Journals of Gerontology: Social Sciences
cite as: J Gerontol B Psychol Sci Soc Sci, 2017, Vol. 72, No. 4, 694–705
doi:10.1093/geronb/gbw142
Advance Access publication October 17, 2016

Original Article

Types of Non-kin Networks and Their Association With Survival in Late Adulthood: A Latent Class Approach

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Received November 12, 2015; Accepted July 13, 2016

Decision Editor: Deborah Carr, PhD

Abstract

Objectives: Integration into social networks is an important determinant of health and survival in late adulthood. We first identify different types of non-kin networks among older adults and second, investigate the association of these types with survival rates.

Method: Official register information on mortality is combined with data from the Longitudinal Aging Study Amsterdam (LASA). The sample includes 2,440 Dutch respondents aged 54–85 at baseline in 1992 and six follow-ups covering a time span of 20 years. Using latent class analysis, respondents are classified into distinct types of non-kin networks, based on differences in number and variation of non-kin relations, social support received from non-kin, and contact frequency with non-kin. Next, membership in network types is related to mortality in a Cox proportional hazard regression model.

Results: There are four latent types of non-kin networks that vary in network size and support. These types differ in their associations with mortality, independent of sociodemographic and health confounders. Older adults integrated into networks high in both number and variation of supportive non-kin contacts have higher chances of survival than older adults embedded in networks low in either amount or variation of support or both.

Discussion: A combination of structural and functional network characteristics should be taken into account when developing intervention programs aiming at increasing social integration outside the family network.

Keywords: Epidemiology—Mortality—Social networks—Social support

Over the last four decades, social epidemiologists have convincingly demonstrated positive effects of integration into social networks on survival (Berkman & Syme, 1979; Ellwardt, van Tilburg, Aartsen, Wittek, & Steverink, 2015; Holt-Lunstad, Smith, & Layton, 2010; Litwin & Shiovitz-Ezra, 2006), with evidence being relatively congruent across general and specific populations, countries, time, and gender. At the same time, social isolation has been argued to be a chronically stressful condition contributing to the accumulation of age-related morbidity and functional decline over the life course, thereby bearing the risk of accelerated aging (Berkman, 1988). As there is large variability in survival, and integration in social networks varies within and across people, there is a growing interest in determining which types of social networks relate to high chances of survival in old age.

Most studies developing network typologies have so far focused on the overall social network including kin and non-kin (e.g., family-based network vs. friends-based network) and subsequently related types to mental health (Fiori & Jager, 2012; Gibney & McGovern, 2011; Litwin & Stoeckel, 2014) and survival (Giles, Glonek, Luszcz, & Andrews, 2005; Litwin & Shiovitz-Ezra, 2006). For example, Giles and colleagues (2005) found that networks of friends and confidants protect against mortality, whereas networks of children and relatives did not, stressing the importance of studying non-kin networks in more detail.

Non-kin networks cover any nonfamilial contacts, such as friends, acquaintances, neighbors, and colleagues. Non-kin networks thus can include more types of social contacts than friends only. A sole focus on non-kin relations might generate new insights, also because non-kin networks differ substantially from kin networks in their formation, provide effective sources of companionship and affirmation, and are subject to great heterogeneity among older adults. Even though more recent efforts have been undertaken to distinguish types exclusively for non-kin networks (Miche, Huxhold, & Stevens, 2013), findings on survival are still scarce. The aim of the present study is twofold. First, to identify different types of non-kin networks in old age and second, to test whether the identified network types vary in their associations with older adults' survival. The theoretical framework will employ the Social Convoy Model (Kahn & Antonucci, 1980) and Socioemotional Selectivity Theory (Carstensen, 1993). Hypothesized associations will be tested with data from the Longitudinal Aging Study Amsterdam (LASA).

Background

Different Types of Social Networks

There is little theorizing specifically on the topic of non-kin networks. However, general theories and empirical findings suggest that social networks vary in the degree of number and variation of supportive relations. The Social Convoy Model (Kahn & Antonucci, 1980) proposes that individuals are surrounded by a network of people, and the composition and quality of this network is shaped throughout the life course. Because gains and losses of social relations diverge among individuals, a range of different types of social convoys exist in adulthood. Those older adults succeeding to enhance both structural (composition, such as number and variation of contacts) and functional (quality, such as social support) aspects in their convoy are believed to benefit most in terms of well-being.

A somewhat different prediction follows from Socioemotional Selectivity Theory (Carstensen, 1993). According to this theory, with age, adults increasingly invest in fewer but more useful relations, so that their social networks become selective with a strong focus on emotional needs. Here, the result of successfully managed social contacts is a reduced, yet highly functional network. Much of the support is homogeneous due to the increased selectivity with respect to socioemotional resources. Despite their diverging predictions regarding well-being, both theories argue that among older adults substantially different types of networks may be delineated based on function and structure.

In support of these theoretical notions, research has consistently shown age-related changes and differences in social networks (Broese van Groenou, Hoogendijk, & van Tilburg, 2013; Cornwell, Schumm, Laumann, Kim, & Kim, 2014; van Tilburg, 1998; Wrzus, Hänel, Wagner, & Neyer, 2013), as well as age-dependent effects of social networks on well-being (Litwin & Stoeckel, 2013). Yet, although kin networks tend to be stable over the life span, significant changes have been observed primarily in the non-kin network, with an estimated reduction of one person per decade starting at the age of 60–65 years (Wrzus et al., 2013). This reduction is partly explained by age-related life events, including job exit, relocation, and discontinuation of contact with in-laws and mutual friends after divorce or loss of a spouse. Furthermore, non-kin relations are typically less stable, as they ground on reciprocity, which may dissolve when interpersonal exchange is unbalanced (Klein Ikkink & van Tilburg, 1998).

