial regression models estimating change in standardized value of SoVI (using power function for technological hazards)

	Log Likelihood	Likelihood ratio with SDM
Spatial Durbin Model	-824.966	
Spatial Lag Model	-838.708	27.483*
Spatial Error Model	-838.234	26.536*

**p*< .05, ***p*< .01, ****p*< .001; df=16

Table C4: Models estimating change in standardized value of SoVI (using WCPE function for technological hazards)

Variables	OLS	Spatial Lag	Spatial Durbin	Spatial Error
(Intercept)	-0.492 (0.195)*	-0.124 (0.188)	-0.277 (0.503)	-0.625 (0.254)*
zfldrt:pchcvgr	-0.013 (0.018)	-0.014 (0.017)	-0.009 (0.017)	-0.017 (0.017)
zfldrt:pctcugr	0.004 (0.007)	0.001 (0.007)	0.002 (0.007)	0 (0.007)
pchcvgr:zcpe1	-0.016 (0.011)	-0.018 (0.01)	-0.019 (0.011)	-0.018 (0.009)
pctcugr:zcpe1	-0.015 (0.012)	-0.015 (0.012)	-0.02 (0.012)	-0.016 (0.011)
Pchcvgr	0.048 (0.015)**	0.035 (0.014)*	0.03 (0.014)*	0.035 (0.014)*
Pctcugr	0.001 (0.005)	0 (0.005)	0 (0.005)	0 (0.005)
Zfldrt	-0.01 (0.029)	-0.011 (0.027)	-0.028 (0.033)	-0.021 (0.031)
zcpe1	-0.005 (0.036)	0.027 (0.033)	0.062 (0.039)	0.033 (0.035)
Popgr	0 (0)	0 (0)	0 (0)	0 (0)
Blkgr	0.03 (0.004)***	0.022 (0.004)***	0.026 (0.004)***	0.025 (0.004)***
Hspgr	0.033 (0.003)***	0.025 (0.003)***	0.029 (0.003)***	0.03 (0.003)
mdrnt2000	0 (0)	0 (0)*	0 (0)*	0 (0)*
pov2000	-0.022 (0.005)***	-0.016 (0.005)***	-0.017 (0.005)**	-0.019 (0.005)***

Table C4 (cont.)

hsp2000	0.009 (0.002)***	0.006 (0.002)**	0.013 (0.003)***	0.01 (0.002)***
shrblk2000	0.01 (0.002)***	0.007 (0.002)***	0.015 (0.003)***	0.011 (0.002)***
cbd_dist	0.01 (0.006)	-0.001 (0.005)	-0.033 (0.045)	0.019 (0.011)
lag.pchcvgr			0.009 (0.06)	
lag.pctcugr			0.008 (0.028)	
lag.zfldrt			0.123 (0.097)	
lag.zpowr			-0.193 (0.187)	
lag.popgr			0 (0.001)	
lag.blkgr			0.016 (0.013)	
lag.hspgr			-0.008 (0.009)	
lag.mdrnt2000			0.001 (0)	
lag.pov2000			0.009 (0.016)	
lag.hsp2000			-0.008 (0.006)	
lag.shrblk2000			-0.014 (0.006)*	
lag.cbd_dist			0.021 (0.05)	
lag.zfldrt:pchcvgr			0.088 (0.071)	
lag.zfldrt:pctcugr			0.019 (0.031)	
lag.pchcvgr:zpowr			0.024 (0.072)	
lag.pctcugr:zpowr			-0.094 (0.091)	
rho/lambda		0.592 (0.059)***	0.518 (0.075)***	0.676 (0.062)***
Adj.R2	0.2834			
AIC	1787.633	1716.6	1717.7	1714.3
Log likelihood	-875.8167	-839.3218	-823.8262	-838.1588

**p*< .05, ***p*< .01, ****p*< .001

Table C5: Lagrange Multiplier diagnostics for OLS model estimating change in standardized value of SoVI (using WCPE function for technological hazards)

	Statistic	df	p-value
LM (error)	106.362	1	0.000
LM (lag)	104.920	1	0.000
Robust LM (error)	9.817	1	0.002
Robust LM (lag)	8.375	1	0.004
SARMA	114.737	2	0.000

Table C6: Likelihood Ratio (LR) test for spatial regression models estimating change in standardized value of SoVI (using WCPE function for technological hazards)

	Log Likelihood	Likelihood ratio with SDM
Spatial Durbin Model	-823.826	
Spatial Lag Model	-839.3218	30.991*
Spatial Error Model	-838.1588	28.665*

**p*< .05, ***p*< .01, ****p*< .001; df=16

Table C7: Models estimating change in % of population under poverty (using power function for technological hazards)

