SOCIAL NETWORKS AND SOCIAL INEQUALITY IN LATER LIFE

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The projected growth of the older adult population in the United States coincides with deepening social inequalities. This dissertation is motivated by the observation that social network ties profoundly shape older adults' quality of life, but that some of the most consequential features of these networks have yet to be incorporated into frameworks for understanding social stratification across the life course. In this dissertation, I examine how properties of older adults' personal social networks intersect with dimensions of social inequality that are among the key social determinants of later life well-being. Each chapter uses data from the National Social Life, Health, and Aging Project (NSHAP), a population-based, longitudinal study of community-residing older adults in the United States, in a series of descriptive and multivariable analyses designed to assess the focal research questions. The first chapter explores how older adults' personal networks are shaped by childhood circumstances. I find that higher parental socioeconomic status during childhood is associated larger, less kin-based, and more expansive personal networks, while higher levels of childhood family happiness are associated with denser and more kin-centric social networks in later life. The second chapter proposes that personal networks are a social context that carries implications for older adults' perceptions of discrimination. I find that more kin-based personal networks predict less frequent experiences of discrimination; however, among black older adults who experience more frequent discrimination, more kin-based personal networks are associated with race-based discrimination. The third chapter argues that the stability of older adults' personal networks is a function of residential neighborhood conditions, including concentrated disadvantage, residential instability, and social ties. I suggest that there may be

nuances in how the stability of kin and non-kin ties are shaped by these conditions. I find that neighborhood concentrated disadvantage is associated with the loss of kin network ties over time, but that higher levels of neighborhood social ties predict higher rates of non-kin turnover – that is, the addition and loss of non-kin network members over time. I conclude the dissertation with a discussion of common themes and directions for future research that emerged across the three chapters.

BIOGRAPHICAL SKETCH

Alyssa Goldman earned a Bachelor of Arts in Psychology and Government from Cornell University in 2007 and a Master of Arts in Social Sciences from the University of Chicago in 2008. Her doctoral research spans the areas of social networks, the life course, social inequality, health, and criminal justice system contact.

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PREFACE

A consistent finding from social network research is that personal relationships profoundly influence individual well-being (Smith and Christakis 2008; Valente 2010). Our close personal ties structure the information that we are exposed to, the decisions that we make, the beliefs that we hold, and the behaviors and perspectives that shape everyday life. Over the past twenty years, scholars have called for greater attention to how macro-level social forces condition the structure and characteristics of social network ties (Berkman et al. 2000; Umberson, Crosnoe, and Reczek 2010). A deeper understanding of the intersection of social-structural conditions and personal social networks is needed to advance research on how these relationships shape individual well-being and overall quality of life, and how they contribute to persistent and widening population disparities (Berkman et al. 2000; Umberson and Montez 2010).

A long line of sociological research has paid attention to how properties of personal networks are tied to social and economic stratification. By and large, this work has expanded our understanding of how race/ethnicity, education, and other individual-level measures of attainment correlate with personal network structures, leading to broad hypotheses about how these associations could perpetuate social inequalities (Ajrouch, Antonucci, and Webster 2016; Ajrouch, Blandon, and Antonucci 2005; Cornwell 2015; Fischer and Beresford 2015; Mickelson and Kubzansky 2003; Schafer and Vargas 2016). Despite these insights, the predominant frameworks used to study health and social inequalities continue to link individual social position with certain experiences, fundamental causes, or systems of exposure (Link and Phelan 1995; Phelan and Link 2015; Phelan, Link, and Tehranifar 2010; Riley 2020). There has been less attention to how these experiences, causes, and systems intersect with personal networks.

Furthermore, studies that connect social networks with individual social position often

assume that these associations reflect the concentration of certain experiences and exposures within certain social groups, and which restrict or promote access to advantageous social networks. For example, exposure to stable, high-status occupations is one explanation for why individuals of higher socioeconomic status tend to have larger, more expansive network structures (e.g., Ajrouch et al. 2005). While the concentration of these experiences may be a key mechanism, there is likely to be heterogeneity or gradations in these stratifying exposures, even within social groups.

This dissertation works in the spirit of earlier calls to integrate the structure of social relationships into studies of social stratification. A main contribution of this work is in shifting prior frameworks for thinking about social networks and stratification beyond questions of how individual-level indictors (e.g., race/ethnicity, income, education) correlate with personal network properties. Instead, I aim to demonstrate how personal social networks intersect with key exposures and experiences that characterize social inequality. I focus on how personal network structure and dynamics relate to three dimensions of inequality that have garnered significant research attention in the past twenty years, particularly regarding their role in individual and population-level well-being. These three dimensions include childhood (dis)advantage, everyday discrimination, and neighborhood conditions.

In each chapter, I build the argument that prior theory and empirical research provide reasons to view these experiences and exposures as intersecting with those properties of personal networks that are implicated in individual behaviors, decision-making, and access to resources. I suggest why we might expect associations above and beyond individual-level indicators of social position. I argue that the structure of such networks is, in some cases, influenced by these experiences (i.e., childhood circumstances, neighborhood conditions). In another case, I argue

that characteristics of personal networks shape these experiences (i.e., everyday discrimination). This dissertation does not aim to evaluate the role of social networks in the linkage between these dimensions of inequality and health. Rather, I use these three cases to emphasize personal networks as a context that intersects with those social-structural conditions that are key determinants of well-being, apart from individual attributes, and suggest that these connections can shed light on why differences in well-being persist across social groups.

THE LATER LIFE CONTEXT

The relevance of personal networks is established at multiple stages of the life course (Alwin, Felmlee, and Kreager 2018). This dissertation focuses on later life – a period characterized by numerous social and economic inequalities that make population aging a stratified process in and of itself (Abramson and Portacolone 2017; Abramson 2015, 2016; Carr 2019).

Qualities of later life make this a compelling period of the life course for observing the intersection of social inequalities and personal networks. On the one hand, later life represents a time when individuals across sociodemographic groups are likely to face a shared set of vulnerabilities. Declining mobility, diminishing energy to accomplish routine tasks, and the death of close friends and family are among the changes and challenges that individuals across social positions tend to experience as they age (Abramson 2015). The degree to which older adults can successfully navigate these challenges may depend in part on the resources accessible through their personal networks (Cornwell, Laumann, and Schumm 2008; Seeman 2000; Umberson, Crosnoe, and Reczek 2010). Differences in social groups' well-being and quality of life may partly reflect inequalities in personal network structure and stability.

At the same time, later life social network resources are likely to reflect a lifetime of

different circumstances and vulnerabilities that individuals experienced earlier in the life span, and these differences are inextricably linked with social position. I explore this idea in greater depth in Chapter 1, but it is worth mentioning the implications of this concept for the overall goals of the dissertation. Put simply, extensive literature – particularly in the area of health disparities – demonstrates that social position is associated with differences in when and during which stage of the life span individuals are exposed to certain experiences and stressors that are likely to shape both social networks and well-being. For example, blacks are more likely than whites to experience the death of a friend or family member earlier in the life course (Umberson 2017). The accumulation of exposure to various forms of social and economic exclusion beginning early in the life course contributes to the poorer health of black women relative to more advantaged populations (i.e., the "weathering hypothesis"), including higher rates of chronic conditions and disabilities at earlier ages (Geronimus 1992; Umberson and Montez 2010; Walsemann, Geronimus, and Gee 2008; Warner and Brown 2011).

Thus, observations of personal social networks that begin later in life do not account for preceding experiences that likely shape how older adults use their social networks and the structure of those networks. This limits researchers' ability to infer how associations between later life personal networks and other phenomena might reflect trajectories of (dis)advantage. At the same time, however, these associations can be thought of as existing above and beyond unobservable aspects of personal histories that determine the types of personal networks that individuals have as they enter later life. Throughout the dissertation, I return to the need for future research to examine these research questions in ways that connect with earlier stages of the life course.

THE NATIONAL SOCIAL LIFE, HEALTH, AND AGING PROJECT

This dissertation relies on data from the National Social Life, Health, and Aging Project (NSHAP). The NSHAP is a nationally representative, longitudinal study of community-residing older adults in the United States that includes an oversample of African Americans and Hispanics. The NSHAP collects a wide range of information on respondents' health and social relationships, including physical and mental well-being, medication use, health behaviors, social activity, marital quality and history, cognitive health, and sensory function. Data collection includes a combination of approximately two-hour in-home interviews and biomeasure collection conducted by the National Opinion Research Center (NORC), as well as a supplemental self-administered questionnaire (e.g., leave-behind questionnaire, or LBQ) that respondents return to NORC by mail (Suzman 2009).

To date, the NSHAP includes three waves of data collection. Wave 1, collected in 2005-2006, surveyed 3,005 older adults ages 57 to 85 ("Cohort 1"), and has an overall weighted response rate of 75.5%. Wave 2, collected in 2011-2012, surveyed 3,377 older adults, including 2,261 returning Wave 1 respondents (a conditional response rate of 89%), 907 partners of the returning Wave 1 respondents, and 209 eligible but non-interviewed Wave 1 respondents. Wave 3, conducted in 2015-2016, includes 4,777 respondents, 2,371 of whom are Wave 2 respondents, and 1,554 of whom participated in all three waves. Wave 3 also included interviews with 2,368 new cohort respondents ("Cohort 2"). A total of 38 Wave 3 respondents were interviewed at Wave 1 but not at Wave 2. The conditional response rate for the Wave 1 ("Cohort 1") respondents is 89.2% at Wave 3.

The structure and content of the NSHAP surveys are generally similar across all three waves, with the exception of certain sets of questions that were either removed from the survey

(e.g., alternative medicine use), modified (e.g., cognitive health), or added (e.g., neighborhood context, Internet use) after the first wave. At each wave, respondents were prompted with the "important matters" name generator to elicit information on their personal social networks:

> *From time to time, most people discuss things that are important to them with others. For example, these may include good or bad things that happen to you, problems you are having, or important concerns you may have. Looking back over the last 12 months, who are the people with whom you most often discussed things that were important to you?*

This instrument is often used in survey research to gather information about respondents closest, most supportive social ties (Marsden 1987; Paik and Sanchagrin 2013), including their relationship to each network member (i.e., "alter"), how often they speak with each alter, and how often each alter speaks with every other alter named. At Waves 2 and 3, respondents who had taken part in a prior wave of the NSHAP were administered an additional set of questions to collect information about changes in the composition of their social network. Respondents were shown a list of the alters who they named in the prior survey(s), and were asked to indicate which of the alters from these prior lists, if any, were the same individuals who the respondent named in the current survey. In this way, NSHAP users can discern which members of respondents' networks are additions, deletions, or stable/continuous network members across survey waves.

It is worth noting that other datasets such as the Health and Retirement Study (HRS) are widely used to examine issues of social inequality in later life. However, the absence of a social network module makes this type of dataset less useful for considering the relevance and dynamics of older adults' closest social relationships, beyond broad reports of social support. Over the course of the three waves, the NSHAP has also expanded its collection of information on respondents' experiences with various social-structural conditions to include reports of early life conditions (Waves 2 and 3) and everyday discrimination (Wave 3), and has linked all three

waves with data from the American Community Survey on respondents' census tracts. These measures, combined with the social network module, make the NSHAP an ideal dataset for examining these research questions among the older adult population in the U.S. context.

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CHAPTER 1: THE EARLY LIFE ORIGINS OF LATER LIFE NETWORKS

ABSTRACT

Personal social networks profoundly influence a wide range of outcomes throughout the life course. But little research has considered how some of the most consequential features of individuals' social networks may be shaped by the enduring influence of exposures and experience in early life – the most vulnerable developmental period in the life course. This study uses nationally representative data from the National Social Life, Health, and Aging Project (NSHAP) (N = 4,063) to examine how childhood circumstances may shape the structure of older adults' personal social networks. The analyses show that higher childhood socioeconomic status is associated with what are often considered to be more advantageous features of older adults' personal social networks, including larger network size and a more expansive, less kin-based network structure. At the same time, higher levels of family happiness in childhood are associated with greater network density and more kin-centric network composition, which may reflect greater access to social support and overall network intimacy across the life course. The results suggest that studies of the relative advantages of social network structure may benefit from contextualizing individuals' social networks in terms of their social origins. I close by discussing the need for additional research on the life-course bases of the link between childhood circumstances and later-life network properties, and what role this connection plays in shaping later-life well-being.

INTRODUCTION

The interconnectedness of human lives touches nearly every facet of social life. The relevance of social networks has been established at multiple points across the life course, including adolescence and young adulthood (Bearman and Moody 2004), midlife (Liebler and Sandefur 2002), and later life (Cornwell, Laumann, and Schumm 2008). An abundance of research shows that social networks shape numerous individual outcomes within each of these life stages, including educational and occupational attainment, access to social support and social capital, and overall health and well-being, among others (e.g., Alwin, Felmlee, and Kreager 2018; House, Umberson, and Landis 1988; McDonald and Mair 2010; Umberson, Crosnoe, and Reczek 2010).

At the same time, the past twenty years have witnessed a monumental expansion in our understanding of how early life experiences shape these same types of opportunities and conditions across the life course. Specifically, exposure to childhood (dis)advantage – e.g., family socioeconomic status (SES), exposure to adversity, family structure – appears to structure social advantage and well-being across multiple domains in adulthood, including educational attainment and earnings, marriage and family structure, criminal activity, health and mortality, social functioning and community ties, and other lifestyle measures (Goodman, Joyce, and Smith 2011; Hayward and Gorman 2004; Huesmann, Eron, and Dubow 2002; Repetti, Taylor, and Seeman 2002; Andersson 2018).

Despite the robustness of these findings, less work has linked these two lines of research by considering how properties of later life personal social networks are life-course phenomena shaped by individuals' own histories. There are good reasons to adopt a life-course perspective when studying social networks. For one, the life-course perspective emphasizes the inherently

interconnected nature of human lives (Alwin 2012; Elder 1994). Life-course events and stages are not experienced in isolation. Rather, individual trajectories are inherently social, as individuals are "linked" through their relationships with others who influence one another within and across life stages (Carr 2018; Elder 1994). Furthermore, other research shows that social networks are shaped by a range of life-course factors, including education, marriage, parenthood, retirement, and widowhood (Kalmijn 2003; Wrzus et al. 2013; Zettel and Rook 2004), many of which are also shaped by early life circumstances.

But while we know that social connectedness characterizes individuals' progression through the life course, less research has considered how early life-course factors shape individuals' social network structure later in life. This study aims to bridge the interconnectedness of life stages with the interconnectedness of human lives, considering how early life experiences may structure some of the most consequential features of older adults' social connections. Accordingly, this paper considers how circumstances in childhood – a key developmental period of the life course – influence the relational structure in which later life is embedded – a life stage characterized by numerous personal and social changes (Crosnoe and Elder 2002).

I propose that childhood circumstances may have enduring effects on how community-dwelling older adults in the United States maintain their social networks as they age. Using data from the National Social Life, Health, and Aging Project, I examine how aspects of childhood may shape personal social networks in later life. Results suggest that early life circumstances set in motion distinct trajectories of social resource cultivation across the life span that persist to affect features of one's closest social ties in later years. I conclude by considering the implications of these findings for future studies on the intersection of social networks and the life

course.

THEORETICAL BACKGROUND

Personal Social Network Structure and the Life-Course Perspective

Personal social networks represent individuals' immediate social context – that is, those strong ties with whom individuals often engage in support exchange, and who provide information and other resources that influence individuals' decision-making, behavior, and dispositions (Fischer 2011; Marsden 1987). Rather than exclusively focus on individual attributes and outcomes, the social network perspective emphasizes patterns in the structural linkages that provide access to those resources, opportunities, and behavioral constraints that shape many of the individual outcomes that are of primary interest to social scientists (Wellman 1983).

Studies of social network structure specifically recognize that individuals' lives are defined in important ways by their connections to others, and also emphasize the connections *among* social network members, which can shape individuals' access to social and other benefits. Larger social networks, for example, are generally considered to be advantageous in that they represent greater social integration, less social isolation, and more resource alternatives, despite the potential for a higher level of demand from more network ties (Umberson et al. 2010; Umberson and Montez 2010).

The benefits of higher and lower levels of connectedness among network members can be nuanced, and often depend on individual needs, interests, and particular outcomes. The concept of social network capital, for example, asserts that key social resources are embedded in the ties *among* one's network members (Coleman 1988). Dense social networks, marked by

strong ties among network members, can provide a sense of trust, facilitate the availability of social supports and companionship, and coordinate around meeting network members' needs (Domínguez and Watkins 2003; Hurlbert, Haines, and Beggs 2000).

At the same time, expansive network structures marked by weak or absent ties among network members (i.e., bridging positions) can also offer advantages. Access to opportunities such as jobs, for example, are more likely when one's personal network members are less likely to socialize with one another, as this network structure reduces redundancy in information and advice (Burt 2005; Granovetter 1973), and also lessens normative pressures around an individual's opinions, behaviors, and decision-making (Feld 1981). Lower levels of network density can also represent a less restrictive social network, so that an individual's well-being is less vulnerable or dependent on a single cluster of densely connected individuals (Fiori, Smith, and Antonucci 2007).

The relative benefits of different levels of network density are also relevant to social network composition. As individuals age, their social networks often become more kin-centric (Carstensen 1992; Marsden 1987). Kin ties are likely to be long-standing, familiar social relationships, who are well positioned to monitor one another's needs (particularly kin that co-reside) and assist in older adults' navigation of later-life challenges such as medical treatment and health care decision-making (Schafer 2013). Nevertheless, non-kin ties (e.g., friends, neighbors) may broaden the range of information and advice that one considers, perhaps as a result of being less embedded in the network, and representing an individual's access to and involvement in diverse "social milieu" (Litwin and Shiovitz-Ezra 2011; Schafer 2013).

Scholars have used a range of theoretical orientations to explain the development of social network structure – that is, how patterns in the connections among one's network

members come to exist. Some orientations draw on foundational network theory, suggesting that varying degrees of density (or bridging) reflect structural opportunities or constraints in the time, space, and activity shared by network members (Feld 1981; Wellman 1983). Other perspectives draw on more agentic processes, whereby individuals seek out network structures that best align with their personal goals (Burt 1992; Gould and Fernandez 1989). Another set of frameworks proposes that aspects of the social environment that reflect dimensions of social inequality (e.g., neighborhood disadvantage) act as macro-level constraints on network structure (Desmond 2012; York Cornwell and Behler 2015; Small 2007).

Another dominant perspective – and one that is most relevant to the current study – views social network structure as a product of life-course experiences (Alwin et al. 2018). Marriage and parenthood, for example, increase the overlap between spouses' network ties (e.g., Kalmijn 2003). Retirement can lead to a decrease in network size (Settels et al. 2018), while aging and declining health may compromise one's abilities to maintain a more expansive network structure (Cornwell 2009; Schafer 2012). Studies within this perspective recognize the social interdependencies, or "linked lives," that shape the life course (Antonucci et al. 2010; Elder 1994). Indeed, the social network perspective emphasizes the timing, contingency, and interconnectedness of the social structure (Emirbayer 1997), much in the same way that the life-course perspective emphasizes these same qualities in the context of experiences and events within individuals' lives (Alwin 2012; Elder 1994). Nevertheless, far less work has linked these perspectives in the context of childhood, even though the relational qualities and individual outcomes that are associated with social network structure are also closely related to many of the same outcomes linked to early life conditions (Andersson 2018; van Groenou and van Tilburg 2003).

Indeed, (dis)advantage during these formative years predicts well-being and achievement along several dimensions of adulthood. For example, lower socioeconomic status and adversity during childhood are associated with lower levels of attainment and earnings (e.g., Case, Fertig, and Paxson 2005), marital instability and lower marital quality (Conger, Conger, and Martin 2010), less social support (e.g., Ferraro et al. 2016), and worse health (Haas 2007, 2008) later in the life course.

Much of this work hinges on the notion that childhood and adolescence are especially vulnerable developmental periods. Events and exposures during this time are more likely to have a lasting impact on life trajectories than are experiences that take place in later periods of the life course (Ben-Shlomo and Kuh 2002; Smith 2009). Additionally, socioeconomic position and other attributes of early social contexts (e.g., family, neighborhood) are key determinants of the sequence of social-structural processes that individuals face across the life course, and that contribute to the stratification of personal resources in adulthood (Willson et al. 2007). To this end, the current study bridges the longstanding idea that social networks are personal resources that evolve, in part, from the processes that structure individual social position (Laumann 1966), with the well-established persistence of social position across the life span (Case et al. 2005), thus expanding our understanding of how early life reverberates throughout the life course.

Childhood Circumstances and Social Network Structure

Early empirical studies of social networks arose out of a focus on stratification, with the observation that individuals tend to confine their closest social ties to those of similar social class or status (Warner and Lunt 1941). Educational and occupational attainment were proposed to be among the primary forces that stratify individuals within society, and that ultimately structure the

development of “interactional networks” with other individuals (Laumann 1966). Indeed, opportunities for social contact are in many ways determined by mechanisms of stratification such as educational and occupational attainment, as well as the broader set of activities and lifestyle contexts that structure social interaction. The concepts of network propinquity and homophily are fundamental to this linkage, as individuals only have access to those who are around them by virtue of these mechanisms (Blau 1977; McPherson et al. 2001).

A large literature shows that social networks are themselves dimensions of social stratification, reflecting the opportunities or lack thereof to develop more advantageous and beneficial network structures. Higher socioeconomic status is associated with larger and more expansive personal networks (Marsden 1987; Moore 1990) and greater access to social capital (i.e., resources embedded in social network ties) (Lin 1999, 2000). Higher education, high-prestige occupations, and resource-rich neighborhoods are among the contexts that provide opportunities for cultivating expansive, diverse network ties outside of the family context (Ajrouch, Blandon, and Antonucci 2005; van Groenou and van Tilburg 2003; Small 2007). Socioeconomic status is a key determinant of health, too, and better health allows individuals to maintain more expansive network structures (Cornwell 2009; Schafer 2012).

Given the longstanding evidence linking social advantages in adulthood and social network structure, early life (dis)advantage may be associated with later life social networks through the persistence of social position across generations and the accumulation of disadvantage across the life course (van Groenou and van Tilburg 2003; Lin 1999; Willson et al. 2007). The “social patterning” of opportunity means that individuals who face social disadvantage early in life are more likely to face social disadvantage later in life (Case et al. 2005; Preston, Hill, and Drevenstedt 1998), such that early disadvantage sets off “cascading”

socioeconomic and lifestyle events (Hayward and Gorman 2004, p. 88) that impede opportunities for upward mobility, resource accumulation, and well-being in adulthood. Indeed, social capital access at a given point in time is dependent on "initial positions," namely parental resources, from a prior time (Lin 1999).

Individuals with lower familial socioeconomic status during childhood may therefore exhibit properties of personal social networks that are associated with lower socioeconomic status in adulthood as a result of the accumulation or persistence of social disadvantage across life stages. These properties may include smaller networks that reflect fewer opportunities during adolescence, young adulthood, and midlife to develop a greater number of close social ties (van Groenou and van Tilburg 2003), as well as denser, more kin-centric personal networks that require fewer resources to maintain and that reflect a greater reliance on network ties to fulfill immediate practical and instrumental needs (e.g., housing, income) (Domínguez and Watkins 2003; Hurlbert et al. 2000). Andersson (2018) finds that higher levels of parental education are associated with less kin-based patterns of social connectedness, including more non-kin network members, more frequent socializing with friends, and less frequent socializing with relatives. This study relied on data from the General Social Survey, a nationally representative sample of the U.S. population ages 18 and older, which leaves open the question of whether childhood socioeconomic status as well as other aspects of childhood shape some of the most consequential features of personal networks in later periods of the life course.

Indeed, even apart from childhood socioeconomic status, other characteristics of the family unit during childhood may predict social position in adulthood. Poorer parent-child relationship quality and less parental support, for example, are associated with lower levels of educational achievement and attainment, potentially by diminishing children's ability to take

advantage of parental resources (e.g., financial resources) to support their achievement (Astone and McLanahan 1991; Coleman 1988). Even after accounting for parental socioeconomic status, poor family relationship quality during childhood is associated with greater economic adversity in mid-adulthood, which may reflect a more stressful, less supportive family environment (Berg et al. 2017). Other work finds that even when controlling for a comprehensive set of childhood socioeconomic measures, unmeasured family factors still shape labor market outcomes in adulthood (Smith 2009). Collectively, this work suggests that features of family ties during childhood – as individuals' initial social context – may shape the sequence of structural determinants of social position in adulthood and into later life, independent of familial socioeconomic status, and in ways that are consequential for social network structure.

Even apart from adult social position, lifelong patterns of relationship development may be shaped through early socialization and family socioeconomic status. Children adopt skills in social relationship development from early exposure to parents and peers, whose own networks reflect opportunities and constraints in the broader environment (Singh-Manoux and Marmot 2005). The notion of parents as socialization agents has been widely applied to studies of intergenerational influence in health, education, occupation, and other opportunities (Jonsson et al. 2009). This concept may apply to social connections and, in particular, social network structure and its association with parental social position (Singh-Manoux and Marmot 2005). Individuals may be socialized to maintain patterns of personal network structure that are similar to those of their parents, or that yield a particular type of support (van Groenou and van Tilburg 2003).

Importantly, prior research also shows that childhood circumstances shape features of adult social relationships, and in ways that may shape personal network structure later in life,

independent of socioeconomic circumstances in adulthood. Early life stress and disadvantage are associated with greater relationship strain and loss later in life (e.g., Ferraro, Schafer, and Wilkinson 2016; Umberson et al. 2014). This association may be due in part to the link between childhood circumstances and certain behavioral processes such as social withdrawal and risky health behaviors (e.g., substance use) that have direct implications for relationship quality in adulthood (Umberson et al. 2016). Other research emphasizes how disadvantage, adversity, and quality of family life foster certain psychosocial tendencies (e.g., anger, anxiety, hypervigilance, diminished self-efficacy) that endure over the life span to ultimately compromise social relationship quality later in life (Merz and Jak 2013; Repetti et al. 2002). These linkages are likely among the various pathways through which childhood circumstances may shape later life social network structure. To date, however, there has been less overt consideration of the consequences of early life from a relational perspective, including one's relationships with others (dyadic level) and, to a lesser extent, the relationships *among* an individual's close social ties (triadic level). In Table 1.1, I expand on the range of social-structural processes that provide strong reason to expect that later life network structure echoes a lifetime of experiences and circumstances that are rooted in childhood.

[Table 1.1 about here]

It is important to note that the processes in Table 1.1 should not be considered as existing independently from one another. For example, health, education, and labor market participation are strong correlates of one another. Rather, these processes can be thought of as a web of intersecting and interacting events and circumstances that individuals face across life stages, and that are directly and indirectly shaped by childhood conditions, as well as predictive of social network structure.

THE PRESENT STUDY

In light of these possible mechanisms, I examine how various dimensions of childhood are associated with older adults' personal social network size, density, and composition using a nationally representative sample of community-residing older adults in the United States. Childhood disadvantage may be associated with smaller, denser networks that facilitate access to social support to compensate for a lack of material resources, and that require fewer personal resources to maintain. Individuals from more advantaged family backgrounds may have more expansive and less kin-centric networks, to the extent that childhood conditions provide them with more opportunities to form and sustain ties outside of the family context. A key contribution of this study is in expanding the focus on the life course and social relationships beyond individual social tendencies, or the quality of a particular relationship (e.g., spouse, child) (Carr and Springer 2010). This focus recognizes that individuals' lives are influenced by a broader social network of close others, and that the processes that structure those relationships are likely to be influenced by childhood circumstances.

DATA AND METHODS

To fully address this research question requires a dataset that collects information about respondents' personal social network structure, as well as measures of childhood circumstances. To my knowledge, there exists no nationally representative dataset that systematically tracks individuals' social networks from early through later life, and that allows for a comprehensive assessment of how the various experiences that take place between early and later life could account for any associations between childhood measures and later life networks. The National Social Life, Health, and Aging Project (NSHAP) offers a unique opportunity to shed light on this

research question. The NSHAP is a nationally representative study of older adults in the United States that collects both retrospective measures of respondents' childhood circumstances, as well as longitudinal data on their personal social networks.

The overall goal of the NSHAP is to better understand how health and social context intersect to influence older adults' well-being (Suzman 2009). The Wave 1 cohort includes 3,005 older adults born between 1920 and 1947 who were ages 57-85 at baseline (2005-2006), with a weighted response rate of 75.5%. Wave 2 (2010-2011) includes 3,377 returning respondents and their co-resident partners, if applicable, yielding a conditional response rate of 89%. Wave 3 (2015-2016) includes returning respondents and their partners, if applicable (N=2,409; a conditional response rate of 89.2% among returning baseline respondents), and a new cohort of respondents born between 1948 and 1965 and their co-resident partners (N=2,368). At each wave, data collection consisted of in-home interviews conducted by the National Opinion Research Center (NORC), which included the collection of personal social network information (described below). Following the in-home interview, respondents were also asked to complete a leave-behind questionnaire (LBQ) to be returned to NORC by mail.

Using a sample of older adults has certain advantages for addressing this research question, namely the ability to examine the influence of childhood circumstances on social networks across the broadest span of the life course. Nevertheless, age is also a key determinant of social network structure. According to socioemotional selectivity theory, for example, as individuals as age, they focus increasingly on maintaining only their most emotionally rewarding social ties (Carstensen 1992). Older ages are also accompanied by a number of life-course transitions, including retirement, widowhood, and declining health, that shift individuals' daily lives in ways that also shift social network structure (Wrzus et al. 2013). Thus, any differences in

network structure that are observed in this analysis may be somewhat muted, to the extent that age-related processes further alter personal networks, above and beyond any direct or indirect influence of childhood circumstances that may have been more prominently observed earlier in the life course.

Measures of Social Network Structure

My primary argument is that later life network structure is partly a function of childhood circumstances. At each wave of the NSHAP, respondents were asked to name up to five individuals (i.e., alters) with whom they discussed "important matters" in the prior year. These alters comprise Roster A of the social network module.[1] This name generator is commonly used to elicit individuals' core social confidants, including their strongest and most intimate social ties, with whom they are most likely to exchange resources and support (Marsden 1987; c.f. Bearman and Parigi 2004). The NSHAP network module in particular is regarded as the "gold standard" in population survey-based network delineation (Paik and Sanchagrin 2013). As part of this module, respondents were asked about their relationship to each alter (e.g., spouse, friend, child), whether each alter lives with them, how often they speak with each alter, and how often each alter speaks with every other alter (0 = "have never spoken to each other," 8 = "every day").[2]

The social network outcomes that I use in this study include social network size,

[1]If respondents had a spouse/partner who was not named as part of Roster A, s/he was included as Roster B. At Waves 1 and 2 only, respondents were given the option to name one other person who was included in Roster C. I limit the measurement of social network variables to Roster A to facilitate comparisons across survey waves.

[2] Respondents were not asked to specify the mode of contact between themselves and their network members or among network members, but if respondents asked, they were told that talking over the telephone and personal email may be included when responding to questions about frequency of contact.

composition, and the connectivity among individuals' social network members (i.e., network density). Social network size is measured as the total number of alters named, and social network composition is measured as the number of alters who are kin (spouse/partner, parent, child, step-child, grandchild, sibling, in-law, other relative). Following prior research using the NSHAP network data, social network density is measured as a count of the number of ties that exist among the alters in the respondent's network (a tie "exists" if alters speak with one another at least annually) (e.g., Cornwell et al. 2008). This count depends on network size, which dictates the number of possible ties in the network. I account for this constraint in the regression modeling strategy explained below. Alternate measures of network connectivity produce results that are consistent with those presented here, including a measure of bridging potential and a measure of density as the proportion of ties that exist in the network (Appendix Table 1.1).

Measures of Childhood Circumstances

At Waves 2 and 3, the NSHAP respondents were asked several questions about their childhood as part of the LBQ. Respondents were asked to indicate the highest grade completed by their father and mother, separately, as "no formal education," "1-11 grades," "12 high school graduate," "13-15 some college," "16 college graduate," "17 or more post college," "other," or "don't know." I use these variables to construct a measure of childhood socioeconomic status. I categorize responses as either "less than high school," "high school completed," or "more than high school." I also create a "missing" category (e.g., Hayward and Gorman 2004) to include respondents who reported that they "don't know" their parents' education, or who did not answer this question on the LBQ. By creating this "missing" category, I aim to avoid excluding respondents from the analyses who were unfamiliar with their parents' education, perhaps

because they grew up in unstable or otherwise complex household arrangements, but who report on other dimensions of their childhood (described below). Results are consistent when these respondents are excluded from the analyses.[3] The final measure uses the highest reported level of parental education. If education is missing for one parent, I use the educational attainment that is reported for the other parent.

Respondents were also asked questions referring to the time when they were 6 to 16 years old: 1) childhood health status (1 = "poor," 5 = "excellent"), 2) how financially well off their family was (1 = "not so well off at all," 5 = "very well off"), 3) whether or not they lived with both parents, 4) to rate their agreement with the statement: "When I was growing up, my family life was always happy" (1 = "disagree very much," 6 = "agree very much"), and 5) whether or not they ever experienced or witnessed any violent events (assault, beating, shooting, murder, or rape).

Collectively, these questions represent the full breadth of childhood measures collected by the NSHAP. Although retrospective in nature, and therefore prone to recall bias, these questions are representative of the types of questions asked on other nationally representative surveys of adults in mid to later life, and that have been used to make key inferences about the enduring nature of childhood conditions (e.g., Ferraro et al. 2016; Haas 2007; Hayward and Gorman 2004). Additionally, prior research finds retrospective reports to be a reliable data source for studying the influence of childhood on later life at the population level (Haas 2007).

I include each childhood measure individually in my analysis, given that each represents a different dimension of childhood adversity or disadvantage. I also considered using a single

[3] I exclude 41 respondents from the final analytic sample who selected "other" as the highest grade completed for both parents. Estimates are highly consistent when these respondents are coded as "missing" for parental education.

composite score that standardized and summed each of the childhood measures (other than parental education, which remained categorical). The results of the analyses that used the composite measure were substantively similar to those presented here (available upon request). I ultimately chose to present the models that include each childhood measure separately, as these models yield more information about which dimensions of childhood are most relevant to social network structure across the life course.

Covariates

All models control for race/ethnicity, coded as white, black, Hispanic non-black, and other race, as well as gender. As Table 1.1 suggests, the structure of older adults' social networks is influenced by numerous social, health, and other lifestyle determinants that evolve across the life course, and that are also shaped by childhood circumstances. The NSHAP measures some of these factors, which I account for in the models. Educational attainment is categorized as less than high school, high school or equivalent, or more than high school, consistent with the categories used for parental education.[4] I also account for respondent age (divided by 10 to make the coefficient more meaningful), marital status (married/partnered, divorced or separated, widowed, or never married), employment (whether the respondent is currently working), and the number of children that the respondent reports having given birth to or fathered.

Because later life health is associated with network structure and is also shaped by early life conditions (Cornwell 2009; Hayward and Gorman 2004), I control for self-rated physical

[4] In supplementary models, I considered categorical and continuous measures of respondent income (separately). The size and significance of childhood measures in these models were highly consistent with those presented here. Higher levels of income (continuous) were significantly associated with larger network size (IRR = 1.107, $p < .01$), but were not significantly associated with network density or number of kin in the network.

health, as well as depressive symptoms and functional health to capture more specific dimensions of mental and physical well-being. Depression is measured as the average of 11 standardized items from the Center for Epidemiologic Studies Depression Scale (CES-D), asking respondents how often they experienced things like "felt sad" or "could not get going" in the past week. Functional health is measured as the average of 9 standardized items assessing respondents' difficulty completing basic daily activities and routine tasks such as getting dressed, with higher scores indicating greater functional impairment.

