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BENEFITS AND DETRIMENTS OF DISASTER-RELATED SHIFTS IN NEIGHBORHOOD POVERTY: THE MEDIATING ROLE OF CONTEXTUAL RESOURCES AND STRESSORS

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ABSTRACT

Benefits And Detriments of Disaster-Related Shifts in Neighborhood Poverty:

The Mediating Role of Contextual Resources and Stressors

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Recent decades have witnessed the increasing spatial concentration of poverty and affluence in the United States (Biscoff & Reardon, 2013). Given well-documented links between neighborhood economic contexts and wellbeing (Chow et al., 2005), this has the potential to exacerbate disparities in health, particularly for people with limited neighborhood choice. However, limited research has systematically examined the neighborhood features underlying these links. A more nuanced understanding of why neighborhood poverty matters is essential for promoting equitable neighborhood development.

Using rigorous analytic techniques that account for the dynamic nature of neighborhoods and help adjust for selection bias, I considered two complementary questions: 1) do observed neighborhood resources and stressors mediate associations between neighborhood poverty and wellbeing within and between individuals; and 2) how do observed versus perceived changes in neighborhood features mediate links between neighborhood poverty and wellbeing? I combined individual-level longitudinal data from the Post-Katrina Study of Resilience and Recovery with administrative neighborhood data drawn from the Census Bureau, FBI, and EPA. Analyses focused on a sample of 606 participants – primarily young Black mothers with low levels of income – who were affected by Hurricane Katrina, most of whom experienced some period of forced relocation. Participants were surveyed once before (2003/04) and twice after (2006/07; 2009) the hurricane.

Results paint a complex picture. Contrasting with prior research, total effects of neighborhood poverty on wellbeing were limited. However, changes in neighborhood poverty were linked to wellbeing indirectly through intermediary neighborhood features, with results pointing to benefits and detriments of rising neighborhood poverty. Results were driven by those who changed neighborhoods over the course of the study. For participants that lived in the same New Orleans neighborhood across waves, changes in neighborhood poverty proved less consequential. Overall, results suggest that rather than treating neighborhood poverty as uniformly problematic for wellbeing, efforts to promote health equity should identify and build upon existing assets of neighborhoods, like affordability and amenity access, while also reducing stressors.

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In elementary school, my science teacher told me that she had written a 100+ page book about insects to get her doctorate degree. In that moment, I vowed never to pursue a Ph.D. And yet here I am, having just completed a 200+ page dissertation. This represents the culmination of many years of work on my part, but many more years of intellectual stimulation and encouragement from those around me. I am so grateful to all those who contributed to this accomplishment: my family, my teachers, my friends, my partner, my colleagues, my activist community, and so many others. Though I cannot name you all, rest assured that your role is deeply appreciated.

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CHAPTER 1: INTRODUCTION

There is good reason to believe that neighborhoods matter for wellbeing. People have residential preferences guided by concrete ideas about what they want from their local context, and they leverage their resources – however limited – towards those goals (Darrah & Deluca, 2014; Frenkel et al., 2013; Krysan & Farley, 2002; Lawton et al., 2013; McAuley & Nutty, 1982; Wood, 2014). Ideally, the communities in which people live can provide access to important goods and services, a sense of safety and security, spaces for recreation and social engagement, opportunities for educational and vocational success, and a sense of cohesion and attachment (Bruin & Cook, 1997; Darrah & Deluca, 2014; Ellen et al., 2001; Galster, 2012; Sampson et al., 2002). However, opportunity-rich, safe, and supportive communities are not accessible to all.

Systemic racism, exclusionary zoning practices, and market forces have contributed to the creation and maintenance of segregated and unequal neighborhood environments (Dreier et al., 2012). And while recent decades have witnessed hard-won declines in racial segregation, they have also seen rising neighborhood-based economic segregation among families and within urban areas (Owens, 2016; Reardon et al., 2015). This means that people with limited financial resources are far more likely to live in an economically disenfranchised community than an affluent one, while those with high levels of income are more likely to live in an economically prosperous community than a poor one. Moreover, this reality is racialized: across the income spectrum, Black and Hispanic families live in communities with income levels that are 5-12% lower than White households with similar earnings (Reardon et al., 2015). Black families are also far more likely than White families to experience neighborhood disadvantage across generations and are less likely to move into and remain in low poverty communities (Sharkey, 2013). These patterns reflect and reinforce the stratified nature of US society, leading to differential access to well-resourced, safe neighborhoods.

These inequities are particularly concerning given evidence that neighborhood economic composition is implicated in individual wellbeing above and beyond the effects of individual-level economic resources. In short, living in a neighborhood with high levels of poverty seems to hinder healthy functioning (Do & Finch, 2008; Galea et al., 2007), while living in a neighborhood with a high concentration of affluence appears to be promotive of physical and psychological wellbeing (Weden et al., 2008; Wen et al., 2003). Existing literature provides strong support for the connection between the neighborhood economic context and self-reported health (Pickett & Pearl, 2001; Riva et al., 2007) as well as cumulative biological risk (Finch et al., 2010; Robinette et al., 2016; Schulz et al., 2012, 2013), while findings have been more mixed in relation to mental health (Mair et al., 2008). However, a general reliance on cross-sectional, correlational studies means there is still uncertainty as to whether observed associations are reflective of a causal link between the neighborhood economic context and wellbeing or are driven by selection bias – for instance, individuals with chronic health conditions selecting into high poverty communities, perhaps as a result of limited resources.

Notably, however, the best experimental evidence to-date indicates that shifts in neighborhood poverty are causally related to adult wellbeing. Studies show that parents with limited financial resources who were provided the opportunity to move their families from high to low poverty areas saw short- and long-term improvements in mental and physical health compared to those who did not receive this opportunity, as well as those who moved to moderate poverty neighborhoods (Katz et al., 2001; Leventhal & Brooks-Gunn, 2003; Ludwig et al., 2012). However, a key limitation of this work is that it could not determine what it was about moving to lower poverty neighborhoods that promoted participants' health and wellbeing. Theoretical explanations suggest that differential exposure to stressors such as crime and disorder; the relative strength of community social processes including collective trust, social support, and social norms; and variations in access to and quality of institutional resources may underly these associations (Galster, 2012; Sampson et al., 2002). Empirical evidence provides piecemeal support for these explanations, with disorder and neighborhood social processes frequently being identified as significant mediators of links between neighborhood disadvantage and wellbeing (Ellen et al., 2001; Mair et al., 2008; Sampson et al., 2002). However, other potential mechanisms such as institutional resources have received far less attention, making it difficult to parse which aspects of the neighborhood environment are most important for promoting health and wellbeing. There is thus a need to more clearly delineate the mechanisms linking the neighborhood economic context to individual functioning. A better understanding of the contextual factors that drive effects of neighborhood poverty will allow for more informed action towards the creation of equitable, supportive communities. This is a crucial step towards undoing the harm of segregation and supporting the wellbeing of those facing economic and racial marginalization.

Using a unique dataset that combines longitudinal survey data on adults affected by Hurricane Katrina with federal administrative data on observable neighborhood conditions over time, this research seeks to uncover the neighborhood features that link neighborhood poverty to individual wellbeing. The primary goal of this work is to consider which aspects of the neighborhood context contribute to the healthy functioning of young, predominantly Black mothers with limited economic resources, considering both observed neighborhood features and residents' subjective perceptions of those features over time. To accomplish this, I examined several complementary research questions. First, I considered how the presence of observed neighborhood resources and stressors mediates the relationship between neighborhood poverty and wellbeing, both within individuals over time and between individuals. Second, to better tap into participants' subjective experiences of their neighborhood context, I examined how observed and perceived shifts in the neighborhood context jointly serve as mechanisms linking neighborhood poverty to individual wellbeing. Finally, for each of these questions, I assessed how these processes differ for those who moved to a new neighborhood versus experiencing change within a single neighborhood over time. In building a more nuanced understanding of links between neighborhood poverty and wellbeing, scholars will be better equipped to challenge the normative transmission of inequity through neighborhood contexts and support equity-focused neighborhood development.

CHAPTER 2: LITERATURE REVIEW

Wellbeing is not distributed evenly across neighborhoods. To the contrary, decades of research suggests that people who live in high poverty neighborhoods tend to have worse mental and physical health outcomes than those in more advantaged, lower poverty neighborhoods (Chow et al., 2005; Ellen et al., 2001). The concentration of wellbeing in more affluent neighborhoods is partially reflective of the fact that these neighborhoods are, by definition, comprised of more affluent people, who tend to have better mental and physical health than those with fewer economic resources (Kawachi et al., 2010). At the same time, research suggests that associations between the neighborhood economic composition and wellbeing—hereafter referred to as neighborhood SES effects for the sake of simplicity—persist when controlling for potential confounding variables such as family income, suggesting that people of similar income levels tend to be better off living in areas with low versus high levels of disadvantage (Do & Finch, 2008; Galea et al., 2007; Sharp et al., 2015). Moreover, there is some evidence that for families with limited economic resources, having the opportunity to move to a lower poverty area can improve peoples' health and psychological functioning (Cooper et al., 2014; Katz et al., 2001; Leventhal & Brooks-Gunn, 2003; Ludwig et al., 2012). This suggests that the economic conditions of one's neighborhood may have a causal effect on one's wellbeing, such that living in more economically advantaged area provides a better shot at a healthy, happy life. The present dissertation seeks to unravel the mechanisms that drive this connection.

In the literature review that follows, I will outline leading theoretical perspectives on the pathways through which the neighborhood economic context relates to health and wellbeing, describe the economic and racial dynamics that impact neighborhood residence, summarize the existing literature base linking the neighborhood economic context with adult wellbeing, assess the empirical evidence on the neighborhood resources and stressors potentially underlying these links, and describe the unique contributions of this dissertation.

Theoretical Perspectives on Neighborhood Effects

Given that the present research is positioned at the intersection of several fields, a number of complementary theoretical perspectives guide this work. Building on these perspectives, I propose an integrated framework to describe how structural features of the neighborhood context may affect human functioning.

I first draw on a social determinants of health framework, which argues that health is a product of social conditions rather than being the simple result of individual-level factors. In 1995, Link and Phelan proposed that proximal causes of disease (and, by extension, other aspects of health) are not equally distributed across the population because peoples' circumstances are shaped by "fundamental causes" of disease – wealth, class, race, gender and other factors that affect peoples' access to power and resources as a result of social stratification. They argued that as long as people do not have equal access to the social and material resources that would allow their health to flourish, efforts to mitigate health inequities will fall short, as disparities will re-emerge so long as the root causes of inequities remain intact (Braveman & Gottlieb, 2014; Link & Phelan, 1995). Because of this, it is essential for research to identify the social conditions that put people at risk of and offer protection from health problems (Link & Phelan, 1995).

Neighborhood contexts are an essential part of this picture (Booth et al., 2018; Schulz & Northridge, 2004). Not only do neighborhoods reflect social stratification along economic and racial lines; the uneven distribution of resources and stressors across neighborhoods also plays an important role in reinforcing and reproducing inequality over time (Chetty et al., 2018; Dreier et al., 2012; Rothstein, 2017; Turner, 2008). In short, the neighborhoods in which people live can be viewed as a key social determinant of health: structural neighborhood features create social conditions under which it is more or less possible for individuals to maintain good health and wellbeing.

In line with this view, Bronfenbrenner's bioecological theory proposes that human development is driven by regular interactions between individuals and the people, objects, and symbols in their environment (Bronfenbrenner & Morris, 2007; Rosa & Tudge, 2013). Context is of the utmost importance from this perspective because the contexts in which people are embedded impact the nature of their interactions with the world, thereby shaping their interests, skills, attitudes, behaviors, and ultimately their life course. In this way, the bioecological model of human development overlaps with a social determinants of health framework. However, as a person-centered model, this theory highlights the importance of considering individuals' perceptions and experiences of their context rather than treating context only as a directly observable, static environment (Bronfenbrenner & Morris, 2007). From a bioecological perspective, most neighborhood characteristics thus lie at the intersection of objective and subjective reality, with causal links between neighborhood features and individual functioning likely being mediated by peoples' perceptions of and experiences with those features (Bronfenbrenner & Morris, 2007; Rosa & Tudge, 2013).

Finally, to understand how neighborhoods shape the social context and thus individual wellbeing, it is useful to consider theoretical work on neighborhoods. While theories on neighborhood effects are diverse in focus, most consider the role of institutional resources, social dynamics, and/or physical features on individual functioning (Ellen & O'Regan, 2011; Galster, 2012; Leventhal et al., 2015). Theories focused on institutional resources propose that the availability and quality of amenities, schools, day care facilities, social services, medical care, shopping centers, employment opportunities, public services, and other institutional resources influence peoples' wellbeing by impacting the goods and services they can access and the opportunities they have on a regular basis (Ellen et al., 2001; Galster, 2012; Leventhal et al., 2015; Sampson et al., 2002). Neighborhood social/interactional dynamics – including collective efficacy, social norms, social ties and interactions, relationships, and crime and violence – are theorized to impact individual functioning in various ways (Ellen et al., 2001; Galster, 2012; Leventhal et al., 2015; Sampson et al., 2002). For instance, the theory of collective efficacy suggests that socially cohesive and orderly neighborhoods in which people work together for the common good may reduce the prevalence of contextual stressors and improve peoples' feelings of efficacy (Sampson, 2003). Meanwhile, other social dynamics have the potential to act as assets or stressors. For instance, interactions with neighbors may generally be supportive of health and wellbeing if they promote collective trust or connect people to important resources otherwise unavailable, as theories of social capital would suggest (Kawachi et al., 2004). Alternatively, such interactions could prove problematic if they involve discrimination, upward social comparisons, or competition for finite resources (Galster, 2012; Leventhal et al., 2015). Several scholars have also called attention to the importance of environmental/physical conditions of neighborhoods including walkability, upkeep, disorder, and pollution (Ellen et al., 2001; Galster, 2012). Some of these conditions may impact mental and physical health directly by activating a physiological stress response, triggering health problems such as asthma attacks, inducing psychological distress, or, conversely, improving peoples' moods, while others may affect health and happiness indirectly by influencing peoples' everyday behaviors and interactions (Ellen et al., 2001; Galster, 2012; Schulz et al., 2012). Physical and environmental stressors have also been theorized to have gradual or cumulative impacts on wellbeing through the process of "weathering," wherein chronic stress experienced over time causes physiological wear-and-tear, which contributes to increased vulnerability to health problems (Ellen et al., 2001; Geronimus, 1992).

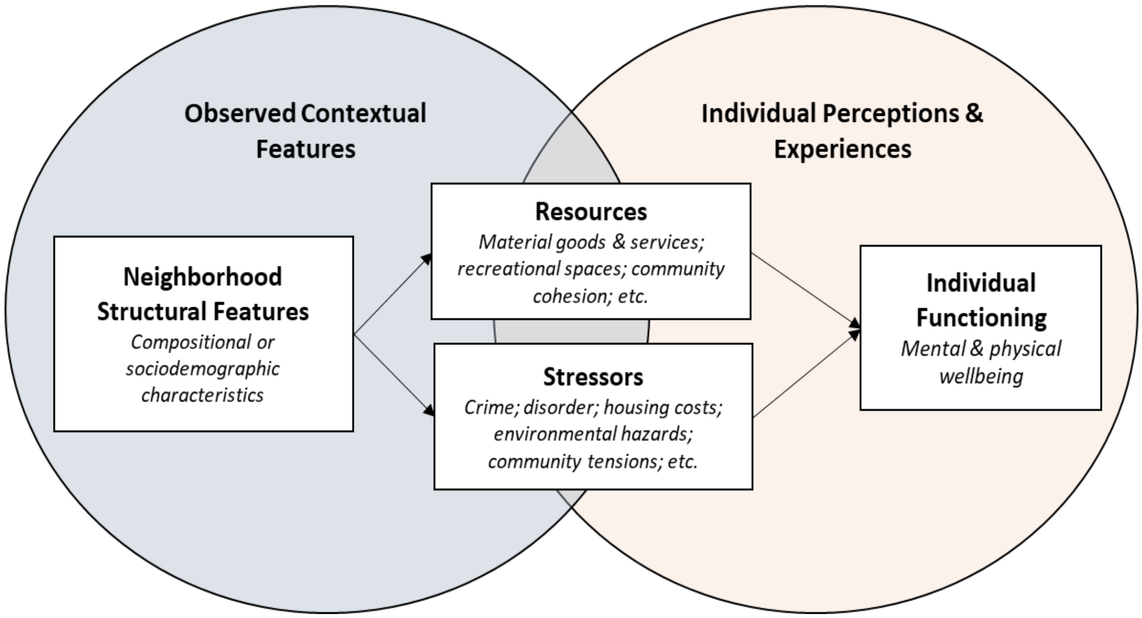
While theories of neighborhood effects point to a myriad of potentially influential neighborhood features, they have a few important limitations. One is that they do not speak directly to the role of neighborhood structural features in shaping wellbeing, instead focusing on contextual resources and stressors that are more proximally implicated in wellbeing. This is despite the fact that structural features – that is, the compositional and sociodemographic characteristics of a neighborhood space (Leventhal et al., 2015; Sampson et al., 2002) – have been studied extensively in relation to health outcomes (Arcaya et al., 2016), are a primary target of place-based policy interventions (Clampet-Lundquist, 2004; Dreier et al., 2012; Lees et al., 2010), and seem to drive the presence or absence of health-related neighborhood features (Booth et al., 2018; Dreier et al., 2012; Sharkey, 2013). Although identifying the neighborhood features that are most directly related to individual functioning is important, it is also critical to contextualize these features by considering how they are shaped by larger social conditions (Link & Phelan, 1995), including economic and racial stratification.

Considered within this framework, compositional features of neighborhoods may have a dual role in shaping wellbeing. For example, the proportion of neighborhood residents living under the federal poverty line is likely to impact how much contact someone has with low-resourced neighbors, which has the potential to be promotive or harmful depending on the nature of those interactions. However, neighborhood poverty may exert an influence on wellbeing irrespective of interactions with neighbors, as compositional factors also drive the level of investment a neighborhood receives, the kinds of resources and services available in it, the likelihood that residents will be exposed to contextual stressors, the quality of public services, how cohesive the neighborhood is, and how land is managed (Chow et al., 2005; Schulz & Northridge, 2004; Sharkey, 2013). In other words, the composition of a neighborhood shapes peoples' exposure to proximal community features including institutional resources, social dynamics, and physical features that are likely most important for peoples' everyday functioning.

With all of this in mind, I propose an integrated theoretical model to explain how neighborhood structural features may be causally linked with individual functioning (Figure 1). This model asserts that the effects of neighborhood composition are largely transmitted through neighborhood resources and stressors. Neighborhood resources include both material goods and services and social resources, such as collective efficacy and supportive social networks. Stressors encompass physical, social, and economic challenges, such as pollution, crime, disorder, community tensions, and high costs of

Figure 1

An Integrated Theoretical Framework of Neighborhood Effects



living. Resources and stressors are situated at the intersection of observed contextual features and individual perceptions, experiences, and behaviors. Because the relations between observed and perceived features (and between resources and stressors) are likely to depend on the neighborhood features under investigation, they are not fully explicated here. However, by naming this intersection, this model invites researchers to consider the importance of peoples' perceptions and experiences in defining neighborhood effects.

It is important to note that this model is not all encompassing, and that the effects of structural features, resources, and stressors are undoubtedly further mediated by individuals' interactions with the world (Bronfenbrenner & Morris, 2007; Link & Phelan, 1995). Moreover, the nature of the proposed mediating pathways may differ by individual social location. For instance, the presence of high-quality grocery stores nearby may promote health and wellbeing for some residents, but positive effects are likely to be contingent on residents having the economic resources to shop at such stores. Nevertheless, this model should be a useful tool for exploring effects of neighborhood structural features on individual functioning.

Income, Race, and Neighborhood Choice

The importance of delineating how and why the neighborhood economic context matters for individual wellbeing is elevated by the fact that many families have limited neighborhood choice. Individual economic resources play a major role in maintaining this pattern, as well-resourced, low stress neighborhoods tend to be expensive, making these areas unaffordable to many (Gilderbloom et al., 2015; Hanna, 2007; Nguyen-Hoang & Yinger, 2011; Pope & Pope, 2012; Troy & Grove, 2008). While families across the income spectrum may balance competing needs and desires when deciding where to live, those with more limited economic resources are faced with more difficult trade-offs, such as having to choose between housing quality and neighborhood safety (Rosenblatt & Deluca, 2012; Wood, 2014). Differential buying power likely contributes to the persistence of neighborhood economic segregation in the US context, with affluent households increasingly self-segregating into wealthy communities and economically disadvantaged families having to choose between affordable options (Reardon et al., 2015).

Moreover, racial discrimination in lending, housing markets, and government policies has contributed to the ongoing importance of race in limiting neighborhood choice as well (Roscigno et al., 2009; Rothstein, 2017; Turner, 2008; Villemez, 1980). Research has documented persistent racial and ethnic inequities in neighborhood economic conditions: in 2010, for example, the median poverty rate of census tracts in which Black households lived was 18.9%, compared to 8.6% for White households (Firebaugh & Farrell, 2016). Moreover, evidence suggests that at all levels of individual income, Black and Hispanic households live in neighborhoods with substantially lower median income levels than similarly resourced White and Asian households (Reardon et al., 2015), and that Black families are far more likely than White families to experience neighborhood poverty over successive generations (Sharkey, 2013). While these patterns may be partially explained by differential interest in (or aversion to) particular community features (e.g., neighborhood diversity; Havekes et al., 2016; Krysan et al., 2009), they are also reflective of discriminatory policies and practices that constrain the neighborhood choices of specific racial groups (Roscigno et al., 2009; Turner, 2008). This underscores the vastly different economic contexts experienced by those who occupy different positions in the US economic and racial hierarchy, with implications for peoples' access to supportive amenities and exposure to contextual stressors.

These inequities in neighborhood choice make it all the more important to understand how the neighborhood context comes to matter for residents. While the experimental research on neighborhoods (reviewed below) suggests that parents facing economic and racial marginalization may benefit from moving to lower poverty areas, it is essential to explore the specific neighborhood features that make the difference. By more clearly delineating the resource and stress mechanisms through which the neighborhood economic context can promote wellbeing for these families, we will be better equipped to promote the development of more supportive communities for all.

The Neighborhood Economic Context and Wellbeing

Insights from Correlational Research

There is a large and ever-growing base of research on connections between the neighborhood context and individual functioning. Several systematic reviews published within the last two decades have documented this work (D. Kim, 2008; Mair et al., 2008; Pickett & Pearl, 2001; Riva et al., 2007; Truong & Ma, 2006), and a recent review of study characteristics by Arcaya and colleagues (2016) notes a substantive uptick in research on neighborhoods and health in the mid 2000's. Collectively, this work provides modest evidence of connections between the neighborhood economic context and mental and physical health, with conclusions varying by outcome. In a 2001 review of epidemiological studies, Pickett and Pearl found relatively strong support for neighborhood SES effects on health, with 23 out of 25 studies linking neighborhood SES (broadly conceived) and health outcomes above and beyond the influence of individual characteristics. While studies on self-reported health were few in number, associations were largely consistent: residents of more disadvantaged neighborhoods were more likely to report fair or poor health than those in more advantaged neighborhoods, even when individual sociodemographic variables were accounted for (Pickett & Pearl, 2001). More recently, Riva and colleagues (2007) reaffirmed this assertion, with significant links emerging in 37 out of 39 studies reporting on connections between some measure of area SES (broadly conceived) and self-reported health.

In contrast, neighborhood SES connections to mental health outcomes appear to be less consistent. Though relevant reviews note significant links between neighborhood characteristics and psychological functioning across a majority of studies evaluated, associations with structural features were less consistent than with social features, such as violence, disorder, and social interactions (D. Kim, 2008; Mair et al., 2008; Truong & Ma, 2006). Important to note is that this pattern could be reflective of unexamined mediation between neighborhood SES and wellbeing through neighborhood social characteristics. Depressive symptoms were linked to neighborhood SES in approximately half of relevant studies considered by Kim (2008) and Mair and colleagues (2008), with even clearer support for this association in more representative samples and studies using longitudinal designs. More recently, connections between neighborhood SES and various components of mental health have been documented across geographic locales, in a diversity of samples, and using various conceptualizations of neighborhood SES (Astell-Burt & Feng, 2015; Finch et al., 2010; Galea et al., 2007). Though far from conclusive, this body of work demonstrates that physical and mental health are connected to the neighborhood economic context in which people live.

A persistent challenge of this literature is the fact that the majority of research on neighborhoods and wellbeing is cross-sectional and correlational in nature (Arcaya et al., 2016; Mair et al., 2008). As a result, causal inference is made impossible. For one thing, people choose where to live, which means that while spatial differences in wellbeing *may* be the result of causal effects of the neighborhood environment, they may instead be an artifact of selection bias or of some third factor that is driving both wellbeing and neighborhood of residence. The most obvious of these potential third variables is individual-level SES, which has an established causal relationship with mental and physical health (Kawachi et al., 2010; Lorant et al., 2003), impacts which neighborhoods people can select into (Clark & Ledwith, 2007), and directly contributes to the economic composition of the given neighborhood. The vast majority of studies on effects of neighborhood economic composition therefore directly model the contributions of individual-level income, along with other potential confounders, which allows for an assessment of whether the neighborhood economic context is independently associated with wellbeing. Yet even with these controls, caution must be taken in interpreting results, as unobserved third variables (e.g., family stress; line of work) could still be driving associations. Moreover, the directionality of relations between neighborhood economic composition and individual outcomes cannot be established in cross-sectional, correlational studies, as physical or mental health challenges may contribute to peoples' residence in disadvantaged areas for a variety of reasons (Arcaya et al., 2014). As many scholars have commented, these challenges underscore the need for more diversity of research designs, including longitudinal investigations, experimental studies, quasi-experimental studies, and use of natural experiments that can help to establish directionality and rule out alternative explanations (Arcaya et al., 2016; Ellen & Turner, 1997; Mair et al., 2008; Pickett & Pearl, 2001)

Given the right methodological approach, longitudinal research can provide a more rigorous test of potential neighborhood effects than do cross-sectional designs. Though findings of existing longitudinal studies are somewhat mixed, a critical assessment of the evidence points to modest support for causal effects of neighborhood disadvantage. In a study using nationally representative panel data from 1980-1997, Do and Finch (2008) examined relations between neighborhood poverty and self-reported health using two alternative modeling techniques designed to address different sources of bias: a baseline adjustment framework using propensity score weighting, and fixed-effects modeling. Conclusions were parallel across the two techniques: propensity score models revealed that people were significantly more likely to report poor health if they resided in high poverty neighborhoods, while fixed effects models found that increasing neighborhood poverty was associated with increasing odds of reporting poor health. Findings from this study provide further evidence of the connection between the neighborhood economic context and general health. While still limited in important ways, this research minimizes several sources of bias, thus providing some of the best evidence of possible causal neighborhood effects that correlational research can provide.

A contrasting example comes from the Los Angeles Family and Neighborhoods Survey (LAFANS), a well-known neighborhood study that used a stratified random sample of 65 neighborhoods in Los Angeles area. In this investigation, researchers found that although adults living in disadvantaged neighborhoods were significantly more likely to report having poor health than their counterparts in more advantaged areas, within-person effects of changing neighborhood SES were *not* evident (Sharp et al., 2015). In other words, increasing levels of neighborhood disadvantage between waves 1 and 2 were *not* linked to an increasing likelihood of reporting poor health between waves, in contrast to results of the Do and Finch study. While this could be reflective of the real absence of neighborhood SES effects within this sample, there are several alternative explanations worth considering. For one thing, it is possible that the absence of neighborhood effects was an artifact of limited change over time in either neighborhood disadvantage or health, which may itself have been related to the use of a disadvantage composite rather than a basic measure of neighborhood poverty. It might also have been related to a limited time scale, as Do and Finch (2008) considered changes over a 13-year period, while Sharp and colleagues considered change over a 6-year period. While studies generally suggest that the neighborhood economic context is connected with residents' health, further research is needed to clarify whether these represent causal relations.

Other longitudinal evidence of neighborhood effects focused on mental health comes from a natural experiment in which seven public housing developments were set to be demolished in Atlanta, Georgia, forcing the relocation of residents (Cooper et al., 2014). Researchers recruited a sample of 172 adults living in these developments – oversampling those with high levels of substance use – and followed them for four waves post-relocation. Using a growth curve model incorporating a regression discontinuity design to capture the one-time random dislocation from public housing, results showed that participants saw reductions in both depressive symptoms and neighborhood economic disadvantage from pre- to post-relocation. Follow-up multivariate analyses revealed that improvements in neighborhood economic conditions predicted reductions in depressive symptoms over time. While the small and geographically limited nature of the sample means that findings may not generalize beyond Atlanta public housing residents, these findings provide evidence that changing neighborhood characteristics are significantly linked with parallel changes in psychological functioning under some conditions.

The existing literature on neighborhood economic composition and wellbeing thus paints a complicated picture. At face value, physical and psychological health tend to be concentrated in advantaged neighborhoods. While there is a good deal of evidence that this is not simply an artifact of neighborhood composition, the largely cross-sectional, correlational nature of the existing research limits our ability determine whether the neighborhood context actually exerts a causal influence on peoples' health and wellbeing. While longitudinal research provides some preliminary evidence in favor of causal links, problems of selection and third variable bias cannot be eliminated. Experimental research therefore remains the gold-standard for assessing causal relations.

Experimental Evidence: MTO, Yonkers, and Beyond

The most compelling evidence of causal neighborhood effects is drawn from experimental and quasi-experimental mobility programs. Mobility programs seek to improve the wellbeing of economically disadvantaged families by providing them the opportunity to move to more advantaged neighborhoods, either through housing vouchers or the creation of new affordable housing. The most notable example is Moving to Opportunity (MTO), a program in which approximately 4,500 predominantly Black and Hispanic families living in high poverty neighborhoods in five US cities were randomly assigned to one of three groups: 1) the experimental group, in which families received a housing voucher and support to move to a low poverty neighborhood, 2) the section 8 group, in which families received a general housing voucher that could be used in any neighborhood, or c) the control group, in which families did not receive rental assistance through MTO (Ludwig et al., 2013). Over three quarters of applicants reported enrolling in the program because they wanted to get away from "gangs and drugs," with roughly half reporting that they were also interested in better schools for their children and housing quality improvements (Ludwig et al., 2012). This program provided researchers a unique opportunity to examine how changing the economic context in which families lived impacted various aspects of their lives, including their health, psychological functioning, and wellbeing.

Short-term evaluations in Boston and New York demonstrated that two to three years after program entry, positive effects of moving to lower-poverty neighborhoods were evident. In New York, adults in the experimental group reported fewer symptoms of depression and lower psychological distress than those in the control group (Leventhal & Brooks-Gunn, 2003), while in Boston, the experimental group and the section 8 group reported greater improvements in general health and feelings of "calm and peace" during the past week than did the control group (Katz et al., 2001). Long-term evaluations of the program demonstrate persistent effects on several components of wellbeing. Though no effects emerged in relation to self-rated health, the experimental group experienced significantly lower psychological distress, a reduced prevalence of diabetes and obesity, marginally reduced incidence of major depressive disorder, and sizable improvements in feelings of happiness and life satisfaction relative to the control group 10 to 15 years after program entry (Ludwig et al., 2012, 2013; Sanbonmatsu et al., 2012). Results thus indicate that for economically disadvantaged families, having the opportunity to move to a low poverty neighborhood contributes to improvements in health and wellbeing.

This picture is complicated by the results of several other mobility studies involving the development of affordable housing complexes in low poverty areas. The Yonkers Project, which was the direct result of court-ordered desegregation of a specific public housing development in New York, is one such example. Though the primary intent was to re-house public housing residents so as to remedy neighborhood racial segregation, this project provided the opportunity to study how moving to newly constructed publicly funded row houses in predominantly White, suburban areas impacted Black and Latino residents (W. J. Wilson, 2010). In this project, families in high poverty neighborhoods entered a lottery for the chance to relocate to newly constructed housing in several middle-class communities. While the opportunity to move was randomized, data were collected only after relocation had occurred. Consequently, comparisons could be made between “movers” and a control group of “stayers,” but changes from baseline to post relocation could not be assessed.

The results of the Yonkers Project provide a tempered view of neighborhood effects. Two years after relocation, movers reported marginally fewer health problems than stayers, but did not differ in terms of depressive or anxiety symptoms (Fauth et al., 2004). At seven years post-relocation, results were largely parallel, with movers and stayers reporting similar levels of physical and mental health (Fauth et al., 2008). Notably, however, consideration of cumulative neighborhood effects demonstrated that movers who *remained* in middle-class neighborhoods seven years post-relocation reported better physical health than movers who returned to high poverty neighborhoods and stayers who remained in high poverty neighborhoods (Fauth et al., 2008). This suggests that neighborhood effects may be at play, with stable residence in relatively low-poverty neighborhoods promoting physical health. However, the directionality of this relationship cannot be fully established, as movers who returned to high poverty neighborhoods may have had more health problems. Thus, it remains unclear whether this association represents a causal effect of the neighborhood environment, or an artifact of differential mobility among those with health problems.

That there were no effects on depressive or anxiety symptoms in the short or long run is somewhat surprising, especially because movers did report lower levels of neighborhood disorder, danger, and victimization than stayers, along with higher cohesion and fewer housing problems, all of which have been linked with mental health in other research (Cooper et al., 2014; G. W. Evans et al., 2000; Mair et al., 2015; Ross, 2000). However, it is important to note that the contentious nature of the Yonkers Project might explain these null results. Stark opposition to the introduction of affordable housing in Yonkers middle-income communities likely bred a hostile atmosphere for movers, which could have countered mental health benefits that might otherwise have emerged (Fauth et al., 2004, 2008). This highlights one of the key challenges of experimental and quasi-experimental neighborhood research: while residence in low-poverty neighborhoods can be randomized to some degree, mobility programs have the potential to alter the dynamics of neighborhoods to which people are moving. In this case, dynamics shifted in a way that may have undermined hypothesized benefits of moving to these more advantaged neighborhoods.

Relatively similar conclusions can be drawn from a smaller-scale mobility project known as Monitoring Mt. Laurel. Following a legal challenge to restrictive zoning in Mount Laurel, New Jersey, this project centered on the creation of an affordable housing development in one suburban neighborhood (Casciano & Massey, 2012). In an evaluation of program effects roughly a decade after program initiation, movers reported similar levels of anxiety to a matched sample of those still on the waiting list. However, significant *indirect* effects of relocation on anxiety symptoms were evident, as movers reported experiencing less neighborhood disorder than the control group, which was linked to lower incidence of negative life events, which contributed to lower anxiety (Casciano & Massey, 2012). As with the Yonkers Project, the absence of overall differences in anxiety between movers and stayers may be reflective of the existence of additional causal pathways working in the opposite direction. For instance, while improvements in housing and neighborhood quality may have reduced feelings of anxiety for some movers, experiences of discrimination or the loss of neighborhood social networks may have produced elevated feelings of stress for others.

This collection of experimental and quasi-experimental evidence, while limited in breadth, provides important insights into the potential causal effects of neighborhood economic composition on adult wellbeing. Findings from MTO indicate that for economically disadvantaged families interested in moving out of high-poverty neighborhoods, the opportunity to move to a low poverty neighborhood had significant short- and long-term benefits on several aspects of health and wellbeing. Meanwhile, mobility projects involving the creation of affordable housing in suburban neighborhoods had more limited benefits for health and psychological functioning. As noted above, however, it is important to contextualize these finding, as the racial and class dynamics at play in these two projects set them apart from MTO. Though all three study samples were comprised primarily Black and Latino participants, MTO involved the relocation of individual families into private rental units in a low-poverty neighborhood of their choice. In contrast, Yonkers and Monitoring Mt. Laurel involved the creation of new affordable developments in suburban neighborhoods. While the stipulation that families in the MTO experimental group had to move to neighborhoods with a poverty rate lower than 10% meant that these families generally moved to predominantly White neighborhoods, many had moved on to moderate poverty neighborhoods by the 10-15 year follow up. Long-term evaluations of the importance of neighborhood poverty relative to racial composition found that for MTO participants, the share of minority residents in the neighborhood at large *promoted* subjective well-being when tract poverty was controlled (Ludwig et al., 2012). This underscores the possibility that having a large share of White neighbors may hinder wellbeing for Black and Latino families, that having a sizable share of neighbors from the same racial or ethnic background is beneficial, or both. Viewed through this lens, the absence of mental health benefits in Yonkers and Mt. Laurel should be seen not as evidence *against* causal neighborhood effects, but as an indication of the myriad of potential pathways through which the neighborhood context can impact wellbeing.

It is also worth noting that although MTO is the best large-scale experimental study of neighborhood effects to date, it suffered from a few key challenges to validity. For one thing, despite being framed as a study of neighborhood effects, MTO actually tested the effects of being offered the opportunity to move to a different neighborhood. Though moving to a new neighborhood does change the context in many ways (as discussed above), the conditions under which effects are likely to emerge remain opaque. For instance, the shock of mobility could magnify the benefits of improving conditions; alternatively, the strains of moving could undercut potential benefits. Moreover, it remains unclear whether similar effects would emerge in response to declines in neighborhood poverty within a given neighborhood over time. Research conducted using the LAFANS dataset found that shifts in neighborhood composition resulting from a move were related to different trajectories of residential satisfaction than were similar shifts occurring within LA neighborhoods over time (Sharp, 2018). While this study did not consider links between neighborhood features and wellbeing, results suggest that peoples' perceptions of neighborhood change may differ according to how that change occurs.

Another key concern with the MTO study is that there were relatively low take-up rates within the experimental groups, with only about 50% of the experimental group and 60% of the Section 8 group using the vouchers offered to them (Ludwig et al., 2012). This means that although random assignment was employed, it was not actualized, leaving open the possibility of unobserved baseline differences between movers and stayers. Because any unobserved differences should have been distributed between the experimental and control group through random assignment, the use of Intent-to-Treat estimates provides a conservative estimate of neighborhood effects, accounting for these potential differences between experimental movers and stayers. All the same, this has important implications for the generalizability of findings. While all participants in MTO had an expressed interest in moving out of their current neighborhoods (which limits generalizability in itself), it is possible that only families with the highest motivation to move were likely to feel effects. Given these limitations, even the results of MTO should be viewed with some caution. All the same, interpreted within the context of the larger neighborhood effects literature, MTO provides some of the most convincing evidence of causal neighborhood effects on wellbeing.

Several additional limitations of the experimental and quasi-experimental neighborhood literature inform the current project. First, it remains unclear from these evaluations whether concentrated poverty, affluence, or some other neighborhood feature is the primary structural antecedent of differential experiences across neighborhoods. While some correlational research has evaluated the relative importance of different markers of the economic context in relation to self-reported health (Browning & Cagney, 2003; Weden et al., 2008; Wen et al., 2003), similar evaluations have not been undertaken within the experimental literature. A second, related limitation is that experimental mobility programs are generally unable to explain the forces that drive neighborhood effects (Sampson et al., 2002). This is true even for Monitoring Mt. Laurel, in which Casciano and Massey explicitly tested a mediation model linking neighborhood change to anxiety through perceived disorder (2012). The problem is that when families move to lower-poverty neighborhoods, more than just the neighborhood economic composition changes; a whole host of contextual characteristics shift at once. For mobility studies involving relocation to one or a few neighborhoods, this makes it difficult or impossible to isolate the mediating role of different neighborhood-level mechanisms (e.g., improvements in safety versus amenities versus housing quality). For studies like MTO that involve movement to a larger array of neighborhoods with varying characteristics, pulling apart the relative contributions of different neighborhood resources and stressors is more realistic; yet mediating pathways have generally not been tested within the context of this study. Unfortunately, inattention to these contextual mediators makes it difficult to determine whether discrepancies in findings between studies are related to study design, the unique context of each project, or something else. Moreover, there is a need to clarify whether links between reductions in neighborhood poverty and wellbeing are unique to individuals changing neighborhoods, or if similar (or elevated) benefits occur for those experiencing within-neighborhood declines in neighborhood poverty.

Underlying Mechanisms

Contextual Resources and Stressors

Following early efforts to explicate the various mechanisms that might explain the importance of the neighborhood context for individual functioning, empirical evidence on these mechanisms has mounted. A good deal of research documents spatial disparities in community resources and stressors (Acevedo-Garcia et al., 2020; Chetty et al., 2018; Coley et al., 2021; Rutan & Desmond, 2021; Sampson et al., 1997), disparities that seem to coincide with the economic and racial composition of local contexts. For example, neighborhood disadvantage has been linked to heightened crime, disorder, and pollution as well as low access to supermarkets, pharmacies with adequate medications, clean and safe recreational spaces, healthy food options, and informal social control (Amstislavski et al., 2012; Bower et al., 2014; Estabrooks et al., 2003; Hajat et al., 2013; Kalnins & Dowell, 2017; J. Kim, 2010; Kirk & Laub, 2010; Larson et al., 2009; Papachristos et al., 2011; Schulz et al., 2008; Simon et al., 2008). While neighborhood poverty has also been found to predict the presence of select amenities such as convenience stores (Bower et al., 2014) and reduced housing costs (Kull & Coley, 2014), these assets seems unlikely to offset the consequences of decades-long disinvestment and neglect. This uneven distribution of resources and services across neighborhoods may contribute to spatial disparities in wellbeing.

In line with this idea, another body of research has considered whether the presence of one or more neighborhood characteristics contributes to individual health and psychological functioning (Ahern & Galea, 2011; Downey & Van Willigen, 2005; Gong et al., 2016; Mair et al., 2008; Ross, 2000; Sampson et al., 1997; Yang & Matthews, 2010). Neighborhood disorder has been identified as one of the most consistent predictors of wellbeing, with higher disorder being linked with heightened distress and poorer health (D. Kim, 2008; Mair et al., 2008, 2015; Ross, 2000; Steptoe & Feldman, 2001; Wen et al., 2003). Measures of disorder generally tap into physical decay and low social control, with items relating to the presence of graffiti, noise, litter, vacant housing, crime, drug and alcohol use, loitering, the absence of neighborly trust, lot upkeep and the like, thus representing a compilation of both physical and social contextual stressors (Ross & Mirowsky, 1999). However, there is a good deal of variation between studies, with some researchers disaggregating physical dimensions of disorder from social dimensions (Cooper et al., 2014; Schulz et al., 2013; Wen et al., 2003, 2006), focusing on order rather than disorder (Weden et al., 2008; Wen et al., 2006), or collapsing disorder with other neighborhood features (Weden et al., 2008). These inconsistencies make studies less comparable and limit the practical significance of findings, particularly insofar as it becomes difficult to identify which stressors are most salient to residents and how it is that they take effect. For example, indicators of noise, pollution, and toxic dumping are sometimes (but not always) included in measures of disorder (e.g., Schulz et al., 2008). While these factors may have a primarily psychological impact by providing residents visual evidence of disorder and disinvestment, they could alternatively (or additionally) impact residents at a biological level. In this case, grouping these features with others that have a primarily psychological impact may conflate two distinct mechanisms through which the neighborhood context impacts peoples' lives. This has implications both for our theoretical understanding of neighborhoods and for our ability to identify effective points of intervention.

With respect to contextual resources, neighborhood social supports have been frequently linked with wellbeing, with higher levels of support, connectedness, and collective efficacy appearing to protect against health maladies (Mair et al., 2008; Riva et al., 2007; Sampson et al., 2002). In contrast, very few studies have examined the role of institutional resources and services on wellbeing (Galster, 2012; Sampson et al., 2002). This is a striking oversight given that neighborhood amenities are a primary driver of housing costs and residential preferences (Benefield, 2009; Holme, 2002), suggesting that people expect these amenities to impact their quality of life. In fact, the presence of amenities has been linked with neighborhood satisfaction (Hur & Morrow-Jones, 2008), pointing to the potential importance of neighborhood resources for peoples' wellbeing.

While the aforementioned work has contributed to the identification of pathways through which neighborhoods come to matter for residents, it is also limited in important ways. Most notably, some proposed pathways have received far more empirical attention than others. For example, there is a relatively sizable base of research on the importance of neighborhood disorder and social processes—most notably collective efficacy and various indicators of social capital—for individual functioning, and a relative dearth of information on other mechanisms including local institutional resources and environmental hazards (Ellen et al., 2001; Mair et al., 2008; Sampson et al., 2002). Yet even where relations between neighborhood features and individual functioning are relatively well-established, there is still some question as to whether these contextual resources and stressors mediate effects of the neighborhood economic context.