Altogether these developments—convoy building, socioemotional selection mechanisms, and age-related events—contribute to the evolution of a heterogeneous set of (non-kin) social networks among the older population. Few empirical works have indeed identified different types of friendship and non-kin networks. Using qualitative interviews among older U.S. citizens, Matthews (1986) created a theoretical typology of three friendship styles: the discerning style, which is characterized by forming deep and long-lasting friendships; the independent style, which is characterized by the opposite as individuals with this style are reluctant to commit to friends for life; and the acquisitive style, which lies somewhat in the middle of the former two, as individuals with this latter style invest in close friendships while establishing new friendships throughout the life course. Miche and colleagues (2013) later refined these styles in their study among older German citizens, using an extended definition of non-kin relations (note that although they included any non-kin, they continued to use the friendship label) and latent class analysis (LCA). They found four types: discerning, independent, selectively acquisitive, and unconditionally acquisitive. The latter two types mainly differed in network size, with the unconditional type maintaining more non-kin relations than the selective type.

The latter two study results have in common that network types diverge in number, quality, and variations of relations. In the following, we refer to variation as a structural characteristic of networks, that is, differences that may occur with respect to contact frequency, supportiveness, and social roles among the relations within a personal network. A network consisting of weak and strong contacts like Matthews' (1986) acquisitive style, for instance, is more varied than a network solely consisting of strong contacts like Matthews' discerning style.

To sum up, general theories on network evolution (Social Convoy Model and Socioemotional Selectivity Theory) and specific results on non-kin point to systematic differences in the structure and function of older adults' networks. We therefore expect:

Hypothesis 1: Based on the number and variation of relations with non-kin, different types of non-kin networks can be delineated.

Association With Health and Survival

If social convoys contain structural and functional resources that contribute to life chances, and non-kin relations are a key driver of heterogeneity in convoys, the question arises whether the different types of non-kin networks are associated with variations in older adults' survival. Non-kin relations are seen to uniquely reduce mortality risk beyond benefits of the family, also because they differ in the degree of voluntariness and diversity.

Voluntariness, here defined as the commitment to a relationship by choice, is an important aspect of social relationships. Previous research has shown that social network exchanges promote well-being only when they are effective in reducing stress and improving coping (Rook, 2015). Whereas kin relations are involuntarily prescribed a priori by relatedness rather than contact quality, non-kin relations—especially friendships—are mostly voluntary and reflect a sense of personal control: Individuals can deliberately select non-kin contacts into their network that they expect to be helpful (Carstensen, 1993), but terminate ambivalent or dysfunctional ones (Lang, 2000).

Diversity, here defined as enacting various social roles in a network, has been positively associated with health and survival (Barefoot, Grønbaek, Jensen, Schnohr, & Prescott, 2005; Cohen, Doyle, Skoner, Rabin, & Gwaltney, 1997; Ellwardt, van Tilburg, & Aartsen, 2015; Ellwardt, van Tilburg, Aartsen, Wittek, et al., 2015). Non-kin relations likely add diversity to the overall network, as they vary in their social roles (e.g., being friend, neighbor, former colleague), intensity, and resourcefulness. But also diversity within non-kin networks encompasses benefits, as social support is less often redundant than in homogeneous (kin) networks where network members are mostly interconnected and share similar backgrounds, knowledge, and assets. Different types of contacts thus often provide different kinds of support. Support from non-kin contacts may be even specialized in certain domains (Agneessens, Waege, & Lievens, 2006)—for example, receive emotional support from friends, instrumental help from neighbors, advice from former colleagues—and accessed flexibly in response to occurring needs without overusing single supporters. As such, not only great number of supportive relations but also heterogeneity in support, as well as variation of strong and weak relations can facilitate benefits. On the one hand, although only a limited number of balanced relations can be maintained at high intensity levels, a small number of good friends (e.g., multifunctional contacts) may suffice to cover an individual's core needs. Weak ties on the other hand operate as a reserve that can be intensified to mobilize additional resources and thereby supplement or even replace strong relations exiting the network or failing to satisfactorily respond to demands. Finally, a mix of strong and weak non-kin ties is an attribute of bridging social capital (i.e., connecting otherwise disconnected people from diverse backgrounds), which has been inversely related with poor health (Iwase et al., 2012).

According to these arguments on voluntariness and diversity, both enhanced function and complex structure in non-kin networks relate to high well-being. This prediction is in line with the Social Convoy Model but in contrast with Socioemotional Selectivity Theory, which assumes positive effects of highly functional yet homogeneous networks. Based on our arguments and on theorizing from the Social Convoy Model, we expect longest survival for older adults embedded in non-kin network types that are high in both number and variation of contacts and support.

Hypothesis 2: The greater the number and variation of relations in a non-kin network type, the higher is the chance of survival.

In the following, using data from the LASA, we first model different types of networks based on number and variation in non-kin relations and next compare risk of mortality among those types.

