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Authors: Eleonora Patacchini, Gary V. Engelhardt

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CENTER *for* RETIREMENT RESEARCH *at* BOSTON COLLEGE

WORK, RETIREMENT, AND SOCIAL NETWORKS AT OLDER AGES

Eleonora Patacchini and Gary V. Engelhardt

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Center for Retirement Research at Boston College
Hovey House
140 Commonwealth Avenue
Chestnut Hill, MA 02467
Tel: 617-552-1762 Fax: 617-552-0191
http://crr.bc.edu

Eleonora Patacchini is a professor of economics at Cornell University. Gary V. Engelhardt is the Melvin A. Eggers Economics Faculty Scholar and Chair of the Economics Department at Syracuse University. The research reported herein was pursuant to a grant from the U.S. Social Security Administration (SSA) funded as part of the Retirement Research Consortium. The findings and conclusions expressed are solely those of the author and do not represent the views of SSA, any agency of the federal government, Cornell University, Syracuse University, or Boston College. Neither the United States Government nor any agency thereof, nor any of their employees, makes any warranty, express or implied, or assumes any legal liability or responsibility for the accuracy, completeness, or usefulness of the contents of this report. Reference herein to any specific commercial product, process or service by trade name, trademark, manufacturer, or otherwise does not necessarily constitute or imply endorsement, recommendation or favoring by the United States Government or any agency thereof. The authors thank Benjamin Cornwell for providing code for making network measures in the NSHAP, Jordan Stanley for excellent research assistance, and Jason Fichtner for comments. All errors are their own.

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Center for Retirement Research at Boston College
Hovey House
140 Commonwealth Ave
Chestnut Hill, MA 02467
Tel: 617-552-1762   Fax: 617-552-0191
http://crr.bc.edu

Affiliated Institutions:
The Brookings Institution
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Abstract

This paper examines the impact of work and retirement on the size, density, and composition of older Americans' social networks. It uses novel panel data from the first two waves of the National Social Life, Health, and Aging Project. Critical components of the analysis include the development of an instrumental variable fixed-effect estimation strategy based on Social Security age-eligibility rules to isolate the causal effect of labor supply on networks.

The paper found that:

- Labor supply raises (and retirement lowers) the size and density of one's social network;
- The estimated elasticity of the social network size to the labor force participation rate is 0.25;
- The estimated elasticity of network size to hours worked is 0.16;
- The estimated elasticity of network size to the retirement rate is 0.12; and
- Most of these effects occur for women and individuals with a post-secondary education.

The policy implications of the findings are:

- Any future changes in Social Security early and full benefit ages will change the social networks of older individuals; and
- This may reduce the pool of individuals who provide social support to older individuals.

Introduction

The role of family, friends, and neighbors in providing social support at older ages has been a longstanding topic of interest in public health and the sociology and demography of aging. In contrast, the role of social networks in shaping—and being shaped by—economic decisions has relatively recently generated substantial attention among economists (Benhabib, Bisin, Jackson, 2011; Jackson and Zenou, 2013). One area of emphasis has been the impact of social networks on education, employment, and labor supply outcomes, particularly for younger individuals. Social connections may aid in finding employment (Montgomery, 1991; Ioannides and Datcher Loury, 2004; Calvó-Armengol and Jackson, 2004; Bayer, Ross, and Topa, 2008), and there may be peer effects and other social interactions in labor supply and education (Woittiez and Kapteyn, 1998; Brock and Durlauf, 2001; Grodner and Kniesner, 2006, 2008; Calvo, Patacchini, and Zenou, 2009). However, there has been little work on older individuals, and little work on the reverse channel: the impact of work and employment on social networks and social connectedness.[1] In particular, employment may provide opportunities to expand one's social network, or may crowd out the time necessary to foster social ties. Transitions out of the labor force at older ages may have the potential to induce large changes in social networks.

This paper has a simple goal: to examine the impact of work and retirement on social networks. It uses novel data on older Americans from the first two waves of the National Social Life, Health, and Aging Project (NSHAP). In particular, the NSHAP gathered egocentric data on the social network of each respondent. These data are used to examine how changes in labor force participation, hours worked, and retirement affect network size, composition, and a variety of metrics of network density for older individuals.

A fundamental empirical challenge in identifying causal effects of labor supply on social networks is that labor force attachment is not assigned randomly across individuals. An important contribution of the empirical analysis is the development of a panel instrumental variable (IV) identification strategy to circumvent these difficulties and isolate causal impacts. The IV approach, detailed below, relies on a large literature in labor and public economics showing that age-based eligibility rules for claiming Social Security benefits have important effects in reducing labor force participation and hours worked by, and inducing retirement

[1] Axtell and Epstein (2003) is one exception.

among older individuals (Feldstein and Liebman, 2000; Krueger and Meyer, 2000). The first wave of the NSHAP was administered in 2005-6; the second wave was in 2010-11. In the five-year window between waves, individuals from different birth years hit the Social Security eligibility ages at different points, which yields differential exposure to incentives to reduce labor supply and retire that is non-linear in age. Given widespread knowledge among older individuals of the age-eligibility rules for Social Security, this program-induced variation in labor supply is plausibly exogenous with respect to individual choices about social networks.

For individuals in the later stages of their working careers, defined in this paper as ages 57-70, there is a strong first-stage relationship between age eligibility for Social Security and labor force participation, hours, and retirement, respectively, in the NSHAP panel. For example, controlling for marital status, age (linearly), and a broad array of health characteristics, attaining the Social Security Early Entitlement Age (EEA) of 62 is associated with an 11 percentage-point reduction in the labor force participation rate and a 19 percentage-point increase in self-reported retirement, respectively. Attainment of age 65—the Social Security Full Benefit Age (FBA) for many cohorts—is associated with a 5 percentage-point reduction in labor force participation and an 11 percentage-point reduction in retirement, respectively.

Based on the IV approach, there are two primary findings about the link between work, retirement, and social networks at older ages. First, labor supply raises (and retirement lowers) the size and density of one's social network. The estimated elasticity of the social network size to the labor force participation rate is 0.25. The estimated elasticity of network size to hours worked is 0.16. The estimated elasticity of network size to the retirement rate is 0.12. Second, most of these effects occur for women and individuals with a post-secondary education. Work and retirement have little impact on the size of the social network for men and the lesser educated. The paper also explores how work and retirement affect the composition of network members. Unfortunately, these estimates were too imprecise to draw firm conclusions.

The remainder of the paper is organized as follows. Section 1 briefly reviews the related literature. Section 2 describes the NSHAP data and lays out basic cross-sectional patterns between labor supply and the size, density, and composition of social networks. Section 3 describes the econometric specification and outlines the IV strategy. The main findings and some extensions are presented in section 4. There is a brief conclusion.