Unfortunately, most empirical research in this area has been rather piecemeal, focusing on the potential mediating role of only one or two neighborhood characteristics at a time. Several studies demonstrate the pitfalls of this approach. For instance, building on a large base of research documenting the mediating role of social capital on health outcomes, Steptoe and Feldman (2001) elected to test whether the effects of social capital would be partly explained by neighborhood problems. Though they did not test a full mediation model, they did find that a) neighborhood SES was predictive of both social capital and neighborhood problems, and b) that both neighborhood problems and social capital predicted health, psychological distress, and physical impairment. These results suggested that links between social capital and wellbeing were likely overstated in prior research, as the role of other contextual factors (such as neighborhood problems) was generally not being accounted for.

Another prime example comes from a series of studies using a large probability sample of adults in Illinois. Using this data, Ross (2000) found that neighborhood disadvantage predicted heightened depressive symptoms, and that this relation was fully explained by perceived neighborhood disorder. However, neighborhood disorder was the only mediating pathway examined, leaving open the possibility that other contextual forces might be driving this apparent effect. In fact, using the same sample, Kim (2010) found that the relation between neighborhood disadvantage and depressive symptoms was mediated by both disorder and social relationships, though in opposite directions. In this case, social relationships did not explain away the relation between neighborhood disadvantage and health. However, a focus on only one mediating pathway provided Ross with an oversimplified view of what makes the neighborhood economic context meaningful. Moreover, it remains possible that the effects of disorder might be partly accounted for by social capital, access to recreational facilities, environmental hazards, or other contextual factors. This highlights that failure to consider an array of mediating pathways limits our ability to rule out alternative explanations, which is a necessary step towards the identification of causal pathways.

A limited collection of studies has examined the degree to which multiple contextual resources and stressors mediate the connection between the neighborhood economic context and peoples' wellbeing. The most comprehensive of these efforts explicitly tests multiple mediating pathways between the neighborhood economic context and markers of wellbeing. Of the studies that examine neighborhood disorder as one of several potential mediators of neighborhood economic effects, all have found support for this pathway (J. Kim, 2010; Schulz et al., 2012, 2013; Wen et al., 2003). Studies that consider both neighborhood disorder and neighborhood social supports simultaneously have generally found that both pathways play a significant role in transmitting the neighborhood economic context to individual functioning (J. Kim, 2010; Wen et al., 2003), though other research has found that measures of neighborhood cohesion, collective efficacy, social norms, and social ties are *not* significant mediators of this relation (Browning & Cagney, 2003; Robinette et al., 2016). The limited array of work focusing more specifically on violence, crime, and safety in concert with other neighborhood factors has generally found that these factors are related to stress and wellbeing, but not above and beyond the effects of general neighborhood disorder (Cooper et al., 2014; Robinette et al., 2016; Schulz et al., 2012; Wen et al., 2003). Only one of the aforementioned studies examined institutional resources as a potential mediator, finding that local health resources did *not* help explain the relation between neighborhood affluence and health in a Chicago sample (Wen et al., 2003). Importantly, however, this study only considered youth-focused health services, such as mental health and substance use counseling for young people. It remains to be seen whether other institutional resources play a more important role for adults' healthy functioning.

This collection of research provides some evidence that environmental stressors and social resources help explain connections between the economic composition of peoples' neighborhoods and their functioning. However, variation in study samples, contextual factors examined, and methodological rigor of studies makes it challenging to draw clear conclusions. Unfortunately, the only study that investigated a full mediation model using a nationally representative sample collapsed all neighborhood features including satisfaction, air quality, upkeep, safety, neighborhood problems, and presence of recreational facilities into a single composite of overall quality (Weden et al., 2008). They found that both disadvantage and advantage predicted self-reported health, and that this was largely explained by perceived neighborhood quality. While this study provides useful evidence of the importance of both disadvantage and affluence for health, its practical implications are limited by our inability to identify which aspects of neighborhood quality drove these associations.

In sum, there is a good deal of evidence that contextual resources and stressors are implicated in individual wellbeing. However, limited research has empirically examined to what degree these resources and stressors drive the relationship between neighborhood economic composition and individual wellbeing. Research generally suggests that more disadvantaged neighborhoods have higher levels of disorder and environmental stress, including crime, violence, vacant housing, litter, poor maintenance and upkeep, noise, air pollution, contamination, etc. than their less advantaged counterparts, and that this contributes to worse health and higher psychological distress for residents. There are also some indications that neighborhoods with more affluent residents have higher levels of collective efficacy, neighborhood social ties, and social networks, and that these social resources are connected to wellbeing. However, these findings are much less consistent.

Measuring Mechanisms: Observed and Perceived Neighborhood Features

Beyond considering which neighborhood features are most important for individual wellbeing, there is also a need to more carefully delineate the relative importance of observed versus perceived measures of the environment. Some contextual features including crime, pollution, physical order/disorder, and resource availability and quality can be captured either through use of observed neighborhood-level measures, or through residents' individualized assessments of those features. Other aspects of context like neighborhood social dynamics and norms generally necessitate a reliance on peoples' subjective assessments of their environment, though some researchers use observed measures (e.g., alcohol outlet density) to proxy aspects of the social environment (Cooper et al., 2014).

For methodological reasons, there has been a push to avoid individual-level measures of the neighborhood context. It has been noted by several scholars that study designs that rely on individual reports of the neighborhood context may be prone to same-reporter bias, wherein associations between contextual features and individual wellbeing are inflated because peoples' wellbeing is likely to impact how they evaluate their context (e.g., Riva et al., 2007; Sampson et al., 2002). This is proposed to lead to an overestimation of neighborhood effects. To help address this problem, scholars have suggested gathering neighborhood-level data separately from individual reports, either through administrative sources, systematic social observations undertaken by trained observers, or community surveys that allow for the aggregation of individual-level data at the neighborhood level (Leventhal & Brooks-Gunn, 2000; Sampson, 2003). Using the latter method, even measures of the social environment that rely on peoples' subjective assessments of their context can be used to create neighborhood-level markers of the social environment that may or may not align with any given individual's perception of the environment.

While this is an important measurement consideration, particularly insofar as it encourages researchers to avoid shortcuts that may undermine their research goals, it should not be taken to suggest that measuring individuals' perceptions of contextual resources and stressors – both physical and social in nature – are unimportant. As discussed previously, contexts become meaningful because of how they impact peoples' attitudes, experiences, and behaviors (Bronfenbrenner & Morris, 2007). It is therefore critical to evaluate how both observed neighborhood features (measured at the neighborhood level) and perceptions of those features (measured at the individual level) are implicated in wellbeing. Focusing solely on observed neighborhood features leaves half of the neighborhood effects story unexplored.

Existing literature generally supports the assertion that both observed and perceived neighborhood features matter. Much of this work suggests that subjective assessments of neighborhood features are more predictive of individual wellbeing than are objective measures, and that subjective measures mediate associations between objective measures and wellbeing (D. Kim, 2008; Mair et al., 2008; Schulz et al., 2012; Weden et al., 2008; Wen et al., 2003). However, most research does not assess observed and perceived measures of the same construct, instead comparing the predictive power of structural neighborhood characteristics such as neighborhood poverty against perceptions of more specific neighborhood features, like safety or disorder. Unfortunately, this work does little to elucidate whether and to what degree observed and perceived measures of specific neighborhood characteristics align, and how they work together (or in conflict) to inform physical and psychological functioning.

Though few and far between, there are several studies that have simultaneously considered the importance of observed and perceived measures of the same construct. The best example comes from a study by Schulz and colleagues (2013), who examined how observed and perceived measures of environmental stress mediated the association between neighborhood poverty and cumulative biological risk (CBR). The authors used systematic social observations at the census block level to objectively measure neighborhood-level disorder and relied on individual reports of neighborhood social and physical stress to tap into individuals' perceptions. They found that both observed and perceived assessments of environmental stress helped explain the link between neighborhood poverty and cumulative biological risk, controlling for individual characteristics. Interestingly, they also found that these associations worked independently from one another. In other words, while it was expected that the effects of observed disorder might work *through* perceived disorder, Schulz and colleagues did not find support for a mediating relationship. They took this to mean that while objective and subjective measures of the neighborhood are correlated, subjective views of the environment are not simply re-interpretations of the objective world. Instead, perceptions of the environment are likely interpreted through one's prior experiences and social position, leading to unique contributions to wellbeing (Schulz et al., 2013). In another example, for a sample of Atlanta residents forced out of public housing developments, improved economic conditions were linked to depression via perceptions of reduced violence, but *not* via actual shifts in violent crime rates (Cooper et al., 2014). While the observed neighborhood measure was not predictive in this case, this study provides further evidence of the separable nature of objective and subjective assessments of environmental stressors. Whether this applies to neighborhood resources as well remains to be seen.

The Present Research

The Study Context

To address the limitations of the existing literature base, I considered links between neighborhood SES and wellbeing within a sample of mostly Black mothers with limited financial means who experienced natural-disaster induced neighborhood change. This research began in 2003 as part of the Opening Doors Study, a multi-site randomized program designed to improve retention in community college as a means of promoting health. The New Orleans sample was comprised of parents with young children, with an experimental manipulation involving the receipt of academic scholarships and targeted counseling to support college retention. Participants had completed baseline surveys prior to the time Hurricane Katrina hit the city in August, 2005. A second wave of data collection was in process when the disaster hit. Following Hurricane Katrina, the Opening Doors study was reconceptualized as the Post-Katrina Study of Resilience and Recovery (RISK). The first post-Katrina follow-up happened in 2006/2007, with another taking place in 2009.

In order to most effectively contextualize study participants' experiences over this period, it useful to consider the landscape of New Orleans before and after the hurricane. Prior to the disaster, New Orleans was already a changing city. For many years prior to the hurricane, policymakers had been working to promote the tourism industry as a way to draw investment (Gladstone & Préau, 2008). Moreover, the federal government had begun to implement HOPE VI public housing redevelopment, which involved the demolition of large public housing projects in favor of mixed-income communities, oftentimes at the expense of low-income Black residents who had trouble finding housing elsewhere, were displaced for long periods, or were unable to return altogether due to a large reduction in affordable units (Goetz, 2011; Quigley, 2007; Slater, 2008). Commentators have pointed to HOPE VI as an example of state-led gentrification, wherein middle- and upper-class people are encouraged to occupy an area under the guise of de-concentrating poverty for the benefit of the poor (Goetz, 2011). While the objectives may have been more well-meaning than that argument would suggest, initial redevelopment was not promising: of a New Orleans public housing complex with roughly 1500 units, only 100 affordable units were retained, and a Walmart was built in the unused space (Quigley, 2007).

Despite affordable housing challenges, however, rent was still relatively low and vacancy rates relatively high in most lower-income neighborhoods (Bates & Green, 2009), suggesting continued disinvestment in those areas by the local government, businesses, and well-resourced individuals. Also unique to New Orleans was that prior to the hurricane, 67% of the population was Black, 27% was White, and less than 6% was Hispanic, Asian, Native American, or Native Hawaiian or Pacific Islander (U.S. Census

Bureau, 2015). New Orleans had relatively low median household income, and 38% of children under 18 were living in poverty (Masozera et al., 2007). While some neighborhoods represented a mix of race and/or income groups, the majority were either affluent White communities or moderate/low-income Black communities (Lovett, 2015).

When Katrina hit, differences in vulnerability and risk were laid bare. The devastation in low-income communities was most obvious, as residents of these communities were not always equipped to evacuate and were therefore left in dangerous and precarious situations (Smith, 2006). To make matters worse, less than a month after Hurricane Katrina hade made landfall, evacuation orders were made in response to the imminent arrival of another massive storm, Hurricane Rita (Mayer et al., 2008). Though effects were less severe in New Orleans compared to those of Hurricane Katrina, levees that had been rapidly repaired after Katrina were damaged, leading to further flooding and destruction in low-lying (generally lower income) neighborhoods (Green et al., 2007a; Mayer et al., 2008). Interesting to note, however, is that hurricane-related destruction was not limited to low-resourced communities. In fact, most areas of the city were hit with flooding and wind, despite affluent neighborhoods frequently occupying higher ground (Smith, 2006). This contributed to the massive displacement of residents, with 400,000 people being forced to leave their homes because of the devastation (Masozera et al., 2007). However, it has been well-established that neighborhood socioeconomic conditions before the storm had a major impact on how much assistance people could access, who could return and on what timetable, and how much input people had in redevelopment planning (Gotham & Greenberg, 2014; Masozera et al., 2007; Peacock et al., 2018; Smith, 2006).

Inequitable recovery was evident as early as December of 2005, only four months after Katrina made landfall. By this time, most White evacuees had been able to return home, but less than 40% of Black evacuees were back (Logan, 2009). Of those who remained displaced, two out of three White evacuees were in Louisiana, in contrast to one out of four Black evacuees (Logan, 2009). Moreover, whereas White evacuees who returned to New Orleans had similar income levels to those who remained displaced, Black evacuees who remained displaced had substantially lower income levels than White and Black families who returned to New Orleans (Logan, 2009). The Brookings Institute similarly reported that several years following Katrina, the city's population was smaller, older, more educated, and less poor than the population had been in the 1990's (cited in Gladstone & Préau, 2008). This suggests that barriers to returning were greater for Black than for White residents, and even more so for working class and low-income Black community members.

Hurricane Katrina was an exogenous force that ushered in rapid neighborhood change via temporary or permanent relocation as well as hurricane-related destruction and revitalization within New Orleans. Because many participants of the present study were forcibly displaced from their homes and neighborhoods, some of the selection factors that would normally bias estimates of neighborhood effects are minimized. Moreover, those who remained in New Orleans experienced a rapidly changing local environment both immediately after the hurricane, and through the subsequent clean-up and revitalization period. This provides an important opportunity to examine how peoples' physical and psychological functioning changed in response to shifting neighborhood conditions, acknowledging the direct impact of the hurricane itself. Not only will this knowledge contribute to our general understanding of how contextual factors can support wellbeing; it will also provide insights into the community features that support recovery in the wake of natural disasters.

Research Goals and Questions

The goal of this project is to assess how specific neighborhood resources and stressors transmit community economic composition to wellbeing within this context of rapid neighborhood change. By examining the specific pathways that make the socioeconomic context meaningful to residents, I aimed to unravel questions provoked by prior work with implications for place-based policies. The research questions guiding this investigation are as follows:

1) For parents with limited financial means directly affected by hurricane Katrina, to what degree do observed neighborhood resources (basic amenities, health services) and stressors (crime, pollution, housing costs) mediate the association between the neighborhood economic context and wellbeing over time?
    a. How do processes differ for residents experiencing neighborhood change within one neighborhood over time, versus residents experiencing mobility-related change?
2) What are the relative contributions of observed versus perceived neighborhood change in explaining the connection between the neighborhood economic context and wellbeing?
    a. How do processes differ for residents experiencing neighborhood change within one neighborhood over time, versus residents experiencing mobility-related change?

Novel Contributions

This work will extend existing knowledge in several ways. First and foremost, data were collected before and after an exogenous shock, which will enable me to examine the consequences of neighborhood change in a way that minimizes biases present in cross-sectional and some longitudinal studies. While this study is particular in its focus on parents with low levels of income affected by Hurricane Katrina and should thus be evaluated in context, the insights it provides will have implications for theory and practice.

Second, it will consider how multiple mediating pathways transmit neighborhood poverty to wellbeing, attending both to specific environmental stressors (pollution, crime, cost of living) and several institutional resources and services that have been largely understudied thus far. By assessing the importance of contextual resources and stressors simultaneously, this work will help to elucidate the specific pathways through which the neighborhood economic context becomes meaningful to individual functioning.

Finally, this research considers the degree to which participants' perceptions of neighborhood change align with observed measures of neighborhood change. This is important because measures of perception tap into participants' experiences of their neighborhood context, which may contribute more directly to wellbeing than observed neighborhood characteristics. Understanding how these subjective evaluations contribute to the relation between neighborhood poverty and healthy functioning is critical for identifying neighborhood features that are most salient to residents, and that have the most potential as a means of intervention.

Ultimately, by identifying specific neighborhood features that constrain and enhance peoples' ability to pursue a happy and healthy life, this research seeks to elucidate the most viable levers for addressing the uneven distribution of wellbeing across families and locales.

CHAPTER 3: METHODS

Data and Participants

Individual-Level Data

Data were drawn from the Post-Katrina Study of Resilience and Recovery, a longitudinal study that followed 1019 predominantly low-income mothers affected by Hurricane Katrina. Baseline data were collected between 2003 and 2005 as part of the Opening Doors study, a multi-site randomized program designed to promote health by improving retention in community colleges. In New Orleans, eligible students – those who were enrolled in the West Jefferson campus of the Louisiana Technical College or Delgado Community College and had at least one child under the age of 18 – were recruited through phone calls, flyers, mailing, and news media (Brock & LeBlanc, 2005). Students who attended an information session or met with the Opening Doors staff and consented to participate in the study were then randomly assigned to the experimental or control group (Brock & LeBlanc, 2005). Those in the experimental group would receive scholarships tied to academic performance, as well as supplemental counseling (Brock & LeBlanc, 2005). However, the arrival of Hurricane Katrina in 2005 led researchers to reframe and extend the project in order to study the recovery of participants, a majority of whom were displaced as a result of the hurricane. Participants were followed wherever they moved.

Seventy percent of the baseline sample were successfully contacted in 2007 for the first post-Katrina follow-up (PK1), and 71% of the original participants participated in the second follow-up in 2009 (PK2). Data collection involved quantitative surveys assessing mental and physical health, social support, and economic and employment outcomes, with child behavioral outcomes and neighborhood-focused measures added in PK2. Participants' home addresses at each wave were matched with geocoded data at the census tract level. For this dissertation, I focus on the sample of participants for whom geocoded addresses were available across waves ($N = 606$).

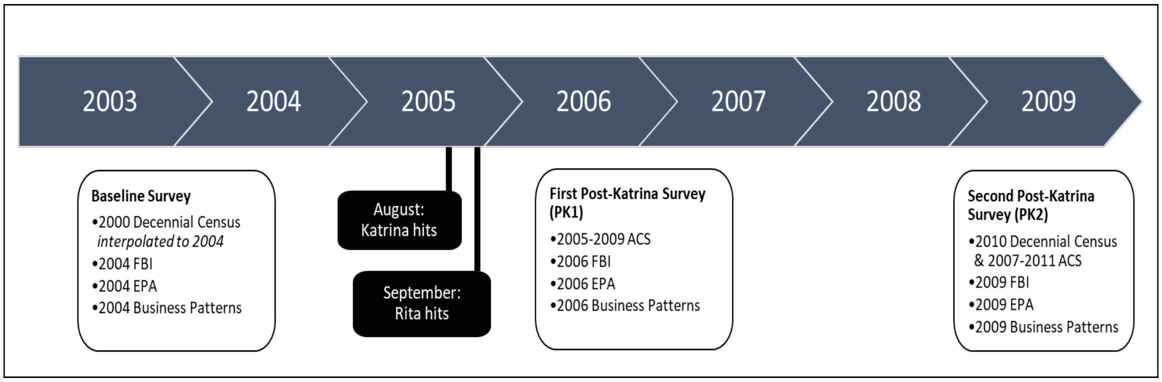
This dataset provides a unique opportunity to address the research questions at hand. Over half of participants were displaced from their homes as a result of Hurricane Katrina, forcing a period of semi-random relocation. Moreover, the devastation caused by the flood meant that not only did most New Orleans neighborhoods experience an immediate demographic shock due to disaster-related displacement, but they also required substantial reinvestment in the years to follow (Smith, 2006). This paved the way for a rapid bout of redevelopment, which ushered in major shifts in the socioeconomic and racial composition of the city, leaving it Whiter and more affluent than before (Gladstone & Préau, 2008). As such, the entire sample experienced some form of neighborhood change, regardless of whether they remained in or returned to their pre-Katrina neighborhood or more permanently relocated. Though the circumstances surrounding this sample are unique in many ways, the relocation of residents and reorganization of neighborhoods in response to the hurricane provided a critical opportunity for investigating rapid neighborhood change along several key dimensions.

Neighborhood-Level Data

Participants' home locations at each wave of data collection were geolocated using ArcGIS, allowing longitudinal administrative data on observed neighborhood features to be joined with individual-level data through census tract identifiers. Neighborhood composition and observed community resource and stress measures were

Figure 2

Timeline of Neighborhood Data Source Integration



drawn from the Decennial Census, the American Community Survey (ACS), the Federal Bureau of Investigation's (FBI) Uniform Crime Reporting database (UCR), the Environmental Protection Agency's (EPA) Toxic Release Inventory (TRI), and Zip Code Business Patterns (ZBP). Data from years parallel to each wave of data collection were matched to residents' census tract of residence at each wave (see Figure 2 for more detail).

It is important to note that not all administrative data were available at the same geographic level. Tract-level data were available from the Decennial Census and the ACS. In contrast, UCR data were reported at the precinct level and allow for aggregation up to the zip code level, which were then matched to Zip Code Tabulation Areas (ZCTAs), which are geographic approximations of zip codes. This is the case for Business Patterns data as well, as the smallest geographic unit at which data were released is the zip code. Meanwhile, TRI data were reported at the facility level, with facilities matched to geographic locations using longitude/latitude coordinates.

A key challenge of longitudinal geographic data is that census tract and zip code boundaries change over time. In order to make data comparisons across time, it is thus necessary to adjust tract and zip code level data to consistent geographic boundaries. To accomplish this, I used two tools: the Longitudinal Tract Database (Logan et al., 2014; Manson et al., 2020) and a Beta Test version of the Zip Code Crosswalk (Bailey & Helmuth, n.d.). Using the Longitudinal Tract Database, I was able to adjust post-2000 Census/ACS data to 2000 boundaries, which made these data comparable over time. The Zip Code Crosswalk worked in a similar but distinct manner, assigning each zip code to a "zip code cluster." For zip codes that did not change between 2000 and 2010, zip codes and zip code clusters were equivalent. For zip codes that did change, however, the cluster represented a group of zip codes that had been either consolidated or split over time. By aggregating zip-code level data to the zip code cluster level, I created consistent geographic boundaries across years, allowing comparison of zip code data over those years.

Once boundaries were made consistent across years, I used ArcGIS to spatially join data at different geographic levels to census tract identifiers. This step was made necessary by the fact that the RISK data contained only census tract identifiers. However, it also provided an opportunity to explore alternate neighborhood conceptualizations that may better represent the neighborhood contexts people interact with than do traditional boundaries. The use of administrative boundaries such as census tracts to capture the neighborhood context is widespread, and there is a sizable body of research that suggests that these boundaries constitute reasonable proxies of peoples' residential contexts (Riva et al., 2007; Sampson et al., 2002). However, these boundaries have been seen to diverge from peoples' conceptualizations of their neighborhoods (e.g., Coulton et al., 2001). This may be partly explained by the fact that if someone lives close to a census tract boundary, the residential context they experience is likely to encompass parts of several different census tracts. This becomes a methodological problem primarily where there is discontinuity in neighborhood features between contiguous neighborhoods – for instance, a census tract with few amenities is bordered by one or more tracts with a high number of amenities (Sampson et al., 2002).

With this issue in mind, I employed a procedure developed with similar contextual data (Miller et al., 2019) to create several alternative measures of the neighborhood context. This involved using ArcGIS to construct aggregate measures of neighborhood features within 0.5, 1.0, and 2.0 miles of the center of participants' census tract of residence. In most cases, indicators were constructed to represent the average value of all tracts (or zip codes) that occupy space within the given radius: for instance, the average poverty rate of all census tracts within 0.5 mile of the tract center, or the average number of health services of all zip codes within a 1-mile radius. For TRI pollution data, on the other hand, I calculated the sum of pollutants released from TRI facilities within the given radius, which was made possible by the release of latitude/longitude information for each facility. Measures that were created using the smallest radius (0.5 miles) should approximate the characteristics of the original census tract or zip code, except in cases where the tract is smaller than usual or irregular in shape. In contrast, measures created using the larger radii include data from more of the surrounding tracts/zip codes/TRI facilities. Consequently, these measures better represent relative continuity (or lack thereof) between contiguous geographies (Coulton, 2012).

Comparing these alternative measures is useful for considering the degree to which the arbitrary nature of neighborhood boundaries impacts estimates of neighborhood effects, known as the Modifiable Area Unit Problem (MAUP; Arcaya et al., 2016). For example, it provides a means to empirically test whether widening these boundaries so as to capture the characteristics of proximal areas provides a more or less effective representation of peoples' neighborhood spaces than simply measuring characteristics at the census tract level. Moreover, this procedure allows for the merging of zip code data at the tract level. While collapsing zip codes characteristics to the tract level does not fully resolve the differences between these geographies, it does make them more practically comparable, particularly at larger radii.

Given that the focus of this dissertation is to identify specific neighborhood factors that mediate links between the economic context and wellbeing, a primary goal of this process was to identify the most effective operationalization of the neighborhood context across different indicators. I therefore decided to select one radius to use across all neighborhood indicators, rather than using different radii for each variable. To assess which radius most effectively captured the neighborhood context, I ran correlations within and across waves. I first compared the strength of associations between neighborhood poverty and affluence and neighborhood features at each radius. Correlations tended to be strongest at the 2-mile radius. Results were similar when considering alignment between participants' perceptions of neighborhood change and observed change. For example, perceived changes in neighborhood crime were more strongly correlated with observed changes in neighborhood crime within a 2-mile radius than a 1-mile or 0.5-mile radius. Finally, correlations were run between neighborhood features and outcome variables, but no clear conclusions could be drawn regarding the relative strength of the different measures. Given parallel conclusions across the first several sets of correlations, I elected to use neighborhood measures that aggregated data within a 2-mile radius of participants' home census tracts.

Measures

Neighborhood Economic Context

To operationalize the neighborhood economic context, I drew a measure of neighborhood poverty from the Decennial Census and the ACS. This measure reflected the proportion of residents in the census tract whose annual income fell under the federal poverty line for that year. Neighborhood poverty was normally distributed, so no transformations were necessary.

Observed Neighborhood Features

Resources

Data on local resources were drawn from Business Patterns, which provides yearly data on businesses in the U.S. that have paid employees. Zip code level data can be used to ascertain the number and types of businesses operating in each zip code, based on North American Industry Classification System (NAICS) codes. Two primary neighborhood measures of neighborhood resources were constructed from Business Patterns data. *Basic amenities* measured the number of grocery and drug stores in the neighborhood. *Health services* is a count of doctor's offices, hospitals, family planning centers, mental health offices, and substance abuse services available in the neighborhood. The specific business types included in each measure and their corresponding North American Industry Classification System (NAICS) codes are

Table 1

Business Types Included in Resource Measures

Resource Indicator	Businesses Types & NAICS Codes
Basic amenities	Supermarkets and other grocery (except convenience) stores (44511), Pharmacies and drug stores (44511)
Health services	Offices of physicians (6211); Offices of dentists (6212); Offices of other health practitioners (6213; includes chiropractors, optometrists, mental health practitioners, physical, occupational, and speech therapists and audiologists, etc.); Family planning centers (62141); Outpatient mental health and substance abuse centers (62142); General medical and surgical hospitals (6221)

included in Table 1. The measure of basic amenities did not require any transformation. However, health services was highly skewed across waves. This was best resolved through the use of a square root transformation.

Several additional resource measures were constructed but were ultimately not included in final models. These were counts of *leisure services*, *educational services*, and *social services* within the zip code. Health resources and leisure services were correlated above 0.60, as were educational services, social services, and amenities. Consequently, including them as separate predictors in the same model was likely to cause issues of multicollinearity. After running a series of alternative models, I elected to use health services in place of leisure services, and basic amenities in place of educational and social services. In addition to being stronger correlates of wellbeing, these measures also have more face validity: health services are theoretically most directly connected to physical and mental health, while amenities like grocery stores and pharmacies may have elevated relevance in peoples' everyday lives compared to other kinds of local services.

Stressors

This research focused on three specific neighborhood stressors: neighborhood crime, pollution, and housing costs. Data on precinct-level crime were drawn from the FBI's Uniform Crime Reporting (UCR) database. Prior research using UCR data has found that crimes involving serious bodily injury, the theft of high-value property, incidents involving strangers, and breaking and entering are more likely to show up in official statistics than other crimes, in part because civilians tend to view these acts as serious violations of social order (Gove et al., 1985). I therefore constructed a measure of "focal crime" by summing the number of homicides, vehicle thefts, and instances of breaking-and-entering that were reported for each month over a given year within a precinct. To minimize missing data and improve the reliability of estimates, I created an average monthly count for each year rather than summing across months. Data for all precincts within a given zip code were then averaged, which permitted data to be matched with spatial geographies – in this case, zip codes. While it would have been preferrable to sum precinct-level data within each zip code, high rates of missing data at the precinct level would have biased estimates downwards, rendering them less reliable. The given measure is best understood as the average precinct-level monthly crime reports within a given zip code, rather than the total monthly crime count within a given zip code. To normalize its distribution, focal crime was transformed using a natural log.

Second, a measure of environmental pollution was drawn from the EPA's Toxic Release Inventory, which publishes annual reports on the industrial release of chemicals that have the potential to impact human and environmental health (Environmental Protection Agency, 2019). The TRI provides data on the amount of toxic chemicals released through air and water from each TRI site. Because the latitude and longitude of each site is provided, these chemical releases could be matched to specific geographic locations. I constructed neighborhood-level measures of air pollution by summing the amount of Clean Air Act chemicals that were released from all TRI sites within 2.0 miles of the center of each census tract in the U.S.

Given prior research suggesting that simply the number of toxic release sites in one's neighborhood is related to mental health and stress (Downey & Van Willigen, 2005; Yang & Matthews, 2010), there is some reason to expect that incremental increases in toxins at the neighborhood level may also have implications for residents' wellbeing. However, this measure of pollution was highly skewed: 40-50% of tracts had no air pollution released from TRI sites within the given radius, and there was a very non-normal distribution with a strong right skew for non-zero values. To account for this, I constructed a categorical indicator wherein roughly 15% of the sample was included in each non-zero category. Categories were no air pollution (0 pounds), low levels of air pollution (between 0 and 150 pounds), moderate levels of air pollution (between 150 and 10,000 pounds), and high levels of air pollution (10,000 pounds or more). The varying range between categories underscores the uneven nature of TRI site releases.

Finally, to capture local housing costs, median home values were pulled from the Decennial Census and the American Community Survey at the census tract level. This measure was adjusted for inflation up to 2009-dollar amounts. This measure was transformed using a natural log to normalize the distribution.

Several alternative operationalizations of neighborhood stress variables were tested. In the realm of neighborhood crime, I constructed counts of all violent crimes and all property crimes, as well as crime rate indicators (per 10,000 residents). Counts were consistently less skewed than were rates. Property crime was less connected to neighborhood economic composition and wellbeing than violent and focal crime, with focal crime being most strongly connected to neighborhood economic composition. For this reason, as well as the aforementioned research indicating that reports of focal crimes may be more reliable than reports of other types of crime (Gove et al., 1985), I chose to use this measure in final models.

For pollution, I created three alternative measures: releases of dioxin/dioxin-like compounds, releases of carcinogens, and total releases. While I had originally planned to use the dioxin measure due to its specific links to human health (White & Birnbaum, 2016), there were so few non-zero cases that this variable was not functional for the present study. Measures of air pollution and total pollution had a more manageable distribution, while the carcinogens indicator was somewhere in between. All indicators operated similarly when included in RQ1 models. I elected to focus on air pollution given evidence that air pollution has acute effects on health (Brunekreef & Holgate, 2002; Stieb et al., 2002) and thus may have more immediate implications for wellbeing than pollutants that become problematic primarily through long-term exposure.

Perceived Neighborhood Features

At PK2, all residents reported on how their current neighborhood compared to their pre-Katrina neighborhood in terms of social and material features of the environment. For participants who had returned to their original neighborhoods by this time (*N*=142), these measures reflect perceptions of how their original neighborhood changed over the study period. For these participants, the survey question read: "How does the neighborhood compare to how it was before Katrina in terms of [neighborhood feature]." For those who had *not* returned (*N*=464), these measures reflect comparisons of two different neighborhoods. The question for these participants read: "How does this neighborhood compare to your pre-Katrina neighborhood in terms of [neighborhood feature]." For both questions, response categories ranged from a lot better (1) to a lot worse (5).

Because a primary goal of this research is to assess how observed and perceived assessments of specific neighborhood features contribute to wellbeing, I focus here on the measures of perceived change that are most parallel to the aforementioned observed measures. In the realm of neighborhood resources, participants reported on how their pre/post Katrina neighborhoods compared in terms of the availability of grocery stores and drug stores, termed *perceived changes in amenities*. In terms of neighborhood stressors, participants reported on *perceived changes in housing costs* and *perceived changes in crime*. Relatively low correlations between these measures (*r*=-0.21 to 0.11) allowed for their use as independent predictors, rather than as composites. Perceived changes in amenities were reverse-coded so that for all perceived neighborhood change measures, a higher value can be understood as more of the given construct. In other words, a high score for changing amenities indicates *improving* amenity access, whereas a high score for changing costs and changing crime indicates *worsening* costs and crime, respectively. Skew was a bit high on the perceived cost measure but was resolved by combining the categories "somewhat better" and "a lot better." Other perceived change measures had normal distributions.

Individual Wellbeing

Physical Health

At each wave of data collection, participants were asked how they would rate their general health. They responded using a 5-point scale ranging from 1 (excellent) to 5 (poor). Though general health is often dichotomized due to limited variability (e.g., Do & Finch, 2008; Sharp et al., 2015; Wen et al., 2003), relatively low skew made it possible to treat it as continuous measure in this case. This measure was reverse coded so that high scores indicate better health and low scores indicate worse health.

A measure of somatic symptoms was constructed from a series of indicators related to health conditions. At baseline, participants were asked to report on lifetime diagnoses of several physical health conditions including asthma, back troubles, digestive problems, migraines/headaches, anemia, diabetes, hypertension, high cholesterol, and heart conditions; at subsequent waves, participants were asked whether they had experienced these health problems in the past year. Principle components analysis with promax rotation indicated that back troubles, digestive problems, and migraines/headaches loaded onto a distinct factor across waves. These three items were summed to create an index of somatic symptom at each wave.

Psychological Functioning

Psychological functioning was assessed using three measures. First, the K6 Psychological Distress scale was used to assess non-specific mood and anxiety disorder symptoms. Respondents were asked how often in the past 30 days from 0 (none of the time) to 4 (all the time) they felt nervous, hopeless, restless or fidgety, depressed, worthless, and overwhelmed. Overall scores were computed by summing these items, such that higher scores represent higher levels of non-specific psychological distress. Reliability was moderate across waves (α=0.76 at baseline, α=0.78 at PK1, α=0.80 at PK2). Values were skewed, with few participants reporting high levels of psychological distress across all waves. As such, this measure was transformed using a natural log.

Second, a subset of questions from the Perceived Stress Scale (PSS; Cohen, 1994) measured the degree to which participants considered their life to be stressful, unpredictable, or overloaded (e.g., "in the last 30 days, how often have you felt that you were unable to control the important things in your life?"). Participants rated four items on a scale of 0 (never) to 4 (very often), with a midpoint of 2 (sometimes). Overall scores were computed by summing these items at each wave, with higher scores indicating higher levels of stress. Reliability was moderate at PK1 and PK2 (α=0.72, α=0.73) but was low at baseline (α=0.55).

Finally, happiness was measured using a single item. As with general health, participants were asked to report their general level of happiness considering their life at present, with responses ranging from 1 (very happy) to 4 (not at all happy). This item was reverse coded so that higher values represented higher levels of happiness. Given a reasonably normal distribution, this measure was treated as continuous.

Type of Neighborhood Change

In addition to primary analyses, I considered whether the processes linking the economic context to wellbeing varied for different types of neighborhood change. Because of the uniqueness of the New Orleans context in terms of post-disaster change and redevelopment, it seemed particularly important to contrast neighborhood change happening within New Orleans neighborhoods over time with other types of neighborhood change, i.e., shifts that occur through moves to new neighborhoods, as well as changes happening within new neighborhoods over time.

To accomplish this within the constraints of a limited sample size, I created a dichotomous indicator that differentiated stayers from movers for each primary research question. As described in more detail in the analytic plan section below, for RQ1, a mixed effects framework was employed to consider associations between neighborhood factors and wellbeing, both within individuals over time and between individuals. Within this analytic framework, stayers were those who were living in the same New Orleans area census tract across all three waves (N=113), while movers were those who were living in another tract for at least one wave (N=493). As such, neighborhood change refers to shifts within New Orleans neighborhoods over time for stayers, while it captures a broader range of types of neighborhood change for movers.

Whereas RQ1 analyses used data from all three waves, RQ2 analyses focused on observed and perceived shifts in neighborhood features between baseline and PK2. As such, for this set of analyses, stayers were those who were living in their original New Orleans area census tract at PK2 (N=142), while movers were those who were living in a different census tract at PK2 (N=464).

Covariates

The exogenous shock of Hurricane Katrina forced a period of relatively random relocation for most participants, which helps to curtail selection concerns. Still, people were impacted by the hurricane with varying levels of severity, which likely had spillover effects onto where people ended up post-disaster, how much decision-making power they had, and what trade-offs they made. As such, while the circumstances of this study add an element of randomness to peoples' neighborhood experiences, an array of covariates were included in each model to control for individual and family characteristics that may impact where people live and how they function mentally and physically.

Given different modeling strategies for RQ1 and RQ2, covariates also varied between the two sets of analyses. For RQ1, covariates were included at two levels: within-individuals over time, and between individuals. The decomposition of within- and between-person slopes was accomplished in *Mplus* using latent mean centering, which is described in more detail in the Analytic Plan. This strategy is akin to individually mean centering covariates to construct within-person measures, while grand mean centering covariates to construct between-person measures. Covariates included marital status (married or not), highest degree attained (college degree or less), household size, personal earnings in the past month, receipt of public benefits (receiving or not), and whether participants had moved tracts since the last wave. Participant race/ethnicity (Black or other race) was also included, but only at the between level due to its time-invariant nature. Measure of employment and gender were also included initially but were ultimately cut due to the absence of any significant associations with wellbeing. Given that Hurricanes Katrina and Rita were disruptive to participants both in terms of their neighborhood context and their overall wellbeing, two measures of disaster impact were also included. The first of these was a dichotomous measure of whether the participant experienced the death of someone close as a result of Hurricanes Katrina or Rita (Arcaya et al., 2014). The second was a count of the number of hurricane-related traumas the participant experienced. Participants reported whether, in the aftermath of these two hurricanes, they had lacked enough water, lacked enough food, lacked medicine, lacked medical care, lacked knowledge of their children's safety, lacked knowledge of a family members' safety, had a family member that lacked medical care, or felt their life was in danger. These stressors were summed to create a scale of hurricane trauma (Arcaya et al., 2014; Calvo et al., 2015; Lowe et al., 2015; Raker et al., 2020).

The meaning of each of these covariates differed at the within versus the between level. At the within-person level, covariates tap into individual-level differences across waves. Estimates can be interpreted as the average "effect" of changing marital status, for instance. At the between level, on the other hand, people were compared to one another based on their average characteristics across waves. For dichotomous indicators such as marriage, estimates tap into differences between people who were married for all waves versus no waves.

For hurricane impact covariates, modeling was more complicated. This is because these covariates include components of both time-invariant and time-varying constructs. At the within person level, both hurricane impact covariates were coded as zero before the hurricanes made landfall; a challenge was determining how to code their values at PK2 versus PK1. Theoretically, if these measures were intended to tap into *acute* effects of the hurricane, they should be recoded back to zero at PK2, as has been done in prior research (Lowe et al., 2014). However, if they were expected to have long-term effects, they should retain their true (PK1) values for later waves as well. If there are non-linear effects, on the other hand, with associations dissipating slowly over time, an alternate method of coding is necessary. I tested each of the aforementioned options. Enduring effects of hurricane impact were evident at PK2, suggesting that recoding values to zero at PK2 would be inappropriate. A version of the variables that adjusted PK2 values to half of the PK1 values performed better than a version where values were held constant between PK1 and PK2. As such, these non-linear measures were selected as the final hurricane impact control variables for RQ1.

For RQ2, a similar collection of covariates was included, with a few additions. Parallel measures included personal monthly earnings, household size, receipt of public assistance, and hurricane impact covariates. Marital status and employment were also included in an earlier iteration but were never significant predictors, so were removed for the sake of model parsimony. A dichotomous measure of whether participants had moved tracts since baseline (i.e., whether they were stayers or movers) was also included in main analyses. An additional hurricane-impact covariate was added to tap into peoples' post-Katrina mobility by counting the number of moves made in the first year after the hurricane. This measure was not included in RQ1 analyses due to the absence of parallel mobility measures at baseline and PK2. Finally, models also controlled for baseline values on the outcome variables. For instance, in modeling associations between neighborhood features and general health, baseline health was included as a control. This allowed me to adjust for unmeasured factors with a time-invariant effect on the outcome. Moreover, it also helped account for ceiling effects, as those who reported higher levels of health initially could not show as much positive change as those who had initially reported lower levels, while those who started with lower levels of health at baseline only had upwards to move. By adding this control, other coefficients can be understood as associations between x and y at average levels of baseline y.

Given the structure of RQ2 models, time-varying covariates were constructed as change scores from baseline to PK2. For continuous covariates, change scores were created by subtracting baseline values from PK2 values. Receipt of public assistance was coded as starting, stopping, or stably receiving public assistance between baseline and PK2. Time invariant covariates – i.e., baseline wellbeing indicators, moving since baseline, and hurricane impact covariates – were included without additional adjustments.

Analytic Plan

Preliminary Data Work

Data cleaning was completed using Stata 15.0. Normality was assessed for all continuous measures, and transformations were performed where appropriate. Missing data was handled differently for each research question due to differences between estimators, as discussed in more detail below. Because the analytic sample included only participants with census tract identifiers across all waves, it was important to assess differential attrition. I therefore ran t-tests to compare the analytic sample to the full sample at baseline.

While Hurricanes Katrina and Rita created an exogenous shock that forced most participants from their homes for some time, questions remain about how random peoples' experiences were in the aftermath of the hurricane. For one thing, participants' pre-Katrina characteristics – e.g., their level of resources, or conversely, their social vulnerability – may have impacted their likelihood of being displaced in the first place, as well as their ability to return to the New Orleans area. This could indicate differential agency amongst participants, challenging the assumption that all participants' post-disaster experiences were more random than usual. Of particular interest is the level of randomness in participants' exposure to neighborhood poverty over the course of the study.

To consider these questions, I ran t-tests to compare the baseline characteristics of a) those who were displaced from their neighborhoods versus those who were not, b) of those displaced, those who returned to their neighborhoods by PK1 versus those who did not, and c) of those *still* displaced at PK1, those who returned to their neighborhoods by PK2 versus those who did not. This was followed by a series of OLS regression analyses that considered whether participants' baseline characteristics were related to the economic composition of their neighborhood at PK1 and PK2. Because I could only compare observed characteristics, it is possible that unobserved baseline differences between participants could account for their post-Katrina circumstances, in part. However, these tests provide some insight into whether peoples' post-disaster movements were associated with measured individual differences.

Research Question 1

As noted above, analyses focused on the sample of participants for whom neighborhood of residence was known at baseline, PK1, and PK2 ($N = 606$). To address my first research question, I estimated multi-level mixed effects structural equation models to examine whether - within and between individuals - shifts in neighborhood economic composition were linked to shifts in wellbeing over time, and whether these links were mediated by changes in the presence of specific resources and stressors in the neighborhood over the same period. Mixed effects models have the advantage of simultaneously estimating fixed and random effects. By considering *within-person* change over time, unmeasured factors that have a consistent effect on the outcome of interest can be ruled out as potential third variables (Allison, 2011). Meanwhile, biases in the estimation of random effects that result from the conflation of within- and between-person effects are minimized through the simultaneous modeling of fixed-effects.

To accomplish this, I used a latent mean centering approach recommended by Hamaker and Muthen (2020) to effectively separate the within- and between-person slopes. Within-person mean centering is a common strategy for fixed-effects modeling that allows us to compare individuals to themselves over time. Latent mean centering is an extension of this approach, where it is assumed that the observed mean value for an individual is part of a larger distribution, rather than representing their "true" mean. This is the recommended approach with a small number of repeated measures, as is the case in this study (Hamaker & Muthén, 2020; Lüdtke et al., 2008). The simple equations below illustrate this approach, where y_{it} represents the outcome variable for individual *i* at time *t*, $\mu_{y,i}$ represents the latent mean of *y* for individual *i* across time, x_{it} represents a vector of time varying predictors for individual *i* at time *t*, $\mu_{x,i}$ represents the latent mean of *x* for individual *i* across time, e_{it} represents the residual error term for individual *i* at time *t*, γ_{00} represents the time-invariant intercept, and u_{0i} represents the time-invariant residual error for individual *i* across time.