Method

Study Population

LASA is a nationally representative follow-up study in the Netherlands focusing on physical, emotional, and social functioning in later life. Participants aged 54–85 years at baseline were recruited from municipality registries within three geographic regions. There was slight oversampling of older and male participants. Using the same face-to-face interviews and self-administered questionnaires, data have been collected every 3 years since 1992. Our study population covered seven waves until 2011/2012. The first LASA observation included 3,107 respondents. On average, 81% of the respondents were reinterviewed in each follow-up, 12% had died, 2% were physically or cognitively incapable to be interviewed, 5% refused to be reinterviewed, and less than 1% could not be contacted due to a residential relocation to another country or an unknown destination.

All predictors and confounders in the analysis were observed at all follow-ups. The sample only included observations that had complete information on all variables used in the analysis and a minimum of two non-kin relations at this time point of observation. The latter criterion was chosen because, conceptually, a network consists of multiple relations, and analytically, variation between a respondent's relations was assessed. Among the 2,561 eligible cases, item nonresponse on average was less than 5% across all follow-ups. The 2,440 included respondents (53% were women) were followed for a maximum of 20 years and on average had 3.0 valid observations, resulting in a total of 7,304 observations. Supplementary Table SM1 lists the number of respondents for the different time points of observations.

Predictors: Network Variables

Number and variation of non-kin relations were operationalized using information on number, contact frequency, and support quantity across non-kin. Measures of non-kin relations were retrieved from a personal network module in the questionnaire (van Tilburg, 1998). Respondents were asked to identify people with whom they had regular and important socially active contacts and subsequently reported on the nature of their relationships with the nine most frequent contacts, other than the partner. All kin relations were disregarded in the construction of the non-kin measures. Similar to Miche and colleagues (2013), for each of the four predictors mentioned in the following sections, we computed one score for number (or amount) and one for variation.

Non-kin relations

Number of non-kin relations equals the sum of identified contacts who did not have a family tie with the respondent. Variation in non-kin relations is based on counting the number of the different social roles, such as close friend, acquaintance, neighbor, (former) colleague, member of volunteering, or other organizations. Number of contacts and variation in social roles are also known as network size and network diversity.

Contact frequency

Frequency of contact was obtained through asking "How often are you in touch with [name]?" Answers ranged from "1 = never" to "8 = daily." To capture the amount, scores of contact frequency were averaged across all non-kin relations of a respondent. Variation was reflected by the standard deviation of a respondent's contact frequency across all non-kin relations.

Emotional support

For the nine most frequent contacts—whether kin or non-kin—several follow-up questions were asked, including questions on support. For emotional support received, one question asked "How often in the past year did you talk to [name] about your personal experiences and feelings?" Possible responses included "1 = never" to "4 = often." As done before, average and standard deviation were computed for non-kin to determine amount and variation of emotional support across a respondent's non-kin relations.

Instrumental support

For instrumental support received, another question asked "How often in the past year did [name] help you with daily tasks in and around the house?" Answers ranged from "1 = never" to "4 = often," and average and standard deviation assessed amount and variation.

In a final step, still following Miche and colleagues (2013), we recoded all eight scores into "1 = low," "2 = medium," and "3 = high" using tertiles. Working with three-category variables eased the interpretation of classes and avoided the problem of sparseness that typically occurs when using (continuous) variables with large number of categories in LCA.

Outcome: Mortality

Through linkage with population register data, participants' vital status was known up to November 1, 2013. We observed vital status in the period from a participant's first interview date until 5 years after a participant's last interview date, but no later than the register data's end point. In case of death during that period, the observation ended at the participant's decease date. Our 5-year cutoff value was longer than the study's regular 3-year follow-up interval but shorter than two intervals. This ensured coverage of interviews that needed multiple attempts to establish contact with interviewees, while constraining the temporal distance between predictors and outcomes of mortality.

Confounders

Sociodemographic variables

The analysis controlled for respondents' gender, level of educational attainment (ranging from 1 = elementary school not completed to 9 = university education), and age at baseline. Age was recoded into groups when used as a stratifying variable (54–59, 60–64, 65–74, and 75–85 years). Next to these confounders, a comprehensive set of health variables relevant for mortality risk was included in the analysis.

Physical health

Respondents' physical conditions were determined by counting their number of reported chronic diseases, including cancer, arthritis, cardiovascular accident (stroke), diabetes, and malfunctioning of lung, heart, and arteries. Furthermore, a six-item scale measured functional ability, with high sum scores indicating good physical functioning (Katz, Ford, Moskowitz, Jackson, & Jaffe, 1963).

Mental health

Two self-report scales and one screening assessed respondents' mental health. Depressive symptoms experienced within the past week were captured with the 20-item Center for Epidemiological Studies Depression (CES-D) scale (Radloff, 1977). Anxiety feelings over the past 4 weeks were retrieved from the seven-item Hospital Anxiety and Depression Scale (HADS; Zigmond & Snaith, 1983). Strong symptomatology was signified by high sum scores on these scales. The widely used Mini-Mental State Examination (MMSE) screening instrument measured respondents' cognitive functioning (Folstein, Folstein, & McHugh, 1975). This 23-item index encompasses the dimensions of recall, orientation, registration, attention, language, and construction. Higher scores pointed at better cognitive functioning.

Social variables

The analysis included two confounders that potentially influence non-kin networks and risk of mortality. First, respondents indicated whether they had a partner (1 = yes) or not. Second, the size of the kin network was computed by counting the total number of kin relations generated in the personal network module as described previously.