Related Literature

This study is connected to three interrelated strands of the literature. The first is a large literature at the intersection of sociology, demography, and gerontology that has examined the importance of social networks for the elderly. This includes the relationship between network size and measures of social capital (Cornwell, et al., 2008), network changes over the life course (Hartup and Stevens, 1999; Wrzus et al., 2013), and the impact of social networks on behavioral outcomes. Much of this work has focused on health outcomes and generally finds that smaller social networks and social isolation are associated with adverse impacts on life satisfaction and physical and mental health outcomes (Lubben, 1988; Litwin, 2001; Fiori et al., 2007; Price et al., 2009; Hawton, et al., 2011; Litwin and Shiovitz-Ezra, 2011; Coyle and Dugan, 2012; Shiovitz-Ezra and Litwin, 2012). There has been some work on retirement specifically. This includes Lancee and Radl (2012), who found that formal networks were associated with later retirement and informal networks were associated with earlier retirement.

The economics literature has paid comparatively less attention to social networks until relatively recently (Benhabib, Bisin, Jackson, 2011; Jackson and Zenou, 2013) and little attention to networks among the elderly. In particular, retirement may either crowd in or crowd out network size. A second set of studies has focused on theoretical economic models of network link formation and destruction, including Ehrhardt, et al. (2006), Carrillo and Gaduh (2012), Lageras and Seim (2012), and Hellman and Staudigl (2014), among others. These studies typically model endogenous network destruction as occurring with a constant rate of decay. Unfortunately, since employment can either be a substitute or complement to networks for older individuals, these studies provide few strong predictions for the impact of retirement on social networks.

Finally, there is a third, smaller set of studies that is most closely related to this analysis. Fletcher (2014) examined the impact of retirement on social networks using data on individuals form 16 countries collected in Wave 4 of the *Survey of Health, Ageing and Retirement in Europe* (SHARE). SHARE is a representative sample of individuals 50 and older. In addition to detailed questions on employment, economic status, and health asked in all waves, it asked in Wave 4 about family, friends, neighbors and acquaintances with which the respondent had discussed important matters in the last twelve months: "Who are the people with whom you most often discussed important things?" This generated cross-sectional egocentric data on "discussion" networks.[2] Fletcher (2014) modeled social network measures as a function of retirement status:

$$N_{ic} = \alpha + \beta R_{ic} + \boldsymbol{\gamma}\mathbf{X}_{ic} + \psi_c + u_{ic}\,, \tag{0.1}$$

where i and c index individual and country, respectively, N is a social network measure, R is an indicator variable for retirement status, $\mathbf{X}$ is a vector of explanatory variables that accounts for differences in observable characteristics across individuals that might be correlated both with network measures and retirement, ψ is a country fixed effect, and u is a disturbance term. The focal parameter is β, which measures the marginal impact of retirement on social networks. As retirement might be endogenous, Fletcher followed Willis and Rohwedder (2010) and used age-based eligibility rules for public pensions as an instrument for R, where the first-stage was modeled as

$$R_{ic} = \kappa + \theta I(Age_{ic} > Eligible_c) + \boldsymbol{\xi}\mathbf{X}_{ic} + \psi_c + \varepsilon_{ic}\,. \tag{0.2}$$

The instrument was an indicator variable I for where the individual's age exceeded the eligibility age for public pension benefits, and, hence varied by age and country. Consequently, Fletcher (2014) presented IV estimates with standard errors clustered by single year of age and country.[3] Those estimates suggested that retirement had little impact on social network size.

Börsch-Supan and Schuth (2016) also used the Wave 4 data from SHARE and examined the role of social networks and retirement in affecting cognitive decline in older adults. In particular, there is a large literature on the impact of retirement on physical and mental health, including Charles (2004), Adam et al. (2007), Willis and Rohwedder (2010), Bonsang et al. (2012), Coe et al. (2012), Insler (2014), Eibich (2015), Mazzonna and Peracchi (2016), among others. Börsch-Supan and Schuth (2016) modeled retirement as having an impact on cognitive health through two pathways: first, a direct pathway, as examined in the previous studies; and, second, an indirect pathway through reductions in social network size, which, in turn, decrease

[2] The social network module was not asked in Waves 1-3.
[3] There were 16 age groups and 16 countries, yielding 256 age-by-year cells for the clustered errors.

cognitive health. The idea of the latter is that employment, even if unenjoyable, provides grist for cognitive functioning. They modeled cognitive health as a function of retirement status and network size, and instrumented network size using an indicator variable *I* for where the individual's age exceeded the eligibility age for public pension benefits and regional social capital measures. In contrast to Fletcher (2014), their estimates suggested that retirement lowers the size of social networks. Overall, there does not appear to be a consensus set of estimates on the impact of retirement on social networks.

Data and Descriptive Statistics

The empirical analysis uses data from the first two waves of the National Social Life, Health, and Aging Project (NSHAP). The first wave, conducted in 2005-6, is a nationally representative stratified random sample of just over 3,000 adults ages 57-85. The second wave, conducted in 2010-11, contains nearly 3,400 interviews covering surviving Wave 1 respondents and their spouses, partners, or romantic partners. Both waves of the NSHAP collected basic information on demographics and employment status, including self-reported labor-market status (currently working, retired, disabled and unable to work, unemployed or laid off and looking for work, homemaker, or other), whether worked for pay in the last week, and the number of hours worked for pay in the last week. In addition, there is extensive information on self-reported health, detailed disease conditions, and limits to activities of daily living (ADLs).

The sample for the empirical analysis is limited to 1,338 individuals, who were 57-70 years old in Wave 1 and survived to Wave 2. Column 1 of Panel A of Table 1 shows means of selected characteristics for individuals in the sample. The sample is primarily married, white, with more than a high school education. Panel B shows sample means at baseline for the three labor supply measures used in the analysis. Just under half reported being retired; 45 percent reported having worked for pay in the last week (these two categories are not necessarily mutually exclusive). The mean number of hours worked was 16.4, and mean conditional on working was 36.6 hours (not shown).

Panel C shows means of selected health characteristics for individuals in the sample. The first set of measures are based on a question to the respondent to rate his/her health as either excellent, very good, good, fair, or poor. The second measure is the number of limits to activities of daily living (ADLs). The NSHAP collects information on seven activities—bathing, eating, dressing, walking across a room, walking one block, getting in and out of bed, and using the toilet—each designed to measure various dimensions of an individual's ability to function in his/her residential space. For each of the seven tasks, a 1 was recorded if the respondent had difficulty with that task and a zero otherwise. The scores are summed for the seven tasks, so that the ADL measure in the table ranges from 0 (no difficulties with any of the tasks) to 7 (difficulties with all of the tasks). So, a higher value of the measure means a worse functional status.