Variables	OLS	Spatial Lag	Spatial Durbin	Spatial Error
(Intercept)	-0.146 (1.822)	0.092 (1.782)	2.308 (4.876)	-1.087 (2.111)
zfldrt:pchcvgr	-0.158 (0.172)	-0.192 (0.168)	-0.181 (0.167)	-0.241 (0.165)
zfldrt:pctcugr	0.029 (0.068)	0.02 (0.066)	0 (0.065)	0.012 (0.064)
pchcvgr:zpowr	-0.017 (0.104)	-0.029 (0.101)	-0.12 (0.102)	-0.054 (0.099)
pctcugr:zpowr	0.278 (0.093)**	0.274 (0.091)**	0.212 (0.089)*	0.273 (0.089)**
Pchcvgr	0.343 (0.141)*	0.287 (0.138)*	0.256 (0.139)	0.284 (0.138)*
Pctcugr	0.154 (0.051)**	0.144 (0.05)**	0.142 (0.049)**	0.15 (0.049)**
Zfldrt	0.551 (0.272)*	0.46 (0.266)	0.304 (0.319)	0.449 (0.288)
Zpowr	-0.849 (0.341)*	-0.619 (0.333)	0.219 (0.421)	-0.358 (0.367)
Popgr	-0.01 (0.003)***	-0.008 (0.003)**	-0.01 (0.003)**	-0.009 (0.003)***
Blkgr	0.174 (0.037)***	0.155 (0.037)***	0.22 (0.039)***	0.187 (0.038)***
Hspgr	0.312 (0.027)**	0.278 (0.029)***	0.334 (0.032)***	0.316 (0.029)***
mdrnt2000	-0.003 (0.002)	-0.003 (0.002)	-0.003 (0.002)	-0.003 (0.002)
pov2000	-0.274 (0.046)***	-0.244 (0.045)***	-0.288 (0.051)***	-0.277 (0.048)***
hsp2000	0.139 (0.018)***	0.115 (0.019)***	0.184 (0.027)***	0.148 (0.021)***
shrblk2000	0.09 (0.018)***	0.076 (0.018)***	0.166 (0.029)***	0.105 (0.021)***
cbd_dist	0.062 (0.052)	0.019 (0.053)	-0.305 (0.439)	0.096 (0.078)
lag.pchcvgr			0.068 (0.589)	
lag.pctcugr			-0.079 (0.261)	
lag.zfldrt			1.155 (0.938)	
lag.zpowr			-1.308 (1.481)	
lag.popgr			0.01 (0.009)	
lag.blkgr			-0.123 (0.12)	
lag.hspgr			-0.061 (0.091)	
lag.mdrnt2000			0.002 (0.005)	
lag.pov2000			0.206 (0.152)	
lag.hsp2000			-0.137 (0.062)*	
lag.shrblk2000			-0.209 (0.062)***	
lag.cbd_dist			0.233 (0.481)	
lag.zfldrt:pchcvgr			1.581 (0.694)*	
lag.zfldrt:pctcugr			-0.067 (0.319)	
lag.pchcvgr:zpowr			-0.136 (0.588)	
lag.pctcugr:zpowr			-0.565 (0.59)	
rho/lambda		0.308 (0.074)***	0.284 (0.091)**	0.482 (0.08)***
Adj.R2	0.2872			
AIC	5222.408	5208.6	5198.1	5196.5
Log likelihood	-2593.204	-2585.282	-2564.032	-2579.226

**p*< .05, ***p*< .01, ****p*< .001

Table C8: Lagrange Multiplier diagnostics for OLS model estimating change in % of population under poverty (using power function for technological hazards)

	Statistic	df	p-value
LM (error)	32.925	1	0.000
LM (lag)	18.926	1	0.000
Robust LM (error)	14.241	1	0.000
Robust LM (lag)	0.242	1	0.623
SARMA	33.167	2	0.000

Table C9: Likelihood Ratio (LR) test for spatial regression models estimating change in % of population under poverty (using power function for technological hazards)

	Log Likelihood	Likelihood ratio with SDM
Spatial Durbin Model	-2564.03	
Spatial Lag Model	-2585.28	42.499***
Spatial Error Model	-2579.23	30.386*

*p< .05, **p< .01, ***p< .001; df=16

Table C10: Models estimating change in % of population under poverty (using WCPE function for technological hazards)

Variables	OLS	Spatial Lag	Spatial Durbin	Spatial Error
(Intercept)	-0.173 (1.821)	0.133 (1.778)	0.524 (4.846)	-1.088 (2.109)
zfldrt:pchcvgr	-0.122 (0.172)	-0.16 (0.167)	-0.159 (0.166)	-0.211 (0.165)
zfldrt:pctcugr	-0.002 (0.067)	-0.012 (0.065)	-0.013 (0.064)	-0.017 (0.064)
pchcvgr:zcpe1	-0.096 (0.1)	-0.11 (0.097)	-0.105 (0.109)	-0.109 (0.093)
pctcugr:zcpe1	0.38 (0.116)**	0.373 (0.113)***	0.341 (0.115)**	0.349 (0.11)**
Pchcvgr	0.308 (0.141)*	0.246 (0.137)	0.239 (0.138)	0.243 (0.137)
Pctcugr	0.167 (0.051)**	0.157 (0.05)**	0.155 (0.05)**	0.161 (0.049)**
Zfldrt	0.559 (0.272)*	0.462 (0.265)	0.324 (0.32)	0.452 (0.288)
zcpe1	-0.181 (0.333)	-0.002 (0.325)	0.359 (0.38)	0.084 (0.335)
Popgr	-0.01 (0.003)***	-0.008 (0.003)**	-0.01 (0.003)**	-0.009 (0.003)***
Blkgr	0.171 (0.037)***	0.15 (0.036)***	0.217 (0.039)***	0.182 (0.038)***
Hspgr	0.317 (0.028)***	0.28 (0.029)***	0.336 (0.032)***	0.317 (0.029)***
mdrnt2000	-0.002 (0.002)	-0.003 (0.002)	-0.003 (0.002)	-0.003 (0.002)
pov2000	-0.279 (0.046)***	-0.245 (0.045)***	-0.283 (0.051)***	-0.276 (0.048)***
hsp2000	0.135 (0.018)***	0.109 (0.019)***	0.183 (0.028)***	0.144 (0.021)***
shrblk2000	0.09 (0.018)***	0.075 (0.018)***	0.163 (0.029)***	0.105 (0.021)***
cbd_dist	0.071 (0.052)	0.024 (0.053)	-0.256 (0.439)	0.106 (0.078)
lag.pchcvgr			0.324 (0.581)	
lag.pctcugr			-0.084 (0.273)	
lag.zfldrt			0.785 (0.938)	
lag.zpowr			-3.002 (1.815)	
lag.popgr			0.012 (0.009)	

Table C10 (cont.)

lag.blkgr			-0.092 (0.121)	
lag.hspgr			-0.083 (0.092)	
lag.mdrnt2000			0.003 (0.005)	
lag.pov2000			0.19 (0.152)	
lag.hsp2000			-0.122 (0.061)*	
lag.shrblk2000			-0.182 (0.061)**	
lag.cbd_dist			0.179 (0.479)	
lag.zfldrt:pchcvgr			1.616 (0.691)*	
lag.zfldrt:pctcugr			0.126 (0.3)	
lag.pchcvgr:zpowr			0.252 (0.701)	
lag.pctcugr:zpowr			0.204 (0.88)	
rho/lambda		0.328 (0.074)***	0.316 (0.089)***	0.483 (0.08)***
Adj.R2	0.2869			
AIC	5222.682	5206.3	5198.1	5194.7
Log likelihood	-2593.341	-2584.14	-2564.033	-2578.334
Moran's I for residuals	0.117***		0.125***	

**p*< .05, ***p*< .01, ****p*< .001

Table C11: Lagrange Multiplier diagnostics for OLS model estimating change in % of population under poverty (using WCPE function for technological hazards)