Statistical Analysis

The analytical strategy to identify non-kin networks and to examine their association with survival was twofold. To test our first hypothesis, we used an exploratory approach: In a LCA, respondents with similar network patterns were grouped into classes, so that each class represented a distinct non-kin network type. To test our second hypothesis, we used an explanatory approach: Membership in the previously identified classes was associated with mortality in a series of Cox proportional hazard regressions. Both approaches are detailed in the following.

Latent class analysis

LCA proves useful when one does not wish to use a priori assumptions on the number and characteristics of classes (types), but aim for exploration of empirical data instead. The result is a latent categorical variable that describes qualitative differences between classes, which are treated as mutually exclusive and exhaustive. Crucially, individual posterior probabilities of latent class membership are retained: A four-class solution, for instance, generates four probability values (sum is one) for every individual. Ideally, an individual has high probability for membership in one of the classes and low probabilities for the remaining.

All LCA models were estimated with the recently developed LCA Stata Plugin (version 1.1) by Lanza, Dziak, Huang, Wagner, and Collins (2014). The procedure went as follows. Using the three-category network predictors number, contact frequency, and emotional and instrumental support received at all follow-ups, we first ran an unconditional LCA to determine the optimal number of latent classes. Parameters were constrained to be equal across follow-ups to control for nestedness in follow-ups and ensure that the meaning of the latent classes was invariant over time. Starting from a single-class model, we stepwise increased the number of classes until the model fit leveled off and interpretation of the classes facilitated nonredundant network types. Next, we wanted to avoid that sociodemographic characteristics confounded the association between network class membership and mortality. Therefore, the previously selected model was re-estimated conditionally on the control variables age, gender, and education in a multinominal logistic regression framework, a procedure recognized as conditional LCA.

Cox proportional hazard regression models

Using Cox regressions, we predicted mortality depending on the respondents' latent class membership in the non-kin network types. Latent class membership was treated as a time-varying covariate, so that respondents could change membership in every follow-up. To date, there are two common approaches to LCA with distal outcomes (Lanza, Tan, & Bray, 2013). First, through maximum-probability assignment individuals are assigned to the class corresponding with their highest posterior probability. This so-called best class is treated as a discrete rather than latent predictor in the Cox regression. Problematically, this approach likely produces biased estimates if best class membership is determined with relatively low certainty (low maximum probability).

The second approach uses multiple pseudoclass draws (Lanza et al., 2013). Class membership is randomly drawn from the individuals' posterior probability distribution. This so-called pseudoclass is next used as a discrete regressor in the analysis, like before. This time, however, the classify-analyze procedure is repeated multiple times (typically 20 draws), and regression results are combined afterwards. This iterative procedure reduces the aforementioned uncertainty bias. In our robustness analysis, we performed 1,000 iterations and inspected whether or not the resulting hazard ratios (HR) included insignificant parameter estimates of HR = 1.

All Cox models controlled for education. Moreover, they were stratified for gender and age groups, thus controlling for differences in baseline death hazards among the strata of men and women, and among age groups. We proceeded in four modeling steps. The first model included class membership in non-kin network types together with education. In three consecutive steps, the models were adjusted for physical health, mental health, and social variables.

Results

Latent Non-kin Network Types

Hypothesis 1 stated that different types of non-kin networks can be delineated based on the number and variation of relations with non-kin. Correlations between the eight predictor variables were mostly low to moderate (see Supplementary Table SM2), supporting the construction of a latent typology rather than a unidimensional scale. The series of unconditional LCA revealed four classes, as the model fit improved vastly until that number and leveled off thereafter. Moreover, additional classes became substantially very similar in their interpretation to those already estimated, so that we disregarded solutions with more classes in favor of nonredundancy and parsimony. Model fit (Bayesian information criterion = 18,491) and relative entropy (0.85) were satisfactory in the four-class solution as compared to other solutions. Fit statistics for models with up to seven classes are presented in Supplementary Table SM3. A conditional LCA with four classes—where age, gender, and education acted as covariates—showed a significant improvement in model fit for inclusion of each covariate, so that we continued with the estimates from this final LCA.

Based on the final LCA, we assigned respondents to the class corresponding with their maximum probability and inspected prevalence and distribution of the three-category network variables across classes. Table 1 provides an overview. Maximum probabilities were generally high ($p \geq .91$), implying low uncertainty in the assignment procedure. Class prevalence was distributed rather evenly, ranging from 22% to 31%. All variables but emotional support differed significantly in their probabilities across classes.

Our interpretation of the four non-kin network types (classes) unfolded two major dimensions, which we label as large-small and supportive-unsupportive. The first dimension described mainly network size and diversity: Large networks featured many relations and multiple roles but low contact frequency. In contrast, small networks had low dispersion of roles and high contact frequency. The second dimension delineated the degree to that individuals received (mostly instrumental) support: Respondents in supportive networks used much help from their contacts, whereas respondents pertaining to unsupportive networks relied less on assistance from others.