Analytic Strategy

I use a series of multivariable regression models to evaluate how early life is associated with social network size, density, and kin composition. I use Poisson models to predict social network size, as the outcome is a count of network members. As an alternative examination of social integration, I also present a set of logit models that predict whether respondents fill their network rosters with the maximum possible number of ties (i.e., whether respondents have a "large network," defined as 5 alters). Next, I use Poisson models to predict network density as a count of the number of ties that exist among alters. Network size is used to calculate the number of possible ties that could exist (n*[n-1]/2), and this measure is used as the exposure variable. Finally, I use Poisson models to predict the number of kin network members, using network size as the exposure variable.[5] These models are intended to shed additional light on the idea that childhood circumstances may influence the extent to which individuals develop close social ties outside of the family context, thus potentially accessing more diverse social domains. For each outcome, I first consider the role of childhood measures while controlling for sociodemographic

[5] Likelihood ratio tests indicate that Poisson is a more appropriate modeling strategy than negative binomial regression for network density and for number of kin network members.

characteristics (race/ethnicity and gender). I then add measures of attainment, health, and other life-course factors to the models to consider whether any association between childhood measures and later life networks may be explained by these adulthood covariates.

The analytic sample includes those respondents who provided information on childhood measures at Wave 2 or Wave 3 and who were age 50 or older at the time when they were interviewed. All covariates are measured at the survey wave when early childhood measures were first administered to respondents, so that these models essentially rely on a pooled cross-sectional sample of older adults surveyed at Waves 2 and 3. [6] All models also include a fixed effect for the survey wave (2 or 3) from which the respondent's measures are collected.

Of the 4,730 respondents that reported on their social network and returned the LBQ, missing data on sociodemographic, life-course, and health covariates accounts for approximately 7% of those excluded from the analytic sample. An additional 7% are excluded due to non-response to the questions about childhood circumstances. Supplementary analyses indicate that respondents excluded due to missing data on childhood measures have somewhat smaller (M = 3.61 versus M = 3.83; t = 2.86; $p < .01$ by unweighted t-test) and less kin-centric social networks (M = 2.28 versus M = 2.51; t = 2.83; $p < .01$ by unweighted t-test) compared to those included in the analytic sample, but that these two groups do not differ on the basis of social network density. Models predicting social network density also exclude respondents who named zero or one network member, and who therefore were not able to report on the presence or absence of ties *among* network alters. Models predicting the number of kin ties exclude respondents with zero network members, who have no ties to report as either kin or non-kin. These restrictions result in final analytic samples of 4,063 for models predicting social network size, 4,034 for

[6] Returning Wave 2 respondents were given a version of the LBQ at Wave 3 that did not include the childhood measures (i.e., respondents were only asked to report on the childhood measures once).

models predicting number of kin network members, and 3,759 for models predicting social network density.

To help reduce bias that may result from excluding respondents who have smaller social networks, and to more systematically account for exclusion from the models due to missing data, I create a propensity score for each respondent that reflects their probability of being included in the final models. This process uses logistic regression to predict inclusion in the final analytic samples on the basis of sociodemographic, life-course, and health measures. I then multiply the inverse of these probabilities by the person-level weights provided by the NSHAP that adjust for selection and non-response and apply these final weights to all models. This weighting adjustment helps to generate estimates that better resemble those that would have been generated had all respondents been included in the final models (Morgan and Todd 2008). Standard errors are adjusted for clustering and stratification in the NSHAP sampling design.

RESULTS

Table 1.2 includes descriptive statistics for the main variables included in the models. On average, respondents named between 3 and 4 network members (range is 0 to 5), and between 2 and 3 kin. With regard to density, respondents tend to report that between 4 and 5 ties exist among their network alters. As this count depends on network size, it can also be useful to consider alternate measures of network density to characterize the analytic sample. On average, respondents' networks are relatively dense, with 74% of possible pairs of ties reported as "existing" (i.e., 74% of possible network pairs are in contact at least once a year).

Turning to childhood measures, just over 30% of the sample reports that at least one parent earned more than a high school degree, and just over 25% report less than a high school

degree as the highest level of parental education. The majority of respondents (82.9%) report that they lived with both parents, while approximately 19% report that they experienced or witnessed a violent event between ages 6 and 16. On average, respondents report their family to have been between "not so well off" and "average" financially, and childhood health as between "very good" and "excellent." Respondents tended to agree moderately (between "a little" and "pretty much") with the statement: "When I was growing up, my family life was always happy."

[Table 1.2 about here]

There is also considerable variation across dimensions of early life, suggesting that respondents' childhood circumstances are not entirely clustered around relatively negative or positive experiences. Whereas 83% of those whose parents earned less than a high school degree reported having lived with both parents during childhood, a comparable 86% of those with a parent earning more than a high school degree report the same living arrangement. Likewise, reports of family happiness are comparable within categories of parent education. Just under 25% of respondents who report either the highest or lowest levels of parental education also report levels of family life happiness in the highest third of the distribution of this variable. Approximately one third of those with the highest levels of parental education rate their childhood family happiness in the bottom third, compared to 40% of those with the lowest levels of parental education. In general, childhood measures are weakly correlated, and diagnostics suggest that multicollinearity among these measures is not problematic in the regression models.

Childhood Circumstances and Social Network Structure

The regression model results suggest that properties of network structure are patterned by aspects of early life. In Model 1 of Table 1.3, higher levels of parental education are associated

with larger social networks in later life, before accounting for adulthood measures. Those with a parent who earned a high school degree or more than a high school degree named network members at significantly higher rates relative to those whose parents earned less than a high school degree (incidence rate ratio [IRR] = 1.074 and 1.119, respectively; $p < .001$ for both coefficients).

Model 2 of Table 1.3 reveals that the association between parental education and network size remains statistically significant even when accounting for adult attainment, marital status, and later life health. Although declining somewhat when accounting for these later-life measures, the magnitude of parental education remains comparable to other factors identified as key structural determinants of older adults' network size, such as neighborhood concentrated disadvantage and disorder (York Cornwell and Behler 2015). Those respondents whose parents earned a high school degree named network members at a 4.7% higher rate than respondents whose parents earned less than a high school degree (IRR = 1.047, $p < .01$). Respondents whose parents earned more than a high school degree named network members at a 5.6% higher rate than those whose parents earned less than a high school degree (IRR = 1.056, $p < .01$).

Importantly, these models provide evidence that several life-course events also shape social network size. With regard to attainment in adulthood, respondents with a high school degree or more than a high school degree named network members at 6.8% and 16.1% higher rates, respectively (IRR = 1.068, $p < .05$ and IRR = 1.161, $p < .001$), compared to those respondents with less than a high school degree. Whereas employment and marital status are not significant predictors of network size, higher levels of self-rated health are associated with a 1.9% higher rate of naming network members (IRR = 1.019; $p < .05$). Each additional child is also significantly associated with a larger social network (IRR = 1.014; $p < .001$).

Figure 1.1 illustrates predicted network size by parental education and respondent education to facilitate a comparison of how childhood and adult socioeconomic statuses contribute to later life network structure. As this figure shows, having more than a high school degree and having a parent with more than a high school degree each predict similar network sizes (3.95 versus 3.89); however, the difference in predicted network size between the highest and lowest levels of respondent education (.55) is more than 2.5 times the predicted difference between the highest and lowest levels of parental education (.20).

[Figure 1.1 about here]

Models 3 and 4 examine network size in terms of whether respondents fill their network rosters with the maximum number of alters (five). These results are generally consistent with the findings from the Poisson models. While these model estimates are represented using log odds, the coefficients can also be interpreted in terms of predicted probabilities. After calculating average marginal effects from the findings in Model 3 (Mood 2010), respondents with a parent who had more than a high school education are .152 more likely to have a large social network relative to those with the lowest levels of parental education ($p < .001$). This difference declines by nearly 55% in Model 4 when accounting for life-course events and attainment, although higher levels of parental education are still associated with an 8.3 percentage point increase in the likelihood of having a large social network compared to those with the lowest levels of parental education ($p < .01$). This difference is approximately half the size of the difference in the likelihood of having a large network that is observed between the highest and lowest levels of respondent education (17.1 percentage points; $p < .001$). In this set of models, living with both parents during childhood is also associated with a .04 increase in the likelihood of having a large social network relative to those who report a different childhood household structure ($p < .05$).

[Table 1.3 about here]

Models 1 and 2 of Table 1.4 indicate that social network density is also in part a function of individuals' social origins, and that different childhood measures demonstrate different directionality in predicting network density.[7] Before accounting for later life measures (Model 1), higher levels of parental education are significantly associated with lower levels of network density (IRR = .916, $p < .001$) relative to those with the lowest levels of parental education. At the same time, older adults who reported higher levels of family happiness and better health during childhood have denser social networks in later life (IRR = 1.028, $p < .001$ and IRR = 1.016, $p < .05$, respectively). Exposure to a violent event, however, is associated with less connectivity among network members (IRR = .962, $p < .05$).

The statistical significance of the childhood measures is robust to accounting for later life covariates (Model 2). Respondents with the highest levels of parental education reported ties among network members at a 5.8% lower rate than respondents with the lowest levels of parental education (IRR = .942, $p < .01$). Each increase in reported level of family happiness during childhood is associated with a 2.3% higher rate of connectivity among network members (IRR = 1.023, $p < .001$). Childhood health remains associated with higher levels of network density (IRR = 1.015, $p < .05$), and exposure to violent events remains associated with lower levels of network density (IRR = .961, $p < .05$), changing little in magnitude with the inclusion of adulthood covariates.

Respondent's own attainment and life-course factors are also key determinants of network density. Respondents with more than a high school degree have an 8.2% lower rate of

[7] These associations emerge in the same directions and with the same levels of statistical significance in simpler bivariate models that use only parental education and only family happiness to predict social network outcomes.

ties among alters, on average, compared to older adults who earned less than a high school degree (IRR = .918, $p < .01$).[8] Figure 1.2 shows predicted network density by parental and respondent education, with density modeled as the proportion of ties that exist in the network in order to facilitate interpretation of predicted values across respondents with different network sizes. As this figure illustrates, the highest levels of education are associated with similar levels of network density for both parental and respondents' own education (.72 for both groups). The difference in predicted density between the highest and lowest levels of respondent education (.08) is roughly twice the size of the difference between the corresponding levels of parental education (.04).

[Figure 1.2 about here]

Results are similar when predicting bridging potential (i.e., whether there is at least one pair of poorly connected network members), yet coefficients exhibit opposite directionality, as bridging represents the *absence* rather than the *presence* of ties among alters (Appendix Table 1.1). In terms of predicted probabilities, those with the highest levels of parental education are nearly .10 more likely to exhibit bridging potential than those with the lowest levels of parental education ($p < .001$).

Finally, Models 3 and 4 predict the number of kin network members that respondents named. Before accounting for life-course events, respondents with parents who earned a high school degree or more named kin ties at a significantly lower rate than those whose parents earned less than a high school degree (IRR = .914, $p < .001$ and IRR = .897, $p < .001$, respectively). Higher levels of family happiness are associated with higher rates of naming kin

[8] With the inclusion of the full set of covariates, age is inversely associated with network density (IRR = .959, $p < .001$). Supplementary analyses suggest that this association is explained by other social network properties, including co-residency and frequency of interaction with network members (Appendix Table 1.2).

ties (IRR = 1.022, $p < .001$). These associations are generally robust to the inclusion of other life-course and attainment covariates (Model 4), which slightly reduce the statistical significance of childhood measures. Those who have parents with a high school degree or more than a high school degree reported fewer kin in their networks compared to older adults who have the lowest levels of parental education (IRR = .933, $p < .01$; IRR = .939, $p < .05$, respectively). Higher levels of family happiness remain significantly associated with the inclusion of more kin (IRR = 1.017; $p < .01$). Likewise, respondents with more than a high school degree named kin at a 7.6% lower rate than those who have less than a high school degree (IRR = .924, $p < .05$).

[Table 1.4 about here]

Figures 1.3 shows the predicted number of kin by parental and respondent education. On average, respondents with the highest levels of parental education include 2.40 kin network members, which is similar to the number of kin predicted among those with the corresponding level of respondent education (2.37). Likewise, the difference between the highest and lowest levels of parental education (.16) is quite similar to the difference between the highest and lowest levels of respondent education (.20). Socioeconomic status in childhood and adulthood appear to have comparable associations with the inclusion of kin in one's personal social network later in life.

[Figure 1.3 about here]

In supplementary models (Appendix Table 1.3), I consider whether the influence of early life on social network structure may be cumulative, to the extent that *changes* in social network structure between Waves 1 and 2 are also predicted by childhood measures. These models use social network and other covariates from Wave 1, retrospective childhood measures (as first reported at Wave 2), and also account for changes in life-course measures (marital and

employment status) between Waves 1 and 2. The equations for each social network outcome take the following form, where *t* refers to Wave 2, and *t-(t-1)* refers to the period between Waves 1 and 2:

$$NetworkOutcome_{it} = \alpha + ß_1 NetworkOutcome_{it-1} + ß_2 Childhood_{it} + ß_3 Health_{it-1} + ß_4 Marital_{it-1} + ß_5 Age_{it-1} + ß_6 Employed_{it-1} + ß_7 BecameWidowed_{it-(t-1)} + ß_8 BecameRetired_{it-(t-1)} + ß_9 Race_{it} + ß_{10} Education_{it} + ß_{11} Gender_{it} + \epsilon_t \quad (1.1)$$

The findings in Appendix Table 1.3 indicate that although there are no associations between childhood measures and changes in network size or number of kin, higher levels of family happiness and childhood health are associated with increasingly denser networks ($p < .05$) over the course of the five-year period. Parental education is not significantly associated with changes in network density.

DISCUSSION AND CONCLUSIONS

How does social structure shape the lives of older adults? The enduring influence of childhood on mid- and later-life outcomes is well-established. This study contributes to a growing body of research bridging the life-course perspective with social network studies (Alwin et al. 2018), broadening the scope of outcomes affected by early life to include those at the structural, relational level. The findings suggest that childhood circumstances shape the connectivity of those social bonds that are arguably most consequential for older adults' well-being, and that are key social resources used to navigate numerous transitions that take place in later life (Umberson et al. 2010). Higher parental education is associated with larger, more expansive, and less kin-based social networks. Predicted differences in these outcomes between the highest and lowest

levels of parental education are estimated to be between 40% and 80% the size of the predicted differences between the corresponding levels of respondent's own education. At the same time, other dimensions of childhood – in particular, higher levels of family happiness – are associated with denser and more kin-centric networks in later life.

The importance of these findings can be contextualized within the extensive and nuanced literature on how social network structure shapes later life well-being. For example, among older adults, larger social networks are associated with better cognitive health (Kotwal et al. 2016) and lower disability risk (Mendes de Leon et al. 2001), while smaller networks are tied to higher levels of inflammation and cardiovascular risk (Ford, Loucks, and Berkman 2006). Greater network density can shield older adults from abuse and exploitation (Schafer and Koltai 2015), and contributes to perceived social connectedness and support, which are linked with better self-rated health (York Cornwell and Waite 2009). At the same time, lower network density is associated with alternative medicine use (Goldman and Cornwell 2015) and lower body mass index (Lee et al. 2013), which may reflect network access to diverse sources of health information, weaker enforcement of norms, and greater self-efficacy and independence. With regard to network composition, more family-oriented networks are associated with worse subjective well-being, higher levels of alcohol abuse, and greater physical inactivity relative to older adults with diverse or friend-based networks, potentially reflecting the relative resourcefulness of non-kin ties (Shiovitz-Ezra and Litwin 2012).

Collectively, these applications of social network theory demonstrate that whether a particular network structure (e.g., higher versus lower network density) is beneficial depends in part on individual needs (e.g., material resources, declining health) and the particular outcome of interest (e.g., advice, information, health care decisions, coordinated support). A key contribution

of this study is the notion that whether a particular network structure reflects personal advantages may depend on an individual's social origins and the various resources and barriers that these origins yield across life stages, thereby contributing to stratification in social connectedness later in life.

This theoretical component dovetails well with key tenets of the life-course perspective, namely the historical contingencies and interdependences of social relationships (Elder 1994). Situating individuals' social relationships in the context of their personal trajectories adds insight to how we interpret the meaning of network ties – not only in terms of the resources and outcomes that they generate, but also the social origins that shape their development. For older adults with more advantaged backgrounds, lower levels of network density may represent access to distinct pools of resources and information, fewer normative pressures, and greater independence accrued across the life course (e.g., Lin 1999). Likewise, ties among network members may reflect a capacity for trust, social support, and resource exchange (Hurlbert et al. 2000). For older adults reporting lower levels of childhood family happiness, however, lower levels of density may signal the absence of a coordinated network. Stressful or adverse childhood family circumstances could lead to difficulties in maintaining social ties later in life (e.g., Umberson et al. 2016), ultimately leaving individuals to be more socially isolated. At the same time, higher levels of network connectivity among older adults with lower childhood socioeconomic status may signal structural constraint or a greater need for coordinated support from network members, in part to compensate for a lack of material resources (e.g., Domínguez and Watkins 2003).

These results emphasize the co-existence of these structural dimensions, given that different childhood circumstances predict different aspects of later life network structure. We can

consider that those from the most advantaged backgrounds – those with high levels of parental socioeconomic status and high family happiness – could be doubly advantaged in their later life network structure, having the ability to benefit from a large network that includes both kin and non-kin, as well as some degree of both density *and* expansiveness (Burt 2005). Put differently, these results suggest that studies of social networks as personal resources may benefit from considering that structurally similar networks may be functionally distinct. These distinctions may emanate from individuals' social origins.

Although the NSHAP collects extensive information on older adults' social lives, this analysis only accounts for some of the processes (e.g., education, marriage, children) that could explain these associations. Future research should attend to the broader range of potential mechanisms considered in Table 1.1 that transpire between childhood and later life and that likely influence the pattern of close social connections that individuals maintain (e.g., occupation, spells of unemployment, health problems, neighborhood exposures, residential mobility, psychosocial tendencies, stress exposure), as well as other measures of attainment in adulthood such as assets and income. Even apart from attainment, positive family experiences (e.g., family happiness) early in life may foster one's proclivity and capacity to maintain a close, supportive network throughout the life course.

Other distinctions and potential sources of heterogeneity are important for future work to consider. For instance, racial minorities' exposure to institutional racism and discrimination across the life course may hinder the degree to which childhood advantages translate into later life network advantages. More broadly, further examination is needed to consider how the link between childhood and later life social network properties may be moderated by adulthood circumstances (e.g., Andersson 2018; van Groenou and van Tilburg 2003).

Future research may extend this work by using a longitudinal dataset that surveys respondents across the life span, and that collects data on individuals' life histories as they transpire, including tracking properties of individuals' personal social networks through early, mid, and later life. This type of dataset would allow for a more rigorous assessment of whether age-related changes in network structure partially mediate the differences in later life network structure that are associated with childhood circumstances, and in a way that can help to account for endogeneity bias. It is worth noting that supplemental models indicate that respondent age does not moderate the associations between childhood circumstances and network size or kin composition, and suggest only a marginal widening of network density between those with the highest and lowest levels of parental education as they age. These results support the general idea that the events and processes most responsible for these findings take place prior to later life, leaving a footprint on individuals' personal networks that does not appear to diminish over the course of later life. Additionally, because the NSHAP respondents are age 50 and older, the analytic sample misses respondents who die prior to age 50, and whose life expectancy may be significantly shaped by childhood circumstances (e.g., Hayward and Gorman 2004). Thus, selection on the basis of age is another consideration for future research.

The use of retrospective reports also introduces potential endogeneity bias due to respondents forgetting or choosing not to disclose certain aspects of their childhood circumstances. Nevertheless, recent work finds that retrospective reports are meaningfully associated with outcomes later on in life, including physical and cognitive health (Reuben et al. 2016), and that childhood measures are reported with considerable consistency over time (Haas 2007). Individuals' perceptions of the past are believed to hold important value in shaping later life outcomes, despite certain inaccuracies (Reuben et al. 2016). In the present study, respondent

recollections of family happiness, for instance, may be remembered more favorably (Ferraro et al. 2016), thereby downwardly biasing results, whereas measures that do not involve rating experiences, such as parental education and living with both parents, may be less prone to recall bias.

The role of social media is also an important avenue for future research. One-third of seniors regularly use social networking sites (Zickuhr and Madden 2012). Older adults consider digital media to be a meaningful way of exchanging social support (Quan-Haase, Mo, and Wellman 2017), and one that may allow those from more disadvantaged backgrounds to overcome structural barriers that could otherwise preclude the development of larger, more diverse social networks. In supplemental analyses I find that among older adults with lower levels of parental education, being in the younger NSHAP cohort is associated with significantly lower levels of network density compared to respondents in the older cohort, which may reflect network advantages garnered through the expansion of social media use in recent decades. Future research may also use data from online social networks to consider whether childhood circumstances shape features of individuals' more expansive network structures, including those social ties that are not considered to be network confidants, but who are still important sources of information and influence.

In conclusion, this study adds to emerging research that suggests that individuals' social resources throughout the life course may be shaped by childhood (e.g., Ferraro et al. 2016; Umberson et al. 2014; Andersson 2018). These findings draw particular attention to childhood as a potentially important, yet relatively overlooked determinant of personal network structure, which could function as a mechanism for many of the disparate outcomes faced by older adults (health and otherwise), including those already studied in the context of early life determinants.

Much has been made in sociological theory of childhood socialization and later status attainment, including occupation and education, but less work has considered how childhood socialization could manifest at the relational level. Future research may examine social network structure from a perspective of intergenerational transmission or socialization, further contributing to how we understand the intersection of life-course principles and social networks.

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Table 1.1 Mechanisms by which childhood circumstances shape social network structure throughout the life course.

Childhood Factors	Association with Social Networks
Schooling	Markers of educational achievement, including tests scores and high school graduation, are influenced by childhood disadvantage, including poverty and stress exposure (McEwen and McEwen 2017; Wodtke, Harding, and Elwert 2011). Educational achievement can indirectly shape network structure through its influence on later measures of attainment.
Socioeconomic attainment	Childhood health and socioeconomic status are key determinants of educational attainment and earnings in adulthood (Case, Fertig, and Paxson 2005). Educational attainment provides individuals with opportunities to cultivate a wider network of social resources outside of the family, via higher education institutions and occupational attainment, as well as through having more resources to sustain and utilize larger, more diverse (e.g., non-kin) social networks (van Groenou and van Tilburg 2003).
Labor force participation, occupational attainment, and work	Childhood family background and health are strongly predictive of occupational status and attainment in adulthood (Smith 2009), which are key contexts for network development (Laumann 1966, 1973; Lin 1999). Occupations that are less prestigious, characterized by non-standard work hours, contingent employment, or high turnover hinder opportunities to form close ties with others in the workplace, and reduce opportunities to develop a more diverse set of ties outside of the kin context (Ajrouch et al. 2005; Kalleberg, Reskin, and Hudson 2000).
Neighborhood (dis)advantage	Neighborhood disadvantage, including poverty, exhibits considerable continuity across the life course (South et al. 2016; Swisher, Kuhl, and Chavez 2013), and is associated with smaller and less accessed social networks (York Cornwell and Behler 2015). High rates of residential turnover and fewer neighborhood institutions and community resources also preclude the neighborhood as a context for forming ties with non-kin (e.g., Small 2006).
Residential mobility	Individuals who maintain residency in same geographic area across the life course may have denser network structures, likely forming close ties from overlapping social contexts (Feld 1981). Frequent geographic mobility, which may be motivated by occupational and educational opportunities, is associated with sparser network structures (Viry 2012).
Social relationship quality	Aspects of childhood disadvantage are associated with greater relationship strain and less social support in adulthood, including among family ties (Ferraro et al. 2016; Umberson et al. 2014), which could be reflected in a smaller and less tightly-knit personal network.
Psychosocial tendencies	Psychosocial tendencies that originate in childhood disadvantage and endure over the life course (e.g., Bridgett et al. 2015; Elo 2009) may predispose individuals to maintain certain structural features of their social networks.

	Mistrust and hypervigilance, for instance, may make one more likely to maintain a tighter-knit, densely connected personal network of close and trusted others. A lasting sense of self-efficacy and self-regulation may support the development of a more expansive network structure.
Propinquity and homophily	Individuals tend to form ties with others of similar education and social class (McPherson et al. 2001; Blau 1977), and likely with others of similar sociodemographic background and life history. A preponderance of disadvantaged circumstances among one's core confidants may lead to a stressful, high-need network, ultimately straining ties, lessening available support (Offer and Fischer 2018), and resulting in a smaller, more isolating network structure.
Family formation, partnership, and family instability	Childhood (dis)advantage and adversity contribute to a dynamic interplay between socioeconomic status and family dynamics, including age at first birth, non-marital childbirth, and the likelihood, quality, and stability of marital relationships (Conger et al. 2010; Williams and Finch 2019). Family dynamics, structure, and size can shape resource and support needs across the life course, as well as the role of kin in personal networks.
Cognitive and verbal development	Concentrated disadvantage and lower socioeconomic status during childhood are associated with lower verbal (Sampson, Sharkey, and Raudenbush 2008) and cognitive (Greenfield and Moorman 2019) abilities, which can debilitate individual attainment later in the life course, and which are also associated with smaller, denser, and more kin-centric social networks (Kotwal et al. 2016).
Physical and mental health	Childhood disadvantage and adversity can have direct and indirect influences on a range of physical and mental health indicators throughout adulthood (Haas 2008; Hayward and Gorman 2004). Health is a key determinant of older adults' social network structure (Cornwell 2009; Schafer 2012).
Mortality	Individuals from disadvantaged social origins are more likely to experience the death of kin or other close social ties across the life course, which can lead to structural and compositional changes in later life networks (Umberson et al. 2017; Zettel and Rook 2004).
Offending and institutional contact	Childhood family characteristics predict adult criminality (Huesmann et al. 2002). An individual's criminal justice system contact can lead to avoidance of other surveilling institutions such as educational and labor market institutions that can contribute to stratification (Brayne 2014), as well as to the evasion of social relationships and social interactions (Goffman 2009) in ways that could shape personal network structure in enduring ways.
Stress exposure	Exposure to chronic stressors in childhood contributes to heightened emotional reactivity and poor coping strategies, more stressful social relationships, and social withdrawal later in life (Repetti et al. 2002), which may lead to smaller and more fragmented, less supportive personal network structures.

Table 1.2 Descriptive Statistics of Key Variables (N = 4,063).

Variable	Proportion or Weighted Mean (SD)
Social Network Outcomes	
Social network size (Range: 0 – 5)	
0	.007
1	.065
2	.111
3	.179
4	.181
5	.456
Number of kin network members (Range: 0 – 5)	
0	.073
1	.193
2	.239
3	.239
4	.166
5	.091
Social network density [a]	
Number of ties among network alters (Range: 0 – 10)	4.781 (3.067)
Proportion of ties that exist among network members	.739 (.293)
Childhood Measures	
Parental education (highest level)	
Less than HS	.252
HS or equivalent	.326
More than HS	.306
Missing	.116
Family happiness from age 6 – 16 (Range: 1 – 6)	4.362 (1.487)
Lived with both parents from age 6 – 16	.829
Witnessed or experienced violent event from age 6 – 16	.190
Childhood health from age 6 – 16 (Range: 1 – 5)	4.115 (.949)
Family well off from age 6 – 16 (Range: 1 – 5)	2.589 (.954)
Sociodemographic and Life-Course Covariates	
Age (divided by 10)	6.525 (.925)
Female (1 = yes)	.542
Race/ethnicity	
White	.733
Black	.130
Hispanic, non-black	.102
Other	.035
Educational attainment	
Less than high school	.137
High school or equivalent	.238
More than high school	.625
Marital status	
Married/partnered	.729
Separated/divorced	.110
Widowed	.124
Never married	.037
Employed (1 = yes)	.365
Number of children	2.503 (1.766)
Health Status	

Self-rated physical health (Range: 1 to 5)	3.259 (1.042)
Standardized depression score (Range: -.622 – 3.021)	.013 (.594)
Standardized functional health score (Range: -.366 – 6.895)	-.065 (.634)

Note: Means are weighted using respondent-level weights provided by the NSHAP that are adjusted for survey design and selection into the analytic sample.

[a] Means are calculated from respondents in the analytic sample who named at least two network members (N = 3,759).

Table 1.3 Coefficients from Poisson Models Predicting Older Adults' Social Network Size (Incidence Rate Ratios) and Logit Models Predicting Having a Large Network (Log Odds).

	Network Size (Poisson)		Large Network (5 network members) (Logit)	
Predictor	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Parental education *(Ref = Less than high school)*				
High school or equivalent	1.074***	1.047**	.295**	.194
	(1.037 - 1.112)	(1.012 - 1.084)	(.079 - .511)	(-.038 - .426)
More than high school	1.119***	1.056**	.635***	.357**
	(1.085 - 1.153)	(1.022 - 1.090)	(.444 - .827)	(.142 - .572)
Missing	.946	.971	-.257	-.134
	(.892 - 1.004)	(.917 - 1.029)	(-.541 - .027)	(-.428 - .159)
Family happiness	1.006	1.005	.029	.021
	(.997 - 1.016)	(.996 - 1.014)	(-.032 - .090)	(-.040 - .082)
Lived with both parents	1.017	1.011	.203*	.185*
	(.987 - 1.047)	(.983 - 1.040)	(.036 - .369)	(.020 - .351)
Witnessed or experienced a violent event	.971	.975	-.128	-.111
	(.936 - 1.007)	(.941 - 1.011)	(-.337 - .080)	(-.319 - .098)
Childhood health	1.008	.997	.028	-.020
	(.994 - 1.021)	(.985 - 1.010)	(-.049 - .106)	(-.098 - .058)
Family well off	.992	.992	-.029	-.028
	(.978 - 1.006)	(.979 - 1.006)	(-.106 - .048)	(-.106 - .051)
Female	1.129***	1.131***	.569***	.592***
	(1.101 - 1.157)	(1.103 - 1.160)	(.422 - .715)	(.439 - .745)
Race/ethnicity *(Ref = White)*				
Black	.947**	.957*	-.246*	-.219*
	(.909 - .986)	(.921 - .995)	(-.460 - -.032)	(-.427 - -.011)
Hispanic, non-black	.969	.981	-.158	-.119
	(.919 - 1.022)	(.931 - 1.034)	(-.398 - .081)	(-.381 - .143)
Other	.919*	.910**	-.495*	-.553*
	(.857 - .986)	(.850 - .973)	(-.915 - -.075)	(-.972 - -.133)
Age		.990		-.038
		(.972 - 1.009)		(-.146 - .070)
Educational attainment *(Ref = Less*				

than high school)				
High school or equivalent		1.068*		.245
		(1.011 - 1.128)		(-.035 - .524)
More than high school		1.161***		.744***
		(1.103 - 1.223)		(.472 - 1.016)
Marital status *(Ref = Married/partnered)*				
Separated/divorced		.984		-.027
		(.950 - 1.020)		(-.238 - .185)
Widowed		.968		-.105
		(.927 - 1.012)		(-.366 - .156)
Never married		.936		-.175
		(.867 - 1.010)		(-.539 - .189)
Employed		.995		-.058
		(.961 - 1.030)		(-.241 - .124)
Number of children		1.014***		.084***
		(1.007 - 1.021)		(.041 - .127)
Self-rated physical health		1.019*		.081
		(1.003 - 1.035)		(-.006 - .168)
Survey wave	.994	.994	-.068	-.041
	(.963 - 1.026)	(.960 - 1.030)	(-.242 - .105)	(-.244 - .162)
Constant	2.897***	3.071***	-1.017***	-1.407**
	(2.628 - 3.193)	(2.619 - 3.601)	(-1.463 - -.570)	(-2.354 - -.460)
F (df)	16.61*** (13, 83)	13.47*** (24, 72)	12.02*** (13, 83)	10.61*** (24, 72)
N	4063		4063	

Note: All models are weighted using respondent-level weights provided by the NSHAP that are adjusted for survey design and selection into the analytic sample. Models 2 and 4 include controls for depression and functional health which are not significant and are not shown due to space constraints.

*p < .05; **p < .01; ***p < .001 (Two-tailed tests). 95% confidence intervals appear in parentheses.

Table 1.4 Incidence Rate Ratios from Poisson Models Predicting Older Adults' Social Network Density and Number of Kin Network Members.

	Network Density		Number of Kin Network Members	
Predictor	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Parental education *(Ref = Less than high school)*				
High school or equivalent	.971	.983	.914***	.933**
	(.935 - 1.008)	(.948 - 1.018)	(.874 - .957)	(.891 - .976)
More than high school	.916***	.942**	.897***	.939*
	(.880 - .954)	(.905 - .980)	(.852 - .945)	(.892 - .988)
Missing	.992	.973	.981	.961
	(.943 - 1.042)	(.928 - 1.021)	(.930 - 1.035)	(.910 - 1.016)
Family happiness	1.028***	1.023***	1.022***	1.017**
	(1.017 - 1.040)	(1.012 - 1.034)	(1.010 - 1.034)	(1.005 - 1.029)
Lived with both parents	1.020	1.026	.998	1.001
	(.977 - 1.065)	(.985 - 1.070)	(.947 - 1.052)	(.951 - 1.054)
Witnessed or experienced a violent event	.962*	.961*	.965	.973
	(.928 - .999)	(.925 - .999)	(.922 - 1.009)	(.929 - 1.019)
Childhood health	1.016*	1.015*	1.009	1.010
	(1.001 - 1.031)	(1.001 - 1.031)	(.991 - 1.028)	(.992 - 1.028)
Family well off	.990	.993	.993	.997
	(.975 - 1.004)	(.979 - 1.008)	(.974 - 1.013)	(.978 - 1.017)
Female	.950***	.962*		1.012
	(.923 - .978)	(.935 - .991)		(.984 - 1.042)
Race/ethnicity *(Ref = White)*				
Black	1.072*	1.088**	1.025	1.051*
	(1.017 - 1.130)	(1.032 - 1.147)	(.981 - 1.072)	(1.006 - 1.099)
Hispanic, non-black	1.044	.978	1.090*	1.026
	(.980 - 1.113)	(.918 - 1.041)	(1.017 - 1.167)	(.954 - 1.103)
Other	1.084*	1.102**	1.034	1.047
	(1.012 - 1.162)	(1.039 - 1.168)	(.940 - 1.136)	(.953 - 1.151)
Age		.959***		.976*
		(.939 - .980)		(.954 - .999)
Educational attainment *(Ref = Less than high school)*				

High school or equivalent		.966		.992
		(.915 - 1.020)		(.930 - 1.059)
More than high school		.918**		.924*
		(.873 - .965)		(.864 - .988)
Marital status *(Ref = Married/partnered)*				
Separated/divorced		.821***		.798***
		(.786 - .858)		(.755 - .843)
Widowed		.923**		.956
		(.874 - .975)		(.912 - 1.001)
Never married		.829***		.753***
		(.766 - .897)		(.666 - .851)
Employed		.978		.961
		(.951 - 1.007)		(.920 - 1.004)
Number of children		1.028***		1.036***
		(1.019 - 1.038)		(1.026 - 1.046)
Self-rated physical heath		.982*		.989
		(.967 - .998)		(.970 - 1.007)
Survey wave	.958*	.948**	.979	1.006
	(.925 - .992)	(.910 - .986)	(.942 - 1.018)	(.965 - 1.048)
Constant	.689***	.953	.612***	.742**
	(.630 - .753)	(.793 - 1.146)	(.552 - .679)	(.605 - .911)
F (df)	7.57*** (13, 83)	18.26*** (24, 72)	5.49*** (13, 83)	8.91*** (24, 72)
N	3759		4034	

Note: All models are weighted using respondent-level weights provided by the NSHAP that are adjusted for survey design and selection into the analytic sample. Models predicting network density are limited to respondents who named at least two network members, and therefore had the opportunity to report on ties among network members. Models predicting network kin are limited to respondents with at least one network member. Network size is used as the exposure variable in the models predicting number of kin network members. Models 2 and 4 include controls for depression and functional health which are not shown due to space constraints.
*$p < .05$; **$p < .01$; ***$p < .001$ (Two-tailed tests). 95% confidence intervals appear in parentheses.