	Statistic	df	p-value
LM (error)	38.620	1	0.000
LM (lag)	22.746	1	0.000
Robust LM (error)	16.127	1	0.000
Robust LM (lag)	0.253	1	0.615
SARMA	38.873	2	0.000

Table C12: Likelihood Ratio (LR) test for spatial regression models estimating change in % of population under poverty (using WCPE function for technological hazards)

	Log Likelihood	Likelihood ratio with SDM
Spatial Durbin Model	-2564.033	
Spatial Lag Model	-2584.14	40.214***
Spatial Error Model	-2578.334	28.602*

**p*< .05, ***p*< .01, ****p*< .001; df=16

Table C13: Models estimating change in % of population Black and under poverty (using power function for technological hazards)

Variables	OLS	Spatial Lag	Spatial Durbin	Spatial Error
(Intercept)	0.162 (0.886)	0.248 (0.86)	2.481 (2.365)	-0.198 (1.06)
zfldrt:pchcvgr	0.072 (0.084)	0.095 (0.081)	0.069 (0.081)	0.078 (0.08)
zfldrt:pctcugr	-0.037 (0.033)	-0.045 (0.032)	-0.045 (0.032)	-0.049 (0.031)
pchcvgr:zpowr	-0.016 (0.05)	-0.016 (0.049)	-0.054 (0.05)	-0.025 (0.048)
pctcugr:zpowr	0.054 (0.045)	0.053 (0.044)	0.038 (0.043)	0.055 (0.043)
Pchcvgr	0.37 (0.069)***	0.328 (0.067)***	0.296 (0.067)***	0.333 (0.067)***
Pctcugr	0.026 (0.025)	0.028 (0.024)	0.025 (0.024)	0.026 (0.024)
Zfldrt	0.272 (0.132)*	0.223 (0.128)	-0.049 (0.155)	0.134 (0.141)
Zpowr	-0.044 (0.166)	0.031 (0.161)	0.328 (0.204)	0.143 (0.18)
Popgr	-0.003 (0.001)*	-0.002 (0.001)	-0.003 (0.001)	-0.002 (0.001)
Blkgr	0.255 (0.018)***	0.242 (0.018)***	0.273 (0.019)***	0.263 (0.018)***
Hspgr	0.003 (0.013)	-0.005 (0.013)	0.003 (0.016)	0.003 (0.014)
mdrnt2000	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)
pov2000	-0.135 (0.022)***	-0.117 (0.022)***	-0.113 (0.025)***	-0.123 (0.023)***
hsp2000	0.053 (0.009)***	0.046 (0.009)***	0.04 (0.013)**	0.048 (0.01)***
shrblk2000	0.043 (0.009)***	0.041 (0.009)***	0.064 (0.014)***	0.047 (0.01)***
cbd_dist	0.003 (0.025)	-0.019 (0.025)	-0.069 (0.213)	0.014 (0.041)
lag.pchcvgr			0.079 (0.288)	
lag.pctcugr			-0.069 (0.126)	
lag.zfldrt			1.09 (0.455)*	
lag.zpowr			-0.363 (0.711)	
lag.popgr			0.006 (0.004)	
lag.blkgr			-0.173 (0.061)**	
lag.hspgr			-0.024 (0.041)	
lag.mdrnt2000			-0.001 (0.002)	
lag.pov2000			-0.025 (0.074)	
lag.hsp2000			0.014 (0.03)	
lag.shrblk2000			-0.07 (0.03)*	
lag.cbd_dist			0.039 (0.233)	
lag.zfldrt:pchcvgr			-0.086 (0.336)	
lag.zfldrt:pctcugr			0.128 (0.154)	
lag.pchcvgr:zpowr			-0.146 (0.285)	
lag.pctcugr:zpowr			-0.295 (0.285)	
rho/lambda		0.397 (0.072)***	0.395 (0.085)***	0.54 (0.075)***
Adj.R2	0.3327			
AIC	4113.338	4092.2	4087	4084
Log likelihood	-2038.669	-2027.111	-2008.487	-2023.006
Moran’s I for residuals	0.069***		0.075***	

**p*< .05, ***p*< .01, ****p*< .001

Table C14: Lagrange Multiplier diagnostics for OLS model estimating change in % of population Black and under poverty (using power function for technological hazards)

	Statistic	df	p-value
LM (error)	32.176	1	0.000
LM (lag)	25.299	1	0.000
Robust LM (error)	7.153	1	0.008
Robust LM (lag)	0.276	1	0.599
SARMA	32.452	2	0.000

Table C15: Likelihood Ratio (LR) test for spatial regression models estimating change in % of population Black and under poverty (using power function for technological hazards)

	Log Likelihood	Likelihood ratio with SDM
Spatial Durbin Model	-2008.49	
Spatial Lag Model	-2027.11	37.247**
Spatial Error Model	-2023.01	29.037*

**p* < .05, ***p* < .01, ****p* < .001; df=16

Table C16: Models estimating change in % of population Black and under poverty (using WCPE function for technological hazards)

Variables	OLS	Spatial Lag	Spatial Durbin	Spatial Error
(Intercept)	0.181 (0.885)	0.282 (0.858)	2.407 (2.346)	-0.158 (1.056)
zfldrt:pchcvgr	0.08 (0.083)	0.103 (0.081)	0.082 (0.08)	0.086 (0.08)
zfldrt:pctcugr	-0.043 (0.032)	-0.051 (0.031)	-0.046 (0.031)	-0.054 (0.031)
pchcvgr:zcpe1	-0.01 (0.049)	-0.011 (0.047)	-0.045 (0.053)	-0.016 (0.045)
pctcugr:zcpe1	0.094 (0.056)	0.098 (0.054)	0.069 (0.056)	0.102 (0.053)
Pchcvgr	0.362 (0.068)***	0.32 (0.066)***	0.296 (0.067)***	0.325 (0.067)***
Pctcugr	0.031 (0.025)	0.033 (0.024)	0.026 (0.024)	0.031 (0.024)
Zfldrt	0.271 (0.132)*	0.221 (0.128)	-0.046 (0.155)	0.131 (0.141)
zcpe1	-0.006 (0.162)	0.034 (0.157)	0.283 (0.184)	0.104 (0.163)
Popgr	-0.003 (0.001)*	-0.002 (0.001)	-0.003 (0.001)	-0.003 (0.001)
Blkgr	0.254 (0.018)***	0.241 (0.018)***	0.272 (0.019)***	0.262 (0.018)***
Hspgr	0.004 (0.013)	-0.004 (0.013)	0.004 (0.015)	0.004 (0.014)
mdrnt2000	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)
pov2000	-0.135 (0.022)***	-0.116 (0.022)***	-0.109 (0.025)***	-0.122 (0.023)***
hsp2000	0.052 (0.009)***	0.045 (0.009)***	0.042 (0.013)**	0.047 (0.01)***
shrblk2000	0.043 (0.009)***	0.041 (0.009)***	0.064 (0.014)***	0.047 (0.01)***
cbd_dist	0.004 (0.025)	-0.019 (0.025)	-0.104 (0.213)	0.013 (0.041)
lag.pchcvgr			0.161 (0.284)	
lag.pctcugr			-0.16 (0.132)	
lag.zfldrt			0.988 (0.456)*	
lag.zpowr			-0.363 (0.872)	
lag.popgr			0.007 (0.004)	