Table 1. Descriptive Statistics and Probabilities of the Three-Category Non-kin Network Variables Across Latent Classes (N_{ind} = 2,440, N_{obs} = 7,304)

	Class 1	Class 2	Class 3	Class 4
Statistic	Large-supportive	Small-unsupportive	Small-supportive	Large-unsupportive
Latent class prevalence[a]	0.23	0.31	0.22	0.24
Mean of maximum posterior probability[b]	0.93	0.92	0.91	0.92
SD of maximum posterior probability[b]	0.12	0.12	0.14	0.13
Probabilities of variables[c]				
Number/amount				
Non-kin relations				
Low	0.01	**0.63**	**0.33**	0.03
Medium	0.24	0.16	0.27	**0.33**
High	**0.54**	0.03	0.02	**0.42**
Emotional support				
Low	0.16	**0.41**	0.21	0.22
Medium	0.28	0.26	0.21	0.25
High	0.26	0.24	0.26	0.24
Instrumental support				
Low	0.00	**0.55**	0.00	**0.45**
Medium	**0.52**	0.05	**0.41**	0.03
High	**0.35**	0.17	**0.41**	0.07
Contact frequency				
Low	0.30	0.24	0.13	**0.33**
Medium	0.29	0.26	0.19	0.26
High	0.10	**0.43**	**0.36**	0.11
Variation				
Non-kin relations				
Low	0.06	**0.52**	0.31	0.11
Medium	**0.40**	0.04	0.16	**0.40**
High	**0.59**	0.00	0.01	**0.40**
Emotional support				
Low	0.09	**0.51**	0.20	0.20
Medium	0.29	0.20	0.24	0.27
High	**0.36**	0.16	0.23	0.25
Instrumental support				
Low	0.00	**0.56**	0.00	**0.43**
Medium	**0.56**	0.00	**0.44**	0.00
High	**0.50**	0.00	**0.50**	0.00
Contact frequency				
Low	0.04	**0.59**	0.28	0.08
Medium	**0.33**	0.16	0.17	**0.34**
High	**0.33**	0.17	0.21	0.29

Note: LCA = latent class analysis; *SD* = standard deviation.
[a]Covariates included in the conditional LCA: age at baseline, gender, and education. [b]Mean and *SD* were computed from the maximum probability values, that is, the highest out of the four latent class probabilities, across respondents. [c]Probabilities ≥ 0.33 are printed in bold.

Class 1: large-supportive

The first class was characterized by an extensive number of non-kin relations (11.1 on average) and medium to high amount of instrumental support. Moreover, an outstanding feature of this type was the highest variation on all network variables. Note that although amount of emotional support did not differ from other classes, the greater variation indicated presence of few highly supportive relations (besides less supportive). Altogether, this network type was largest, most varied and contained much social support, thereby being highly functional and complex in structure.

Class 2: small-unsupportive

The second class resembled the opposite of the previous type to a great extent (hence the reverse labeling). Both number and variation in network relations were lowest (3.5 non-kin relations on average), and respondents reported least support as compared to those in other non-kin network types. However, contact was mostly frequent, perhaps also because meeting resources were allocated to a select social circle. In sum, these networks were rather small and unsupportive with little differentiation among relations.

Class 3: small-supportive

The third class included networks that were somewhat small, with low to medium number of non-kin relations (4.4 on average). A distinctive feature in this type was the increased focus on frequent, instrumentally supportive relations. Respondents may have been needier than those of other classes, as they relied on a network of relatively few but potentially useful contacts. Variation was low to moderate, with most dispersion in the amount of instrumental support. Overall, this network type was functional but limited in complexity.

Class 4: large-unsupportive

The fourth class stood in stark contrast to the third class and constituted a hybrid of the first two. Respondents reported many different relations (9.5 on average), resulting in a large and varied non-kin network. However, connections were considerably weak with little instrumental support and infrequent contact. Individuals in this last network type may be described as active networkers who stay comparatively independent of others.

Altogether these results confirmed our first hypothesis. Several networks types could be empirically distinguished. These types appeared to differ meaningfully in the number and variation of older adults' relations with non-kin and the amount of social support.

Associations of Non-kin Network Types With Mortality Risk

In Hypothesis 2, we expected highest survival rates for older adults embedded in network types characterized by high number of and variation in relations. Class 1 (large-supportive) resembled this type most and thus should have had lowest risk of mortality. We used this class as the reference category in the subsequent Cox regressions.

Table 2 presents four Cox models on mortality risk with the latent non-kin networks (classes) as predictors. Models 1–4 show the relative hazard for membership in Classes 2–4 as compared to membership in Class 1, with stepwise adjustment for confounders. Mortality of individuals in the latent non-kin network Classes 2–4 was significantly higher than for their counterparts in Class 1. This effect showed across all models, so that the lower mortality risk in Class 1 was explained by neither of the confounding variables. Interestingly, in the fully adjusted model, HR between Classes 2 and 4 hardly differed, suggesting there was little variability in mortality risk between these classes (HR_{Class2} = 1.463, confidence interval [CI] = 1.165–1.836; HR_{Class3} = 1.468, CI = 1.161–1.856; HR_{Class4} = 1.435, CI = 1.123–1.834). Most of the health confounders influenced the risk of mortality significantly. Respondents with a partner and a large kin network originally had lower chances of dying, but these associations disappeared when controlling for physical or mental health.

Based on these findings, our second hypothesis was supported. Older adults with networks containing many diverse contacts had higher survival chances than their counterparts with few unvaried contacts.

Robustness Tests

We performed additional tests to rule out that findings were sensitive to uncertainty in the respondents' assignment to latent classes, attributed to specific subgroups, or based on selection and attrition. These robustness checks included all confounding variables from the final Model 4 and stratifiers where applicable.