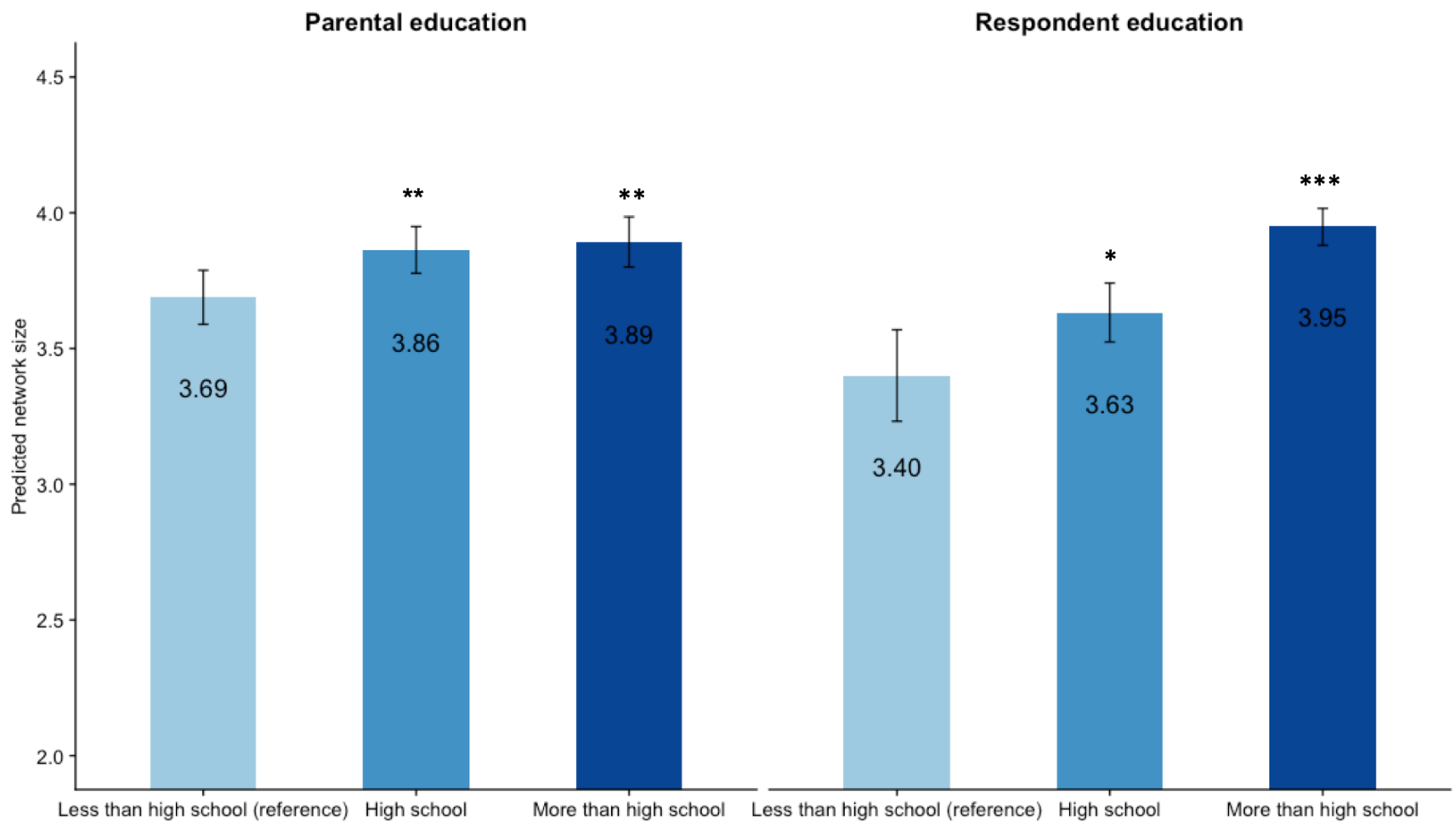

Figure 1.1 Predicted social network size by parental education and respondent education. Predicted values represent average adjusted predictions derived from Model 2 of Table 1.3.
**p* < .05; ***p* < .01; ****p* < .001 (Two-tailed tests). "Less than high school" is the reference category for all significance testing.

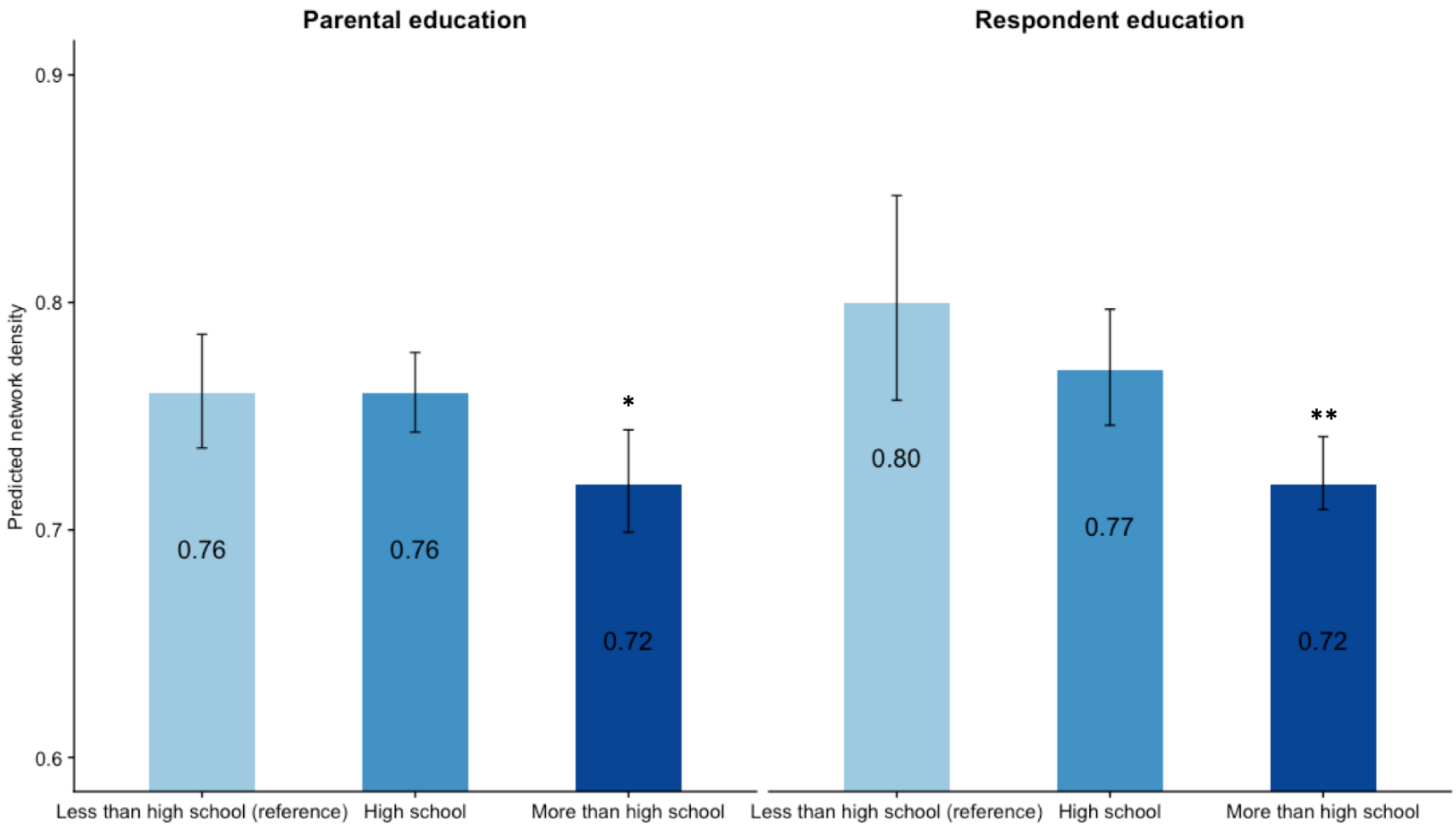

Figure 1.2 Predicted social network density by parental education and respondent education. For ease of graphical interpretation and comparison across respondents with different network sizes, predicted values represent average adjusted predictions from an ordinary least squares regression that models social network density as the proportion of ties that exist in a respondent's network, using the same set of covariates shown in Model 2 of Table 1.4.
*$p < .05$; **$p < .01$; ***$p < .001$ (Two-tailed tests). "Less than high school" is the reference category for all significance testing.

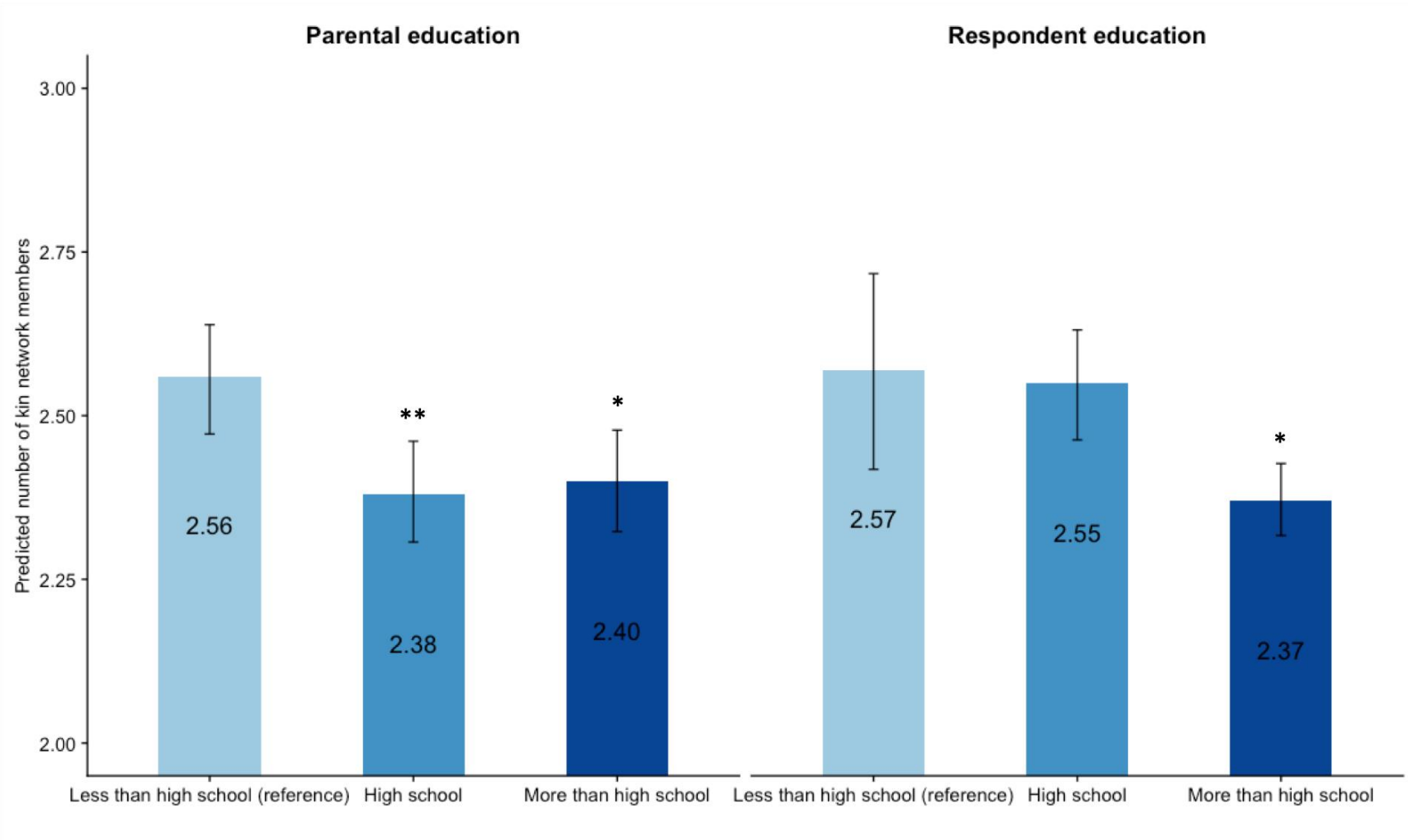

Figure 1.3 Predicted number of kin network members by parental education and respondent education. Predicted values represent average adjusted predictions derived from Model 4 of Table 1.4.
**p* < .05; ***p* < .01; ****p* < .001 (Two-tailed tests). "Less than high school" is the reference category for all significance testing.

Appendix Table 1.1 Coefficients from Logistic Regression Models Predicting Social Network Bridging Potential (Odds Ratios) and Ordinary Least Squares Models Predicting Social Network Density as the Proportion of Ties that Exist (N = 3,759).

Predictor	**Bridging Potential (Odds Ratios)**	**Network Density as Proportion (OLS)**
Parental education *(Ref = Less than high school)*		
High school or equivalent	1.110	-.001
	(.933 - 1.321)	(-.029 - .027)
More than high school	1.523***	-.040*
	(1.225 - 1.893)	(-.076 - -.003)
Missing	1.186	-.021
	(.832 - 1.692)	(-.071 - .030)
Family happiness	.905***	.015***
	(.854 - .959)	(.007 - .023)
Lived with both parents	.994	-.004
	(.807 - 1.224)	(-.035 - .027)
Witnessed or experienced a violent event	1.053	-.015
	(.811 - 1.367)	(-.049 - .019)
Childhood health	.958	.012
	(.882 - 1.041)	(-.001 - .024)
Family well off	1.043	-.004
	(.956 - 1.137)	(-.015 - .007)
Constant	.658	.921***
	(.188 - 2.303)	(.763 - 1.079)
F (df)	10.73*** (24, 72)	10.90*** (24, 72)

Note: Analytic sample is limited to respondents who named at least two network members, and therefore had the opportunity to report on ties among network members. Models include controls for all covariates used in the main analyses (shown in Table 1.2).
*$p < .05$; **$p < .01$; ***$p < .001$ (Two-tailed tests). 95% confidence intervals appear in parentheses.

Appendix Table 1.2 Incidence Rate Ratios from Poisson Models Predicting Social Network Density and Number of Kin Network Members, Controlling for Social Network Covariates.

Predictor	Network Density	Number of Kin
Parental education *(Ref = Less than high school)*		
High school or equivalent	.979	.937**
	(.948 - 1.012)	(.896 - .979)
More than high school	.946**	.938**
	(.912 - .982)	(.896 - .983)
Missing	.962	.960
	(.919 - 1.007)	(.909 - 1.013)
Family happiness	1.017***	1.016**
	(1.008 - 1.027)	(1.005 - 1.027)
Lived with both parents	1.022	1.003
	(.985 - 1.061)	(.957 - 1.051)
Witnessed or experienced a violent event	.964*	.969
	(.930 - .999)	(.926 - 1.014)
Childhood health	1.012	1.006
	(.998 - 1.027)	(.989 - 1.024)
Family well off	.990	.992
	(.978 - 1.003)	(.975 - 1.009)
Network size	.994	1.016
	(.979 - 1.011)	(.998 - 1.033)
Proportion of network members that live with the respondent	1.614***	2.218***
	(1.488 - 1.752)	(2.032 - 2.421)
Average frequency of contact with network members	1.162***	1.037*
	(1.135 - 1.190)	(1.007 - 1.067)
Constant	.266***	.370***
	(.204 - .346)	(.277 - .494)
F(df)	34.19*** (27, 69)	34.57*** (27, 69)
N	3759	4029

Note: Analytic sample for network density is limited to respondents who named at least two network members, and therefore had the opportunity to report on ties among network members. Models include controls for all covariates used in the main analyses (shown in Table 1.2).
*$p < .05$; **$p < .01$; ***$p < .001$ (Two-tailed tests). 95% confidence intervals appear in parentheses.

Appendix Table 1.3 Coefficients from Lagged Dependent Variable Poisson and OLS Models Predicting Older Adults' Social Network Size (Incidence Rate Ratios), Density (OLS), and Number of Kin Network Members (Incidence Rate Ratios) at Wave 2.

Predictor	Network Size W2 (Poisson)	Network Density W2 (OLS)	Number of Kin W2 (Poisson)
Network size W1	1.082***		
	(1.064 - 1.101)		
Network density W1		.206***	
		(.138 - .274)	
Number of kin W1			1.146***
			(1.112 - 1.182)
Parental education *(Ref = Less than high school)*			
High school or equivalent	1.010	-.013	.986
	(.964 - 1.058)	(-.049 - .023)	(.914 - 1.063)
More than high school	1.023	-.033	.987
	(.976 - 1.071)	(-.078 - .011)	(.898 - 1.085)
Missing	.966	-.030	.972
	(.899 - 1.038)	(-.080 - .020)	(.867 - 1.089)
Family happiness	1.000	.015*	1.017
	(.987 - 1.012)	(.004 - .027)	(.997 - 1.039)
Lived with both parents	1.021	.011	.969
	(.974 - 1.071)	(-.043 - .065)	(.901 - 1.043)
Witnessed or experienced a violent event	.993	-.017	.941
	(.939 - 1.051)	(-.060 - .026)	(.858 - 1.033)
Childhood health	.999	.018*	1.029
	(.982 - 1.016)	(.000 - .035)	(.994 - 1.065)
Family well off	1.004	-.014	.994
	(.983 - 1.025)	(-.031 - .003)	(.965 - 1.024)
Constant	2.166***	.689***	1.590*
	(1.746 - 2.687)	(.473 - .905)	(1.119 - 2.257)
R^2		.151	
F(df)	13.58*** (26, 25)	10.27*** (26, 25)	6.21*** (26, 25)
N	1640	1400	1615

Note: All models include controls for baseline (Wave 1) age, gender, educational attainment, race/ethnicity, marital status, employment status, self-rated health, depression, functional health, and number of children, as well as changes in marital status and employment status between Waves 1 and 2. Models predicting social network density are limited to respondents who named at least two network members at Waves 1 and 2. Density is modeled as the proportion of ties that exist in a respondent's network. Models are weighted using Wave 1 respondent level weights that adjust for selection and attrition across waves, and account for the NSHAP survey design.
*$p < .05$; **$p < .01$; ***$p < .001$ (Two-tailed tests). 95% confidence intervals appear in parentheses.

CHAPTER 2: PERCEIVED DISCRIMINATION IN LATER LIFE: A SOCIAL NETWORK APPROACH

ABSTRACT

What factors shape the perception that one is being discriminated against? Existing perspectives tend to focus on individual characteristics (e.g., race/ethnicity, age) as key determinants of perceived discrimination. This paper examines the idea that aspects of individuals' larger social contexts – including their personal social networks – also play a role in these perceptions, and that the underlying processes may differ by race. Using data from black and white older adults surveyed at Wave 3 of the National Social Life, Health, and Aging Project (N = 3,159), I consider how properties of personal social networks are associated with the frequency and type of individuals' everyday discrimination experiences. Results indicate that more kin-centric personal networks protect against older adults' perceptions of everyday discrimination, but that this protective effect may only exist among whites. Among blacks, more kin-centric networks are associated with a higher likelihood that more frequent discrimination is race-related. I propose several reasons why more kin-centric networks may play a different role in the discrimination experiences of whites and blacks, drawing on social network, identity, and racial socialization literatures. I close by suggesting that social network composition may be a source of heterogeneity in the link between individual characteristics, perceived discrimination, and inequality.

INTRODUCTION

Personal experiences with discrimination in everyday life contribute to the persistence of racial, gender, and other forms of inequality in important outcomes such as employment, criminal offending, housing, and health (Kessler, Mickelson, and Williams 1999; Pager and Shepherd 2008; Quillian 2006). Increasing research highlights discrimination as a driver of racial health disparities in the United States (Williams and Mohammed 2009). Indeed, perceptions of discrimination are associated with higher levels of stress biomarkers (Berger and Sarnyai 2015), chronic conditions (e.g., Dolezsar et al. 2014), and accelerated aging (Chae et al. 2014) among blacks compared to whites, along with a host of other physical, mental, and emotional health consequences (Pascoe and Smart Richman 2009).

To date, sociological perspectives on discrimination have focused largely on those individual-level characteristics that are often the basis of this experience – namely age, gender, race/ethnicity, religion, and sexual orientation (e.g., Burt, Simons, and Gibbons 2012; Rivera 2017; Tilcsik 2011; Vogt Yuan 2007). A smaller set of studies draws attention to factors beyond the individual, finding that neighborhood social composition also shapes perceived discrimination, above and beyond individual characteristics (Hunt et al. 2007; Stokes and Moorman 2016). This research highlights the role of social environmental processes in determining the potential for discriminatory social interactions to occur (Feagin 1991; Hagestad and Uhlenberg 2005).

Scholars have not paid as much attention to the role of the social networks in which individuals are embedded. As I argue in this paper, personal social networks have the potential to shape perceptions of discrimination in consequential ways. Research has already demonstrated that the close social ties that comprise personal networks can profoundly influence individuals'

belief structures, identities, and attitudes toward events in their day-to-day lives (e.g., Friedkin and Johnsen 1990; Hogg and Rinella 2018; Marsden and Friedkin 1993; McFarland and Pals 2005; Sinclair, et al. 2005; Walker and Lynn 2013; Valente 2010). Furthermore, individuals depend on personal network members for social support following experiences that are perceived as stressful or threatening (e.g., Thoits 2011; Cohen and McKay 1984). I argue that these structures provide opportunities for network members to influence one another's perceptions of everyday experiences, including discrimination. These perceptions may be shaped directly, in part, by network members' own perceptions of discriminatory treatment, which may be discussed among network ties. In other words, personal networks provide a key social context for learning about how close others are evaluating and responding to similar social interactions, in addition to shaping individuals' beliefs about certain social identities that may be the target of discriminatory treatment.

Beyond being generally influential, personal network members may also shape the salience of and beliefs about those aspects of individual identity that are the basis of discrimination. Particularly among racial minorities, social identity theory and research demonstrate that a more salient racial identity is linked with heightened group identification and perceptions of discrimination against the group (Kaiser and Major 2006; Sellers and Shelton 2003). Along these lines, it is reasonable to hypothesize that the presence of same-race network members strengthens one's racial identity, or certain beliefs about one's racial identity that ultimately shape perceptions of race-based mistreatment. In combination, social network and identity theories offer strong reasons to believe that perceptions of everyday discrimination are determined, in part, by interpersonal processes that occur within personal social networks.

In this paper, I use data from Wave 3 of the National Social Life, Health, and Aging

Project (NSHAP) to shed light on the question: How are features of personal social networks associated with perceptions of everyday discrimination? The NSHAP is unique in that it is the only nationally representative dataset that allows for examining the potential link between personal social network properties and everyday discrimination among older adults. Exploring this research question among the older adult population is further advantageous, as the sample as a whole is broadly vulnerable to various forms of discrimination, including ageism (Gee, Pavalko, and Long 2007). My analyses will suggest that personal network composition – in particular, the extent to which one surrounds oneself with kin network ties – plays a role in shaping the frequency and type of perceived discrimination that individuals experience, but that the nature of these associations may differ between black and white older adults.

THE SOCIAL BASES OF PERCEIVED DISCRIMINATION

It is well-established that discrimination is a fundamental contributor to the persistence of inequality along various dimensions in the United States (Pager and Shepherd 2008; Quillian 2006; Williams 2018). Despite their subjective nature, individual perceptions of discrimination – that is, the awareness or judgment that one has been mistreated because of their social group membership – represent a consequential measure of discriminatory experience that is generally treated by social scientists at face value (Major, Quinton, and McCoy 2002). Indeed, self-reported perceptions of discrimination are key measures of social experiences and individuals' sense of justice, given the robust connection between these perceptions and several macro-level measures of structural inequality (Gee et al. 2007; Kaiser and Major 2006; Kessler et al. 1999; Schulz et al. 2006).

Audit studies and other experimental designs are a more objective means of assessing the

prevalence of discrimination in access to opportunities such as employment and housing (Pager 2007; Tilcsik 2011). However, individuals who are discriminated against in these scenarios are not necessarily aware of this mistreatment. Awareness, or the perception of discrimination, is a primary means through which discrimination is consequential (Ajrouch et al. 2010). Self-reports of discrimination are the basis for much of the literature linking discrimination with physical, mental, and emotional well-being (e.g., Schulz et al. 2000; Williams et al. 2012; Williams and Mohammed 2009). A key mechanism of this association is individuals' assessment of discriminatory treatment as a stressor, and the subsequent health consequences of stress experience (Pascoe and Smart Richman 2009; Williams 2018). Likewise, a major theoretical premise of this paper is the notion that personal network ties have the ability to shape individuals' evaluations of personal experiences, particularly those that are stressful (Thoits 2011). Individual perceptions are therefore a meaningful measure of discriminatory treatment, and one that is especially appropriate to assess in the context of social network structure.[9]

Not surprisingly, most approaches to understanding perceived discrimination focus on individual-level social characteristics like age, race/ethnicity, and gender, as these are most often the attributed bases of discriminatory treatment. Indeed, stigmatized and historically disadvantaged social groups are more likely to experience discrimination on the basis of such characteristics. For example, blacks are more likely to report discrimination on the basis of race/ethnicity compared to whites (89.7% versus 21.1%), and women are more likely to report discrimination on the basis of gender compared to men (47.9% versus 11.4%) (Gee et al. 2007; Kessler et al. 1999; Williams et al. 1997).

Nevertheless, according to widely cited nationally representative research by Kessler and

[9] Ajrouch and colleagues (2010) usefully summarize the value of perceptions of discrimination by citing the Thomas dictum – that is, if people define situations as real, they are real in their consequences.

colleagues (1999), approximately 60% of Americans report experiencing some form of chronic, everyday discrimination – including over 90% of blacks and over 50% of whites. Just over one-third of whites and one-third of males report at least one major discriminatory event in their lifetime, compared to nearly 50% of blacks and 34.3% of females. Higher percentages of whites attribute their discrimination experience to gender (39.2%), age (25.7%), and appearance (28.9%) compared to blacks, nearly 90% of whom attribute discrimination experience to race (Kessler et al. 1999).

Thus, discrimination is experienced across social groups in the United States, although it is generally more concentrated among historically marginalized groups, and particularly on the basis of the identities that distinguish those social groups (e.g., race/ethnicity, gender). The overall pervasiveness of perceived discrimination supports a key assumption of this and other studies on this topic, which is that in theory, any member of the population can experience perceived discrimination. As I expand on in subsequent sections, however, there is good reason to believe that the meaning of these perceptions is wholly different across social groups, particularly among blacks and whites, and in ways that are likely to intersect with properties of individuals' personal networks.

Neighborhood and Institutional Contexts

Sociologists have begun to consider the role of larger social contexts in shaping individuals' perceptions of discrimination, acknowledging that perceived discrimination is a more general phenomenon that is sometimes decoupled from individual-level traits (Bobo and Fox 2006; Feagin 1991; Welch et al. 2001). This work stems in part from the idea that the social environments where individuals spend significant portions of their time serve as the settings that

structure opportunities for social interactions that are potentially discriminatory (Cagney 2006; Feagin 1991; Hagestad and Uhlenberg 2005). The social composition of these contexts can therefore make certain forms of discrimination more or less likely.

Among blacks, for example, perceived racial discrimination is lowest for those residing in neighborhoods with a higher percentage of blacks (Hunt et al. 2007). For minorities, being in places with a higher composition of minorities may make interactions with majority groups less likely, thus buffering against potential discrimination while also serving as a source of social support (Halpern and Nazroo 2000; Hunt et al. 2007). Similarly, neighborhoods that have a higher proportion of older adults protect against perceptions of ageism among individuals entering later life (Stokes and Moorman 2016).

Institutional and organizational contexts exhibit similar findings, as exposure to mostly same-race co-workers tends to diminish perceptions of racial discrimination (Stainback and Irvin 2012). Blacks experience the highest levels of perceived discrimination in contexts where they are numerically fewest (Krysan and Farley 2002). Among whites, higher levels of contact with racial minorities in the workplace is positively associated with racial discrimination. This phenomenon may reflect status anxiety or group threat, and may be exacerbated by whites being less accustomed to contexts where they are the racial minority (Mueller et al. 1999; Stainback and Irvin 2012). Collectively, this work suggests that being surrounded by in-group members protects against perceptions of discrimination against the group.

The Role of Personal Social Relationships

Taken together, this work suggests that the general social context – including social relationships – plays a role in shaping individuals' exposure to and perceptions of discrimination.

Interpersonal processes are implicit in much of the social psychological literature on this topic, which draws largely on self-categorization and social identity processes to predict when individuals will perceive discrimination. Specifically, social identity theory states that an individual's self-concept arises out of their perceived membership in a social group(s), and their comparisons between in-group and out-group members (Stryker and Burke 2000). Individuals are more likely to perceive discrimination when they are aware of the stigmatized status of an attribute or group with which they identify or self-categorize (Operario and Fiske 2001). When an aspect of one's identity is salient (e.g., race, ethnicity, age, gender), the individual will perceive greater between-group (rather than within-group) differences (Turner et al. 1989), and be more sensitive to stigmatization and discrimination on the basis of that identity (Major et al. 2002). Thus, aspects of the social context with which one feels a personal connection (e.g., interpersonal ties) may be just as important as its more general socio-demographic composition (e.g., neighborhood composition), to the extent that these social connections influence the salience of one's social identity.

Personal social connections may also shape individuals' sensitivity to and interpretation of potentially discriminatory interactions. In addition to identity processes, interpersonal relationships serve as primary sources of social support used to cope with stressful, threatening, or otherwise negative events (Thoits 2011). Discrimination is psychologically painful because it directly threatens a core part of one's social identity (Branscombe, Schmitt, and Harvey 1999; Schmitt and Branscombe 2002), and signals to an individual that s/he is devalued on the basis of that identity (Harris-Britt et al. 2007). Close, supportive social ties are often sought after following experiences that are perceived as discriminatory, as individuals seek feelings of belongingness and acceptance, and enhanced psychological well-being (e.g., Branscombe et al.

1999).

A key premise of the current study, however, is that interpersonal connections – including those sought after for social support - also involve exposure to others' interpretations of whether an event that they recount was in fact discriminatory. Individuals may revise their evaluations of whether they have experienced discrimination based on the opinions of trusted others. Indeed, individuals' self-evaluations of their identities are likely to align with the views of their close social ties as a means of maintaining social bonds (i.e., the affiliative social tuning hypothesis) (Sinclair et al. 2005). Further, a fundamental basis of tie formation is the attraction to people who raise one's self-esteem and make them feel good about themselves (Sinclair et al. 2005; Mead 1934). Perceptions of whether a given interaction was discriminatory may therefore be subject to whether close social ties diminish or strengthen those individual identities that are the targets of mistreatment, and in ways that align with an individual's positive self-image. In these ways, close social relationships may directly influence individual perceptions of experiences as discriminatory, constituting a potentially influential, yet relatively overlooked determinant of perceived discrimination.

PERSONAL SOCIAL NETWORKS

In this paper, I argue that one concrete aspect of the social context that provides a source of support, identity, and a prism for interpreting potentially discriminatory acts is the personal ("egocentric") social network. These networks are typically comprised of one's most intimate and strongest social ties, with whom individuals exchange support, call on for advice, and discuss issues of personal importance (Fischer 1982, 2011; Marsden 1987; Wellman and Wortley 1990). Core network ties are regarded as a main pathway through which "influence processes

and normative pressures operate" (Marsden 1987, p. 123), and through which individuals are integrated into society (Fischer 1982). Indeed, shared perspectives are a fundamental basis of maintaining close social relationships (Hogg and Rinella 2018; Skorinko and Sinclair 2018). Prior research documents that personal social networks tend to be small, kin-based, and relatively dense, and exhibit similarity among network members on the basis of sociodemographic characteristics, attitudes, and belief structures (Marsden 1988; McPherson, Smith-Lovin, and Cook 2001). Race especially is one of the strongest predictors of tie formation, with social networks typically characterized by a high degree of racial homogeneity (McPherson et al. 2001; Wimmer and Lewis 2010)

Individuals may be especially likely to discuss potentially discriminatory experiences with close confidants, given that these events are often distressing (Schmitt and Branscombe 2002; Williams et al. 2012), leading them to seek social support. Social networks play a key role in how an individual interprets and responds to stressful or problematic situations (Cohen and McKay 1984; Thoits 2011). To this end, perceptions of discrimination may be shaped through discussion with network members who affirm or refute one's recounting of a given event as discriminatory. Network members' perceptions of their own experiences of unfair treatment may influence these interpretations, to the extent that they have had similar experiences that they have judged as discriminatory, in turn corroborating (or refuting) a network member's perceptions of their own experiences.

Various properties of personal networks may be especially relevant to perceptions of discrimination. Generally speaking, a larger social network and more frequent interaction with one's network members are fundamental indicators of social integration and available social support (Berkman et al. 2000; Marsden 1987). Individuals who have larger personal networks

are more likely to have a network that includes at least one member who has experienced discrimination, and who is positioned to corroborate or refute an individual's own experiences as discriminatory or not. Put differently, larger networks offer a larger pool of collective experience for an individual to draw on when evaluating their own interactions.

The more frequently that one accesses their social network members, the greater the potential to share experiences with and influence one another (e.g., Hank 2007). More frequent interaction with network members may also indicate time spent physically together in spaces where discrimination can occur. For example, frequently accessed network members may be assisting one another with medical appointments and other routine activities (e.g., grocery shopping) – contexts where there is potential for discriminatory interactions to take place (Stepanikova and Oates 2017). More frequent shared experience could allow network members to witness and collectively interpret social interactions as discriminatory or not.

But the fact that discrimination is, by definition, linked to categories of personal identity and social group membership (Kaiser and Major 2006) suggests that the relevance of social network processes may extend beyond broad conceptualizations of social support and interaction to those network properties most pertinent to the particular social identity that is the target of discriminatory treatment. One of the most relevant structural features of personal social networks for perceived discrimination may therefore be homogeneity – that is, the degree to which members of a social network are similar along one or more identities (Louch 2000; Marsden 1988). Networks of individuals who are similar along a particular trait – e.g., race, religion, social class – can increase the salience of that identity for network members (McFarland and Pals 2005; Walker and Lynn 2013) and help to identify discriminatory treatment on that basis. Likewise, personal networks that are more heterogeneous along certain identities may function to

lessen reports of discriminatory treatment, dissuading individuals (or otherwise not corroborating) that they were mistreated on the basis of that identity.

Kin network members are especially likely to exhibit racial similarity but, even more so, are likely to represent shared belief systems and personal histories that originate in the family context and that have implications for perceived discrimination in ways that are distinct from other types of network members. This argument pertains especially to racial differences in discrimination. Indeed, racial socialization practices begin in the family context during early childhood and endure across the life course, preparing children for the types of prejudiced interactions – or lack thereof – that they may encounter in the future (Hagerman 2014; Hughes et al. 2006; Hughes and Chen 1997). Through this socialization, families (often parents) cultivate individuals' knowledge about racial hierarchy, conditioning their expectations for the types of treatment that they can expect based on their racial identity (Bonilla-Silva 1997, 2006; Rollins and Hunter 2013).