Within-person equation (fixed effects)**:**

$$y_{it} = \mu_{y,i} + \beta^{w}(x_{it} - \mu_{x,i}) + e_{it}.$$

Between-person equation (random effects):

$$\mu_{y,i} = \gamma_{00} + \beta^{b}\mu_{x,i} + u_{0i}$$

Reconfigured within-person equation:

$$(y_{it} - \mu_{y,i}) = \beta^{w}(x_{it} - \mu_{x,i}) + e_{it}.$$

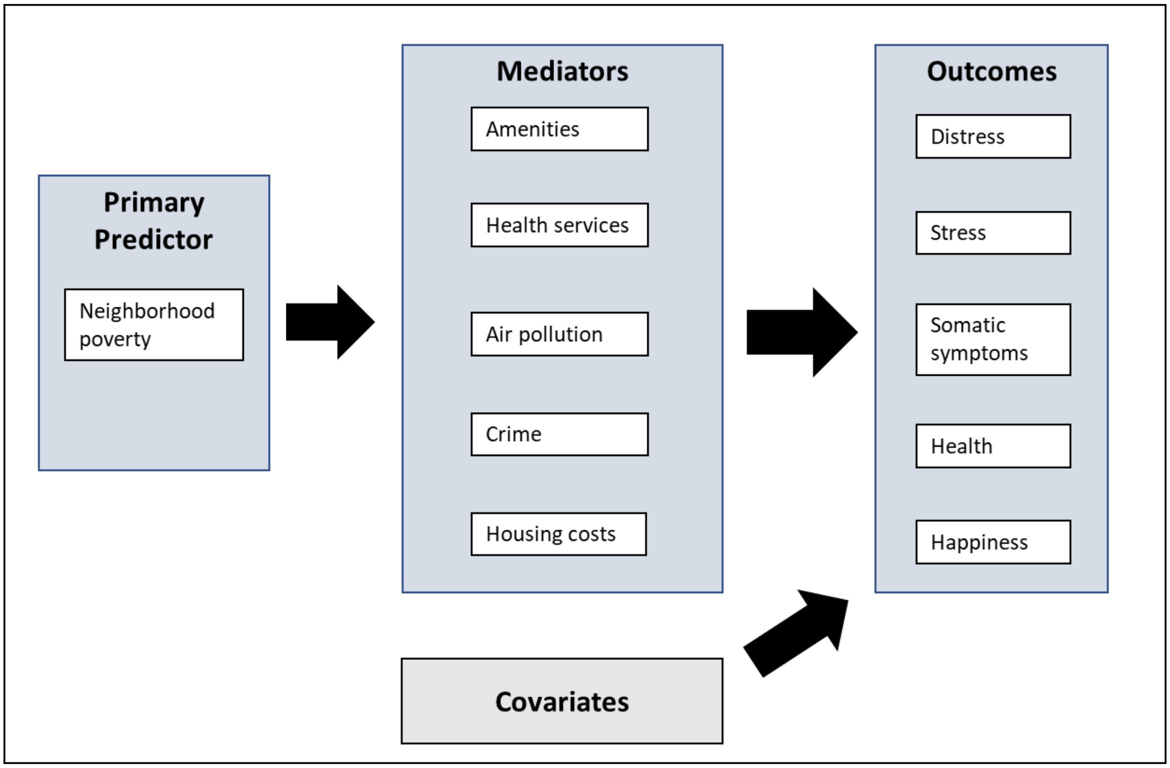
At each time point, I predicted an individual's latent mean centered outcome from their latent mean centered predictors, along with any time varying covariates (not pictured in the above equations). The within-person random intercept $\mu_{y,i}$, aka the within-person latent mean on the outcome variable, was predicted from an individual's latent mean on the predictors, in addition to time invariant covariates.

I applied this strategy in *Mplus* version 8.5 using the Bayes estimator. Data were structured as multilevel such that time points were clustered within individuals. All continuous variables were standardized across waves to facilitate model convergence and the interpretation of results. Across waves, missing data ranged from 1% to 8% for key predictors and outcomes, and from 0% to 16% for covariates. Missing data was minimal at baseline and PK2, with higher rates of missingness at PK1. The Bayes estimator uses a strategy akin to full information maximum likelihood to estimate missing values (Muthén, 2013; Muthén & Muthén, 2017).

Path models were constructed in parallel at the within and between level, with covariates included as predictors of outcome variables. Primary pathways of interest are visualized in Figure 3. Covariances between neighborhood resources and stressors were included to account for the correlated nature of these mediators at the within- and the between-level. To strengthen model fit, covariances between all predictors (including covariates) were included at the within-level (this is discussed in more detail in chapter 4). When using the Bayes estimator, latent mean centering of predictors and mediators is automatic for variables that are modeled at both the within- and the between-level (Muthén, 2021b). Given the complexity of these models, each outcome variable was considered separately to support model convergence.

Figure 3

RQ1 Conceptual Model



Note: This conceptual model is applicable to both fixed- and random-effects portions of RQ1.

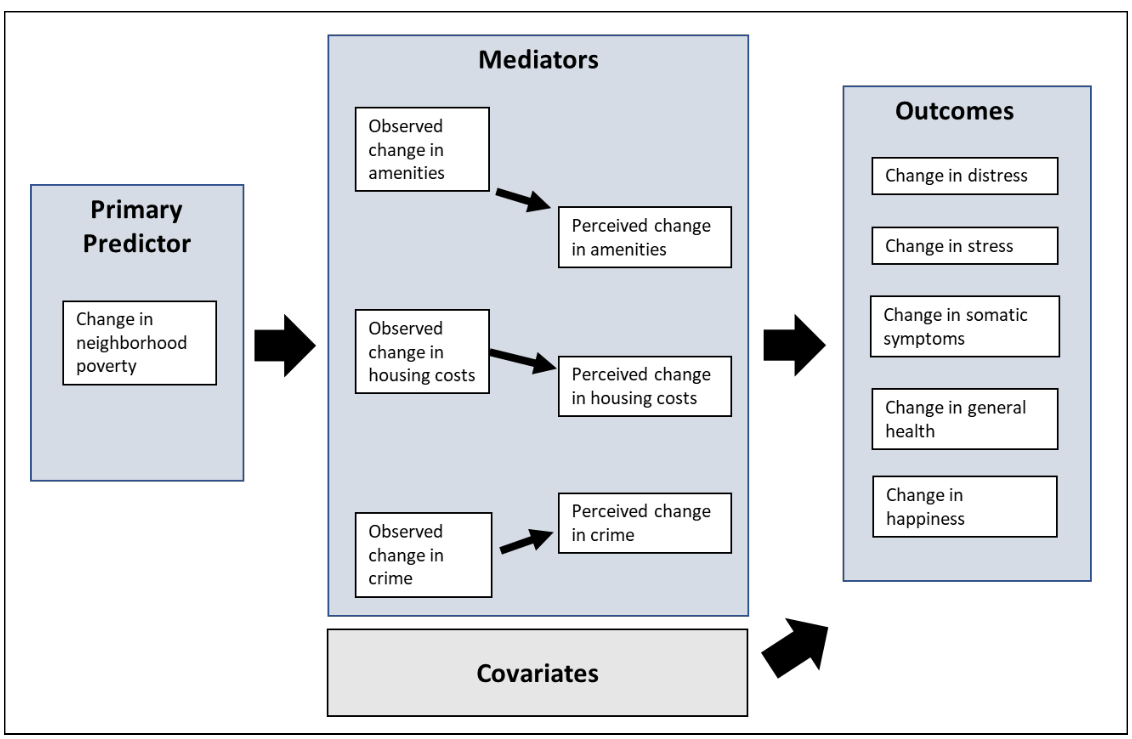
Research Question 2

To address my second research question, I used structural equation modeling to analyze the degree to which *perceived* and *observed* neighborhood change transmits neighborhood poverty to wellbeing. Because perceived changes in neighborhood conditions were assessed through retrospective reports collected at PK2, it was not possible to use a fixed effects framework to address this question. Instead, I computed change scores for all measures collected over time and analyzing the association between changes in the neighborhood economic context and changes in wellbeing as mediated by observed and perceived changes in neighborhood characteristics. This conceptual model is presented in Figure 4. For all continuous variables, change scores were computed by subtracting baseline values from PK2 values. As with RQ1, covariates were included as predictors of outcomes. Covariances were included between observed neighborhood change measures, between perceived neighborhood change measures, and between indicators of wellbeing. As is standard in *Mplus*, covariances were also included between all covariates, and between covariates and other predictors.

As with RQ1, all continuous indicators were standardized to make coefficients more comparable and results more easily interpretable. For key predictors and outcomes, missing data ranged from 0% to 30%, with the highest rates of missingness for perceived change indicators. For covariates, missingness was generally low (0% to 5%), with two exceptions. Change in earnings from baseline to PK2 was missing at 23%, and post-

Figure 4

RQ2 Conceptual Model



Katrina mobility (i.e., the number of moves participants made in the first year post-Katrina) was missing at 40%. Analyses were completed using maximum likelihood estimation with robust standard errors (MLR). This method produces standard errors and chi-square test statistics that are robust to non-normality and non-independence of observations, even in the presence of missing data (Muthén & Muthén, 2017).

Moderation Analyses

As previously discussed, one goal of this dissertation was to test whether the relation between neighborhood features and wellbeing depends on the nature of neighborhood change. In *Mplus*, the most effective way to test moderation with a categorical variable within an SEM framework is through the use of multigroup modeling. Multigroup modeling is a flexible strategy that allows researchers to test for significant differences in measurement and model structure between two or more groups.

Unfortunately, a key constraint of the Bayes estimator is that it does not allow multigroup modeling. While there are some potential workarounds, these are not available for multilevel models. As such, for RQ1, I estimated models separately for stayers and movers. This is parallel to running a fully unconstrained multigroup model in which the two groups – stayers and movers – are allowed to vary across all model parameters. Comparing stayers and movers in this way permits a general assessment of how things may differ for the two groups but does not allow assessment of significant differences in parameters across the two groups.

For RQ2, on the other hand, I was able to conduct multigroup analyses. I undertook this process in several steps. First, I ran models for stayers and movers separately (as with RQ1) to confirm that model fit was adequate for each group independently. Second, I ran two sets of models: fully unconstrained models, wherein all parameters (path coefficients, intercepts, variances, and residual variances) are freely estimated for stayers and movers, and fully constrained models, wherein key parameters of interest (i.e., path coefficients) are constrained to be equal between the two groups. In the case of RQ2 analyses, I left covariate pathways and covariance pathways unconstrained in both sets of models, as these are not the primary pathways of interest. Next, I tested differences in model fit between the constrained and unconstrained models using the Satorra-Bentler scaled chi-square test and log likelihood, as is required with the MLR estimator (Muthén, n.d.; Satorra, 2000; Satorra & Bentler, 2010). If a significant difference in model fit was evident, I then constrained one parameter at a time and tested this model against the fully unconstrained model. This allowed me to assess whether constraining each pathway weakened model fit, which would suggest that it should be left unconstrained. If no significant difference in model fit emerged, on the other hand, that pathway was constrained for a more parsimonious model. Once all primary pathways were tested, I constructed the final multigroup models. These models represent the most parsimonious versions of the initial multigroup models, as they constrain parameters that are not significantly different between the two groups, while allowing parameters that *are* significantly different to be freely estimated for stayers and movers.

Alternative Model Specifications

I ran an alternative set of models using a measure of neighborhood affluence in place of neighborhood poverty. While neighborhood poverty and neighborhood affluence are highly correlated with one another (r= -0.75), they are conceptually distinct and have been seen to relate to neighborhood characteristics and wellbeing in divergent ways

(Alegría et al., 2014; Browning & Cagney, 2003; Weden et al., 2008; Wen et al., 2003). Because most research evaluates neighborhood poverty or disadvantage as the key indicator of the neighborhood economic context, it remains unclear whether effects of neighborhood economic composition are driven by concentrated poverty, the absence of affluence, or some combination of the two (Pickett & Pearl, 2001). When possible, it is therefore important to more clearly delineate the unique contributions of poverty and affluence to wellbeing.

Neighborhood affluence was measured as the proportion of residents in the census tract with a household income of $100,000 or more that year (approximately twice the mean U.S. household income). As with other neighborhood measures, the final indicator represented the average affluence of all census tracts within a 2-mile radius of each person's home census tract. To reduce skew, this variable was transformed using a natural log.

CHAPTER 4: RESULTS

Preliminary Analyses

Sample Descriptives

Sample descriptives at each wave are presented in Table 2. The analytic sample (*N*=606) was predominantly female (93%) and Black or African American (85%). Ten percent of participants were White, less than 3% were Latinx, and less than 2% identified as another race. At baseline, the average age of participants was roughly 25 years old, most were single (76%), most had a high school degree (96%), half were currently employed (50%), and most were receiving some form of public assistance (70%).

Participants' households ranged from 1 to 9 people (average of 3.69 people), they were responsible for 1 to 6 children (average of 1.79 children), and earned an average of $536 per month.

By the final wave, participants were 30 years old on average, the proportion single dropped to 55% while the percent cohabitating and married rose to 15% and 30% respectively, about 15% of the sample had received a college degree, most were employed (76%), and a smaller majority was receiving public assistance (54%). The average household size and number of children rose slightly by PK2 (to 4.12 and 2.12, respectively), and participants' average monthly earnings rose as well to $1,395.

Hurricane impact descriptives are included in Table 3. Almost all participants were evacuated as a result of Hurricane Katrina or Hurricane Rita (98%). Nearly 40% experienced the death of a loved one due to one of these two hurricanes, and participants reported experiencing an average of 3.43 out of 8 hurricane-related traumas. In the first year after Katrina, participants reported moving an average of 2.67 times, with a minimum of zero moves and a maximum of 8. About 37% of participants had returned to their original census tract by PK1, while only 23% were living in their original census tract at PK2.

Descriptively, the mental and physical wellbeing of participants generally worsened after Hurricanes Katrina and Rita, except in the case of perceived stress. The average psychological distress of the sample was lowest at baseline (M = 4.88) and highest at PK1 (M = 6.14). Somatic symptoms rose from an average of .38 to 1.16 symptoms between baseline and PK1, with PK2 levels remaining at heightened levels (M =1.15). Similarly, average levels of general health declined between baseline and PK1 from 4.06 to 3.51, with further declines by PK2 (M = 3.34). Average levels of happiness were highest at baseline (M = 3.31) and lowest at PK1 (3.17), with PK2 levels in between (M = 3.25). In contrast, participants' average perceived stress was highest at baseline (M = 5.43) and lowest at PK1 (M = 5.05). For all wellbeing measures, there was greater variance in the physical and mental wellbeing of participants at later waves.

Neighborhood Descriptives

Descriptive statistics on participants' neighborhoods over time are presented in Table 4. These neighborhood features are reflective of the average characteristics of neighborhoods (i.e., census tracts, zip codes) within 2 miles of an individual's home census tract. At baseline, participants lived in communities where roughly 22% of residents were at or below the federal poverty level on average. Participants' neighborhoods held an average of 17 basic amenities (grocery stores and pharmacies) and 41 health-related businesses (doctors' offices, etc.). Eighteen focal crimes were reported in participants' neighborhoods each month, on average, and roughly 45,600 pounds of air pollution was released within 2 miles of participants' home census tracts. At baseline, neighborhood housing values averaged out to approximately $145,900.

At PK2, participants' neighborhoods had a 20% poverty rate. This reflects a very slight decline in neighborhood poverty from baseline. In terms of neighborhood resources, by PK2, participants' communities housed an average of 11 basic amenities, down from nearly 17 at baseline, and approximately 40 health services, parallel to baseline amounts. Average releases of air pollution within participants' neighborhoods rose to 57,700 pounds by PK2 after a slight lowering at PK1. In contrast, participants' neighborhoods had lower levels of reported crime in PK1 and PK2 than at baseline, down to roughly 11 monthly reports on average. Meanwhile, housing values grew over time, rising to approximately $163,700 by PK2 (adjusting for inflation).

These shifts are reflective of two types of neighborhood change – change within neighborhoods over time, and changes that result from participants moving to new neighborhoods across waves. Because within-neighborhood changes tend to happen gradually, most of the overall shifts in neighborhood features seen in Table 4 are likely driven by moves. This is supported by the fact that over time, there is growing variance in nearly all neighborhood features, as evidenced by higher standard deviations and widening ranges. The exceptions are basic amenities and crime, wherein both the mean and the standard deviation declined over time.

Correlations

RQ1 Analytic Variables

Correlations between indicators of wellbeing and neighborhood predictors are presented in Table 5. All wellbeing indicators were significantly correlated with one another, with links ranging from r=-0.23 between health and somatic symptoms to r=0.55 between distress and stress. Psychological distress, stress, and somatic symptoms were positively linked with one another, and were negatively linked with health and happiness, which worked in the same direction.

Associations between neighborhood indicators were more variable. Neighborhood poverty was also significantly associated with higher amenities (r=0.31) and crime (r=0.30), and with lower health services (r=-0.28), air pollution (r=-0.10), and housing costs (r=-0.32). Interestingly, neighborhood amenities were positively correlated with health resources (r=0.45), crime (r=0.21), and housing values (r=0.08) at statistically significant levels, even though neighborhood amenities were related to neighborhood SES indicators in the reverse direction than were health resources and housing values. Moreover, neighborhood crime was *inversely* related to neighborhood pollution (r=-0.12), and positively associated with housing costs (r=0.08), though correlations were small in size. There was also a moderate correlation between health services and housing costs (r=0.37). The small-to-moderate size of neighborhood correlations meant that collinearity was not likely to be a major analytic problem.

Connections between neighborhood features and indicators of wellbeing were also present, though these were generally smaller in magnitude than the aforementioned associations. While neighborhood factors were not significantly related to distress, neighborhood poverty surprisingly was negatively associated with stress (r=-0.05) and somatic symptoms (-0.08), and positively correlated with health (r=.05) and happiness (r=.07). Like neighborhood poverty, neighborhood amenities were significantly correlated with lower somatic symptoms (r=-0.14) and higher happiness (r=0.12), but at nearly twice the magnitude. Meanwhile, health services and housing costs were significantly correlated with higher somatic symptoms (r=.05 and .09, respectively) and lower happiness (r=-0.05 and -0.08, respectively). At a basic descriptive level, it appears that somatic symptoms and happiness are most connected to neighborhood features. Of course, more rigorous analyses are needed to assess directionality of these connections and to parse out shared variance among different neighborhood features and indicators of wellbeing.

RQ2 Analytic Variables

Given that my second research question requires the use of change scores, I also ran a set of correlations to consider associations between changes in wellbeing and observed and perceived changes in neighborhood features from baseline to PK2. Whereas perceived change was reported by participants at PK2, observed changes in both wellbeing and neighborhood features were computed by subtracting baseline values from PK2 values. These correlations are presented in Table 6.

Considering links between indicators of wellbeing, results are well-aligned with those of Table 5. Changes in distress, stress, and somatic symptoms were generally aligned, as a positive change in one was significantly associated with positive change in the others (r=0.21-0.54). Meanwhile, these indicators were negatively linked with changes in health and happiness (r=-0.19-0.36), while changes in health were positively correlated with changes in happiness (r=0.23). All associations between wellbeing change scores were small-to-moderate in size, ranging from -0.19 to 0.54, and all were in expected directions.

Turning to correlations between neighborhood change indicators, most neighborhood change correlations were more moderate in size. In terms of observed changes in neighborhood features, increasing poverty was correlated with observed increases in amenities (r=0.32) and crime (r=0.25), but observed *decreases* in housing costs (r=-0.27). These patterns mirror findings from Table 5. Correlations with perception variables varied slightly, as increases in neighborhood poverty were correlated with perceived *decreases* in amenities (r=-0.11), perceived *increases* in crime (r=0.23), and were unrelated with perceived changes in costs.

Significant associations between different aspects of neighborhood change were generally small-to-moderate in size, ranging from r=0.08 between observed changes in amenities and changes in housing costs to r=0.43 between observed changes in amenities and changes in crime. As expected, observed changes in amenities were positively correlated with perceived changes in amenities (r=0.17), observed changes in crime were positively associated with perceived changes in crime (r=0.09), and observed changes in costs were positively associated with perceived changes in costs (r=0.09), though these latter two associations were only marginally significant.

Connections between neighborhood change and change in wellbeing were sparse. The only significant associations that emerged were for perceived changes in crime, wherein perceptions of heightening crime were positively associated with changes in stress (r=0.15) and somatic symptoms (r=0.11), and negatively linked with changes in health (r=-0.12). The small-to-moderate size of most of these associations indicates that once again, multicollinearity was unlikely to be a major modeling issue for RQ2.

Testing for Differential Attrition

In order to assess differential attrition over time, I ran a series of t-tests to compare the final analytic sample (N=606) with the sample of participants who dropped out due to missing location data at either PK1 or PK2 (N=413). Results are presented in Table 7. Comparing baseline characteristics, the final analytic sample was very similar to the sample of participants who dropped out over time. There were no significant differences in marital status, education level, employment, race/ethnicity, sex, household composition, or earnings between the two groups. Baseline levels of psychological distress, somatic symptoms, and happiness were also parallel between the groups, though differences in stress and health approached significance, with the analytic sample reporting marginally lower stress and worse health than those who dropped out of the sample. Holistically, results suggest that attrition was relatively random, at least in terms of observed baseline characteristics.

Displacement from and Returns to New Orleans

Differences in Displacement by Baseline Characteristics

I ran a series of independent sample t-tests to consider whether those displaced by the hurricane (i.e., those who reported living somewhere else for a period after Hurricane Katrina or Rita; n = 432) were different in systematic ways from those who were not displaced (n = 168) along baseline characteristics. Results of these analyses are included in Table 8. Results show that compared to those who were not displaced, those who were displaced were more likely to be receiving public assistance at baseline, had higher levels of psychological distress, and were more likely to be Black. However, the two groups were similar in terms of marital status, education, employment, gender, household size, number of children, monthly earnings, and indicators of wellbeing other than psychological distress. This suggests that even within this restricted sample, displacement was more likely for those with heightened social vulnerability along some specific lines.

Differences in Returns by Baseline Characteristics

Restricting the sample to those who were displaced by Hurricane Katrina or Rita (N = 432), I next ran t-tests to consider whether those who returned to their pre-Katrina parish by PK1 (n = 127) were systematically different along baseline covariates from those who did not return (n = 192). Results are presented in Table 8. Compared to those who returned to the original parish by PK1, those who remained displaced at PK1 were more likely to have been receiving public assistance at baseline and were more likely to be Black. No other significant differences emerged. This points to parallel inequities in both initial displacement and in returning to one's original parish.

Finally, considering those who remained displaced at PK1 (n = 192), I ran an additional set of t-tests to compare those who returned to their original parish by PK2 (n = 68) to those who did not (n = 124). Compared to those who returned to their original parish by PK2, those who remained displaced were less likely to be female, and more likely to have been employed at baseline. No other significant differences between the two groups emerged.

Selection into Neighborhoods

To consider the degree to which participants' exposure to neighborhood poverty post-disaster was related to pre-Katrina social vulnerability, I ran a series of OLS regressions in Stata 15.0 that tested associations between participants' baseline characteristics, including indicators of baseline wellbeing, and the poverty of residents' neighborhoods at PK1 and PK2. Regressions adjusted for baseline clustering of participants within census tracts. Findings are presented in Table 9.

Results indicate that only baseline marital status and race/ethnicity were significantly associated with participants' subsequent neighborhood economic composition. Participants who were married at baseline were living in neighborhoods with 0.35 SD less poverty at PK1 than those who were not married. This pattern was replicated at PK2, though the associations were slightly weaker, with those married at baseline living in neighborhoods with 0.28 SD less poverty than those who were unmarried at baseline. At PK2, non-Black participants were living in neighborhoods with

0.53 SD less poverty than Black participants. Meanwhile, baseline wellbeing, household composition, employment, earnings, and sex were unrelated to the economic composition of participants' neighborhoods post-Katrina.

These results indicate that in terms of these observed characteristics, differential selection and/or sorting into neighborhood poverty post-Katrina was quite limited in the present sample. However, marital status may have afforded participants greater neighborhood choice (perhaps via higher household income, which may not be effectively captured by personal monthly earnings). Meanwhile, results suggest that Black participants lived in higher poverty neighborhoods than those of other racial/ethnic groups at PK2, on average. This aligns with work documenting racial disparities in exposure to neighborhood disadvantage (Reardon et al., 2015; Sharkey, 2013), as well as research on the racialized nature of disaster recovery (Gotham & Greenberg, 2014; Groen & Polivka, 2010). While these findings do not preclude the possibility that unobserved characteristics impacted peoples' choice of neighborhoods, they do provide evidence that selection into neighborhood poverty was not significantly associated with measured individual characteristics or functioning of participants at baseline.

Research Question 1

Mediation models investigating the associations between neighborhood economic composition and wellbeing were run separately for each measure of wellbeing to support model convergence. All continuous variables were standardized, such that coefficients can be interpreted as standard deviation unit shifts from the sample mean. The full array of RQ1 covariates predicted the outcome variables at both the within and the between level, with participant race added at the between level.

Model Fit

The Bayes estimator, which is required for individual latent mean centering in *Mplus*, does not provide standard model fit statistics. Instead, this estimator employs a technique known as Bayesian Posterior Predictive Checking using Chi-Square (Asparouhov & Muthén, 2017). For any given model run using the Bayes estimator, a 95% confidence interval is provided for the difference between the observed and replicated chi-square values. A 95% confidence interval that includes zero, where the Posterior Predictive p-value (PPP) is greater than 0.05, demonstrates good model fit (Muthén, 2021a). A non-significant PPP is an indication that there is no statistical difference between the observed and replicated chi-square values using this estimation technique (Muthén, 2021a).

Information on model fit for RQ1 models is included in Table 10. The final presented models represent an attempt to balance model fit with the theoretical integrity of the models at hand. Initial models, which were largely parallel to the final models, demonstrated poor fit, with a 95% CI starting at 800. In response to this finding, alternative models were constructed that maintained all primary model pathways but varied the role of covariates. Model fit was improved drastically by the inclusion of covariances between covariates (e.g., earnings, household size, etc.) and neighborhood features within the fixed-effects portion of the model. Though the current models represent the most effective resolution of model fit issues, model fit remains relatively poor, with *p*-values below 0.05 for all models. However, model fit improved for models run separately for stayers and movers (shown in Table 13), which suggests that low model fit for primarily models may be related to divergent patterns between stayers and movers.

Within Individuals, Changes in Neighborhood Poverty Predicting Changes in Wellbeing

SEM results considering associations between neighborhood poverty and wellbeing are shown in Table 11 and Figure 5, with indirect, direct, and total effects presented in Table 12. Within individuals over time, changes in neighborhood poverty had both positive and negative connections with individual wellbeing. Surprisingly, neighborhood poverty was related to *improvements* in physical health outcomes through several observed neighborhood features. Neighborhood poverty was unexpectedly related to a *positive* shift in amenities (0.39 SD), which in turn predicted declines in somatic symptoms (-0.11 SD) and improvements in health (0.11 SD). This resulted in significant indirect effects, wherein neighborhood poverty was significantly linked to *lower* somatic symptoms and *better* health through increasing neighborhood amenities, with small effect sizes (-0.04 SD and 0.04 SD, respectively). A significant negative indirect effect of neighborhood poverty on somatic symptoms also emerged through health resources (-0.02 SD). Neighborhood poverty predicted declining health services (-0.30 SD), which in turn showed an unexpected *positive* link to somatic symptoms (0.08 SD), indicating that experiencing a decline in neighborhood health resources was associated with a decrease in somatic symptoms.

Turning to mediation through observed stressors, neighborhood poverty was significantly associated with improvements in physical wellbeing through home costs, but not crime or pollution. Increases in neighborhood poverty were related to decreases in neighborhood home costs (-0.35 SD), which showed a positive association with somatic symptoms (0.10 SD) and a negative association with health (-0.07 SD). This resulted in small indirect effects of neighborhood poverty on somatic symptoms and health through decreasing housing costs (-0.03 SD and 0.02 SD, respectively). Shifting neighborhood poverty was also positively associated with shifting crime (0.27 SD), but neighborhood crime was not significantly related to individual wellbeing, resulting in the absence of indirect effects through this pathway. Meanwhile, links between neighborhood poverty and air pollution and between air pollution and wellbeing were nonsignificant.

Despite neighborhood poverty consistently predicting lower somatic symptoms and improved health through these mediating pathways, no total effects of neighborhood poverty on wellbeing emerged. This was due to the presence of opposing direct effects, wherein neighborhood poverty directly predicted higher somatic symptoms (0.08 SD) and worse health (-0.07 SD, p<.10)

Between Individuals, Neighborhood Poverty Predicting Wellbeing

As seen in Table 11, Table 12 and Figure 5, comparing across individuals, connections between neighborhood poverty and wellbeing were relatively limited. While neighborhood poverty was significantly associated with all observed neighborhood features, neighborhood features were rarely associated with individual wellbeing at significant levels. As expected, and in line with fixed-effects findings, results indicate that relatively high poverty neighborhoods had fewer health services (0.24 - 0.25 SDs), higher crime (0.35 - 0.36 SDs), and lower housing costs (0.25 SD) than lower poverty neighborhoods. Neighborhood poverty was also associated with *more* amenities (0.22 - 0.23 SDs), a finding that was surprising but was consistent with fixed-effects findings.

Neighborhood poverty was also unexpectedly associated with *lower* levels of air pollution (0.17 to 0.18 SD), which in turn predicted lower somatic symptoms (0.16 SD), resulting in a small negative indirect effect (-0.03 SD). No direct or total effects of neighborhood poverty on wellbeing were present, and no other indirect effects reached significance.

Role of Covariates

Within Individuals

Several time-varying control variables were included as predictors of wellbeing. Results are included in Table 11. As expected, moving, experiencing hurricane-related death, and hurricane-related trauma were related to worsening wellbeing. Hurricane-related death predicted higher distress, stress, and somatic symptoms (0.27 - 0.53 SD), while moving and hurricane-related trauma predicted higher somatic symptoms and worse health (0.12 – 0.29 SD). Education and earnings showed unexpectedly mixed links with wellbeing, with individuals reporting higher somatic symptoms and worse health after earning a college degree (0.27 - 0.28 SD), while earnings predicted lower stress (0.08 SD) but worse physical health outcomes (0.06 – 0.07 SD). Individual shifts in marital status, household size, and receipt of public assistance were not significantly related to shifts in wellbeing.

Between Individuals

Comparing across individuals, findings diverged in some ways from patterns of associations that emerged within individuals over time. Parallel to within-person findings, hurricane-related stressors predicted worse wellbeing, with hurricane-related death predicting higher distress, stress, and somatic symptoms and worse health (0.46 – 0.55

SD), and hurricane-related trauma predicting worse wellbeing across all indicators (0.46 - 1.00 SD). Moving was also predictive of higher distress (2.38 SD). Meanwhile, education and earnings were associated with wellbeing in expected directions at the between level, with a college degree predicting better health (0.89 SD) and higher earnings predicting fewer somatic symptoms and better health (0.39 – 0.40 SD). Receiving public assistance was associated with worse wellbeing across several indicators of wellbeing, with large effect sizes (0.73 – 1.16 SD). One additional covariate – participant race/ethnicity – was included as a predictor of wellbeing at the between level as well. Results indicate that participants who identified themselves as White, Latino/a/x, or another race reported 0.38 SD more somatic symptoms and 0.24 SD worse health compared to those who identified as Black.

Differences by Type of Neighborhood Change

Because multigroup modeling is not available for models using the Bayes estimator, differences in patterns of associations between neighborhood economic composition and wellbeing via neighborhood features were assessed by estimating models separately for those who lived in the same census tract across all waves, *stayers*, versus those who resided in a different census tract for at least one wave, *movers*. For stayers, neighborhood change was always a product of shifts within the same neighborhood over time. For movers, neighborhood change was reflective of moving to a new neighborhood at least once, in addition to within-neighborhood changes for people who resided in the same tract for two out of the three waves.

Running separate models for these two groups is parallel to running fully unconstrained multigroup models. In describing results, I focus on overarching similarities and differences in associations for stayers versus movers. However, it is important to note that because of the constraints of the Bayes estimator, I could not test differences in specific pathways for stayers versus movers. As such, differences must be interpreted with caution.

Model Fit

As with primary RQ1 models, model fit was assessed through Bayesian Posterior Predictive Checking using Chi-Square. Results are displayed in Table 13. Model fit was good for the stayer sample, as the difference between observed and replicated chi-square values was no different from zero (posterior predictive *p-value*s were always above 0.05). For movers, however, model fit was not as strong. Though the 95% CI for the difference between observed and replicated chi-square values included zero for all outcomes, two out of five associated significance tests indicate that the difference between observed and replicated chi-square values may be different from zero (p=0.04), with the other three significance tests just surpassing statistical significance (p=0.05).

Within Individuals, Changes in Neighborhood Poverty Predicting Changes in Wellbeing

Results for neighborhood poverty models run separately for stayers and movers are presented in Table 14, Table 15, and Figure 6. Indirect, direct, and total effects of neighborhood poverty on wellbeing are presented in Table 16 and Table 17. Considering within-person change over time, links between neighborhood poverty and wellbeing generally diverged between stayers and movers. Notably, most indirect effects that emerged in primary analyses were driven by the mover sample. Considering the role of neighborhood resources, results show that changes in neighborhood poverty were related to changes in amenities only for movers (0.40 SD). Moreover, shifts in amenities were related to wellbeing only for movers. Consequently, significant indirect effects of neighborhood poverty on somatic symptoms (-0.06 SD) and health (0.06 SD) via rising amenities were present only for movers. Meanwhile, changes in neighborhood poverty were negatively associated with changes in health services among stayers (0.34 SD) as well as movers (0.29 SD), but links between health services and wellbeing were once again present only for movers. As with amenities, this led to a significant indirect effect only for movers, where changes in neighborhood poverty were negatively associated with changes in somatic symptoms via decreasing health services (-0.03 SD) for those who changed neighborhoods over the course of the study.

Findings were similarly inconsistent between movers and stayers in relation to observed neighborhood stressors as potential mediators. Among stayers, neighborhood poverty was unexpectedly associated with *increasing* costs (0.40 SD), which in turn predicted increases in stress (0.57 SD) and somatic symptoms (0.86 SD). This resulted in positive indirect effects of neighborhood poverty on stress (0.21 SD) and somatic symptoms (0.33 SD) via rising home costs. Meanwhile, among movers, neighborhood poverty was associated with *decreasing* home costs for movers (0.36 SD), which was associated with declining somatic symptoms (0.08 SD) and, unexpectedly, *rising* stress (0.07 SD). Consequently, among movers, changing neighborhood poverty had a positive indirect effect on stress (0.03 SD) and a negative indirect effect on somatic symptoms (-0.03 SD) via decreasing home costs. Notable differences between stayers and movers also emerged in associations between neighborhood poverty and the remaining neighborhood stressors. Shifts in neighborhood poverty were positively associated with shifts in crime for movers (0.26 SD) but not stayers. More surprising, shifts in neighborhood poverty were *negatively* related to shifts in air pollution for stayers (-0.36 SD), while no such link emerged for movers. However, neither pollution nor crime were related to wellbeing, so no indirect effects through these pathways emerged. Collectively, these results indicate that patterns of neighborhood change differed for those experiencing change in one New Orleans neighborhood over time versus those who experienced mobility-related change.

Considering the accumulation of direct and indirect effects, no significant total effects of neighborhood poverty on wellbeing were present for stayers or movers. Among movers, total indirect effects of neighborhood poverty on somatic symptoms and health reached significance. However, increasing neighborhood poverty was *directly* related to higher somatic symptoms (0.08 SD), resulting in a null total effect of neighborhood poverty on somatic symptoms. Similarly, a negative (though non-significant) association between neighborhood poverty and health led to a null total effect of neighborhood poverty on health among movers. As such, despite neighborhood poverty being linked to wellbeing in divergent ways between movers and stayers, total effects of neighborhood poverty were absent for both groups.

Between Individuals, Neighborhood Poverty Predicting Wellbeing

Comparing individuals based on their average individual and neighborhood characteristics across waves, links between neighborhood poverty and wellbeing emerged only for movers, as neighborhood features did not significantly predict wellbeing for stayers. However, links between neighborhood poverty and neighborhood features were generally parallel for stayers and movers, in contrast to the fixed-effects portion of the model. For both stayers and movers, neighborhood poverty was predictive of having fewer neighborhood health services (~-0.31 SD and ~-0.25 SD), higher levels of neighborhood crime (~0.26 SD and ~0.41 SD), lower neighborhood home costs (~-0.23 SD and ~-0.25 SD), and, unexpectedly, *lower* levels of neighborhood air pollution (~-0.19 S and ~-0.20 SD), though this latter link only approached significance for stayers. Among movers, neighborhood health services were linked to *lower* somatic symptoms (-0.76 SD), resulting in a positive indirect effect of neighborhood poverty on somatic symptoms (0.18 SD). Also among movers, lower levels of air pollution in higher poverty neighborhoods were associated with lower somatic symptoms (0.41 SD), contributing to a negative indirect effect of neighborhood poverty on somatic symptoms (-0.08 SD). Among stayers, neighborhood features did not predict wellbeing, leading to the absence of parallel indirect effects. Results showed one additional divergence in findings for stayers versus movers, wherein neighborhood poverty significantly predicted having more neighborhood amenities only for movers (0.21 SD). Heightened amenities were in turn unexpectedly associated with *higher* somatic symptoms for movers (1.05 SD), leading to a significant indirect effect of neighborhood poverty on somatic symptoms through this path (0.21 SD).

Taken together, results show that neighborhood poverty was significantly related to wellbeing only for movers, and only in relation to somatic symptoms. Among movers, positive effects of neighborhood poverty on somatic symptoms through amenities and health services were countered by a negative effect through pollution, contributing to the absence of a significant total indirect effect. There were no significant direct effects of neighborhood poverty on wellbeing for movers or stayers, nor were there total effects of neighborhood poverty for either group.

Role of Covariates

Parallel to primary models, models run separately for stayers and movers included covariates as predictors of wellbeing. Results are included in Table 14 and Table 15. Parallel covariates were included as predictors of wellbeing both within and between individuals, except that participant race was also included within the random effects portion of the model. Because the stayer sample lived in the same tract across all waves, neighborhood moves was excluded in this model.

Within Individuals. Comparing covariate pathways between stayers and movers, it is clear that most associations that emerged in primary models were driven by the mover sample. Among movers, associations between covariates and indicators of wellbeing had coefficients that ranged from -0.09 SD between earnings and stress to 0.64 SD between hurricane-related loss and somatic symptoms. As with primary models, among movers, hurricane trauma and death were related to worse wellbeing, and earning a college degree was unexpectedly linked with worse wellbeing. In contrast, among stayers, covariates did not significantly predict wellbeing, perhaps due to the smaller sample of stayers.

Between Individuals. Within the random effects portion of the model, covariate pathways generally diverged between movers and stayers. Similar to fixed-effects covariate findings, most associations found in primary models were driven by the mover sample. Non-Black participants reported higher somatic symptoms than Black participants for stayers and movers (0.47 SD and 0.38 SD). On the other hand, average household size was significantly linked with worse wellbeing only for stayers (0.31 SD), while receiving public assistance, experiencing a hurricane-related death, and hurricane-related trauma were significantly associated with worse wellbeing only for movers (with coefficients ranging from -0.60 to -1.44). Earnings and college education were also related to better wellbeing only among movers (with coefficients ranging from 0.28 SD to 1.17 SD). At face value, these differences suggest that individual-level characteristics and hurricane stressors are less connected to wellbeing among stayers than movers. However, it may be that stayer estimates are simply less precise due to the smaller size of the stayer group. This hypothesis is generally borne out by the larger standard deviations (the Bayes version of standard errors) for stayer estimates.

Research Question 2

Using change scores from baseline to PK2, RQ2 considers how observed and perceived changes in neighborhood features mediate links between neighborhood economic composition and wellbeing. Data were standardized, so all coefficients represent changes in standard deviation units relative to the sample mean. In other words, change in neighborhood features and wellbeing is relative to average levels of change for the given indicator.

Model Fit

Model fit statistics are included in Table 18. Based on standard cutoff criteria for model fit indices (D. Hooper et al., 2008; Schreiber et al., 2006), model fit appears to be good. Comparative Fit Index (CFI) and the Tucker-Lewis Index (TRI) estimates were at or above 0.95, Root Mean Square Error of Approximation (RMSEA) values were under 0.06, and Standardized Root Mean Square Residual (SRMS) values were well under 0.08.

Changes in Neighborhood Poverty Predicting Changes in Wellbeing

Final full-sample RQ2 poverty model results are presented in Table 19 and Figure 7, with indirect, direct, and total effects presented in Table 20. Changes in neighborhood poverty from baseline to PK2 were positively associated with observed changes in amenities (0.32 SD), which were in turn unexpectedly linked to an *increase* in stress (0.08 SD), resulting in a significant positive indirect effect of neighborhood poverty on stress through rising amenities (0.03 SD). Observed changes in amenities were also positively linked to perceived changes in amenity availability (0.25 SD), which was unexpectedly associated with an *increase* in somatic symptoms (0.11 SD). In contrast, a positive change in neighborhood poverty was directly linked with a perceived *decline* in amenity availability (0.22 SD), which in turn predicted lower somatic symptoms (0.11 SD). However, neither indirect effect involving perceived shifts in amenities reached significance.

Shifts in neighborhood poverty were also negatively associated with observed changes in neighborhood housing costs (-0.27 SD) and positively associated with observed changes in crime (0.25 SD), but neither of these neighborhood features was significantly related to perceived changes in the same construct or to changes in wellbeing. However, changes in neighborhood poverty positively predicted *perceived* changes in crime (0.26 SD), which in turn predicted increases in stress (0.09 SD) and somatic symptoms (0.14 SD) and decreases in health (0.14 SD). Indirect effects of neighborhood poverty on somatic symptoms (0.04 SD) and health (-0.04 SD) through perceived increases in crime reached significance, while the indirect effect of neighborhood poverty on stress only approached significance.

One direct link between changing neighborhood poverty and wellbeing was present, with increasing neighborhood poverty unexpectedly predicting lower stress (or conversely, declining poverty predicting a rise in stress; 0.08 SD). This direct effect counteracted indirect effects of changing neighborhood poverty on stress, resulting in the absence of a total effect. Total effects also did not emerge for any other indicators of wellbeing, likely due to the small size of indirect effects and the presence of opposing (though non-significant) indirect and direct effects.

Role of Covariates

As in RQ1, covariates were included as predictors of wellbeing. Results are included in Table 19. Baseline levels of wellbeing were negatively associated with change in wellbeing over time, with coefficients ranging from -0.39 SD for somatic symptoms to -0.65 SD for happiness. For example, those with relatively high stress at baseline generally experienced a decline in stress across waves (0.56 SD). This may be explained by regression to the mean and/or ceiling and floor effects, where those with high initial values have limited room to move upwards while those with low initial values have limited room to move downwards. As expected, an increase in earnings over the course of the study was linked to improved wellbeing across several indicators (coefficients ranged from 0.09 SD to 0.12 SD), while experiencing hurricane-related trauma or death was related to worsening wellbeing (coefficients ranged from 0.16 SD to 0.24 SD). Several piecemeal associations also emerged: increasing household size was linked with declines in distress (0.07 SD), stopping *and* starting receipt of public assistance were linked with increases in happiness compared to stably receiving public assistance (0.16 SD and 0.22 SD), and high post-Katrina mobility was linked with an increase in somatic symptoms (0.11 SD).

Multigroup Models

Moderation by type of neighborhood change was tested in several steps. I report results from two of these steps here – models run separately for those who were residing in the same New Orleans neighborhood at baseline and PK2 (stayers) versus those who had moved neighborhoods by PK2 (movers), and final multigroup models that are more parsimonious versions of these models (see chapter 3 for full description). Below, I describe differences between movers and stayers that are robust across these two modeling strategies, with coefficients drawn from the final multigroup models unless otherwise noted.