The final health measure is a count of the number of medical conditions a doctor had ever told the individual that he/she had. The nine conditions were high blood pressure, diabetes, cancer, lung disease, heart failure, heart attack, stroke, arthritis, and dementia. The index ranges from 0 (the absence of all nine conditions) to 9 (the presence of all nine conditions). A larger index value indicates poorer health.

The most important feature of the NSHAP for the purposes of this study is that it gathered social network roster information for each individual. Specifically, each respondent (the "ego") was asked to name members (the "alters") of his/her social network, using the following script:

> "Now we are going to ask you some questions about your relationships with other people. We will begin by identifying some of the people you interact with on a regular basis…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?"

For individuals without a spouse, partner, or romantic partner, up to five names were allowed; for individuals with a spouse, partner, or romantic partner, up to six names were allowed. Information on the labor supply, demographics (other than gender and age), and health of the alters was not gathered. Hence, these data are what are known as *egocentric* social network data. Like the SHARE data used by Fletcher (2014) and Börsch-Supan and Schuth (2016), the NSHAP measures "discussion" networks.

Column 1 of Panel A in Table 2 shows the mean network size for the sample of 1,338 individuals from Wave 1 who appeared in Table 1, measured as the number of alters named plus the respondent. The sample mean is 4.4 persons. Then for each person named, gender and relationship to the respondent was recorded. Column 1 of Panel B shows the distribution of alters across relationship type. About 20 percent of network members are spouses, partners, or romantic partners; almost 28 percent are children; and 12 percent are siblings. Friends make up just under a quarter, and co-workers represent under 3 percent of social networks. Just over 61 percent of members are women.

For each potential pair of individuals named on the roster, the NSHAP then asked each respondent the frequency with which the two individuals in the pair talk to each other. From this information, a variety of measures of social network connectedness were constructed. These have been validated in sociological studies and shown to be associated with life-course factors (Borgatti, 2003; Cornwell, 2009; Cornwell et al., 2008, 2009).

Column 1 of Panel C shows sample means for four network measures. The first is the number of alter pairs. This is count of the number of pairwise interactions between members on the network roster. The mean is 8.55. The second is network density, defined as the number of actual alter pairs divided by the potential number of alter pairs (if all individuals on the roster were pairwise connected to all others). Density runs on a scale from 0 to 1. Sample mean density is 0.852, which indicates that the actual interactions among individuals on the network roster represent about 85 percent of all potential (pairwise) interactions. The third is contact frequency, which is constructed from the self-reported questions about the frequency of contacts of the respondents with alters and is measured in days per year. For example, the sample mean is 204.5, which says that the average respondent talks to members of his/her social network 204.5 out of 365 days of the year, where “talk” refers to in person, over the phone, or by email. The final network measure is average closeness. For each individual on the roster, the respondent was asked “How close do you feel your relationship is? Would you say it is not very close, somewhat close, very close, or extremely close?” Although these are ordinal responses, the convention from the social networks literature in sociology was followed, which scores each response with a cardinal value (1=very close, 2=somewhat close, 3=very close, and 4=extremely close), and those values were averaged across alters in the network. The sample mean for the average closeness measure is 3.15, which says that the typical relationship between the respondent and alter in the sample is "very close."

Columns 2 and 3 show sample means for baseline network characteristics for the sub-samples of individuals who reported they were working for pay and not working for pay at the time of the baseline interview, respectively. For each measure (row), column 4 calculates the difference between the two means and indicates whether the difference in means is statistically different from zero at the 10 percent level of significance (one asterisk) or the 5 percent level of significance (two asterisks). Therefore, column 4 measures the simple cross-sectional differences in social network size and composition between those in and out of the labor force. In panel A, there are small differences in network size that are not statistically significant. In panel B, those in the labor force have a higher fraction of their social network comprised of co-workers, and a lower fraction from friends and neighbors. Aggregating across all kin (parents/parents-in-law, children, siblings and other relatives), there are no discernible differences between the two groups. There is a similar pattern in column 5-7 that appears on the intensive margin of work, based on the number of hours worked, conditional on working: those who work more than 20 hours per week have a greater (lesser) share of their social network made up of co-workers (friends and neighbors). Columns 8-10 show similar calculations, but based on self-reported retirement status. Here, the patterns are reversed: those who are retired have a lesser (greater) share of their social network made up of co-workers (friends and neighbors). Overall, it appears that there is a shift in the composition away from friends and neighbors and toward co-workers when working, which reverses itself when retired.

Econometric Framework and Identification Strategy

While suggestive, the simple cross-sectional patterns in Table 2 between social network and labor supply measures are not necessarily causal for potentially three reasons. First, there are many differences in observable characteristics between those working and not working that may account for the differences in social network outcomes. Second, there similarly may be differences in *unobservable* characteristics between those working and not working. To account for these, the analysis moves to a regression-based approach and exploits the fact that the labor supply and social networks questions from Wave 1 of the NSHAP were repeated in Wave 2, administered five years later in 2010-11, yielding longitudinal information and allowing for panel data analysis.

Specifically, let i and t index individual and calendar year, respectively. Then the reduced-form linear regression specification of the relationship between social networks and labor supply can be written as

$$N_{it} = \alpha + \beta H_{it} + \boldsymbol{\gamma}\mathbf{X}_{it} + u_{it}\,, \tag{0.3}$$

where N is a social network measure, such as in Table 2, H is a measure of labor supply, $\mathbf{X}$ is a vector of explanatory variables that accounts for differences in observable characteristics across individuals that might be correlated both with network measures and labor supply, and u is a disturbance term. The focal parameter is β, which measures the marginal impact of labor supply on social connectedness.

As noted, unobserved heterogeneity in social connectedness in u that is correlated with labor-market attachment would render standard estimates of β biased and inconsistent. Hence, u is modeled as

$$u_{it} = \gamma_t + \eta_i + v_{it} \tag{0.4}$$

where γ is a time effect, η is time-invariant individual-specific heterogeneity in social connectedness, and v is an error term that varies within individual over time. Then a standard fixed-effect (within) estimator can be applied to estimate the (time-varying) parameters in (0.3). Let the symbol $\bullet$ denote variation in a variable that occurs "within" an individual (over time), then with two waves of the NSHAP, estimation of (0.3)-(0.4) by fixed effects implies the model can be re-written as

$$N_{\bullet t} = \beta H_{\bullet t} + \boldsymbol{\gamma}\mathbf{X}_{\bullet t} + \gamma + v_{\bullet t}\,, \tag{0.5}$$

where the estimate of the focal parameter β is identified by cross-time variation in labor supply within an individual, i.e. changes in labor supply between Waves 1 and 2 for the same individual.[4]

The final reason why the cross-sectional correlations in Table 2 might not be causal is classic endogeneity. As has been modeled extensively in the existing literature, social networks may affect labor supply, implying reverse causality in (0.3). That is, the cross-time variation in labor supply within an individual might not be exogenous, even conditional on cross-time within variation in observables: $Cov(H_{\bullet t}, v_{\bullet t} \mid \mathbf{X}_{\bullet t}) \neq 0$. In the presence of endogeneity, even fixed-effect estimates of β will be biased and inconsistent.