For black families, these practices typically involve fostering a heightened sense vigilance against race-based mistreatment given the long history of social disadvantage and racism experienced by blacks in the United States, and cultivating a strong sense of racial consciousness, pride, and positive racial identity (Hicken et al. 2013; Hughes et al. 2006). A higher presence of kin in blacks' personal networks may increase individuals' identification of racial discrimination, in part by representing higher levels of racial homogeneity and in part by heightening the salience of and positive association with racial identity. The more that race represents a core aspect of an individual's overall identity, the more that the salience of racial identity is linked to perceived discrimination (Kaiser and Major 2006; Sellers and Shelton 2003).

White families, for whom discrimination is overall less prevalent, are more likely to

effectively socialize children *not* to expect mistreatment based on race or other identities (Bonilla-Silva 2006). Scholars highlight that even when done unconsciously (Bonilla-Silva 1997), white families implicitly socialize children into privileged positions within the social hierarchy (Hagerman 2014). Following a lifetime of relatively un-stigmatized social status, white older adults (particularly those of higher socioeconomic status) enter later life with fewer strategies for dealing with discrimination compared to black older adults who are more likely to have endured race-based mistreatment in varying degrees throughout their lifetime (Abramson 2015, 2016). Indeed, age-based discrimination in later years is oftentimes whites' first experience of discrimination (Abramson 2015, 2016). Even in the case of perceived ageism, however, family ties may be especially relevant. Since the family is a primary context for sustained cross-age relationships, kin ties are particularly well-positioned to provide a source of age integration that overcomes age-related stigma and prejudice (Hagestad and Uhlenberg 2005).

The potentially different roles of network kin in shaping perceived discrimination among blacks and whites also prompts a more general consideration of racial differences in the types of identities that are likely to be targeted in discriminatory interactions. For white older adults, the role of network members in shaping perceptions of discrimination may be more dissuading and oriented toward supporting self-esteem. This role may be due to the more fluid, subjective properties of the identities most likely to be targeted in whites' potentially discriminatory interactions. For example, regarding ageism, which whites are 1.5 times as likely as blacks to report as the main reason for discrimination (Kessler et al. 1999), the meaning of an individual's age (i.e., whether one is "old" versus "young") is relative across the life course and across social and institutional contexts. An individual's identity is not rooted in the category of "older adult" in the same way that race is a life-long, ascribed, stable identity with culturally entrenched

meaning, and for which discrimination is anticipated (and more likely experienced) throughout the life span (Hicken et al. 2013; Gee et al. 2012). Likewise, in the case of interactions that may be discriminatory based on appearance – a more subjective, localized aspect of identity (Schmitt and Branscombe 2002) – a larger, more intimate personal network may offer more sources of potential support who act to persuade an individual that their perceptions of mistreatment are incorrect (e.g., "You are not overweight" or "You look so young for your age"), ultimately reducing perceptions of discrimination.

In sum, potentially discriminatory encounters carry wholly different meanings for blacks and whites, and social networks – as contexts that influence the salience of various identities (Stryker and Burke 2000; Walker and Lynn 2013) – may also be implicated differently in processing experiences as discriminatory or not. When potentially discriminatory interactions relate to more fluid categories of social identity, the social network context may resolve discomfort arising from one's "ideal" identity and the identity that is a basis of unfair treatment (Stryker and Burke 2000). When a target attribute is ascribed, and especially in the case of race, similarly-identified network members may be a source of solidarity, affirming the interaction as discriminatory and heightening one's sense of identification and cohesion with the group (Sellers and Shelton 2003). In this sense, network properties that reflect social support – i.e., networks that are large, high contact, and kin-centric – may be especially relevant to whites' perceived discrimination, while racial homogeneity and in particular, kin composition, may be especially relevant to perceptions of discrimination among blacks. Underlying both possibilities is the more general idea that the motivation to develop a shared reality with network members will be particularly strong when individuals experience interactions that target aspects of one's identity (Hogg and Rinella 2018).

THE PRESENT STUDY

The goal of this study is to provide an initial examination into how aspects of older adults' personal social networks may shape perceptions of discrimination, above and beyond other individual and social environmental factors. I test this possibility using data from Wave 3 of the National Social Life, Health, and Aging Project (NSHAP), considering how personal social network properties are associated with the frequency and type of perceived discrimination. Throughout the analysis I attend to racial differences. This focus is motivated by the stark differences among blacks and whites in both expected and experienced discrimination across the life course, and which I argue may relate to how personal network members influence perceived discrimination in later life.

It is important to recognize that personal network relationships and perceptions of discrimination are likely to intersect in dynamic ways over time, and in ways that I cannot fully account for in this study. I examine the proposition that personal network properties influence perceptions of discrimination, but I cannot analytically distinguish this relationship from the possibility that discrimination also influences social network properties. In addition, social networks themselves reflect a variety social-structural processes that are associated with those individual identities that are often targets of discrimination. For example, women tend to have larger and more diverse personal networks than men (Moore 1990). Compared to whites, blacks tend to maintain smaller, more kin-based, and more frequently contacted personal network ties, although these racial differences diminish with age (Ajrouch, Antonucci, and Janevic 2001).

The life trajectories of whites and blacks are also distinct in terms of the opportunities for discriminatory experience. For instance, blacks demonstrate lower rates of moving into white neighborhoods (South and Crowder 1998), while preferences for same-race neighbors (Charles

2000) may reduce opportunities for racial discrimination in everyday interactions (Hunt et al. 2007). Gee and colleagues (2012) also underscore that among blacks young adulthood is more often characterized by unemployment and/or underemployment, incarceration, and poor health. These experiences have implications for individuals' contact with institutions and organizations such as the healthcare and criminal justice systems, which are key sources of institutional racism and discrimination (Burt et al. 2012; Stepanikova and Oates 2017).

A comprehensive understanding of how personal histories of social network change and discrimination experiences influence perceived discrimination later in life is beyond the scope of this study. Despite these limitations, the significance of discrimination in maintaining disparities in well-being and access to resources in the United States (Colen et al. 2018; Williams 2018) calls for a stronger understanding of the social bases of perceived discrimination. I use the findings from this study to argue that older adults' core social networks are an important, yet relatively overlooked social foreground that intersect with consequential perceptions of unfair treatment.

DATA AND METHODS

The National Social Life, Health, and Aging Project

To begin to shed light on the question of how personal social networks shape perceptions of discrimination, I use data from the National Social Life, Health, and Aging Project (NSHAP). The NSHAP is a population-based panel study of non-institutionalized older adults in the United States (Suzman 2009). The overall goal of the NSHAP is to better understand how health and social context intersect to influence older adults' well-being as they age. At each wave, data collection consisted of in-home interviews conducted by the National Opinion Research Center

(NORC), which included the collection of personal social network information. Following the in-home interview, respondents were also asked to complete a leave-behind questionnaire (LBQ) to be returned to NORC by mail.

This study relies on data collected at Wave 3 (2015-2016). The sample includes returning respondents who participated in Waves 1 and/or 2 and their partners (N = 2,409), if applicable, as well as a new cohort of respondents born between 1948 and 1965 and their co-resident partners (N = 2,368). Although the NSHAP includes three waves of data collection, each of which collects information about respondents' personal social networks, Wave 3 is the first survey to ask about respondents' perceptions of everyday discrimination. To my knowledge, Wave 3 of the NSHAP is the only nationally representative dataset that collects information about both personal social networks and everyday discrimination, allowing for this type of study.

The NSHAP is also useful for exploring this topic because older adults are more susceptible to experiencing age-based discrimination (Vogt Yuan 2007). Although perceptions of discrimination of all kinds tend to decrease with age, the probability of attributing unfair treatment to ageism increases between early and mid-late adulthood (Gee et al. 2007). Thus, given my interest in exploring how social network properties may operate differently in shaping different types of discrimination, the older adult sample allows for these types of comparisons among respondents who are arguably more universally vulnerable to different types of discrimination than is a younger population-based sample.

Perceived Discrimination

The Everyday Discrimination Scale (EDS) is among the most widely used survey-based scales to measure chronic discrimination experiences – that is, those perceptions of unfair

treatment on the basis of gender, race, ethnicity, age, appearance, or other individual attributes that take place as part of what are considered to be normal, routine daily encounters (Lewis et al. 2012; Williams et al. 1997). Beginning in Wave 3, the NSHAP included two items from the nine-item EDS as part of the LBQ. Respondents were asked: "In your day-to-day life, how often have you been treated with less courtesy than other people?" and, separately, "In your day-to-day life, how often have people acted as if they're better than you are?" Responses were coded using the following scale: 0 = never, 1 = less than once a year, 2 = about once or twice a year, 3 = several times a year, 4 = about once a month, 5 = every week, and 6 = several times a week. These two questions are used (separately) as the two main outcome variables in my assessments of frequency of discrimination experience.

As less than 5% of the analytic sample selected each of the three most frequent responses (about once a month, every week, and several times a week), I collapse these three response categories into a single category so that the most frequent response category represents "about once a month or more often." The frequency of each of the two types of discrimination experiences is therefore modeled as having five possible categories: never (= 0), less than once a year (= 1), about once or twice a year (= 2), several times a year (= 3), or about once a month or more often (= 4).

Following the two EDS items, respondents were also asked: "When these things happen in your day-to-day life, what do you think is the main reason(s) for them?" Response options included: ancestry or national origins, race, age, gender, height or weight, shade of skin color, sexual orientation, and other. Respondents were able to select multiple reasons, and this question was asked once on the LBQ (i.e., respondents were not asked to provide separate "reasons" following each of the two EDS items). To assess how the types of discrimination experience are

distributed in the sample, I create binary indicators of whether a respondent provided an affirmative response to each of the following six categories: race/ethnicity; age; gender; height or weight; sexual orientation; or other (unspecified). I code any affirmative responses on the basis ancestry or national origins, race, or shade of skin color as racial/ethnic discrimination.

Social Network Measures

At each wave, the NSHAP administered the following name generator as part of the in-home interview: "*From time to time, most people discuss things that are important to them with others. For example, these may include good things or bad things that happen to you, problems you are having, or important concerns you may have. Looking back over the last 12 months, who are the people with whom you most often discussed things that were important to you?"* This name generator is commonly used to elicit individuals' core social confidants, including their strongest and most intimate social ties, with whom they are most likely to exchange resources and social support (Marsden 1987).

Respondents could name up to five network members (i.e., "alters"). Following the enumeration of their network members, respondents were asked to provide information about each alter, including their relationship to each alter (e.g., spouse, friend, neighbor) and how often they speak with each alter (1 = "less than once a year," 8 = "everyday").

From this information, I construct three measures designed to capture the structural and compositional aspects of respondents' personal networks that are likely to influence individuals' perceptions of discrimination, based on the range of mechanisms outlined earlier. Social network size is a count of the total number of alters named, ranging from 1 to 5, and serves as a general measure of social integration (Marsden 1987), as well as the number of distinct sources of

potential support, advice, and personal experience that one has to call on in their network. Frequency of contact is an average of how often a respondent reports being in touch with their network members, and is a useful proxy for potential support exchange, familiarity, and communication (e.g., Hank 2007).

Proportion kin is the proportion of alters who are related to the respondent by blood or marriage (i.e., spouse/partner, parent, parent in-law, child, stepchild, grandchild, sibling, other in-law, or other relative). This measure captures network composition and the extent to which one's social network members are drawn from a single social context (i.e., the family). Family ties tend to be long-standing relationships with individuals of similar social background, and who may be particularly influential in shaping how individuals perceive aspects of their identity as part of everyday interactions. While data on network members' race, age, and other characteristics could be used to construct other measures of network homogeneity, this information is not collected as part of the NSHAP.[10] Thus, proportion kin serves as a measure of how kin-centric respondents' personal networks are, as well as the best available approximation of racial homogeneity in the network.

Sociodemographic and Social Environment Measures

In line with prior research, I account for several sociodemographic and social environmental measures that are associated with perceptions of discrimination. Individual characteristics include gender and age. Residential census tract characteristics are drawn from the 2011-2015 American Community Survey (ACS). I include the proportion of black, non-Hispanic residents and the proportion of residents over the age of 65 as covariates. These

[10] The NSHAP only collects information on the age of network members who live in the same household as the respondent.

measures likely capture aspects of neighborhood composition that are relevant to two of the most prevalent bases of perceived discrimination in the sample: racial/ethnic discrimination and ageism.

I also account for respondents' perceptions of neighborhood collective efficacy, which I measure as a scale of eight items assessing respondents' perceptions of neighborhood characteristics such as social cohesion, trust, and social connectedness within their neighborhood (α =.79) (Sampson, Morenoff, and Earls 1999). As the local neighborhood provides a key opportunity structure for older adults to interact with others (e.g., Stokes and Moorman 2016), respondents' perceptions of local collective efficacy may influence their likelihood of spending time in their neighborhood, thereby influencing their likelihood of exposure to unfair treatment through interactions with others.

Control Variables

I include a number of life-course and health-related covariates that are likely to be related to both discrimination experiences and social network measures (Gee et al. 2007; Kessler et al. 1999; Williams 2018). These include whether the respondent has attended college/university, is married/partnered, and whether the respondent is retired at Wave 3. Health covariates include whether the respondent reports good, very good, or excellent self-rated physical health (=1). I also account for respondents' functional health, as mobility issues may limit the extent to which respondents are able to move about independently in their day-to-day lives, thus limiting their exposure to social interactions that may or may not be discriminatory. I measure functional health as the average of standardized responses to 9 items assessing respondents' difficulty completing basic daily activities independently (e.g., eating, dressing), with higher scores

indicating greater functional impairment.

I also control for respondents' reports of available social support, which I measure as a scale of how often respondents report that they can open up to and rely on family and friends (α = .69). Many properties of personal social networks - including those that I consider in this study - are also associated with social support (Haines, Beggs, and Hurlbert 2011). It is therefore important to consider whether any social network correlates of perceived discrimination exist net of, or are explained by, more broadly available social support. Finally, religious communities serve as formal sources of in-group solidarity and support for many older adults (Lim and Putnam 2010). I therefore control for frequency of attending religious services using a 5-point scale (0 = "never," 5= "several times a week").

Analytic Strategy

The analyses proceed in two stages. First, I use descriptive analyses to consider racial differences in the frequency of discrimination experience, as well as social network and other key covariates. Next, I move to multivariable analyses to consider whether the frequency of discrimination is a function of social network properties, above and beyond individual-level and other social-structural predictors. I use generalized ordered logit models to examine how social network factors are associated with the frequency of reporting each of the two items from the EDS, separately, given that frequency is measured using an ordinal scale (0 = "never," 1 = "less than once a year," 2 = "about once or twice a year," 3 = "several times a year," and 4 = "about once a month or more frequently").

An ordered logit model assumes that the odds of being in a higher versus lower category of the dependent variable are the same across levels of the dependent variable for each

independent variable (i.e., the proportional odds assumption) (Long and Freese 2001; Williams 2016). However, Brant tests indicate that this assumption is violated in ordered logit models predicting the frequency at which respondents report that others act as if they are better than they are (χ^2 = 153.76; $p < .001$), and in ordered logit models predicting the frequency at which respondents report being treated with less courtesy than others (χ^2= 152.13; $p < .001$). An alternative analytic strategy is the partial proportional odds model, which relaxes the parallel lines constraint for those variables where it is not required (i.e., those variables where the odds of being in a higher versus lower category of the outcome are the same across all comparisons), thereby creating a more parsimonious model that estimates fewer parameters (Williams 2016). However, adjusted Wald tests indicate that even in partial proportional odds models, the parallel lines assumption is violated (F = 2.78, $p < .001$ in the full model predicting the frequency of others acting as if they are better, and F = 2.50, $p < .001$ in the full model predicting the frequency of being treated with less courtesy). These tests indicate that there are likely to be important differences in how certain covariates predict these outcomes across different levels of the outcomes.

I therefore use generalized ordered logit models that fully relax the parallel lines assumption by allowing the coefficients for each independent variable to vary across each category of the dependent variable. Thus, the estimates include four sets of coefficients for each independent variable. These coefficients can be thought of as the coefficients from cumulative logit models that predict reporting discrimination frequency in any of the higher categories at each level of the dependent variable (Williams 2016). For example, the first set of coefficients represents the odds of experiencing the EDS item more often than “never” (1 vs. 2, 3, 4, and 5), and the second set of coefficients represents the odds of experiencing the EDS item more often

than “never” or “less than once a year” (1 and 2 vs. 3, 4, and 5), and so forth. The fourth and final set of coefficients represents the odds of reporting discrimination in the four lower categories (“never,” “less than once a year,” “about once or twice a year,” or “several times a year”) versus the highest category (“about once a month or more frequently”). I extend these findings with a second set of generalized ordered logit models that include race by social network interaction terms to consider whether race moderates any of the main effects.

In the second stage of the analysis, I focus on whether the type of discrimination that respondents experience is also a function of personal network properties. In these analyses, I restrict the sample to those respondents who report experiencing at least some discrimination (i.e., respondents who report more than “never” on either of the two frequency questions), and who therefore have some discrimination experience that could be attributed to an identity. These models are guided by prior research on the main reasons for perceived discrimination (Kessler et al. 1999), as well as the descriptive analyses in the current study that examine racial differences in the prevalence of “main reasons” for discrimination. Specifically, I model the experience of racial discrimination among blacks as a function of social network and other covariates and, in separate models, the experience of age-based discrimination among white older adults using the same set of covariates.

Wave 3 of the NSHAP included 3,899 interviews with black and white respondents who were ages 50 and older at the time of the interview. The most significant source of missing data comes from the fact that perceived discrimination was measured using the leave-behind questionnaire, which some of these respondents (approximately 13.3%) did not return to NORC. Of the remaining 3,380 respondents, 28 were excluded because they reported that they did not have a social network at Wave 3, or they were missing data on social network characteristics. An

additional 4.8% of respondents were excluded due to missing data on one or more covariates. Supplementary unweighted t-tests reveal that respondents excluded from the analytic sample due to missing covariates did not differ significantly from those included in the analysis based on how frequently they experience either of the two discrimination measures. Among respondents with non-missing data on all covariates, 41 did not provide a response to the question of how often others act as if they are better than they are, and 42 did not provide a response to the question of how often they are treated with less courtesy than other people. Final sample sizes include 3,150 for models predicting the frequency of being treated with less courtesy than other people, and 3,151 for models predicting the frequency of others acting as if they are better. Models predicting the "main reason" for discrimination are based on the 1,936 respondents (329 blacks and 1,607 whites) in these analytic samples who report at least some discrimination experience (i.e., more often than "never" on either of the two discrimination measures).

To help account for respondents' exclusion due to missing data, I use inverse probability weighting to attenuate bias that may result from exclusion based on not returning the LBQ or missing data on other covariates. This process involves first using a logit model with data from all black and white Wave 3 respondents ages 50 and older to predict inclusion in the final analytic sample based on a number of sociodemographic, life course, and health measures, including race/ethnicity. Next, I multiply the inverse of the predicted probabilities derived from the logit model by the person-level weights provided by the NSHAP that adjust for selection and non-response. I then apply these final weights to all model estimates. This process gives greater weight to those respondents who most resemble those excluded from the models on the basis of missing data, generating estimates that better resemble the estimates that would be generated had all respondents been included in the analysis (Morgan and Todd 2008). It is also important to

note that although tract-level variables are included in the models, variance in neighborhood context is at the respondent level, and so multi-level models are not warranted.

RESULTS

My main goal is to assess whether aspects of perceived discrimination among black and white older adults, namely the frequency and type of discriminatory treatment, could be a function of social network properties. To examine this question, I begin by comparing the distributions of the main variables used in the regression models among black and white respondents. I compare means using survey adjusted Wald tests and proportions using unweighted Chi-squared tests.

As shown in Table 2.1, blacks are generally more likely than whites to experience higher levels of both everyday discrimination measures, although the majority of respondents in both racial groups report some discrimination experience. A significantly higher proportion of blacks (.427) report "never" in response to how often others acted as they are better than they are, compared to 37.9% if white respondents ($\chi 2 = 4.366$, $p < .05$). Blacks are significantly more likely than whites, however, to report that they experience this form of discrimination "about once a month or more frequently" (13% of blacks versus 7.5% of whites; $\chi 2 = 17.719$, $p < .001$). A similar pattern is evident when comparing the distribution of respondents' experiences of how often they are treated with less courtesy than other people. A significantly lower proportion of blacks (.221) report this experience as occurring "less than once a year," compared to 26.3% of whites ($\chi 2 = 4.021$, $p < .05$). Black older adults are more likely than whites to report more frequent experience of this form of discrimination. Just over ten percent of blacks report this discriminatory treatment as occurring "several times a year," compared to just over six percent of whites ($\chi 2 = 12.753$, $p < .001$). Likewise, approximately 12.5% of blacks report this

discriminatory treatment as occurring "about once a month or more frequently," compared to just over seven percent of white older adults ($\chi 2 = 15.817$, $p < .001$).

Turning to the social network measures, respondents tend to maintain relatively large and intimate personal social networks, with significant differences across racial groups. On average, respondents name between three and four network members (with a maximum of 5 allowed). Blacks' networks are significantly smaller than those of whites, but also exhibit significantly more frequent contact with network members (between "several times a week" and "everyday") than do whites' networks (between "once a week" and "several times a week"). Kin members comprise a notable proportion of network members, including 65% of network members, on average, among black respondents, and 62.2% of network members among white respondents. Proportion kin does not significantly differ by race.

On average, black respondents are significantly younger than whites, are less likely to have attended college, are less likely to be retired, and are less likely to be married/partnered. Blacks report significantly worse self-rated physical health compared to whites and have higher levels of functional limitations. Other key racial differences emerge along social and contextual covariates. Blacks attend religious services significantly more frequently than do whites, but also report significantly lower levels of social support and lower neighborhood collective efficacy. At the residential tract-level, black respondents live in tracts characterized by a significantly higher proportion of blacks (52.7%) compared to white respondents (6.7%), but a significantly lower proportion of older adults (13.5% among blacks, 16.4% among whites).

[Table 2.1 about here]

Next, I examine the results of multivariable generalized ordered logit models to consider how social network factors predict the frequency of discrimination when accounting for

individual, neighborhood, and other social factors that could shape this experience. Table 2.2 presents the odds ratios from generalized ordered logit models that predict how frequently respondents report that others act as if they are better than they are in their day-to-day lives. This model includes the full set of covariates shown in Table 2.1.

Among the social network predictors, network size and frequency of contact with network members do not appear to shape how frequently respondents experience this form of discriminatory treatment. A higher proportion of kin in one's personal network, however, is significantly associated with lower odds of reporting more frequent discrimination across each cumulative logit model. The magnitude of this association increases slightly across the categories of discrimination frequency (odds ratio [OR] = .648 when comparing "never" vs. more frequent categories, $p < .05$; OR = .502 when comparing "never" through "several times a year" vs. "about once a month or more frequently," $p < .01$). Thus, a more kin-centric network appears to protect against more frequent experience of this type of discrimination.

With regard to individual-level covariates, age is significantly associated with lower odds of respondents reporting that others more frequently act as if they are better than they are, and this association is relatively consistent across categories (OR between .935 and .940; $p < .001$ at all thresholds). Women also demonstrate lower odds than men of reporting more frequent experience of this type of discrimination (OR between .738 and .811; $p < .05$), although these gender differences do not reach statistical significance when comparing the odds of experiencing the most frequent level of discrimination versus less frequent levels. Being black is associated with higher odds of experiencing higher levels of discriminatory treatment when predicting experiences more frequently than "about once or twice a year" (OR = 1.494; $p < .05$) or more frequently than "several times a year" (OR = 1.882; $p < .05$). College education is also associated

with higher odds of reporting some amount of discrimination (OR = 1.390, $p < .001$) – i.e., more often than "never."

The findings from this model suggest that other social and contextual factors also shape the frequency of discrimination experience. Higher levels of neighborhood collective efficacy appear to protect against more frequent discrimination experience, and the magnitude of this association increases across thresholds (OR = .819, $p < .05$ in the cumulative logit predicting more frequent than "never"; OR = .562, $p < .001$ in predicting more often than "several times a year"). Higher levels of social support and a higher percentage of blacks in respondents' residential tracts are each associated with significantly lower odds of experiencing this form of discrimination more often than "about once or twice a year" (OR = .819, $p < .05$ and OR = .410, $p < .01$, respectively).

[Table 2.2 about here]

Table 2.3 presents the results from generalized ordered logit models predicting the frequency at which respondents report that they are treated with less courtesy than other people in their day-to-day lives. This outcome is the second of the two EDS items that are asked in the NSHAP. Like the first set of multivariable results, network size and frequency of contact with network members are not significantly associated with the frequency of this form of discrimination. A more kin-centric personal network, however, appears to protect against this type of mistreatment. Higher levels of proportion kin are associated 44% lower odds of experiencing this form of discrimination more often than "less than once a year" ($p < .001$) and 56.3% lower odds of reporting this experience more often than "about once or twice a year" ($p < .001$).

Women also demonstrate significantly lower odds than men of reporting that this form of

discrimination occurs more often than “less than once a year” (OR = .786, $p < .05$). In this model, however, there are no significant differences between blacks and whites. College attendance exhibits statistically significant associations with discrimination frequency, but the direction of this association changes across thresholds. Specifically, older adults who attend college have higher odds of reporting at least some experience with this type of discrimination, i.e., more often than “never” (OR = 1.332, $p < .05$). At the same time, college attendance is inversely associated with the highest frequency of discrimination experience (OR = .664, $p < .05$). Individual health is also relevant, as better self-rated health is associated with significantly lower odds of experiencing this form of discrimination more often than “less than once a year” (OR = .751, $p < .05$), as well as more often than all higher frequency thresholds.

As with the first discrimination item, social and contextual factors also shape how often respondents report that they are treated with less courtesy than other people. Higher levels of social support are associated with lower odds of experiencing this type of discrimination more often than “less than once a year” (OR = .764, $p < .001$), and also more often than “about once or twice a year” ($p < .714$, $p < .001$). Other more specific potential sources of social support, however, are associated with more frequent discrimination experience. In particular, older adults who report more frequent religious attendance demonstrate significantly higher odds of reporting more frequent occurrence of this form of discrimination (OR = 1.081, $p < .01$ for more often than “never,” and OR = 1.085, $p < .05$ for more often than “about once or twice a year.”)

Across each of the cumulative logit models, higher levels of collective efficacy are associated with significantly lower odds of more frequent discrimination. The magnitude of this association ranges from 19.9% lower odds ($p < .05$ for more often than “never”) to 34.8% lower odds ($p < .001$ for more often than “several times a year”). A higher percentage of blacks in

respondents' residential tracts is associated with significantly lower odds of experiencing only the highest levels of this form of discrimination (OR = .354, p <.05 for more often than "several times a year"). There are no statistically significant associations between the percentage of tract residents ages 65 and older and the frequency of being treated with less courtesy than other people.

[Table 2.3 about here]

Both models (Tables 2.2 and 2.3) indicate that a higher proportion of kin in one's personal network is significantly associated with less frequent discrimination experience. I next examined generalized ordered logit models that include a race by proportion kin interaction term. This interaction term is used to assess whether network kin composition may differentially shape how frequently black and white older adults experience discrimination.

I do not find evidence that race moderates the relationship between proportion kin and how often respondents report that they are treated with less courtesy than other people. However, race does appear to moderate the association between proportion kin and how often respondents perceive others acting as if they are better than they are in their day-to-day lives. The interaction term reaches statistical significance when predicting whether respondents report that they experience this form of discrimination more often than "less than once a year" (OR = 2.306, p < .05) and more often than "about once or twice a year" (OR = 2.659, p < .05).

Figure 2.1 illustrates this interaction using the adjusted predictions from the model estimates predicting whether discrimination experiences occur more often than "about once or twice a year." Predicted probabilities for black respondents are represented by the dashed purple line, and probabilities for white respondents are represented by the solid green line. As this figure demonstrates, more kin-centric personal networks are associated with a decreasing

likelihood of white respondents experiencing this form of discrimination more often than "about once or twice a year." Indeed, there is a .13 decline in predicted probability when comparing white respondents with no kin in their networks to white respondents who have entirely kin-based personal networks. Among black older adults, higher levels of proportion kin are associated with a slight increase in the likelihood of experiencing more frequent levels of this type of discrimination, although the slope of this line is relatively flat compared to the trend for whites. Blacks who have entirely kin-based networks exhibit a .03 increase in the probability of experiencing discrimination more often than "about once or twice a year" compared to blacks who have no kin in their network. The full model results are presented in Appendix Tables 2.1 and 2.2.

[Figure 2.1 about here]

In the final stage of the analysis, I turn to the question of whether the reason for discriminatory treatment is partly a function of social network properties, above and beyond individual and other social factors. Figure 2.2 depicts the proportion of black and white respondents, separately, who report each of the personal attributes as the main reason for experiencing discriminatory treatment. This distribution reflects those respondents who were included in the analyses reported in Tables 2.2 and 2.3, who reported some discrimination experience (i.e., more than "never" for either of the two measures), and who also responded to the follow-up question that asked them to indicate what they thought to be the main reason for the discriminatory treatment (respondents could select multiple "main reasons").

A notable proportion of both black and white older adults select "age" as the main reason for discriminatory treatment, including 39% of whites and 25% of blacks. The majority of blacks (64%) indicate race/ethnicity as the main reason for discriminatory treatment, compared to just

7% of whites. Nearly half of whites (46%) indicate that there was some "other reason" for the discrimination that they experienced, with smaller percentages of older adults indicating gender (11% of whites, 16% of blacks), height or weight (11% of whites, 5% of blacks), or sexual orientation (1% of whites, 3% of blacks) as the main reason.

[Figure 2.2 about here]

Given these patterns, I focus on predicting the two most prevalent and specified "main reasons" for each racial group, including age discrimination among white respondents and racial/ethnic discrimination among black respondents.[11] The first model is this series is limited to respondents in the main sample who report any discrimination experience (i.e., more often than "never"). The second model is limited to respondents who experience discrimination at least "about once or twice a year." Given that proportion kin is associated with discrimination experience, intentionally selecting on respondents with more frequent discrimination experience provides a more stringent circumstance under which to test the potentially multifaceted role of personal networks in shaping perceived discrimination. Put differently, if more kin-centric networks protect against discrimination experience, especially for whites, what is the relevance of network factors, if any, among those who perceive discrimination at least annually and who have a lower proportion of kin? Among blacks, for whom frequency of discrimination is less related to network factors, are social networks relevant for those experiencing higher levels of discrimination?

[11] In supplementary models, I also predicted discrimination for "other reason" among white respondents, since this reason – although non-specific- was selected by the highest proportion (46%) of white respondents in the sample. The results suggest that discrimination for some "other reason" is significantly shaped by younger age (log odds = -.047, $p < .001$), better self-rated health (log odds = .409, $p < .05$), and more frequent religious service attendance (log odds = .067, $p < .05$). It is possible that these respondents attribute discriminatory treatment to social class/socioeconomic circumstances, religion, political affiliation, or other belief systems that were not included as options in the NSHAP. Additional research is needed to understand the specific reasons that comprise this category.

Table 2.4 presents the average marginal effects (AMEs) from logistic regression models predicting whether blacks report race/ethnicity as a main reason for experiencing discrimination. A more kin-based personal network is associated with a 14.3 percentage point increase in the probability of reporting race/ethnicity-based discrimination among blacks who report any degree of discrimination ($p < .10$), and a 20.5 percentage point increase in the probability when the sample is limited to blacks who report discrimination at least annually ($p < .05$). An adjusted Wald test indicates that the proportion kin coefficients are marginally different across these two models ($F = 3.41$, $p = .07$). While network size and frequency of contact with network members are not significantly associated with blacks' experience of racial/ethnic discrimination, a higher proportion of blacks in respondents' residential tract is associated with a significantly lower likelihood of attributing discriminatory experiences to one's race/ethnicity (AME = -.410, $p <.001$ in Model 1 and AME = -.466, $p < .001$ in Model 2). Additionally, poorer functional health is associated with a 13.3 percentage point decline in attributing discrimination to race/ethnicity among blacks who experience discrimination at least annually ($p < .01$).

[Table 2.4 about here]

Turning to white respondents, for whom age is the most selected, specific reason for discrimination, I examined whether social network factors were associated with age-based discrimination. The results in Table 2.5 suggest that age-based discrimination is largely a function of respondent age. A one-year increase in age is associated with a 1.4 percentage point increase in the likelihood of attributing discriminatory treatment to age ($p < .001$). Women are less likely to report age-based discrimination than are men (AME = -.060, $p < .05$), as are older adults who report better self-rated health (AME = -.070, $p < .05$). A larger personal network is associated with a higher likelihood of reporting age-based discrimination among whites who

report any discrimination (AME = .025, p <.05). Supplementary analyses indicate that only when accounting for religious service attendance and social support does network size reach statistical significance (adjusted Wald test: F = 3.12, p < .10). This suggests that network size alone does not shape age-based discrimination, but that its correlation with higher levels of social support and religious attendance drive this association.

[Table 2.5 about here]

The logit models described above rely on subsamples of the larger analytic sample based on race and frequency of discrimination. To test the robustness of these findings, I examined a multinomial logit model that used an alternate, combined specification of the two sets of outcomes (frequency and reason for discrimination) as the dependent variable, and that relied on data from the full analytic sample (blacks and whites who do and do not report any discrimination). Outcome categories were coded as follows: 0 = no discrimination reported (i.e., "never"); 1 = some amount of discrimination reported, and race/ethnicity is selected as a main reason; 2 = some amount of discrimination reported and another main reason was selected.[12] Category 1 was used as the base outcome.

Black respondents had significantly lower relative log odds compared to whites of experiencing no discrimination (multinomial log odds = -2.445, p < .001) versus discrimination for race/ethnicity. Likewise, blacks had significantly lower relative log odds compared to whites of experiencing discrimination for a reason other than race/ethnicity (multinomial log odds = -3.518, p < .001) versus experiencing racial/ethnic discrimination.

The inclusion of an interaction term between race and proportion kin lends further support to the findings in the main analyses (multinomial log odds for black by proportion kin

[12] If respondents selected race/ethnicity and another main reason, they were coded as experiencing race/ethnicity as the main reason (category 1).

interaction term = -1.154; p = .06). In terms of adjusted predictions, blacks with no kin in their network are approximately 9.3 percentage points less likely to report race/ethnicity as the main reason for discrimination (predicted probability = .459) than are blacks whose networks are comprised entirely of kin (predicted probability = .552).

DISCUSSION

Understanding discrimination is key to understanding an important source of variation in a number of consequential individual outcomes. The majority of sociological perspectives consider perceptions of discrimination to be a function of individual characteristics and, to some extent, the broader social environment (e.g., Hunt et al. 2007; Monk 2015; Stokes and Moorman 2016). This study extends this structural perspective by examining the possibility that the frequency and type of perceived discrimination that individuals experience may be partly determined by properties of those core network relationships that are characterized by frequent interaction and support exchange, and that have the potential to shape how individuals' perceive their own social identities in everyday interactions (Fischer 2011; McFarland and Pals 2005; Merolla et al. 2012; Wellman and Wortley 1990; Walker and Lynn 2013).