Model Fit

Model fit indices for multigroup models are presented in Table 21. CFI values were above .95, and RMSEA and SRMR values were below .06 for the fully unconstrained and the final multigroup models. Though TLI values were just below .95 for both sets of multigroup models, fit indices generally point to good fit.

Turning to comparisons between unconstrained and final multigroup models, sample-size adjusted Bayes Information Criterion (BIC) values suggest that the final multigroup models are slightly better fitting than the fully unconstrained models, as the BIC is smaller for the final models (Schreiber et al., 2006). This is likely due to the fact that the final models are more parsimonious, with fewer pathways left unconstrained. Meanwhile, results from the Satorra-Bentler scaled chi-square difference tests (Satorra, 2000; Satorra & Bentler, 2010) indicate that the final multigroup models are no different (i.e., no *worse*-fitting) than the fully unconstrained models. In all, results suggest good model fit for both sets of models, with the final multigroup models representing the best fit.

Changes in Neighborhood Poverty Predicting Changes in Wellbeing for Stayers versus Movers

Results are presented in Table 22 and are visualized in Figure 8, with indirect, direct, and total effects displayed in Table 23. In both the fully unconstrained and the final multigroup models, links between changes in neighborhood poverty and changes in observed neighborhood features were significant only for movers. For those who relocated, changes in neighborhood poverty from baseline to PK2 were positively associated with observed changes in amenities (0.31 SD) and crime (0.26 SD) and negatively associated with observed changes in costs (-0.31 SD). No such associations emerged for stayers. Meanwhile, associations between mediating neighborhood features and indicators of wellbeing were not significantly different for movers versus stayers, so these pathways were constrained to be equal in the final multigroup model. For both groups, an observed increase in amenities was associated with a rise in stress (0.08 SD), while observed shifts in costs and crime were not linked to wellbeing. Given differences in associations between neighborhood poverty and amenities between stayers and movers, this resulted in a significant positive indirect effect of changing poverty on stress (0.02 SD) through increasing amenities only for movers.

Meanwhile, changes in neighborhood poverty were negatively associated with perceived changes in amenities for both movers and stayers (-0.21 SD), which were positively linked with changes in somatic symptoms for both groups (0.12 SD).

Additionally, as in primary analyses, observed changes in amenities were positively linked to perceived changes in amenities (0.25 SD). While these links were only significant for movers in fully unconstrained model, results of model fit comparisons indicated that they were not statistically different between groups. They were therefore constrained to be equal for movers and stayers. This resulted in the only parallel indirect effect between movers and stayers, where changes in neighborhood poverty were negatively linked to somatic symptoms (-0.02 SD) through a perceived loss in amenities. For movers, however, this association was countered by a small but significant positive indirect effect of neighborhood poverty on somatic symptoms (0.01) through observed and then perceived changes in amenities.

An additional divergence occurred in relation to perceived crime. For movers, changes in neighborhood poverty were positively associated with perceived changes in crime (0.24 SD), while no significant link emerged for stayers. For both movers and stayers, a perceived rise in crime was associated with a rise in stress (0.09 SD) and somatic symptoms (0.14 SD), and a decrease in health (0.13 SD) and happiness (0.09 SD). As with amenities, while these associations were generally driven by the mover sample, they were not significantly different between movers and stayers. Given these associations, indirect effects of neighborhood poverty through perceived crime were only possible for movers. Several indirect effects reached significance, with changes in neighborhood poverty predicting increased somatic symptoms (0.03 SD) and lower health (-0.03 SD) among movers through perceptions of rising crime, while indirect effects on stress and happiness only approached significance.

While indirect effects of neighborhood poverty on wellbeing were more common for movers, total effects of neighborhood poverty were present only for stayers. Among stayers, changes in neighborhood poverty were negatively associated with stress (-0.29 SD), a total effect that was largely driven by a marginally significant direct effect of increasing neighborhood poverty on decreasing stress (-0.27 SD, $p<.10$). A significant total effect of neighborhood poverty on happiness (0.32 SD) also emerged for stayers, driven by a significant direct effect of increasing neighborhood poverty on increasing happiness (0.32 SD). In contrast, for movers, no direct or total effects of neighborhood poverty reached significance.

Role of Covariates

As with primary models, covariates were included to predict outcome variables. These pathways are not included in multigroup tables due to the length of these tables; however, the aforementioned results control for the same array of covariates as the primary models, with the exception of the "moved tracts" variable which is accounted for in the multigroup structure of the analyses.

While most links between covariates and wellbeing change scores within unconstrained and final multigroup models are relatively consistent with those identified in primary models, a few divergences are worth noting. One is that most covariate associations were largely driven by the mover sample. Among stayers, only baseline wellbeing and hurricane-related trauma were consistent predictors of outcomes, with higher baseline scores on wellbeing indicators predicting declines in those indicators over time, and hurricane trauma predicting worse mental and physical health (with effect sizes ranging from 0.18 to 0.72 SD). In contrast, associations that were present in primary models between earnings, household size, public assistance, hurricane-related death, and post-Katrina mobility and wellbeing change scores were generally present only for movers in multigroup models. This may point to overarching differences between those who lived in the same tract over time versus those who lived elsewhere for at least one wave. On the other hand, both the larger sample size and greater variability across indicators in the mover sample may have increased power and precision in estimation for this group.

Alternate Model Specifications

As previously noted, alternate models were run using neighborhood affluence in place of neighborhood poverty. Results of full affluence models including fit indices are included in the appendix. An abbreviated summary of results is presented below.

Descriptives

Whereas neighborhood poverty rates stayed relatively consistent across waves, neighborhood affluence shifted more drastically. As seen in Table 4, at baseline, participants lived in communities where approximately 11% of residents were affluent, making $100,000 or more in annual income. At PK2, the average rate of neighborhood affluence had risen to 17%. Correlations between RQ1 model variables, included in Table 5, show that neighborhood affluence was linked with lower amenities (r=-0.24) and crime (r=-0.14), and with higher health services (r=0.38), and housing costs (r=0.68), though affluence was not significantly correlated with pollution. In terms of outcome measures, neighborhood affluence was significantly correlated with higher somatic symptoms (r=0.18) and lower health (r=-0.06) and happiness (r=-0.16). Considering correlations between RQ2 indicators, included in Table 6, changes in neighborhood affluence were associated only with observed increases in housing costs (*r*=0.60) and perceptions of decreasing crime (*r*=-0.15).

Results of preliminary regression analyses (shown in Table 24) indicate that selection into neighborhood affluence based on baseline characteristics was limited. Those who were married at baseline had higher neighborhood affluence at PK1 than those who were not married, while non-Black participants lived in more affluent neighborhoods at PK2 than did Black participants. However, neither baseline health problems nor other individual characteristics selected participants into more affluent neighborhoods over time. These findings mirror results for neighborhood poverty.

RQ1 Results

Results of RQ1 analyses are included in Table 26 and Table 27 and pictured in Figure 9. Within RQ1 models, links between neighborhood affluence and wellbeing were not significantly mediated by observed neighborhood features within or between individuals. Within individuals, neighborhood affluence was associated with higher health services (0.30 SD) and costs (0.64 SD) and lower amenities (~-0.34 SD) and crime (-0.12 SD); however, none of these neighborhood features were linked with wellbeing. Between individuals, neighborhood affluence was linked to higher health resources (0.61 SD) and costs (0.76 SD) and lower crime (-0.20 SD), none of which were linked to wellbeing. However, neighborhood affluence was directly linked to lower happiness (-0.38 SD).

In comparing RQ1 results for stayers versus movers (see Table 29, Table 30, and Figure 10), several key differences emerged. Between individuals, neighborhood affluence was unrelated to wellbeing for both movers and stayers. In contrast, within individuals, shifts in neighborhood affluence were indirectly related to shifts in wellbeing for both movers and stayers, but through different mediating pathways. For both groups, within individuals, neighborhood affluence predicted a drop in amenities (~-0.51 SD for stayers; ~-0.35 SD for movers) and crime (~-0.12 SD for stayers and movers), and an increase in costs (~0.71 SD for stayers, ~0.63 SD for movers). Changes in costs were linked to heightened somatic symptoms only for stayers (0.85 SD), while changes in amenities were associated with declines in somatic symptoms (-0.10 SD) and improvements in health (0.09 SD) only for movers. For stayers, there was thus a positive indirect effect of neighborhood affluence on somatic symptoms via rising home costs (0.60 SD), while for movers, there was a positive indirect effect on somatic symptoms (0.04 SD) and a negative indirect effect on health (-0.03 SD) via declining amenities. However, among stayers, neighborhood affluence was also unexpectedly associated with *declining* health services (-0.15 SD; contrasting with a positive association among movers), which was in turn linked to lower distress only for stayers (0.83 SD). This resulted in a negative indirect effect of neighborhood affluence on distress for stayers (-0.11 SD). Meanwhile, among movers, there was a negative direct link between shifts in neighborhood affluence and health (-0.10 SD).

Overall, results of RQ1 analyses were similar to those from neighborhood poverty models, though associations between neighborhood features and wellbeing were attenuated in models that used neighborhood affluence. Links between neighborhood economic composition and neighborhood resources and stressors were generally mirrored when using neighborhood affluence instead of neighborhood poverty; however, for stayers, changes in neighborhood affluence and neighborhood poverty *both* negatively predicted health resources. This may point to the unique nature of neighborhood change within New Orleans neighborhoods through these years.

RQ2 Results

Results of RQ2 analyses are included in Table 34, Table 35, and Figure 11. Shifts in neighborhood affluence were related to a perceived rise in amenities (0.15 SD) and a perceived decline in crime (-0.23 SD), but were unrelated to observed changes in amenities and crime, in contrast to poverty models. Though perceived shifts in amenities predicted heightened somatic symptoms (0.11 SD), no indirect effect through this pathway emerged. Perceived changes in crime were positively linked with stress (0.09 SD) and somatic symptoms (0.13 SD) and negatively linked with health (-0.15 SD). Given these connections, shifts in neighborhood affluence were significantly related to changes in somatic symptoms (-0.03 SD) and health (0.03 SD) through a perceived decline in crime, though the potential effect on stress was not significant. Shifts in neighborhood affluence were also related to an observed rise in costs (0.60 SD), but home costs were not linked to wellbeing. Finally, mirroring neighborhood poverty models, neighborhood affluence directly predicted heightened stress (0.11 SD).

Turning to multigroup analyses (shown in Table 37, Table 38, and Figure 12), links between neighborhood affluence and observed neighborhood features differed for stayers versus movers; otherwise, models were parallel between the two groups. First considering parallel links, for stayers and movers, changes in neighborhood affluence were associated with perceptions of lessening crime (-0.19 SD), which were in turn related to lower stress (0.09 SD), lower somatic symptoms (0.14 SD), better health (-0.14 SD), and heightened happiness (-0.09 SD). However, only the indirect effect of changes in neighborhood affluence on health was significant (0.03 SD). Neighborhood affluence was also positively linked to changes in amenities for both groups (0.14 SD), which surprisingly predicted heightened somatic symptoms (0.12 SD), though no significant indirect effect through this pathway emerged.

Considering divergent associations, one indirect effect was present only for stayers: changes in neighborhood affluence were linked to a sizable observed increase in amenities (1.21 SD), which predicted perceptions of improved amenities (0.21 SD), which in turn predicted *heightened* somatic symptoms (0.12 SD), resulting in an unexpected positive indirect effect of neighborhood affluence on somatic symptoms (0.03 SD). Also unique to stayers was that shifts in neighborhood affluence were unexpectedly associated with an observed *rise* in crime (0.58 SD), though observed shifts in crime were unrelated to wellbeing. Finally, one indirect effect emerged only for movers: changes in neighborhood affluence were unexpectedly linked to *lower* distress through heightened home costs (-0.06 SD). While observed changes in home costs were surprisingly associated with lower distress for both movers and stayers (-0.09 SD), shifts in neighborhood affluence were related to rising home costs only for movers (0.64 SD).

As with RQ1 models, patterns of findings were relatively similar when using neighborhood affluence in place of neighborhood poverty. In full sample analyses, the key difference was that changes in neighborhood affluence did not predicted observed changes in amenities or crime, whereas changes in neighborhood poverty were predictive of all observed shifts in neighborhood features. Multigroup analyses suggest that neighborhood poverty was a stronger predictor of neighborhood features for movers, while neighborhood affluence was a stronger predictor for stayers. Interestingly, for stayers, shifts in neighborhood affluence predicted increasing amenities and crime, while for movers, shifts in neighborhood poverty predicted increasing amenities and crime. As with RQ1 stayer findings, this points to the potentially unique circumstances of neighborhood change in New Orleans over this period.

CHAPTER 5: DISCUSSION

A large body of literature documents associations between the neighborhood economic context and individual wellbeing (Do & Finch, 2008; Finch et al., 2010; Ludwig et al., 2012; Pickett & Pearl, 2001; Sampson et al., 2002). Research generally indicates that that those who live in relatively low poverty neighborhoods tend to report better physical and mental health than those in higher poverty neighborhoods, with some research also finding that individuals and families with low levels of income experience psychological and health benefits from moving to and remaining in relatively low poverty neighborhoods (Cooper et al., 2014; Fauth et al., 2004, 2008; Ludwig et al., 2012, 2013). Though these findings suggest that neighborhood poverty and/or affluence have a causal impact on peoples' mental and physical wellness, more research is needed to clarify why and under what circumstances the neighborhood economic context affects health and wellbeing. Without a more nuanced understanding of these links, policy efforts to improve the health and wellbeing of those facing marginalization are likely to fall short.

This dissertation sought to unpack links between the neighborhood economic context and wellbeing through two lines of inquiry. First, using a mixed-effects framework, it examined the degree to which observable resources and stressors within the residential context mediated associations between the neighborhood economic context and wellbeing both within- and between individuals, drawing attention to several understudied components of the neighborhood context including institutional resources, housing costs, and pollution. Second, this work considered whether observed changes in neighborhood features aligned with peoples' perceptions of change, and how both observed and perceived changes in neighborhood resources and stressors helped explain associations between the neighborhood economic context and wellbeing. To further clarify the nature of these links, primary analyses were followed by multigroup analyses that considered how patterns diverged for those who experienced change in one neighborhood over time versus those who experienced residential mobility over the study period.

Findings from this dissertation add nuance to the existing literature. Focusing on a sample of young parents with limited financial means, all of whom experienced some form of rapid neighborhood change in the aftermath of Hurricane Katrina, overall effects of neighborhood economic composition on wellbeing were quite limited. This is not to say, however, that the economic composition of peoples' neighborhoods was unrelated to their wellbeing. Rather, associations were complicated, with indirect effects offsetting direct effects, different indirect effects offsetting one another, and patterns of associations diverging between movers and stayers. Considering all mediating pathways, mixed effects models generally pointed to *positive* links between neighborhood poverty and wellbeing, contrasting with most prior literature. On the other hand, change models that considered mediation through perceptions of neighborhood change in addition to observed neighborhood change generally found *negative* links between neighborhood poverty and wellbeing, though some divergent pathways emerged here as well.

To fully explicate these results, the following discussion is broken into several sections. I first discuss overarching takeaways from the present research, considering both sets of models holistically. Next, I focus more specifically on takeaways from RQ1 and RQ2 analyses, highlighting how the present work fits into the larger literature and speculating on the potential drivers of unexpected results. I then discuss how results shift when considering links between neighborhood poverty and wellbeing for stayers separately for movers, exploring potential explanations for divergent findings. Finally, I touch on the role of neighborhood poverty versus neighborhood affluence on wellbeing. I wrap up with a discussion of general implications, limitations, and future directions.

How Neighborhood Economic Composition is Connected to Wellbeing

This dissertation sought to unpack links between structural neighborhood features and individual functioning. To do so, I considered an array of resources and stressors within the neighborhood context that have been theorized to drive associations between neighborhood economic composition and wellbeing. Findings provided support for some hypothesized pathways while countering others. While findings are complex and vary by research question, several overarching conclusions can be drawn from this collection of analyses.

First, in contrast to much of the prior literature, results of the present research point to benefits of neighborhood poverty as well as detriments. One place this is evident is in links between neighborhood poverty and neighborhood resources and stressors. In line with existing literature (Graif et al., 2014; Sampson et al., 1997; Van Sandt et al., 2021), the present research found heightened levels of crime and fewer health services in high poverty communities. However, neighborhoods with high levels of poverty tended to also have more amenities, lower costs, and lower pollution than neighborhoods with lower levels of poverty. Though some of these links may be unique to the present sample, their presence here underscores the importance of recognizing assets that may accompany neighborhood poverty, as well as losses that may occur as neighborhood poverty declines and/or people move to lower poverty neighborhoods. While prior research has found that social connectedness and place attachment are critical resources in many underserved communities (August, 2014; Chamlee-Wright & Storr, 2009; Clampet-Lundquist, 2007; Shelby, 2017), the present research highlights additional community assets that warrant further exploration.

Links between neighborhood poverty and wellbeing were more complex, but findings similarly point to some benefits and some disadvantages. RQ1 analyses revealed that neighborhood poverty was related to *improvements* in physical health through observed neighborhood features, both within individuals over time and between individuals. However, benefits transmitted through indirect effects were generally offset by opposing direct effects. For instance, within individuals, a rise in neighborhood poverty was associated with a *decline* in somatic symptoms through mediating pathways but was directly linked with a *rise* in somatic symptoms. As a consequence of opposing associations, no total effects of neighborhood poverty on wellbeing emerged in RQ1 analyses. RQ2 models also found evidence of both positive and negative links between neighborhood poverty and wellbeing, though patterns differed. Increases in neighborhood poverty from baseline to PK2 were generally associated with *worsening* wellbeing over this period through mediating pathways. However, increases in neighborhood poverty were also *directly* linked with lessening stress, pointing to select benefits. As with RQ1, the presence of opposing direct and indirect effects led to the absence of total effects of neighborhood poverty on wellbeing. These findings add nuance to our existing understanding of these links, demonstrating that structural neighborhood features like concentrated poverty are not simply beneficial or harmful, but are instead related to individual wellbeing in complex ways. Though causation cannot be established here, findings suggests that the economic composition of the neighborhood may become meaningful for peoples' functioning by shaping what resources and stressors are present within that context, as well peoples' perceptions of their context. As discussed in more detail later, however, some of these connections worked in unexpected ways.

Second, of the various indicators of mental and physical wellbeing considered in the present study, results indicate that somatic symptoms and general health were most consistently connected to neighborhood features. In contrast, psychological distress and happiness were not significantly associated with neighborhood features in primary models, while stress was predicted by neighborhood characteristics only in RQ2 models. This seems to suggest that physical aspects of health may be more sensitive to effects of the neighborhood context than psychological aspects of health. This generally aligns with prior research, which has found more consistent connections between neighborhood SES and physical health than between neighborhood SES and mental health outcomes (Mair et al., 2008; Pickett & Pearl, 2001; Riva et al., 2007). The fact that links between changing neighborhood poverty and changing stress emerged in RQ2 models is also somewhat aligned with existing literature, as there is some evidence of neighborhood effects on allostatic load (Finch et al., 2010; Robinette et al., 2016; Schulz et al., 2013). While the present research does not consider allostatic load per se, measures of perceived stress and somatic symptoms seem most likely to capture physiological stress, which may underly longer-term health effects of the neighborhood context (Ellen et al., 2001; Geronimus, 1992). Despite the general absence of significant associations with distress and happiness, it is important to note that indirect links between the neighborhood economic context and these indicators through alternate mediating pathways may exist. For example, there is relatively strong evidence that neighborhood social dynamics are related to residents' mental health (Ellen et al., 2001; Mair et al., 2008). Because these dynamics were not examined in the present study, we cannot dismiss the possibility that neighborhood poverty is connected to mental health through these factors.

Finally, results generally suggest that *changes* in the neighborhood context are more relevant to wellbeing than average neighborhood characteristics. Whereas neighborhood poverty was rarely associated with wellbeing within the random effects portion of RQ1 models, changes in neighborhood features were related to several indicators of wellbeing through diverse mediating pathways, both in RQ1 and RQ2 analyses. The importance of neighborhood change has been documented in several other studies (Do & Finch, 2008; Kirk & Laub, 2010). However, given that most studies of neighborhood effects are cross-sectional in nature (Arcaya et al., 2016), the importance of neighborhood change relative to average neighborhood features is less well understood. Even with longitudinal data, standard random-effects models produce estimates that are a mix of within- and between-person effects (Hamaker & Muthén, 2020). As such, links between neighborhood features and wellbeing found in prior work typically reflect combined effects of average neighborhood features and shifts in neighborhood features (Hamaker & Muthén, 2020).

The modeling techniques used in the present study have the advantage of capturing change over time while also providing a more rigorous test of associations than do standard random effects models. In particular, using a mixed-effects modeling framework disentangles within- and between-person associations, which reduces bias and produces more meaningful estimates, while the use of change scores approximates a fixed effects model with just two time points, reducing bias caused by unmeasured factors with time-invariant effects on the outcome (Allison, 2011; Dalecki & Willits, 1991; Hamaker & Muthén, 2020). While the use of these more nuanced techniques may be responsible for the elevated relevance of neighborhood change in the present models, these findings could alternatively be related to the unique nature of the present sample. In particular, the destruction and dislocation caused by Hurricane Katrina likely produced elevated within-person variability in neighborhood features and individual wellbeing. This may have improved the precision of within-person estimates in comparison to other studies of neighborhood change, in addition to reducing the stability of average neighborhood estimates.

In any case, findings of the present study provide compelling evidence that select neighborhood features – in particular, amenities, housing costs, and perceived crime – are implicated in peoples' wellbeing. However, the relative dearth of random effects brings up important questions. For example, if changes in neighborhood features are related to changes in wellbeing within individuals, why would parallel associations be absent when comparing neighborhood contexts across individuals, as in the random effects portion of RQ1? One potential explanation is that changes in neighborhood features have short-term implications for wellbeing, but that people adjust to the new normal after some time has passed. While no research of which I am aware has tested this specific hypothesis, some evidence does suggest that links between family-level mobility and children's functioning dissipate over time (Coley & Kull, 2016). However, results of several mobility studies point to both short- and long-term benefits of relocation, particularly for those who remained in lower poverty neighborhoods over time (Fauth et al., 2004, 2008; Leventhal

& Brooks-Gunn, 2003; Ludwig et al., 2013)**,** and in at least one case, even when moves were involuntary (Cooper et al., 2014). This seems to suggest that effects of neighborhood change are not temporary, at least for those who move to more advantaged communities. However, it is unclear whether this applies to change happening within a given neighborhood over time. Alternatively, average levels of neighborhood poverty may be unrelated to average levels of wellbeing because across the sample, those average values are reflective of diverse experiences of neighborhood change. For example, two individuals could live in neighborhoods with similar levels of neighborhood poverty on average, but those neighborhoods could have gone through opposite trajectories of change over the course of the study. As such, the general absence of random effects in RQ1 could be an artifact of the estimation process. While questions remain, these findings underscore the importance of considering the dynamic nature of neighborhoods and wellbeing.

Of course, examining effects of neighborhood economic composition on wellbeing without attention to potential mediating pathways muddles our understanding of how the neighborhood context becomes meaningful for individuals. In the following sections, I discuss the mediating role of observed and perceived neighborhood resources and stressors, consider how patterns of associations diverge between stayers and movers, and discuss the relative importance of neighborhood poverty versus neighborhood affluence.

RQ1: The Mediating Role of Observed Resources and Stressors

RQ1 analyses considered the degree to which neighborhood amenities, health services, pollutants, crime, and costs, measured using administrative data, mediated the relation between the neighborhood economic context and individual wellbeing. Given findings from the limited research on neighborhood resources (Bower et al., 2014; Larson et al., 2009; Van Sandt et al., 2021), I generally expected that both amenities and health resources would be more highly concentrated in affluent, low poverty neighborhoods, and that these resources would be supportive of wellbeing. In line with expectations, neighborhood poverty negatively predicted health services both within and between individuals. However, neighborhood health services were surprisingly associated with *higher* somatic symptoms within the fixed effects portion of the model, indicating that for individuals, gaining neighborhood health services predicted *worsening* wellbeing (or, conversely, losing neighborhood health services predicted improvements in wellbeing). Prior research provides limited insights into these associations. Recent research shows that in the U.S., county population size and density predict the presence of health care services (Van Sandt et al., 2021). The negative link between health services and wellbeing could thus be driven by shifts in population size or some correlated change. On the other hand, this link could be reflective of people with more mental or physical health problems choosing to live in neighborhoods with a greater availability of health service.

In contrast to health services, basic amenities including grocery stores and pharmacies were more highly concentrated in higher poverty neighborhoods, with changes in poverty positively predicting changes in amenities. While these patterns diverge in some ways from prior research (Larson et al., 2009; Zenk et al., 2005), they are not entirely inconsistent with prior work. While there is evidence that large supermarkets and pharmacies tend to be *less* accessible in higher poverty areas than in more affluent ones, small, independently owned grocery stores and pharmacies are generally *more* prevalent in higher poverty neighborhoods (Amstislavski et al., 2012; Bower et al., 2014). Also contrasting with health services, basic amenities appeared to be supportive of wellbeing. Within individuals, a rise in the presence of basic amenities within the neighborhood was linked with improvements in physical health outcomes. However, no such links emerged between individuals: those who lived in neighborhoods with more basic amenities than others across waves generally reported similar wellbeing to their counterparts in neighborhoods with fewer amenities. This divergence suggests that the emergence of new amenities may have greater consequences than the mere presence of amenities. Indeed, neighborhoods with many amenities may have a higher portion of amenities that are inaccessible, underfunded, or lack the goods and services people are looking for. However, gaining access to new amenities – whether through moving or the emergence of a new store in one's neighborhood – may encourage the use of these amenities, with benefits for wellbeing. This aligns with quasi-experimental research showing that the opening of a supermarket in the Bronx, New York was related to increased availability of food in the home and increased consumption of healthy foods for residents living nearby (Rogus et al., 2018), though other studies have found more limited benefits of new grocery stores on healthy consumption and health outcomes (Abeykoon et al., 2017). While no parallel work exists in relation to pharmacies, gaining access to more pharmacies may improve peoples' chances of finding the right medicines, receiving public health services, accessing basic household necessities, and getting health advice (Amstislavski et al., 2012; Christensen & Farris, 2006; Eades et al., 2011).

In relation to neighborhood stressors, results again provided some support for hypotheses while also providing some counter evidence. Past research suggests that violent crime, risk of victimization, and exposure to violence are more prevalent in high than low poverty neighborhoods (Graif et al., 2014; Sampson et al., 1997). In the present sample, neighborhood poverty predicted higher crime both within individuals over time and between individuals, in line with expectations. In other words, not only was reported crime higher, on average, in higher poverty neighborhoods; an increase in neighborhood poverty was also associated with an increase in crime. Of the stressors included in the present mediation models, crime has been studied with the most frequency (Cooper et al., 2014; Mair et al., 2008; Sampson et al., 2002; Wen et al., 2003), though it is frequently collapsed with other neighborhood stressors into a general measure of social disorder (Casciano & Massey, 2012; J. Kim, 2010; Ross, 2000; Ross & Mirowsky, 1999; Sampson et al., 2002). Notably, findings from the present study indicate that incidents of focal crime were generally unrelated to mental and physical wellbeing. This is not altogether surprising. While there is evidence that neighborhood crime and violence are implicated in wellbeing, findings are relatively mixed, with perceptions of crime being investigated with more frequency and generally being more predictive than observed measures (Cooper et al., 2014; Ellen et al., 2001; J. Kim, 2010; Mair et al., 2008; Rees-Punia et al., 2018; Ross, 2000; Schulz et al., 2013; Wen et al., 2003; Wilson-Genderson & Pruchno, 2013). This aligns with RQ2 findings, discussed in more detail in the next section. Measuring crime at a smaller geographic scale does not seem to produce more consistent effects (Cooper et al., 2014; Wen et al., 2003; Wilson-Genderson & Pruchno, 2013), though this is an important area for further exploration (Yu & Lippert, 2016).

Meanwhile, I hypothesized that neighborhood home costs would be lower in higher poverty communities. This was confirmed both within and between individuals in the present sample. However, neighborhood home costs were related to wellbeing only within the fixed effects portion of the model. Living in a neighborhood with relatively low home costs over the course of the study was unrelated to wellbeing, but *changes* in neighborhood home costs were more consequential, with lowering neighborhood home costs predicting decreasing somatic symptoms and improving health (or, conversely, increasing home costs predicting worsening physical wellbeing). This may be reflective of people spending less of their earnings on housing, leaving more for other essentials including food, health care, and leisure activities (Kirkpatrick & Tarasuk, 2007; Meyers et al., 2005). It could also be that declining home costs allows people to buy into higher quality housing, with benefits for physical health (Boyd et al., 2010; Rosenblatt & Deluca, 2012; Wood, 2014) .

Interestingly, however, links between neighborhood economic composition and pollution largely countered expectations. Up to this point, most research has found that TRI sites and pollutants tend to be concentrated in or near high poverty communities, especially those with a high proportion of people of color (Bodenreider et al., 2019; Johnson et al., 2016; Kalnins & Dowell, 2017; Wang & Feliberty, 2009; S. M. Wilson et al., 2012). In the present study, however, higher levels of neighborhood poverty were associated with *lower* levels of air pollution. This pattern was significantly only in the random effects portion of the model, where the effect was small in size (0.18 SD). Low levels of pollution in higher poverty neighborhoods may reflect something unique about New Orleans or areas that participants migrated to, as prior research has documented heterogeneity in the neighborhood SES-pollution link across different cities (Hajat et al., 2013). These possibilities are discussed in more depth in the section on differences by neighborhood type. However, as expected, pollution was consistently associated with worse physical health outcomes (Brender et al., 2011; Chi et al., 2016; L. G. Hooper & Kaufman, 2018). Those who lived in neighborhoods with relatively high air pollution across waves also generally reported heightened somatic symptoms. While within-individual effects on health (0.05 SD) did not reach significance, slightly larger effects at the between level (~0.15 SD) suggest that seemingly trivial short-term consequences of rising air pollution may have meaningful health consequences in the long term.

Given these associations, several significant indirect effects of neighborhood poverty on wellbeing emerged. While mediation occurred both within individuals over time and between individuals, more associations emerged at the within level. First, those living in higher poverty neighborhoods than others across waves had significantly lower somatic symptoms as mediated by lower levels of air pollution. Second, within individuals over time, increasing neighborhood poverty was associated with decreases in somatic symptoms through increasing amenities and decreasing health services and home costs, with shifts in amenities and home costs also linked to improving general health. Taken together, these results tell a relatively complex story regarding indirect effects of neighborhood poverty on wellbeing. Considering both fixed and random effects, neighborhood poverty was found to support physical wellbeing through proximal neighborhood features, though some mechanisms – namely pollution and health services – worked in unexpected directions. This draws attention to unexplored strengths of high poverty neighborhoods, countering the oft-made assumption that concentrated poverty is overwhelmingly problematic for wellbeing.

RQ2: Mediation through Observed and Perceived Neighborhood Change

Like RQ1 models, RQ2 models considered associations between neighborhood poverty and wellbeing. However, rather than examining mediation through only observed neighborhood features, RQ2 examined the contributions of observed and perceived measures of neighborhood features. Moreover, RQ2 models focused on changes that occurred in neighborhoods and individual wellbeing over the full study period, from baseline to PK2. Three neighborhood features were considered as potential mediators: basic amenities, local housing costs, and crime.

RQ2 analyses revealed that observed changes in neighborhood features were often misaligned with perceived changes in these features. Of the three neighborhood features considered in RQ2 models, observed changes predicted perceived changes only in the case of amenities. While associations between observed and perceived changes in costs and crime were in the expected direction, they did not reach statistical significance. Similar discrepancies have been noted in prior research on neighborhood disorder and violence (Cooper et al., 2014; Lorenc et al., 2012; Schulz et al., 2013), though other research has found that perceptions of neighborhood features mediate links between observed measures and wellbeing (Schulz et al., 2012; Weden et al., 2008; Wen et al., 2003). The present study is unique in assessing alignment between objective and subjective measures of neighborhood change, as opposed to point-in-time estimates of the neighborhood context. Moreover, limited research (e.g., Cooper et al., 2014; Wilson-Genderson & Pruchno, 2013) has considered alignment between observed and perceived measures of a specific neighborhood feature, rather than assessing observed versus perceived neighborhood quality more generally (Schulz et al., 2013; Weden et al., 2008).

These unique contributions of the present work may contribute to the given discrepancies between administrative and resident-reported measures of neighborhood characteristics.

Differences also emerged in associations between the neighborhood economic context and observed versus perceived changes in neighborhood features. Results showed only one case were observed and perceived changes in neighborhood features were similarly connected to shifts in the neighborhood economic context. In this unique case, increasing neighborhood poverty from baseline to PK2 was significantly associated with both observed and perceived increases in crime over this period, despite observed and perceived changes not being significantly related to one another. In contrast, increasing neighborhood poverty was significantly associated with observed declines in home costs, but *not* with perceived declines in costs. Even more striking, an increase in neighborhood poverty over the course of the study was associated with an observed increase in neighborhood amenities but a *perceived* decrease in amenity availability.

Taken together, these findings indicate that changes in the economic context of the neighborhood were more predictive of peoples' perceptions of amenities and crime than were observed changes in amenities and crime over the same period. Moreover, peoples' perceptions of change actually diverged from observed change in some cases. There are a few potential explanations for these patterns. One is that people use mental shortcuts to make assessments of neighborhood change, which includes reliance on biases and assumptions, as well as subjective experiences. This aligns with prior research that has found that views of neighborhood disorder are more strongly connected to the racial and economic context of neighborhoods than to observed disorder, that racial biases seem to underlie misalignment in observed and perceived disorder, and that such biases are attenuated in more cohesive communities (Sampson & Raudenbush, 2004; Wickes et al., 2013). It may thus be that if residents observe a proliferation of affluent, white residents, they may assume this means improvements in amenities and decreases in crime, even in the absence of observed changes in these features. On the other hand, residents who observe rising levels of poverty may assume that this comes with a loss of amenities and increases in crime. Of course, it is also possible that people perceive a loss of amenities because the amenities that they themselves use are being lost, even if amenities are becoming more common overall. An alternative explanation is that the neighborhood context captured through observed measures diverges from the neighborhood context that people actually interact with (Campbell et al., 2009; Coulton et al., 2012, 2013). For instance, peoples' perceptions of change may correspond with a much smaller area than observed measures are tapping into (Colabianchi et al., 2014; Coulton et al., 2013).

In line with prior research (Cooper et al., 2014; Rees-Punia et al., 2018; Weden et al., 2008), peoples' perceptions of neighborhood change were generally more predictive of their wellbeing than were observed changes in neighborhood features. Perceived changes in crime emerged as the strongest and most consistent predictor of worsening wellbeing across several indicators, with perceptions of amenity availability also positively predicting somatic symptoms. Meanwhile, of the observed neighborhood change mediators, only amenities was a significant predictor of wellbeing. While significant effects appeared to be slightly stronger for perception measures, effect sizes were small across the board, ranging from 0.08 to 0.15 SD.

Overall, RQ2 findings illustrate that although both observed and perceived changes in the neighborhood context played a role in mediating links between shifts in neighborhood poverty and wellbeing, peoples' perceptions sometimes diverged from observed measures. The relative importance of perceived crime in linking neighborhood poverty and wellbeing complements prior literature that has documented links between peoples' subjective assessments of neighborhood crime and violence and their mental and physical health (Cooper et al., 2014; D. Kim, 2008; J. Kim, 2010; Rees-Punia et al., 2018; Ross, 2000; Wilson-Genderson & Pruchno, 2013). Whereas most prior work has used cross-sectional data, the present research shows that perceived shifts in crime were associated with shifts in mental and physical wellbeing, pointing to the potential for causal relations. While it is possible that these links are an artifact of same-reporter bias, such biases would be expected to emerge across more perceived change indicators. The fact that significant links with wellbeing emerge for some but not all perception measures seems to suggest that measurement bias is not the primary driver of these associations. Finally, in contrast to RQ1 findings, neighborhood poverty was generally implicated in *worse* wellbeing through indirect effects, though a single direct effect showed that rising neighborhood poverty from baseline to PK2 also predicted *lessening* stress over this period. This direct effect may be partly accounted for by unexamined mediators such as neighborhood social support or belonging, which have the potential to strengthen in the face of growing poverty or weaken in the presence of increasing affluence (Keene et al., 2010, 2013).

Differences by Type of Neighborhood Change

Relatively little research differentiates between different forms of neighborhood change. To attend to this shortcoming, the present research assessed links between neighborhood features and wellbeing for those who lived in the same New Orleans neighborhood over study waves versus those who experienced some neighborhood mobility. While there is generally good reason to expect that people will react differently to changes happening in their neighborhood versus changes resulting from a move to a new neighborhood (Jackson & Mare, 2009; Sharp, 2018), this distinction was particularly important in the present research given the unique nature of this dataset. Not only is New Orleans a unique city in general, but Hurricane Katrina caused massive destruction and displacement (Green et al., 2007b; Masozera et al., 2007; Smith, 2006). This undoubtedly shifted the trajectories of New Orleans neighborhoods, leading to immediate physical and demographic shifts and ushering in a period of rapid redevelopment (Groen & Polivka, 2010; van Holm & Wyczalkowski, 2019). At the same time, residential mobility was also somewhat unique in the present study, as most participants experienced some period of forced displacement post-disaster, which turned into permanent relocation for many. While these circumstances are unique as far as neighborhood research goes, natural disasters, redevelopment, and displacement are persistent phenomenon affecting a large number of people (Desmond & Shollenberger, 2015; M. Evans, 2020; Fullilove & Wallace, 2011; Lee & Evans, 2020; Morrow-Jones & Morrow-Jones, 1991). As such, the results of this research should be informative beyond this particular study context.

Most findings observed in primary analyses appear to be driven by the mover sample. Considering RQ1 and RQ2 analyses together, findings suggest that for those who changed neighborhoods over the course of the study, neighborhood poverty was related to wellbeing mainly through neighborhood resources and stressors, rather than directly. For those who lived in the same New Orleans neighborhood over time, however, neighborhood poverty was less related to wellbeing. While this may be partly due to the larger sample of movers, it also seems to be related to substantive differences in patterns of associations for stayers versus movers. In RQ2 analyses, these differences were clear, as the multigroup modeling process allowed for identification of significant differences in associations between stayers and movers. For RQ1 analyses, on the other hand, conclusions about which associations are meaningfully different between movers and stayers are more speculative. In particular, the absence of significant links within the stayer sample could be a product of higher levels of measurement imprecision and lower statistical power in this smaller sample. However, significant associations that worked in *opposite* directions for stayers versus movers are likely to tap into more meaningful differences in experiences between the two groups.

The Importance of Observed and Perceived Neighborhood Change for Stayers versus Movers

RQ2 analyses, which considered changes in individual and neighborhood characteristics from baseline to PK2, suggest that neighborhood poverty shaped neighborhood features and wellbeing differently for stayers versus movers. For those who lived in the same New Orleans census tract at baseline and PK2, changes in neighborhood poverty over that period were largely unrelated to changes in neighborhood features. In contrast, changes in neighborhood poverty resulting from a *move* were accompanied by observed and perceived shifts in neighborhood features. In practical terms, moving to a neighborhood with higher levels of poverty generally meant moving to a neighborhood with more amenities (though people perceived fewer amenities), lower home costs (though people did not perceive shifts in costs), and higher crime (which was reflected in perceptions). These differences resulted in the presence of significant indirect effects of neighborhood poverty on wellbeing for movers, with a rise in neighborhood poverty generally predicting *worsening* wellbeing. For stayers, on the other hand, where associations did emerge, rising neighborhood poverty was linked with *improving* wellbeing. In fact, changes in neighborhood poverty *directly* predicted changes in happiness among stayers, indicating that increases in neighborhood poverty from baseline to PK2 were related to increases in happiness over that period.

There are a few potential reasons for these divergences. The most obvious explanation is that even in the aftermath of Hurricane Katrina, changes within New Orleans neighborhoods over the 5/6 year study period may have been muted compared to changes resulting from a move to an entirely new neighborhood (Coulton et al., 2012). For instance, while the hurricane inducted immediate sociodemographic changes within New Orleans neighborhoods (Fussell et al., 2010; Kamel, 2012), it is possible that changes in neighborhood resources and stressors lagged behind or did not follow the same trajectory. However, as discussed in more detail in the next section, RQ2 affluence results (included in the appendix) showed that changes in neighborhood *affluence* <u>were</u> associated with observed shifts in neighborhood features for stayers. This counters the hypothesis that null associations resulted from more limited shifts in neighborhood features within the stayer sample. Instead, it seems likely that these divergent patterns for stayers and movers are reflective of the intense destruction and subsequent gentrification that took place in New Orleans neighborhoods over this period. Along these lines, the unexpected positive link between neighborhood poverty and happiness that emerged for stayers may be a consequence of *declines* in poverty: if residents of high poverty neighborhoods had close ties and strong place attachment pre-Katrina as research suggests (Chamlee-Wright & Storr, 2009), the loss of poor neighbors and/or an in-migration of new, more affluent residents may have contributed to a decline in happiness, with these changes altering the look and feel of the neighborhood (Davidson, 2010; Parekh, 2015). Findings from RQ2 affluence models support this idea, as discussed in more detail below.

The Importance of Observed Neighborhood Features for Stayers versus Movers

RQ1 analyses also revealed key differences in patterns of results for stayers versus movers. As with RQ2, there were far fewer associations between neighborhood poverty and wellbeing among stayers than movers, both within individuals over time and between individuals. This was partly due to the fact that neighborhood poverty was less predictive of neighborhood features within the stayer sample than the mover sample. Moreover, for those who lived in the same New Orleans census tract across waves, neighborhood resources and stressors were rarely significantly linked to wellbeing. There were, however, a few notable exceptions.

While findings from primary RQ1 and RQ2 models generally showed that higher levels of neighborhood poverty were linked to *lower* neighborhood housing costs, RQ1 fixed effects results indicate that for stayers, changes in neighborhood poverty were *positively* linked with changes in housing costs. In practical terms, this suggests that people who experienced a rise in neighborhood poverty within their original neighborhoods also experienced a rise in neighborhood housing costs. This may be reflective of differential destruction and revitalization in the post-disaster context. Homes that had lower baseline values were evaluated as having more intense damage from the hurricanes, and homeowners whose homes were lower-value pre-Katrina received less funding to rebuild (Bates & Green, 2009; Fussell et al., 2010; Kamel, 2012). This likely led to the inflation of home values in high poverty neighborhoods, as low-value homes were more likely to be destroyed and less likely to be rebuilt, resulting in a smaller housing stock that contained mostly higher value homes. Moreover, in the aftermath of the hurricane, the city elected to demolish all public housing in favor of mixed-income developments (Goetz, 2011; Logan, 2009; Quigley, 2007). It is therefore likely that home values were driven up further by the creation of new housing intended to draw more affluent residents (Gotham & Greenberg, 2014). In contrast, for those who moved neighborhoods over the course of the study, changes in neighborhood poverty negatively predicted changes in home costs, suggesting that moving to a higher poverty neighborhood was generally accompanied by a relative decline in neighborhood home costs.

These findings are further complicated by the presence of both parallel and divergent links between neighborhood housing costs and wellbeing for stayers versus movers. For stayers, shifts in neighborhood home costs were positively associated with shifts in stress and somatic symptoms, suggesting that rising costs have negative implications for wellbeing. This meant that for those living in the same New Orleans neighborhood over time, relative increases in neighborhood poverty were linked with *worsening* mental and physical wellbeing through rising home costs. For movers, however, patterns were less consistent. For those who changed neighborhoods, shifts in home costs were positively linked with shifts in somatic symptoms, as with stayers. However, they were also *negatively* linked to shifts in stress, showing both negative and positive implications for wellbeing. This may be reflective of the measure of home costs

– median home values – tapping into several different components of the neighborhood context for the mover sample. For instance, neighborhoods with relatively high poverty and low home values are likely to have worse government services, lower quality housing, and more physical disorder than more affluent, higher cost neighborhoods, in addition to having lower housing costs (Acevedo-Garcia et al., 2016; Ellen et al., 2001; Galster, 2012; Troy & Grove, 2008). Increases in stress related to lowering neighborhood home costs among movers may therefore be reflective of people moving into neighborhoods with lower quality housing or heightened disorder (Kull & Coley, 2014). In contrast, for the stayer sample, rising costs in the context of rising neighborhood poverty may be doubly challenging. For instance, the creation of new, high quality housing has the potential to increase local housing costs without leading to improvements in most existing housing. As such, changes in neighborhood home costs may mean different things to people living in one neighborhood over time versus people experiencing some neighborhood mobility.