Multiple pseudodraws

The estimates from the 1,000 Cox models using pseudo-class draws strongly indicated robustness of the results from the previous Cox models using maximum-probability assignment. In Figure 1, all estimates were larger than HR = 1 (range: 1.151–1.715) and were distributed on a unimodal slim normal curve without signs of skewness. On average estimated effects were slightly lower (means: HR_{Class2} = 1.381, HR_{Class3} = 1.383, HR_{Class4} = 1.383), suggesting they may have been overestimated in the maximum-probability condition, which disregarded uncertainty in the assignment of classes. Class 3 was most sensitive to uncertainty as estimates spread out most.

Gender and age

Although we summarize the findings for the subgroups here, detailed results may be retrieved from Supplementary Tables SM4 to SM9. There were no noticeable differences in the association of non-kin network type with mortality between the group of men and women, with one exception.

Table 2. Hazard Ratios and Confidence Intervals From Cox Proportional Hazard Regression Models on Mortality Risk, Using Maximum-Probability Assignment for the Latent Classes, With Stepwise Adjustment for Confounders (N_{ind} = 2,440, N_{obs} = 7,304)

	Model 1		Model 2		Model 3		Model 4	
Variable	HR	CI	HR	CI	HR	CI	HR	CI
Latent non-kin network types[a]								
Class 1 (ref.)	Ref.		Ref.		Ref.		Ref.	
Class 2	1.513***	(1.212, 1.889)	1.513***	(1.210, 1.891)	1.474**	(1.176, 1.847)	1.463**	(1.165, 1.836)
Class 3	1.565***	(1.242, 1.972)	1.521***	(1.206, 1.919)	1.494**	(1.183, 1.886)	1.468**	(1.161, 1.856)
Class 4	1.344*	(1.053, 1.714)	1.404**	(1.100, 1.793)	1.419**	(1.111, 1.813)	1.435*	(1.123, 1.834)
Sociodemographic variable[b]								
Education	0.967	(0.932, 1.004)	0.990	(0.953, 1.028)	1.006	(0.968, 1.046)	1.005	(0.967, 1.045)
Health variables								
Chronic diseases			1.243***	(1.168, 1.323)	1.238***	(1.162, 1.319)	1.238***	(1.163, 1.319)
Physical functioning			0.941***	(0.927, 0.954)	0.951***	(0.936, 0.965)	0.952***	(0.937, 0.966)
Depression					1.023**	(1.009, 1.037)	1.021**	(1.007, 1.035)
Anxiety					0.969*	(0.940, 0.999)	0.972	(0.943, 1.002)
Cognitive functioning (MMSE)					0.962**	(0.939, 0.986)	0.963**	(0.939, 0.987)
Social variables								
Partner							0.881	(0.742, 1.047)
Size of kin network							0.992	(0.978, 1.007)

Note: CI = confidence interval; HR = hazard ratio; MMSE = Mini-Mental State Examination.
[a]Class 1 = large-supportive, Class 2 = small-unsupportive, Class 3 = small-supportive, Class 4 = large-unsupportive. [b]All models were stratified by gender and age groups.
*p < .05, **p < .01, ***p < .001.

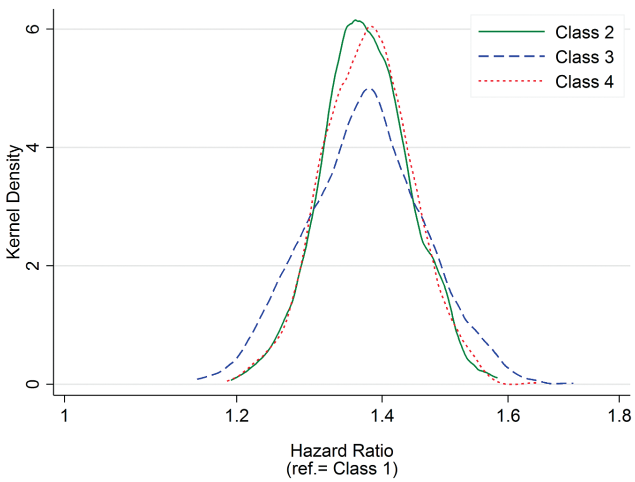

Figure 1. Distribution of hazard ratios (HR) from 1,000 Cox proportional hazard regression models on mortality risk, using pseudoclass draws for the assignment of latent classes. Latent class membership was randomly assigned based on a respondent's posterior probability distribution and subsequently tested as a predictor in the Cox model. The model included Class 1 as the reference category and all confounders (HRs not shown). This procedure was iterated 1,000 times. Class 1 = large-supportive, Class 2 = small-unsupportive, Class 3 = small-supportive, Class 4 = large-unsupportive.

Women in Class 3 (small-supportive) and Class 1 (large-supportive) did not significantly differ in death hazards. Thus, membership in Class 3, that is, having few versus many support relations, affected men somewhat stronger than women. Similarly, no systematic differences existed

