Disability Dynamics and Social Networks of Older Adults in Europe

Extended Abstract prepared for the European Population Conference 2020

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Abstract

Health status and social networks have rarely been analyzed dynamically. We explore empirically if and how social network changes relate to the disability dynamics across time among middle-aged and older people in 12 European countries. Data came from 21,514 respondents from SHARE (Survey of Health, Ageing and Retirement in Europe). Respondents were aged 55 years and over and were followed-up over about 7 years. Six social network characteristics – reflecting both constant and varying qualities of the network – were used, based on respondents' reports in wave 4 and 6 of the survey. Multi-state modelling was used to investigate links between social network characteristics, health state transitions over time, and death. Individuals with a larger social network size at baseline and those having close emotional ties to other network members had a decreased risk of health decline (hazard ratios 0.96 and 0.95) – controlling for age, gender, education, and country of residence. A social network containing friends at baseline is linked to health recovery (hazard ratio 1.10). Compared to models where each social network measure was entered separately, co-adjusting for all social network measures lead to a change in the statistical significance of the association of having family members as a part of the social network. In all, there is some first evidence that social network characteristics are linked to the disability dynamics of older Europeans. In further analyses we will refine the multistate models, conduct further robustness checks, and investigate crossnational differences in the illness-death process.

Background

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Only a minority of European countries have aged successfully in terms of healthy life years during the last decades. Studying social networks in health outcomes helps to understand how the surrounding social environment, particularly interactions with other people, influences disability trajectories over time. We are particularly interested how social network changes relate to older people's disability dynamics across European countries. Although health and social networks are not fixed statuses, it has not been common so far to analyze both of them dynamically. Previous studies suggest on the

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one hand that richer social networks (in terms of size, quality, and diversity) contribute to better health outcomes (Litwin 1998). On the other hand, when disabilities develop, there are also multiple pathways of development of social relationships and networks. For example, disabled people can become more restricted in their communication and so networks may become smaller. Also, close ties (i.e. family or friends) mobilize to support the disabled person, and hence network size may even increase and communication may intensify (Cornwell 2009). We are interested in understanding how network changes relate to the changing disability status among European middle-aged and older people across time.

Data, Measures, and Method

This study draws on data from Waves 4, 5, 6 and 7 of SHARE (Börsch-Supan et al., 2013). SHARE is a longitudinal, cross-national data-set about the health, socio-economic status and social relations of middle-aged and older Europeans. Data collection for the waves used in the current study took place in 2010–2011 (Wave 4), 2013 (Wave 5), 2015 (Wave 6), and 2017 (Wave 7). We limited our sample to men and women aged 55 or older with complete information on their health status and social network characteristics in all four waves. Persons were excluded from the analysis if they only had a single data point i.e. no health transitions were recorded, if they did not have a baseline health measurement, or if they had any missing social network information (n = 205,276 person-waves observations). For each respondent in our sample we thus have four observations. These selection criteria resulted in a sample of 86,056 person-waves observations nested in 12,404 women and 9,110 men.

Social Network Characteristics. Social network data were collected at two waves. Our main interest is in social network change and how it relates to the disability dynamics, specifically the illness-death process. We measure network change using multiple parameters that capture the number of persons who were named as social network members at Wave 4 but who were not named as social network members at Wave 6 (network members "lost") as well as parameters that reflect the number of social network members who were named at Wave 6 but not named as such at Wave 4 (network members "added"). To allow for non-linear associations and to ensure that results do not merely reflect differences in the number of social network members named at either Wave 4 or Wave 6, measures are entered into the models using indicators of the specific number of confidants lost or added per respondent. This measuring approach is similar to that used by Cornwell and Laumann (2015).

Health. Physical health was assessed at each wave using a direct question about whether or not respondents were limited in activities because of health. Health states were assigned as follows: no limitation/ healthy (= 1) and limitation/ limited (=2). For computational efficiency the last group merges the two categories "limited, but not severely" and "severely limited" from the original SHARE questionnaire. We treat the health states as interval-censored. This is because we assume that aging is a multi-state process which takes place in continuous time but the transition between the health states is only observed, however, at pre-scheduled panel waves. Health states are thus intervalcensored. Respondents' exact death times are known, however.