Beyond home costs, several other differences in associations between stayers and movers are worth noting. One is a unique association that emerged for stayers and not movers: for individuals living in the same New Orleans census tract over time, changes in neighborhood poverty *negatively* predicted changes in air pollution released from TRI facilities. At face value, this seems likely to correspond to something unique about the New Orleans context, perhaps related to hurricane effects. However, this association was also negative among movers, albeit imprecise and non-significant, which challenges the assumption that this pattern is unique to New Orleans. One possibility is that this association is reflective of macro-economic trends. For example, if there was a federally mandated expansion of air pollutant reporting at the same time that neighborhood poverty was generally declining, changes in air pollution could appear to be inversely related with changes in neighborhood poverty. Such trends would be most likely to show up in an examination of the same neighborhood over time, as this would capture changes in pollutant releases from specific TRI facilities. Indeed, some research suggests chemical releases from TRI facilities have generally decreased over time, though declines were generally strongest in *high* income areas (Kalnins & Dowell, 2017). Given that this link diverges from most prior research findings, further investigation is needed to draw any concrete conclusions.

Considering findings collectively, results from RQ1 and RQ2 analyses suggest that links between neighborhood poverty and wellbeing depend on the type of neighborhood change that has occurred. While neighborhood poverty was generally unrelated to wellbeing for those who lived in the same New Orleans neighborhood across waves, the few associations that did emerge pointed to negative consequences through rising home costs. Over the full study period, however, evidence pointed to select benefits of changes in neighborhood poverty, or, conversely, detriments of declining poverty. While patterns of neighborhood change experienced by stayers were undoubtedly somewhat unique given the disaster context of the study, there is some reason to believe that similar patterns may emerge in other contexts. For instance, some have argued that while the intensity of damage and disruption caused by Hurricane Katrina was unique, patterns of neighborhood change that occurred post-disaster were not (Gladstone & Préau, 2008; Gotham & Greenberg, 2014; Peacock et al., 2018). Indeed, some research suggests that hurricane-related destruction hastened gentrification processes that had begun pre-Katrina (Gladstone & Préau, 2008; van Holm & Wyczalkowski, 2019). Stayer findings may thus be informative in considering how changes in the economic composition of specific neighborhoods may be implicated in wellbeing, particularly in areas with existing economic and racial segregation, where place attachment among poor residents is high, and where urban revitalization is on the rise.

For movers, results point to benefits and detriments of changing neighborhood poverty on wellbeing, effects that were generally mediated through observed and perceived shifts in neighborhood assets and hazards. Given that Hurricane Katrina was responsible for the initial dislocation of participants from their original neighborhoods of residence, findings of the present study may be most generalizable to for those facing involuntary moves in response to natural disasters, evictions, foreclosures, or loss of place due to gentrification or revitalization (DeLuca et al., 2019; M. Evans, 2020; Fullilove & Wallace, 2011; Kleit et al., 2016; Lee & Evans, 2020; Morrow-Jones & Morrow-Jones, 1991). However, given evidence that unplanned, reactive moves – i.e., those that are precipitated by unanticipated problems with housing, landlords, etc. -- may be the norm for many low-income renters in urban areas (DeLuca et al., 2019; Desmond & Shollenberger, 2015), this research may be widely generalizable. While some forms of forced displacement tend to result in moves to more disadvantaged neighborhoods and worse housing (Desmond & Shollenberger, 2015), the present research provides insights into how people fare across a wider range of neighborhood contexts.

Role of Neighborhood Affluence versus Neighborhood Poverty

Given economic segregation within the U.S., neighborhoods with high levels of poverty tend to have low levels of affluence, and vice versa. In the present sample, for instance, neighborhood poverty and affluence were highly correlated with one another ($r = -0.75$). However, there is some reason to expect that neighborhood poverty and affluence play different roles in shaping the neighborhood context and individual wellbeing, particularly for residents with limited financial means (Alegría et al., 2014; Browning & Cagney, 2003; Weden et al., 2008; Wen et al., 2003). To consider this possibility, I examined the effects of neighborhood affluence in separate models. Though the breadth of results led me to focus on neighborhood poverty models in Chapter 4, a few key differences between neighborhood poverty and affluence models are worth noting. Results of neighborhood affluence models can be found in the appendix.

One key takeaway is that neighborhood affluence and neighborhood poverty seem to drive the presence of different neighborhood features. Considering results from RQ1 and RQ2 primary analyses, neighborhood affluence was more strongly connected to health services and home costs than was neighborhood poverty, whereas neighborhood poverty was more strongly related to the presence of amenities and crime than was neighborhood affluence. This suggests that it is primarily a concentration of more affluence residents, rather than the absence of poor residents, that is associated with the presence of health services and heightened home costs, whereas a concentration of residents in poverty drives the presence of basic amenities and heightened crime reports. However, the directionality of these links requires further investigation. For instance, rising home costs resulting from new-build developments could reduce neighborhood poverty by making it difficult for households with low levels of income to remain in the neighborhood, while neighborhood crime could lead to rising neighborhood poverty by prompting higher income residents to move (Kirk & Laub, 2010).

Also notable is that neighborhood affluence tended to be more weakly linked with wellbeing than was neighborhood poverty, particularly for movers and particularly in relation to RQ1. In mixed effects models, significant links between neighborhood resources and stressors and wellbeing were generally absent, though people who lived in more affluent neighborhoods over time generally reported *worse* happiness. In neighborhood change models, however, it was links between neighborhood affluence and observed neighborhood features that were attenuated, likely due to the focus on amenities and crime in these models, which generally appeared to be driven by poverty rather than affluence. Considered holistically, results thus suggest that neighborhood affluence is unrelated to wellbeing through observed neighborhood features (contrasting with poverty models), is directly related to lower happiness, and predicts improved wellbeing via perceptions of declining crime (parallel to poverty models).

While limited prior research has assessed the importance of neighborhood affluence for wellbeing, what research does exist has found it to be predictive of improved health outcomes, even after accounting for neighborhood disadvantage (Browning & Cagney, 2003; Johnson Jr., 2008; Kane et al., 2017; Wen et al., 2003). In line with this literature, the present research found that neighborhood affluence delivered some benefits to participant health and wellness through perceptions of declining neighborhood crime. However, prior research has also documented reduced benefits of neighborhood affluence for Black as opposed to White individuals (Johnson Jr., 2008;

Kane et al., 2017), with some research finding that census tract affluence actually *increased* African Americans' likelihood of having a depressive disorder (Alegría et al., 2014). Given that the present sample is comprised primarily of Black women, the attenuated role of neighborhood affluence compared to neighborhood poverty is also relatively aligned with prior literature, as is the finding that participants in more affluent neighborhoods were less happy than their peers in less affluent communities. These findings may point to heightened levels of discrimination and social exclusion in neighborhoods with high levels of affluence, which also tend to be largely White as a consequence of racial stratification (Alegría et al., 2014; Johnson Jr., 2008; Reardon et al., 2015). Indeed, it is possible that observed links between the neighborhood economic context and wellbeing were partly driven by the racial composition of the neighborhood, which was not explicitly examined in this dissertation due to issues of collinearity.

One final divergence in the role of neighborhood poverty versus affluence is worth noting. In multigroup models, neighborhood poverty was largely unrelated to wellbeing among stayers. In RQ2 models, this was due to the general absence of associations between changes in neighborhood poverty and changes in observed or perceived neighborhood features for this group. Interestingly, however, shifts in neighborhood *affluence* from baseline to PK2 *were* significantly related to both observed and perceived neighborhood features, with several of these associations working in an unexpected direction. Among those who lived in New Orleans neighborhoods across waves, changes in neighborhood affluence were *positively* linked with observed changes in amenities and observed changes in crime, though these links were only present in RQ2 results. These findings, which contrast with patterns for movers and for the full sample, may tap into the unique nature of neighborhood change in a post-disaster context, particularly over the full period from baseline to PK2. The positive link between affluence and amenities for stayers may point to more rapid recovery for businesses in areas with more affluent residents. Indeed, one report on business reopenings in New Orleans noted that businesses affected by flooding opened more quickly when they were in wealthy versus poor neighborhoods (Campanella, 2007). Moreover, businesses serving wealthy clientele were more likely to reopen than businesses serving lower income residents (Campanella, 2007). Evidence suggests that the elevated presence of affluent residents may also have prompted heightened levels of policing in these neighborhoods in the post-disaster context (Barrios, 2010; Parekh, 2015). The fact that changes in neighborhood affluence seemed to drive these links for stayers may be related to the fact that neighborhood affluence increased in almost all New Orleans neighborhoods over this period, even in neighborhoods where poverty was also increasing. All of this reflects the approach to recovery that was employed in post-Katrina New Orleans. Rather than prioritizing equitable recovery and attending to the needs of residents with limited resources, policymakers focused on market-based revitalization that would draw tourists and middle- and high-income residents to the city (Goetz, 2011; Logan, 2009; van Holm & Wyczalkowski, 2019). This meant that processes of gentrification that had already begun pre-Katrina were hastened by the disaster and the government's approach to recovery, which generally favored individuals and businesses that were well-resourced before the disaster (Campanella, 2007; Gladstone & Préau, 2008; Lovett, 2015; Peacock et al., 2018; Slater, 2008).

Implications

This work was guided by several different theoretical perspectives – social determinants of health, bioecological systems theory, and neighborhood effects theories – which I combined into one overarching theoretical model. Two key questions are embedded within this proposed theoretical model. First, are associations between structural neighborhood features and wellbeing explained by intermediary neighborhood resources and stressors? Second, what role do objective and subjective assessments of the neighborhood context play? In relation to the first question, the answer is complex. There were very few total effects of neighborhood poverty across different models. However, results generally suggested that neighborhood poverty was connected to wellbeing through resources and stressors, which supports the idea that the neighborhood poverty shapes the social context in a way that makes wellbeing more or less attainable. What is complicated about this picture is that neighborhood poverty appeared to be promotive of wellbeing through some pathways, but harmful through others. A benefit of the present theoretical framework is that it allows for identification of these diverse pathways. However, it may be important to reconsider whether the neighborhood economic context is a fundamental determinant of health in itself, or if it is instead one of the many mediating factors through which individual-level SES is related to wellbeing (Link & Phelan, 1995). In relation to the second question, the present study provides evidence that perceptions of the neighborhood context are uniquely implicated in wellbeing. While some theories (e.g., collective efficacy; Sampson et al., 1997) imply that peoples' perceptions of the neighborhood are important in shaping their interactions with the neighborhood space and the people within it, the proposed framework makes explicit the importance of peoples' experiences and perceptions. Overall, the findings of this research support the use of this overarching theoretical model.

Methodologically, a challenge of the present research was that I was unable to use a consistent modeling strategy for RQ1 and RQ2 analyses. Perhaps as a consequence of this, there were several differences in findings between RQ1 and RQ2 analyses. First, indirect effects of neighborhood poverty appeared to be beneficial for wellbeing in RQ1 models, whereas in RQ2 models, indirect effects were more often harmful. Moreover, whereas neighborhood poverty was predictive only of physical health indicators in RQ1 models, links with stress also emerged in RQ2 models. The most obvious explanation for these discrepancies is that each model examined different mediating pathways. RQ1 models considered a wider array of unique neighborhood features as potential mediators, resulting in estimates that adjusted for more neighborhood features than did RQ2 models. Moreover, in RQ2 models, the inclusion of perception measures may have drawn variance from observed measures, contributing to discrepancies between RQ1 and RQ2 findings. Of course, as noted above, it is also possible that the use of different modeling techniques for each analysis played a role. In addition to the use of mixed-effects models versus change scores, RQ2 models considered change from baseline to PK2, whereas RQ1 models drew on data from all waves. Given that most participants experienced the largest neighborhood changes between baseline and PK1, change scores computed over a longer timespan may have allowed for the emergence of lagged or long-term effects would not have emerged in fixed-effects models. On the flip side, the longer period of change could have missed more nuanced shifts over short periods. While it is impossible to come to any clear conclusions about these differences here, the divergent findings evident in the present study underscore the potential utility of using alternative methods to examine a given research question. For instance, running a random effects model, a mixed-effects model, a change score model, and a lagged model to investigate neighborhood effects would allow for careful consideration of any divergent findings, with the potential of identifying the source of divergences. This would add clarity and nuance to our understanding of past research.

Turning to practical implications of the present research, it is first important to highlight that the present work did not entirely align with prior literature. As noted above, total effects of neighborhood poverty on wellbeing were relatively limited, with indirect effects pointing to benefits of changes in neighborhood poverty as well as downsides. This contrasts with a large body of research that has found neighborhood poverty to contribute directly to worse health (Cooper et al., 2014; Do & Finch, 2008; Galea et al., 2007; Schulz et al., 2013; Steptoe & Feldman, 2001). Interpreted within the broader literature of neighborhood effects, however, the present findings may offer useful insights. Research on relocation of low-income households to low poverty communities and poverty deconcentration through social mixing have often found that reducing neighborhood poverty has more limited impacts on wellbeing than expected (Casciano & Massey, 2012; Fauth et al., 2004, 2008; Sanbonmatsu et al., 2012). While existing evidence points to experiences of stigmatization, loss of "sense of place," loss of social networks, and other such shifts in social dynamics as a partial explanation for these attenuated benefits (August, 2014; Boyd, 2008; Clampet-Lundquist, 2007; Galster, 2007; Keene & Padilla, 2010), the present research suggests that lower costs and greater amenity access in neighborhoods with elevated poverty may play a role as well. This research thus draws attention to underexplored assets of neighborhoods, as well as highlighting that even in the absence of direct links between neighborhood economic composition and wellbeing, the neighborhood economic context may shape community assets and hazards in consequential ways.

The present research also found that patterns of associations differed for those who experienced neighborhood change through different mechanisms. While I focused on differences for stayers versus movers, there is good reason to expect variations along other lines as well. For instance, in the present study, most participants experienced some period of forced displacement. While some participants were able to make their way home eventually, others did not. Sometimes this was a choice; other times it was a necessity (Chamlee-Wright & Storr, 2009). There is little question that people who are forced to relocate – due to natural disasters, evictions, or life circumstances – are likely to have different (probably worse) experiences than those who want to relocate, even when they end up in "better" neighborhoods (Chamlee-Wright & Storr, 2009; Desmond & Shollenberger, 2015; M. Evans, 2020). In contrast, those who are most unhappy in their current situation have the most to gain from moving, and may thus be able to overlook downsides of a new context. These complexities do not negate the importance of neighborhood features for either group; rather, they highlight the contextual nature of these links. Moreover, just as peoples' perceptions of neighborhood change may depend on their own experiences, preferences, and circumstances, neighborhood dynamics may also vary a good deal between different locales. Indeed, the present study is unique just by virtue of the fact that the study began in New Orleans, a city with intense disadvantage as well as deep history, connectedness, and culture that may have elevated the sense of loss people felt upon dislocation (Barrios, 2010; Chamlee-Wright & Storr, 2009; Parekh, 2015). Overall, these complexities underscore the importance of recognizing and exploring variable links between neighborhood composition and wellbeing by characteristics of individuals and communities and highlights the importance of fitting place-based policies to local needs, rather than assuming one size fits all.

Though this research did not focus specifically on disaster recovery, the results suggest some potential implications in this realm. The fact that for stayers there was some evidence of rising neighborhood costs in neighborhoods with rising affluence *and* rising poverty suggests that post-disaster, concerted efforts should be made to maintain the affordability in the area and to avoid gentrification that may displace longtime residents or change the nature of their neighborhoods entirely (Davidson, 2008; Gotham & Greenberg, 2014; Parekh, 2015; van Holm & Wyczalkowski, 2019). Without such efforts, inequitable recovery is inevitable (Gotham & Greenberg, 2014). For movers, implications are less clear, though results generally suggest that it is important not to assume that concentrated poverty is altogether detrimental to peoples' wellbeing. In fact, the assets of a high poverty neighborhood may offset or even outweigh its downsides in some cases. As such, following disasters and in general, families should be supported in locating the housing and neighborhoods with the features they are likely to benefit from, accounting for both the challenges and the assets of any given area.

Limitations and Future Directions

The present research is not without limitations. As with all research that is correlational in nature, causal conclusions cannot be drawn. While the use of rigorous modeling strategies with longitudinal data reduces many of the biases of random effects modeling and better isolates associations, it is still possible that unmeasured individual or contextual factors were responsible for some results. In particular, there are many neighborhood factors that were not included in the present investigation that could underlie some of the associations found in given analyses. For example, measures of neighborhood social dynamics were not available. In the case that such dynamics are highly correlated with one of the neighborhood features under investigation, such as neighborhood amenities, what appeared to be effects of changing amenities could in fact be effects of shifting levels of neighborhood social support or collective efficacy.

Another limitation of mixed-effects modeling and the use of change scores is that although neighborhoods are treated as dynamic, these models do not account for length of neighborhood residence. Rather, they consider how changes in neighborhood features over a particular time period correspond with changes in wellbeing over that same time period. This is unlikely to capture lagged or cumulative effects of neighborhood exposure, which have been documented in prior work. While the present research did find compelling evidence of relatively immediate effects of changes in neighborhood features on wellbeing, the presence of some discrepancies between RQ1 and RQ2 findings and between fixed- and random-effects results suggest that neighborhood features may have different implications in the short- versus long-term. This warrants further investigation.

Issues of model fit in primary RQ1 models highlight one additional modeling limitation. As previously noted, the models I presented were the most effective resolution of an effort to balance model fit and theoretical validity of models. Model fit could be further improved by the inclusion of individual change covariates as predictors of neighborhood economic composition and mediators within the fixed effects portion of the model. While this would make sense in the sample of movers, as changes in individual circumstances could impact peoples' choice of neighborhood, it made little sense for stayers. For those who lived in the same tract over time, an individual change in marital status or earnings would not be likely to impact the level of poverty in the neighborhood, or the number of amenities. I therefore elected a solution that was worse fitting, but more conceptually valid for the full sample. Model fit indices for models run separately for stayers and movers demonstrate that model fit was, in fact, better for stayers than movers. This underscores that the two forms of neighborhood change examined here are distinct, and that the role of individual covariates may differ between them. That said, it is worth noting that relatively little has been written about the validity of Bayesian posterior predictive checking as a test of model fit for multilevel models considering individual fixed effects. It is therefore possible that this test is too strict for the present models, or that it only speaks to the fit of the fixed- or random-effects portion of the model.

Effectively measuring neighborhood features was another challenge. For instance, resource availability was represented by simple counts of particular types of businesses within the neighborhood. While such measures do have practical meaning, they do not tap into resource quality or accessibility, which may be important determinants of how useful resources actually are to people. Pollution was also a relatively rough measure, as I was only able to tap into pollution released from TRI facilities. Not only was this measure incredibly skewed; it also underestimated the amount of pollution present in many neighborhoods, as industrial facilities are just one of many sources of pollution (L. G. Hooper & Kaufman, 2018). This may help explain why findings from the present study differed from prior research results (Chi et al., 2016; Kershaw et al., 2013). In terms of stress measures, neighborhood crime was measured with relatively high imprecision. Part of this imprecision comes from the fact that crime was reported at the precinct-level, then was aggregated up to the zip code level, and then was averaged within 2 miles of each census tract. Moreover, these reports are voluntary, leading to relatively high levels of missingness compared to other neighborhood data. It is also critical to note that while reported crime may be reflective of the real number of crimes occurring in a precinct, it may be more reflective of the level of police presence in the given precinct, as well as the degree to which police are trusted and/or relied on (Kochel, 2011; Kruger et al., 2016). In contrast, measures drawn from the Decennial Census and ACS – namely neighborhood economic composition and home costs – are more precise, both in terms of what they are measuring and their geographic precision.

The use of aggregated neighborhood measures in the present study represents both a strength and a limitation. As described in the methods section, all neighborhood data had to be merged in at the census tract level, despite not all data be available at that level. While there were multiple ways to accomplish this, I chose to average the characteristics of all zip codes that were within a 2-mile radius of participants' census tracts of residence. This approach had several benefits. One is that it mitigates challenges associated with the use of standard neighborhood measures – for instance, that people living at the edge of a census tract may experience a different neighborhood context than someone in the middle of the tract, depending on how similar or different contiguous tracts are (Coulton, 2012; Sampson et al., 2002). Moreover, given variability in the size of census tracts and zip codes across the U.S., this aggregation approach makes neighborhood geographies more comparable (Miller et al., 2019). Despite these benefits, it is possible that some community features are more meaningful at either a smaller or larger geographic scale given peoples' activity patterns and the mechanisms through which these features impact individual functioning (Coley et al., 2021; Miller et al., 2019). For instance, effects of pollution may be much more intense for people living next to a TRI facility than for those living a mile away as a consequence of more intense, cumulative exposure. This is another area that warrants further exploration.

It is also important to note that due to variable constraints, I was unable to use a consistent modeling strategy for both research questions. Rather than being asked at each wave how they viewed aspects of the neighborhood context, participants were asked about their perceptions of neighborhood change at PK2. Consequently, the variables used in the present study captured perceptions of change instead of changes in perceptions. This made it impossible to use a mixed-effects modeling strategy as was employed for RQ1. Instead, I computed change scores and examined associations within a random effects framework. The use of different modeling strategies made it more difficult to compare findings across models. Still, results of RQ2 models make a unique contribution to the literature. A primary strength of perception measures is that they capture peoples' interpretation of their neighborhood context, filtered through their own experiences. This research provided a unique look at how peoples' perceptions of neighborhood change correspond both with observed changes, and with changes in their own wellbeing over time. It would be informative for future research to unpack how people evaluate neighborhood change versus static neighborhood features, and the degree to which this is informed by individual characteristics and prior experiences.

For practical and analytic reasons, it was necessary to select a limited number of neighborhood features to investigate as potential mediators of neighborhood SES effects. Part of the goal was to understand the unique contributions of specific types of neighborhood features given that these features are likely to impact individuals in different ways. For instance, whereas exposure to pollution may have a direct impact on wellbeing, neighborhood amenities may be relevant because they provide immediate access to necessities such as food and medicine or because they provide an avenue for social interaction with neighbors. However, the reality is that many neighborhood features cluster together, making it difficult to isolate the importance of any single amenity or stressor. While I did test several resource composites before deciding to focus specifically on amenities and health services, it is possible that unexplored combinations of neighborhood resources and stressors are more meaningful for wellbeing than any individual neighborhood feature. Because of this, it may be useful for future research to consider how neighborhood features cluster together, and how these clusters are implicated in wellbeing. Work of this nature would be complemented by research exploring how people make decisions on where to live, what aspects of the neighborhood context are important and salient to them, how they navigate their neighborhoods, and what changes they would ideally like to see in their neighborhoods. Qualitative investigations of these issues to-date (e.g., August, 2016; Rosenblatt & Deluca, 2012; Shelby, 2017) have made important contributions to the neighborhood effects literature, contextualizing our understanding of how neighborhoods come to matter.

The use of the RISK dataset for this study also came with a few important limitations. While these data were generally well-suited to the present research, the sample and study context were unique. For one thing, a major natural disaster occurred over the course of the study. Moreover, because the RISK study began as a randomized experiment on college retention, all participants were enrolled in community college at baseline. These features limit generalizability in clear ways. While there is some reason to believe that patterns of neighborhood change observed in the present study may occur beyond the disaster context (Gladstone & Préau, 2008; Slater, 2008), it is possible that disaster-related displacement and recovery changed how people viewed and related to their neighborhoods. More research is needed to specifically consider how natural disasters change peoples' experiences of their neighborhood contexts, beyond their impact on neighborhoods themselves.

Finally, a key limitation of the present work is that neighborhood racial composition was not examined in conjunction with neighborhood economic composition. These aspects of neighborhood composition tend to be highly correlated; in the present study, for instance, neighborhood poverty was correlated with neighborhood percent White at $r = -0.69$. While this makes it difficult to disentangle the effects of economic versus racial composition, it may be that the combination of these factors is more consequential than either one alone. For instance, many have argued that increasing neighborhood Whiteness may offset potential benefits of neighborhood affluence for low-income households of color by prompting discrimination and stigmatization, thus disrupting healthy functioning (Joseph, 2008; Keene & Padilla, 2010; Shmool et al., 2015). These dynamics may explain why neighborhood affluence has been found to be more promotive of health for White versus Black individuals (Johnson Jr., 2008; Kane et al., 2017). Given that the sample of this study was comprised primarily of Black women with limited financial means, it is possible and perhaps likely that peoples' experiences of changing neighborhood poverty were impacted by shifting racial dynamics. While investigation of these connections was beyond the scope of the present research, this is an important next step towards understanding how compositional factors shape neighborhood features to support or limit wellbeing. With a more nuanced understanding of these dynamics, we will gain a fuller understanding of what neighborhood equity can and should look like.

Conclusion

Associations between neighborhood economic composition and individual wellbeing have been well documented in prior literature (Arcaya et al., 2016; Mair et al., 2008; Pickett & Pearl, 2001; Riva et al., 2007). However, examining effects of neighborhood economic composition on wellbeing without attention to potential mediating pathways makes it difficult to fully grasp how, why, and under what circumstances neighborhood poverty has consequences for mental and physical health. The present research contributes to the existing body of work by attending to numerous resources and stressors within the neighborhood context that may drive associations between neighborhood economic composition and wellbeing.

Findings underscore that neighborhood poverty is connected with an array of neighborhood resources and stressors, and that these factors help explain how the economic composition of the neighborhood is connected to wellbeing for parents with limited financial resources. In general, results suggest that changes in neighborhood poverty are more relevant to wellbeing than average levels of neighborhood poverty; that links with wellbeing are most consistently mediated through amenities and home costs as well as perceived changes in crime; that physical health may be more sensitive to neighborhood effects than are mental and emotional health; and that neighborhood poverty appears to be supportive of wellbeing in some ways, and harmful in other ways. A few surprising associations are also worth noting. Air pollution released from TRI facilities was unexpectedly lower in higher poverty communities, which was connected to better health, while gaining neighborhood health resources appeared to worsen wellbeing. While these findings may be unique to these study circumstances, they warrant further exploration. Overall, findings add nuance to existing literature, in addition to raising important questions for future research.

The present work has several key strengths. One is its focus on a sample of young, predominantly Black mothers. This is a population that is often the target of mobility interventions (Comey et al., 2012; Fauth et al., 2004), as the combined effects of limited financial resources and discriminatory practices tend to limit neighborhood choice for this group more than others (Desmond & Gershenson, 2017; Rosenblatt & Deluca, 2012; Sharkey, 2013; South & Crowder, 1998). In focusing on a relatively restricted group, I was able to consider variability in neighborhood experiences within this group. Such variability has the potential to be washed out in larger, more heterogenous samples in which some people have a great deal of control over their neighborhoods and their health, while others face barriers in both regards. In other words, focusing on a sample wherein many people face similar barriers reduces selection bias and provides a clearer view of how and why the neighborhood context matters for people within these circumstances. While this reduces generalizability, it also provides valuable insights that may help promote access to opportunity and wellbeing for low-resourced individuals and families. In the methodological realm, the use rigorous modeling techniques was another strength. In particular, the use of mixed-effects models allowed for differentiation between within- and between person associations, which reduced bias and allowed for a more nuanced view of associations to emerge (Hamaker & Muthén, 2020). This was made possible by the fact that there were elevated levels of neighborhood change within this sample. Not only did many participants have to relocate at least temporarily as a result of Hurricane Katrina; rapid neighborhood change also occurred in New Orleans due to hurricane-related destruction and revitalization efforts. As such, while the natural disaster context of this study makes it relatively unique in the neighborhood effects literature, it allowed for consideration of neighborhoods as dynamic entities, as well as the differentiation between mobility-related change and change occurring in a particular neighborhood over time.

The present work challenges the assumption that simply changing the economic composition of a neighborhood will result in improved wellbeing for those with limited financial means. Given that all neighborhoods are comprised of an array of assets and hazards, reducing poverty may have unintended negative consequences, even if it also reduces the prevalence of select stressors and/or draws additional resources to the area. It may therefore be best for policy interventions focused on improving the health and wellbeing of underserved individuals and communities to instead consider how to make all neighborhoods – those that are poor and those that are affluent – more supportive. This approach necessitates an understanding of the local context and careful identification of structural forces (e.g., the real estate market, elevated political sway of wealthy residents) that may create barriers to effective neighborhood change. In recognizing the complex manner in which structural neighborhood features shape the wellbeing of those with limited neighborhood choice, we become better equipped to create neighborhood change that has meaningful consequences for health equity.

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TABLES & FIGURES

Table 2

Individual Level Descriptives by Wave

	Baseline				PK1				PK2			
Variable	**N**	**Mean (SD)**	**Min**	**Max**	**N**	**Mean (SD)**	**Min**	**Max**	**N**	**Mean (SD)**	**Min**	**Max**
Age	606	25.03 (4.44)	18	35	477	27.25 (4.62)	19	37	597	30.05 (4.45)	22	40
HH size	584	3.69 (1.49)	1	9	471	4.01 (1.74)	1	11	600	4.13 (1.49)	2	10
Children	603	1.79 (1.05)	1	6	400	2.03 (1.15)	0	6	600	2.12 (1.13)	0	6
Monthly personal earnings ($)	586	536.43 (677.21)	0	3319	449	705.87 (904.55)	0	3308	485	1394.63 (1231.75)	0	6000
Psychological distress	587	4.88 (4.10)	0	24	477	6.14 (4.89)	0	24	604	5.66 (4.82)	0	23
Perceived stress	596	5.43 (3.20)	0	14	477	5.05 (3.48)	0	16	604	5.16 (3.52)	0	16
Somatic symptoms	595	0.38 (0.65)	0	3	477	1.16 (1.01)	0	3	605	1.15 (1.02)	0	3
General health	599	4.06 (0.86)	1	5	477	3.51 (1.03)	1	5	606	3.34 (1.06)	1	5
General happiness	589	3.31 (0.62)	1	4	478	3.17 (0.67)	1	4	606	3.25 (0.68)	1	4
	N	**Proportion**			**N**	**Proportion**			**N**	**Proportion**		
Marital status												
Single	599	75.79			477	51.36			599	55.09		
Cohabiting	599	6.51			477	20.55			599	15.19		
Married	599	17.70			477	28.09			599	29.72		
Education												
Less than HS	604	3.97			481	2.29			606	1.16		
HS degree	604	95.53			481	92.31			606	83.33		
College degree	604	0.50			481	5.41			606	15.51		
Employed	604	50.00			479	53.44			533	76.36		
Receiving pub. assist.	597	70.18			378	83.33			600	53.83		
Move tracts since last wave		-			606	62.05			606	63.86		
Race/Ethnicity												

Black, not Latinx	591	84.94		
White, not Latinx	591	10.32		
Latinx	591	2.88		
Other race	591	1.86		
Sex: Female	606	93.23		

Table 3

Hurricane Impact Descriptives

Variable	N	Proportion		
Evacuated due to Katrina or Rita	601	97.50		
Death of loved one due to Katrina or Rita	606	39.11		
Living in pre-Katrina tract at PK1	606	37.95		
Living in pre-Katrina tract at PK2	606	23.43		
	N	**Mean (SD)**	**Min**	**Max**
Level of trauma related to Katrina or Rita	602	3.43 (2.34)	0	8
Number of moves in first year post-Katrina	366	2.67 (1.96)	0	9

Table 4

Neighborhood Descriptives by Wave

	Baseline				PK1				PK2			
	N	Mean (SD)	Min	Max	N	Mean (SD)	Min	Max	N	Mean (SD)	Min	Max
Percent poverty	606	22.13 (7.09)	4.92	35.43	591	19.22 (6.98)	2.89	38.44	606	19.75 (7.82)	1.60	42.10
Percent affluence	606	10.73 (4.12)	1.90	27.73	591	14.31 (6.58)	0.63	40.51	606	16.64 (7.61)	3.31	49.35
Basic amenities	593	16.73 (6.39)	1	31	581	11.27 (4.82)	0	25	591	10.75 (4.90)	0	31
Health services	593	40.72 (19.02)	0	118	581	43.56 (26.54)	0	152	591	39.71 (27.00)	0	152
Air pollution (10,000 lb. units)	606	4.56 (24.40)	0	251.55	591	4.29 (27.73)	0	271.59	606	5.77 (43.42)	0	433.72
Focal crime	593	18.37 (27.76)	0	101	581	11.24 (23.07)	0	190	591	11.13 (19.42)	0	135
Housing values ($10,000 units)	606	14.59 (3.21)	6.69	27.25	591	15.22 (4.65)	5.47	33.80	606	16.37 (4.66)	5.74	36.50

Table 5

Correlations on RQ1 Analytic Variables

		1	2	3	4	5	6	7	8	9	10	11
1	Psychological distress (logged)	-										
2	Perceived stress	0.55**										
3	Somatic symptoms	0.38**	0.26**									
4	Health	-0.41**	-0.45**	-0.23**								
5	Happiness	-0.30**	-0.29**	-0.37**	0.27**							
6	Neigh. % poverty	-0.01	-0.05*	-0.08**	0.05*	0.07**						
7	Neigh. % affluence	0.03	0.03	0.18**	-0.06*	-0.16**	-0.75**					
8	Neigh. basic amenities	-0.03	0.02	-0.14**	0.05†	0.12**	0.31**	-0.24**				
9	Neigh. health services (sqrt)	0.03	0.01	0.05*	-0.01	-0.05*	-0.28**	0.38**	0.45**			
10	Neigh. air pollution (logged)	-0.01	-0.02	-0.04	0.02	0.00	-0.10**	-0.03	0.03	0.04†		
11	Neigh. focal crime	0.00	0.02	-0.04	0.00	0.01	0.30**	-0.14**	0.21**	-0.06*	-0.12**	
12	Neigh. housing costs	-0.01	0.02	0.09**	-0.05†	-0.08**	-0.32**	0.68**	0.08**	0.37**	-0.05*	0.08**

Note: ***p*<0.01; **p*<0.05; † *p*<0.10

Table 6

Correlations on RQ2 Analytic Variables

		1	2	3	4	5	6	7	8	9	10	11	12
1	Change in distress	–											
2	Change in stress	0.54 **											
3	Change in somatic symptoms	0.30 **	0.21 **										
4	Change in health	-0.22 **	-0.24 **	-0.30 **									
5	Change in happiness	-0.33 **	-0.36 **	-0.19 **	0.23 **								
6	Change in % poverty	0.01	-0.01	-0.04	-0.03	0.03							
7	Change in % affluence	-0.03	0.03	0.04	0.02	-0.03	-0.74 **						
8	Observed change in amenities	0.01	0.07	0.01	0.02	0.04	0.32 **	-0.07					
9	Observed change in crime	0.02	0.08 †	0.06	-0.04	0.00	0.25 **	-0.03	0.43 **				
10	Observed change in housing costs	-0.03	0.02	0.03	0.03	-0.06	-0.27 **	0.60 **	0.08 *	0.08 †			
11	Perceived change in amenities	0.02	-0.04	0.07	0.03	0.05	-0.11 *	0.09 †	0.17 **	0.10 *	-0.02		
12	Perceived change in crime	0.07	0.15 **	0.11 *	-0.12 *	-0.09 †	0.23 **	-0.15 **	0.13 **	0.09 †	0.01	-0.22 **	
13	Perceived change in costs	0.01	0.05	0.04	0.00	-0.06	-0.03	0.01	-0.06	0.00	0.09 †	-0.10 *	-0.12 *

Note: ***p*<0.01; **p*<0.05; † *p*<0.10

Table 7

T-tests Comparing Analytic Sample to Dropped Sample

	Analytic Sample N=606		Dropped Sample N=413		Two-Sample T-Test Results			
Baseline Characteristics	n	**proportion**	n	**proportion**	*df*	*t-value*	*p-value*	
Married	599	17.70	404	20.79	1001	1.23	0.22	
Less than hs ed	604	3.97	413	2.66	980	-1.17	0.24	
Currently employed	604	50.00	413	53.51	1015	1.10	0.27	
Receiving pub. assist.	597	70.18	399	69.17	994	-0.34	0.73	
Own home	528	20.32	187	19.32	713	0.30	0.77	
Black, not Latinx	591	84.94	394	85.28	983	0.15	0.88	
Other race	591	15.06	394	14.72	983	-0.15	0.88	
Female	606	93.23	413	91.28	815	-1.13	0.26	
		mean (SD)		**mean (SD)**	*df*	*t-value*	*p-value*	
Household size	584	3.69 (1.49)	400	3.58 (1.48)	982	-1.13	0.26	
Number of children	603	1.79 (1.05)	411	1.83 (0.99)	1012	0.64	0.52	
Monthly earnings	586	536.43 (677.21)	400	585.32 (698.78)	984	1.10	0.27	
Psychological distress	587	4.88 (4.01)	384	5.01 (4.18)	969	0.51	0.61	
Perceived stress	596	5.43 (3.20)	399	5.81 (3.11)	993	1.86	0.06	†
Somatic symptoms	595	0.38 (0.65)	396	0.38 (0.64)	989	-0.11	0.92	
General health	599	4.06 (0.86)	399	4.15 (0.81)	996	1.71	0.09	†
General happiness	589	3.31 (0.62)	392	3.27 (0.64)	979	-0.84	0.40	

Note: ***p*<0.01; **p*<0.05; † *p*<0.10

Table 8

T-tests on Displacement and Returns

	Not displaced by hurricane (N = 168)		Displaced by hurricane (N = 432)				
Baseline Characteristics	**n**	**proportion**	**n**	**proportion**	*df*	*t-value*	
Married	165	20.00	428	16.59	591	0.98	
Less than high school education	168	3.57	430	4.19	596	-0.34	
Currently employed	168	47.02	430	51.16	596	-0.91	
Receiving public assistance	166	62.05	425	73.41	589	-2.73	**
Black, not Latinx	165	76.36	420	88.81	238	-3.40	**
Other race	165	23.64	420	11.19	238	3.40	**
Female	168	95.24	432	92.59	371	1.27	
		mean (sd)		**mean (sd)**	*df*	*t-value*	
Household size	159	3.79 (1.45)	419	3.65 (1.50)	576	1.03	
Number of children	168	1.72 (0.90)	429	1.82 (1.11)	375	-1.09	
Monthly earnings	162	507.63 (668.35)	418	547.17 (681.12)	578	-0.63	
Social support	166	3.21 (0.45)	427	3.22 (0.45)	591	-0.22	
Psychological distress	160	4.31 (3.42)	421	5.06 (4.29)	357	-2.20	*
Perceived stress	165	5.49 (2.92)	425	5.38 (3.29)	335	0.40	
Somatic symptoms	162	0.44 (0.71)	427	0.35 (0.61)	255	1.34	
General health	166	4.06 (0.86)	427	4.06 (0.86)	591	0.05	
General happiness	163	3.35 (0.60)	421	3.29 (0.62)	582	0.97	
Of those displaced (N = 432)	Returned to original parish by PK1 (N = 127)		Remained displaced at PK1 (N = 192)				
	n	**proportion**	**n**	**proportion**	*df*	*t-value*	
Married	125	23.2	191	15.18	240	-1.53	
Less than high school education	127	3.94	191	3.66	320	-0.14	

Currently employed	126	50.79	191	50.79	319	0.11	
Receiving public assistance	127	66.14	187	79.14	245	2.44	*
Black, not Latinx	125	82.40	187	92.51	202	-2.58	*
Other race	125	17.60	187	7.49	202	-2.58	*
Female	127	93.70	192	94.79	321	0.23	
		mean (sd)		**mean (sd)**	*df*	*t-value*	
Household size	124	3.72 (1.43)	187	3.69 (1.50)	313	-0.10	
Number of children	127	1.94 (1.17)	190	1.81 (1.16)	319	-0.88	
Monthly earnings	124	557.42 (686.87)	183	515.44 (681.07)	309	-0.45	
Social support	127	3.18 (0.49)	189	3.24 (0.44)	318	1.28	
Psychological distress	125	4.88 (4.13)	187	5.02 (4.39)	314	0.36	
Perceived stress	126	5.29 (3.11)	189	5.32 (3.46)	317	0.19	
Somatic symptoms	127	0.34 (0.62)	189	0.32 (0.54)	318	0.11	
General health	127	4.06 (0.81)	190	4.01 (0.90)	319	-0.50	
General happiness	125	3.31 (0.65)	186	3.3 (0.59)	312	-0.31	

Of those still displaced (N = 192)	Returned to original parish by PK2 (N = 68)		Remained displaced at PK2 (N = 124)				
Baseline Characteristics	**n**	**proportion**	**n**	**proportion**	*df*	*t-value*	
Married	68	14.71	123	15.45	227	0.27	
Less than high school education	67	2.99	124	4.03	228	0.46	
Currently employed	68	39.71	123	56.91	228	2.30	*
Receiving public assistance	65	83.08	122	77.05	224	-1.00	
Black, not Latinx	65	92.31	122	92.62	188	-0.08	
Other race	65	7.69	122	7.38	185	-0.08	
Female	68	97.06	124	93.55	208	-2.20	*
		mean (sd)		**mean (sd)**	*df*	*t-value*	
Household size	66	3.83 (1.57)	121	3.61 (1.46)	223	-1.02	
Number of children	68	1.79 (1.20)	122	1.82 (1.14)	227	0.27	
Monthly earnings	64	405.09 (612.46)	119	574.8 (710.64)	219	1.57	

Social support	68	3.26 (0.46)	121	3.24 (0.44)	226	-0.38	
Psychological distress	68	4.34 (4.34)	119	5.41 (4.39)	224	1.72	†
Perceived stress	68	5.37 (3.34)	121	5.30 (3.54)	226	0.13	
Somatic symptoms	68	0.35 (0.59)	121	0.31 (0.51)	226	0.04	
General health	68	3.90 (0.81)	122	4.07 (0.95)	226	1.36	
General happiness	67	3.28 (0.57)	119	3.30 (0.60)	221	-0.09	

Note: $^{**}p<0.01$; $^{*}p<0.05$; † $p<0.10$

Table 9

Baseline Characteristics Predicting Neighborhood Poverty

Baseline Characteristics	**PK1 Neighborhood Poverty β (SE)**		**PK2 Neighborhood Poverty β (SE)**	
Psychological distress (logged)	-0.03 (0.05)		0.01 (0.06)	
Perceived stress	0.03 (0.05)		-0.08 (0.06)	
General health	0.01 (0.05)		0.03 (0.06)	
General happiness	-0.01 (0.05)		-0.03 (0.06)	
Somatic symptoms	-0.02 (0.08)		0.09 (0.08)	
Married	-0.35 (0.10)	**	-0.28 (0.12)	*
Less than HS education	-0.19 (0.19)		-0.11 (0.22)	
Household size (logged)	-0.02 (0.04)		0.04 (0.04)	
Currently employed	0.18 (0.43)		0.32 (0.71)	
Monthly earnings	-0.17 (0.22)		-0.24 (0.37)	
Receiving public assistance	0.07 (0.09)		-0.05 (0.10)	
Female	0.08 (0.17)		-0.06 (0.22)	
Race: Not Black	-0.27 (0.14)	†	-0.53 (0.14)	**
Intercept	-0.30 (0.33)		-0.05 (0.44)	

Note: Regressions adjusted for baseline clustering of individuals within tracts. ***p*<0.01; **p*<0.05; † *p*<0.10

Table 10

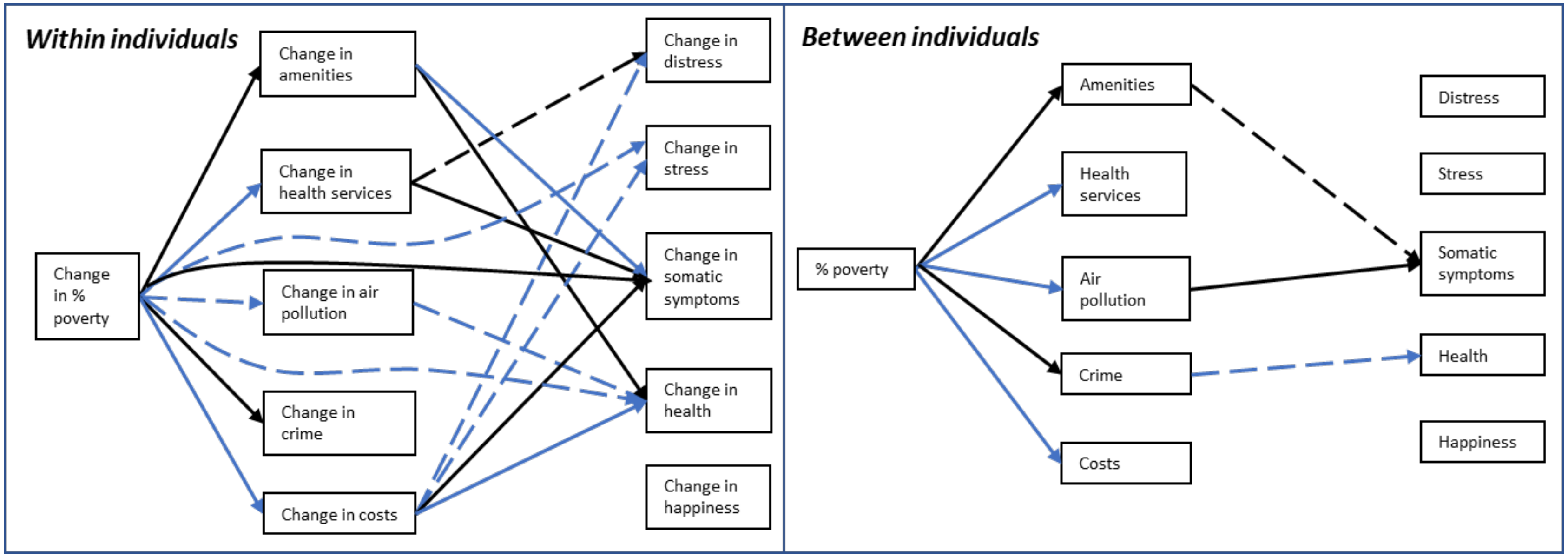
RQ1 Model Fit for Neighborhood Poverty Models

	[95% CI]		*p-value*
Distress	[20.22,	160.83]	0.01
Stress	[21.96,	170.43]	0.01
Somatic	[23.11,	168.76]	0.00
Health	[21.59,	163.96]	0.01
Happiness	[24.97,	163.29]	0.00

Note: 95% CI refers to the 95% Confidence Interval for the Difference Between the Observed and the Replicated Chi-Square Values. P-value refers to the Posterior Predictive p-value.