To address this final concern, the following instrumental variable approach is used. There is a voluminous literature in labor and public economics that shows that age-based eligibility rules for Social Security have important effects in reducing labor force participation and hours worked by, and inducing retirement among, older individuals (Feldstein and Liebman, 2000; Krueger and Meyer, 2000). In light of this, labor supply is modeled as a function of age-based Social Security eligibility rules. These rules are non-linear in age and plausibly unrelated to the strength of social networks and social connectedness. Specifically, the first-stage model is

$$H_{\bullet t} = \kappa + \theta_1 D_{\bullet t}^{Age>=EEA} + \theta_2 D_{\bullet t}^{Age>=65} + \theta_3 D_{\bullet t}^{Age>=FBA} + \boldsymbol{\psi}\mathbf{X}_{\bullet t} + \varepsilon_{\bullet t}, \qquad (0.6)$$

where the instrument set, denoted as $\mathbf{Z}$, is composed as follows: $D^{Age>=EEA}$ is a dummy variable that takes on a value of one if the individual has attained the Social Security early entitlement age (*EEA*), which is 62; $D^{Age>=65}$ is a dummy variable that takes on a value of one if the individual has attained age 65; and $D^{Age>=FBA}$ is a dummy variable that takes on a value of one if the individual has attained the full benefit age (FBA), which is 65 for those born in 1937 and earlier, rises by two months for every birth year 1938-42, respectively, and is 66 for those born in 1943-1954.

To be valid, the instrument set must satisfy three conditions. First, the instruments must be relevant, $Cov(H_{\bullet t}, \mathbf{Z}_{\bullet t} \mid \mathbf{X}_{\bullet t}) \neq 0$. In practice, the instruments are highly correlated with all

[4] With only two waves of data, γ_t in (0.4) reduces to γ and becomes the intercept in the fixed-effects model.

three measures of labor supply: labor force participation, hours, and retirement. Column 1 of Table 3 shows the first-stage fixed-effect estimates of θ_1, θ_2, and θ_3 in (0.6), where $\mathbf{X}$ contains controls for marital status (married, widowed, and separated/divorced), age (linearly), self-reported health status (excellent, very good, good, fair), number of limits to activities of daily living (ADLs), and the number of medical conditions.[5] From the table, attaining the Social Security Early Entitlement Age (EEA) of 62 is associated with an 11.3 percentage-point reduction in the labor force participation rate (i.e., $\hat{\theta}_1 = -0.113$). Attainment of age 65 is associated with a 6.1 percentage-point reduction in labor force participation (i.e., $\hat{\theta}_2 = -0.061$). For those born 1938-1942, the FBA rose by 2 months per year of birth, reaching 66 for those born in 1943. The youngest birth cohort in the analysis sample is 1948. For those born 1944-1948, the FBA is 66. Therefore, variation in $D^{Age>=FBA}$ in (0.6) that is independent of $D^{AGE>=65}$ is essentially year-of-birth variation from the increase in the FBA for those born in 1938-1948. In column 1, conditional on $D^{Age>=EEA}$ and $D^{AGE>=65}$, attainment of the FBA is associated with a small reduction in labor force participation (i.e., $\hat{\theta}_3 = -0.003$) that is not statistically different from zero at conventional levels.[6] The *F*-statistic associated with the test of the null hypothesis that the instrument set is not relevant (i.e., $H_0 : \theta_1 = \theta_2 = \theta_3 = 0$) is 7.73, with a *p*-value of 0.0001. Columns 4 and 7 show the first-stage fixed-effect estimates of θ_1, θ_2, and θ_3 when the labor supply measures are hours and retirement status. The results are similar, and the associated *F*-statistics indicate that the instrument set is not weak, based on the rule of thumb of Staiger and Stock (1997).[7]

Second, the instrument must be excludable. That is, conditional on marital status, age, and health characteristics, attaining the Social Security eligibility ages should not have had an impact on social networks, except through labor supply H. Finally, the instrument must be exogenous, $Cov(\mathrm{Z}_{\bullet t}, v_{\bullet t} \mid \mathbf{X}_{\bullet t}) = 0$. The fundamental identifying assumption is that, conditional

[5] The excluded group is never married individuals in poor health.
[6] This result is qualitatively consistent with the findings of Blau and Behaghel (2012).
[7] One mechanism that is explicitly ruled out by assumption is that the labor-supply responsiveness to Social Security eligibility—the θ's in (0.6)—is itself not a function of the size and composition of the social network. Given widespread knowledge among older individuals of the age-eligibility rules for Social Security, we do not believe this to be a problem in this case.

on observables ($\mathbf{X}$), the variation in age-eligibility for Social Security across-time within an individual is uncorrelated with any factors varying across time within an individual in the error, $v_{\bullet t}$. In the five-year window between waves, individuals from different birth years hit the Social Security eligibility ages at different points, which yields differential exposure to incentives to reduce labor supply and retire that is non-linear in age. This variation is assumed to be exogenous. Another way of stating this assumption is that social networks would have otherwise evolved smoothly for an individual across time in the absence of Social Security eligibility rules having had been in place.

Estimation Results

Basic Results. Column 1 of Table 4 presents the basic IV estimation results, which control for marital status, age, and the self-reported health, ADL, medical conditions listed in panel C of Table 1. Each cell in the table is an estimate of the focal parameter β from a separate regression of (0.5). The estimate indicates the impact of a one-unit change in the labor supply measure on the dependent variable. For column 1 of the table, the dependent variable is the natural logarithm of network size, which means that β is interpreted as the percentage change in network size for a one-unit change the labor supply measure. In panel A, the labor supply measure is a dummy variable for whether the respondent worked for pay in the last week. A one-unit change means moving from not working to working. The associated IV estimate of β in column 1 is $\hat{\beta} = 0.418$, which says that a transition into the labor force is associated with an estimated 41.8 percent increase in the size of one's social network.[8] With a standard error of 0.217, this estimate is statistically different from zero at the 5.4 percent of significance. At the sample mean labor force participation rate of 44.8 percent (column 1, panel B of Table 1), this estimate implies an elasticity of network size to the labor force participation rate of 0.19. This elasticity is shown in square brackets in the table.

Column 1 of panel B shows an isomorphic estimate using hours worked as the measure of labor supply. The IV estimate of β is $\hat{\beta} = 0.0076$, which says that an additional hour worked raises the size of the social network by three-quarters of a percentage point. Evaluated at the

[8] The associated first-stage is shown in column 1 of Table 3.

sample mean hours of 16.4 (column 1, panel B of Table 1), this implies an elasticity of network size to hours worked of 0.12.