Covariates. Several factors co-vary with health, social network change, and network features, including age, gender, and education. Age is modeled linearly (and shifted so that the coefficient reflects age since baseline at Wave 4). Gender is coded 1 if the respondent is a man and 0 if the respondent is a woman. Education is measured with a categorical variable, distinguishing low (International Standard Classification of Education (ISCED) 0–2; pre-primary to lower secondary education –ref–), medium (ISCED 3–4; upper secondary to post-secondary non-tertiary education) and high (ISCED 5-6; tertiary education) levels of educational attainment². We include country dummies in our analysis, too (Estonia –ref–). Because patterns of network change may depend on the baseline network structure, we also include controls for baseline network size (ranging from 0 to 7), whether or not the network includes friends at baseline $(0 = no, 1 = yes)$, whether or not the network includes family at baseline (0 = no, 1= yes), and emotional closeness to network members at baseline (ranging from $1 = not$ very close to $4 =$ extremely close). Descriptive statistics of these and other key variables are presented in Table 1. Figures 1 and 2 additionally provide a descriptive overview of two social network measures – size and emotional closeness to network members – split by country.

> *** Table 1 about here *** *** Figures 1 and 2 about here ***

The associations between the predictor variables and disability dynamics were investigated by using multi-state models. Multi-state models are an extension of competing risks models and describe how respondents move between a series of states in continuous time (Jackson 2011). If a respondent is in state $S(t)$ at time t, the movement on the discrete state space $1, \ldots, R$ is then governed by transition intensities $q_{rs}(t, z(t))$: $r, s = 1, ..., R$. Transition intensities in turn may depend on time t, or, more generally, also on a set of individual-level or time-dependent explanatory variables $z(t)$. The intensity represents the instantaneous risk of moving from state r to state $\neq r$:

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q_{rs}(t, z(t)) = P(S(t) = r)/\delta t .
$$

The q_{rs} form a $R \times R$ matrix Q whose rows sum to zero, so that the diagonal entries are defined by

$$
q_{rs} = -\sum_{s \neq r} q_{rs}.
$$

Specifically, we assume a model as shown in Figure 3 – with two living states ("no limitation/ healthy" and "limitation/ limited") and death as an absorbing state. Respondents can advance to having a limitation (transition $1 \rightarrow 2$) or recover from having a limitation (transition $2 \rightarrow 1$), or die from any living state. The probability of individual *i* being in state s at wave w is conditional on the state occupied and observed covariates, $z(.)$, at the previous wave $si(w-1)$ and $zi(w-1)$ but not at any waves prior to this point. Because we apply this model to panel data – where the state $S_i(t)$ is only known at a finite series of times – it also relies on the Markov assumption that future evolution only depends on the current state. That is, $q_{rs}(t, z(t), F_t)$ is independent of F_t , the observation history of the process up to the time preceding t . However, the model is not explicitly Markovian as the transition intensities are related to age, which is a time-dependent covariate. Neither is it a semi-Markov model as the time since entry into the state is not accounted for. To include the time to reach each state is complex because the exact times of state entry are unknown (interval censoring).

*** Figure 3 about here ***

For now we restricted the sample to include fully observed respondents (from Wave 4 to Wave 7), but in future analyses we will account for people who were (partially) lost to follow-up or alive at the end of the study but in an unknown state with censoring ($n = 4602$). For such individuals, their likelihood will then be taken as a weighted sum of likelihoods through all possible values for the

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 2 For 536 respondents information on educational attainment is missing across all panel waves.

unobserved state. Initial state probabilities were estimated from the data, taking into account misclassification. The Nelder–Mead optimization method was used to maximize the likelihood. Likelihood ratio tests were used to compare models after the inclusion of each social network measure; the best fitting model contained all six social network measures (χ^2 = 20.06(4), p<.05). Data were analyzed using R version 3.5.3 (R Development Core Team 2010) and the 'msm' package in R (Jackson 2011).

Preliminary Results

Table 2 shows the distribution of state transitions for the analytic sample. We can see in this first overview that several transitions occur over the period of observation (Wave 4 to Wave 7) and that transitions can and do occur from state 2 back to state 1. Note firstly that only the frequencies of the transitions for 1 \rightarrow 2 and 2 \rightarrow 3 represent one-off transitions, whereas the frequencies for 1 \rightarrow 3 can be due to transitions $1 \rightarrow 3$ and $1 \rightarrow 2 \rightarrow 3$.

> *** Table 2 about here *** *** Figure 4 about here ***

Output from two multi-state models is presented in Tables 3 and 4. The results for each single social network measure, adjusted for age, gender, education, and country, are shown in Table 3. Note that due to computation intensity we restricted transition to death to be 1. This speeds up computation and allows calculation of a likelihood maximum for two transition specific hazards, $q_{\rm rs}(t)$ – from state 1 to state 2 (becoming limited) and from state 2 to state 1 (becoming healthy). Only three social network measures differ significantly from zero: social network size at W4, social network contains family members at W4, and emotional closeness to social network members at W4. They seem to be associated with a decreased risk of physical health.