Figure 5

RQ1 SEM Results: Neighborhood Poverty Predicting Wellbeing Within and Between Individuals



Note: Solid pathways represent significant associations (p<.05), while dashed pathways approach significance (p<.10). Black pathways represent positive links, and blue pathways negative links. The following covariates were included as predictors of outcome variables: marital status, education, household size, earnings, receipt of public assistance, moves, hurricane-related death, hurricane related trauma, and, at the between level only, race/ethnicity.

Table 11

RQ1 SEM Results: Neighborhood Poverty Predicting Wellbeing

	Distress	Stress	Somatic Symptoms	Health	Happiness
	β (SD)	β (SD)	β (SD)	β (SD)	β (SD)
***Within individuals*, changes in neighborhood poverty predicting changes in neighborhood features**					
% pov → amenities	0.39 (0.03) **	0.39 (0.03) **	0.39 (0.03) **	0.39 (0.03) **	0.39 (0.03) **
% pov → health services	-0.30 (0.03) **	-0.30 (0.03) **	-0.30 (0.03) **	-0.30 (0.03) **	-0.30 (0.03) **
% pov → air pollution	-0.05 (0.03) †	-0.05 (0.03) †	-0.05 (0.03) †	-0.05 (0.03) †	-0.05 (0.03) †
% pov → crime	0.27 (0.03) **	0.27 (0.03) **	0.27 (0.03) **	0.27 (0.03) **	0.27 (0.03) **
% pov → housing costs	-0.35 (0.03) **	-0.35 (0.03) **	-0.35 (0.03) **	-0.35 (0.03) **	-0.35 (0.03) **
***Within individuals*, changes in neighborhood features predicting changes in wellbeing**					
amenities → outcome	-0.04 (0.04)	0.03 (0.04)	-0.11 (0.04) **	0.11 (0.04) **	0.05 (0.04)
health services → outcome	0.07 (0.04) †	0.03 (0.04)	0.08 (0.04) *	-0.03 (0.04)	-0.03 (0.04)
air pollution → outcome	-0.01 (0.03)	-0.04 (0.03)	-0.04 (0.03)	-0.05 (0.03) †	0.03 (0.03)
crime → outcome	0.03 (0.03)	0.05 (0.04)	0.00 (0.03)	0.02 (0.03)	0.02 (0.04)
housing costs → outcome	-0.06 (0.03) †	-0.06 (0.03) †	0.10 (0.03) **	-0.07 (0.03) *	-0.04 (0.04)
% poverty → outcome	0.02 (0.04)	-0.08 (0.04) †	0.08 (0.04) *	-0.07 (0.04) †	-0.02 (0.04)
***Between individuals*, neighborhood poverty predicting neighborhood features**					
% pov → amenities	0.22 (0.06) **	0.23 (0.06) **	0.22 (0.06) **	0.22 (0.06) **	0.22 (0.06) **
% pov → health services	-0.25 (0.06) **	-0.24 (0.06) **	-0.25 (0.06) **	-0.25 (0.06) **	-0.25 (0.06) **
% pov → air pollution	-0.18 (0.06) **	-0.17 (0.06) **	-0.18 (0.06) **	-0.17 (0.06) **	-0.18 (0.06) **
% pov → crime	0.36 (0.06) **	0.36 (0.06) **	0.36 (0.06) **	0.35 (0.06) **	0.36 (0.06) **
% pov → housing costs	-0.25 (0.06) **	-0.25 (0.06) **	-0.25 (0.06) **	-0.26 (0.06) **	-0.25 (0.06) **
***Between individuals*, neighborhood features predicting wellbeing**					
amenities → outcome	-0.10 (0.16)	-0.04 (0.17)	0.29 (0.15) †	-0.18 (0.16)	-0.01 (0.16)

health services → outcome	0.03 (0.14)	-0.07 (0.15)	-0.14 (0.13)	-0.07 (0.14)	0.04 (0.13)
air pollution → outcome	0.03 (0.08)	0.03 (0.07)	0.16 (0.07) *	-0.06 (0.08)	-0.05 (0.08)
crime → outcome	-0.02 (0.07)	0.02 (0.07)	0.00 (0.07)	-0.14 (0.07) †	-0.07 (0.07)
housing costs → outcome	0.07 (0.10)	0.11 (0.10)	-0.05 (0.09)	0.06 (0.09)	-0.05 (0.09)
% poverty → outcome	-0.01 (0.09)	-0.10 (0.10)	-0.08 (0.09)	0.14 (0.10)	0.14 (0.09)
***Within individuals*, time-varying covariates predicting changes in wellbeing**					
married	0.05 (0.08)	0.09 (0.08)	0.09 (0.08)	-0.04 (0.08)	0.04 (0.09)
college degree	-0.11 (0.11)	-0.07 (0.12)	0.27 (0.10) *	-0.29 (0.11) **	0.18 (0.12)
household size	0.00 (0.03)	0.00 (0.03)	0.03 (0.03)	-0.02 (0.03)	-0.02 (0.03)
earnings	-0.01 (0.03)	-0.08 (0.03) **	0.06 (0.03) *	-0.06 (0.03) *	0.05 (0.03)
receiving public assistance	0.04 (0.07)	-0.11 (0.07) †	0.00 (0.06)	0.06 (0.07)	-0.09 (0.07)
moved since last wave	-0.02 (0.06)	-0.06 (0.06)	0.25 (0.06) **	-0.29 (0.06) **	-0.09 (0.07)
hurricane-related death	0.39 (0.11) **	0.27 (0.11) *	0.53 (0.10) **	0.01 (0.10)	-0.08 (0.11)
hurricane-related trauma	0.04 (0.04)	-0.03 (0.04)	0.16 (0.03) **	-0.12 (0.03) **	-0.03 (0.04)
***Between individuals*, covariates predicting wellbeing**					
avg. waves married	0.00 (0.15)	0.10 (0.14)	0.06 (0.13)	0.01 (0.14)	0.26 (0.14) †
avg. waves with college degree	0.15 (0.42)	-0.45 (0.39)	-0.44 (0.34)	0.89 (0.37) **	0.68 (0.4) †
avg. household size	-0.10 (0.07)	-0.05 (0.07)	-0.08 (0.07)	0.13 (0.07) †	0.07 (0.08)
avg. earnings	-0.14 (0.16)	-0.08 (0.15)	-0.39 (0.15) **	0.40 (0.20) *	-0.04 (0.15)
avg. waves receiving pub. assist.	0.47 (0.29) †	0.87 (0.33) **	0.70 (0.26) **	-1.19 (0.30) **	-0.23 (0.30)
avg. waves moved	2.38 (1.39) *	1.40 (1.34)	-2.24 (2.42)	1.81 (1.15) †	-0.49 (1.93)
hurricane-related death	0.55 (0.25) *	0.46 (0.24) †	0.56 (0.22) **	-0.48 (0.26) *	-0.31 (0.26)
hurricane-related trauma	0.99 (0.21) **	0.99 (0.24) **	0.53 (0.20) **	-0.58 (0.24) *	-0.48 (0.27) *
race (base: Black)					
other race	0.17 (0.09) †	0.14 (0.10)	0.38 (0.08) **	-0.24 (0.09) *	-0.11 (0.09)
Intercepts					
amenities	-0.01 (0.03)	-0.01 (0.03)	-0.01 (0.03)	-0.01 (0.03)	-0.01 (0.03)
health services	0.01 (0.03)	0.01 (0.03)	0.01 (0.03)	0.01 (0.03)	0.01 (0.03)
air pollution	0.00 (0.03)	0.00 (0.03)	0.00 (0.03)	0.00 (0.03)	0.00 (0.03)

crime	0.00 (0.03)	0.00 (0.03)	0.00 (0.03)	0.00 (0.03)	0.00 (0.03)
housing costs	0.00 (0.03)	0.00 (0.03)	0.00 (0.03)	0.00 (0.03)	0.00 (0.03)
outcome	-1.48 (0.61) *	-1.26 (0.58) *	0.37 (1.05)	0.08 (0.52)	0.33 (0.86)

[a] The Bayes Estimator produces a posterior standard deviation estimate in place of a standard error. ***p*<0.01; **p*<0.05; † *p*<0.10

Table 12

RQ1 Indirect, Direct, and Total Effects of Neighborhood Poverty

	Distress	**Stress**	**Somatic Symptoms**	**Health**	**Happiness**
Within Individuals	β (SD)	β (SD)	β (SD)	β (SD)	β (SD)
% poverty via amenities	-0.02 (0.02)	0.01 (0.02)	-0.04 (0.02) **	0.04 (0.02) **	0.02 (0.02)
% poverty via health services	-0.02 (0.01) †	-0.01 (0.01)	-0.02 (0.01) *	0.01 (0.01)	0.01 (0.01)
% poverty via air pollution	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
% poverty via crime	0.01 (0.01)	0.01 (0.01)	0.00 (0.01)	0.01 (0.01)	0.01 (0.01)
% poverty via housing costs	0.02 (0.01) †	0.02 (0.01) †	-0.03 (0.01) **	0.02 (0.01) *	0.01 (0.01)
Total Indirect Effect	-0.01 (0.03)	0.04 (0.03)	-0.10 (0.03) **	0.09 (0.03) **	0.05 (0.03)
Direct Effect	0.02 (0.04)	-0.08 (0.04) †	0.08 (0.04) *	-0.07 (0.04) †	-0.02 (0.04)
Total Effect	**0.02 (0.03)**	**-0.04 (0.03)**	**-0.01 (0.03)**	**0.02 (0.03)**	**0.03 (0.04)**
Between Individuals	β (SD)	β (SD)	β (SD)	β (SD)	β (SD)
Specific Indirect Effects					
% poverty via amenities	-0.02 (0.04)	-0.01 (0.04)	0.06 (0.04) †	-0.04 (0.04)	0.00 (0.04)
% poverty via health services	-0.01 (0.03)	0.02 (0.04)	0.03 (0.04)	0.02 (0.04)	-0.01 (0.03)
% poverty via air pollution	0.00 (0.02)	0.00 (0.01)	-0.03 (0.02) *	0.01 (0.01)	0.01 (0.01)
% poverty via crime	-0.01 (0.03)	0.01 (0.03)	0.00 (0.03)	-0.05 (0.03) †	-0.03 (0.03)
% poverty via housing costs	-0.02 (0.02)	-0.03 (0.03)	0.01 (0.02)	-0.01 (0.02)	0.01 (0.02)

Total Indirect Effect	-0.06 (0.08)	-0.02 (0.08)	0.08 (0.08)	-0.08 (0.08)	-0.02 (0.08)
Direct Effect	-0.01 (0.09)	-0.10 (0.10)	-0.08 (0.09)	0.14 (0.10)	0.14 (0.09)
Total Effect	**-0.08 (0.07)**	**-0.12 (0.07) †**	**0.00 (0.06)**	**0.06 (0.07)**	**0.13 (0.07) †**

[a] The Bayes Estimator produces a posterior standard deviation estimate in place of a standard error. ***p*<0.01; **p*<0.05; † *p*<0.10

Table 13

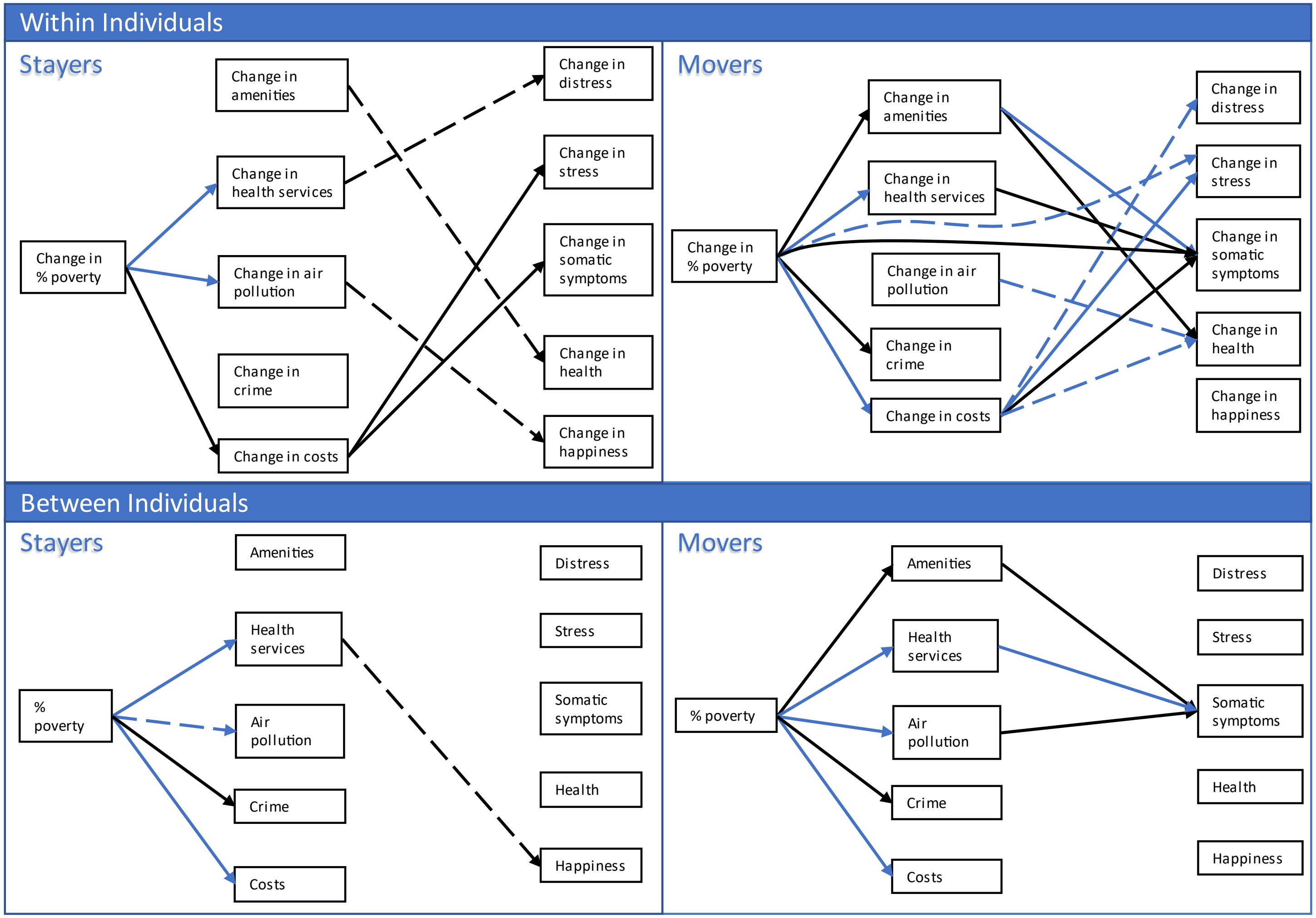
RQ1 Model Fit for Poverty Models: Stayers vs. Movers

	Stayers			**Movers**		
	[95% CI]		***p-value***	**[95% CI]**		***p-value***
Distress	[-37.38,	97.98]	0.18	[-8.01,	126.86]	0.04
Stress	[-34.48,	93.13]	0.18	[-8.28,	129.28]	0.04
Somatic	[-32.61,	99.13]	0.16	[-9.33,	129.15]	0.05
Health	[-33.10,	99.42]	0.16	[-7.00,	126.32]	0.05
Happiness	[-34.35,	93.71]	0.17	[-11.28,	124.97]	0.05

Note: 95% CI refers to the 95% Confidence Interval for the Difference Between the Observed and the Replicated Chi-Square Values. *p-value* refers to the Posterior Predictive p-value.

Figure 6

RQ1 SEM Results: Neighborhood Poverty Predicting Wellbeing for Stayers vs. Movers



Note: Solid pathways represent significant associations ($p<.05$), while dashed pathways approach significance ($p<.10$). Black pathways represent positive links, and blue pathways negative links. The following covariates were included as predictors of outcome variables: marital status, education, household size, earnings, receipt of public assistance, hurricane-related death, hurricane related trauma, and, at the between level only, race/ethnicity.

Table 14

RQ1 SEM Results: Neighborhood Poverty Part I for Stayers vs. Movers

	Distress		Stress	
	Stayers	**Movers**	**Stayers**	**Movers**
	β (SD)	β (SD)	β (SD)	β (SD)
Within individuals, changes in neighborhood poverty predicting changes in neighborhood features				
% pov → amenities	0.28 (0.18)	0.40 (0.03) **	0.27 (0.18)	0.40 (0.03) **
% pov → health services	-0.34 (0.09) **	-0.29 (0.03) **	-0.34 (0.08) **	-0.29 (0.03) **
% pov → air pollution	-0.36 (0.12) **	-0.04 (0.03)	-0.35 (0.12) **	-0.04 (0.03)
% pov → crime	0.06 (0.04)	0.26 (0.03) **	0.05 (0.04)	0.27 (0.03) **
% pov → housing costs	0.40 (0.10) **	-0.36 (0.03) **	0.40 (0.10) **	-0.36 (0.03) **
***Within individuals*, changes in neighborhood features predicting changes in wellbeing**				
amenities → outcome	-0.08 (0.2)	-0.04 (0.04)	0.07 (0.19)	0.03 (0.04)
health services → outcome	0.68 (0.36) †	0.06 (0.04)	0.40 (0.35)	0.03 (0.04)
air pollution → outcome	0.02 (0.17)	-0.02 (0.03)	-0.16 (0.16)	-0.03 (0.03)
crime → outcome	-0.10 (0.68)	0.03 (0.03)	0.18 (0.65)	0.06 (0.04)
housing costs → outcome	0.25 (0.26)	-0.06 (0.03) †	0.57 (0.25) *	-0.07 (0.04) *
% poverty → outcome	0.07 (0.34)	0.02 (0.04)	-0.33 (0.32)	-0.08 (0.04) †
***Between individuals*, neighborhood poverty predicting neighborhood features**				
% pov → amenities	0.14 (0.12)	0.21 (0.07) **	0.14 (0.12)	0.20 (0.07) **

% pov → health services	-0.31 (0.13) *	-0.25 (0.08) **	-0.31 (0.12) *	-0.24 (0.08) **
% pov → air pollution	-0.19 (0.12) †	-0.20 (0.08) **	-0.20 (0.12) †	-0.20 (0.08) *
% pov → crime	0.27 (0.12) *	0.41 (0.08) **	0.26 (0.12) *	0.41 (0.08) **
% pov → housing costs	-0.23 (0.1) *	-0.25 (0.08) **	-0.23 (0.10) *	-0.25 (0.08) **
***Between individuals*, neighborhood features predicting wellbeing**				
amenities → outcome	0.20 (0.16)	-0.38 (0.98)	0.16 (0.13)	-0.60 (1.59)
health services → outcome	-0.10 (0.14)	0.16 (0.73)	-0.10 (0.12)	0.29 (1.41)
air pollution → outcome	-0.05 (0.09)	0.07 (0.37)	0.08 (0.08)	-0.11 (0.46)
crime → outcome	-0.07 (0.10)	-0.01 (0.20)	-0.01 (0.08)	-0.05 (0.27)
housing costs → outcome	0.00 (0.13)	0.13 (0.20)	-0.02 (0.12)	0.19 (0.30)
% poverty → outcome	-0.08 (0.12)	0.02 (0.33)	-0.14 (0.11)	0.05 (0.60)
***Within individuals,* time-varying covariates predicting wellbeing**				
married	0.25 (0.20)	0.02 (0.09)	0.35 (0.19) †	0.04 (0.09)
college degree	0.11 (0.27)	-0.21 (0.12) †	-0.22 (0.26)	-0.09 (0.13)
household size	-0.03 (0.10)	0.00 (0.04)	0.09 (0.09)	-0.03 (0.04)
earnings	0.05 (0.08)	-0.04 (0.03)	-0.08 (0.07)	-0.09 (0.04) **
receiving public assistance	0.09 (0.16)	0.02 (0.07)	-0.08 (0.15)	-0.10 (0.08)
hurricane-related death	0.23 (0.30)	0.43 (0.11) **	0.44 (0.28)	0.23 (0.12) †
hurricane-related trauma	0.07 (0.09)	0.03 (0.04)	-0.12 (0.09)	-0.03 (0.04)
***Between individuals*, covariates predicting wellbeing**				
avg. waves married	-0.10 (0.35)	0.00 (0.16)	-0.06 (0.32)	0.16 (0.17)
avg. waves with college degree	0.47 (0.79)	-0.02 (0.53)	-0.42 (0.69)	-0.34 (0.53)
avg. household size	-0.31 (0.16) *	-0.03 (0.09)	-0.25 (0.14) †	0.04 (0.09)
avg. earnings	-0.76 (1.63)	-0.09 (0.16)	-0.51 (1.24)	0.00 (0.17)
avg. waves receiving pub. assist.	0.31 (0.60)	0.53 (0.39)	0.44 (0.58)	0.91 (0.39) *
hurricane-related death	0.23 (0.59)	0.57 (0.28) †	0.16 (0.53)	0.49 (0.27) †
hurricane-related trauma	0.95 (1.86)	1.20 (0.43) **	0.87 (1.81)	1.22 (0.32) **
race (base: Black)	0.15 (0.19)	0.20 (0.11) †	0.06 (0.17)	0.15 (0.11)
Intercepts				
amenities	0.03 (0.09)	-0.02 (0.03)	0.03 (0.09)	-0.02 (0.03)
health services	-0.14 (0.10)	0.04 (0.03)	-0.14 (0.10)	0.04 (0.03)

air pollution	0.05 (0.10)	-0.01 (0.03)	0.05 (0.09)	-0.01 (0.03)
crime	-0.09 (0.10)	0.02 (0.03)	-0.08 (0.09)	0.02 (0.03)
housing costs	0.01 (0.08)	0.00 (0.03)	0.01 (0.08)	0.00 (0.03)
outcome	-0.38 (0.43)	-0.48 (0.29) †	-0.20 (0.41)	-0.72 (0.30) *

[a] The Bayes Estimator produces a posterior standard deviation estimate in place of a standard error. ***p*<0.01; **p*<0.05; † *p*<0.10

Table 15

RQ1 SEM Results: Neighborhood Poverty Part II for Stayers vs. Movers

	Somatic Symptoms		Health		Happiness	
	Stayers	**Movers**	**Stayers**	**Movers**	**Stayers**	**Movers**
	β (SD)	β (SD)	β (SD)	β (SD)	β (SD)	β (SD)
Within individuals, changes in neighborhood poverty predicting changes in neighborhood features						
% pov → amenities	0.28 (0.18)	0.40 (0.03) **	0.30 (0.19) †	0.40 (0.03) **	0.27 (0.18)	0.41 (0.03) **
% pov → health services	-0.34 (0.08) **	-0.29 (0.03) **	-0.34 (0.09) **	-0.29 (0.03) **	-0.35 (0.08) **	-0.29 (0.03) **
% pov → air pollution	-0.35 (0.12) **	-0.04 (0.03)	-0.35 (0.12) **	-0.04 (0.03)	-0.35 (0.12) **	-0.04 (0.03)
% pov → crime	0.06 (0.04)	0.26 (0.03) **	0.06 (0.04)	0.26 (0.03) **	0.06 (0.04)	0.27 (0.03) **
% pov → housing costs	0.39 (0.10) **	-0.36 (0.03) **	0.39 (0.10) **	-0.37 (0.03) **	0.40 (0.10) **	-0.36 (0.03) **
***Within individuals*, changes in neighborhood features predicting changes in wellbeing**						
amenities → outcome	-0.11 (0.17)	-0.14 (0.04) **	0.35 (0.19) †	0.15 (0.04) **	0.15 (0.19)	0.06 (0.04)
health services → outcome	0.37 (0.32)	0.10 (0.04) *	-0.50 (0.34)	-0.05 (0.04)	-0.40 (0.34)	-0.03 (0.04)
air pollution → outcome	-0.18 (0.14)	-0.05 (0.03)	0.21 (0.16)	-0.05 (0.03)	0.31 (0.16) †	0.03 (0.03)
crime → outcome	0.33 (0.59)	0.02 (0.03)	-0.02 (0.63)	0.00 (0.03)	0.09 (0.63)	0.01 (0.04)
housing costs → outcome	0.86 (0.22) **	0.08 (0.03) *	-0.34 (0.24)	-0.06 (0.03) †	-0.05 (0.24)	-0.04 (0.04)
% poverty → outcome	-0.04 (0.28)	0.08 (0.04) *	0.08 (0.31)	-0.06 (0.04)	-0.18 (0.31)	-0.01 (0.04)
***Between individuals,* neighborhood poverty predicting neighborhood features**						
% pov → amenities	0.13 (0.12)	0.21 (0.07) **	0.14 (0.12)	0.21 (0.07) **	0.14 (0.12)	0.15 (0.07) *

% pov → health services	-0.32 (0.12) **	-0.25 (0.08) **	-0.31 (0.12) *	-0.25 (0.08) **	-0.31 (0.12) *	-0.26 (0.08) **
% pov → air pollution	-0.20 (0.12) †	-0.20 (0.08) *	-0.19 (0.12) †	-0.21 (0.08) **	-0.19 (0.12) †	-0.20 (0.08) *
% pov → crime	0.26 (0.12) *	0.41 (0.08) **	0.27 (0.12) *	0.41 (0.08) **	0.27 (0.12) *	0.39 (0.08) **
% pov → housing costs	-0.23 (0.10) *	-0.25 (0.08) **	-0.23 (0.10) *	-0.25 (0.09) **	-0.23 (0.10) *	-0.26 (0.08) **
***Between individuals*, neighborhood features predicting wellbeing**						
amenities → outcome	0.21 (0.14)	1.05 (0.54) *	-0.15 (0.14)	-0.42 (0.62)	-0.21 (0.14)	-0.42 (96.26)
health services → outcome	0.04 (0.12)	-0.76 (0.37) *	-0.08 (0.13)	0.11 (0.49)	0.22 (0.12) †	0.30 (61.77)
air pollution → outcome	0.09 (0.08)	0.41 (0.20) *	-0.11 (0.09)	-0.06 (0.22)	0.06 (0.09)	-0.26 (5.81)
crime → outcome	-0.02 (0.09)	0.09 (0.17)	-0.09 (0.09)	-0.18 (0.16)	0.01 (0.09)	-0.20 (8.91)
housing costs → outcome	-0.06 (0.13)	0.05 (0.21)	0.03 (0.13)	0.06 (0.17)	-0.12 (0.12)	0.03 (5.08)
% poverty → outcome	0.01 (0.11)	-0.32 (0.26)	0.02 (0.11)	0.25 (0.26)	0.17 (0.11)	0.31 (31.87)
***Within individuals*, time-varying covariates predicting changes in wellbeing**						
married	-0.02 (0.17)	0.14 (0.08) †	-0.06 (0.18)	-0.08 (0.09)	0.02 (0.18)	0.04 (0.10)
college degree	0.04 (0.23)	0.29 (0.12) *	0.05 (0.26)	-0.38 (0.12) **	0.22 (0.26)	0.18 (0.14)
household size	0.01 (0.08)	0.05 (0.03)	0.04 (0.09)	-0.04 (0.03)	-0.01 (0.09)	-0.02 (0.04)
earnings	0.11 (0.07)	0.03 (0.03)	-0.14 (0.08) †	-0.03 (0.03)	-0.01 (0.07)	0.06 (0.04) †
receiving public assistance	0.25 (0.13) †	-0.08 (0.07)	0.06 (0.16)	0.08 (0.07)	-0.26 (0.15) †	-0.05 (0.08)
hurricane-related death	0.21 (0.25)	0.64 (0.11) **	-0.10 (0.27)	-0.04 (0.11)	-0.07 (0.28)	-0.12 (0.12)
hurricane-related trauma	0.14 (0.08) †	0.22 (0.04) **	-0.09 (0.08)	-0.20 (0.04) **	-0.05 (0.08)	-0.04 (0.04)
***Between individuals*, covariates predicting wellbeing**						
avg. waves married	0.02 (0.32)	0.08 (0.14)	0.06 (0.33)	0.00 (0.17)	0.28 (0.33)	0.27 (0.17)
avg. waves with college degree	-0.41 (0.73)	-0.47 (0.44)	0.33 (0.76)	1.12 (0.54) *	0.16 (0.80)	0.97 (0.52) †
avg. household size	-0.31 (0.15) *	-0.03 (0.08)	0.14 (0.15)	0.12 (0.09)	0.06 (0.15)	0.08 (0.09)
avg. earnings	-0.77 (1.04)	-0.28 (0.14) *	0.68 (1.35)	0.20 (0.17)	0.40 (1.93)	-0.06 (0.17)
avg. waves receiving pub. assist.	0.60 (0.66)	0.76 (0.33) *	-0.54 (0.61)	-1.46 (0.44) **	-0.05 (0.66)	-0.31 (0.39)
hurricane-related death	-0.80 (0.56)	0.7 (0.25) **	0.76 (0.59)	-0.6 (0.29) *	-0.19 (0.59)	-0.29 (0.27)
hurricane-related trauma	1.12 (2.13)	0.35 (0.29)	-1.21 (1.40)	-0.47 (0.33)	-0.62 (2.91)	-0.47 (0.33) †
race (base: Black)	0.49 (0.19) *	0.39 (0.10) **	-0.54 (0.19) **	-0.14 (0.11)	-0.03 (0.19)	-0.12 (0.11)

Intercepts						
amenities	0.03 (0.09)	-0.02 (0.03)	0.03 (0.09)	-0.01 (0.03)	0.03 (0.09)	0.00 (0.03)
health services	-0.13 (0.10)	0.04 (0.03)	-0.14 (0.10)	0.04 (0.03)	-0.14 (0.10)	0.04 (0.03)
air pollution	0.05 (0.09)	-0.01 (0.03)	0.05 (0.10)	-0.01 (0.03)	0.05 (0.09)	-0.01 (0.03)
crime	-0.09 (0.09)	0.02 (0.03)	-0.09 (0.09)	0.02 (0.03)	-0.09 (0.09)	0.02 (0.03)
housing costs	0.00 (0.08)	0.00 (0.03)	0.00 (0.08)	0.00 (0.03)	0.00 (0.08)	0.00 (0.03)
outcome	-0.36 (0.45)	-0.63 (0.25) **	0.28 (0.42)	1.05 (0.32) **	0.04 (0.48)	0.11 (0.58)

[a] The Bayes Estimator produces a posterior standard deviation estimate in place of a standard error. ***p*<0.01; **p*<0.05; † *p*<0.10

Table 16

RQ1 Indirect, Direct, and Total Effects of Neighborhood Poverty Part I for Stayers vs. Movers

	Distress		Stress	
	Stayers	**Movers**	**Stayers**	**Movers**
Within Individuals	β (SD)	β (SD)	β (SD)	β (SD)
Specific Indirect Effects				
% poverty via amenities	-0.01 (0.07)	-0.02 (0.02)	0.01 (0.06)	0.01 (0.02)
% poverty via health services	-0.22 (0.14) †	-0.02 (0.01)	-0.13 (0.13)	-0.01 (0.01)
% poverty via air pollution	-0.01 (0.06)	0.00 (0.00)	0.05 (0.06)	0.00 (0.00)
% poverty via crime	0.00 (0.05)	0.01 (0.01)	0.00 (0.05)	0.02 (0.01)
% poverty via housing costs	0.09 (0.11)	0.02 (0.01) †	0.21 (0.11) *	0.03 (0.01) *
Total Indirect Effect	-0.17 (0.21)	0.00 (0.03)	0.17 (0.20)	0.05 (0.03) †
Direct Effect	0.07 (0.34)	0.02 (0.04)	-0.33 (0.32)	-0.08 (0.04) †
Total Effect	**-0.11 (0.28)**	**0.02 (0.03)**	**-0.16 (0.27)**	**-0.03 (0.04)**
Between Individuals				
Specific Indirect Effects				

% poverty via amenities	0.02 (0.04)	-0.07 (0.20)	0.02 (0.03)	-0.10 (0.33)
% poverty via health services	0.03 (0.05)	-0.04 (0.18)	0.03 (0.04)	-0.06 (0.34)
% poverty via air pollution	0.01 (0.02)	-0.01 (0.09)	-0.01 (0.02)	0.02 (0.10)
% poverty via crime	-0.01 (0.03)	0.00 (0.08)	0.00 (0.02)	-0.02 (0.12)
% poverty via housing costs	0.00 (0.03)	-0.03 (0.06)	0.00 (0.03)	-0.04 (0.08)
Total Indirect Effect	0.05 (0.08)	-0.16 (0.33)	0.04 (0.07)	-0.22 (0.60)
Direct Effect	-0.08 (0.12)	0.02 (0.33)	-0.14 (0.11)	0.05 (0.60)
Total Effect	**-0.04 (0.10)**	**-0.14 (0.10)**	**-0.09 (0.09)**	**-0.17 (0.09) †**

[a] The Bayes Estimator produces a posterior standard deviation estimate in place of a standard error. ***p*<0.01; **p*<0.05; † *p*<0.10

Table 17

RQ1 Indirect, Direct, and Total Effects of Neighborhood Poverty Part II for Stayers vs. Movers

	Somatic Symptoms		Health		Happiness	
	Stayers	**Movers**	**Stayers**	**Movers**	**Stayers**	**Movers**
Within Individuals	*β* (SD)	*β* (SD)	*β* (SD)	*β* (SD)	*β* (SD)	*β* (SD)
Specific Indirect Effects						
% pov via amenities	-0.02 (0.06)	-0.06 (0.02) **	0.09 (0.10)	0.06 (0.02) **	0.03 (0.07)	0.03 (0.02)
% pov via health services	-0.12 (0.12)	-0.03 (0.01) *	0.16 (0.13)	0.01 (0.01)	0.13 (0.13)	0.01 (0.01)
% pov via air pollution	0.06 (0.06)	0.00 (0.00)	-0.07 (0.06)	0.00 (0.00)	-0.10 (0.07) †	0.00 (0.00)
% pov via crime	0.01 (0.04)	0.01 (0.01)	0.00 (0.05)	0.00 (0.01)	0.00 (0.05)	0.00 (0.01)
% pov via housing costs	0.33 (0.12) **	-0.03 (0.01) *	-0.13 (0.1)	0.02 (0.01) †	-0.02 (0.10)	0.01 (0.01)
Total Indirect Effect	0.26 (0.19)	-0.11 (0.03) **	0.07 (0.21)	0.10 (0.03) **	0.06 (0.20)	0.05 (0.03) †
Direct Effect	-0.04 (0.28)	0.08 (0.04) *	0.08 (0.31)	-0.06 (0.04)	-0.18 (0.31)	-0.01 (0.04)
Total Effect	**0.23 (0.25)**	**-0.03 (0.03)**	**0.14 (0.27)**	**0.04 (0.03)**	**-0.11 (0.27)**	**0.04 (0.04)**
Between Individuals						
Specific Indirect Effects						

% pov via amenities	0.02 (0.03)	0.21 (0.14) *	-0.01 (0.03)	-0.08 (0.14)	-0.02 (0.04)	-0.06 (13.59)
% pov via health services	-0.01 (0.04)	0.18 (0.12) *	0.02 (0.04)	-0.03 (0.13)	-0.06 (0.05) †	-0.07 (16.41)
% pov via air pollution	-0.01 (0.02)	-0.08 (0.06) *	0.02 (0.02)	0.01 (0.05)	-0.01 (0.02)	0.04 (1.21)
% pov via crime	0.00 (0.03)	0.03 (0.07)	-0.02 (0.03)	-0.07 (0.07)	0.00 (0.03)	-0.08 (3.50)
% pov via housing costs	0.01 (0.03)	-0.01 (0.05)	-0.01 (0.03)	-0.01 (0.05)	0.02 (0.03)	-0.01 (1.30)
Total Indirect Effect	0.00 (0.07)	0.33 (0.25) †	-0.01 (0.07)	-0.18 (0.26)	-0.08 (0.07)	-0.17 (31.87)
Direct Effect	0.01 (0.11)	-0.32 (0.26)	0.02 (0.11)	0.25 (0.26)	0.17 (0.11)	0.31 (31.87)
Total Effect	**0.00 (0.10)**	**0.02 (0.08)**	**0.02 (0.10)**	**0.07 (0.09)**	**0.09 (0.09)**	**0.15 (0.09)**

[a] The Bayes Estimator produces a posterior standard deviation estimate in place of a standard error. ***p*<0.01; **p*<0.05; † *p*<0.10

Table 18

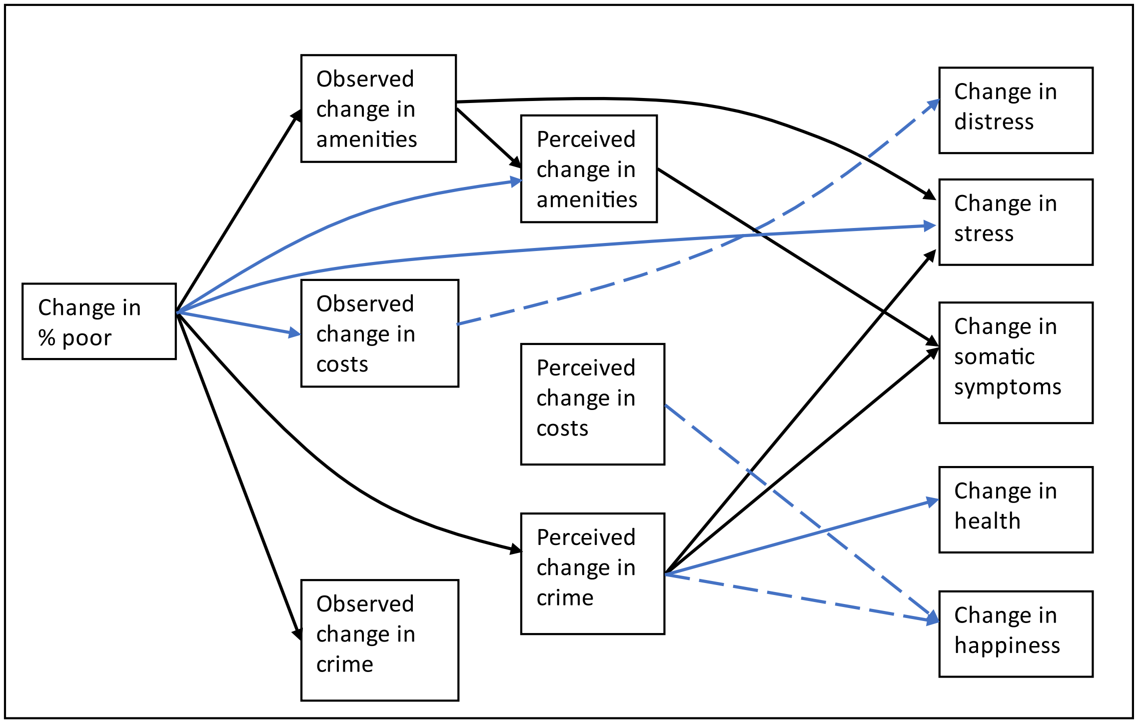
RQ2 Neighborhood Poverty Model Fit

CFI	TLI	RMSEA	[90% CI]	SRMR
0.98	0.95	0.03	[0.02 0.04]	0.03

Note: CFI = comparative fit index; TLI = Tucker-Lewis index; SRMR = standardized root mean square residual; RMSEA = root mean square error of approximation; CI = confidence interval.

Figure 7

RQ2 Main Path Analysis: Changes in Neighborhood Poverty Predicting Changes in Wellbeing



Note: Solid pathways represent significant associations ($p<.05$), while dashed pathways approach significance ($p<.10$). Black pathways represent positive links, and blue pathways negative links. The following covariates were included as predictors of outcome variables: baseline outcome, change in earnings, change in household size, change in receipt of public assistance, moving since baseline, hurricane-related trauma, hurricane-related death, and post-Katrina mobility.