Finally, column 1 of panel C shows the IV estimate when the measure of labor supply is a dummy variable for whether the respondent self-reported he/she was retired. The associated IV estimate of β is $\hat{\beta} = -0.195$, which says that retirement is associated with an estimated 19.5 percent decrease in the size of one's social network. With a standard error of 0.121, this estimate is statistically different from zero only at the 10.8 percent of significance. At the sample mean labor force participation rate of 47.5 percent (column 1, panel B of Table 1), this estimate implies an elasticity of network size to the retirement rate of 0.09.

Many individuals obtain health insurance coverage at age 65 through Medicare. This is the same as the FBA for those born in 1937 and earlier. Moreover, health insurance coverage itself may be correlated with social networks independent of labor supply, which would violate the exclusion restriction on the instrument set. To address this, column 2 in Table 4 repeats the IV estimation in column 1, but now controlling directly for health insurance coverage, which is measured in the NSHAP. When health insurance is controlled for directly, all the identifying variation in $D^{Age>=65}$ comes from the FBA being at 65 for those born in 1937 or earlier. The IV estimates for all three measures of labor supply are similar to those in column 1.

When an individual attains the EEA or FBA, the probability of working changes, but so, too, does income. If labor supply falls, earned income falls (mechanically), and if Social Security benefits are claimed, Social Security income rises. Since income may be correlated with the size of one's social network, it is important to control directly for income in the regression specification. Specifically, column 3 of Table 4 expands the list of control variables to account directly for both family income and assets. The estimates of β for all three labor supply measures are qualitatively similar.

Columns 4-6 of Table 4 show IV estimates when the dependent variable is the natural logarithm of the number of alter pairs in the network, which measures pairwise interactions between members. These estimates show a pattern similar to those for network size: labor supply significantly raises pairwise interaction; retirement lowers pairwise interaction.

Extensions. Table 5 shows IV estimates of the impact of the labor supply measures using the other network measures from Table 2 that capture the composition of the network as measured by the relationship type (spouse, partner, romantic partner; kin; friend or neighbor; co-worker, and others) and gender. Similarly, Table 6 shows estimates of the impact of the labor supply measures using contact frequency and the average closeness of the relationships in the network. Unfortunately, the estimates in both tables are imprecise, and firm conclusions cannot be drawn.

Table 7 presents IV estimates of β for the richest model from Table 4 (i.e., column 3 in Table 4, which controls for marital status, age, health, health insurance coverage, income, and assets), but on selected sub-samples split by demographics. For example, columns 1 and 3 of Table 7 show separate estimates of the impact of labor supply on network size for men and women, respectively. Men show very little responsiveness—almost all of the impact of labor supply on network size in Table 4 is loaded onto women. Columns 3 and 4 show separate estimates by educational attainment. Work has little impact on network size for individuals with a high school degree or less. Almost all of the full sample impact from Table 4 is loaded onto those with post-secondary education. Finally, columns 5 and 6 show estimates split by race. Differences in the impact of work on network size are not as sharp as those based on gender and education. Table 8, which focuses on the number of alter pairs, has a similar flavor.

There is a long literature in economics that examines joint retirement among spouses (e.g., Hurd, 1989; Gustman and Steinmeier, 2005). In the current context, a spouse's eligibility for Social Security may influence a married individual's retirement plans. To account for this, Table 9 shows a separate set of estimates for individuals who were married in the baseline year of 2005. Specifically, column 1 shows IV estimates of β for the richest model from Table 4 (i.e., column 3 in Table 4, which controls for marital status, age, health, health insurance coverage, income, and assets), using just the individual's age eligibility for Social Security as instruments. The estimates are similar to those in Table 4. Column 2 shows IV estimates of β for the same specification as in column 1, but for the subset of married individuals with non-missing information on their spouse's age. The estimates do not differ substantially. Finally, in column 3, both the individual's and the spouse's age-eligibility variables are used as instruments. Again, the IV estimates of the impact of labor supply on social network size are similar to those in Table 4.

Conclusion

This paper used novel data on older Americans from the first two waves of the National Social Life, Health, and Aging Project (NSHAP) to examine how changes in labor force participation, hours worked, and retirement affect network size, composition, and a variety of metrics of network density for older individuals. A key empirical innovation was the development of a panel instrumental variable (IV) identification strategy that used age-eligibility rules for claiming Social Security benefits to generate instruments to isolate the causal impact of labor supply on social networks.

There were two primary findings. First, labor supply raises (and retirement lowers) the size and density of one's social network. The estimated elasticity of the social network size to the labor force participation rate is 0.25. The estimated elasticity of network size to hours worked is 0.16. The estimated elasticity of network size to the retirement rate is 0.12. Second, most of these effects occur for women and individuals with a post-secondary education. Work and retirement has little impact on the size of the social network for men and the lesser educated.

There are three natural extensions to the analysis. The first is to link social networks to the supply of social support to more directly get at the impact of retirement on social support. The NSHAP contains detailed information on social support. The second is to examine more sophisticated measures of network density (Cornwell, 2009). Finally, the third wave of the NSHAP, administered in 2015-6, will be released soon, at which point the youngest individuals in the analysis sample (57 year olds in 2005-6) will have passed the EEA and FBA. This will yield more variation in labor supply and help better identify and sharpen the IV estimates. These are clear avenues for future research.

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Table 1. *Sample Means of Selected Socio-Economic Characteristics at Baseline (in 2005-6) for All Individuals Ages 57-70 and by Sub-Sample, Standard Deviations in Parentheses*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variable	All	Men	Women	High School or Less	More than High School	White	Non-White
A. Demographic Characteristics							
Married	0.729	0.839	0.626	0.700	0.751	0.782	0.567
Divorced/Separated	0.136	0.095	0.175	0.143	0.131	0.109	0.220
Widowed	0.105	0.041	0.166	0.136	0.086	0.089	0.155
Never Married	0.029	0.025	0.033	0.025	0.032	0.020	0.058
Age	63.3	63.2	63.5	63.7	63.1	63.2	63.7
	(3.9)	(4.0)	(3.9)	(3.9)	(3.9)	(3.9)	(4.1)
Women	0.513	0	1	0.541	0.496	0.501	0.552
High School or Less	0.385	0.364	0.406	1	0	0.339	0.527
More than High School	0.615	0.636	0.594	0	1	0.661	0.473
White	0.755	0.774	0.737	0.665	0.811	1	0
B. Labor Supply Measures							
Self-Reported Retired	0.475	0.516	0.437	0.452	0.490	0.479	0.463
Worked Last Week for Pay	0.448	0.519	0.380	0.351	0.509	0.475	0.363
Hours Worked Last Week	16.4	20.3	12.7	12.6	18.8	17.6	12.8
	(20.9)	(22.8)	(18.3)	(19.2)	(21.6)	(21.4)	(19.0)
C. Health Characteristics							
Self-Reported Health Excellent	0.146	0.158	0.134	0.095	0.178	0.165	0.089
Self-Reported Health Very Good	0.349	0.380	0.320	0.267	0.401	0.391	0.220
Self-Reported Health Good	0.295	0.265	0.324	0.309	0.286	0.276	0.355
Self-Reported Health Fair	0.163	0.157	0.169	0.247	0.111	0.128	0.272
Self-Reported Health Poor	0.046	0.040	0.053	0.082	0.024	0.041	0.064
Number of Limits to Activities of Daily Living (ADLs)	0.648	0.439	0.846	0.913	0.482	0.521	1.040
Number of Medical Conditions	2.1	1.9	2.2	2.3	1.9	2.0	2.5
	(1.6)	(1.6)	(1.6)	(1.7)	(1.5)	(1.5)	(1.7)
Covered by Health Insurance	0.803	0.799	0.808	0.758	0.832	0.838	0.698