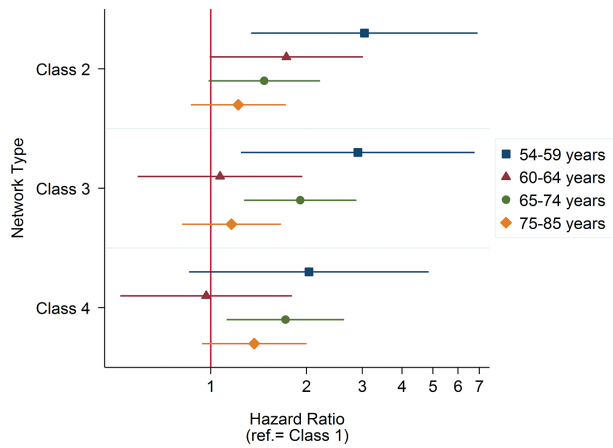

Figure 2. Hazard ratios and confidence intervals of the latent classes from four Cox proportional hazard regression models on mortality risk, separate by age groups. Separate Cox models using the latent class with the maximum probability were performed for four age groups at baseline ($N_{54–59\ years}$ = 419, $N_{60–64\ years}$ = 453, $N_{65–74\ years}$ = 791, $N_{75–85\ years}$ = 777). The models included estimates of all confounding variables (not shown). Class 1 = large-supportive, Class 2 = small-unsupportive, Class 3 = small-supportive, Class 4 = large-unsupportive.

between age groups, so that the overall findings could not be ascribed to a single age group (see Figure 2). Effects of network type were less pronounced in older age and seemed to wash out among respondents aged 75 and older; however, these differences were not significant. Note that CIs were larger among younger cohorts due to smaller sample sizes and less deaths.

Selection effects

We inspected all confounders across latent classes to exclude alternative explanations, most importantly selection into classes. Mean comparisons show that physical health scores did not differ substantially among classes (see Table 3). We also re-estimated classes in a conditional LCA including all confounders this time and subsequently reran the Cox regressions using these classes. Results turned out nearly identical with effects sizes of the classes being slightly higher. Furthermore, in spite of the absent direct effect of having a partner and number of kin relations on survival in the fully adjusted model, they still may have operated as stimulants of contacts with non-kin. However, even though respondents with larger kin networks reported more non-kin relations, size of the kin network neither mediated nor moderated effects of non-kin networks in an interaction test. Altogether, increased survival in Class 1 did not rest on a selection bias toward healthy and sociable respondents.

Attrition bias

The sample composition became increasingly selective with each follow-up. Compared to respondents with follow-up data, respondents without follow-up data were more often men, were older, had more often health issues, and had smaller and less diverse non-kin networks with less frequent contacts in the previous observation. Note that respondents also left our sample when size of the non-kin network dropped below two. Average network size was slightly smaller (−0.43 relations) in the last observation as compared to earlier observations. Thus, respondents with very small non-kin networks may have been underrepresented in later follow-ups.

Discussion

The present study was motivated by the argument that in late adulthood heterogeneous networks of non-kin relations exist and that they are one of the drivers of differences in older adults' well-being and survival. We tested and confirmed these assumptions through constructing latent non-kin network types among an older Dutch population and associating them with mortality risk, covering a time span of up to 20 years. Similar to previous findings from Miche and colleagues (2013), our results yielded a well-fitted model with four delineated network types that differed substantially in their interpretation with respect to the number and variation in supportive contacts with non-kin. Crucially, mortality risk clearly varied, with most survivors pertaining to the large-supportive type: Neither contact with many non-kin relations nor receipt of much support alone facilitated higher chances of survival, but a combination of both. This effect showed net of important health factors, sociodemographic variables, number of kin relations, and uncertainty in the LCA classifying procedure. To our knowledge, this study is among the first that presented a network typology specifically for non-kin and subsequently investigated associations with survival.

Theoretical Implications

Non-kin relations have barely received attention in their own right but served as a vehicle in the study of older adults' overall social networks until now. This seems even more surprising given the considerable variability in the patterns of older adults' non-kin relations in both our study and previous research (Wrzus et al., 2013). Our typology turned out highly congruent with Miche and colleagues' (2013) findings in a German population-based sample: The large-supportive type was comparable to the unconditionally acquisitive type, where older adults had many varied contacts. The small-unsupportive type mirrored the independent type with few, emotionally distant contacts.

Table 3. Means and Standard Deviations of Confounders Among Latent Classes of Non-kin Network Types (Pooled Across Observations, N_{ind} = 2,440, N_{obs} = 7,304)

	Class 1 (N_{obs} = 1,708)		Class 2 (N_{obs} = 2,258)		Class 3 (N_{obs} = 1,610)		Class 4 (N_{obs} = 1,728)	
	Large-supportive		Small-unsupportive		Small-supportive		Large-unsupportive	
Confounder	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Health variables								
Chronic diseases	1.20	1.13	1.16	1.12	1.32	1.22	1.04	1.03
Physical functioning	27.17	4.48	26.77	4.72	26.16	5.02	27.96	3.79
Depression	8.30	7.16	7.84	7.13	9.27	8.14	6.91	6.56
Anxiety	2.98	3.07	2.62	3.10	3.16	3.61	2.44	2.85
Cognitive functioning (MMSE)	28.00	1.91	26.78	2.87	26.96	2.60	27.83	2.01
Social variables								
Partner	59.6%	—	64.8%	—	52.7%	—	72.3%	—
Size of kin network	10.34	6.42	8.30	4.77	8.02	4.89	10.51	5.78

Note: M = means; MMSE = Mini-Mental State Examination; *SD* = standard deviation.

Furthermore, we showed that life chances are influenced by the composition and quality of the individuals' networks of non-kin and that social-epidemiological frameworks ignoring these influences are incomplete. Our results suggest that not all older adults may equally benefit from social interactions with non-kin. Positive effects on survival were most pronounced when non-kin networks featured a strong alliance of structural and functional aspects.