Table 19

RQ2 Main Path Analysis: Changes in Neighborhood Poverty Predicting Changes in Wellbeing

	β (SD)	β (SD)	β (SD)	β (SD)	β (SD)
Changes in neighborhood poverty predicting observed and perceived changes in neighborhood features					
% pov → obs. amenities	0.32 (0.04) **				
% pov → perc. amenities	-0.22 (0.06) **				
% pov → obs. costs	-0.27 (0.05) **				
% pov → perc. costs	-0.01 (0.06)				
% pov → obs. crime	0.25 (0.04) **				
% pov → perc. crime	0.26 (0.06) **				
Observed changes in neighborhood features predicting perceived changes					
obs. → perc. amenities	0.25 (0.06) **				
obs. → perc. costs	0.10 (0.07)				
obs. → perc. crime	0.10 (0.07)				
Changes in neighborhood features predicting changes in wellbeing					
	Distress	**Stress**	**Somatic Symptoms**	**Health**	**Happiness**
observed amenities	0.04 (0.04)	0.08 (0.04) *	0.03 (0.04)	0.02 (0.05)	-0.01 (0.04)
perceived amenities	0.01 (0.04)	-0.01 (0.04)	0.11 (0.05) *	0.01 (0.05)	0.04 (0.04)
observed home values	-0.06 (0.04) †	-0.03 (0.03)	-0.01 (0.04)	0.03 (0.04)	-0.02 (0.04)
perceived costs	0.04 (0.04)	0.04 (0.04)	0.00 (0.05)	0.00 (0.04)	-0.07 (0.04) †
observed crime	-0.02 (0.04)	0.01 (0.04)	0.02 (0.04)	-0.03 (0.04)	0.03 (0.04)
perceived crime	0.06 (0.04)	0.09 (0.04) *	0.14 (0.05) **	-0.14 (0.05) **	-0.08 (0.04) †
% poverty	-0.01 (0.04)	-0.08 (0.04) *	-0.04 (0.05)	0.04 (0.05)	0.02 (0.04)
Covariates predicting changes in wellbeing					

outcome at W0	-0.56 (0.03) **	-0.61 (0.03) **	-0.39 (0.03) **	-0.47 (0.03) **	-0.65 (0.03) **
Δ earnings	-0.12 (0.04) **	-0.11 (0.04) **	-0.02 (0.05)	0.08 (0.04) †	0.09 (0.04) *
Δ household size	-0.07 (0.03) *	-0.06 (0.03) †	-0.04 (0.04)	0.02 (0.03)	0.04 (0.03)
receipt of public assistance (base: stable)					
started public assistance	-0.16 (0.11)	-0.03 (0.12)	-0.04 (0.13)	-0.05 (0.13)	0.22 (0.11) *
stopped public assistance	-0.02 (0.09)	0.13 (0.08)	-0.05 (0.09)	0.03 (0.09)	0.16 (0.08) *
moved tracts since W0	0.08 (0.09)	-0.05 (0.08)	0.09 (0.10)	-0.18 (0.09) *	-0.07 (0.08)
hurricane-related trauma	0.17 (0.04) **	0.16 (0.03) **	0.15 (0.04) **	-0.11 (0.04) **	-0.04 (0.03)
hurricane-related death	0.17 (0.08) *	0.04 (0.07)	0.24 (0.08) **	-0.14 (0.08) †	0.02 (0.07)
post-Katrina mobility	-0.08 (0.05) †	0.00 (0.04)	0.11 (0.05) *	0.06 (0.04)	-0.05 (0.04)

Note: ***p*<0.01; **p*<0.05; † *p*<0.10

Table 20

RQ2 Indirect, Direct, and Total Effects of Changes in Neighborhood Poverty on Changes in Wellbeing

	Distress	**Stress**	**Somatic Symptoms**	**Health**	**Happiness**
	β (SD)	*β* (SD)	*β* (SD)	*β* (SD)	*β* (SD)
Specific Indirect Effects					
% pov via observed amenities	0.01 (0.01)	0.03 (0.01) *	0.01 (0.01)	0.01 (0.02)	0.00 (0.01)
% pov via perceived amenities	0.00 (0.01)	0.00 (0.01)	-0.02 (0.01) †	0.00 (0.01)	-0.01 (0.01)
% pov → obs. amenities → perc. amenities	0.00 (0.00)	0.00 (0.00)	0.01 (0.01) †	0.00 (0.00)	0.00 (0.00)
% pov via observed crime	-0.01 (0.01)	0.00 (0.01)	0.01 (0.01)	-0.01 (0.01)	0.01 (0.01)
% pov via perceived crime	0.02 (0.01)	0.02 (0.01) †	0.04 (0.02) *	-0.04 (0.02) *	-0.02 (0.01) †
% pov → obs.crime → perc. crime	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
% pov via observed home costs	0.02 (0.01)	0.01 (0.01)	0.00 (0.01)	-0.01 (0.01)	0.01 (0.01)
% pov via perceived costs	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)

% pov → obs. home costs → perc. costs	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Total Indirect Effect	0.04 (0.02)	0.06 (0.02) **	0.04 (0.03)	-0.05 (0.03) †	-0.01 (0.02)
Direct Effect	-0.01 (0.04)	-0.08 (0.04) *	-0.04 (0.05)	0.04 (0.05)	0.02 (0.04)
Total Effect	**0.03 (0.04)**	**-0.01 (0.03)**	**-0.01 (0.04)**	**-0.01 (0.04)**	**0.00 (0.04)**

Note: **p<0.01; *p<0.05; † p<0.10

Table 21

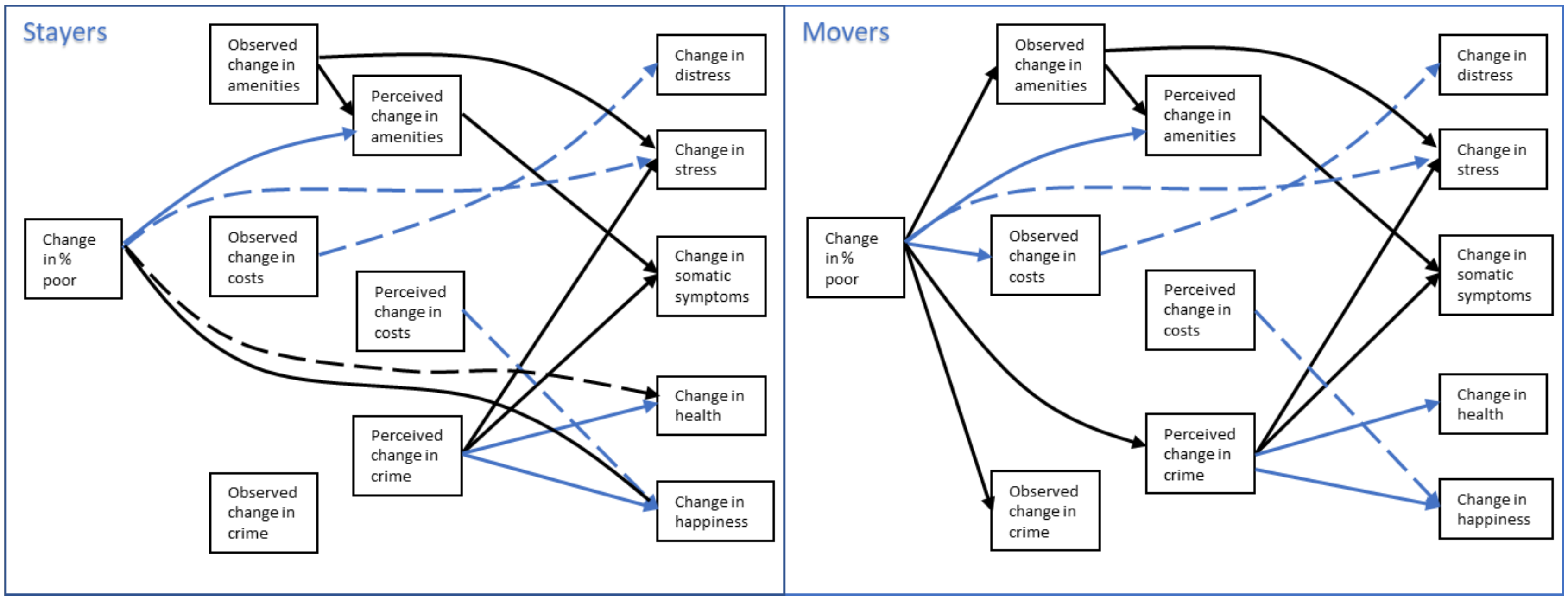
RQ2 Neighborhood Poverty Model Fit for Multigroup Models

	CFI	TLI	RMSEA	[90% CI]	SRMR	Adjusted BIC	χ^2 (df)	Δdf	$\Delta\chi^2$ (TRd)	*p*
Unconstrained	0.96	0.92	0.04	[0.03, 0.05]	0.05	32379.85	239.79 (209)	-		
Final	0.96	0.94	0.03	[0.02, 0.04]	0.05	32291.85	324.75 (246)	37	31.19	0.74

Note: CFI = comparative fit index; TLI = Tucker-Lewis index; SRMR = standardized root mean square residual; RMSEA = root mean square error of approximation; CI = confidence interval; BIC = Bayes information criterion. Due to use of the MLR estimator, the Satorra-Bentler scaled chi-square different test (TRd) was computed in place of a standard chi-square difference test.

Figure 8

RQ2 Neighborhood Poverty Final Multigroup Path Models for Stayers vs. Movers



Note: Solid pathways represent significant associations (*p*<.05), while dashed pathways approach significance (*p*<.10). Black pathways represent positive links, and blue pathways negative links. The following covariates were included as predictors of outcome variables: baseline outcome, change in earnings, change in household size, change in receipt of public assistance, hurricane-related trauma, hurricane-related death, and post-Katrina mobility.

Table 22

RQ2 Main Path Analysis: Changes in Neighborhood Poverty Predicting Changes in Wellbeing

	Fully Unconstrained		Final Multigroup	
	Stayers	**Movers**	**Stayers**	**Movers**
	β (SD)	β (SD)	β (SD)	β (SD)
Changes in neighborhood poverty predicting observed and perceived changes in neighborhood features				
% pov → obs. amenities	-0.03 (0.19)	0.31 (0.04) **	-0.09 (0.2)	0.31 (0.04) **
% pov → perc. amenities	-0.24 (0.18)	-0.21 (0.07) **	-0.21 (0.06) **	-0.21 (0.06) **
% pov → obs. costs	-0.02 (0.05)	-0.31 (0.05) **	-0.02 (0.05)	-0.31 (0.05) **
% pov → perc. costs	-0.16 (0.18)	-0.02 (0.06)	-0.03 (0.06)	-0.03 (0.06)
% pov → obs. crime	0.11 (0.10)	0.26 (0.05) **	0.08 (0.11)	0.26 (0.05) **
% pov → perc. crime	-0.12 (0.16)	0.24 (0.06) **	-0.11 (0.17)	0.24 (0.06) **
Observed changes in neighborhood features predicting perceived changes				
obs. → perc. amenities	0.20 (0.13)	0.26 (0.06) **	0.25 (0.06) **	0.25 (0.06) **
obs. → perc. costs	-0.21 (0.49)	0.10 (0.07)	0.09 (0.07)	0.09 (0.07)
obs. → perc. crime	0.02 (0.16)	0.02 (0.06)	0.02 (0.06)	0.02 (0.06)
Neighborhood features predicting changes in wellbeing				
observed amenities → distress	0.01 (0.17)	0.02 (0.04)	0.03 (0.04)	0.03 (0.04)
perceived amenities → distress	-0.02 (0.09)	0.02 (0.05)	0.01 (0.04)	0.01 (0.04)
observed costs → distress	0.34 (0.51)	-0.06 (0.04) †	-0.06 (0.04) †	-0.06 (0.04) †
perceived costs → distress	0.03 (0.09)	0.05 (0.04)	0.04 (0.04)	0.04 (0.04)
observed crime → distress	0.11 (0.24)	-0.01 (0.04)	-0.01 (0.04)	-0.01 (0.04)
perceived crime → distress	0.08 (0.1)	0.03 (0.05)	0.05 (0.04)	0.05 (0.04)

% poverty → distress	-0.13 (0.3)	0.00 (0.04)	-0.01 (0.04)	-0.01 (0.04)
observed amenities → stress	0.22 (0.15)	0.05 (0.04)	0.08 (0.04) *	0.08 (0.04) *
perceived amenities → stress	-0.11 (0.08)	0.05 (0.05)	-0.01 (0.04)	-0.01 (0.04)
observed costs → stress	0.23 (0.44)	-0.03 (0.04)	-0.03 (0.03)	-0.03 (0.03)
perceived costs → stress	0.02 (0.09)	0.06 (0.04)	0.04 (0.04)	0.04 (0.04)
observed crime → stress	0.11 (0.22)	0.01 (0.04)	0.01 (0.04)	0.01 (0.04)
perceived crime → stress	0.09 (0.09)	0.09 (0.05) †	0.09 (0.04) *	0.09 (0.04) *
% poverty → stress	-0.34 (0.18) †	-0.05 (0.04)	-0.27 (0.14) †	-0.07 (0.04) †
observed amenities → somatic	-0.26 (0.16)	0.04 (0.05)	0.02 (0.04)	0.02 (0.04)
perceived amenities → somatic	0.10 (0.09)	0.12 (0.05) *	0.12 (0.05) **	0.12 (0.05) **
observed costs → somatic	0.58 (0.47)	-0.03 (0.04)	-0.01 (0.04)	-0.01 (0.04)
perceived costs → somatic	-0.13 (0.09)	0.05 (0.05)	0.00 (0.05)	0.00 (0.05)
observed crime → somatic	0.17 (0.26)	0.02 (0.04)	0.02 (0.04)	0.02 (0.04)
perceived crime → somatic	0.07 (0.09)	0.16 (0.06) **	0.14 (0.05) **	0.14 (0.05) **
% poverty → somatic	-0.09 (0.21)	-0.06 (0.05)	-0.04 (0.05)	-0.04 (0.05)
observed amenities → health	0.25 (0.16)	0.01 (0.05)	0.02 (0.05)	0.02 (0.05)
perceived amenities → health	-0.02 (0.08)	0.03 (0.06)	0.02 (0.05)	0.02 (0.05)
observed costs → health	0.79 (0.43) †	0.04 (0.04)	0.03 (0.04)	0.03 (0.04)
perceived costs → health	0.12 (0.08)	-0.03 (0.05)	0.01 (0.04)	0.01 (0.04)
observed crime → health	0.02 (0.26)	-0.04 (0.04)	-0.03 (0.04)	-0.03 (0.04)
perceived crime → health	-0.08 (0.08)	-0.16 (0.06) **	-0.13 (0.05) **	-0.13 (0.05) **
% poverty → health	0.39 (0.19) *	0.04 (0.05)	0.33 (0.17) †	0.03 (0.05)
observed amenities → happiness	-0.02 (0.14)	0.00 (0.04)	0.00 (0.04)	0.00 (0.04)
perceived amenities → happiness	0.03 (0.05)	0.03 (0.06)	0.03 (0.04)	0.03 (0.04)

observed costs → happiness	0.38 (0.32)	-0.02 (0.04)	-0.02 (0.04)	-0.02 (0.04)
perceived costs → happiness	-0.04 (0.06)	-0.08 (0.05) †	-0.07 (0.04) †	-0.07 (0.04) †
observed crime → happiness	0.15 (0.19)	0.03 (0.04)	0.03 (0.04)	0.03 (0.04)
perceived crime → happiness	-0.09 (0.06)	-0.08 (0.05)	-0.09 (0.04) *	-0.09 (0.04) *
% poverty → happiness	0.32 (0.16) *	0.01 (0.04)	0.32 (0.14) *	0.01 (0.04)

Note: ***p*<0.01; **p*<0.05; † *p*<0.10. Light grey cells highlight associations that were left unconstrained. The following covariates were included as predictors of outcome variables: baseline outcome, change in earnings, change in household size, change in receipt of public assistance, hurricane-related trauma, hurricane-related death, and post-Katrina mobility.

Table 23

RQ2 Indirect, Direct, and Total Effects of Neighborhood Poverty for Stayers vs. Movers

	Fully Unconstrained		Final Multigroup	
	Stayers	**Movers**	**Stayers**	**Movers**
Specific Indirect Effects				
% pov → observed amenities → distress	0.00 (0.01)	0.01 (0.01)	0.00 (0.01)	0.01 (0.01)
% pov → perceived amenities → distress	0.00 (0.02)	0.00 (0.01)	0.00 (0.01)	0.00 (0.01)
% pov → obs. amenities → perc. amenities → distress	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
% pov → observed crime → distress	0.01 (0.03)	0.00 (0.01)	0.00 (0.00)	0.00 (0.01)
% pov → perceived crime → distress	-0.01 (0.02)	0.01 (0.01)	-0.01 (0.01)	0.01 (0.01)
% pov → obs.crime → perc. crime → distress	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
% pov → observed costs → distress	-0.01 (0.02)	0.02 (0.01) †	0.00 (0.00)	0.02 (0.01) †
% pov → perceived costs → distress	-0.01 (0.02)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
% pov → obs. costs → perc. costs → distress	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)

Total Indirect Effect on Distress	-0.01 (0.05)	0.03 (0.02)	-0.01 (0.02)	0.04 (0.02)
Direct Effect on Distress	-0.13 (0.3)	0.00 (0.04)	-0.01 (0.04)	-0.01 (0.04)
Total Effect on Distress	**-0.13 (0.3)**	**0.03 (0.04)**	**-0.02 (0.04)**	**0.03 (0.04)**
Specific Indirect Effects				
% pov → observed amenities → stress	-0.01 (0.04)	0.02 (0.01)	-0.01 (0.02)	0.02 (0.01) *
% pov → perceived amenities → stress	0.03 (0.03)	-0.01 (0.01)	0.00 (0.01)	0.00 (0.01)
% pov → obs. amenities → perc. amenities → stress	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
% pov → observed crime → stress	0.01 (0.03)	0.00 (0.01)	0.00 (0.00)	0.00 (0.01)
% pov → perceived crime → stress	-0.01 (0.02)	0.02 (0.01) †	-0.01 (0.02)	0.02 (0.01) †
% pov → obs. crime → perc. crime → stress	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
% pov → observed costs → stress	-0.01 (0.01)	0.01 (0.01)	0.00 (0.00)	0.01 (0.01)
% pov → perceived costs → stress	0 (0.02)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
% pov → obs. costs → perc. costs → stress	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Total Indirect Effect on Stress	0.01 (0.07)	0.04 (0.02) †	-0.01 (0.03)	0.06 (0.02) **
Direct Effect on Stress	-0.34 (0.18) †	-0.05 (0.04)	-0.27 (0.14) †	-0.07 (0.04) †
Total Effect on Stress	**-0.33 (0.16) ***	**-0.01 (0.03)**	**-0.29 (0.14) ***	**-0.01 (0.03)**
Specific Indirect Effects				
% pov → observed amenities → somatic	0.01 (0.05)	0.01 (0.01)	0.00 (0.01)	0.01 (0.01)
% pov → perceived amenities → somatic	-0.03 (0.03)	-0.03 (0.01) †	-0.02 (0.01) *	-0.02 (0.01) *
% pov → obs. amenities → perc. amenities → somatic	0.00 (0.00)	0.01 (0.01) †	0.00 (0.01)	0.01 (0.00) *
% pov → observed crime → somatic	0.02 (0.03)	0.01 (0.01)	0.00 (0.00)	0.01 (0.01)
% pov → perceived crime → somatic	-0.01 (0.02)	0.04 (0.02) *	-0.01 (0.02)	0.03 (0.02) *
% pov → obs. crime → perc. crime → somatic	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
% pov → observed costs → somatic	-0.01 (0.03)	0.01 (0.01)	0.00 (0.00)	0.00 (0.01)
% pov → perceived costs → somatic	0.02 (0.03)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
% pov → obs. costs → perc. costs → somatic	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Total Indirect Effect on Somatic	0.00 (0.08)	0.05 (0.03) †	-0.04 (0.03)	0.03 (0.03)
Direct Effect on Somatic	-0.09 (0.21)	-0.06 (0.05)	-0.04 (0.05)	-0.04 (0.05)

Total Effect on Somatic	**-0.09 (0.21)**	**-0.01 (0.04)**	**-0.08 (0.05)**	**-0.01 (0.04)**
Specific Indirect Effects				
% pov → observed amenities → health	-0.01 (0.05)	0.00 (0.02)	0.00 (0.01)	0.01 (0.01)
% pov → perceived amenities → health	0.00 (0.02)	-0.01 (0.01)	0.00 (0.01)	0.00 (0.01)
% pov → obs. amenities → perc. amenities → health	0.00 (0.00)	0.00 (0.01)	0.00 (0.00)	0.00 (0.00)
% pov → observed crime → health	0.00 (0.03)	-0.01 (0.01)	0.00 (0.01)	-0.01 (0.01)
% pov → perceived crime → health	0.01 (0.02)	-0.04 (0.02) *	0.01 (0.02)	-0.03 (0.01) *
% pov → obs. crime → perc. crime → health	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
% pov → observed costs → health	-0.02 (0.04)	-0.01 (0.01)	0.00 (0.00)	-0.01 (0.01)
% pov → perceived costs → health	-0.02 (0.03)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
% pov → obs. costs → perc. costs → health	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Total Indirect Effect on Health	-0.03 (0.08)	-0.06 (0.03) †	0.00 (0.03)	-0.05 (0.03) †
Direct Effect on Health	0.39 (0.19) *	0.04 (0.05)	0.33 (0.17) †	0.03 (0.05)
Total Effect on Health	**0.36 (0.20) †**	**-0.02 (0.04)**	**0.34 (0.17) †**	**-0.02 (0.04)**
Specific Indirect Effects				
% pov → observed amenities → happiness	0.00 (0.01)	0.00 (0.01)	0.00 (0.00)	0.00 (0.01)
% pov → perceived amenities → happiness	-0.01 (0.01)	-0.01 (0.01)	-0.01 (0.01)	-0.01 (0.01)
% pov → obs. amenities → perc. amenities → happiness	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
% pov → observed crime → happiness	0.02 (0.02)	0.01 (0.01)	0.00 (0.01)	0.01 (0.01)
% pov → perceived crime → happiness	0.01 (0.02)	-0.02 (0.01)	0.01 (0.02)	-0.02 (0.01) †
% pov → obs. crime → perc. crime → happiness	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
% pov → observed costs → happiness	-0.01 (0.02)	0.01 (0.01)	0.00 (0.00)	0.01 (0.01)
% pov → perceived costs → happiness	0.01 (0.01)	0.00 (0.01)	0.00 (0.00)	0.00 (0.00)
% pov → obs. costs → perc. costs → happiness	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Total Indirect Effect on Happiness	0.02 (0.04)	0.00 (0.03)	0.01 (0.02)	-0.01 (0.02)
Direct Effect on Happiness	0.32 (0.16) *	0.01 (0.04)	0.32 (0.14) *	0.01 (0.04)
Total Effect on Happiness	**0.34 (0.15) ***	**0.00 (0.04)**	**0.32 (0.14) ***	**0.00 (0.04)**

Note: **$p<0.01$; *$p<0.05$; † $p<0.10$.

APPENDIX

Neighborhood Affluence Model Results

Table 24

Baseline Characteristics Predicting Neighborhood Affluence

Baseline Characteristics	**PK1 Neighborhood Affluence** β (SE)		**PK2 Neighborhood Affluence** β (SE)	
Psychological distress (logged)	0.06 (0.05)		0.00 (0.06)	
Perceived stress	-0.02 (0.06)		0.04 (0.05)	
General health	-0.08 (0.06)		-0.04 (0.05)	
General happiness	-0.04 (0.06)		-0.01 (0.05)	
Somatic symptoms	-0.03 (0.07)		-0.06 (0.07)	
Married	0.29 (0.10)	**	0.22 (0.12)	†
Less than HS education	0.02 (0.24)		-0.05 (0.23)	
Household size (logged)	0.02 (0.04)		0.00 (0.04)	
Currently employed	-0.46 (0.54)		-0.44 (0.58)	
Monthly earnings	0.31 (0.28)		0.29 (0.30)	
Receiving public assistance	0.00 (0.10)		0.01 (0.10)	
Female	-0.20 (0.17)		0.03 (0.21)	
Race: Not Black	0.19 (0.14)		0.37 (0.12)	**
Intercept	0.48 (0.37)		0.55 (0.35)	

Note: Regressions adjusted for baseline clustering of individuals within tracts. ***p*<0.01; **p*<0.05; † *p*<0.10

Table 25

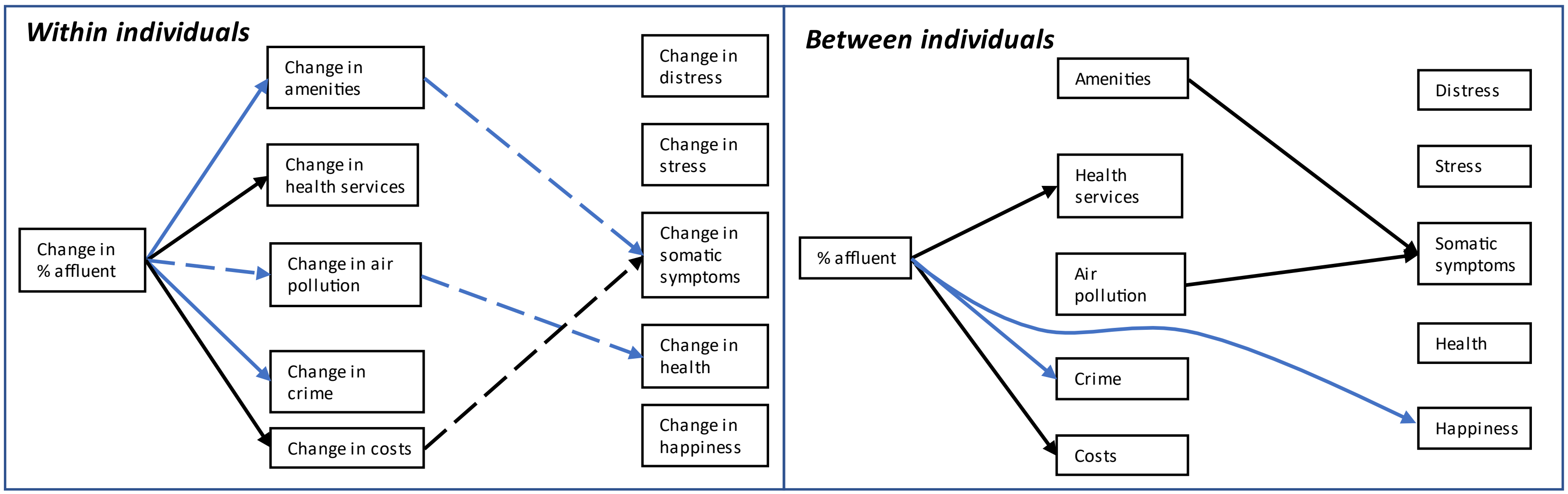
RQ1 Neighborhood Affluence Model Fit

	[95% CI]		*p-value*
Distress	[7.91,	151.58]	0.01
Stress	[2.45,	147.09]	0.02
Somatic	[13.83,	143.96]	0.01
Health	[7.07,	152.76]	0.02
Happiness	[5.74,	153.22]	0.02

Note: 95% CI refers to the 95% Confidence Interval for the Difference Between the Observed and the Replicated Chi-Square Values. P-value refers to the Posterior Predictive p-value.

Figure 9

RQ1 SEM Results: Neighborhood Affluence Predicting Wellbeing Within and Between Individuals



Note: Solid pathways represent significant associations (*p*<.05), while dashed pathways approach significance (*p*<.10). Black pathways represent positive links, and blue pathways negative links. The following covariates were included as predictors of outcome variables: marital status, education, household size, earnings, receipt of public assistance, moves, hurricane-related death, hurricane related trauma, and, at the between level only, race/ethnicity.

Table 26

RQ1 SEM Results: Neighborhood Affluence Predicting Wellbeing

	Distress	**Stress**	**Somatic Symptoms**	**Health**	**Happiness**
	β (SD[a])	*β* (SD)	*β* (SD)	*β* (SD)	*β* (SD)
***Within individuals,* changes in neighborhood affluence predicting changes in neighborhood features**					
% aff → amenities	-0.35 (0.03) **	-0.34 (0.03) **	-0.34 (0.03) **	-0.34 (0.03) **	-0.34 (0.03) **
% aff → health services	0.30 (0.03) **	0.30 (0.03) **	0.30 (0.03) **	0.30 (0.03) **	0.30 (0.03) **
% aff → air pollution	-0.05 (0.03) †	-0.05 (0.03) †	-0.05 (0.03) †	-0.05 (0.03) †	-0.05 (0.03) †
% aff → crime	-0.12 (0.03) **	-0.12 (0.03) **	-0.12 (0.03) **	-0.12 (0.03) **	-0.12 (0.03) **
% aff → housing costs	0.64 (0.02) **	0.64 (0.02) **	0.64 (0.02) **	0.64 (0.02) **	0.64 (0.02) **
***Within individuals*, changes in neighborhood features predicting changes in wellbeing**					
amenities → outcome	-0.04 (0.04)	0.02 (0.04)	-0.07 (0.04) †	0.06 (0.04)	0.06 (0.05)
health services → outcome	0.06 (0.04)	0.05 (0.04)	0.05 (0.04)	0.01 (0.04)	-0.04 (0.04)
air pollution → outcome	-0.01 (0.03)	-0.03 (0.03)	-0.04 (0.03)	-0.05 (0.03) †	0.03 (0.03)
crime → outcome	0.03 (0.03)	0.05 (0.04)	0.01 (0.03)	0.00 (0.03)	0.02 (0.04)
housing costs → outcome	-0.05 (0.04)	-0.07 (0.05)	0.08 (0.04) †	-0.01 (0.04)	-0.07 (0.05)
% affluent → outcome	-0.02 (0.05)	0.04 (0.05)	0 (0.05)	-0.07 (0.05)	0.05 (0.05)
***Between individuals,* neighborhood affluence predicting neighborhood features**					
% aff → amenities	-0.03 (0.08)	-0.04 (0.09)	-0.03 (0.09)	-0.03 (0.09)	-0.03 (0.08)
% aff → health services	0.61 (0.08) **	0.61 (0.09) **	0.61 (0.09) **	0.61 (0.09) **	0.61 (0.08) **
% aff → air pollution	0.09 (0.09)	0.08 (0.09)	0.08 (0.09)	0.08 (0.09)	0.08 (0.09)
% aff → crime	-0.20 (0.09) *	-0.20 (0.09) *	-0.20 (0.09) *	-0.19 (0.09) *	-0.19 (0.09) *
% aff → housing costs	0.76 (0.06) **	0.75 (0.06) **	0.75 (0.07) **	0.76 (0.06) **	0.76 (0.06) **
***Between individuals*, neighborhood features predicting wellbeing**					
amenities → outcome	-0.02 (0.16)	-0.01 (0.15)	0.27 (0.15) †	-0.11 (0.17)	-0.1 (0.17)

health services → outcome	-0.05 (0.14)	-0.13 (0.13)	-0.12 (0.14)	-0.1 (0.15)	0.14 (0.15)
air pollution → outcome	0.03 (0.08)	0.04 (0.07)	0.15 (0.07) *	-0.07 (0.08)	-0.07 (0.08)
crime → outcome	0.00 (0.08)	0.01 (0.07)	-0.01 (0.07)	-0.11 (0.07)	-0.08 (0.07)
housing costs → outcome	-0.04 (0.12)	0.04 (0.11)	-0.08 (0.10)	0.06 (0.12)	0.11 (0.12)
% affluent → outcome	0.25 (0.17)	0.23 (0.16)	0.07 (0.15)	-0.06 (0.17)	-0.38 (0.18) *
***Within individuals,* time-varying covariates predicting changes in wellbeing**					
married	0.05 (0.08)	0.10 (0.08)	0.09 (0.08)	-0.04 (0.08)	0.04 (0.09)
college degree	-0.11 (0.12)	-0.08 (0.12)	0.28 (0.11) **	-0.28 (0.11) *	0.18 (0.12)
household size	0.00 (0.03)	0.00 (0.03)	0.03 (0.03)	-0.02 (0.03)	-0.02 (0.03)
earnings	-0.01 (0.03)	-0.08 (0.03) **	0.07 (0.03) *	-0.06 (0.03) *	0.05 (0.03)
receiving public assistance	0.05 (0.07)	-0.11 (0.07)	0.00 (0.06)	0.05 (0.07)	-0.09 (0.07)
moved since last wave	-0.02 (0.06)	-0.06 (0.07)	0.25 (0.06) **	-0.27 (0.06) **	-0.1 (0.07)
hurricane-related death	0.39 (0.11) **	0.27 (0.11) *	0.53 (0.10) **	0.01 (0.10)	-0.08 (0.11)
hurricane-related trauma	0.04 (0.04)	-0.03 (0.04)	0.16 (0.04) **	-0.12 (0.04) **	-0.03 (0.04)
***Between individuals*, covariates predicting wellbeing**					
avg. waves married	-0.01 (0.15)	0.10 (0.14)	0.05 (0.13)	0.02 (0.14)	0.25 (0.14) †
avg. waves with college degree	0.22 (0.42)	-0.40 (0.41)	-0.54 (0.4)	0.92 (0.43) *	0.68 (0.41)
avg. household size	-0.10 (0.07)	-0.05 (0.07)	-0.08 (0.07)	0.12 (0.07)	0.07 (0.07)
avg. earnings	-0.14 (0.15)	-0.05 (0.17)	-0.42 (0.2) **	0.34 (0.17) *	-0.05 (0.16)
avg. waves receiving pub. assist.	0.43 (0.28)	0.80 (0.33) **	0.76 (0.28) **	-1.13 (0.32) **	-0.21 (0.29)
avg. waves moved	2.46 (1.45) *	1.51 (1.42)	-1.49 (1.17)	1.69 (1.69)	-0.37 (2.01)
hurricane-related death	0.56 (0.22) **	0.46 (0.23) *	0.55 (0.23) *	-0.48 (0.26) †	-0.30 (0.25)
hurricane-related trauma	1.0 (0.2) **	0.97 (0.24) **	0.52 (0.2) *	-0.58 (0.29) *	-0.46 (0.25) *
race (base: Black)					
other race	0.17 (0.09) †	0.16 (0.10) †	0.38 (0.09) **	-0.23 (0.09) *	-0.11 (0.09)
Intercepts					
amenities	-0.01 (0.03)	-0.01 (0.03)	-0.01 (0.03)	-0.01 (0.03)	-0.01 (0.03)
health services	0.01 (0.03)	0.01 (0.03)	0.01 (0.03)	0.01 (0.03)	0.01 (0.03)
air pollution	0.00 (0.03)	0.00 (0.03)	0.00 (0.03)	0.00 (0.03)	0.00 (0.03)

crime	0.00 (0.03)	0.00 (0.03)	0.00 (0.03)	0.00 (0.03)	0.00 (0.03)
housing costs	0.00 (0.02)	0.00 (0.02)	0.00 (0.02)	0.00 (0.02)	0.00 (0.02)
outcome	-1.48 (0.64) **	-1.19 (0.62) *	-0.05 (0.55)	0.06 (0.76)	0.25 (0.86)

Note: [a] The Bayes Estimator produces a posterior standard deviation estimate in place of a standard error. ***p*<0.01; **p*<0.05; † *p*<0.10

Table 27

RQ1 Indirect, Direct, and Total Effects of Neighborhood Affluence on Wellbeing

	Distress	**Stress**	**Somatic Symptoms**	**Health**	**Happiness**
Within Individuals	β (SD)	β (SD)	β (SD)	β (SD)	β (SD)
Specific Indirect Effects					
% affluent via amenities	0.01 (0.02)	-0.01 (0.02)	0.02 (0.01) †	-0.02 (0.01)	-0.02 (0.02)
% affluent via health services	0.02 (0.01)	0.01 (0.01)	0.02 (0.01)	0.00 (0.01)	-0.01 (0.01)
% affluent via air pollution	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
% affluent via crime	0.00 (0.00)	-0.01 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.01)
% affluent via housing costs	-0.03 (0.03)	-0.05 (0.03)	0.05 (0.03) †	-0.01 (0.03)	-0.04 (0.03)
Total Indirect Effect	-0.01 (0.04)	-0.04 (0.04)	0.09 (0.04) *	-0.02 (0.04)	-0.08 (0.04) †
Direct Effect	-0.02 (0.05)	0.04 (0.05)	0.00 (0.05)	-0.07 (0.05) †	0.05 (0.05)
Total Effect	**-0.02 (0.03)**	**0.00 (0.03)**	**0.09 (0.03) ****	**-0.09 (0.03) ****	**-0.03 (0.03)**
Between Individuals	β (SD)	β (SD)	β (SD)	β (SD)	β (SD)
Specific Indirect Effects					
% affluent via amenities	0.00 (0.01)	0.00 (0.01)	-0.01 (0.03)	0.00 (0.02)	0.00 (0.02)
% affluent via health services	-0.03 (0.09)	-0.07 (0.09)	-0.07 (0.09)	-0.06 (0.09)	0.08 (0.09)
% affluent via air pollution	0.00 (0.01)	0.00 (0.01)	0.01 (0.02)	0.00 (0.01)	0.00 (0.01)
% affluent via crime	0.00 (0.02)	0.00 (0.02)	0.00 (0.01)	0.02 (0.02)	0.01 (0.02)
% affluent via housing costs	-0.03 (0.09)	0.03 (0.08)	-0.06 (0.08)	0.04 (0.09)	0.08 (0.09)

Total Indirect Effect	-0.06 (0.14)	-0.05 (0.13)	-0.12 (0.13)	0.00 (0.14)	0.18 (0.15)
Direct Effect	0.25 (0.17)	0.23 (0.16)	0.07 (0.15)	-0.06 (0.17)	-0.38 (0.18) *
Total Effect	**0.19 (0.09) ***	**0.18 (0.09) ***	**-0.05 (0.09)**	**-0.07 (0.09)**	**-0.20 (0.09) ***

[a] The Bayes Estimator produces a posterior standard deviation estimate in place of a standard error. ***p*<0.01; **p*<0.05; † *p*<0.10

Table 28

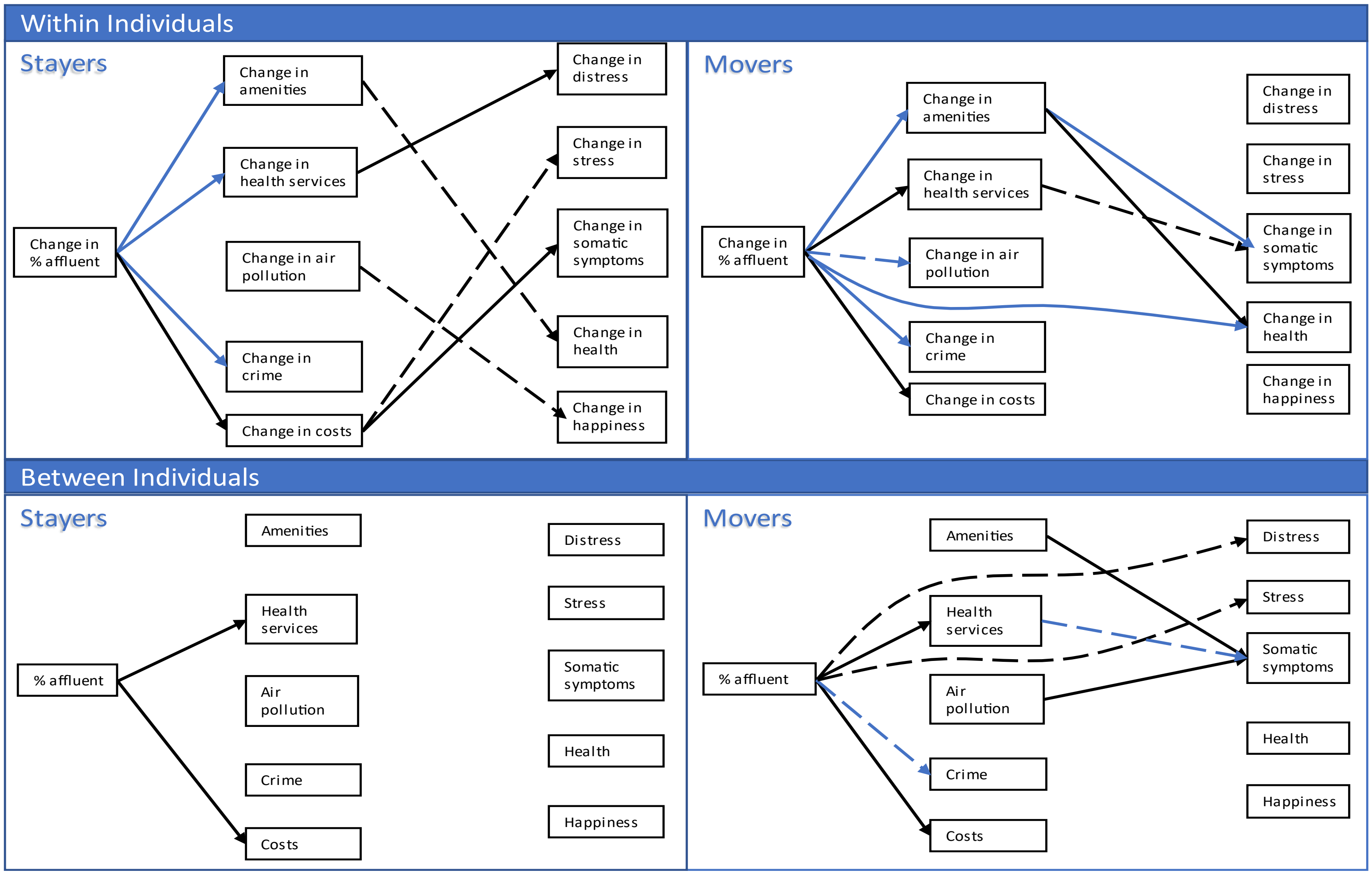
RQ1 Neighborhood Affluence Model Fit: Stayers vs. Movers

	Stayers		**Movers**	
	[95% CI]	***p-value***	**[95% CI]**	***p-value***
Distress	[-26.92, 106.33]	0.11	[-22.09, 107.82]	0.09
Stress	[-36.98, 95.10]	0.20	[-39.28, 90.64]	0.22
Somatic	[-38.19, 98.01]	0.19	[-27.10, 106.42]	0.11
Health	[-32.73, 98.88]	0.18	[-22.76, 109.10]	0.11
Happiness	[-34.72, 95.48]	0.20	[-26.74, 109.53]	0.11

Note: 95% CI refers to the 95% Confidence Interval for the Difference Between the Observed and the Replicated Chi-Square Values. *p-value* refers to the Posterior Predictive p-value.

Figure 10

RQ1 SEM Results: Neighborhood Affluence Predicting Wellbeing for Stayers vs. Movers



Note: Solid pathways represent significant associations ($p<.05$), while dashed pathways approach significance ($p<.10$). Black pathways represent positive links, and blue pathways negative links. The following covariates were included as predictors of outcome variables: marital status, education, household size, earnings, receipt of public assistance, hurricane-related death, hurricane related trauma, and, at the between level only, race/ethnicity.