Table 2. *Selected Network Characteristics at Baseline (in 2005-6) for All Individuals Ages 57-70, and by Baseline Labor-Market Status*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
		Worked Last Week			More than 20 Hours Last Week (Conditional on Working)			Retired		
Variable	All	Yes	No	Difference (2)-(3)	Yes	No	Difference (5)-(6)	Yes	No	Difference (8)-(9)
A. Network Size (Number of Alters)	4.41	4.40	4.42	-0.02	4.32	4.70	-0.38**	4.48	4.35	0.13*
B. Fraction Who Are										
Spouse/Partner/Romantic Partner	0.202	0.207	0.198	0.009	0.213	0.182	0.032**	0.201	0.202	-0.001
Parent/Parent-in-Law	0.029	0.038	0.022	0.016**	0.043	0.019	0.024**	0.020	0.038	-0.018**
Child	0.278	0.271	0.284	-0.013	0.268	0.281	-0.013	0.276	0.281	-0.005
Sibling	0.124	0.119	0.130	-0.011	0.115	0.132	-0.017	0.129	0.121	0.008
Other Relative	0.071	0.062	0.078	-0.016**	0.061	0.064	-0.017	0.075	0.067	0.008
Friend	0.232	0.217	0.245	-0.028**	0.205	0.262	-0.057**	0.251	0.216	0.035**
Neighbor	0.012	0.009	0.014	-0.005*	0.008	0.013	-0.004	0.014	0.010	0.004
Co-Worker	0.028	0.054	0.007	0.047**	0.062	0.022	0.040**	0.014	0.041	-0.027**
Other Non-Relative	0.022	0.023	0.021	0.002	0.023	0.025	-0.003	0.020	0.024	-0.004
Female	0.614	0.601	0.624	-0.023*	0.598	0.613	-0.015	0.605	0.622	-0.017
C. Other Network Measures										
Alter Pairs	8.55	8.46	8.62	-0.16	8.17	9.61	-1.44**	8.83	8.30	0.53
Network Density	0.852	0.840	0.861	-0.021*	0.840	0.844	-0.004	0.849	0.855	-0.006
Contact Frequency	204.5	205.7	203.6	2.1	205.5	206.4	-0.9	202.9	206.0	-3.1
Average Closeness	3.15	3.13	3.16	-0.03	3.14	3.08	0.06	3.13	3.16	-0.03

Table 3. *First-Stage Fixed-Effect Estimates of the Impact of Social Security Eligibility on Selected Measures of Labor Supply for All Individuals Ages 57-70, Standard Errors in Parentheses*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Dependent Variable:								
Instrumental Variables	Worked Last Week			Hours			Retired		
Dummy if age greater than or equal to Early Entitlement Age	-0.113 (0.035)	-0.113 (0.035)	-0.107 (0.038)	-6.494 (1.304)	-6.528 (1.305)	-6.667 (1.448)	0.189 (0.035)	0.190 (0.035)	0.200 (0.038)
Dummy if age greater than or equal to 65	-0.061 (0.036)	-0.061 (0.036)	-0.044 (0.040)	-2.929 (1.361)	-2.940 (1.362)	-1.787 (1.533)	0.105 (0.036)	0.105 (0.036)	0.106 (0.040)
Dummy if age greater than or equal to Full Benefit Age	-0.003 (0.043)	-0.002 (0.043)	-0.036 (0.049)	-0.448 (1.630)	-0.498 (1.632)	-2.078 (1.849)	0.039 (0.043)	0.041 (0.043)	0.056 (0.048)
Partial F-statistic on Instrument Set	7.73	7.70	4.76	16.28	16.37	11.03	21.58	21.68	19.26
Controls									
Marital Status, Age, and Health Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Health Insurance Coverage	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Income and Assets	No	No	Yes	No	No	Yes	No	No	Yes

Note: Each column in the table represents a different specification of the first-stage model. Estimates in each column all come from the same regression.

Table 4. *Instrumental Variable Fixed-Effect Estimates of the Impact of Labor Supply on Selected Measures of Social Networks for All Individuals Ages 57-70, Standard Errors in Parentheses, Elasticities in Square Brackets*

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable:					
Labor Supply Measure Used as the Focal Explanatory Variable	ln(Network Size)			ln(Number of Alter Pairs)		
A. Worked Last Week	0.418	0.403	0.547	0.782	0.755	1.017
	(0.217)	(0.215)	(0.286)	(0.401)	(0.398)	(0.530)
	[0.19]	[0.18]	[0.25]	[0.35]	[0.34]	[0.46]
B. Hours	0.0076	0.0072	0.0098	0.0141	0.0135	0.0182
	(0.0037)	(0.0037)	(0.0045)	(0.0068)	(0.0068)	(0.0083)
	[0.12]	[0.12]	[0.16]	[0.23]	[0.22]	[0.29]
C. Retired	-0.195	-0.180	-0.252	-0.370	-0.344	-0.469
	(0.121)	(0.120)	(0.126)	(0.224)	(0.222)	(0.234)
	[0.09]	[0.09]	[0.12]	[0.18]	[0.16]	[0.22]
Number of Individuals	1,338	1,338	1,285	1,338	1,338	1,285
Controls						
Marital Status, Age, and Health Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Health Insurance Coverage	No	Yes	Yes	No	Yes	Yes
Income and Assets	No	No	Yes	No	No	Yes

Note: Each cell in the table represents a different regression. Each cell gives the estimate of beta in equation (1.3). Elasticities are calculated at the sample means in Table 1. Income and assets are missing for a small number of observations, which accounts for the change in sample size across columns.