Table C16 (cont.)

lag.blkgr			-0.17 (0.061)**	
lag.hspgr			-0.04 (0.042)	
lag.mdrnt2000			-0.001 (0.002)	
lag.pov2000			-0.038 (0.074)	
lag.hsp2000			0.017 (0.03)	
lag.shrblk2000			-0.065 (0.029)*	
lag.cbd_dist			0.072 (0.232)	
lag.zfldrt:pchcvgr			-0.01 (0.334)	
lag.zfldrt:pctcugr			0.183 (0.145)	
lag.pchcvgr:zpowr			-0.137 (0.339)	
lag.pctcugr:zpowr			-0.789 (0.424)	
rho/lambda		0.398 (0.072)***	0.4 (0)***	0.536 (0.075)***
Adj.R2	0.3338			
AIC	4112.064	4090.5	4085.1	4082.7
Log likelihood	-2038.032	-2026.242	-2007.56	-2022.33
Moran's I for residuals	0.07***		0.069***	

**p*< .05, ***p*< .01, ****p*< .001

Table C17: Lagrange Multiplier diagnostics for OLS model estimating change in % of population Black and under poverty (using WCPE function for technological hazards)

	Statistic	df	p-value
LM (error)	33.185	1	0.000
LM (lag)	26.079	1	0.000
Robust LM (error)	7.386	1	0.007
Robust LM (lag)	0.281	1	0.596
SARMA	33.465	2	0.000

Table C18: Likelihood Ratio (LR) test for spatial regression models estimating change in % of population Black and under poverty (using WCPE function for technological hazards)

	Log Likelihood	Likelihood ratio with SDM
Spatial Durbin Model	-2007.56	
Spatial Lag Model	-2026.242	37.364**
Spatial Error Model	-2022.33	29.541*

**p*< .05, ***p*< .01, ****p*< .001; df=16

Table C19: Models estimating change in % of population Hispanic and under poverty (using power function for technological hazards)

Variables	OLS	Spatial Lag	Spatial Durbin	Spatial Error
(Intercept)	-1.812 (1.401)	-1.685 (1.38)	-0.432 (3.794)	-2.233 (1.557)
zfldrt:pchcvgr	-0.2 (0.132)	-0.232 (0.13)	-0.242 (0.13)	-0.275 (0.129)*
zfldrt:pctcugr	0.043 (0.052)	0.041 (0.051)	0.022 (0.051)	0.037 (0.05)
pchcvgr:zpowr	-0.028 (0.08)	-0.034 (0.078)	-0.099 (0.079)	-0.047 (0.077)
pctcugr:zpowr	0.182 (0.071)*	0.179 (0.07)*	0.135 (0.069)	0.176 (0.069)*
Pchcvgr	0.004 (0.109)	-0.012 (0.107)	0 (0.108)	-0.015 (0.107)
Pctcugr	0.097 (0.039)*	0.089 (0.038)*	0.084 (0.038)*	0.095 (0.038)*
Zfldrt	0.404 (0.209)	0.369 (0.206)	0.458 (0.248)	0.416 (0.22)
Zpowr	-0.772 (0.262)**	-0.666 (0.258)**	-0.042 (0.327)	-0.523 (0.279)
Popgr	-0.005 (0.002)*	-0.005 (0.002)*	-0.006 (0.002)*	-0.005 (0.002)*
Blkgr	-0.017 (0.028)	-0.024 (0.028)	0.018 (0.03)	-0.009 (0.029)
Hspgr	0.387 (0.021)***	0.364 (0.023)***	0.402 (0.025)***	0.387 (0.022)***
mdrnt2000	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)
pov2000	-0.077 (0.035)*	-0.067 (0.035)	-0.107 (0.039)**	-0.086 (0.036)*
hsp2000	0.091 (0.014)***	0.078 (0.015)***	0.136 (0.021)***	0.099 (0.015)***
shrblk2000	0.038 (0.014)**	0.03 (0.014)*	0.085 (0.022)***	0.046 (0.016)**
cbd_dist	0.011 (0.04)	-0.002 (0.04)	-0.072 (0.341)	0.027 (0.054)
lag.pchcvgr			-0.074 (0.455)	
lag.pctcugr			-0.048 (0.203)	
lag.zfldrt			-0.208 (0.726)	
lag.zpowr			-1.166 (1.151)	
lag.popgr			0.005 (0.007)	
lag.blkgr			-0.053 (0.093)	
lag.hspgr			-0.032 (0.077)	
lag.mdrnt2000			0.001 (0.004)	
lag.pov2000			0.2 (0.117)	
lag.hsp2000			-0.13 (0.048)**	
lag.shrblk2000			-0.131 (0.048)**	
lag.cbd_dist			-0.007 (0.373)	
lag.zfldrt:pchcvgr			1.69 (0.54)**	
lag.zfldrt:pctcugr			-0.103 (0.247)	
lag.pchcvgr:zpowr			-0.093 (0.457)	
lag.pctcugr:zpowr			-0.145 (0.458)	
rho/lambda		0.195 (0.072)**	0.227 (0.095)*	0.38 (0.087)***
Adj.R2	0.4099			
AIC	4818.134	4813.1	4807.5	4804
Log likelihood	-2391.067	-2387.557	-2368.733	-2382.99
Moran's I for residuals	0.052***			