Perceived discrimination was prevalent among the older adult sample, with the majority of black and white respondents reporting at least some experience of discrimination. Overall, a higher proportion of kin in older adults' personal networks appears to protect against more frequent discrimination experience; however, there is some evidence that this association differs by race in predicting how often others act as if they are better than they are. Among whites, a more kin-centric personal network is associated with significantly less frequent perceived discrimination. Among blacks, a higher proportion of network kin is associated with little overall

change in frequency of discrimination experience between those with more or less kin-centric networks. Black respondents were most likely to report race/ethnicity as the main reason for discrimination, while white respondents were more likely than blacks to report age as the main reason for discrimination. This study provides some evidence that a more kin-centric personal network may increase the likelihood that blacks who experience discrimination in their day-to-day lives cite race/ethnicity as the main reason for discrimination.

Why might the presence of family in older adults' personal networks be especially relevant to perceived discrimination? There are several possible explanations for the main finding that proportion kin and frequency of discrimination are inversely associated. For one, a higher proportion of kin may reflect greater and easier access to social support that diminishes the evaluation of negative or otherwise stressful interpersonal interactions as discriminatory against one's identity. The provision of this support may be distinct from broad indicators of social integration such as network size and frequency of interaction with network members (Marsden 1987; Wellman and Wortley 1990). More so than other network ties, kin are typically older adults' main source of social support (Suanet, van Tilburg, and Broese van Groenou 2013). The close-knit structure of kin ties may also facilitate support access and coordination (Domínguez and Watkins 2003; Hurlbert, Haines, and Beggs 2000) following an event that could be categorized as discriminatory. Support from kin may take the form of helping an older adult to re-evaluate an otherwise discriminatory interaction in a way that no longer seems to negatively target the individual's social identity. Further, older adults who have a higher proportion of kin in their network may spend more of their social time interacting with family, and less time interacting with others in their community who could be potential sources of discrimination.

Importantly, these results call for consideration of the different roles of kin in black and

white older adults' personal networks. Although this study distinguished between the frequency and type of discrimination experience, my explanations for these findings draw on both of these factors. A more kin-centric network may be associated with less frequent discrimination among whites because there may be less overall experience with discrimination within the network. Whereas blacks are more subject to racial discrimination throughout the life course (Gee et al. 2012), those identities or attributes that whites are more likely to cite as reasons for discrimination (e.g., age, weight) are less universally experienced and may peak at different periods over the life span (Gee et al. 2007), leading to a less consistent pool of discrimination experience to draw from in whites' personal networks. Likewise, there is greater potential for heterogeneity among network kin on the basis of identities such as age, appearance, and even health status.[13] Thus, a more kin-centric network could be less likely to corroborate interpretations of ageism, for instance, if there is less similarity on age and less experience with ageism within the network. In this sense, kin network ties among whites are more likely to dissuade rather than confirm a particular experience as discrimination.

An additional possibility draws on a key tenet of identity theory, which is that identities range in stability and fluidity (Stryker and Burke 2000). Age is a more localized and less culturally-entrenched identity than is race. The fluidity of age, for example, could make it easier for kin to dissuade the individual from holding those self-perceptions or identities such as "old" or "elderly" that could be the basis of discrimination. A higher proportion of network kin could also facilitate communication among network members regarding an older adult's stigma or sensitivity toward potential bases of discrimination, including age, appearance, and disability,

[13] Health/disability was not specified as a "main reason" in the NSHAP but is a basis of everyday discrimination in other studies (e.g., Kessler et al. 1999), and may represent the large proportion of respondents who select "other reason" in the NSHAP.

creating an interpersonal context that protects older adults from interpreting day-to-day interactions as mistreatment on the basis of those identities.

By contrast, a higher proportion of kin in blacks' personal networks may indicate a more racially homogenous network that can corroborate older adults' experiences of racial discrimination through alters' recounting of their own personal experiences. Corroboration may also occur through kin ties' direct witness of discrimination by spending time with network members in their day-to-day interactions, especially in spaces with a higher potential for discrimination to take place. For example, family members often accompany older adults to medical visits (Wolff and Roter 2011), and racial minorities are more likely than whites to have someone accompany them on these visits (Sentell et al. 2018). As the health of blacks declines at a faster rate than it does for whites (Ferraro and Farmer 1996), these findings may partly reflect greater contact with the healthcare system among black older adults' and their kin ties – a frequent context of discrimination (Stepanikova and Oates 2017).

Among whites, however, younger kin network members (e.g., adult children, grandchildren) may buffer discrimination experiences when spending time with the respondent as part of day-to-day interactions, as treatment from strangers may be less likely to be laden with age bias when older adults are with these kin members. This scenario could be contrasted with times when an older adult is alone or with similarly aged (non-kin) friends and may be more likely to be mistreated based on their age.

An interesting takeaway from this study is that social network factors are less relevant to how often blacks perceive discrimination in their day-to-day lives but may influence the recognition of racial/ethnic discrimination. The frequency of discrimination among blacks may be more a function of individual and social environmental factors that structure opportunities for

discrimination, such as education, neighborhood, and workplace composition (Abramson, Hashemi, and Sánchez-Jankowski 2015; Hunt et al. 2007). The more general role of kin ties as a basis of racial solidarity may contribute to identifying discrimination as race-based (Hughes et al. 2006). More so than other same-race network members, kin may heighten the salience of blacks' racial identity and, in turn, the awareness of race-based mistreatment (Sellers and Shelton 2003). That these results are observed among an older adult sample of blacks suggests that family-based socialization processes around anticipating racial discrimination may endure across the life course, and may even be reinforced through older adults' participation in socializing younger generations (Hicken et al. 2013; Hughes et al. 2006).

Finally, while this study contributes to the broader literature on racial differences in perceived discrimination, it is worth considering that kin network ties actually function in similar ways among blacks and whites. In both cases, family ties are contributing to individual perceptions of discrimination in directions that are consistent with the enduring racial stratification in the United States. Among whites, kin ties may dissuade individuals from perceiving that discrimination occurred, while blacks' kin ties may heighten awareness of race-based discrimination. This echoes the notion that race is "…an organizing principle of social relationships that shapes the identity of individual actors at the micro level and shapes all spheres of social life at the macro level" (Bonilla-Silva 1997, p. 466). To the extent that family contexts maintain ideologies of racial hierarchy (Bonilla-Silva 2006), more kin-centric networks may help to maintain the health advantages of white older adults relative to blacks by preventing the experience of a key source of mental and physical health adversity.

Limitations and Future Directions

The NSHAP provides one of the first opportunities to examine how individuals' experiences of discrimination are shaped by their personal social networks. Despite the strengths of this dataset, several limitations should be considered. First, although the NSHAP includes three waves of data, questions about discrimination were only administered at Wave 3. The cross-sectional nature of this analysis means that the findings could reflect endogeneity due to reverse causality. Experiences of discrimination could play a role in shaping individuals' personal social networks. Longitudinal data on discrimination and personal network composition would allow for a more rigorous (yet still not definitive) test of the hypothesized directionality.

In the absence of this data, however, I examined supplemental generalized ordered logit models that use lagged (Wave 2) social network measures to predict frequency of perceived discrimination at Wave 3. This model takes the following form, where *t* refers to Wave 3:

$$P(FreqDiscrimination_{it} > j) =$$

$$\exp(\alpha_j + \boldsymbol{ß_j Network_{it-1}} + ß_j SocialContext_{it} + ß_j Sociodemographic_{it} + ß_j LifeCourse_{it} + ß_j Health_{it}) /$$

$$1 + [\exp(\alpha_j + \boldsymbol{ß_j Network_{it-1}} + ß_j SocialContext_{it} + ß_j Sociodemographic_{it} + ß_j LifeCourse_{it} +$$

$$ß_j Health_{it})] \text{ , } j = 1, 2, 3, 4 \tag{2.1}$$

The estimates from these models lend support to the main findings. A higher proportion of kin in one's personal network at Wave 2 is associated with significantly lower odds of reporting that others act as if they are better than them more often than "never" (OR = .636, $p < .05$) and more often than "less than once a year" (OR = .575, $p < .05$) at Wave 3. Likewise, a higher proportion of kin in one's personal network at Wave 2 is associated with significantly lower odds of reporting that others treat them with less courtesy than other people more often than "never" (OR = .636, $p < .05$) and more often than "about once or twice a year" (OR = .492,

$p < .05$) at Wave 3. Race by proportion kin interactions do not reach statistical significance in these models, nor do network measures in models predicting race-based discrimination. These null findings may be a result of the smaller analytic sample of respondents who were interviewed at Waves 2 and 3 (N =1,725), including half the number of black respondents – 140 of whom report any discrimination.

In addition to these findings, research on the intersection of the life course, social networks, and discrimination lends additional theoretical support to the associations as they are modeled in this study. First, kin network ties are key emotional supports for older adults (e.g., Wellman and Wortley 1990). If perceived discrimination – a typically emotionally distressing experience (Williams et al. 2012) – was more heavily influencing social network composition as opposed to vice versa, one would expect that older adults who have the most frequent discrimination experience also have the most kin-centric networks. More frequent racial discrimination may lead black older adults to maintain more kin-centric networks. Among whites, however, I find instead that proportion kin and frequency of discrimination are inversely associated. Likewise, the few studies on whether social support moderates the link between perceived discrimination and health find null results (Pascoe and Smart Richman 2009). This may reflect that the greatest relevance of social ties sequentially precedes the link between discrimination and health – in other words, that social support from network ties is instead shaping perceptions of discrimination experience.

Second, age discrimination peaks twice in the life course: first when individuals are in their twenties, and again in their mid-fifties (Gee et al. 2007). Respondents in the analytic sample are, on average, past the point in the life course when ageism is at its height. Indeed, the findings in Tables 2.2 and 2.3 support the negative relationship between age and frequency of

discrimination experience. Even if earlier experiences of discrimination shaped network kin composition, this influence is likely to have already played out prior to the time when respondents are observed in the NSHAP. Thus, respondents' personal networks at the time they are measured in this study already reflect prior influence of earlier age-based discrimination.

A similar postulation can be made for race-based discrimination. In their conceptual model of racial differences in life trajectories, Gee and colleagues (2012) emphasize that blacks' experiences of racial discrimination may be at their height between early adulthood and midlife. During this period of the life course, blacks are more likely to face discrimination through their interactions with employers, criminal justice personnel, health care professionals, and other social services and social institutions. Even if these experiences lead individuals to prefer a closer-knit network of trusted kin, this influence would already be reflected in the type of social networks that blacks maintain when they enter later life.

Other limitations include the possibility that discrimination experiences are underreported. Members of stigmatized groups may not report discrimination given perceived social costs, to protect one's self-esteem or sense of justice (Kaiser and Major 2006), or to avoid the distress that accompanies admitting to being the victim of discrimination (Williams et al. 2012). It also is worth noting that the NSHAP only collects reports of respondents' perceptions of everyday discrimination. Other studies demonstrate the significance of exposure to major discrimination experiences over the life course such as being fired from a job (e.g., Kessler et al. 1999). Future research should consider how social network factors are associated with major discriminatory experiences, as well as the influence of personal networks on individuals' experiences with multiple forms of discrimination. Additional work should also explore the role of social networks among older adults of other racial/ethnic groups, and among other populations

for whom perceived discrimination is consequential.

CONCLUSION

Rather than thinking of individual identities as the starting point for discriminatory experiences, this work emphasizes that these identities are situated in social contexts such as the family that intersect with broader stratification systems, and that are uniquely positioned to shape their meaning in everyday life. Recent research emphasizes the need to more fully explore a range of individual and social factors that predict discrimination, particularly among blacks for whom this experience is both common and detrimental to health (Monk 2015; Williams 2018). These findings suggest that aspects of individuals' personal networks are a relatively overlooked source of within and between group differences in the link between discrimination experience and health, as well as other outcomes for which racial disparities persist. Future research should more fully consider the social network context as a potential source of heterogeneity in these associations.

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Table 2.1 Descriptive Statistics of Key Variables, by Race.

	Proportion or Mean (SD) [a]	
	Blacks (N = 529)	**Whites (N = 2,622)**
Everyday Discrimination		
"In your day-to-day life, how often have others acted as if they're better than you are?"		
0 = Never	.427*	.379
1 = Less than once a year	.189***	.261
2 = About once or twice a year	.140**	.193
3 = Several time a year	.113	.093
4 = About once a month or more frequently	.130***	.075
"In your day-to-day life, how often have you been treated with less courtesy than other people?"		
0 = Never	.399	.432
1 = Less than once a year	.221*	.263
2 = About once or twice a year	.151	.171
3 = Several time a year	.104***	.061
4 = About once a month or more frequently	.125***	.073
Social Network Variables		
Network size (Range: 1 to 5)	3.610 (1.510)**	3.931 (1.235)
Average frequency of interaction with network members (Range: 0 "never" to 8 "everyday")	7.007 (.929)***	6.728 (.845)
Proportion kin in network (Range: 0 to 1)	.650 (.364)	.622 (.307)
Sociodemographic, Life Course, and Health Covariates		
Age	62.045 (9.763)**	64.313 (9.573)
Female (1 = yes)	.590	.551
Attended college (1 = yes)	.493***	.653
Retired (1 = yes)	.495**	.562
Married/partnered (1 = yes)	.537***	.730
Self-rated physical health (1 = Excellent/very good/good; 0 = Fair/poor)	.707***	.810
Functional limitations (Average of 9 standardized items, Range: -3.46 – 6.140)	.078 (.854)***	-.071 (.625)
Social and Contextual Covariates		
Frequency of attending religious services (0 = "never"; 5 = "several times a week)	2.852 (1.799)***	1.972 (1.732)
Social support (Average of 4 standardized items, Range: -3.046 – 1.140)	-.079 (.785)**	.066 (.693)
Neighborhood collective efficacy (Average of 8 standardized items, range: -2.22 – 1.79)	-.172 (.719)***	.048 (.642)
Proportion black, non-Hispanic in tract	.527 (.363)***	.067 (.117)
Proportion age 65 years and older in tract	.135 (.055)***	.164 (.071)

*$p < .05$, **$p < .01$, ***$p < .001$ (Two-tailed tests). Asterisks indicate significantly different from whites.
[a] Means are weighted using NSHAP Wave 3 respondent-level weights (adjusted for selection) and are survey adjusted. Standard deviations appear in parentheses for continuous variables. Proportions are

unweighted.

Table 2.2 Odds Ratios from Generalized Ordered Logit Model Predicting the Frequency of Others Acting "As if They're Better than You Are" (N = 3,151).[a]

Predictor	Odds of reporting experiencing discrimination more than:			
	Never	Less than once a year	About once or twice a year	Several times a year
Network size	1.043	1.018	1.071	1.083
	(.964 - 1.127)	(.941 - 1.101)	(.981 - 1.170)	(.951 - 1.232)
Frequency of contact with network members	.979	1.032	1.192*	1.201
	(.846 - 1.135)	(.888 - 1.198)	(1.008 - 1.409)	(.950 - 1.519)
Proportion kin in network	.648*	.625**	.530**	.502**
	(.463 - .908)	(.458 - .853)	(.359 - .781)	(.308 - .820)
Age	.940***	.940***	.935***	.936***
	(.929 - .952)	(.929 - .950)	(.920 - .949)	(.914 - .958)
Female	.811*	.806*	.738*	.745
	(.667 - .987)	(.657 - .989)	(.585 - .931)	(.531 - 1.044)
Black	.952	1.013	1.494*	1.882*
	(.656 - 1.380)	(.705 - 1.457)	(1.042 - 2.143)	(1.097 - 3.229)
Attended college	1.390**	1.078	.786	.726
	(1.101 - 1.754)	(.854 - 1.361)	(.591 - 1.045)	(.506 - 1.043)
Retired	.816	.667***	.614***	.709
	(.657 - 1.015)	(.551 - .808)	(.473 - .797)	(.435 - 1.156)
Married/partnered	1.082	.861	1.015	.856
	(.870 - 1.345)	(.701 - 1.058)	(.803 - 1.283)	(.595 - 1.231)
Self-rated health	.914	.808	.710*	.715
	(.721 - 1.160)	(.639 - 1.020)	(.532 - .948)	(.468 - 1.092)
Functional limitations	1.027	1.067	1.169	1.132
	(.862 - 1.225)	(.901 - 1.263)	(.963 - 1.419)	(.879 - 1.457)
Social support	.983	.850	.819*	.812
	(.822 - 1.176)	(.719 - 1.005)	(.686 - .977)	(.649 - 1.015)
Frequency of attending religious services	1.041	1.068*	1.142***	1.079
	(.980 - 1.106)	(1.003 - 1.136)	(1.065 - 1.224)	(.993 - 1.174)
Neighborhood collective efficacy	.819*	.787**	.649***	.562***
	(.687 - .976)	(.680 - .911)	(.546 - .770)	(.445 - .709)
% Black, non-Hispanic in tract	.619	.652	.410**	.391
	(.363 - 1.055)	(.385 - 1.106)	(.216 - .777)	(.129 - 1.182)
% Age 65 and older in tract	.701	2.326	2.915	1.736

	(.203 - 2.425)	(.709 - 7.627)	(.660 - 12.86)	(.221 - 13.62)
Constant	155.9***	51.74***	9.010**	3.980
	(36.43 - 667.2)	(13.79 - 194.2)	(1.861 - 43.62)	(.450 - 35.22)
F (df)	16.33*** (64, 32)			

*$p < .05$, **$p < .01$, ***$p < .001$ (Two-tailed tests). 95% confidence intervals in parentheses.

[a]All estimates are weighted using the NSHAP Wave 3 respondent-level weights that adjust for selection, non-response, and inclusion in the analytic sample, and are survey adjusted.

Table 2.3 Odds Ratios from Generalized Ordered Logit Model Predicting the Frequency of Being "Treated with Less Courtesy than Other People" (N = 3,150).[a]

Predictors	Odds of reporting experiencing discrimination more than:			
	Never	Less than once a year	About once or twice a year	Several times a year
Network size	1.065	1.090*	1.052	1.011
	(.974 - 1.165)	(1.004 - 1.183)	(.955 - 1.158)	(.891 - 1.147)
Frequency of contact with network members	.948	1.046	1.162*	1.152
	(.835 - 1.077)	(.931 - 1.175)	(1.003 - 1.345)	(.936 - 1.418)
Proportion kin in network	.730	.560***	.437***	.478**
	(.531 - 1.005)	(.422 - .744)	(.287 - .664)	(.306 - .746)
Age	.953***	.952***	.956***	.951***
	(.941 - .965)	(.940 - .963)	(.942 - .971)	(.931 - .972)
Female	.866	.786*	.817	.807
	(.716 - 1.047)	(.637 - .970)	(.637 - 1.047)	(.596 - 1.091)
Black	1.166	1.184	1.436	1.696
	(.811 - 1.677)	(.787 - 1.781)	(.893 - 2.307)	(.995 - 2.892)
Attended college	1.332*	1.119	.955	.664*
	(1.064 - 1.667)	(.915 - 1.370)	(.732 - 1.245)	(.459 - .961)
Retired	.858	.793*	.606**	.617
	(.695 - 1.059)	(.632 - .995)	(.444 - .828)	(.372 - 1.024)
Married/partnered	.999	.928	.842	.690*
	(.812 - 1.227)	(.755 - 1.141)	(.649 - 1.092)	(.499 - .955)
Self-rated health	1.004	.751*	.633**	.571**
	(.799 - 1.261)	(.574 - .983)	(.473 - .847)	(.404 - .806)
Functional limitations	1.033	1.024	1.131	1.076
	(.863 - 1.237)	(.834 - 1.256)	(.907 - 1.411)	(.849 - 1.365)
Social support	.933	.764***	.714***	.788
	(.802 - 1.085)	(.658 - .888)	(.603 - .846)	(.612 - 1.016)
Frequency of attending religious services	1.081**	1.059*	1.085*	1.051
	(1.030 - 1.134)	(1.002 - 1.119)	(1.007 - 1.170)	(.958 - 1.154)
Neighborhood collective efficacy	.801*	.669***	.703***	.652***
	(.664 - .968)	(.568 - .789)	(.596 - .828)	(.526 - .808)
% Black, non-Hispanic in tract	.756	.793	.628	.354*
	(.458 - 1.246)	(.470 - 1.338)	(.302 - 1.305)	(.127 - .987)
% Age 65 and older in tract	.711	1.110	.692	.532

	(.193 - 2.617)	(.261 - 4.728)	(.093 - 5.173)	(.078 - 3.647)
Constant	43.93***	13.21***	3.347	4.672
	(10.97 - 175.8)	(4.034 - 43.22)	(.805 - 13.91)	(.622 - 35.12)
F(df)	19.30*** (64,32)			

*$p < .05$, **$p < .01$, ***$p < .001$ (Two-tailed tests). 95% confidence intervals in parentheses.

[a]All estimates are weighted using the NSHAP Wave 3 respondent-level weights that adjust for selection, non-response, and inclusion in the analytic sample, and are survey adjusted.

Table 2.4 Average Marginal Effects from Logistic Regression Models Predicting Race/Ethnicity as the Main Reason for Discrimination, Among Blacks.[a]

Predictors	Blacks reporting *some* discrimination	Blacks reporting at least *yearly* discrimination
Network size	-.023 (.018)	-.017 (.016)
Frequency of contact with network members	.025 (.042)	.015 (.037)
Proportion kin in network	.143† (.080)	.205* (.077)
Age	-.006† (.004)	-.003 (.004)
Female	-.036 (.059)	-.052 (.063)
Attended college	.030 (.042)	.044 (.048)
Retired	-.014 (.068)	-.107 (.076)
Married/partnered	.085 (.052)	.028 (.049)
Self-rated health	-.021 (.046)	-.007 (.056)
Functional limitations	-.049 (.041)	-.133** (.046)
Social support	.023 (.039)	-.002 (.039)
Frequency of attending religious services	-.012 (.015)	-.001 (.013)
Neighborhood collective efficacy	-.039 (.025)	-.066 (.032)
Proportion black, Non-Hispanic in tract	-.410*** (.066)	-.466*** (.059)
Proportion age 65 and older in tract	.304 (.547)	1.269† (.720)
Observations	329	234
F (df)	3.33*** (15, 53)	3.21** (15, 46)

†$p < .10$; *$p < .05$, **$p < .01$, ***$p < .001$ (Two-tailed tests). Standard errors in parentheses.
[a]All estimates are weighted using the NSHAP Wave 3 respondent-level weights that adjust for selection, non-response, and inclusion in the analytic sample, and are survey adjusted. The analytic sample is limited to black respondents who report some discrimination experience and who had non-missing data on the "main reason" for discrimination experience.

Table 2.5 Average Marginal Effects from Logistic Regression Models Predicting Age as the Main Reason for Discrimination, Among Whites.[a]

Predictors	Whites reporting *some* discrimination	Whites reporting at least *yearly* discrimination
Network size	.025* (.010)	.025* (.013)
Frequency of contact with network members	-.000 (.016)	-.010 (.021)
Proportion kin in network	-.047 (.043)	-.017 (.052)
Age	.014*** (.002)	.014*** (.002)
Female	-.060* (.025)	-.058† (.031)
Attended college	-.008 (.027)	.003 (.035)
Retired	.001 (.034)	.031 (.040)
Married/partnered	-.037 (.028)	-.022 (.031)
Self-rated health	-.070* (.035)	-.073 (.044)
Functional limitations	-.023 (.024)	-.039 (.030)
Social support	-.027 (.021)	-.002 (.026)
Frequency of attending religious services	-.013† (.007)	-.015† (.008)
Neighborhood collective efficacy	-.009 (.019)	-.008 (.023)
Proportion black, Non-Hispanic in tract	.029 (.088)	-.010 (.101)
Proportion age 65 and older in tract	-.227 (.161)	-.248 (.195)
Observations	1608	1064
F (df)	9.40*** (15, 81)	7.01*** (15, 80)

†$p < .10$; *$p < .05$, **$p < .01$, ***$p < .001$ (Two-tailed tests). Standard errors in parentheses.
[a]All estimates are weighted using the NSHAP Wave 3 respondent-level weights that adjust for selection, non-response, and inclusion in the analytic sample, and are survey adjusted. The analytic sample is limited to white respondents who report some discrimination experience and who had non-missing data on the "main reason" for discrimination experience.

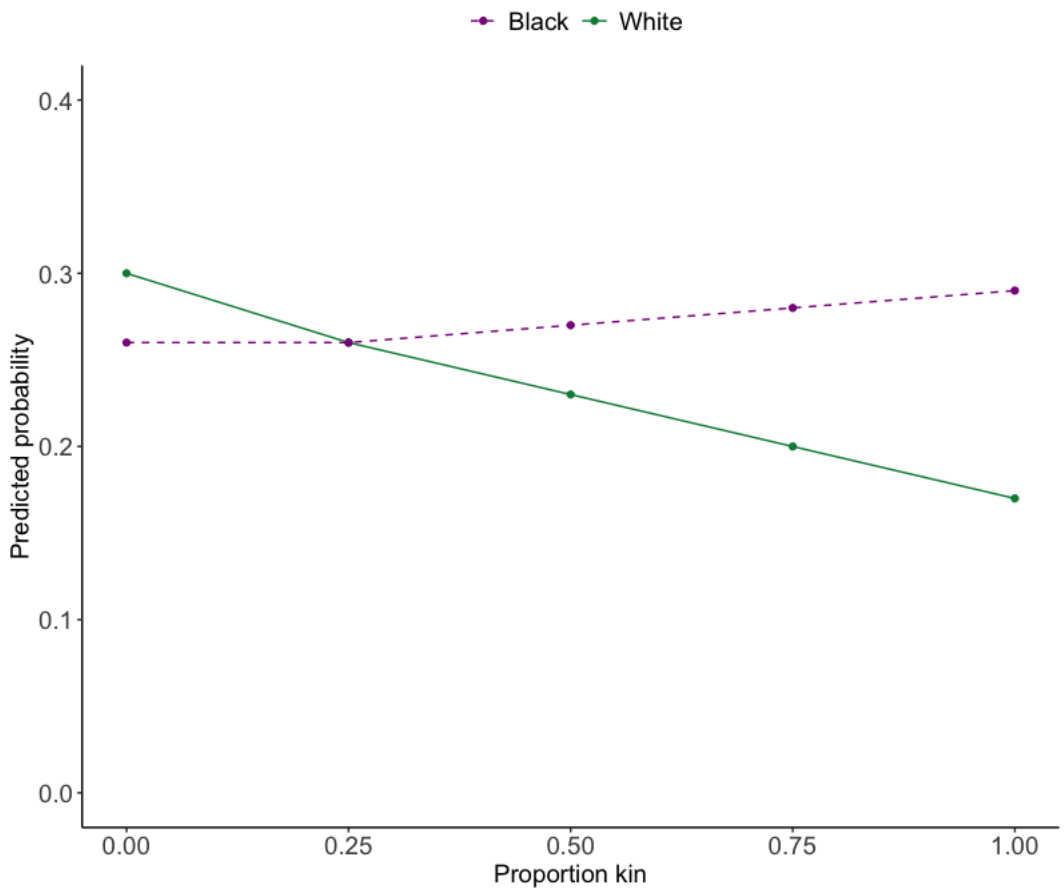

Figure 2.1 Predicted probability of experiencing discrimination more often than "about once or twice a year," by race and proportion kin in respondents' personal networks.
Note: Predicted probabilities are derived from the generalized ordered logit model presented in Appendix Table 2.1, where the frequency of discrimination outcome is how often respondents report that others act "as if they're better than you are."

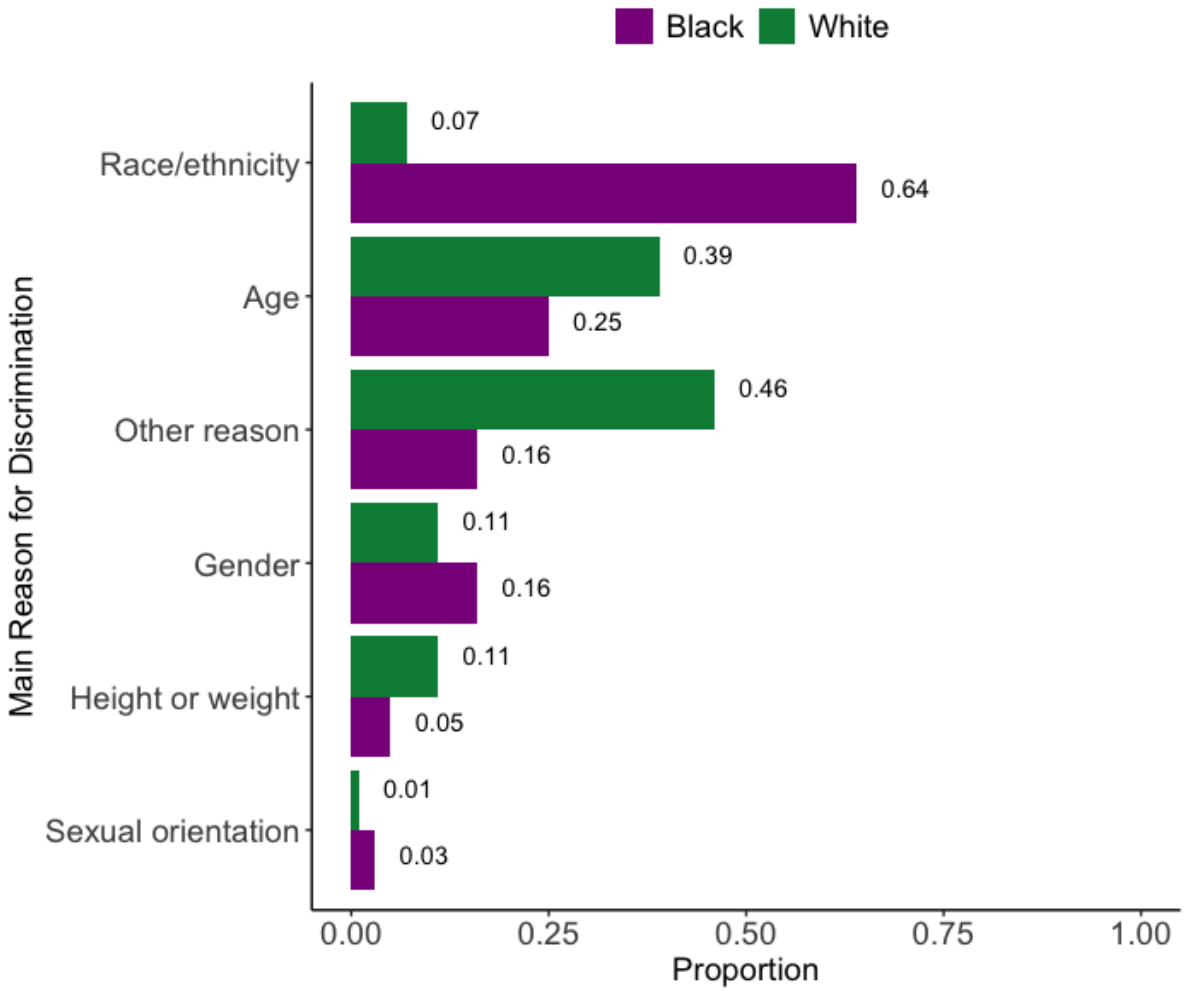

Figure 2.2 Proportion of white and black respondents who report each "main reason" for discriminatory treatment.
Note: Proportions for each racial group sum to more than 1 because respondents were able to select multiple main reasons. Proportions are unweighted and are based on respondents in the main analytic sample (Tables 2.2 and 2.3) who report at least some experience of discrimination, and who had non-missing data on the "main reason" for discrimination experience.

Appendix Table 2.1 Odds Ratios from Generalized Ordered Logit Model Predicting the Frequency of Others Acting "As if They're Better than You Are," Including Race by Proportion Kin Interaction Term (N = 3,151).[a]

Predictors	Odds of reporting experiencing discrimination more than:			
	Never	Less than once a year	About once or twice a year	Several times a year
Network size	1.042	1.017	1.069	1.082
	(.964 - 1.128)	(.941 - 1.098)	(.979 - 1.167)	(.954 - 1.227)
Frequency of contact with network members	.982	1.035	1.191*	1.209
	(.848 - 1.136)	(.891 - 1.202)	(1.009 - 1.406)	(.955 - 1.531)
Proportion kin x Black	1.771	2.306*	2.659*	2.043
	(.719 - 4.359)	(1.053 - 5.050)	(1.019 - 6.936)	(.625 - 6.673)
Proportion kin in network	.600*	.549***	.448***	.449**
	(.407 - .885)	(.390 - .773)	(.289 - .696)	(.263 - .767)
Black	.656	.586	.785	1.161
	(.333 - 1.294)	(.292 - 1.179)	(.374 - 1.647)	(.424 - 3.180)
Age	.941***	.940***	.935***	.935***
	(.929 - .953)	(.930 - .950)	(.921 - .949)	(.914 - .957)
Female	.812*	.810*	.741*	.747
	(.668 - .988)	(.661 - .993)	(.588 - .934)	(.531 - 1.052)
Attended college	1.391**	1.083	.790	.733
	(1.102 - 1.756)	(.858 - 1.367)	(.593 - 1.053)	(.509 - 1.057)
Retired	.816	.667***	.613***	.713
	(.656 - 1.015)	(.549 - .808)	(.473 - .794)	(.436 - 1.164)
Married/partnered	1.089	.867	1.018	.852
	(.877 - 1.353)	(.705 - 1.068)	(.804 - 1.289)	(.590 - 1.231)
Self-rated health	.920	.806	0.710*	.711
	(.726 - 1.166)	(.639 - 1.017)	(.531 - .949)	(.464 - 1.092)
Functional limitations	1.032	1.076	1.179	1.131
	(.865 - 1.230)	(.914 - 1.267)	(.975 - 1.426)	(.879 - 1.457)
Social support	.988	.849	.823*	.809
	(.824 - 1.183)	(.718 - 1.004)	(.690 - .982)	(.648 - 1.011)
Frequency of attending religious services	1.042	1.069*	1.144***	1.081
	(.980 - 1.107)	(1.005 - 1.137)	(1.066 - 1.228)	(.993 - 1.178)
Neighborhood collective efficacy	.813*	.787**	.647***	.563***
	(.681 - .971)	(.679 - .913)	(.545 - .768)	(.447 - .708)
% Black, non-Hispanic in tract	.623	.669	.419**	.405

	(.366 - 1.061)	(.392 - 1.141)	(.224 - .783)	(.137 - 1.194)
% Age 65 and older in tract	.700	2.306	2.965	1.780
	(.202 - 2.419)	(.701 - 7.587)	(.677 - 12.99)	(.225 - 14.11)
Constant	156.8***	54.26***	9.913**	4.133
	(36.68 - 670.1)	(14.46 - 203.6)	(2.108 - 46.61)	(.466 - 36.65)
F(df)	17.16*** (68, 28)			

*$p < .05$, **$p < .01$, ***$p < .001$ (Two-tailed tests). 95% confidence intervals in parentheses.

[a]All estimates are weighted using the NSHAP Wave 3 respondent-level weights that adjust for selection, non-response, and inclusion in the analytic sample, and are survey adjusted.