Table 5. *Instrumental Variable Fixed-Effect Estimates of the Impact of Labor Supply on the Composition of Alters in the Social Network, Ages 57-70, Standard Errors in Parentheses*

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable: Fraction of Network that is					
Labor Supply Measure Used as the Focal Explanatory Variable	Spouse, Partner, or Romantic Partner	Kin	Friend or Neighbor	Co-Worker	All Others	Female
A. Worked Last Week	-0.104	0.047	-0.093	0.069	0.081	0.037
	(0.089)	(0.139)	(0.136)	(0.058)	(0.058)	(0.123)
B. Hours	-0.002	0.0008	-0.0016	0.0015	0.0012	0.0007
	(0.002)	(0.0024)	(0.0023)	(0.0010)	(0.0010)	(0.0021)
C. Retired	0.053	-0.020	0.041	-0.031	-0.043	-0.013
	(0.042)	(0.069)	(0.068)	(0.029)	(0.027)	(0.061)

Note: Each cell in the table represents a different regression. Each cell gives the estimate of beta in equation (1.3).

Table 6. *Instrumental Variable Fixed-Effect Estimates of the Impact of Labor Supply on Contact Frequency and Closeness in the Social Network, Ages 57-70, Standard Errors in Parentheses*

	(1)	(2)
	Dependent Variable:	
Labor Supply Measure Used as the Focal Explanatory Variable	Contact Frequency	Average Closeness
A. Worked Last Week	76.6	0.069
	(100.7)	(0.266)
B. Hours	0.958	0.0010
	(1.696)	(0.0046)
C. Retired	-48.3	-0.037
	(51.5)	(0.137)

Note: Each cell in the table represents a different regression. Each cell gives the estimate of beta in equation (1.3).

Table 7. *Instrumental Variable Fixed-Effect Estimates of the Impact of Labor Supply on the Social Network Size by Population Sub-Group, Ages 57-70, Standard Errors in Parentheses, Elasticities in Square Brackets*

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable: ln(Network Size)					
	Sample:					
Labor Supply Measure Used as the Focal Explanatory Variable	Men	Women	High School of Less	More than High School	White	Non-White
A. Worked Last Week	-0.075	1.168	0.080	0.727	0.736	-0.094
	(0.277)	(0.754)	(0.443)	(0.340)	(0.421)	(0.278)
	[-0.04]	[0.44]	[0.03]	[0.43]	[0.35]	[-0.03]
B. Hours	0.00005	0.019	0.003	0.012	0.011	-0.002
	(0.0051)	(0.009)	(0.007)	(0.005)	(0.005)	(0.007)
	[0.001]	[0.24]	[0.04]	[0.23]	[0.19]	[-0.03]
C. Retired	-0.022	-0.705	-0.014	-0.394	-0.290	-0.287
	(0.146)	(0.302)	(0.204)	(0.167)	(0.168)	(0.182)
	[-0.01]	[-0.31]	[-0.006]	[-0.19]	[-0.14]	[-0.13]

Note: Each cell in the table represents a different regression. Each cell gives the estimate of beta in equation (1.3). Elasticities are calculated at the sample means in Table 1.

Table 8. *Instrumental Variable Fixed-Effect Estimates of the Impact of Labor Supply on the Number of Alter Pairs by Demographic Sub-Group, Ages 57-70, Standard Errors in Parentheses, Elasticities in Square Brackets*

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable: ln(Number of Alter Pairs)					
	Sample:					
Labor Supply Measure Used as the Focal Explanatory Variable	Men	Women	High School of Less	More than High School	White	Non-White
B. Worked Last Week	-0.155	2.253	0.186	1.319	1.305	-0.141
	(0.503)	(1.444)	(0.804)	(0.629)	(0.766)	(0.517)
	[-0.08]	[0.86]	[0.07]	[0.67]	[0.62]	[-0.05]
B. Hours	-0.0003	0.036	0.006	0.022	0.019	-0.002
	(0.0092)	(0.016)	(0.014)	(0.010)	(0.010)	(0.013)
	[-0.006]	[0.45]	[0.08]	[0.41]	[0.33]	[-0.03]
C. Retired	-0.027	-1.348	-0.038	-0.713	-0.528	-0.550
	(0.265)	(0.575)	(0.369)	(0.312)	(0.309)	(0.340)
	[-0.01]	[-0.59]	[-0.02]	[-0.35]	[-0.25]	[-0.25]

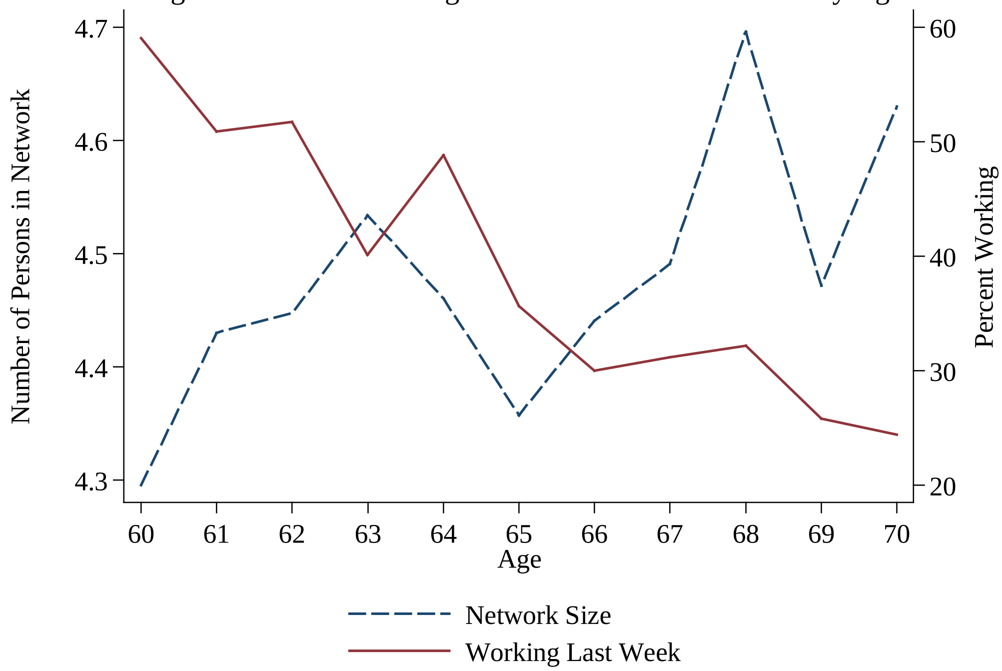
Note: Each cell in the table represents a different regression. Each cell gives the estimate of beta in equation (1.3). Elasticities are calculated at the sample means in Table 1.