$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

Table C20: Lagrange Multiplier diagnostics for OLS model estimating change in % of population Hispanic and under poverty (using power function for technological hazards)

	Statistic	df	p-value
LM (error)	18.781	1	0.000
LM (lag)	7.876	1	0.005
Robust LM (error)	11.202	1	0.001
Robust LM (lag)	0.297	1	0.586
SARMA	19.078	2	0.000

Table C21: Likelihood Ratio (LR) test for spatial regression models estimating change in % of population Hispanic and under poverty (using power function for technological hazards)

	Log Likelihood	Likelihood ratio with SDM
Spatial Durbin Model	-2368.733	
Spatial Lag Model	-2387.557	37.649**
Spatial Error Model	-2382.99	28.513*

*p< .05, **p< .01, ***p< .001; df=16

Table C22: Models estimating change in % of population Hispanic and under poverty (using WCPE function for technological hazards)

Variables	OLS	Spatial Lag	Spatial Durbin	Spatial Error
(Intercept)	-1.887 (1.402)	-1.719 (1.38)	-2.05 (3.771)	-2.305 (1.566)
zfldrt:pchcvgr	-0.175 (0.132)	-0.212 (0.13)	-0.229 (0.129)	-0.258 (0.128)*
zfldrt:pctcugr	0.023 (0.051)	0.021 (0.05)	0.015 (0.05)	0.017 (0.05)
pchcvgr:zcpe1	-0.092 (0.077)	-0.101 (0.076)	-0.075 (0.084)	-0.099 (0.073)
pctcugr:zcpe1	0.258 (0.089)**	0.252 (0.088)**	0.249 (0.09)**	0.229 (0.086)**
Pchcvgr	-0.013 (0.108)	-0.033 (0.106)	-0.008 (0.107)	-0.038 (0.107)
Pctcugr	0.107 (0.039)**	0.098 (0.039)*	0.097 (0.038)*	0.102 (0.038)**
Zfldrt	0.408 (0.209)	0.37 (0.206)	0.475 (0.248)	0.422 (0.22)
zcpe1	-0.273 (0.256)	-0.162 (0.253)	0.073 (0.295)	-0.114 (0.258)
Popgr	-0.005 (0.002)*	-0.005 (0.002)*	-0.006 (0.002)*	-0.005 (0.002)*
Blkgr	-0.019 (0.028)	-0.027 (0.028)	0.016 (0.03)	-0.011 (0.029)
Hspgr	0.39 (0.021)***	0.365 (0.023)	0.403 (0.025)***	0.388 (0.022)***
mdrnt2000	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)
pov2000	-0.082 (0.035)*	-0.07 (0.035)*	-0.106 (0.039)**	-0.088 (0.036)*
hsp2000	0.089 (0.014)***	0.073 (0.015)***	0.134 (0.021)***	0.097 (0.016)***
shrblk2000	0.039 (0.014)**	0.03 (0.014)*	0.083 (0.022)***	0.047 (0.016)**
cbd_dist	0.018 (0.04)	0.003 (0.04)	-0.007 (0.34)	0.036 (0.055)
lag.pchcvgr			0.138 (0.448)	

Table C22 (cont.)

lag.pctcugr			0.012 (0.212)	
lag.zfldrt			-0.454 (0.724)	
lag.zpowr			-2.99 (1.414)*	
lag.popgr			0.007 (0.007)	
lag.blkgr			-0.022 (0.093)	
lag.hspgr			-0.039 (0.077)	
lag.mdrnt2000			0.003 (0.004)	
lag.pov2000			0.192 (0.117)	
lag.hsp2000			-0.117 (0.047)*	
lag.shrblk2000			-0.109 (0.047)*	
lag.cbd_dist			-0.076 (0.372)	
lag.zfldrt:pchcvgr			1.653 (0.536)**	
lag.zfldrt:pctcugr			0.028 (0.232)	
lag.pchcvgr:zpowr			0.357 (0.544)	
lag.pctcugr:zpowr			0.917 (0.684)	
rho/lambda		0.216 (0.072)**	0.243 (0.093)**	0.395 (0.086)***
Adj.R2	0.4081			
AIC	4820.529	4813.8	4804.3	4803.8
Log likelihood	-2392.265	-2387.918	-2367.154	-2382.907
Moran's I for residuals	0.059***			

**p*< .05, ***p*< .01, ****p*< .001

Table C23: Lagrange Multiplier diagnostics for OLS model estimating change in % of population Hispanic and under poverty (using WCPE function for technological hazards)

	Statistic	df	p-value
LM (error)	23.489	1	0.000
LM (lag)	9.920	1	0.002
Robust LM (error)	13.971	1	0.000
Robust LM (lag)	0.402	1	0.526
SARMA	23.891	2	0.000

Table C24: Likelihood Ratio (LR) test for spatial regression models estimating change in % of population Hispanic and under poverty (using WCPE function for technological hazards)

	Log Likelihood	Likelihood ratio with SDM
Spatial Durbin Model	-2367.154	
Spatial Lag Model	-2387.918	41.528***
Spatial Error Model	-2382.907	31.506*

**p*< .05, ***p*< .01, ****p*< .001; df=16

APPENDIX D

HUD GUIDELINE FOR CALCULATING ACCEPTABLE SEPARATION DISTANCE (ASD)

24 CFR §51 (Subpart C) gives instructions for identifying hazardous materials and how to calculate Acceptable Separation Distance (ASD) for developing any kind of HUD assisted project. Appendix I and II of this section gives the list of the hazardous materials and shows the calculation methods to be followed. Those appendices are presented here which might be helpful for planners in case of location decisions for any multi-family low income housing project.

(a) Of HUD to disapprove a project proposal if the siting is too close to a potential hazard not covered by this subpart, and (b) of HUD or any person or other entity to seek to abate or to collect damages occasioned by a nuisance, whether or not covered by the subpart.

Appendix I to Subpart C of Part 51—Specific Hazardous Substances

The following is a list of specific petroleum products and chemicals defined to be hazardous substances under §51.201.