Appendix Table 2.2 Odds Ratios from Generalized Ordered Logit Model Predicting the Frequency of Being "Treated with Less Courtesy than Other People," Including Race by Proportion Kin Interaction Term (N = 3,150).[a]

Predictor	Odds of reporting experiencing discrimination more than:			
	Never	Less than once a year	About once or twice a year	Several times a year
Network size	1.064	1.090*	1.048	1.007
	(.974 - 1.163)	(1.004 - 1.182)	(.952 - 1.154)	(.887 - 1.143)
Frequency of contact with network members	.953	1.046	1.165*	1.156
	(.839 - 1.082)	(.933 - 1.173)	(1.009 - 1.346)	(.939 - 1.425)
Proportion kin x Black	1.703	1.357	2.275	1.835
	(.788 - 3.682)	(.615 - 2.994)	(.920 - 5.628)	(.559 - 6.023)
Proportion kin in network	.673*	.539***	.370***	.423***
	(.474 - .955)	(.394 - .737)	(.242 - .565)	(.273 - .656)
Black	.820	.962	.861	1.164
	(.466 - 1.445)	(.526 - 1.759)	(.406 - 1.825)	(.456 - 2.972)
Age	.953***	.952***	.957***	.951***
	(.941 - .965)	(.941 - .963)	(.943 - .971)	(.931 - .972)
Female	.868	.788*	.829	.806
	(.718 - 1.050)	(.640 - .971)	(.644 - 1.068)	(.588 - 1.104)
Attended college	1.336*	1.123	.956	.667*
	(1.066 - 1.675)	(.917 - 1.375)	(.735 - 1.243)	(.461 - .961)
Retired	.860	.793*	.597**	.608
	(.696 - 1.061)	(.633 - .994)	(.437 - .815)	(.366 - 1.007)
Married/partnered	1.002	.927	.855	.699*
	(.815 - 1.232)	(.754 - 1.140)	(.656 - 1.114)	(.503 - .971)
Self-rated health	1.005	.752*	.639**	.573**
	(.799 - 1.263)	(.575 - .984)	(.480 - .851)	(.410 - .802)
Functional limitations	1.033	1.026	1.152	1.091
	(.864 - 1.235)	(.837 - 1.258)	(.924 - 1.436)	(.861 - 1.384)
Social support	.934	.765***	.718***	.793
	(.804 - 1.086)	(.659 - .888)	(.608 - .849)	(.620 - 1.014)
Frequency of attending religious services	1.082**	1.060*	1.084*	1.049
	(1.030 - 1.135)	(1.003 - 1.121)	(1.006 - 1.168)	(.956 - 1.151)
Neighborhood collective efficacy	.799*	.671***	.700***	.650***
	(.661 - .966)	(.569 - .791)	(.593 - .827)	(.525 - .805)
% Black, non-Hispanic in tract	.768	.802	.635	.361*

	(.464 - 1.273)	(.471 - 1.364)	(.306 - 1.320)	(.131 - .991)
% Age 65 and older in tract	.710	1.099	.707	.553
	(.194 - 2.590)	(.259 - 4.663)	(.092 - 5.420)	(.080 - 3.826)
Constant	44.27***	13.36***	3.444	4.848
	(11.10 - 176.5)	(4.128 - 43.23)	(.839 - 14.14)	(.642 - 36.61)
F (df)	18.88*** (68, 28)			

*$p < .05$, **$p < .01$, ***$p < .001$ (Two-tailed tests). 95% confidence intervals in parentheses.

[a]All estimates are weighted using the NSHAP Wave 3 respondent-level weights that adjust for selection, non-response, and inclusion in the analytic sample, and are survey adjusted.

CHAPTER 3: HOW DO NEIGHBORHOOD CONDITIONS SHAPE THE STABILITY OF OLDER ADULTS' PERSONAL NETWORKS?

ABSTRACT

Existing frameworks tend to consider personal network changes to be a product of life-course transitions, individual social position, or characteristics of the network itself. In this paper, I argue that personal network changes could also be a function of residential neighborhood conditions that can either challenge or promote the stability of core network relationships. I suggest that different neighborhood conditions may be relevant for the stability of kin and non-kin network ties. Using data from three waves of the National Social Life, Health, and Aging Project (N = 1552) linked with data from the American Community Survey, I estimate how structural and social conditions of older adults' neighborhoods shape the stability of their personal network ties. I find that higher levels of neighborhood concentrated disadvantage are associated with the loss of kin network members. Higher levels of neighborhood social interaction, however, are associated with both the loss and addition of non-kin network ties. I conclude by suggesting that the link between neighborhood conditions and personal network stability may be relevant for studies of "neighborhood effects" on well-being. Further, studies of personal network change should pay greater attention to how the broader social context structures the stability of different types of close personal relationships.

INTRODUCTION

In *Foundations of Social Theory*, James Coleman argues that actors' interests in exchanging social resources leads to "the formation of social relationships having some persistence over time" (Coleman 1990, p. 300). He maintains that this persistence contributes to the emergence of social capital, including community-level social resources such as trust and obligation. Despite the implicit importance of stable social ties, close personal relationships vary considerably in their continuity (Fischer and Offer 2019; Mollenhorst, Völker, and Flap 2014; Shaw et al. 2007; Suitor, Wellman, and Morgan 1997; Wellman et al. 1997). Identifying the social processes that drive personal network change is of key concern to sociologists, especially given the extensive evidence linking point-in-time properties of personal network relationships to individual well-being, access to social resources, and life chances more broadly (Berkman et al. 2000; Wellman and Wortley 1990). Changes in personal networks are therefore consequential for how these individual outcomes are achieved (Bookwala 2016; Cornwell and Laumann 2015; Schwartz and Litwin 2017, 2019).

To date, the predominant frameworks used to explain personal network change have focused on structural properties of the networks themselves (size, embeddedness) (e.g., Mollenhorst, Völker, and Flap 2011), as well as individual-level life-course transitions such as parenthood, retirement, and widowhood that shift the composition of individuals' core set of confidants (e.g., Settels, Schafer, and Henkens 2018; Zettel and Rook 2004). More recently, scholars have shown that personal network changes are also associated with aspects of social stratification. For example, racial minorities and individuals with lower levels of attainment experience higher levels of network turnover and more inconsistent access to supportive social ties (Cornwell 2015; Fischer and Beresford 2015; Schafer and Vargas 2016). Taken together,

these findings raise questions about whether the social patterning of network dynamics could contribute to population-level disparities in health and other resources, calling for greater attention to understanding which dimensions of individual social position contribute to this instability.

In this paper, I examine the possibility that personal network stability is a function of structural and social aspects of individuals' residential neighborhoods. This study is motivated by the extensive "neighborhood effects" literature, documenting that neighborhood conditions contribute to inequality across a range of individual outcomes (Sampson, Morenoff, and Gannon-Rowley 2002; Sharkey and Faber 2014), as well as evidence that neighborhood conditions are consequential for personal social resources (Small 2007; Tigges, Browne, and Green 1998; York Cornwell and Behler 2015). I build on the argument that neighborhoods provide residents with resources and opportunities (or lack thereof) that have implications for social relationships, and extend this line of inquiry to suggest that the stability of personal networks may depend, in part, on how neighborhood conditions shape individuals' needs and constrain their opportunities for forming and maintaining close relationships. This study shifts the focus from individual and network-level determinants of social network instability to the residential neighborhood, suggesting that the conditions where people live can constrain or support the consistency of personal network resources.

To investigate this topic, I rely on three waves of data from the National Social Life, Health, and Aging Project (NSHAP), a population-based panel study of older Americans collected at 5-year intervals between 2005/6 and 2015/16, and linked with data on respondents' residential census tracts from the American Community Survey (ACS). Older adults' well-being is especially vulnerable to both social network changes (Cornwell and Laumann 2015) and the

neighborhood environment (Yen, Michael, and Perdue 2009), making this is a particularly important population for understanding the social environmental processes that underly network change. Following the analysis, I discuss the finding that residential contexts matter for personal network change in nuanced ways, particularly regarding the stability of kin versus non-kin ties. I conclude by suggesting that social network instability may be a key factor underlying the robust associations between neighborhood conditions and later life well-being.

LITERATURE REVIEW

The Importance of Personal Network Change

Personal social networks are immensely valuable social resources that shape a wide range of individual outcomes (Berkman et al. 2000; Wellman and Wortley 1990). There is reason to believe that the degree to which individuals can consistently access these ties has implications for how consistently they can draw on these resources. Instability in one's personal network – that is, overtime changes in one's primary social contacts – can lead to uncertainty or lack of reliability in one's access to advice, information, and instrumental and emotional support. Social network change may be especially consequential for older adults who are more likely than younger individuals to face certain life-course transitions (e.g., retirement, widowhood) and age-related declines in health, which could result in a reshuffling in their network ties (Cornwell et al. 2014). As older adults rely on support from their network members to navigate the challenges that accompany these transitions, their well-being may be especially vulnerable to personal network instability.

In addition to providing social support, the typically tight-knit and settled structure of personal networks allows members to monitor one another's well-being and coordinate support

as needed (Hurlbert, Haines, and Beggs 2000; Umberson 1992). This coordination also helps networks to enforce certain normative behaviors and decision-making (Coleman 1990). From a social-psychological standpoint, social network turnover can also be harmful to individuals' sense of belonging, and ultimately contribute to poorer integration and greater social isolation.

It is important to acknowledge that network turnover is not ubiquitously beneficial or detrimental; rather, the addition and loss of network members can have distinct implications for individual outcomes (Feld, Suitor, and Hoegh 2007). For example, the loss of network members is associated with declines in emotional well-being and higher levels of depression (Bookwala 2016; Cornwell and Laumann 2015; Schwartz and Litwin 2017, 2019), particularly with regard to the loss of kin (Bookwala 2016). The addition of network confidants, on the other hand, is associated with better mental, physical, and self-rated health (Cornwell and Laumann 2015; Schwartz and Litwin 2017).

Personal network change could also be advantageous to the extent that newly added ties reflect access to a new set of social resources, particularly the addition of non-kin (e.g., friends, neighbors) with whom other network members may not be familiar. Indeed, a key insight from social network theory is the idea that certain network structures (e.g., bridging) provide individuals with access to novel, non-redundant information and advice (Burt 1992, 2005; Granovetter 1973). Another possibility is that these network advantages could come from the formation of new network confidants, who could offer perspectives and advice that are unique to the individual during a given period of their life.

Network members who are "lost" or otherwise withdrawn from an individual's personal network may not always reflect a detrimental or an undesirable change. Recent research suggests that approximately 15% of network members are considered by individuals to be at times

"demanding or difficult" (Offer and Fischer 2018). Thus, network churn could reflect individuals' ability to shed ties that are not reciprocating support, or who are otherwise problematic, as in the case of network ties who are abusive (Schafer and Koltai 2015). In this context, network losses can be advantageous for an individual's mental health and level of stress, and even allow them more time and resources to invest in more rewarding network ties. In this sense, social network (in)stability matters not only for (in)consistency in accessing network resources, but also for individuals' ability to fulfill personal needs and achieve well-being in ways that may at times depend on a reshuffling of network members.

Why Do Personal Networks Change?

There are several theoretical orientations that have guided empirical studies of social network change. Earlier accounts emphasized that individuals are deliberate with respect to who they add or drop from their support network, seeking to form and maintain ties with those who provide the most returns in exchange for support and other resources (e.g., Homans 1950). This is echoed in perspectives on network formation that emphasize individuals' rational, entrepreneurial approaches to networking (e.g., Burt 1992). Related to the idea that network changes are intentional, other scholars suggest that individuals prefer a certain "type" of social network and make adjustments to their network membership in order to maintain these personal preferences or "signatures" (Fischer and Offer 2019; Heydari et al. 2018).

The life-course perspective has also been used to consider how close social ties change or persist in light of events and transitions that characterize life stages (Alwin, Felmlee, and Kreager 2018). The transition to adulthood, for instance, is often marked by a shrinkage in network size, as individuals leave home and education-based social contexts and enter the labor

force (Bidart and Lavenu 2005). Working-age adults exhibit an increase in social capital available through occupation-based networks (McDonald and Mair 2010), while retirement leads to a shrinkage in network size (Settels et al. 2018). Widowhood, too, can lead to the addition of new ties or the strengthening of existing ties as compensation for the loss of a spouse (Zettel and Rook 2004). Likewise, transitions into new institutional contexts are broadly recognized as key sites of tie formation, particularly among (non-kin) acquaintances (Kalmijn 2012; Small 2009). Entering college or moving into a retirement community, for example, often prompt considerable changes in individuals' networks as they adjust to the new context, routines, and obligations (Small, Deeds Pamphile, and McMahan 2015).

Later life has also been the focus of several theories on this topic, predicated on the notion that an individual's most supportive social ties are dynamic and responsive to varying support needs across life stages (Antonucci et al. 2010). Whereas disengagement theory proposes that older adults gradually withdraw from social activity as they age, becoming increasingly socially isolated (Cummings and Henry 1961), socioemotional selectivity theory states that older adults become more intentional in their social networks, refocusing their social interactions to only their most rewarding, central social ties (Carstensen 1992; Lansford, Sherman, and Antonucci 1998).

Another perspective considers how social network changes are structured by social position. Several recent studies have found that sociodemographic attributes and measures of attainment are correlated with certain changes in individuals' personal social networks. Among older adults, African Americans and those with less education are more likely to experience network loss than whites and those with more education, and these losses are more likely to be attributed to confidant death (Cornwell 2015). In midlife, too, college-educated individuals are

more likely to experience an increase their network advantages (i.e., frequency of contact, social support), particularly in their ties to non-kin (Fischer and Beresford 2015), while less educated older adults exhibit declines in levels of support from non-kin as they age (Shaw et al. 2007). Higher levels of income are also associated with the stability of resourceful ties over time (Schafer and Vargas 2016). The social patterning of these findings suggests that a range of experiences and circumstances correlated with race and socioeconomic status shape the stability of personal network ties (Mickelson and Kubzansky 2003; Schafer and Vargas 2016).

Contextual frameworks. Each of the perspectives reviewed so far generally focuses on how individual-level factors – personal preferences, life events, race/ethnicity, attainment– are associated with social network change. Other accounts of social network instability have taken a more contextual focus, proposing that events, spaces, and structures beyond the individual are relevant to network dynamics. Some of this work conceptualizes individuals' social networks as a local context in and of itself, having structural properties that can either inhibit or promote relationship stability (Martin and Yeung 2006). Social network ties are more likely to be stable if the network members exhibit greater embeddedness (Feld 1997) – that is, if they share a third contact who reinforces their relationship (Martin and Yeung 2006; Mollenhorst et al. 2011). To this end, kin ties are more likely to persist over time than are non-kin ties (Ikkink and van Tilburg 1999). Likewise, ties that exhibit more intensive, reciprocated support exchange are more likely to continue over time than are more unbalanced network relationships (Ikkink and van Tilburg 1999).

While this research recognizes the relevance of contextual factors, there is also good reason to believe that the structural and social characteristics of one's residential neighborhood play an important role in the consistency of personal network ties. This perspective shifts the

contextual focus beyond the interpersonal network environment, recognizing that the conditions that characterize where people live can structure the needs, alternatives, and opportunities for contact with network confidants (Kalmijn 2012).

Prior social network research and theory speak to this point. Foci theory, for instance, proposes that social context is a key predictor of tie formation (Feld 1981), such that any consistent social or physical entity that organizes individuals' joint activity contributes to the stability of that relationship (Feld 1981; Mollenhorst et al. 2011). Empirical studies of core discussion networks support this notion, finding that the availability of "meeting opportunities" (e.g., churches, schools) is a key predictor of network relationship continuity (Mollenhorst et al. 2014). For older adults especially, local establishments such as eateries facilitate the development and maintenance of social relationships that are key sources of social integration outside of formal organizations (Torres 2018). In the next sections, I more fully develop the argument that individuals' social network (in)stability may be structured by characteristics of their residential neighborhood.

Neighborhood Effects and Social Network Structure

My main argument in this paper is that neighborhood conditions also function as a key contextual factor in social network stability that has been largely overlooked in empirical studies of social network turnover, and one that could contribute to how we understand neighborhood factors as affecting individual outcomes. This study also sheds light on whether neighborhood conditions could underly the social patterning of network instability. Until recently, empirical studies of neighborhoods and social networks have existed largely separate from one another, despite the fact that neighborhoods and social networks are both intrinsic to studies of social

disadvantages and disparities (Desmond and An 2015).

Social networks both reflect and contribute to social position, and this phenomenon can be linked to processes that are rooted in the social environment. Earlier work on social networks emphasized individual social class, education, and occupation as structuring opportunities to form social ties in urban environments (Laumann 1966, 1973). A consistent finding in studies of social networks and stratification is that more socially advantaged individuals exhibit more advantageous social network structures that provide individuals with greater social capital and access to social resources (van Groenou and van Tilburg 2003; Lin 1999, 2000). Lower levels of individual attainment are associated with smaller, more kin-based networks that may be important sources of practical and instrumental support in order to compensate for other forms of disadvantage (Ajrouch, Blandon, and Antonucci 2005; Fischer 1982; Marsden 1987; McDonald and Mair 2010; Tigges et al. 1998). In this regard, social networks are often theorized as key mechanisms through which more socially advantaged individuals obtain better outcomes such as occupational prestige and better health (Berkman et al. 2000; Lin 1999).

At the same time, research on "neighborhood effects" is generally concerned with identifying the direct and indirect ways that neighborhoods shape individual outcomes, above and beyond individuals' own social and economic resources (Sampson et al. 2002; Small and Newman 2001; Wilson 1987). The evidence base to support this hypothesis suggests that the social and economic conditions of residential neighborhoods are important contributors to the stratification of individual life chances, broadly speaking. Indeed, a large literature demonstrates that neighborhood disadvantage adversely shapes a range of social, economic, and well-being indicators, including educational attainment, cognitive development, and health (Hill, Ross, and Angel 2005; Sharkey and Faber 2014; Wodtke, Harding, and Elwert 2011). The effects of

residential neighborhoods are thought to accumulate and persist across the life course (Sharkey and Faber 2014; Wodtke et al. 2011).

Earlier sociological work highlights the inherent connection between neighborhood conditions and social connectedness, particularly in urban environments. The spatial and social isolation of poor black neighborhoods has long been considered a key element in sustaining the poor outcomes of residents in these communities (Jencks and Mayer 1990; Massey and Denton 1993; Tigges et al. 1998; Wilson 1987). Likewise, the social structure of communities has been defined in terms of the persisting patterns of social relationships among residents in different social positions (Laumann 1973).

Collectively, these works imply an important social dimension to how context and community are understood. There is growing interest in formally examining how neighborhood conditions shape social network properties, which has led to the broader recognition that spatial context is a key determinant of developing social ties (Small and Adler 2019). Neighborhood context is consequential for social network size and interaction with network members (Small 2007; York Cornwell and Behler 2015). Importantly, these findings pertain to network ties overall, not just with those who reside within an individual's neighborhood, implying that individuals' broader access to personal network resources arises, in part, out of the neighborhood environment.

Thus, contextualizing social network (in)stability in terms of neighborhood characteristics could shed light on whether place-based factors shape personal network turnover, broadly considered – not just the stability of those ties who reside in the neighborhood. This possibility is discussed in foundational work on neighborhood effects. The social isolation of the urban poor refers not only to residents' access to fewer social ties (i.e., network size), but also to

the intermittent nature of contact with those ties to which they do have access (i.e., network stability) (Massey and Denton 1993; Wilson 1987 p. 61). Disadvantaged or otherwise structurally unstable neighborhoods are thought to alienate their residents from mainstream society by compromising sustained contact with social ties in more advantaged and stable places (Tigges et al. 1998; Wilson 1987). Indeed, Wilson (1987, p. 60) notes that instability in ties with family and friends characterizes the life of residents in poor neighborhoods. This begs the question of how specific attributes of residential neighborhoods could be consequential for personal network stability.

Neighborhood Conditions and Network Instability

Research on "neighborhood effects" has focused largely on those social and structural dimensions of neighborhoods that have implications for the social and economic resources that most significantly shape individual life chances (Aneshensel 2009; Sampson et al. 2002). These echo, to some extent, the earlier perspectives offered by Wirth (1938), who suggested that physical structure and the organization of social relationships guide the study of urban life. Structural dimensions refer to neighborhood socioeconomic conditions, including the socioeconomic and sociodemographic profile of its residents and the overall residential stability (Ross, Reynolds, and Geis 2000; Schieman 2005; Wheaton and Clarke 2003). The social dimension refers to the social interactions that take place within a neighborhood, which serve as the building blocks of neighborhood collective efficacy and social organization, and ultimately contribute to the degree of trust, cooperation, and sense of solidarity that individual residents experience (Morenoff, Sampson, and Raudenbush 2001; Sampson, Morenoff, and Earls 1999; Sampson, Raudenbush, and Earls 1997). As I argue below, there is reason to consider that the

structural and social dimensions of individuals' residential neighborhoods may shape the stability of their personal networks.

Concentrated disadvantage. Neighborhood concentrated disadvantage refers to the degree of socioeconomic disadvantage and opportunity in a neighborhood, often measured as a scale of indicators such as poverty rate, unemployment rate, and educational attainment of residents, among others (Sampson 2012; Wilson 1987). There are several ways that residing in a neighborhood with a high level of concentrated disadvantage might shape personal network stability.

For one, living in a neighborhood characterized by concentrated disadvantage can heighten individuals' experiences of stress, poor health, and lack of social control, which can compromise one's capacity to maintain stable social relationships. Applications of the stress process model conceptualize the social context as a key meso-level measure of structural (dis)advantage that can exacerbate exposure to other stressors (Wheaton and Clarke 2003). Noise, air pollution, inaccessible or poorly maintained public spaces, lack of transportation, and walkability are among the aspects of the physical environment that can lead to stress (Diez Roux and Mair 2010).

Likewise, fear, violence, and a lack of social support or cohesion in the social environment can activate the stress response (Diez Roux 2003). Chronic stress is a key contributor to poor cardiovascular health and other chronic conditions, as well as depression (McEwen 1998). Exposure to neighborhood disadvantage can be distressing for individual residents, and lead to engagement in risky health behaviors such as drug use (Aneshensel 2009; Boardman et al. 2001) that can ultimately compromise one's ability to maintain stable social relationships (Umberson et al. 2016).

Second, neighborhoods house social institutions and organizations (e.g., religious organizations, community centers, nonprofit agencies) that provide residents with access to resources and information. These institutions may be especially important "resource brokers" for socially disadvantaged individuals, who may not otherwise have access to certain organizational services, referrals, or other benefits that these neighborhood institutions bridge (Small 2006; Wilson 1987). Neighborhoods characterized by concentrated disadvantage may offer residents a relatively impoverished, less consistent resource network and fewer shared spaces that would otherwise provide opportunities for tie formation (Sampson 2012; Small and Adler 2019). Indeed, establishments such as senior centers, barbershops, social service organizations, churches, and schools are important sites for developing and maintaining stable network ties with both residents and non-residents who visit these locations (van Eijk 2010; Sampson 2012), and especially for older adults (Torres 2018). More disadvantaged neighborhoods may provide only intermittent access to organizations that could connect residents with more resource-rich institutions and individuals outside of their neighborhood (Small 2007).

Thus, neighborhoods characterized by greater concentrated disadvantage may contribute to residents' social network instability by offering fewer and less reliable locations for forming and sustaining network ties, particularly with non-kin. Relationships with non-kin may depend more on common meeting areas and shared spaces than do longer-standing kin ties, the stability of which may be less dependent on neighborhood characteristics.

Third, neighborhoods with high levels of concentrated disadvantaged imply the concentration of individuals experiencing certain aspects of flux or turbulence in their own lives. These experiences could include high levels of job turnover, periods of unemployment and non-standard work hours, family complexity, as well as housing insecurity and frequent residential

changes (Wilson 1987 p. 61-63), which could directly implicate the stability of individuals' social relationships given inconsistency in daily routine. At the same time, at the community level, the concentration of individuals experiencing these factors also implies a lower degree of investment in neighborhood-level social capital. When people are not around on a consistent basis, there is a lower sense of trust and organization, ultimately weakening norms of collective efficacy, and likely eroding residents' investment in organizations and institutions that could promote the stability of social relationships for all residents' network ties (Schieman 2005; Small 2007).

The reasons outlined thus far suggest that socioeconomically disadvantaged neighborhoods will contribute to network instability. An alternative possibility, however, is that individuals respond to social contexts that might otherwise threaten the stability of their core confidant relationships and access to other resources by maintaining an especially close network of trusted others whose reliability and stability is more likely to withstand contextual challenges. Socioeconomically disadvantaged neighborhoods typically feature weaker social organization and higher rates of crime, which may prompt residents to experience fear and distrust, and avoid spending time in their neighborhoods where there might otherwise be opportunities to form non-kin ties (Schieman and Meersman 2004; York Cornwell and Behler 2015). In the face of stressful circumstances or adversity, however, individuals may activate otherwise dormant sources of social support (Wheaton 1985) and strengthen ties with others who they can count on in times of need (Newman 2003; Stack 1974).

Building on social mobilization theory and the concept of "adaptive cohesion" (Schieman 2005), greater concentrated disadvantage may prompt neighborhood residents to develop stable bonds with other community members as a means of collectively helping one another to

overcome hardships in the social environment. To this point, recent work shows that older adults who reside in high poverty neighborhoods are more likely to have a non-kin network member who resides in their local neighborhood than are older adults living in more advantaged areas (York Cornwell and Goldman 2020).

Collectively, this work lends credence to the idea that personal networks respond to neighborhood conditions. Individuals may seek network ties who can be beneficial sources of support in the face of environmental adversity, but also limit the potential expansion of their networks by avoiding spending time in potentially unsafe spaces. Sought-out ties may include long-standing friendships, other local residents who are less likely to move out of the neighborhood, or kin members whose bonds are reinforced through normative obligations and other mutual contacts (Ikkink and van Tilburg 1999).

Residential instability. Residential (in)stability refers to the consistency in who comprises the households in a given neighborhood or census tract (Sampson et al. 1997), otherwise defined as "the flux of residents into and out of neighborhoods over time" (Ross, Reynolds, and Geis 2000, p. 581). Residential instability is thought to be generally disruptive to social networks, leading to the loss of existing social network ties with other residents and preventing the development of new network ties (Coleman 1990; Sampson et al. 1999). Frequent shifts in residents can directly undermine individuals' ability to form stable ties with their neighbors, simply by virtue of having an unstable neighborhood population from which to form social bonds.

At the neighborhood level, high levels of residential instability can weaken social capital and social organization, as the strength of community norms and sanctions that support social control are weakened by a more transient, less consistent population (Coleman 1990; Shaw and

McKay 1942). Residential instability is associated with lower levels of reciprocated exchange and less intergenerational closure than are more residentially stable neighborhoods (Sampson et al. 1999). In this sense, residential instability may also indirectly lead to more unstable network ties, particularly with non-kin neighbors with whom there is no prior, long-standing relationship, due in part to lower levels of neighborhood social capital and social organization that could make residents more inclined to develop ties with one another.

As with the effects of concentrated disadvantage, however, there is reason to consider that residential instability may not have a ubiquitously negative influence on personal network stability. Akin to the prior discussion of "adaptive cohesion," individuals living in more residentially unstable neighborhoods may develop more stable personal networks as a means of more efficiently and reliably accessing social resources amidst a neighborhood population that is in flux (Schieman 2005). Individuals living in residentially unstable neighborhoods may assess the formation of ties with other residents to be a poor investment, given a higher likelihood that residents relocate in the future, thus leading to more stable ties. In other words, instability at the neighborhood level may prompt greater stability at the personal network level as individuals seek to maximize their own consistent access to social support and minimize the degree to which neighborhood conditions undermine this access (Schieman 2005; Wheaton 1985).

Neighborhood social ties. Interpersonal connections among residents are a fundamental social dimension of neighborhoods that shape communities' abilities to provide key collective resources such as informal social control and social capital that can benefit residents' well-being (Coleman 1988, 1990; Sampson et al. 1999). Individuals may benefit from higher levels of social connections among their neighbors even if they themselves do not frequently interact with other residents, as more frequent interaction and information exchange among neighborhoods helps to

lower levels of delinquency and crime (Sampson and Groves 1989), and contributes to the development and improvement of neighborhood resources (Sampson 1991). High levels of neighborhood social ties also reduce individuals' perceptions of neighborhood fear and mistrust (Ross and Jang 2000), which could promote higher levels of visitation and other interaction with kin and non-kin ties.

At the same time, individuals who reside in neighborhoods with a higher level of social connectedness among neighbors may perceive that they have a greater number of alternative sources of social integration and social support (Fischer 1982). Physical propinquity is a fundamental basis of tie formation (Blau 1977; Small and Adler 2019), and the connection between neighborly interaction and tie formation is well established (Small and Adler 2019). Living in a particularly interpersonal environment could prompt individuals to form new network ties with individuals who they meet in their local area, potentially even substituting these new ties for older network relationships that are no longer as beneficial or pertinent. This may be especially the case for older adults who are aging in place, and those who have few kin ties to draw on (Mair 2019; Yen et al. 2009), as well as socially disadvantaged individuals seeking non-kin sources of social support. For example, Desmond (2012) documents the high levels of non-kin turnover among the urban poor. This account ultimately illustrates the benefits of this type of network turnover for individuals in socioeconomically precarious positions whose immediate support needs change quickly (Desmond 2012). Thus, the loss and addition of non-kin overtime may reflect access to a more opportunistic social context that allows for the formation new ties out of interest, need, or some combination of the two.

THE PRESENT STUDY

This paper is guided by three overarching research questions: First, how are neighborhood conditions associated with the stability of older adults' personal social networks? Second, are any associations between neighborhood conditions and network change explained by individual measures of life-course transitions, sociodemographic characteristics, and attainment that prior research shows to shape social network stability? By examining this research question, I also aim to consider whether neighborhood conditions shape social network instability above and beyond individual indicators of social position. And third, I ask how do neighborhood conditions predict the addition and loss of kin versus non-kin network ties?

The stability of non-kin ties may depend heavily on the availability of neighborhood resources that provide opportunities to develop and maintain ties with neighbors and friends, including organizations that facilitate connections with non-kin outside of the residential neighborhood (e.g., Mollenhorst et al. 2014; Torres 2018). Kin ties, on the other hand, are more likely to be maintained out of normative obligations (Bloem, van Tilburg, and Thomése 2008; Fischer and Offer 2019; Thomése et al. 2005). At the same time, kin ties may also be especially vulnerable to socioeconomic strains that are relevant to the neighborhood context (e.g., housing insecurity, unemployment) and that could also limit their availability for support exchange (Goldman and Cornwell 2018). This work motivates the separate considerations of kin and non-kin network changes as a function of neighborhood conditions, given the possibility of different social processes underlying any associations.

DATA AND METHODS

This analysis relies on data from Waves 1, 2, and 3 of the NSHAP, a population-based study of

community-residing older adults in the United States (Suzman 2009). The overall goal of the NSHAP is to better understand how health and social context intersect to influence older adults' well-being as they age. The original cohort (Wave 1) includes 3,005 non-institutionalized older adults ages 57-85 at baseline (2005-2006), with a weighted response rate of 75.5%. Wave 2 (2010-2011) includes 3,377 returning respondents and their co-resident partners, if applicable, yielding a conditional response rate of 89%. Wave 3 (2015-2016) includes returning respondents and their partners, if applicable (N = 2,409), as well as a new cohort of respondents born between 1948 and 1965 and their co-resident partners (N = 2,368). The conditional response rate for returning respondents at Wave 3 is 89.2%. At each wave, data collection consisted of in-home interviews conducted by the National Opinion Research Center (NORC), which included the collection of personal social network information (described below). Following the in-home interview, respondents were also asked to complete a leave-behind questionnaire (LBQ) to be returned to NORC by mail.

Measures of Personal Network Instability

At each wave of the NSHAP, the in-home interviews began by asking respondents to provide information about their personal social network. Respondents were prompted with the "important matters" name generator:

> *From time to time, most people discuss things that are important to them with others. For example, these may include good or bad things that happen to you, problems you are having, or important concerns you may have. Looking back over the last 12 months, who are the people with whom you most often discussed things that were important to you?*

This instrument is often used in survey research to gather information about respondents'

closest, most supportive social ties (Marsden 1987; Paik and Sanchagrin 2013). Respondents could name up to five individuals (i.e., alters) who comprised Roster A of their personal network.[14] Following the enumeration of network members, respondents were asked to categorize their relationship with each alter (e.g., spouse, partner, child, friend), report how often they spoke with each alter, and how often each alter spoke with every other alter.

At Waves 2 and 3, respondents were presented with a list of the network members that they had named at prior waves and were asked to confirm the computer-identified matches between network members who were listed at multiple waves (see Figure 3.1 for an example). From these across-wave comparisons, I code alters named at Wave 2 but not at Wave 3 as lost. Alters named at Wave 3 but not at Wave 2 are coded as additions, and alters named at Waves 2 and 3 are coded as stable (Cornwell et al. 2014). By combining the categorization of alters as lost, added, or stable with the information about how each network member is related to the respondent, I further classify each network change in terms of whether it pertains to a kin or non-kin network member (e.g., kin network loss, kin network addition).

[Figure 3.1 about here]

Scholars have used a range of approaches to measure changes in personal social networks over time. In some cases, network changes are modeled as differences in a feature of social network structure between two time points (e.g., differences in network density, proportion kin, overall number of losses and/or additions) (see Wellman et al. 1997). Other research focuses on social network *consistency*, as opposed to instability, measured as the proportion of times a given alter appears in an individual's network roster, where the denominator is the total number of

[14] Roster B included the respondent's spouse/partner if they had one who was not named as part of Roster A. Waves 1 and 2 also allowed respondents to name one additional network member (Roster C). In this study, I limit all considerations of the social networks to Roster A.

times that network data are collected (Faris and Felmlee 2019). Given that my main concern is with how neighborhood conditions can prompt the formation or loss of network members, I choose to model change rather than stability. Additionally, because different processes can prompt additions and losses, and because these two types of changes are also linked with distinct individual outcomes, my analysis is designed to assess how neighborhood conditions predict the addition and loss of network members separately (Cornwell and Laumann 2015; Donnelly and Hinterlong 2010; Feld et al. 2007). While differences in network size and proportion kin can indicate growth or decline in overall social integration, this type of summary measure can mask the actual degree of turnover in the network.

For the main analyses, I focus on modeling six distinct types of network change: (1) the number of *total* network additions between Waves 2 and 3, (2) the number of *total* network losses between Waves 2 and 3, (3) the number of *kin* network additions between Waves 2 and 3, (4) the number of *kin* network losses between Waves 2 and 3, (5) the number of *non-kin* network additions between Waves 2 and 3, and (6) the number of *non-kin* network losses between Waves 2 and 3. The separate examinations of kin and non-kin changes allow me to consider whether these types of ties may be constrained by different norms, opportunities, and alternatives for contact (Kalmijn 2012).

Neighborhood Conditions

A key advantage of using the NSHAP to address this research question is that respondents' subjective assessments of their neighborhood social characteristics can also be linked with census tract measures from the U.S. Census and the American Community Survey (ACS), making it possible to obtain objective measures of neighborhood disadvantage.

Subjective and objective measures of the social environment can differ in important ways (Bailey et al. 2014). The ability to consider both dimensions allows for a richer, more nuanced portrait of the social environment and its intersection with personal network stability.

I create two measures that serve as my primary indicators of neighborhood structure. The first is a measure of neighborhood concentrated disadvantage (Browning and Cagney 2002; Sampson et al. 1997). I create a scale using five measures from the 2000 U.S. Census and the 2005-2009 ACS, including the percentage of the tract population with income levels below poverty, the percentage of residents ages 25 and older who have less than a high school education, the percentage of residents over age 18 who are unemployed, the percentage of female-headed households, and the median household income in respondents' census tracts at Wave 1. In general, these items are strongly correlated with one another. The scale demonstrates good reliability (alpha = .86). Higher scores on the scale reflect higher levels of concentrated disadvantage in respondents' residential tract.