*** Tables 3 and 4 about here ***

The results for the co-adjusted social network measures, controlled for age, gender, education, and country, are shown in Table 4. Again, because we restricted transitions to death to be 1 only two transitions are estimated for each social network measure. Social network size at W4 and emotional closeness to network members at W4 are associated with a decreased risk of health decline (hazard ratios and 95% confidence intervals for size and emotional closeness: 0.955 [0.934, 0.975] and 0.950 [0.918, 0.982], respectively). A social network containing friends at W4 is linked to health recovery – the positive transition from having a limitation back to no limitation (HR 1.102 [1.035, 1.172]). Compared to the models where each social network measure was entered separately, there were two notable differences in the magnitudes or the statistical significance of the associations: A social network containing family is not significantly associated with health decline anymore, whereas a social network containing friends is significantly associated with health recovery (cf. Tables 3 and 4).

Conclusion and Next Steps:

Our findings are based on the combination of a unique demographic resource and a multi-state modelling approach to data analysis. SHARE is a large European population-based data set with regular bi-annual participant follow-up over several years. However, as in any longitudinal study of ageing, there is respondent attrition due to death and dropout. For our first, preliminary analyses we considered a quite restricted sample. Prospectively, we will further investigate how social network measures are associated with health and mortality of older Europeans taking attrition and dropout explicitly into account. A multi-state model is well suited to address these issues (van den Hout & Matthews 2010). Consideration will specifically give to the following issues:

- Analysis of longitudinal data for ageing processes cannot ignore dropout due to death. We will account for people who were lost to follow-up or alive at the end of the study but in an unknown state with *right censoring*. For such individuals, their likelihood will then be taken as a weighted sum of likelihoods through all possible values for the unobserved state.
- We will have to conduct some missing value imputation on education (536 observations in the restricted sample); depending on what other covariates will be considered, missing values may need to be imputed here too.
- We will re-fit the multi-state model for four transitions to investigate associations between social network measures and health decline and mortality and calculate life expectancies for men and women. (Total residual life expectancy is defined as the sum of occupancy times in each living state and can be calculated by using numerical integration (mid-point rule). Piecewise hazards are then defined to account for the changing risk of transitions by age.). Note that even the presented restricted models have been computationally extensive.
- In future analyses we will conduct robustness checks, for example, by running the models from two different sets of starting values for the transition intensity matrix and by using different optimization methods (Nelder–Mead vs. Broyden–Fletcher–Goldfarb–Shanno).
- Because our interest also lies in assessing differences in older people's disability dynamics across countries, we will consider how specific country characteristics (over and above country dummies) relate to the illness-death process.

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Table 1 Descriptions and means and standard deviations of key variables (N = 21,514)

Source: Survey of Health, Ageing and Retirement in Europe (SHARE), Waves 4 – 7. Own calculations.

Notes: AT = Austria, BE = Belgium, CH = Switzerland, CZ = Czech Republic, DE = Germany, DK = Denmark, EE = Estonia, ES = Spain, FR = France, IT = Italy, SE = Sweden, SI = Slovenia. Standard deviations in italics.

Figure 1 Box plots of social network size at baseline W4 by country (N = 21,648)

Source: Survey of Health, Ageing and Retirement in Europe (SHARE), Waves 4 – 7. Own calculations. Notes: AT = Austria, BE = Belgium, CH = Switzerland, CZ = Czech Republic, DE = Germany, DK = Denmark, EE = Estonia, ES = Spain, FR = France, IT = Italy, SE = Sweden, SI = Slovenia.

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Figure 3 A multi-state model for disease progression with SHARE data

Source: Survey of Health, Ageing and Retirement in Europe (SHARE), Waves 4 – 7. Own calculations.

Table 3 Hazard ratios and 95% confidence intervals for the individual effects of social network measures on health decline

Source: Survey of Health, Ageing and Retirement in Europe (SHARE), Waves 4 – 7. Own calculations.

Notes: Controlled for age, gender, education, and country. State 1: no limitation; State 2: limitation; State 3: dead.

Table 4 Hazard ratios and 95% confidence intervals for the co-adjusted effects of social network measures on health decline

Source: Survey of Health, Ageing and Retirement in Europe (SHARE), Waves 4 – 7. Own calculations.

Notes: Controlled for age, gender, education, and country. State 1: no limitation; State 2: limitation; State 3: dead.