Hazardous Liquids

Acetic Acid	Ethyl Benzene
Acetic Anhydride	Ethyl Dichloride
Acetone	Ethyl Ether
Acrylonitrile	Gasoline
Amyl Acetate	Heptane
Amyl Alcohol	Hexane
Benzene	Isobutyl Acetate
Butyl Acetate	Isobutyl Alcohol
Butyl Acrylate	Isopropyl Acetate
Butyl Alcohol	Isopropyl Alcohol
Carbon Bisulfide	Jet Fuel and Kerosene
Carbon Disulfide	Methyl Alcohol
Cellosolve	Methyl Amyl Alcohol
Cresols	Methyl Cellosolve
Crude Oil (Petroleum)	Methyl Ethyl Ketone
Cumene	Naptha
Cyclohexane	Pentane
No. 2 Diesel Fuel	Propylene Oxide
Ethyl Acetate	Toluene
Ethyl Acrylate	Vinyl Acetate
Ethyl Alcohol	Xylene

Hazardous Gases

Acetaldehyde	Liquefied Natural Gas (LNG)
Butadiene	Liquefied Petroleum Gas (LPG)
Butane	Propane
Ethene	Propylene
Ethylene	Vinyl Chloride
Ethylene Oxide	
Hydrogen	

(Primary Source: "Urban Development Siting with respect to Hazardous Commercial/Industrial Facilities," by Rolf Jensen and Associates, Inc., April 1982)

[49 FR 5105, Feb. 10, 1984; 49 FR 12214, Mar. 29, 1984]

Appendix II to Subpart C of Part 51—Development of Standards; Calculation Methods

I. Background Information Concerning the Standards

(a) *Thermal Radiation:*

(1) *Introduction.* Flammable products stored in above ground containers represent a definite, potential threat to human life and structures in the event of fire. The resulting fireball emits thermal radiation which is absorbed by the surroundings. Combustible structures, such as wooden houses, may be ignited by the thermal radiation being emitted. The radiation can cause severe burn, injuries and even death to exposed persons some distance away from the site of the fire.

(2) *Criteria for Acceptable Separation Distance (ASD).* Wooden buildings, window drapes and trees generally ignite spontaneously when exposed for a relatively long period of time to thermal radiation levels of approximately 10,000 Btu/hr. sq. ft. It will take 15 to 20 minutes for a building to ignite at that degree of thermal intensity. Since the reasonable response time for fire fighting units in urbanized areas is approximately five to ten minutes, a standard of 10,000 BTU/hr. sq. ft. is considered an acceptable level of thermal radiation for buildings.

People in outdoor areas exposed to a thermal radiation flux level of approximately 1,500 Btu/ft^2 hr will suffer intolerable pain after 15 seconds. Longer exposure causes blistering, permanent skin damage, and even death. Since it is assumed that children and the elderly could not take refuge behind walls or run away from the thermal effect of the fire within the 15 seconds before skin blistering occurs, unprotected (outdoor) areas, such as playgrounds, parks, yards, school grounds, etc., must be placed at such a distance from potential fire locations so that the radiation flux level is well below 1500 Btu/ft^2 hr. An acceptable flux level, particularly for elderly people and children, is 450 Btu/ft^2 hr. The skin can be exposed to this degree of thermal radiation for 3 minutes or longer with no serious detrimental effect. The result would be the same as a bad sunburn. Therefore, the standard for areas in which there will be exposed people, e.g. outdoor recreation areas such as playgrounds and parks, is set at 450 Btu/hr. sq. ft. Areas covered also include open space ancillary to residential structures, such as yard areas and vehicle parking areas.

(3) *Acceptable Separation Distance From a Potential Fire Hazard.* This is the actual setback required for the safety of occupied buildings and their inhabitants, and people in open spaces (exposed areas) from a potential fire hazard. The specific distance required for safety from such a hazard depends upon the nature and the volume of the substance. The Technical Guidebook entitled "Urban Development Siting With Respect to Hazardous/Commercial Industrial Facilities," which supplements this regulation, contains the technical guidance required to compute Acceptable Separation Distances (ASD) for those flammable substances most often encountered.

(b) *Blast Overpressure:* The Acceptable Separation Distance (ASD) for people and structures from materials prone to explosion is dependent upon the resultant blast measured in pounds per square inch (psi) overpressure. It has been determined by the military and corroborated by two independent studies conducted for the Department of Housing and Urban Development that 0.5 psi is the acceptable level of blast overpressure for both buildings and occupants, because a frame structure can normally withstand that level of external exertion with no serious structural damage, and it is unlikely that human beings inside the building would normally suffer any serious injury. Using this as the safety standard for blast overpressure, nomographs have been developed from which an ASD can be determined for a given quantity of hazardous substance. These nomographs are contained in the handbook with detailed instructions on their use.

(c) *Hazard evaluation:* The Acceptable Separation Distances for buildings, which are determined for thermal radiation and blast overpressure, delineate separate identifiable danger zones for each potential accident source. For some materials the fire danger zone will have the greatest radius and cover the largest area, while for others the explosion danger zone will be the greatest. For example, conventional petroleum fuel products stored in unpressurized tanks do not emit blast overpressure of dangerous levels when ignited. In most cases, hazardous substances will be stored in pressurized containers. The resulting blast overpressure will be experienced at a greater distance than the resulting thermal radiation for the standards set in Section 51.203. In any event the hazard requiring the greatest separation distance will prevail in determining the location of HUD-assisted projects.

The standards developed for the protection of people and property are given in the following table.

	Thermal radiation	Blast overpressure
Amount of acceptable exposure allowed for building structures.	10,000 BTU/ft² hr.	0.5 psi.
Amount of acceptable exposure allowed for people in open areas.	450 BTU/ft² hr ...	0.5 psi.

Problem Example

The following example is given as a guide to assist in understanding how the procedures are used to determine an acceptable separation distance. The technical data are found in the HUD Guidebook. Liquid propane is used in the example since it is both an explosion and a fire hazard.

In this hypothetical case a proposed housing project is to be located 850 feet from a 30,000 gallon liquid propane (LPG) tank. The objective is to determine the acceptable separation distance from the LPG tank. Since propane is both explosive and fire prone it will be necessary to determine the ASD for both explosion and for fire. The greatest of the two will govern. There is no dike around the tank in this example.

Nomographs from the technical Guidebook have been reproduced to facilitate the solving of the problem.