The second measure of neighborhood structure is an estimate of residential instability. Following prior research (Sampson et al. 1999), I create a scale using the proportion of renter-occupied housing units and the proportion of residents who have moved to a different residence in the past year in respondents' Wave 1 census tracts. This scale demonstrates good reliability (alpha = .73), with higher scores representing greater residential instability.

The third neighborhood measure is a subjective indicator of neighborhood social ties. This measure is based on respondents' reports of how often they and others in their neighborhood: 1) visit with each other, 2) do favors for each other, and 3) ask each other for advice, where 0 = never and 3 = often (York Cornwell and Cagney 2014). Each of these three items measures specific ways that neighbors interact with one another, arguably a more concrete

measure of social exchange at the neighborhood level than more abstract constructs such as social cohesion (e.g., trust, shared values). I create a scale that averages respondents' ratings of these three items, with higher scores representing higher levels of neighborhood social ties. The scale demonstrates good reliability (alpha = .76). I create this scale from the Wave 2 interviews since the NSHAP did not administer these questions at Wave 1.

Covariates

A number of sociodemographic, life-course, and other contextual factors are likely to be associated with both changes in personal social networks and the relationship between neighborhood characteristics and social network changes. While concentrated disadvantage, residential instability, and social ties are the primary neighborhood characteristics that are of interest, other measures of neighborhood structure are also relevant to social network stability. I account for whether respondents reside in an urban, suburban, or rural area (census tract), categorized according to the U.S. Census definition of a Metropolitan Statistical Area (MSA).[15] Relative to rural and suburban areas, urban tracts exhibit greater population and institutional density. Higher density affords residents more opportunities to replace lost ties or form new social network relationships, particularly with non-kin (Fischer 1982). A larger pool of alternatives could also make it more difficult to sustain network ties over time.

Residential tenure may contribute to social network stability, as changing residences can lead to a restructuring of one's personal confidants (Bloem et al. 2008). I therefore account for the total time that respondents report that they have lived in their neighborhood at Wave 1

[15] Respondent census tracts are coded as "urban" if they are located within an MSA or Micropolitan Area, "suburban" if they are located within an MSA or Micropolitan Area but not within a principal city of the MSA or Micropolitan Area, and "rural" if they are neither located within an MSA or Micropolitan Area nor within a principal city of an MSA or Micropolitan Area.

(measured in years). Finally, to account for respondents' own residential mobility and potential exposure to different residential contexts, I include a control for whether respondents moved to a different tract at any point during the ten-year period.

I include a variety of measures to account for important life-course factors. Individual-level covariates include age at Wave 1 (divided by 10, to make the coefficient more meaningful), gender, whether the respondent is black, whether the respondent is Hispanic, and household income in the prior year (divided by 10,000 and then log transformed). Life-course covariates include whether the respondent attended college, self-rated physical health (1 = poor; 5 = excellent), whether the respondent is married/partnered at Wave 1, whether the respondent is widowed at Wave 1, whether the respondent is retired at Wave 1, and number of children. I also control for whether respondents became widowed between Waves 1 and 2 and whether respondents retired between Waves 1 and 2, as these are key life-course transitions that may contribute to shifts in social network structure (e.g., Settels et al. 2018; Zettel and Rook 2004). Household composition may also be relevant. Given respondents' close physical proximity to their household members, a larger number of household members may be associated with greater network continuity and more kin-based personal networks. This factor may also be associated with neighborhood conditions. I therefore control for number of household members.

Analytic Strategy

This study includes a series of descriptive and multivariable analyses designed to assess the relationship between individuals' neighborhood structure and personal network (in)stability. I begin by comparing the distribution of network additions and losses between Waves 2 and 3 across levels of concentrated disadvantage as a primary indicator of neighborhood

socioeconomic status (Sampson et al. 2002).

I then proceed to a series of Poisson models that predict the number of social network additions and losses that respondents experience between Waves 2 and 3 as a function of neighborhood and individual characteristics measured at Wave 1, including Wave 1 network size. Poisson is an appropriate modeling strategy given that the set of outcome variables are counts of network members (added or lost). Likelihood ratio tests indicate that there is no evidence of overdispersion, making the Poisson distribution appropriate.

The first set of models considers overall network additions and losses. The second set of models predicts the number of *kin* network members added and lost between Waves 2 and 3, and the third set predicts the number of *non-kin* network members added and lost during this same timeframe. For all models predicting social network additions, I use network size at Wave 3 as the exposure variable. For models predicting overall social network losses, I use network size at Wave 2 as the exposure variable, given that the number of overall losses that one could possibly experience between Waves 2 and 3 depends on the number of network members named at Wave 2. Models predicting kin and non-kin losses use the number of kin and non-kin named at Wave 2, respectively, as the exposure variables. These models take the following general form, where *t* refers to Wave 3, *t-(t-1)* refers to changes between Waves 2 and 3 (i.e., number of additions, number of losses), *r* represents the exposure, and the outcomes follow the Poisson distribution:

$$\Pr(Y_{it-(t-1)} = y_{it-(t-1)} \mid \mu_i, r_i) = \frac{e^{-\mu_i} r_i (\mu_i r_i)^{y_{it-(t-1)}}}{y_{it-(t-1)}!}$$

where $y = 0, 1, 2, \ldots 5$, and

$\mu_i = r_i \exp(ß_1 ConcentratedDisadvantage_{it-2} + ß_2 ResidentialInstability_{it-2} + ß_3 Urbanicity_{it-2} + ß_4 NeighborhoodSocialTies_{it-1} + ß_5 RespondentMovedTracts_{it-(t-2)} + ß_6 NetworkSize_{it-2} +$

$ß_7 RespondentCovariates_{it-2}$)

(3.1)

I present these models in a stepwise fashion. I first include only neighborhood-level predictors to assess the baseline associations between neighborhood-level characteristics and social network change. I then include individual-level characteristics to examine whether any degree of social network change that is predicted by neighborhood characteristics may be explained by individual sociodemographic characteristics or life-course experiences. All models predicting overall losses and additions include network size at Wave 1 as a covariate. All models predicting kin and non-kin changes include number of kin and non-kin at Wave 1, respectively, as a covariate.

Missing data. Missing data is generally not problematic in the NSHAP. However, 29% of Wave 1 respondents (and 27% of the analytic sample) do not provide information on household income. As income can be an important indicator of individual socioeconomic position, I use multiple imputation with chained equations (20 iterations using "mi impute" in Stata 14) to preserve cases in the analysis that have missing data on income and other covariates used in the models. I include the dependent variables in the imputation equation, but then exclude cases with originally missing values of a particular dependent variable from the respective analyses (von Hippel 2007).

The 1,552 respondents who provide network data at all three waves serve as the basis of the analytic sample. Models predicting network additions use network size at Wave 3 as the exposure variable. Since Poisson models cannot use 0 as an exposure value, these models exclude 20 respondents who have a network size of 0 at Wave 3 (N = 1,532). Models predicting network losses use network size at Wave 2 as the exposure variable, and therefore exclude 5

respondents with a network size of 0 at Wave 2 (N = 1,547). Models predicting the loss of kin exclude 132 respondents who did not include any kin in their Wave 2 network (N = 1,420). Models predicting the loss of non-kin exclude 570 respondents who did not name any non-kin as part of their Wave 2 networks (N = 982).

Selection. The analytic sample is limited to respondents who provide network data at Waves 1, 2, and 3. This restriction calls for attention to selection bias. Sample attrition over the course of the ten-year period is more likely among those who are in worse health at Wave 1 and who are socially disadvantaged, both of which are pertinent to studies of social network stability and neighborhood disadvantage. To help address these differences, I derive the inverse Mills ratio (i.e., non-selection hazard) using a probit model to predict whether each Wave 1 respondent was interviewed at all three waves (N = 3,005). Inclusion in all three waves is modeled as a function of individual sociodemographic characteristics, life-course, and health measures from Wave 1. The inverse Mills ratio is then derived as the probability density function of the linear prediction divided by the cumulative distribution function of the linear prediction. I include the inverse Mills ratio as a covariate in all multivariable models, helping to account for censoring (Heckman 1979; Mills 1926).[16] All analyses are weighted using Wave 1 respondent-level weights provided by the NSHAP, and standard errors are adjusted to account for the stratified

[16] Another common technique to adjust the models for selection is to multiply the respondent-level weights by the inverse of the probabilities derived from a logit model that is used to predict the probability of a given case being included in the final models. These revised weights are then applied to all analyses, effectively giving greater weight to those respondents who most resemble those respondents who are not included in the final sample (Morgan and Todd 2008). In the current analysis, 34 (2%) respondents have missing values on the probability of inclusion because they have missing data on some of the covariates used to predict inclusion. To preserve as many cases as possible, and since the multiple imputation program cannot use imputed weights, I instead use the inverse Mills ratio as a covariate and impute missing values for those 34 individuals. Estimating the models using the inverse probability weights (but excluding the 34 respondents with missing probabilities) yields results that are substantively similar to those presented here.

and clustered nature of the sample (O'Muircheartaigh et al. 2014).

RESULTS

Descriptive Analyses

Table 3.1 includes descriptive statistics for each of the network change measures used as outcomes in the Poisson models. Altogether, these findings indicate that most respondents experience changes in their networks between Waves 2 and 3. Over 80% of respondents report the loss of at least one network member, while a similar percentage report the addition of at least one network member. The addition and loss of kin network members are less common, but still experienced to some extent by over half of respondents (56% and 66%, respectively). Likewise, 55% and 82% of respondents report the addition and loss of non-kin, respectively. Across all six outcomes, considerably fewer respondents (11% or less) report more than three network members joining or exiting their network during this timeframe.

[Table 3.1 about here]

Table 3.2 presents descriptive statistics for the neighborhood condition scales that are the focus of the multivariable models, as well as the composite items of each scale and all other individual-level covariates. Bivariate analyses reveal a strong positive correlation between neighborhood-level residential instability and concentrated disadvantage ($r = .54$; $p < .001$). There are considerably weaker and non-significant negative correlations between neighborhood social ties and concentrated disadvantage ($r = -.02$; $p = .42$) and between neighborhood social ties and residential instability ($r = -.04$; $p = .11$).

[Table 3.2 about here]

Figure 3.2 illustrates the number of respondents experiencing each of the different

possible combinations of overall network additions and losses between Waves 2 and 3, among those residing in the lowest and highest quarters of the distribution of the concentrated disadvantage scale. Although the main analyses also examine other types of alter change and other neighborhood conditions, this bivariate exercise provides useful preliminary insight around whether network change may be patterned by aspects of the social environment. From this figure, it is evident that older adults living in neighborhoods characterized by higher levels of concentrated disadvantage experience more overall change and less stability than those living in neighborhoods with lower levels of concentrated disadvantage. In particular, those cells representing the number of respondents experiencing only losses (red) and those experiencing more losses than additions (orange) are notably more populous (higher) in the graph of respondents living in high levels of disadvantage than are the corresponding cells of the graph representing those respondents in less disadvantaged neighborhoods.

Indeed, 38.0% of older adults living in the top quarter of concentrated disadvantage experience a higher number of network losses than network gains, compared to 22.9% of those in the bottom quarter of concentrated disadvantage. Whereas 9.3% of respondents in the bottom quarter experienced only losses with no network additions, the percentage of respondents in the top quarter experiencing only network losses is nearly twice this level (17.6%). Similar patterns emerge when looking at the addition and loss of kin network members. Between Waves 2 and 3, 47.2% of those living in the top quarter of concentrated disadvantage experienced more losses of kin ties than they did gains, compared to 35.9% of those living in more advantaged neighborhoods. Differences are smaller with regard to non-kin, as 44.8% of those in top quarter of concentrated disadvantage experience more non-kin losses than gains, which is less than the 47.2% of older adults living in the bottom quarter of disadvantage.

[Figure 3.2 about here]

Multivariable Analyses

I begin by reviewing the Poisson models presented in Table 3.3 that predict the overall number of network additions and losses between Waves 2 and 3. My main interest is in the potential role that neighborhood conditions play in network change. Model 1 considers the association between neighborhood-level predictors and the number of network members added. Higher levels of neighborhood social ties are associated with a higher rate of adding network members between Waves 2 and 3 (incidence rate ratio [IRR] = 1.060, $p < .05$). Higher levels of concentrated disadvantage are marginally associated with higher rates of network additions (IRR = 1.054, $p < .10$), while higher levels of residential instability are marginally associated with lower rates of gaining network ties (IRR = .947; $p < .10$). Tract-level urbanicity does not appear to be associated with network additions.

Model 2 examines neighborhood covariates when also accounting for individual-level factors, revealing that higher levels of tract-level residential instability are associated with a 6.5% lower rate of adding network members (IRR = .935, $p < .05$). Higher levels of neighborhood social ties remain positively associated with the addition of network members over the course of the five-year period (IRR = 1.060, $p < .05$). Regarding individual-level covariates, widowhood predicts the addition of network ties at a 17.7% lower rate than those respondents who are not widows (IRR = .823, $p < .01$). Other individual-level covariates do not reach statistical significance in this model.

Turning to overall network losses, Model 3 indicates that several measures of neighborhood conditions are associated with the departure of network alters between Waves 2 and 3. Both higher levels of concentrated disadvantage and neighborhood social ties are each

associated with higher rates of network loss (IRR = 1.121, $p < .01$ and IRR = 1.076, $p < .01$, respectively). Higher levels of residential instability, however, predict lower rates of this same type of change (IRR = .938, $p < .05$). These associations persist after the inclusion of individual-level covariates. As shown in Model 4, concentrated disadvantage and neighborhood social ties remain significantly associated with higher rates of network loss, exhibiting little decline in magnitude (IRR = 1.110, $p < .01$ and IRR = 1.077, $p < .01$, respectively), while residential instability is negatively associated with a higher rate of overall network loss (IRR = .923, $p < .01$). With regard to individual-level covariates, only the association between widowhood and network loss demonstrates statistical significance, with widows exhibiting a lower rate of network loss relative to non-widowed respondents (IRR = .819, $p < .001$).

[Table 3.3 about here]

The next set of models assesses the hypothesis that neighborhood conditions may shape the addition and loss of kin and non-kin network members in different ways. Model 1 of Table 3.4 examines the role of neighborhood-level predictors, revealing that higher levels of concentrated disadvantage are associated with higher rates of adding kin network members between Waves 2 and 3 (IRR = 1.159, $p < .01$). At the same time, higher levels of both residential instability and neighborhood social ties predict lower rates of adding kin network members, at 8.6% and 13.1% lower rates, respectively (IRR = .914, $p < .05$ and IRR = .869, $p < .01$).

When accounting for individual-level covariates, concentrated disadvantage and residential instability are not statistically significant (Model 2). Supplementary analyses indicate that the inclusion of number of children is mainly responsible for mediating the relationship between concentrated disadvantage and the addition of kin ($F = 3.02$; $p = .09$ when comparing

the coefficient for concentrated disadvantage in models that do and do not control for number of children). Respondents who live in more disadvantaged neighborhoods have more children, on average, than those living in more advantaged neighborhoods, and therefore have more kin alternatives to include in their networks. Indeed, in the full model, number of children is associated with a 5.7% higher rate of kin network addition between Waves 2 and 3 (IRR = 1.057, $p < .001$). A higher level of neighborhood social ties remains associated with a 9.8% lower rate of adding kin network members (IRR = .902, $p < .05$).

The findings in Model 3 suggest that neighborhood concentrated disadvantage and residential instability predict the loss of network kin, but in opposite directions. Higher levels of concentrated disadvantage are associated with a 23.4% higher rate of kin network loss (IRR = 1.234, $p < .001$), while higher levels of residential instability are associated with an 11.9% lower rate of kin network loss (IRR = .881, $p < .01$). In this model, there is no statistically significant association between neighborhood social ties and the loss of kin between Waves 2 and 3.

Model 4 shows that these associations are generally robust to the inclusion of individual-level measures. Neighborhood concentrated disadvantage remains associated with an 18.8% higher rate of losing kin members from one's network, while residential instability is associated with an 11.8% lower rate of experiencing this same type of network loss. Individual-level covariates do not reach statistical significance in this model. However, supplementary analyses that use only individual-level covariates to predict kin network loss indicate that blacks lose kin at a marginally higher rate than respondents of other races (IRR = 1.167, $p = .06$). After accounting for concentrated disadvantage, however, this association is no longer marginally significant, suggesting that neighborhood conditions may partly explain racial differences in the stability of older adults' kin network members.

An unexpected finding from this set of models is the opposing directionality of concentrated disadvantage and residential instability in predicting kin network loss. These results warrant further investigation, as these measures are positively correlated with one another (r = .54, $p < .001$). Supplementary analyses indicate that the coefficient for residential instability does not reach statistical significance until concentrated disadvantage is included as a predictor in the model (F = 16.37; $p < .001$ when comparing the coefficient for residential instability in models that do and do not control for concentrated disadvantage). To better understand whether this association manifests within certain subgroups, I examined the relationship between concentrated disadvantage and kin network loss within quartiles of residential instability. The findings from this analysis suggest that residential instability is significantly associated with lower rates of kin network loss among respondents in the third quarter (between the second and third quartiles) of concentrated disadvantage. I revisit these findings in the Discussion section.

[Table 3.4 about here]

The relationships between neighborhood conditions and social network change that are examined in the multivariable models can also be interpreted in terms of predicted values. Figure 3.3 shows the predicted number of kin and non-kin network members (average adjusted predictions) gained and lost by levels of those neighborhood conditions that emerged as significantly influential on these types of network changes. These predictions are derived from a version of Model 4 of Table 3.4 that relies on categorical measures (quarters) of concentrated disadvantage and residential instability rather than continuous measures for ease of interpretation. On average, older adults residing in neighborhoods that fall in the top quarter of concentrated disadvantage experience .37 more kin network losses than those residing in the bottom quarter of concentrated disadvantage ($p < .01$). At the same time, those residing in

neighborhoods in the bottom quarter of residential instability experience .26 more kin network losses than older adults living in the top quarter of residential instability ($p < .01$).

[Figure 3.3 about here]

Finally, the models in Table 3.5 consider how neighborhood conditions predict the addition and loss of non-kin network alters. Neither concentrated disadvantage nor residential instability demonstrate statistically significant associations with the addition of non-kin network members in Model 1. However, higher levels of neighborhood social ties are significantly associated with higher rates of non-kin network additions between Waves 2 and 3 (IRR = 1.218, $p < .001$). This association is robust to the inclusion of individual-level covariates as shown in Model 2 (IRR = 1.201, $p < .001$). In the full model, higher levels of residential instability predict significantly lower rates of non-kin additions (IRR = .901, $p < .05$). Family factors also appear to be relevant, as older adults with more children add non-kin at a significantly lower rate than those with fewer children (IRR = .951, $p < .05$).

The final sequence of models examines whether neighborhood conditions predict the departure of non-kin from respondents' personal networks between Waves 2 and 3. Model 3 of Table 3.5 indicates that concentrated disadvantage and residential instability are less relevant in shaping the loss of non-kin network members than they are in shaping the loss of kin, but that higher levels of neighborhood social ties are associated with a 6.8% higher rate of non-kin network loss over the course of five years (IRR = 1.068, $p < .05$). As shown in Model 4, when individual-level covariates are included, living in neighborhoods with higher levels of social interaction among residents is linked with the loss of non-kin network ties overtime (IRR = 1.071, $p < .05$). With regard to individual-level covariates, widowhood and retirement are marginally associated with a lower rate of non-kin network loss (IRR = .872, $p < .10$ and IRR =

.904, $p < .10$, respectively), while moving to a different tract at some point between Waves 1 and 3 is marginally associated with a higher rate of losing non-kin from one's personal network (IRR = 1.081, $p < .10$).

[Table 3.5 about here]

Figure 3.4 illustrates the degree of non-kin network turnover predicted by different levels of neighborhood social ties. These average adjusted predictions are derived from the estimates presented in Models 2 and 4 of Table 3.5. Older adults who report the highest levels of neighborhood social ties report adding, on average, 1.33 non-kin network ties between Waves 2 and 3, which is approximately .56 more than the number of non-kin additions (.77) reported by those with the lowest levels of neighborhood social ties ($p < .01$). A smaller yet still significant difference is observed with regard to non-kin network loss. Respondents reporting high levels of social interaction in their neighborhoods ("often") lose, on average, 1.60 non-kin from their networks between Waves 2 and 3, compared to 1.30 non-kin losses among those reporting the lowest levels of neighborhood social ties (difference = .30, $p < .05$).

[Figure 3.4 about here]

Supplementary analyses. The Poisson models suggest that neighborhood conditions are relevant for explaining patterns of social network change. I conducted two sets of supplementary models to address potential limitations and extensions of this analytic design. First, research shows that personal social networks may exhibit, to some extent, homeostatic properties, meaning that losses or additions experienced at time 1 tend to be offset by compensating changes at time 2 (Cornwell, Goldman, and Laumann 2020; Fischer and Offer 2019). These findings suggest that any losses or additions between Waves 2 and 3 may occur in response to changes in the network that take place between Waves 1 and 2. This begs the question of whether the

apparent linkage between neighborhood conditions and the social network changes between Waves 2 and 3 exist independent of changes between Waves 1 and 2. Changes between Waves 1 and 2 are likely to shape subsequent changes and are also likely to be shaped by the same neighborhood conditions.

Appendix Table 3.1 presents the results from the full models shown in Tables 3.3, 3.4, and 3.5 when including control variables that reflect changes in the corresponding network outcomes between Waves 1 and 2 (i.e., losses and additions between Waves 1 and 2). These equations take the following general form, where $_{(t-1)-(t-2)}$ refers to network changes between Waves 1 and 2.

$$\Pr(Y_{it-(t-1)} = y_{it-(t-1)} \mid \mu_i, r_i) = \frac{e^{-\mu_i r_i} (\mu_i r_i)^{y_{it-(t-1)}}}{y_{it-(t-1)}!}$$

where $y = 0, 1, 2, \ldots 5$, and

$$\mu_i = r_i \exp(ß_1 ConcentratedDisadvantage_{it-2} + ß_2 ResidentialInstability_{it-2} + ß_3 Urbanicity_{it-2} + ß_4 NeighborhoodSocialTies_{it-1} + ß_5 RespondentMovedTracts_{it-(t-2)} + ß_6 NetworkSize_{it-2} + ß_7 RespondentCovariates_{it-2} + \mathbf{ß_8 NetworkLoss_{i(t-1)-(t-2)}} + \mathbf{ß_9 NetworkAddition_{i(t-1)-(t-2)}}) \quad (3.2)$$

The results show that in most cases, prior losses and additions (between Waves 1 and 2) significantly predict subsequent changes between Waves 2 and 3. Even with strong evidence that personal network changes are a function of prior network changes, however, the role of neighborhood conditions observed in Appendix Table 3.1 are still consistent with the findings in the main analyses, with only slight changes in magnitude in some models. Higher levels of concentrated disadvantage are associated with significantly higher rates of overall and kin network losses (IRR = 1.101, $p < .05$ and IRR = 1.166, $p < .01$, respectively). Higher levels of

residential instability are significantly associated with lower rates of overall and kin network losses (IRR = .919, $p < .001$ and IRR = .886, $p < .01$, respectively), and with lower rates of overall and non-kin network additions (IRR = .927, $p < .01$ and IRR = .888, $p < .01$, respectively). Neighborhood social ties are associated with lower rates of adding kin ties (IRR = .870, $p < .01$), higher rates of adding non-kin ties (IRR = 1.197, $p < .001$), and higher rates of losing non-kin (IRR = 1.054, $p < .05$). Therefore, it seems that neighborhood conditions influence personal network stability independent of prior changes in the network.

Although the findings are robust to alternative specifications of the lagged DV, the Poisson models also exclude respondents who have zero network members at Wave 2 in models predicting network losses, and zero network members at Wave 3 in models predicting network additions. This restriction leaves open the question of whether the findings can be generalized to people who have smaller networks, or whose networks are particularly kin-centric or non-kin-centric, given that network size is also a function of neighborhood conditions (Tigges et al. 1998; York Cornwell and Behler 2015). To address these concerns, I examined trajectories of change in network size and proportion network kin as a function of neighborhood conditions. I use a multilevel modeling strategy that nests repeated measures of individual and neighborhood covariates from each of the three waves (Level 1) within individual respondents (Level 2). This type of model accounts for overtime within-person differences in time-varying individual and neighborhood measures, as well as between-person differences in time-stable factors. In addition to fixed effect parameters, I estimate random effects (individual deviations) for the intercept. The general form of this model is:

$$ProportionKin_{ij} = \beta_0 + \beta_1 Neighborhood_{ij} + \beta_{02} RespondentControls_{ij} + \varepsilon_{ij} + u_i$$

where i represents the value of a variable for a particular respondent at time (wave) j, ε_{ij} is the error for each respondent at each wave, and u_i is the variance around the intercept.

(3.3)

It is important to emphasize that the outcomes in the Poisson models in the main analyses rely on tracking the entrance or departure of *specific* network alters to and from older adults' networks. The multilevel models, on the other hand, are predicting overall growth or decline in network size and kin composition (proportion kin), which are conceptually different measures of network change than are additions and losses.[17] In this sense, the multilevel models are not capturing stability on the basis of *who* comprises the network, but rather more general measures of changes in social integration – overall and by alter type. Nevertheless, they provide a useful alternate view and robustness check, and in a framework that accounts for both within and between respondent variation (Raudenbush and Bryk 2002; Singer and Willett 2003).

As shown in Appendix Table 3.2, the associations between neighborhood conditions and trajectories of personal network change are generally consistent with some of the findings from the main analyses.[18] Concentrated disadvantage is associated with marginal declines in overall network size (IRR = .975, p = .053), while higher levels of residential instability are marginally associated with growth in network size (IRR = 1.017, p = .061). Higher levels of concentrated disadvantage are also associated with statistically significant declines in proportion kin (b = -.022, p < .05). These results lend additional support to the main findings, specifically the notion that overtime trajectories of personal network size and composition are in part a function of

[17] A respondent could, for example, experience the loss of 5 network members and the addition of 5 new network members (i.e., complete network turnover), but would have an overall net change of 0 in their network size.

[18] Neighborhood social ties are not included in this model due to measurement at only two waves (Waves 2 and 3).

neighborhood concentrated disadvantage.

DISCUSSION

This study was driven by growing empirical research that demonstrates the dynamic properties of older adults' personal networks as a reflection of social stratification (e.g., Desmond 2012; Fischer and Beresford 2015; Schafer and Vargas 2016; Cornwell 2015), along with evidence that neighborhood conditions shape some of the most consequential features of older adults' personal networks (Bloem et al. 2008; Schieman 2005; Thomése et al. 2005; York Cornwell and Behler 2015). This paper intended to bridge these literatures, developing a broader structural framework for examining social network change relative to prior traditions of examining more individual-level and interpersonal (network-level) predictors (e.g., Mollenhorst et al. 2011). These analyses collectively indicate that aspects of the social environment influence the addition and loss of older adults' personal network members, and in ways that may differ across kin and non-kin ties. The significant role of neighborhood conditions emerges even when accounting for life-course transitions, health, and social position, which prior research links with personal network change (e.g., Badawy, Schafer, and Sun 2019; Zettel and Rook 2004).

Perhaps most striking of these findings is that older adults living in neighborhoods with higher levels of concentrated disadvantage are at higher risk of losing kin network members. These individuals may be more likely to rely on kin for various forms of support, in part to compensate for individual and neighborhood disadvantages (Kana'Iaupuni et al. 2005; Stack 1974). Further, the finding that no other neighborhood conditions examined in this study appear to shape the *addition* of kin ties suggests that older adults' close family relationships may be especially vulnerable to structurally disadvantaged neighborhoods, without any apparent

contextual force to counteract or compensate for this loss.

Why might neighborhood concentrated disadvantage predict the loss of kin network ties? One possibility is that residents of more disadvantaged neighborhoods are more likely to experience the loss of close kin due to declining health – either one's own health or the health of kin network members – as well as the death of close kin ties. Neighborhood disadvantage is associated with higher odds of all-cause mortality, particularly among whites (Denney, Saint Onge, and Dennis 2018), as well as poor health (Diez Roux 2003; Diez Roux and Mair 2010). Poorer health and elevated mortality risks can be attributed to higher levels of crime and poverty, fewer local health clinics and other health-promoting resources, as well as weak infrastructure and lack of transportation that would otherwise allow access to health services (Denney et al. 2018; Meijer et al. 2012).

Whereas death may be a direct cause of kin network loss, declining health may contribute to the erosion of previously close kin relationships as a result of increasing needs that strain social ties. Certain health challenges may also compromise mobility in ways that do not allow individuals to engage with and provide support to kin to the degree necessary to maintain them as close network ties (Badawy et al. 2019). Neighborhoods can function as potential "ecological stressors" or stress buffers through their institutions and other resources, levels of physical disorder, social disorganization (crime, distrust), and available social support and social capital (Ellen, Mijanovich, and Dillman 2001; Karb et al. 2012). High levels of individual stress or stress within one's personal network could lead to a demanding personal network (Offer and Fischer 2018) that ultimately compromises tie stability.

Structural aspects of disadvantaged neighborhoods may also be relevant for kin tie stability. For example, more socioeconomically disadvantaged areas could have poor access to

transportation that would otherwise allow older adults to visit with kin outside of their neighborhood. Distrust of the residential area might also discourage efforts to go out and see relatives, and constrain one's activity to only more necessary local tasks (Krause 1993).

Given that this study used a sample of older adults, it is also worth considering how neighborhood disadvantage intersects with shifts in the social roles that older adults occupy in their network, and how this intersection might have implications for changes in kin ties. Role shifts that result from what are typically later life transitions (e.g., retirement, widowhood) can prompt a sense of lost social competency (Kuypers and Bengtson 1973) and a renewed sense of fulfillment through kin-based roles such as parenthood and grandparenthood (Bloem et al. 2008; Thomése et al. 2005; Wellman et al. 1997). Living in a more disadvantaged neighborhood, however, is associated with diminished self-efficacy among older adults (Boardman and Robert 2000), which can lead to less participation in supportive relationships (Holahan and Holahan 1987). Higher levels of neighborhood disadvantage could lead to the loss of kin ties by compromising individuals' sense of self-efficacy or control over their lives and their environment, leading them to feel less control over fulfilling the obligations of close kin ties and to ultimately withdraw from these relationships.

It is possible that older adults living in more disadvantaged neighborhoods are losing kin in exchange for some other form of support. I do not find evidence that concentrated disadvantage predicts the addition of non-kin ties. Nevertheless, it is possible that Internet and social media use are providing alternative sources of information, advice, and support for older adults who are experiencing spatial and social isolation (Mok, Wellman, and Basu 2007; Vriens and van Ingen 2018).

Less expected was the finding that higher levels of residential instability appear to protect

against the loss of kin ties. This association manifests among older adults living in neighborhoods that fall just below the highest levels of concentrated disadvantage (between the second and third quartiles). One possibility is that individuals in neighborhoods that are approaching more extreme levels of disadvantage are retaining kin ties as a way of adapting to new levels of instability in the broader neighborhood environment (Schieman 2005). Neighborhoods that fall in the third quarter of concentrated disadvantage may include more recently transient neighborhoods, perhaps as a result of economic decline following the Great Recession or due to other political and institutional forces. The relative novelty of observing higher levels of residential turnover could prompt respondents to draw their kin ties even closer to compensate for new or heightened environmental indications of instability and economic decline.

Neighborhood social ties emerged as especially relevant for changes in non-kin network membership, predicting both the loss and addition of this type of tie. Older adults who perceive higher levels of interaction among neighbors, in the form of favors, advice, and other types of social exchange, may be more likely to participate in such exchanges, thereby having more opportunities to form ties with neighbors and other non-kin. The finding that neighborhood social ties are also associated with the loss of non-kin may reflect greater opportunities within the residential neighborhood for alternative sources of non-kin confidants. As older adults' needs for certain kinds of support and information change over time, a higher degree of non-kin turnover may reflect that older adults who live in neighborhoods with higher levels of social interaction have a wider range of non-kin resources to recruit as needed.

Given recent evidence that suggests that a substantial portion of non-kin ties are not truly "lost" over time (Fischer and Offer 2019), the non-kin ties who are "lost" in this study may

actually be "dormant." In this sense, higher levels of neighborhood social ties may be associated with the expansion of older adults' more peripheral social networks.[19] The finding that higher levels of neighborhood social ties are also negatively associated with the addition of *kin* ties supports the interpretation that areas with more interaction among residents provide more non-kin alternatives whose inclusion in the network may offset the need to recruit kin as key sources of social support. Social capital at the neighborhood level may structure opportunities for accessing different kinds of social capital at the individual network level.

One takeaway from this and other recent studies (e.g., Goldman and Cornwell 2018) is the notion that kin ties are particularly vulnerable to individual and neighborhood indicators of disadvantage. This pattern of findings is somewhat surprising given prior work on network-based predictors of tie instability, which suggest that network members who know one another are less likely to leave the network (Feld 1981; Feld et al. 2007; Mollenhorst et al. 2011). Kin are more likely to be embedded in older adults' networks, but the stability that one might expect from this embeddedness does not follow the findings that emerge here. These results call for greater attention to the contexts surrounding kin relationships, and how the constrains of those contexts may undermine their stability. This work suggests that the role of normative family obligations and structural embeddedness that would otherwise predict kin tie stability may be more nuanced than originally thought, and that scholars should consider how personal and neighborhood disadvantage may undermine these processes.

Limitations and Future Directions

[19] In supplementary analyses, I find that 26.4% of respondents in the analytic sample have an alter who is "lost" between Waves 1 and 2 and who is then added back to the network at Wave 3. This percentage indicates that while some "lost" ties may in fact be dormant, the majority of respondents do not experience "boomerang" ties over the course of the ten-year study period.

The NSHAP offers one of the first opportunities to examine how neighborhood-level measures influence changes in older adults' personal social networks. Nevertheless, this study is not without limitations. For one, the neighborhood measures that I use in this analysis rely on data from respondents' residential census tracts. Although informative of individuals' primary social contexts, older adults spend a considerable portion of their time outside of their residential neighborhood (York Cornwell and Cagney 2017). The spaces that older adults visit to conduct their day-to-day activities may vary in structural and social characteristics, and in ways that may contribute to different levels of personal network change. Future research using activity space data could examine whether extra-residential neighborhood characteristics also play a role in shaping older adults' personal network stability.

Second, the NSHAP does not collect detailed information on why older adults add or lose network confidants, although information on the mortality of "lost" ties could be leveraged in future analyses. Still, this leaves open the question of why exactly respondents add and lose network ties overtime, and the specific ways that neighborhood conditions directly or indirectly influence these changes. Qualitative studies on this topic could help to shed light on the processes that underlie these findings. Likewise, information on the social and economic circumstances of respondents' network alters – including their neighborhood contexts – could speak to how neighborhood conditions experienced within the network as a whole might contribute to network instability.

Finally, the theories outlined in this paper support the notion that neighborhood conditions could shape the stability of personal networks, regardless of whether network members reside in respondents' neighborhoods. Future research could leverage information on the residential location of network alters to better understand whether certain features of the

residential neighborhood are more or less likely to impact local versus non-local network members. Wave 3 of the NSHAP asks respondents to indicate whether each of their non-co-resident network members resides in their local area (i.e., within a 20-minute or one-mile walk). Since this information is not collected about Wave 1 or Wave 2 network alters, I cannot discern whether neighborhood conditions are differentially consequential for the stability of local versus non-local network ties.