At least two theoretical implications follow from this finding. First, it underpins the Social Convoy Model (Fiori, Smith, & Antonucci, 2007), which predicts greatest well-being for older adults who successfully build extensive convoys rich in support and exchange of diverse kinds of beneficial resources. As we have seen, such convoys can comprise a mix of strong and weak ties, perhaps because the latter potentially offer specialized assistance and provide a protective reserve once strong ties are unavailable or lost.

Second, this notion partly puts into perspective Socioemotional Selectivity Theory (Carstensen, 1993). According to this theory, with age, social interactions become increasingly regulated toward emotional skills, and older adults may even actively narrow their social convoy to adapt to age-related needs. Following this reasoning, individuals putting stronger emphasis on functional rather than structural aspects should benefit most from their network. But restricted non-kin networks geared toward few frequent contacts, that is, the small-supportive type, did not facilitate increased chances of survival in our study. To better understand how older adults consciously design non-kin networks to their own advantage, further testing is desirable. Tests of this theory should use more fine-grained predictions and data on socioemotional relationship characteristics, for example, with a focus on affirmation and companionship.

Methodological Implications

Altogether these insights corroborate earlier calls that research studying the heterotypic nature of social networks benefits from developing typologies. Typologies are a useful tool to represent and interpret multifaceted empirical phenomena in a straightforward fashion. Our study covered a comprehensive array of relevant indicators and thereby adequately captured networks in their intrinsic complexity—most centrally their structural characteristics. An advantage of using measures of variation (rather than number or amount only) is that relations with extreme scores have a less distorting effect on the network measure as a whole. Moreover, through an exclusive focus on non-kin relations, which evolve differently than kin relations, we could uncover otherwise hidden pathways from networks to survival. Research designs using single predictors (e.g., network size) or generic concepts of networks (e.g., subsuming kin and non-kin) likely fail to detect some of the important sources of well-being and health in late adulthood.

One concern repeatedly voiced in the literature is reverse causation. There is evidence that networks become increasingly constrained as physical and cognitive limitations progress and the end of life approaches (Aartsen, van Tilburg, Smits, & Knipscheer, 2004). Furthermore, non-kin networks evolve far from random but occur in response to older adults' need for support in the first place. Although we cannot completely rule out alternative mechanisms, we could show that one non-kin network type was uniquely associated with survival, independent of all adjustment variables. In other words, enhanced chances of survival of older adults' belonging to the large-supportive type did not rest on improved health and greater family networks. The insignificant moderation between kin and non-kin networks suggests that disadvantages from restricted non-kin networks are not easily compensated through other kinds of social interactions. This is in line with one previous study reporting greater protective effects against mortality risk of friend networks than kin networks (Giles et al., 2005).

Comprehensive models seeking to explain differences in survival should therefore not neglect the power of social networks, and non-kin relations in particular. However, elaborate information on contacts outside the family is rare in follow-up studies, also because collecting network data is burdensome for respondents. The rich data source of LASA allowed investigating non-kin networks in great detail.

Limitations and Suggestions for Future Research

The LASA data provided extensive ego-centric information on respondents' relations with others, but not on the complete relations between others. Ideally, we would have liked to include structural variables that can only be derived from respondents' complete networks. Examples are density and so-called structural holes, which have been argued to grant access to bonding and bridging social capital (Lin, 2001). The data also did not encompass troublesome aspects of relationships that operate as disruptive stressors to well-being and health (Rook, 2015), as well as degree of voluntariness. Not all non-kin relations emerge and persist based on personal control, and relations with kin can be intensified by choice, so that family members act as close friends, become neighbors or colleagues. Even though we are confident that our overall findings are unbiased against uncertainty in the latent class assignment, we would have favored an integrated framework that directly relates LCA estimates to mortality outcomes in a single modeling step. Recently, modeling distal outcomes within LCA has been made available (Lanza et al., 2013), however, not yet for survival panel data (e.g., Cox regressions). Finally, in our data, there was considerable change between similar non-kin network types (respondents moved either between large or small networks, implying most change in the support dimension). Because of this, future research may shift the focus toward latent trajectories to examine whether transition from one type to another reduces risk of mortality.

Practical Implications

Gerontological practitioners should consider older adults' network composition in their assessments of clients. However, interventions aiming to improve non-kin networks seem difficult. This is because according to the Social Convoy Model networks build up accumulatively over the life span, and older adults may not be as successful in managing their resourceful ties as Socioemotional Selectivity Theory predicts. If any, intervening strategies may not only target adults in later life—because by then the process of network building has already taken place to a large extent—but earlier in the life course. Additional strategies may be directed toward nourishing existing contacts in very old age to reduce the breaking of useful relations.

Importantly, the salience of non-kin networks has likely increased due to societal changes (Suanet, van Tilburg, & Broese van Groenou, 2013), for example, kin networks have been shrinking and dispersing in times of dropping birth rates and rising mobility. Particularly, older adults with limited access to beneficial family ties will have to rely on friends and neighbors for varied support in the future. This will be even more so in health systems designed to promote independent living and postpone movement into institutionalized homes. Because of this, strong reliance on social networks outside the family may become a non-negligible driver of inequality in health and survival in future generations.

Supplementary Material

Supplementary data is available at *The Journals of Gerontology, Series B: Psychological Sciences and Social Sciences* online.

Acknowledgments

L. Ellwardt planned the study, performed all statistical analyses, and wrote the manuscript. M. Aartsen and T. van Tilburg helped to plan the study, advised on the data analysis, and contributed to revising the manuscript.

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