Table 29

RQ1 SEM Results: Neighborhood Affluence Part I for Stayers vs. Movers

	Distress		Stress	
	Stayers	**Movers**	**Stayers**	**Movers**
	β (SD)	β (SD)	β (SD)	β (SD)
Within individuals, changes in neighborhood affluence predicting changes in neighborhood features				
% aff → amenities	-0.51 (0.09) **	-0.35 (0.03) **	-0.51 (0.09) **	-0.35 (0.03) **
% aff → health services	-0.15 (0.04) **	0.31 (0.03) **	-0.15 (0.04) **	0.31 (0.03) **
% aff → air pollution	-0.02 (0.07)	-0.06 (0.03) †	-0.02 (0.07)	-0.06 (0.03) †
% aff → crime	-0.12 (0.02) **	-0.11 (0.03) **	-0.12 (0.02) **	-0.12 (0.03) **
% aff → housing costs	0.71 (0.03) **	0.63 (0.02) **	0.71 (0.03) **	0.63 (0.02) **
***Within individuals*, changes in neighborhood features predicting changes in wellbeing**				
amenities → outcome	-0.08 (0.19)	-0.04 (0.04)	0.04 (0.18)	0.01 (0.04)
health services → outcome	0.83 (0.38) *	0.06 (0.04)	0.61 (0.37)	0.05 (0.04)
air pollution → outcome	0.04 (0.17)	-0.02 (0.03)	-0.12 (0.16)	-0.03 (0.03)
crime → outcome	-0.15 (0.67)	0.04 (0.03)	0.06 (0.64)	0.05 (0.04)
housing costs → outcome	0.59 (0.44)	-0.05 (0.04)	0.71 (0.42) †	-0.07 (0.05)
% affluence → outcome	-0.34 (0.36)	-0.02 (0.05)	-0.19 (0.34)	0.03 (0.05)

***Between individuals*, neighborhood affluence predicting neighborhood features**				
% aff → amenities	-0.01 (0.14)	0.22 (0.18)	0.00 (0.14)	0.22 (0.19)
% aff → health services	0.65 (0.14) **	0.81 (0.17) **	0.66 (0.14) **	0.79 (0.17) **
% aff → air pollution	0.1 (0.14)	0.18 (0.19)	0.09 (0.13)	0.19 (0.2)
% aff → crime	-0.13 (0.15)	-0.31 (0.19) †	-0.13 (0.15)	-0.27 (0.18)
% aff → housing costs	0.67 (0.09) **	0.99 (0.16) **	0.67 (0.09) **	0.98 (0.14) **
***Between individuals*, neighborhood features predicting wellbeing**				
amenities → outcome	0.19 (0.15)	-0.07 (0.70)	0.11 (0.14)	-0.23 (1.25)
health services → outcome	-0.08 (0.15)	-0.26 (0.60)	-0.07 (0.13)	-0.18 (0.91)
air pollution → outcome	-0.03 (0.09)	0.09 (0.30)	0.09 (0.08)	-0.11 (0.66)
crime → outcome	-0.07 (0.10)	0.18 (0.24)	-0.01 (0.09)	0.10 (0.23)
housing costs → outcome	-0.03 (0.14)	-0.32 (0.40)	-0.02 (0.14)	-0.24 (0.52)
% affluence → outcome	0.07 (0.17)	1.05 (0.90) †	0.06 (0.16)	0.92 (0.90) †
***Within individuals*, time-varying covariates predicting wellbeing**				
married	0.25 (0.20)	0.02 (0.09)	0.35 (0.19) †	0.04 (0.09)
college degree	0.10 (0.27)	-0.2 (0.13)	-0.23 (0.26)	-0.10 (0.13)
household size	-0.01 (0.10)	0.00 (0.03)	0.11 (0.09)	-0.03 (0.04)
earnings	0.08 (0.08)	-0.04 (0.03)	-0.06 (0.08)	-0.10 (0.04) **
receiving public assistance	0.10 (0.16)	0.02 (0.07)	-0.07 (0.15)	-0.10 (0.08)
hurricane-related death	0.23 (0.30)	0.43 (0.11) **	0.43 (0.29)	0.23 (0.12) †
hurricane-related trauma	0.09 (0.09)	0.03 (0.04)	-0.09 (0.09)	-0.03 (0.04)
***Between individuals*, covariates predicting wellbeing**				
avg. waves married	-0.08 (0.36)	-0.01 (0.16)	-0.07 (0.31)	0.18 (0.17)
avg. waves with college degree	0.40 (0.74)	-0.08 (0.52)	-0.39 (0.69)	-0.32 (0.51)
avg. household size	-0.33 (0.15) *	-0.03 (0.09)	-0.25 (0.14) †	0.02 (0.09)
avg. earnings	-0.91 (1.36)	-0.09 (0.17)	-0.54 (1.53)	0.03 (0.16)
avg. waves receiving pub. assist.	0.32 (0.66)	0.53 (0.38)	0.42 (0.61)	0.86 (0.39) *

hurricane-related death	0.17 (0.6)	0.56 (0.27) *	0.17 (0.53)	0.44 (0.26) †
hurricane-related trauma	1.20 (2.55)	1.21 (0.39) **	1.00 (1.95)	1.13 (0.31) **
race (base: Black)	0.14 (0.18)	0.20 (0.11) †	0.09 (0.17)	0.16 (0.11)
Intercepts				
amenities	0.01 (0.09)	-0.02 (0.03)	0.02 (0.09)	-0.01 (0.03)
health services	-0.10 (0.09)	0.04 (0.03)	-0.10 (0.09)	0.04 (0.03)
air pollution	0.07 (0.1)	-0.02 (0.03)	0.07 (0.09)	-0.01 (0.03)
crime	-0.11 (0.1)	0.03 (0.03)	-0.11 (0.1)	0.03 (0.03)
housing costs	0.02 (0.07)	-0.01 (0.03)	0.03 (0.07)	-0.01 (0.03)
outcome	-0.38 (0.48)	-0.46 (0.29) †	-0.18 (0.46)	-0.68 (0.29) *

[a] The Bayes Estimator produces a posterior standard deviation estimate in place of a standard error. ***p*<0.01; **p*<0.05; † *p*<0.10

Table 30

RQ1 SEM Results: Neighborhood Affluence Part II for Stayers vs. Movers

	Somatic Symptoms		Health		Happiness	
	Stayers	**Movers**	**Stayers**	**Movers**	**Stayers**	**Movers**
	β (SD)	β (SD)	β (SD)	β (SD)	β (SD)	β (SD)
Within individuals, changes in neighborhood affluence predicting changes in neighborhood features						
% aff → amenities	-0.51 (0.09) **	-0.35 (0.03) **	-0.50 (0.09) **	-0.35 (0.03) **	-0.51 (0.09) **	-0.35 (0.03) **
% aff → health services	-0.15 (0.04) **	0.31 (0.03) **	-0.15 (0.04) **	0.31 (0.03) **	-0.15 (0.04) **	0.31 (0.03) **
% aff → air pollution	-0.02 (0.07)	-0.05 (0.03) †	-0.02 (0.07)	-0.05 (0.03) †	-0.02 (0.07)	-0.06 (0.03) †
% aff → crime	-0.12 (0.02) **	-0.12 (0.03) **	-0.12 (0.02) **	-0.12 (0.03) **	-0.12 (0.02) **	-0.12 (0.03) **
% aff → housing costs	0.70 (0.03) **	0.63 (0.02) **	0.71 (0.03) **	0.63 (0.02) **	0.71 (0.04) **	0.63 (0.02) **

***Within individuals*, changes in neighborhood features predicting changes in wellbeing**						
amenities → outcome	-0.11 (0.17)	-0.10 (0.04) *	0.32 (0.18) †	0.09 (0.04) *	0.10 (0.18)	0.07 (0.05)
health services → outcome	0.41 (0.34)	0.06 (0.04) †	-0.32 (0.36)	0 (0.04)	-0.28 (0.35)	-0.04 (0.05)
air pollution → outcome	-0.19 (0.15)	-0.05 (0.03)	0.24 (0.16)	-0.05 (0.03)	0.31 (0.16) †	0.03 (0.03)
crime → outcome	0.34 (0.59)	0.03 (0.03)	-0.11 (0.65)	-0.01 (0.03)	0.03 (0.63)	0.01 (0.04)
housing costs → outcome	0.85 (0.38) *	0.05 (0.04)	0.03 (0.41)	0.02 (0.04)	-0.03 (0.41)	-0.05 (0.05)
% affluence → outcome	0.00 (0.31)	0.02 (0.05)	-0.37 (0.34)	-0.1 (0.05) *	-0.04 (0.33)	0.03 (0.05)
***Between individuals,* neighborhood affluence predicting neighborhood features**						
% aff → amenities	0.01 (0.14)	0.17 (0.16)	-0.01 (0.14)	0.13 (0.15)	-0.01 (0.15)	0.15 (0.17)
% aff → health services	0.66 (0.14) **	0.78 (0.17) **	0.65 (0.14) **	0.74 (0.15) **	0.64 (0.14) **	0.74 (0.17) **
% aff → air pollution	0.1 (0.14)	0.16 (0.18)	0.09 (0.14)	0.13 (0.17)	0.10 (0.14)	0.18 (0.17)
% aff → crime	-0.14 (0.15)	-0.28 (0.17) †	-0.11 (0.15)	-0.29 (0.17) †	-0.12 (0.15)	-0.27 (0.16) †
% aff → housing costs	0.67 (0.10) **	0.95 (0.13) **	0.67 (0.09) **	0.92 (0.14) **	0.67 (0.10) **	0.96 (0.13) **
***Between individuals*, neighborhood features predicting wellbeing**						
amenities → outcome	0.16 (0.15)	0.77 (0.35) *	-0.13 (0.15)	-0.20 (0.57)	-0.19 (0.15)	-0.02 (0.74)
health services → outcome	0.08 (0.14)	-0.58 (0.33) †	-0.09 (0.14)	-0.05 (0.57)	0.21 (0.14)	0.15 (0.65)
air pollution → outcome	0.10 (0.08)	0.39 (0.2) *	-0.12 (0.09)	-0.05 (0.23)	0.05 (0.09)	-0.12 (0.33)
crime → outcome	-0.03 (0.09)	-0.02 (0.14)	-0.08 (0.09)	-0.10 (0.19)	0.01 (0.09)	-0.17 (0.22)
housing costs → outcome	-0.04 (0.14)	-0.01 (0.28)	0.03 (0.15)	0.08 (0.3)	-0.06 (0.14)	0.26 (0.41)
% affluence → outcome	-0.07 (0.17)	0.11 (0.55)	0.00 (0.17)	-0.09 (0.66)	-0.19 (0.17)	-0.71 (0.81)
***Within individuals,* time-varying covariates predicting changes in wellbeing**						
married	-0.02 (0.17)	0.14 (0.08) †	-0.06 (0.19)	-0.07 (0.09)	0.02 (0.19)	0.03 (0.10)
college degree	0.06 (0.23)	0.28 (0.12) *	0.06 (0.26)	-0.35 (0.12) **	0.21 (0.26)	0.17 (0.14)
household size	0.01 (0.09)	0.05 (0.03)	0.05 (0.09)	-0.04 (0.03)	0.00 (0.09)	-0.02 (0.04)
earnings	0.12 (0.07) †	0.03 (0.03)	-0.12 (0.08)	-0.03 (0.03)	0.00 (0.08)	0.06 (0.04) †
receiving public assistance	0.26 (0.14) †	-0.08 (0.07)	0.04 (0.16)	0.08 (0.07)	-0.25 (0.15) †	-0.05 (0.08)
hurricane-related death	0.21 (0.25)	0.64 (0.11) **	-0.11 (0.28)	-0.03 (0.11)	-0.07 (0.28)	-0.12 (0.12)
hurricane-related trauma	0.14 (0.08) †	0.22 (0.04) **	-0.06 (0.09)	-0.18 (0.04) **	-0.05 (0.09)	-0.04 (0.04)
***Between individuals*, covariates predicting wellbeing**						
avg. waves married	-0.04 (0.32)	0.06 (0.15)	0.06 (0.35)	0.02 (0.16)	0.27 (0.34)	0.28 (0.17) †

avg. waves with college degree	-0.44 (0.73)	-0.54 (0.43)	0.36 (0.73)	1.17 (0.52) *	0.23 (0.81)	0.99 (0.53) *
avg. household size	-0.30 (0.15) *	-0.03 (0.08)	0.14 (0.16)	0.12 (0.09)	0.07 (0.15)	0.08 (0.09)
avg. earnings	-0.91 (1.23) †	-0.30 (0.17) *	0.65 (1.03)	0.20 (0.16)	0.32 (2.49)	-0.07 (0.17)
avg. waves receiving pub. assist.	0.62 (0.59)	0.87 (0.41) **	-0.53 (0.63)	-1.44 (0.46) **	-0.09 (0.87)	-0.30 (0.41)
hurricane-related death	-0.67 (0.56)	0.7 (0.25) **	0.79 (0.57)	-0.62 (0.27) *	-0.09 (0.56)	-0.36 (0.29)
hurricane-related trauma	1.16 (1.97)	0.34 (0.33)	-1.19 (1.88)	-0.52 (0.33) †	-0.78 (2.74)	-0.56 (0.37) †
race (base: Black)	0.47 (0.19) *	0.38 (0.09) **	-0.53 (0.19) *	-0.13 (0.11)	-0.08 (0.18)	-0.12 (0.11)
Intercepts						
amenities	0.02 (0.09)	-0.02 (0.03)	0.01 (0.09)	-0.02 (0.03)	0.01 (0.1)	-0.01 (0.03)
health services	-0.10 (0.09)	0.04 (0.03)	-0.11 (0.09)	0.04 (0.03)	-0.10 (0.09)	0.04 (0.03)
air pollution	0.07 (0.10)	-0.02 (0.03)	0.07 (0.10)	-0.02 (0.03)	0.07 (0.1)	-0.01 (0.03)
crime	-0.12 (0.10)	0.03 (0.03)	-0.11 (0.10)	0.03 (0.03)	-0.11 (0.1)	0.03 (0.03)
housing costs	0.02 (0.07)	-0.01 (0.03)	0.03 (0.07)	-0.01 (0.03)	0.03 (0.07)	-0.01 (0.03)
outcome	-0.34 (0.44)	-0.69 (0.31) **	0.24 (0.46)	1.04 (0.34) **	-0.03 (0.57)	0.14 (0.3)

[a] The Bayes Estimator produces a posterior standard deviation estimate in place of a standard error. ***p*<0.01; **p*<0.05; † *p*<0.10

Table 31

RQ1 Indirect, Direct, and Total Effects of Neighborhood Affluence Part I Stayers vs. Movers

	Distress		Stress	
	Stayers	**Movers**	**Stayers**	**Movers**
Within Individuals	β (SD)	β (SD)	β (SD)	β (SD)
Specific Indirect Effects				
% affluence via amenities	0.04 (0.10)	0.01 (0.02)	-0.02 (0.1)	0.00 (0.02)
% affluence via health services	-0.11 (0.07) *	0.02 (0.01)	-0.08 (0.06)	0.02 (0.01)
% affluence via air pollution	0.00 (0.01)	0.00 (0.00)	0.00 (0.01)	0.00 (0.00)

% affluence via crime	0.02 (0.08)	0.00 (0.00)	-0.01 (0.08)	-0.01 (0.01)
% affluence via housing costs	0.42 (0.31)	-0.03 (0.03)	0.50 (0.30) †	-0.04 (0.03)
Total Indirect Effect	0.36 (0.29)	0.00 (0.04)	0.39 (0.28)	-0.04 (0.04)
Direct Effect	-0.34 (0.36)	-0.02 (0.05)	-0.19 (0.34)	0.03 (0.05)
Total effect	**0.02 (0.20)**	**-0.03 (0.03)**	**0.20 (0.19)**	**-0.01 (0.03)**
Between Individuals				
Specific Indirect Effects				
% affluence via amenities	0.00 (0.03)	-0.01 (0.24)	0.00 (0.03)	-0.03 (0.56)
% affluence via health services	-0.05 (0.10)	-0.20 (0.53)	-0.05 (0.08)	-0.14 (0.80)
% affluence via air pollution	0.00 (0.02)	0.00 (0.10)	0.01 (0.02)	-0.02 (0.33)
% affluence via crime	0.00 (0.02)	-0.05 (0.13)	0.00 (0.02)	-0.02 (0.10)
% affluence via housing costs	-0.02 (0.10)	-0.31 (0.48)	-0.01 (0.09)	-0.23 (0.58)
Total Indirect Effect	-0.07 (0.14)	-0.63 (0.81)	-0.05 (0.12)	-0.51 (0.85)
Direct Effect	0.07 (0.17)	1.05 (0.9) †	0.06 (0.16)	0.92 (0.9) †
Total Effect	**0.00 (0.11)**	**0.39 (0.21) ***	**0.01 (0.10)**	**0.39 (0.17) ****

[a] The Bayes Estimator produces a posterior standard deviation estimate in place of a standard error. ***p*<0.01; **p*<0.05; † *p*<0.10

Table 32

RQ1 Indirect, Direct, and Total Effects of Neighborhood Affluence Part II for Stayers vs. Movers

	Somatic Symptoms		Health		Happiness	
	Stayers	**Movers**	**Stayers**	**Movers**	**Stayers**	**Movers**
Within Individuals	β (SD)	β (SD)	β (SD)	β (SD)	β (SD)	β (SD)
Specific Indirect Effects						
% aff via amenities	0.05 (0.09)	0.04 (0.01) *	-0.16 (0.10) †	-0.03 (0.02) *	-0.05 (0.09)	-0.02 (0.02)
% aff via health services	-0.05 (0.05)	0.02 (0.01) †	0.04 (0.06)	0.00 (0.01)	0.04 (0.06)	-0.01 (0.01)
% aff via air pollution	0.00 (0.02)	0.00 (0.00)	0.00 (0.02)	0.00 (0.00)	0.00 (0.03)	0.00 (0.00)

% aff via crime	-0.04 (0.07)	0.00 (0.00)	0.01 (0.08)	0.00 (0.00)	0.00 (0.08)	0.00 (0.01)
% aff via housing costs	0.60 (0.27) *	0.03 (0.03)	0.02 (0.29)	0.01 (0.03)	-0.02 (0.29)	-0.03 (0.03)
Total Indirect Effect	0.55 (0.25) *	0.08 (0.04) *	-0.09 (0.28)	-0.02 (0.04)	-0.04 (0.27)	-0.07 (0.04) †
Direct Effect	0.00 (0.31)	0.02 (0.05)	-0.37 (0.34)	-0.10 (0.05) *	-0.04 (0.33)	0.03 (0.05)
Total Effect	**0.55 (0.17) ****	**0.10 (0.03) ****	**-0.47 (0.19) ***	**-0.12 (0.03) ****	**-0.09 (0.19)**	**-0.04 (0.03)**
Between Individuals						
Specific Indirect Effects						
% aff via amenities	0.00 (0.03)	0.12 (0.16)	0.00 (0.03)	-0.01 (0.13)	0.00 (0.04)	0.00 (0.26)
% aff via health services	0.05 (0.09)	-0.44 (0.28) †	-0.06 (0.09)	-0.04 (0.45)	0.13 (0.09)	0.10 (0.52)
% aff via air pollution	0.01 (0.02)	0.05 (0.11)	-0.01 (0.02)	0.00 (0.06)	0.00 (0.02)	-0.01 (0.11)
% aff via crime	0.00 (0.02)	0.00 (0.05)	0.01 (0.02)	0.02 (0.07)	0.00 (0.02)	0.04 (0.10)
% aff via housing costs	-0.03 (0.1)	-0.01 (0.28)	0.02 (0.1)	0.07 (0.3)	-0.04 (0.1)	0.24 (0.44)
Total Indirect Effect	0.05 (0.14)	-0.20 (0.48)	-0.05 (0.13)	0.02 (0.59)	0.10 (0.13)	0.41 (0.76)
Direct Effect	-0.07 (0.17)	0.11 (0.55)	0.00 (0.17)	-0.09 (0.66)	-0.19 (0.17)	-0.71 (0.81)
Total Effect	**-0.02 (0.11)**	**-0.09 (0.16)**	**-0.04 (0.11)**	**-0.07 (0.18)**	**-0.08 (0.11)**	**-0.30 (0.18) †**

[a] The Bayes Estimator produces a posterior standard deviation estimate in place of a standard error. **p<0.01; *p<0.05; † p<0.10

Table 33

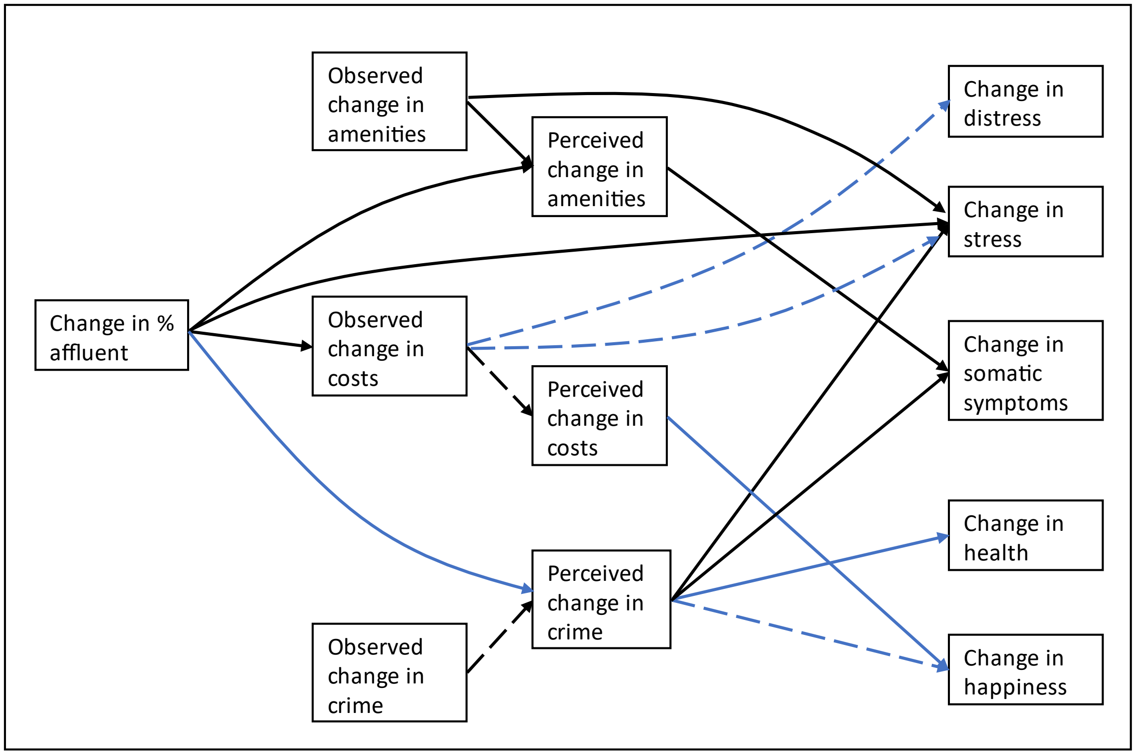
RQ2 Neighborhood Affluence Model Fit Indices

	CFI	TLI	RMSEA	[90% CI]	SRMR
Affluence model	0.97	0.93	0.04	[0.03 0.04]	0.04

Note: CFI = comparative fit index; TLI = Tucker-Lewis index; SRMR = standardized root mean square residual; RMSEA = root mean square error of approximation; CI = confidence interval.

Figure 11

RQ2 Main Path Analysis: Changes in Neighborhood Affluence Predicting Changes in Wellbeing



Note: Solid pathways represent significant associations (*p*<.05), while dashed pathways approach significance (*p*<.10). Black pathways represent positive links, and blue pathways negative links. The following covariates were included as predictors of outcome variables: baseline outcome, change in earnings, change in household size, change in receipt of public assistance, moving since baseline, hurricane-related trauma, hurricane-related death, and post-Katrina mobility.

Table 34

RQ2 Main Path Analysis: Changes in Neighborhood Affluence Predicting Changes in Wellbeing

	β (SD)	β (SD)	β (SD)	β (SD)	β (SD)
Changes in neighborhood affluence predicting observed and perceived changes in neighborhood features					
% aff → obs. amenities	-0.07 (0.04)				
% aff → perc. amenities	0.15 (0.06) *				
% aff → obs. Costs	0.60 (0.04) **				
% aff → perc. costs	-0.10 (0.09)				
% aff → obs. crime	-0.03 (0.05)				
% aff → perc. crime	-0.23 (0.07) **				
Observed changes in neighborhood features predicting perceived changes					
obs. → perc. amenities	0.21 (0.05) **				
obs. → perc. costs	0.15 (0.08) †				
obs. → perc. crime	0.15 (0.08) †				
Changes in neighborhood features predicting changes in wellbeing					
	Distress	**Stress**	**Somatic Symptoms**	**Health**	**Happiness**
observed amenities	0.04 (0.04)	0.08 (0.04) *	0.03 (0.04)	0.02 (0.04)	-0.01 (0.04)
perceived amenities	0.01 (0.04)	-0.01 (0.04)	0.11 (0.05) *	0.02 (0.05)	0.04 (0.04)
observed costs	-0.08 (0.04) †	-0.07 (0.04) †	-0.02 (0.05)	0.06 (0.05)	-0.02 (0.04)
perceived costs	0.04 (0.04)	0.05 (0.04)	0.01 (0.05)	0.00 (0.04)	-0.08 (0.04) *
observed crime	-0.02 (0.04)	0.00 (0.04)	0.01 (0.04)	-0.02 (0.04)	0.04 (0.04)
perceived crime	0.06 (0.04)	0.09 (0.04) *	0.13 (0.05) **	-0.15 (0.05) **	-0.08 (0.04) †
% affluence	0.04 (0.04)	0.11 (0.04) **	0.06 (0.05)	-0.07 (0.05)	-0.02 (0.04)
Covariates predicting changes in wellbeing					
outcome at W0	-0.56 (0.03) **	-0.61 (0.03) **	-0.39 (0.03) **	-0.47 (0.03) **	-0.65 (0.03) **

Δ earnings	-0.12 (0.04) **	-0.11 (0.04) **	-0.02 (0.05)	0.08 (0.04) †	0.09 (0.04) *
Δ household size	-0.07 (0.03) *	-0.06 (0.03) †	-0.04 (0.04)	0.02 (0.03)	0.04 (0.03)
receipt of public assistance (base: stable)					
started public assist.	-0.16 (0.11)	-0.03 (0.12)	-0.04 (0.13)	-0.05 (0.13)	0.22 (0.11) †
stopped public assist.	-0.01 (0.09)	0.14 (0.08) †	-0.04 (0.09)	0.02 (0.09)	0.16 (0.08) *
moved tracts since W0	0.06 (0.09)	-0.06 (0.09)	0.08 (0.10)	-0.17 (0.09) †	-0.07 (0.08)
hurricane-related trauma	0.17 (0.04) **	0.16 (0.03) **	0.16 (0.04) **	-0.11 (0.04) **	-0.04 (0.03)
hurricane-related death	0.17 (0.08) *	0.05 (0.07)	0.24 (0.08) **	-0.14 (0.08) †	0.02 (0.07)
post-Katrina mobility	-0.08 (0.05) †	0.00 (0.04)	0.11 (0.05) *	0.05 (0.05)	-0.05 (0.04)

Note: **p<0.01; *p<0.05; † p<0.10.

Table 35

RQ2 Indirect, Direct, and Total Effects of Changes in Neighborhood Affluence on Changes in Wellbeing

	Distress	**Stress**	**Somatic Symptoms**	**Health**	**Happiness**
	β (SD)	β (SD)	β (SD)	β (SD)	β (SD)
Specific Indirect Effects					
% aff via observed amenities	0.00 (0.00)	-0.01 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
% aff via perceived amenities	0.00 (0.01)	0.00 (0.01)	0.02 (0.01) †	0.00 (0.01)	0.01 (0.01)
% aff → obs. amenities → perc. amenities	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
% aff via observed crime	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
% aff via perceived crime	-0.01 (0.01)	-0.02 (0.01) †	-0.03 (0.02) *	0.03 (0.02) *	0.02 (0.01)
% aff → obs. crime → perc. crime	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
% aff via observed home costs	-0.05 (0.03) †	-0.04 (0.03) †	-0.01 (0.03)	0.03 (0.03)	-0.01 (0.03)
% aff via perceived costs	0.00 (0.01)	-0.01 (0.01)	0.00 (0.01)	0.00 (0.00)	0.01 (0.01)
% aff → obs. home costs → perc costs	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	-0.01 (0.01)

Total Indirect Effect	-0.06 (0.03) *	-0.07 (0.03) *	-0.03 (0.03)	0.07 (0.04) *	0.01 (0.03)
Direct Effect	0.04 (0.04)	0.11 (0.04) **	0.06 (0.05)	-0.07 (0.05)	-0.02 (0.04)
Total Effect	**-0.02 (0.04)**	**0.04 (0.03)**	**0.02 (0.04)**	**0.00 (0.04)**	**0.00 (0.03)**

Note: ***p*<0.01; **p*<0.05; † *p*<0.10

Table 36

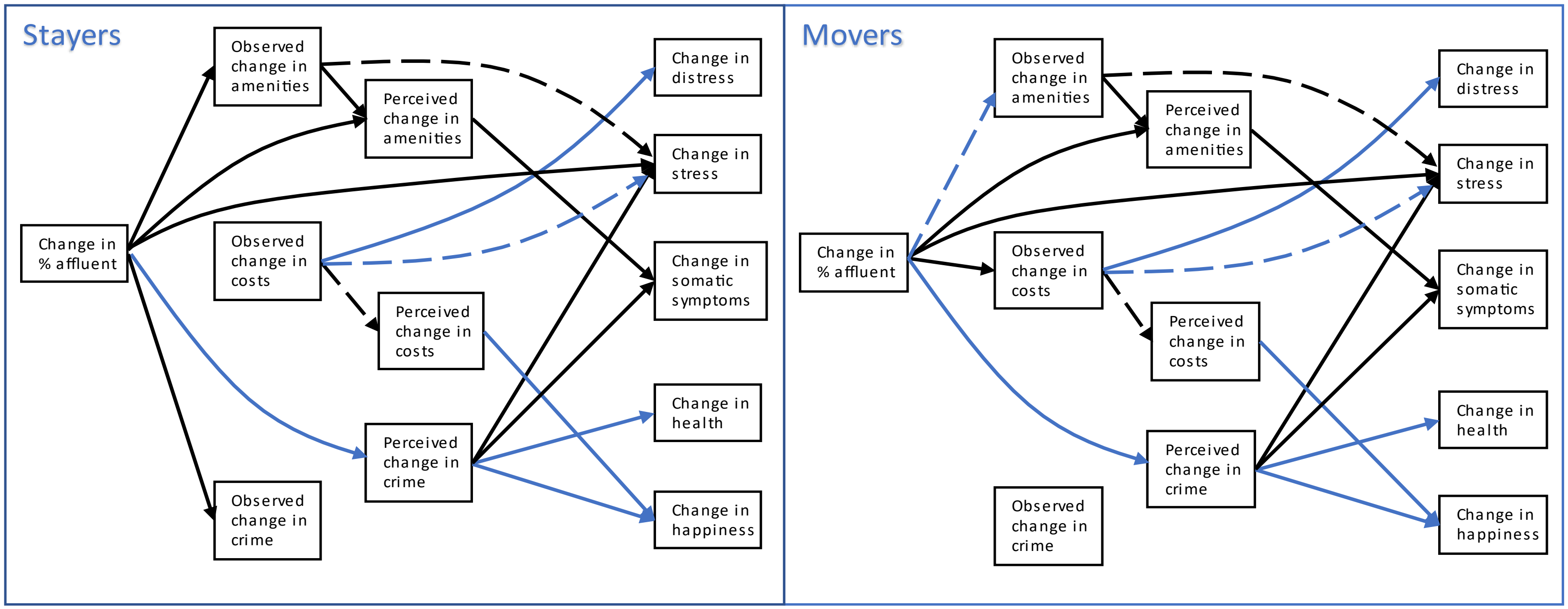
RQ2 Neighborhood Affluence Model Fit for Multigroup Models

	CFI	TLI	RMSEA	[90% CI]	SRMR	Adjusted BIC	χ^2 (df)	Δdf	$\Delta\chi^2$ (TRd)	*p*
Unconstrained	0.97	0.95	0.03	[0.02, 0.04]	0.05	32210.14	270.96 (209)	-	-	
Final	0.98	0.96	0.03	[0.01, 0.04]	0.05	32110.69	304.69 (250)	41	33.5	0.79

Note: CFI = comparative fit index; TLI = Tucker-Lewis index; SRMR = standardized root mean square residual; RMSEA = root mean square error of approximation; CI = confidence interval; BIC = Bayes information criterion. Due to use of the MLR estimator, the Satorra-Bentler scaled chi-square different test (TRd) was computed in place of a standard chi-square difference test.

Figure 15

RQ2 Neighborhood Affluence Final Multigroup Path Models for Stayers vs. Movers



Note: Solid pathways represent significant associations ($p<.05$), while dashed pathways approach significance ($p<.10$). Black pathways represent positive links, and blue pathways negative links. The following covariates were included as predictors of outcome variables: baseline outcome, change in earnings, change in household size, change in receipt of public assistance, hurricane-related trauma, hurricane-related death, and post-Katrina mobility.

Table 37

RQ2 Multigroup Path Analysis: Changes in Neighborhood Affluence Predicting Changes in Wellbeing

	Fully Unconstrained		Final Multigroup	
	Stayers	**Movers**	**Stayers**	**Movers**
	β (SD)	β (SD)	β (SD)	β (SD)
Changes in neighborhood poverty predicting observed and perceived changes in neighborhood features				
% aff → obs. amenities	1.18 (0.22) **	-0.08 (0.05) †	1.21 (0.22) **	-0.08 (0.05) †
% aff → perc. amenities	0.35 (0.26)	0.14 (0.07) *	0.14 (0.06) *	0.14 (0.06) *
% aff → obs. costs	-0.06 (0.04)	0.64 (0.04) **	-0.06 (0.04)	0.64 (0.04) **
% aff → perc. costs	-0.08 (0.22)	-0.10 (0.1)	-0.09 (0.09)	-0.09 (0.09)
% aff → obs. crime	0.57 (0.13) **	-0.04 (0.05)	0.58 (0.13) **	-0.04 (0.05)
% aff → perc. crime	0.04 (0.21)	-0.21 (0.07) **	-0.19 (0.07) **	-0.19 (0.07) **
Observed changes in neighborhood features predicting perceived changes				
obs. → perc. amenities	0.08 (0.15)	0.22 (0.06) **	0.21 (0.05) **	0.21 (0.05) **
obs. → perc. costs	-0.22 (0.49)	0.16 (0.09) †	0.15 (0.09) †	0.15 (0.09) †
obs. → perc. crime	-0.01 (0.18)	0.08 (0.06)	0.08 (0.06)	0.08 (0.06)
Changes in neighborhood features predicting changes in wellbeing				
observed amenities → distress	-0.09 (0.17)	0.03 (0.04)	0.03 (0.04)	0.03 (0.04)
perceived amenities → distress	-0.01 (0.09)	0.01 (0.05)	0.01 (0.04)	0.01 (0.04)
observed costs → distress	0.17 (0.50)	-0.09 (0.05) †	-0.09 (0.04) *	-0.09 (0.04) *
perceived costs → distress	0.02 (0.09)	0.05 (0.04)	0.05 (0.04)	0.05 (0.04)
observed crime → distress	0.02 (0.24)	-0.01 (0.04)	-0.01 (0.04)	-0.01 (0.04)
perceived crime → distress	0.07 (0.1)	0.04 (0.05)	0.05 (0.04)	0.05 (0.04)
% affluence → distress	0.23 (0.26)	0.04 (0.05)	0.05 (0.05)	0.05 (0.05)
observed amenities → stress	0.21 (0.17)	0.05 (0.04)	0.07 (0.04) †	0.07 (0.04) †

perceived amenities → stress	-0.09 (0.08)	0.04 (0.05)	-0.01 (0.04)	-0.01 (0.04)
observed costs → stress	0.20 (0.46)	-0.08 (0.04) †	-0.08 (0.04) †	-0.08 (0.04) †
perceived costs → stress	0.02 (0.09)	0.06 (0.04)	0.04 (0.04)	0.04 (0.04)
observed crime → stress	0.05 (0.23)	0.00 (0.04)	0.00 (0.04)	0.00 (0.04)
perceived crime → stress	0.10 (0.09)	0.1 (0.05) *	0.09 (0.04) *	0.09 (0.04) *
% affluence → stress	0.03 (0.21)	0.11 (0.04) *	0.12 (0.04) **	0.12 (0.04) **
observed amenities → somatic	-0.22 (0.18)	0.04 (0.04)	0.02 (0.04)	0.02 (0.04)
perceived amenities → somatic	0.10 (0.09)	0.13 (0.05) *	0.12 (0.05) **	0.12 (0.05) **
observed costs → somatic	0.69 (0.48)	-0.06 (0.05)	-0.03 (0.05)	-0.03 (0.05)
perceived costs → somatic	-0.12 (0.09)	0.06 (0.05)	0.00 (0.05)	0.00 (0.05)
observed crime → somatic	0.19 (0.26)	0.01 (0.04)	0.01 (0.04)	0.01 (0.04)
perceived crime → somatic	0.07 (0.09)	0.16 (0.06) **	0.14 (0.05) **	0.14 (0.05) **
% affluence → somatic	0.13 (0.27)	0.09 (0.05)	0.06 (0.05)	0.06 (0.05)
observed amenities → health	0.30 (0.18) †	0.00 (0.05)	0.01 (0.04)	0.01 (0.04)
perceived amenities → health	-0.01 (0.08)	0.03 (0.06)	0.02 (0.05)	0.02 (0.05)
observed costs → health	0.80 (0.45) †	0.07 (0.05)	0.06 (0.05)	0.06 (0.05)
perceived costs → health	0.11 (0.08)	-0.04 (0.05)	0.01 (0.04)	0.01 (0.04)
observed crime → health	0.07 (0.26)	-0.03 (0.04)	-0.03 (0.04)	-0.03 (0.04)
perceived crime → health	-0.07 (0.08)	-0.16 (0.05) **	-0.14 (0.05) **	-0.14 (0.05) **
% affluence → health	-0.50 (0.23) *	-0.08 (0.06)	-0.07 (0.05)	-0.07 (0.05)
observed amenities → happiness	-0.01 (0.15)	0.00 (0.04)	-0.01 (0.03)	-0.01 (0.03)
perceived amenities → happiness	0.03 (0.05)	0.03 (0.06)	0.03 (0.04)	0.03 (0.04)
observed costs → happiness	0.39 (0.35)	-0.02 (0.04)	-0.01 (0.04)	-0.01 (0.04)
perceived costs → happiness	-0.05 (0.06)	-0.08 (0.05) †	-0.07 (0.04) *	-0.07 (0.04) *
observed crime → happiness	0.20 (0.19)	0.03 (0.04)	0.04 (0.04)	0.04 (0.04)
perceived crime → happiness	-0.09 (0.06)	-0.08 (0.05)	-0.09 (0.04) *	-0.09 (0.04) *

% affluence → happiness	-0.22 (0.2)	-0.01 (0.04)	-0.02 (0.04)	-0.02 (0.04)

Note: ***p*<0.01; **p*<0.05; † *p*<0.10. Light grey cells highlight associations that were left unconstrained. The following covariates were included as predictors of outcome variables: baseline outcome, change in earnings, change in household size, change in receipt of public assistance, hurricane-related trauma, hurricane-related death, and post-Katrina mobility.

Table 38

RQ2 Indirect, Direct, and Total Effects of Neighborhood Affluence for Stayers vs. Movers

	Fully Unconstrained		Final Multigroup	
	Stayers	**Movers**	**Stayers**	**Movers**
	β (SD)	β (SD)	β (SD)	β (SD)
Specific Indirect Effects				
% aff → observed amenities → distress	-0.10 (0.20)	0.00 (0.00)	0.03 (0.05)	0.00 (0.00)
% aff → perceived amenities → distress	-0.01 (0.03)	0.00 (0.01)	0.00 (0.01)	0.00 (0.01)
% aff → obs. amenities → perc. amenities → distress	0.00 (0.01)	0.00 (0.00)	0.00 (0.01)	0.00 (0.00)
% aff → observed crime → distress	0.01 (0.14)	0.00 (0.00)	-0.01 (0.02)	0.00 (0.00)
% aff → perceived crime → distress	0.00 (0.02)	-0.01 (0.01)	-0.01 (0.01)	-0.01 (0.01)
% aff → obs. crime → perc. crime → distress	0.00 (0.01)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
% aff → observed costs → distress	-0.01 (0.03)	-0.06 (0.03) †	0.01 (0.01)	-0.06 (0.03) *
% aff → perceived costs → distress	0.00 (0.01)	-0.01 (0.01)	0.00 (0.01)	0.00 (0.01)
% aff → obs. costs → perc. costs → distress	0.00 (0.00)	0.01 (0.01)	0.00 (0.00)	0.00 (0.00)
Total Indirect Effect on Distress	-0.11 (0.16)	-0.06 (0.03) †	0.02 (0.05)	-0.07 (0.03) *
Direct Effect on Distress	0.23 (0.26)	0.04 (0.05)	0.05 (0.05)	0.05 (0.05)
Total Effect on Distress	**0.12 (0.23)**	**-0.03 (0.04)**	**0.07 (0.07)**	**-0.02 (0.04)**
Specific Indirect Effects				

% aff → observed amenities → stress	0.25 (0.20)	0.00 (0.00)	0.08 (0.05) †	-0.01 (0.00)
% aff → perceived amenities → stress	-0.03 (0.04)	0.01 (0.01)	0.00 (0.01)	0.00 (0.01)
% aff → obs. amenities → perc. amenities → stress	-0.01 (0.02)	0.00 (0.00)	0.00 (0.01)	0.00 (0.00)
% aff → observed crime → stress	0.03 (0.13)	0.00 (0.00)	0.00 (0.02)	0.00 (0.00)
% aff → perceived crime → stress	0.00 (0.02)	-0.02 (0.01) †	-0.02 (0.01) †	-0.02 (0.01) †
% aff → obs. crime → perc. crime → stress	0.00 (0.01)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
% aff → observed costs → stress	-0.01 (0.03)	-0.05 (0.03) †	0.01 (0.00)	-0.05 (0.03) †
% aff → perceived costs → stress	0.00 (0.01)	-0.01 (0.01)	0.00 (0.01)	0.00 (0.01)
% aff → obs. costs → perc. costs → stress	0.00 (0.00)	0.01 (0.01)	0.00 (0.00)	0.00 (0.00)
Total Indirect Effect on Stress	0.23 (0.16)	-0.07 (0.03) *	0.07 (0.04)	-0.07 (0.03) *
Direct Effect on Stress	0.03 (0.21)	0.11 (0.04) *	0.12 (0.04) **	0.12 (0.04) **
Total Effect on Stress	**0.26 (0.16)**	**0.04 (0.03)**	**0.19 (0.06) ****	**0.04 (0.03)**
Specific Indirect Effects				
% aff → observed amenities → somatic	-0.26 (0.22)	0.00 (0.00)	0.03 (0.05)	0.00 (0.00)
% aff → perceived amenities → somatic	0.03 (0.04)	0.02 (0.01)	0.02 (0.01) †	0.02 (0.01) †
% aff → obs. amenities → perc. amenities → somatic	0.01 (0.02)	0.00 (0.00)	0.03 (0.02) *	0.00 (0.00)
% aff → observed crime → somatic	0.11 (0.15)	0.00 (0.00)	0.01 (0.02)	0.00 (0.00)
% aff → perceived crime → somatic	0.00 (0.02)	-0.03 (0.02) †	-0.03 (0.01) †	-0.03 (0.01) †
% aff → obs. crime → perc. crime → somatic	0.00 (0.01)	0.00 (0.00)	0.01 (0.01)	0.00 (0.00)
% aff → observed costs → somatic	-0.04 (0.04)	-0.04 (0.03)	0.00 (0.00)	-0.02 (0.03)
% aff → perceived costs → somatic	0.01 (0.03)	-0.01 (0.01)	0.00 (0.00)	0.00 (0.00)
% aff → obs. costs → perc. costs → somatic	0.00 (0.00)	0.01 (0.01)	0.00 (0.00)	0.00 (0.00)
Total Indirect Effect on Somatic	-0.14 (0.18)	-0.06 (0.04)	0.06 (0.05)	-0.03 (0.03)
Direct Effect on Somatic	0.13 (0.27)	0.09 (0.05)	0.06 (0.05)	0.06 (0.05)
Total Effect on *Somatic*	**-0.01 (0.21)**	**0.03 (0.04)**	**0.12 (0.07) †**	**0.02 (0.04)**
Specific Indirect Effects				
% aff → observed amenities → health	0.36 (0.21) †	0.00 (0.00)	0.01 (0.05)	0.00 (0.00)
% aff → perceived amenities → health	0.00 (0.03)	0.01 (0.01)	0.00 (0.01)	0.00 (0.01)
% aff → obs. amenities → perc. amenities → health	0.00 (0.01)	0.00 (0.00)	0.01 (0.01)	0.00 (0.00)
% aff → observed crime → health	0.04 (0.15)	0.00 (0.00)	-0.02 (0.03)	0.00 (0.00)
% aff → perceived crime → health	0.00 (0.02)	0.03 (0.02) *	0.03 (0.01) *	0.03 (0.01) *

% aff → obs. crime → perc. crime → health	0.00 (0.01)	0.00 (0.00)	-0.01 (0.01)	0.00 (0.00)
% aff → observed costs → health	-0.05 (0.05)	0.04 (0.03)	0.00 (0.00)	0.04 (0.03)
% aff → perceived costs → health	-0.01 (0.03)	0.00 (0.01)	0.00 (0.00)	0.00 (0.00)
% aff → obs. costs → perc. costs → health	0.00 (0.00)	0.00 (0.01)	0.00 (0.00)	0.00 (0.00)
Total Indirect Effect on Health	0.33 (0.17) †	0.08 (0.04) *	0.02 (0.05)	0.07 (0.04) †
Direct Effect on Health	-0.50 (0.23) *	-0.08 (0.06)	-0.07 (0.05)	-0.07 (0.05)
Total Effect on *Health*	**-0.17 (0.2)**	**0.00 (0.04)**	**-0.05 (0.07)**	**0.00 (0.04)**
Specific Indirect Effects				
% aff → observed amenities → happiness	-0.01 (0.18)	0.00 (0.00)	-0.01 (0.04)	0.00 (0.00)
% aff → perceived amenities → happiness	0.01 (0.02)	0.00 (0.01)	0.00 (0.01)	0.00 (0.01)
% aff → obs. amenities → perc. amenities → happiness	0.00 (0.01)	0.00 (0.00)	0.01 (0.01)	0.00 (0.00)
% aff → observed crime → happiness	0.11 (0.11)	0.00 (0.00)	0.02 (0.02)	0.00 (0.00)
% aff → perceived crime → happiness	0.00 (0.02)	0.02 (0.01)	0.02 (0.01) †	0.02 (0.01) †
% aff → obs. crime → perc. crime → happiness	0.00 (0.01)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
% aff → observed costs → happiness	-0.02 (0.03)	-0.01 (0.03)	0.00 (0.00)	-0.01 (0.03)
% aff → perceived costs → happiness	0.00 (0.01)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)
% aff → obs. costs → perc. costs → happiness	0.00 (0.00)	-0.01 (0.01)	0.00 (0.00)	-0.01 (0.01)
Total Indirect Effect on Happiness	0.10 (0.15)	0.01 (0.03)	0.05 (0.04)	0.01 (0.03)
Direct Effect on Happiness	-0.22 (0.2)	-0.01 (0.04)	-0.02 (0.04)	-0.02 (0.04)
Total Effect on *Happiness*	**-0.12 (0.15)**	**0.00 (0.04)**	**0.02 (0.06)**	**-0.01 (0.03)**

Note: **p<0.01; *p<0.05; † p<0.10.