ASD For Explosion

Use Figure 1 to determine the acceptable separation distance for explosion.

The graph depicted on Figure 1 is predicated on a blast overpressure of 0.5 psi.

The ASD in feet can be determined by applying the quantity of the hazard (in gallons) to the graph.

In this case locate the 30,000 gallon point on the horizontal axis and draw a vertical line from that point to the intersection with the straight line curve. Then draw a horizontal line from the point where the lines cross to the left vertical axis where the ACCEPTABLE SEPARATION DISTANCE of 660 feet is found.

Therefore the ASD for explosion is 660 feet

Since the proposed project site is located 850 feet from the tank it is located at a safe distance with regards to blast overpressure.

30

ACCEPTABLE SEPARATION DISTANCE
BLAST OVERPRESSURE
(NO BLAST BARRIERS)
HAZARDOUS GAS CONTAINER

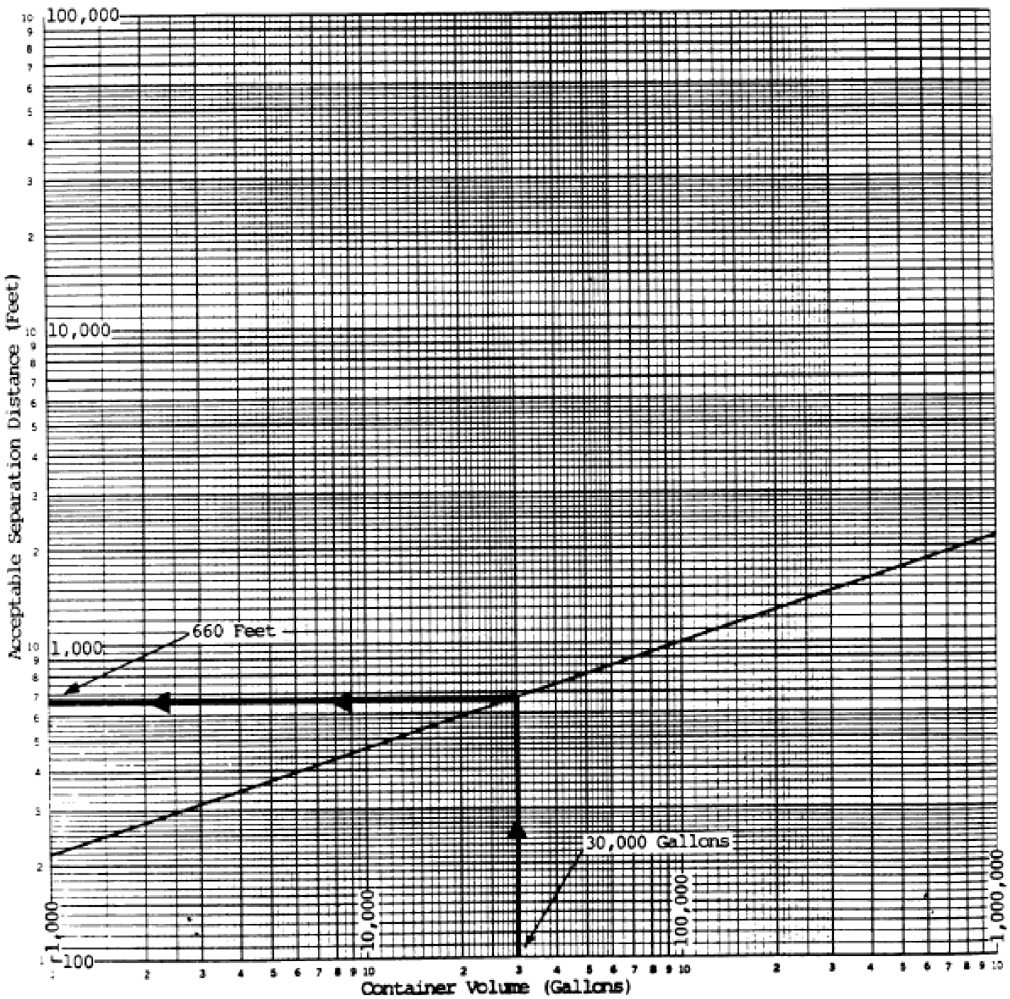


Figure 1

ASD For Fire

To determine the ASD for fire it will be necessary to first find the fire width (diameter of the fireball) on Figure 2. Then apply this to Figure 3 to determine the ASD.

Since there are two safety standards for fire: (a) 10,000 BTU/ft^2 hr. for buildings; and (b) 450 BTU/ft^2 hr. for people in exposed areas, it will be necessary to determine an ASD for each.

To determine the fire width locate the 30,000 gallon point on the horizontal axis on *Figure 2* and draw a vertical line to the straight line curve. Then draw a horizontal line from the point where the lines cross to the left vertical axis where the FIRE WIDTH is found to be *350 feet*.

Now locate the 350 ft. point on the horizontal axis of *Figure 3* and draw a vertical line from that point to curves 1 and 2. Then draw horizontal lines from the points where the lines cross to the left vertical axis where the ACCEPTABLE SEPARATION DISTANCES of *240 feet* for buildings and *1,150 feet* for exposure to people is found.

Based on this the proposed project site is located at a safe distance from a potential fireball. However, exposed playgrounds or other exposed areas of congregation must be at least 1,150 feet from the tank, or be appropriately shielded from a potential fireball.

(Source: HUD Handbook, "Urban Development Siting With Respect to Hazardous Commercial/Industrial Facilities.")