Table 9. *Instrumental Variable Fixed-Effect Estimates of the Impact of Labor Supply on the Log of Network Size for Individuals Married at Baseline in 2005, Ages 57-70, Standard Errors in Parentheses, Elasticities in Square Brackets*

	(1)	(2)	(3)
Labor Supply Measure Used as the Focal Explanatory Variable	All Married	Married with Spouse's Age Not Missing	Married with Spouse's Age Not Missing
C. Worked Last Week	0.375	0.513	0.285
	(0.279)	(0.420)	(0.353)
	[0.14]	[0.21]	[0.12]
B. Hours	0.0070	0.012	0.014
	(0.0045)	(0.006)	(0.006)
	[0.09]	[0.18]	[0.21]
C. Retired	-0.154	-0.378	-0.394
	(0.133)	(0.173)	(0.169)
	[-0.09]	[-0.22]	[-0.23]
Instruments:			
Own Age Eligibility for Early and Normal Social Security Benefits	Yes	Yes	Yes
Spouse's Age Eligibility for Early and Normal Social Security Benefits	No	No	Yes

Note: Each cell in the table represents a different regression. Each cell gives the estimate of beta in equation (1.3). Elasticities are calculated at the sample means. Column 1 is based on 945 individuals who were married at baseline in 2005; Columns 2 and 3 are based on 575 individuals who were married at baseline in 2005 and had non-missing age data for their spouses and whose spouse did not die or divorce by the second wave in 2010.

Figure 1. Percent Working Last Week and Network Size by Age



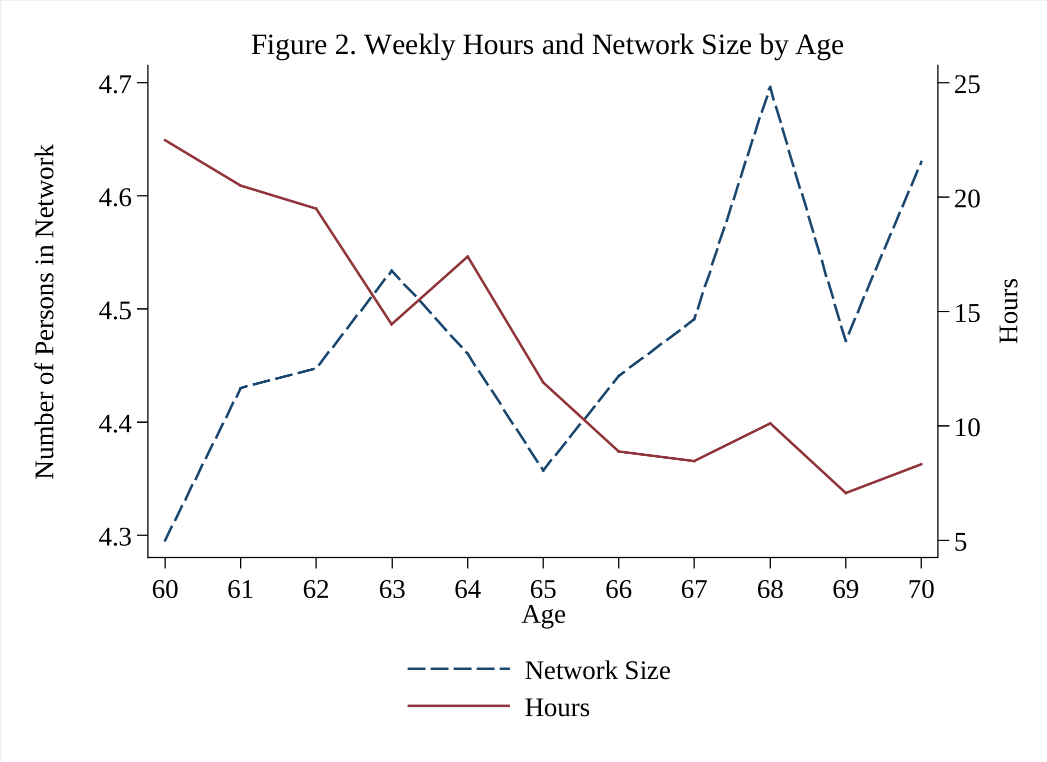


Figure 2. Weekly Hours and Network Size by Age
Number of Persons in Network
4.7
4.6
4.5
4.4
4.3
Hours
25
20
15
10
5
60
61
62
63
64
65
66
67
68
69
70
Age
Network Size
Hours

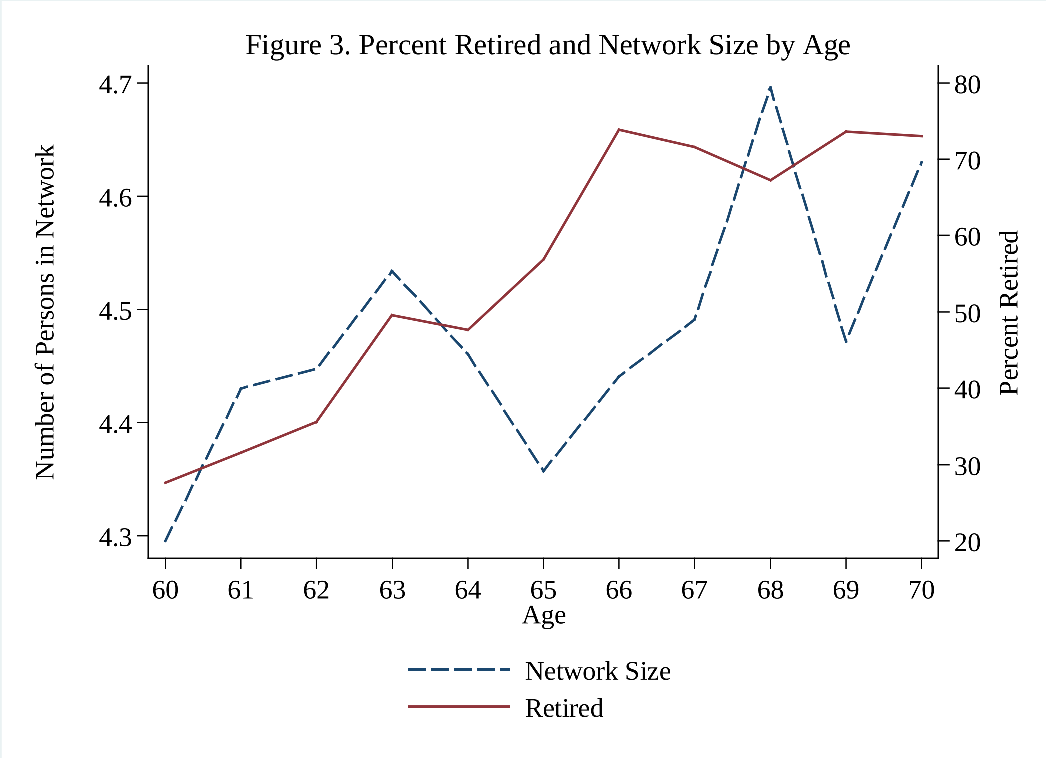


Figure 3. Percent Retired and Network Size by Age
Number of Persons in Network
4.7
4.6
4.5
4.4
4.3
Percent Retired
80
70
60
50
40
30
20
60
61
62
63
64
65
66
67
68
69
70
Age
Network Size
Retired

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