CONCLUSION

Despite these limitations, this study offers compelling evidence that the neighborhood context plays a role in the stability of older adults' personal network ties, even after accounting for individual measures of social position and life-course factors that reflect predominant theoretical orientations on this topic (e.g., Fischer and Beresford 2015; Schafer and Vargas 2016; Zettel and Rook 2004). It is well documented that later life is a time of personal and social change, as older adults become increasingly dependent on their social ties and increasingly vulnerable to their residential environments (e.g., Yen et al. 2009). Personal network stability is constrained in nuanced ways by the structural and social characteristics of residential environments, and in ways that may be consequential for older adults' well-being. These findings call for greater attention to the social environment in studies of network change as a stratified process. Further, scholars working within the expansive "neighborhood effects" literature should incorporate personal network stability in their conceptual models. Social ties are key mechanisms through which neighborhoods shape individual outcomes, though this concept generally refers to collective efficacy generated by ties among residents (Morenoff et al. 2001; Sampson et al. 2002). As personal network changes may also promote or hinder older adults' well-being,

neighborhood determinants of health could also be exacerbated or diminished through their influence on personal network stability.

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Table 3.1 Proportion of Respondents Reporting Each Number of Social Network Change Outcomes Used in the Main Analyses.[a]

# Network members	Added[b] W2 → W3	Lost[c] W2→W3	Kin Added[b] W2→W3	Kin Lost[d] W2→ W3	Non-Kin Added[b] W2→W3	Non-Kin Lost[e] W2→W3
0	.16	.15	.44	.34	.45	.18
1	.23	.26	.30	.36	.26	.42
2	.26	.25	.17	.18	.18	.24
3	.20	.20	.07	.08	.07	.12
4	.11	.10	.02	.03	.03	.04
5	.03	.04	.003	.01	.01	.01

[a]Proportions are unweighted and are calculated using one of the 20 imputed datasets.
[b]Calculated among the 1532 respondents who named at least one network member at Wave 3.
[c]Calculated among the 1547 respondents who named at least one network member at Wave 2.
[d]Calculated among the 1420 respondents who named at least one kin network member at Wave 2.
[e]Calculated among the 982 respondents who named at least one non-kin network member at Wave 2.

Table 3.2 Descriptive Statistics of Key Covariates in the Main Analysis (N = 1,552).[a]

Variable	Proportion or Weighted Mean	Standard Deviation
Residential Neighborhood Context		
Tract-level concentrated disadvantage scale (α = .86)[b]	**-.14**	**.74**
(Average of standardized items; range: -2.23 – 2.50)		
Percentage in poverty	13.35	10.91
Percentage of female-headed households	12.72	7.39
Median household income	55,610.28	25,476.09
Percentage unemployed	4.75	2.65
Percentage with less than a high school degree	45.83	16.09
Tract-level residential instability scale (α = .73)[b]	**-.08**	**.83**
(Average of standardized items; range: -1.47 – 4.40)		
Percentage of renter-occupied housing units	28.30	17.30
Percentage of movers	14.84	7.59
Neighborhood social ties scale W2 (α = .76)[b]	**1.55**	**.71**
(Average of items; range: 0 = never; 3 = often)		
How often do you and people in this area visit in each other's homes or when you meet on the street?	1.76	.90
How often do you and people in this area do favors for each other?	1.93	.78
How often do you and other people in this area ask each other for advice about personal things?	.96	.88
Urbanicity of residential tract		
Urban	.45	
Suburban	.50	
Rural	.05	
Respondent Covariates		
Age (in decades)	6.57	.65
Female (=1)	.54	
Attended college (=1)	.53	

Black (=1)	.16	
Hispanic (=1)	.11	
Income in the prior year (divided by 10,000 and logged)	1.46	.92
Married/partnered (=1)	.69	
Widowed (=1)	.15	
Became widowed W1→W2 (=1)	.07	
Retired (=1)	.57	
Became retired W1 → W2 (=1)	.20	
Self-rated physical health (1 = poor; 5 = excellent)	3.49	1.02
Network size	3.65	1.40
Respondent moved to a different tract between W1 and W3 (=1)	.32	
Residential tenure (years)	20.61	16.19
Number of household members	1.09	.97
Number of children	2.89	1.88

[a]All covariates are measured using the Wave 1 (baseline) survey of the NSHAP unless otherwise noted. Means and proportions are calculated using one of the 20 imputed datasets. Means are weighted using baseline (Wave 1) respondent-level weights provided by the NSHAP that adjust for age and urbanicity and are adjusted for the NSHAP survey design.
[b]Means and standard deviations for scale items are based on non-imputed data from respondents interviewed at all three waves and are weighted using baseline (Wave 1) respondent-level weights provided by the NSHAP that adjust for age and urbanicity.

Table 3.3 Incidence Rate Ratios from Poisson Models Predicting the Number of Overall Network Additions and Losses Between Waves 2 and 3.[a]

	Number of Overall Network Additions W2 to W3		Number of Overall Network Losses W2 to W3	
	Model 1	Model 2	Model 3	Model 4
Concentrated disadvantage	1.054†	1.049	1.121**	1.110**
	(.997 - 1.114)	(.991 - 1.110)	(1.054 - 1.193)	(1.032 - 1.195)
Residential instability	.947†	.935*	.938*	.923**
	(.894 - 1.003)	(.884 - .989)	(.888 - .990)	(.873 - .976)
Neighborhood social ties	1.060*	1.060*	1.076**	1.077**
	(1.002 - 1.120)	(1.003 - 1.121)	(1.023 - 1.132)	(1.023 - 1.133)
Urbanicity *(Ref = Urban)*				
Suburban	.955	.953	1.004	.995
	(.879 - 1.036)	(.880 - 1.032)	(.910 - 1.107)	(.900 - 1.100)
Rural	.879	.888	.944	.948
	(.687 - 1.124)	(.698 - 1.129)	(.726 - 1.228)	(.738 - 1.218)
Age		1.039		1.078
		(.933 - 1.156)		(.954 - 1.217)
Female		.933		.961
		(.862 - 1.010)		(.890 - 1.037)
Attended college		.994		1.002
		(.923 - 1.070)		(.932 - 1.077)
Black		1.006		1.028
		(.916 - 1.104)		(.916 - 1.154)
Hispanic		.996		1.049
		(.896 - 1.108)		(.903 - 1.218)
Income		.970		.965
		(.916 - 1.026)		(.915 - 1.018)
Retired		.961		.987
		(.872 - 1.059)		(.883 - 1.103)
Widowed		.823**		.819***
		(.734 - .922)		(.747 - .899)

Respondent moved to a different tract W1→W3		1.054		1.076*
		(.977 - 1.138)		(1.011 - 1.145)
Residential tenure (years)		.999		.999
		(.996 - 1.002)		(.996 - 1.001)
Number of household members		.993		.996
		(.966 - 1.021)		(.961 - 1.032)
Number of children		1.005		1.005
		(.988 - 1.023)		(.986 - 1.024)
F(df)	4.30*** (7, 48.0)	3.09*** (23, 47.7)	6.34*** (7, 47.9)	5.49*** (23, 47.8)
N	1532	1532	1547	1547

†$p < .10$; *$p < .05$; **$p < .01$; ***$p < .001$ (two-sided tests). 95% confidence intervals in parentheses.

[a]All models control for the inverse Mills ratio and network size at Wave 1. Models 2 and 4 also control for self-rated health at Wave 1, whether the respondent has a spouse/partner at Wave 1, whether the respondent became retired between Waves 1 and 2, and whether the respondent became widowed between Waves 1 and 2.

Table 3.4 Incidence Rate Ratios from Poisson Models Predicting the Number of Kin Additions and Losses Between Waves 2 and 3.

	Number of Kin Network Additions W2 to W3		Number of Kin Network Losses W2 to W3	
	Model 1	Model 2	Model 3	Model 4
Concentrated disadvantage	1.159**	1.059	1.234***	1.188**
	(1.061 - 1.265)	(.950 - 1.181)	(1.131 - 1.345)	(1.068 - 1.320)
Residential instability	.914*	.947	.881**	.882**
	(.844 - .989)	(.868 - 1.033)	(.811 - .957)	(.811 - 0.958)
Neighborhood social ties	.869**	.902*	1.039	1.046
	(.796 - .948)	(.825 - .986)	(.961 - 1.123)	(.970 - 1.128)
Urbanicity *(Ref = Urban)*				
Suburban	1.025	1.030	1.022	1.010
	(.888 - 1.183)	(.890 - 1.193)	(.875 - 1.193)	(.864 - 1.182)
Rural	.775	.802	.816	.814
	(.553 - 1.087)	(.550 - 1.168)	(.596 - 1.118)	(.594 - 1.115)
Age		.972		1.131
		(.808 - 1.170)		(.958 - 1.335)
Female		.996		.932
		(.855 - 1.161)		(.831 - 1.044)
Attended college		.908		.943
		(.776 - 1.063)		(.833 - 1.067)
Black		1.187		1.048
		(.959 - 1.469)		(.867 - 1.267)
Hispanic		1.267**		1.078
		(1.083 - 1.481)		(.888 - 1.307)
Income		1.007		.960
		(.913 - 1.110)		(.873 - 1.056)
Retired		.876		1.083
		(.747 - 1.028)		(.927 - 1.265)
Widowed		.891		.858
		(.726 - 1.095)		(.715 - 1.028)

Respondent moved to a different tract W1→W3		1.011		1.047
		(.842 - 1.215)		(.929 - 1.180)
Residential tenure (years)		1.002		1.000
		(.997 - 1.007)		(.996 - 1.004)
Number of household members		1.036		1.013
		(.982 - 1.092)		(.964 - 1.064)
Number of children		1.057***		1.020
		(1.025 - 1.090)		(.995 - 1.045)
F(df)	6.29*** (7, 48.0)	14.81*** (23, 47.8)	5.08*** (7, 48.0)	4.85*** (23, 47.9)
N	1532	1532	1420	1420

*$p < .05$; **$p < .01$; ***$p < .001$ (two-sided tests). 95% confidence intervals in parentheses.

[a]All models control for the inverse Mills ratio and number of kin network members at Wave 1. Models 2 and 4 also control for self-rated health at Wave 1, whether the respondent has a spouse/partner at Wave 1, whether the respondent became retired between Waves 1 and 2, and whether the respondent became widowed between Waves 1 and 2.

Table 3.5 Incidence Rate Ratios from Poisson Models Predicting the Number of Non-Kin Additions and Losses Between Waves 2 and 3.

	Number of Non-Kin Network Additions W2 to W3		Number of Non-Kin Network Losses W2 to W3	
	Model 1	Model 2	Model 3	Model 4
Concentrated disadvantage	1.003	1.049	1.016	1.010
	(.919 - 1.094)	(.939 - 1.172)	(.962 - 1.074)	(.949 - 1.075)
Residential instability	.931	.901*	1.003	.995
	(.859 - 1.009)	(.826 - .983)	(.950 - 1.059)	(.943 - 1.050)
Neighborhood social ties	1.218***	1.201***	1.068*	1.071*
	(1.125 - 1.319)	(1.109 - 1.301)	(1.008 - 1.131)	(1.015 - 1.130)
Urbanicity *(Ref = Urban)*				
Suburban	.915	.900	.980	.981
	(.790 - 1.059)	(.772 - 1.049)	(.909 - 1.057)	(.909 - 1.058)
Rural	.882	.894	1.118	1.118
	(.607 - 1.281)	(.601 - 1.331)	(.961 - 1.302)	(.964 - 1.297)
Age		1.028		1.059
		(.840 - 1.259)		(.926 - 1.210)
Female		.875		.989
		(.762 - 1.005)		(.899 - 1.087)
Attended college		1.065		.992
		(.918 - 1.235)		(.890 - 1.105)
Black		.883		1.020
		(.715 - 1.089)		(.907 - 1.147)
Hispanic		.851		.962
		(.667 - 1.087)		(.830 - 1.114)
Income		.938		.973
		(.863 - 1.021)		(.912 - 1.038)
Retired		1.035		.904†
		(.835 - 1.284)		(.816 - 1.002)
Widowed		.823		.872†
		(.652 - 1.039)		(.758 - 1.004)

Respondent moved to a different tract W1→W3		1.070		1.081†
		(.901 - 1.269)		(.994 - 1.175)
Residential tenure (years)		.997		.999
		(.992 - 1.001)		(.996 - 1.002)
Number of household members		.954		.993
		(.878 - 1.036)		(.951 - 1.037)
Number of children		.951*		1.006
		(.910 - .994)		(.981 - 1.032)
F(df)	12.05*** (7, 48.0)	10.59*** (23, 47.7)	5.30*** (7, 48.0)	5.09*** (23, 47.7)
N	1532	1532	982	982

†$p < .10$; *$p < .05$; **$p < .01$; ***$p < .001$ (two-sided tests). 95% confidence intervals in parentheses.

[a]All models control for the inverse Mills ratio and the number of non-kin network members at Wave 1. Models 2 and 4 also control for self-rated health at Wave 1, whether the respondent has a spouse/partner at Wave 1, whether the respondent became retired between Waves 1 and 2, and whether the respondent became widowed between Waves 1 and 2.

Figures

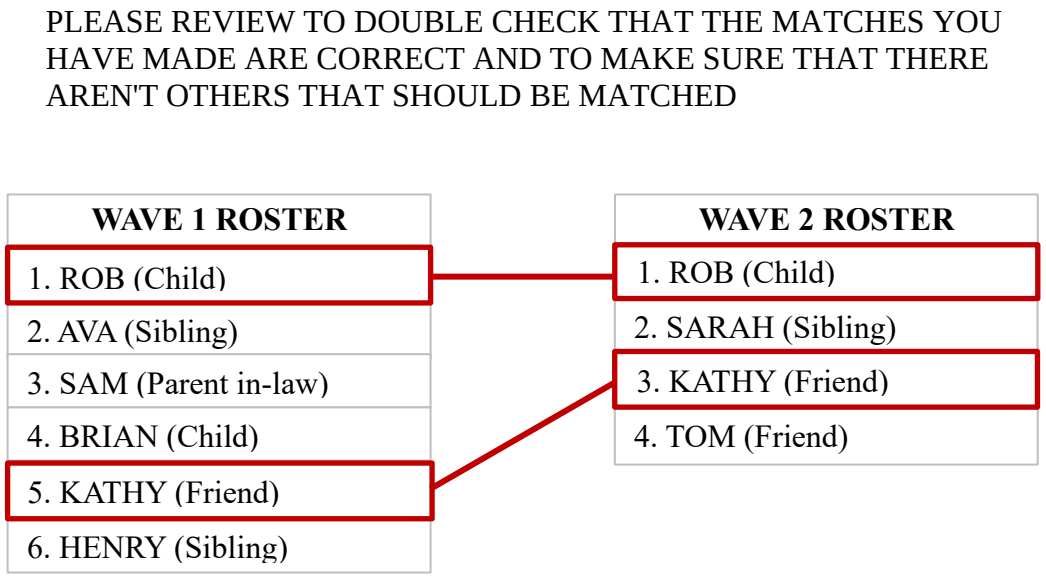
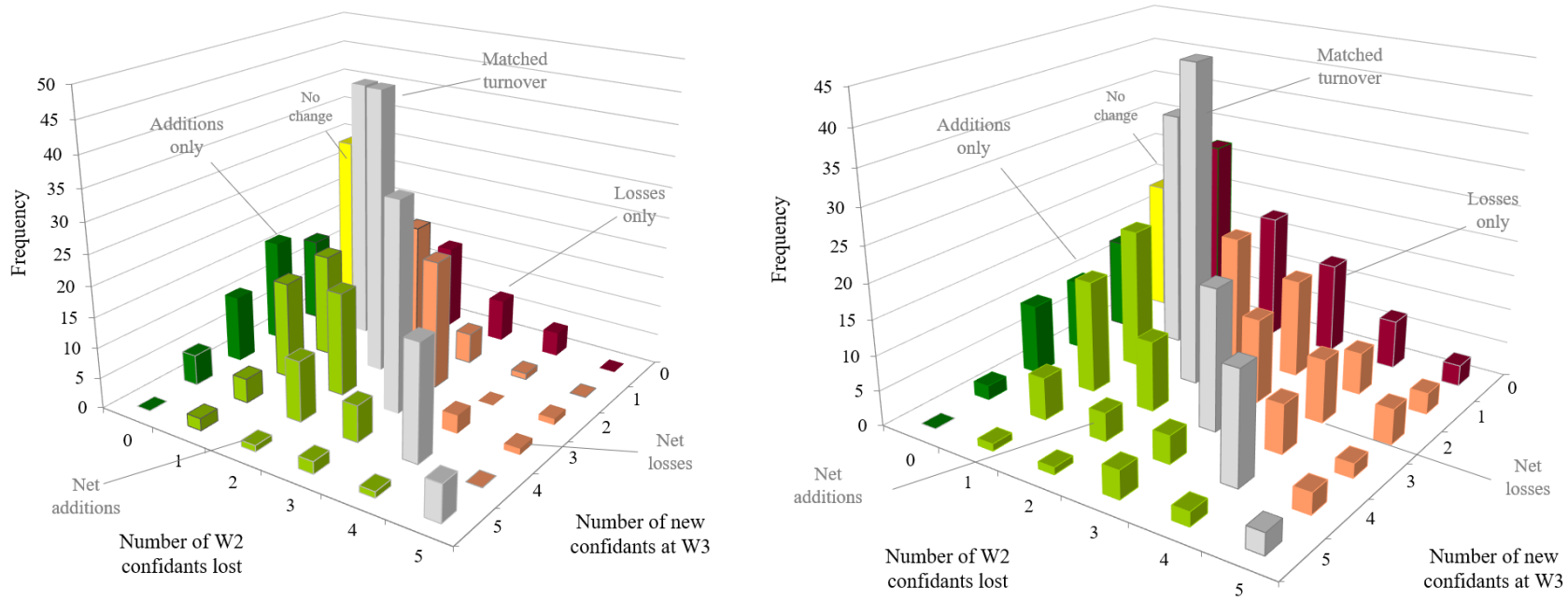


Figure 3.1 Sample screenshot of the network roster matching exercise completed by a hypothetical NSHAP respondent.



Low concentrated disadvantage **High concentrated disadvantage**

Figure 3.2 Distribution of network members added and lost between Waves 2 and 3, by bottom and top quarter of neighborhood concentrated disadvantage at Wave 1.

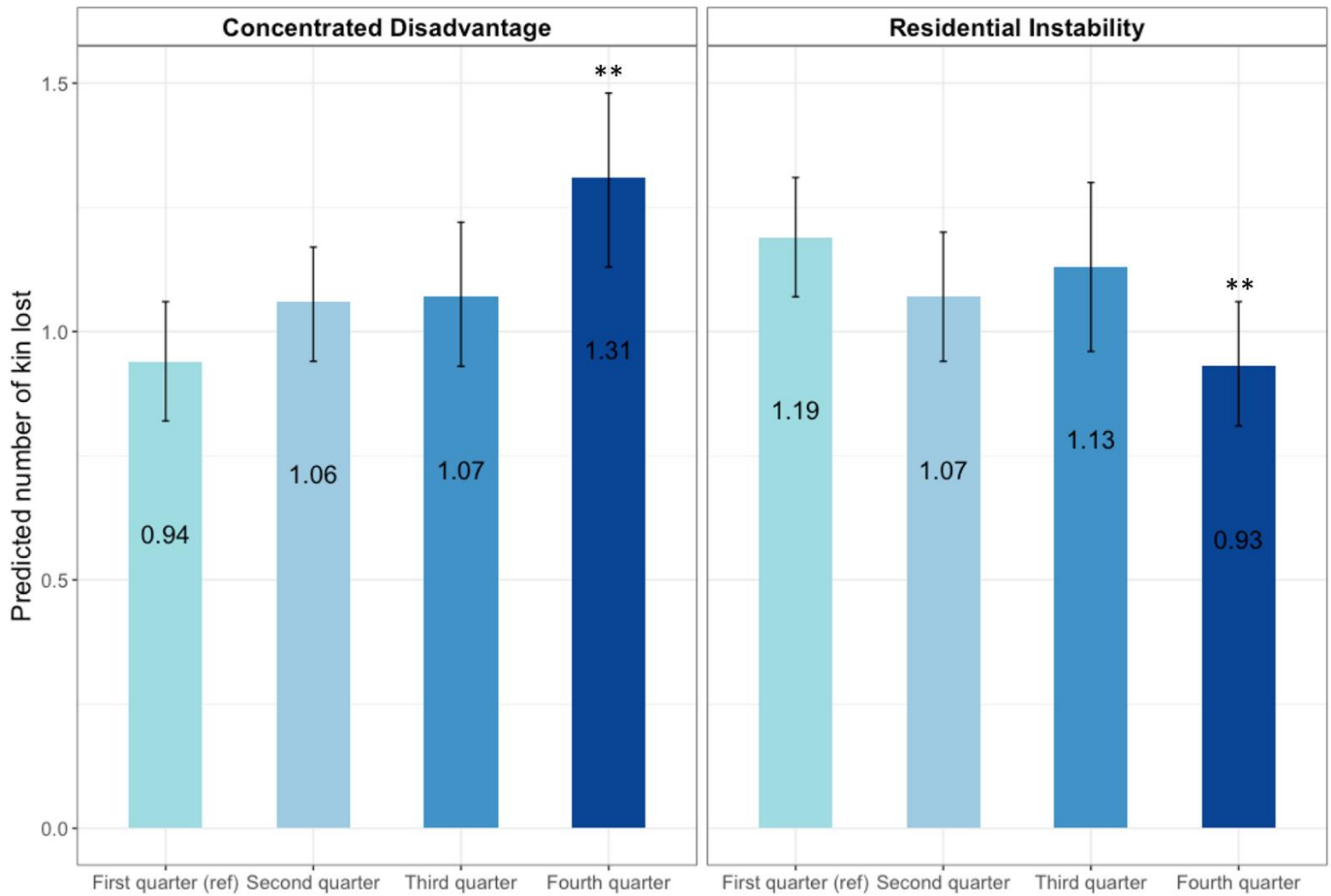


Figure 3.3 Predicted number of kin network losses between Waves 2 and 3, by quarters of neighborhood concentrated disadvantage and residential instability at Wave 1. Predicted values represent average adjusted predictions that are derived from models that include the full set of covariates presented in Table 3.4.
*$p < .05$; **$p < .01$; ***$p < .001$ (Two-sided tests).

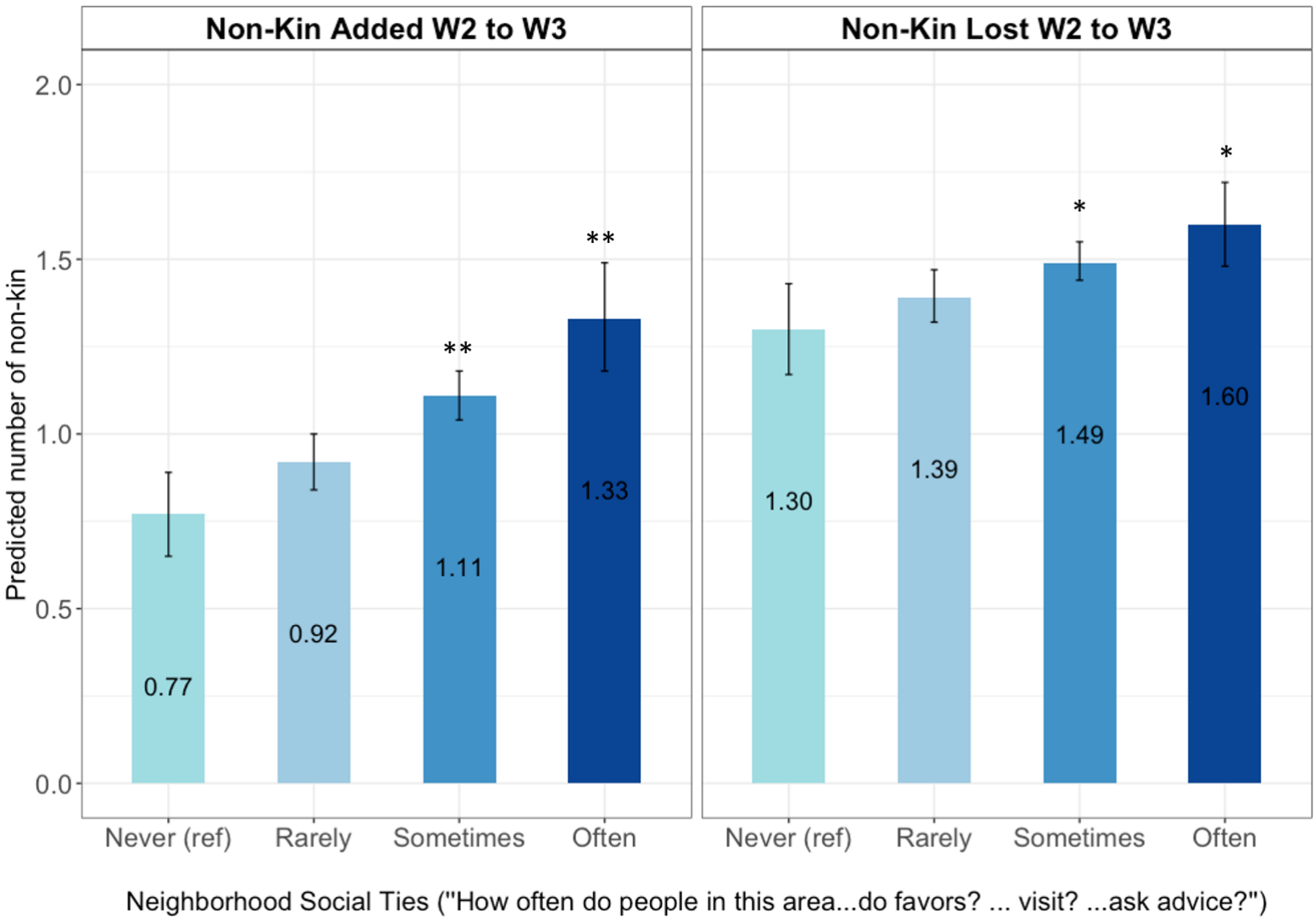


Figure 3.4 Predicted number of non-kin network additions and losses between Waves 2 and 3, by level of neighborhood social ties at Wave 2. Predicted values represent average adjusted predictions that are derived from models that use the full set of covariates presented in Table 3.5.
*$p < .05$; **$p < .01$; ***$p < .001$ (Two-sided tests).

Appendix Table 3.1 Incidence Rate Ratios from Poisson Models Predicting the Number of Network Additions and Losses Between Waves 2 and 3, Including Changes between Waves 1 and 2 as Covariates.[a]

	Number of Network Additions W2 to W3			Number of Network Losses W2 to W3		
	Overall	Kin	Non-Kin	Overall	Kin	Non-Kin
Concentrated disadvantage	1.040	1.052	1.055	1.101*	1.166**	1.016
	(.992 - 1.090)	(.947 - 1.169)	(.944 - 1.180)	(1.022 - 1.185)	(1.054 - 1.291)	(.953 - 1.082)
Residential instability	.927**	.966	.888**	.919***	.886**	.983
	(.884 - .973)	(.898 - 1.040)	(.818 - .964)	(.877 - .964)	(.815 - .964)	(.937 - 1.032)
Neighborhood social ties	1.050	.870**	1.197***	1.033	1.029	1.054*
	(.996 - 1.107)	(.791 - .957)	(1.104 - 1.298)	(.984 - 1.085)	(.953 - 1.111)	(1.003 - 1.109)
Overall Additions W1-W2	.926***			1.154***		
	(.907 - .946)			(1.118 - 1.192)		
Overall Losses W1-W2	1.327***			1.041*		
	(1.293 - 1.362)			(1.001 - 1.083)		
Kin Additions W1-W2		.860***			1.116***	
		(.805 - .918)			(1.073 - 1.162)	
Kin Losses W1-W2		1.467***			1.079**	
		(1.385 - 1.555)			(1.022 - 1.138)	
Non-Kin Additions W1-W2			1.034			1.078***
			(.976 - 1.095)			(1.049 - 1.109)
Non-Kin Losses W1-W2			1.254***			1.127***
			(1.104 - 1.424)			(1.061 - 1.196)
N	1532	1532	1532	1547	1420	982

†$p < 10$; *$p < .05$; **$p < .01$; ***$p < .001$ (Two-sided tests). 95% confidence intervals in parentheses.

[a]All models include the full set of covariates that are included in the main analyses. Coefficients and statistical significance of neighborhood measures are consistent when additions and losses between Waves 1 and 2 are modeled as factor variables.

Appendix Table 3.2 Coefficients from Multilevel Models Predicting Growth/Decline in Network Size and Proportion Kin, Waves 1 to 3.[a]

Predictors	Network Size (Poisson)	Proportion Kin (OLS)
Fixed effect parameters		
Concentrated disadvantage	.975†	-.022*
	(.951, 1.000)	(-.045, -.0001)
Residential instability	1.017†	.002
	(.999, 1.035)	(-.018, .021)
Age	1.074***	-.041***
	(1.047, 1.101)	(-.063, -.019)
Female	1.081***	-.032†
	(1.045, 1.117)	(-.066, .002)
Black	.898**	-.001
	(.843, .956)	(-.058, .057)
Hispanic	.839***	.074**
	(.786, .895)	(.023, .126)
Attended college	1.025	-.059**
	(.989, 1.063)	(-.093, -.025)
Random effects parameters		
Level 1 residual		.058***
Level 2 intercept	9.77e-34***	.033***
Number of observations	3536	3526
Number of respondents	1269	1269
Log pseudolikelihood	-7109.35	-639.62

†$p < .10$; *$p < .05$; **$p < .01$; ***$p < .001$ (Two-sided tests). 95% confidence intervals in parentheses are based on robust standard errors. Models are weighted using respondent-level baseline (Wave 1) weights that adjust for probability of selection and non-response and are based on non-imputed data.

[a]All models include controls for marital status, retired status, urbanicity, residential tenure, number of household members, income (4 categories), number of children, whether the respondent moved to a different census tract between waves 1 and 3, and the inverse Mills ratio. Coefficients in the Poisson model (network size) are incidence rate ratios.

CONCLUSION

The overarching goal of this dissertation was to recast central questions about later life inequality using a social network perspective. Childhood disadvantage, everyday discrimination, and neighborhood conditions are each the focus of well-established literatures that document their profound influence on inequalities in individual well-being across the life course (e.g., Hayward and Gorman 2004; Hill, Ross, and Angel 2005; Williams 2018). At the outset of each chapter, I conveyed the different degrees to which existing perspectives attend to close personal relationships when either explaining or predicting these phenomena. The common backdrop of these chapters is the recognition that personal social networks both arise out of social stratification and contribute to social inequalities (Ajrouch, Blandon, and Antonucci 2005; Lin 1999, 2000; Marsden 1987; Moore 1990). The shared motivation for these papers came from identifying ways that social network theory can shed new light on the origins and consequences of key experiences and exposures that characterize social inequality.

The findings from Chapters 1 and 3 suggest that personal network structure and stability can arise out of familial and social environmental exposures at various points in the life course. In Chapter 2, I show how personal networks contribute to perceptions of everyday discrimination, including how frequently discrimination is experienced and the basis of such treatment. Collectively, these papers expand our knowledge of how key social determinants of well-being intersect with personal social networks. Importantly, these findings emerge above and beyond individual indicators of social position, which have been the lynchpin of much of the empirical literature connecting social inequality and social network structure.

A common theme that emerged from each of the three chapters relates to the role of kin. An overarching insight from this dissertation is that more socially advantaged individuals can

use kin ties in more advantageous ways. A happier family life during childhood is associated with denser, more kin-centric networks later in life, which may reflect the availability of a strong base of coordinated social support. At the same time, a more advantaged socioeconomic position in childhood predicts fewer kin ties, indicating that early social position shapes an individual's capacity to cultivate close ties outside of the family context, counterbalancing the types of resources that are most likely to be provided by kin. More kin-centric networks also protect against experiences of everyday discrimination, but this association may exist mainly among white older adults – a group that is more likely to first face discrimination in later life (Abramson 2015). Those who live in more advantaged neighborhoods are also more likely to retain kin in their networks overtime, suggesting that close family relationships may be more reliable sources of social support for those living in more affluent areas.

Kin are generally regarded as primary sources of support in later life (e.g., Suanet, van Tilburg, and Broese van Groenou 2013). However, the findings from this dissertation caution that the nature of older adults' reliance on kin may be especially tied to certain vulnerabilities and disadvantages that stem from broader structural conditions. The ways that older adults can leverage kin ties as social resources should be contextualized within an individual's personal and family history.

Throughout this dissertation, I emphasized the value of examining these research questions in the context of later life. This is a period of the life course when individuals may be especially reliant on their social networks for advice, support, and social integration (Fiori, Antonucci, and Cortina 2006; Wellman and Wortley 1990; Yang et al. 2016). As older adults can face a common set of challenges that accompany later life, including their own or network members' declining health, aging in and of itself becomes a stratified process. The social and

economic resources that are available to older adults can profoundly influence the quality and longevity of later years (Abramson 2015; Carr 2019).

Nevertheless, the life course perspective warrants future considerations of these topics among representative samples of children, adolescents, and young adults, into mid-life. As emphasized in Chapter 1, the stratification of life chances presents itself well before later life, even in utero (Hayward and Gorman 2004), such that individuals enter later life already on unequal footing, having potentially experienced a lifetime of social (dis)advantage (Walsemann, Geronimus, and Gee 2008).

The NSHAP sample is inherently reflective of selection based on survival to age 50 or age 65, depending on the survey cohort. These selection issues raise questions about how the research topics that I examined might yield different results earlier in the life span and, as underscored in Chapter 1, how the findings may be shaped by experiences and circumstances that are tied to social position and that precede the period of the life course when NSHAP respondents are observed. Perceptions of discrimination are also likely to be shaped by earlier experiences of discriminatory treatment and earlier social contexts (Gee, Walsemann, and Brondolo 2012), which can contribute to later awareness of and perhaps even vigilance against discrimination, as well as the types of close ties that individuals maintain. Likewise, neighborhood selection and segregation earlier in the life course may be associated with individuals' preferences to maintain a particular type of network structure, as well as with neighborhood conditions later in life. These chapters warrant future consideration of these topics with younger samples or, ideally, studies that survey individuals on the wide range of social network and other relevant factors from childhood through later life.

Throughout this dissertation, I have emphasized the well-established linkage between

personal social networks and individual health (Smith and Christakis 2008; Valente 2010). This emphasis is partly to motivate the importance of studying properties of these close social ties, but also because health is such a salient feature of later life and a key dimension of population-level disparities. As childhood disadvantage, discrimination experiences, and neighborhood conditions are each determinants of physical and mental well-being (Diez Roux and Mair 2010; Gee and Ford 2011; Haas 2008), an important next step in this research is to ask how the findings in these chapters intersect with individual health trajectories. For example, can the "long arm" of early life on later life health be partly attributed to the role of childhood conditions in shaping personal network structure and the resources that these networks yield? Is perceived discrimination a pathway through which personal network composition influences older adults' physical and mental well-being? Likewise, do patterns of personal network stability explain, to some extent, "neighborhood effects" on well-being, and in ways that differ based on the stability of kin versus non-kin network members? By incorporating questions that attend to the intersection of personal networks with exposures and experiences that reflect social-structural conditions, we may better understand the social bases of well-being.

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