FIRE WIDTH - UNCONFINED SPILL
HAZARDOUS GAS CONTAINER
NOT DIKED

32

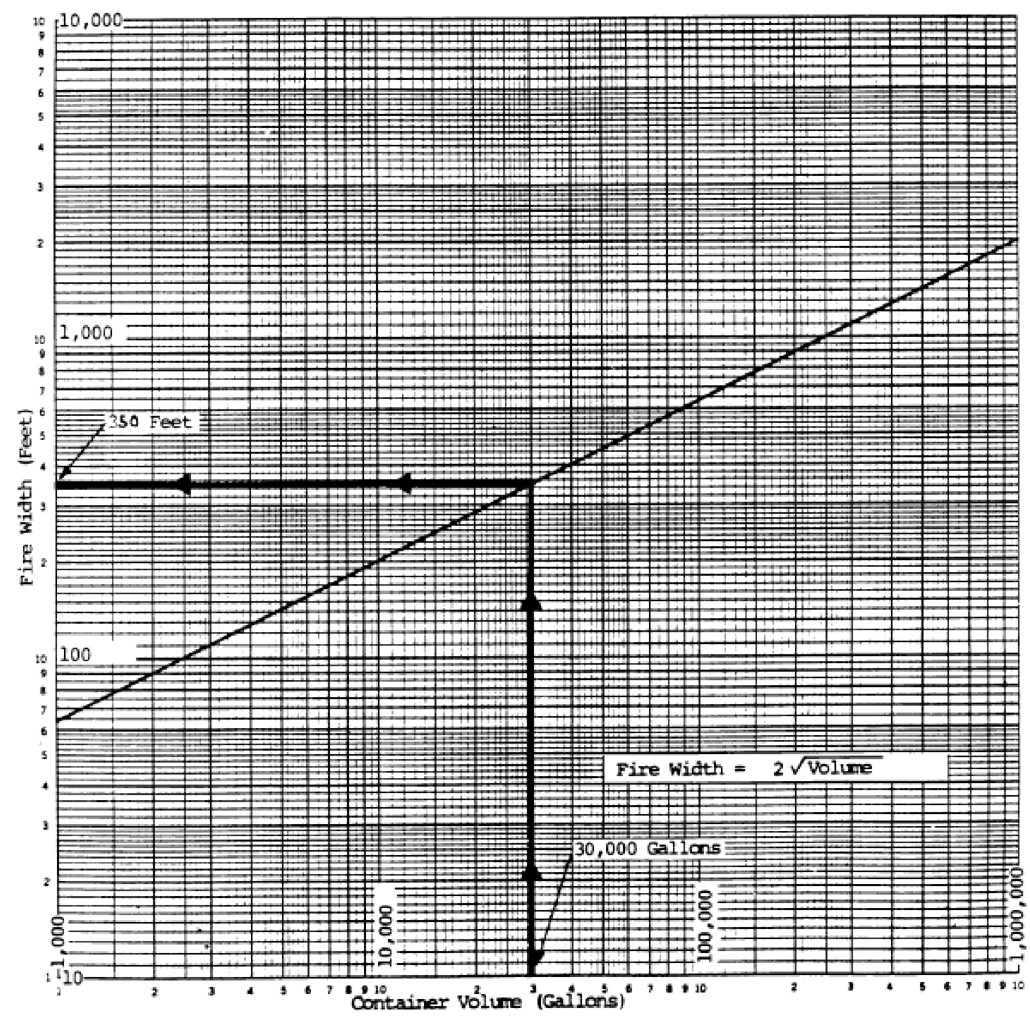


Figure 2

ACCEPTABLE SEPERATION DISTANCE
HAZARDOUS GAS CONTAINER
DIKED/UNDIKED

33

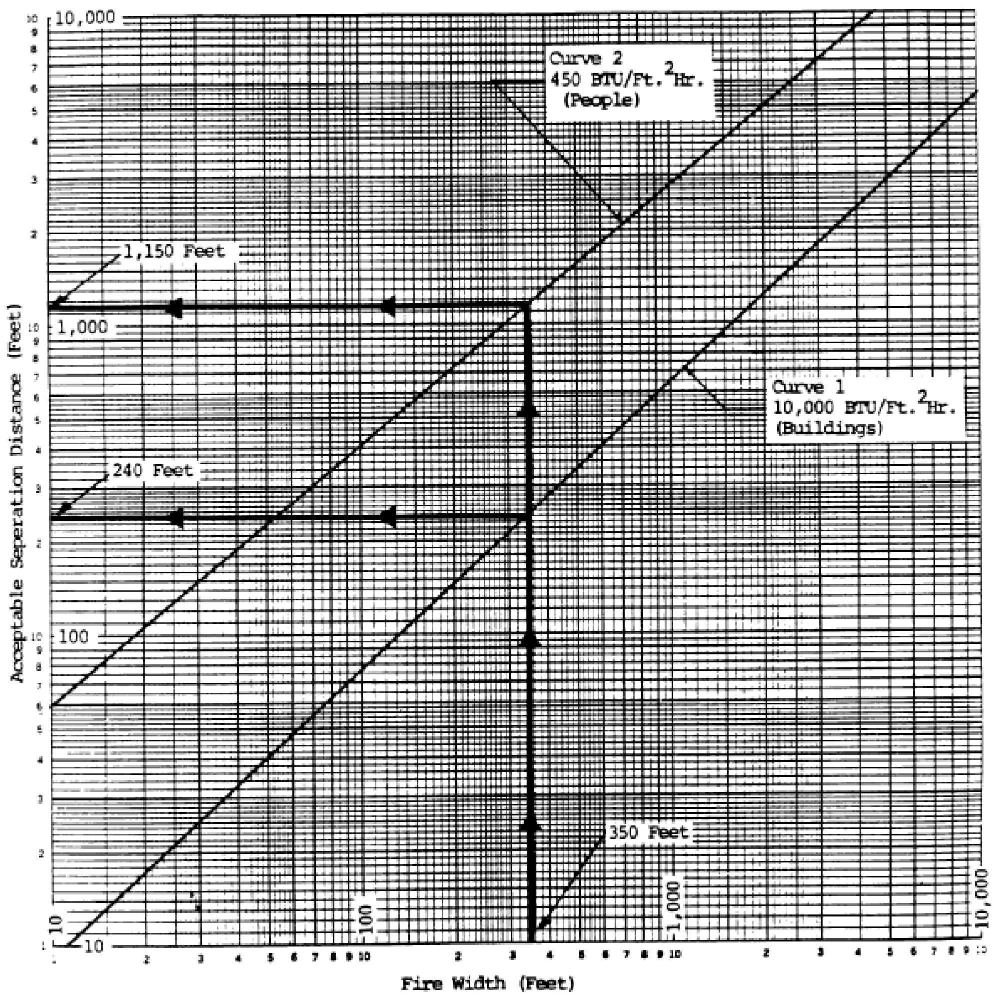


Figure 3

[49 FR 5105, Feb. 10, 1984; 49 FR 12214, Mar. 29, 1984]